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Editorial

A research journal is a periodical that contains articles, reports, and reviews of books written by experts and researchers in a particular field of study who report the results of research in that field. The articles are intended to be read by other experts and researchers to gain fact-based knowledge, and they are typically much more sophisticated and advanced than the articles found in general magazines.

NCCS Peer-Reviewed Research Journal is a scholarly journal that incorporates articles based on research on management, administration, technology, and social issues. This research journal is published by the National College of Computer Studies (NCCS), Paknajol Marg, Kathmandu, every year on an annual basis. From this year, NCCS is going to publish “NCCS Peer-Reviewed Research Journal” regularly, which includes articles on Computer technology, management, administration, and other social and economic issues.

This fourth issue 2025 covers different articles from various disciplines of science and society, like economics, sociology, population, computer studies, management, etc. We hope this volume will contribute to generating new knowledge on management, technology, the economy, and the development processes of society, as well as the country. We would like to thank all the reviewers, like Prof. Dr. Krishna Ojha, Dr. Sunil Acharya, Prof. Dr. Madhav Prasad Dahal, Dr. Narayan Prasad Timilsena, Mr. Dadhi Ghimire, Mr. Bipin Timilsina, Ujjwal Achrya, and the authors.

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Socio-Economic Effects of Panauti Small Hydro Electricity Project on Panauti Municipality of Kavrepalanchok District of Nepal

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Abstract

There are approximately 6,000 small and large rivers in Nepal, which provide significant potential for hydropower development. Hydropower is considered one of the most important sources of energy supply for the country. The studies focus on the socio-economic impacts of the small hydroelectricity projects on local communities in the Kavrepalanchok district. Primary data were used as the main source of information, collected through a sample survey. Using a simple random sampling technique, 95 households were selected as the sample population. Descriptive statistics were applied to analyze the data. The study concludes that small hydroelectricity projects have had significant socio-economic impacts on the local people in the study area. These projects have positively influenced the lives of the sample population by increasing children's learning time and improving school education. In addition, the projects have contributed to better access to physical facilities such as safe drinking water, modern housing, improved sanitation systems, and transportation services. They have also helped enhance the pricing of agricultural products, as well as the development of industries and trade. Furthermore, small hydroelectric projects have supported improvements in income, health, and education, thereby raising the overall living standards of rural people in the project-affected areas.

Keyword: socio-economic, impact, hydro-electricity, project & small

1. Background of the Study

Although Nepal is rich in natural resources, it remains one of the poorest countries in the world. Approximately 25.4 percent of the total population lives below the poverty line (NPC Report, 2010). Hydropower projects can play a significant role in reducing poverty and improving the living standards of the Nepalese people by providing reliable and sustainable energy (AEPC, 2009). Nepal’s distinct topography—with its high hills, more than 6,000 rivers, and countless rivulets—offers immense opportunities for both large and small-scale hydropower development (Siwakoti & Bhandari, 2005).

Nepal is considered the fourth richest nation in the world and the second in Asia, after China, in terms of water capital (Dahal, 2015). According to Hydro Solution's estimates, Nepal’s total hydropower potential is around 43,000 MW, while a widely accepted figure is 83,000 MW (Karki, 1995). Nepal has over a century of experience in generating electricity from hydropower. The Pharping Hydropower Plant, with a modest capacity of 500 kW, began operation on May 22, 1911 (B.S. 1968, Jestha 9). While the rest of the world, including our neighboring countries, has made rapid advancements in power generation, Nepal's total installed hydropower capacity stood at just 3600 MW as of 2024 (NEA, 2024).

Energy plays a crucial role in everyday human life, from their household's work, such as cooking and cleaning, to superior industrial applications for space searching and nuclear power. Various sources—such as wind, fossil fuels, nuclear, solar, and hydro energy—are used to meet energy demands. Empirical studies have shown a strong correlation between energy consumption and economic growth (Acharya, 1983). Therefore, Nepal can accelerate its economic development by harnessing hydropower. By increasing productivity and replacing traditional biomass like firewood with electricity for cooking, heating, and lighting, hydropower can enhance economic welfare and reduce pollution. Furthermore, it can help the country conserve foreign exchange by lowering dependence on imported petroleum products, thus contributing to a reduction in the trade deficit (Bhattarai, 2008).

In Nepal, hydropower accounts for the largest part of the energy sources. Different countries, such as Switzerland, Canada, Norway, New Zealand, and Sweden, have successfully harnessed their water resources for energy. As water is a renewable resource with almost zero emissions, hydropower is considered an environmentally friendly energy source (Dahal, 2025). The commercial sources of energy used in Nepal include coal, petroleum products, and electricity. However, Nepal lacks domestic fossil fuel reserves, resulting in heavy reliance on costly fuel imports. Additionally, the country's challenging geography hinders the transportation and distribution of petroleum products, particularly in remote areas (WECS, 2002). Therefore, hydropower is the most suitable energy source for a country like Nepal.

For developing countries like Nepal, decentralized renewable energy sources—often promoted as tools for sustainable development—can help overcome energy access challenges. They can deliver clean electricity to remote locations that are difficult to connect to the central grid (Thompson et al., 2024). Modern innovations also allow energy generation and storage through urban water systems. Researchers have explored the use of surplus energy from water and wastewater systems for micro-hydropower (MHP). Additionally, the gravitational potential energy of stored water in high-rise buildings presents a sustainable option for distributed energy storage using micro-pumped storage (MPS) systems (Boroomandnia et al., 2022). In Nepal, micro-hydro plants producing up to 100 kW have helped supply power to isolated rural communities (Bhandari et al., 2023).

Hydropower projects are categorized based on their electricity generation capacity and project scheme. They are usually classified by size (generation capacity) and type (run-of-river, reservoir, or pumped storage).

According to the Nepal Electricity Authority, hydropower projects are classified as follows:

> -Power generation capacity 100 MW or more, feeding into a large hydropower project, 20 MW to 100 MW, almost always grid-connected is medium hydropower project, 1 MW to 20 MW, usually grid-connected small hydropower project and 100 kW to 1 MW, which may be stand-alone, connected to a mini-grid, or grid-connected is mini hydropower project (Dahal, 2024).

Though there is no commonly approved categorization for "small" and "large" hydropower projects, as definitions vary from country to country. A country's classification is often important because it determines which projects are eligible for specific support policies for either small or large hydropower development.

Panauti Hydropower Project (PHP)

The Panauti Hydropower Station is a small-scale hydroelectric project located on the Roshi Khola in Khopasi-12, Panauti Municipality, Kavrepalanchok District. It has an installed capacity of 2.4 MW and an annual energy generation capacity of 6.97 GWh. The station is situated 35 kilometers east of Kathmandu, the capital city of Nepal. The project was commissioned in 1965 with technical and financial assistance from the former Soviet Union, at a total cost of NPR 27 million. It was designed to operate with only two generating units at a time, while the third unit serves as a standby. A power canal, 3,721 meters long and capable of discharging 3.2 m^3/s, runs from the head works to the reservoir. This canal also includes seven outlet gates used for irrigation purposes in the Khopasi area (NEC, 1983).

The Government of Nepal is currently supporting the rehabilitation of this plant. Under the rehabilitation program, rewinding of stator coils, replacement of switchgear and protection systems, and mechanical repairs in Units No. 1 and 3 are underway. In addition to these works, the plant also requires refurbishment of the excitation and governing systems, as well as the replacement or repair of outdoor transformers and switchyard components.

2. Objective

The major objective of this study is to find out the socio-economic status of small hydroelectricity projects in the rural people of Nepal, with reference to Panauti Municipality of Kavrepalanchok District.

3. Research Methodology

This study used different methods to accomplish it.

3.1. Research Design

It aims to examine the socio-economic status of the respondents with the help of some determinant variables, such as electricity usage, its impact on education, savings and income, and time and other economic activities (Dahal, 2022 & 2024). The study is designed within an exploratory, descriptive, and analytical framework to evaluate the impact of a small hydropower project. Primary data were collected through a questionnaire survey using semi-structured questionnaires for information gathering (Dahal, 2022 & 2024). Data management and analysis were conducted using the

Statistical Package for the Social Sciences (SPSS) software, with descriptive statistics employed as the main analytical tool (Dahal, 2025).

3.2. Sampling design

This study analyzes the socio-economic effects of a Small Hydroelectricity Project (SHEP) on the rural population of Khopasi, Ward No. 12, Panauti Municipality, in the Kavrepalanchok District. It focuses on assessing the impact of the project on the affected communities surrounding the project area. The study adopts an exploratory, descriptive, and analytical framework to examine the socio-economic effects of the project on the local community.

3.3. Sample Size

The entire number of households in Khopasi, Panauti Municipality, constitutes the population (universe) of this research. A sample comprising approximately 10% of these households was selected using a simple random sampling technique. The total population is 950 households, and the sample size is 95 households. Information collected from the sample households was entered into the Statistical Package for the Social Sciences (SPSS) software and analyzed using descriptive statistics.

4. Result and Discussion

4.1 Energy Consumption for Lighting Purposes

Electricity and kerosene are the main sources of energy used for lighting in the project-affected area. The number of households (HHs) using electricity has increased, while the number of HHs using kerosene has decreased after the completion of the project, as shown in the following table.

Table 1.

Energy Consumption

S. No.	Sources of Energy	Before Project (%)	After Project (%)	Percentage Change
01	Electricity	86	100	+14
02	Kerosene	14	0	-14
	Total	**100**	**100**	

Source: Field Survey, 2019

Table 1 shows that only 14 percent of households used kerosene for lighting purposes, which has now dropped to zero. After the implementation of the project, the number of households using electricity increased by 14 percent, and currently, all households (100%) use electricity for lighting. It is the optimistic impacts of the project on the local community.

Electricity has contributed to changing their lifestyles and daily activities. For example, it has helped children to study in the evening and made other tasks easier. According to the local people, electricity has also contributed to forest conservation and helped control soil erosion, which otherwise worsens flood and landslide risks. As a result, the local people are happy with the Panauti Hydropower-Electricity Project, which has started generating electricity.

4.2. Effect on Drinking Water Facility

The availability of drinking water facilities for people in the sample area serves as an indicator to measure the economic impact of the hydroelectricity project. In the study area, there are mainly two sources of drinking water: supplied (piped) water and natural sources such as rivers (Khola) or wells. The impact on the drinking water sector before and after the implementation of the project is presented in the table below.

Table 2.

Drinking Water Facility in the Study Area (%)

S. No.	Sources of Water	BP)	(AP)	Percentage Change
01	Piped Supplied	54	86	+32
02	Khola/Well	46	14	-39
	Total	**100**	**100**	

Source: Field Survey, 2019

Table 2 shows that after the implementation of the project, the number of households with access to supplied drinking water increased from 54 percent to 86 percent, while the number of households using water from Khola (streams) or wells decreased from 46 percent to 14 percent. This indicates that the hydroelectricity project played a vital role in providing safe drinking water to the sampled households. The improvement is attributed to the project's financial support for purchasing GI and HDP pipes, constructing water tanks, and other necessary infrastructure for safe drinking water. As a result, some households have gained access to improved water facilities. Therefore, the project has played a positive role in the drinking water and sanitation sector.

4.3 Effect on Sanitation

Sanitation facilities are an important indicator for measuring the socio-economic effects on people in the sample area, as they also reflect the living standards of the population. From the survey conducted in the sample area, it was found that people using modern types of toilets are more aware of sanitation issues, and their living standards are relatively better. The impact of the small hydroelectricity project on the use of modern toilets as a form of improved sanitation is described below.

Table: 3

Toilet Used in Sample Area Households (%)

S. No.	Types of Toilet	Before Project	After Project	% Change
01	Pakki/Modern	36	44	+08
02	Kacchi (Deepwhole cover)	44	48	+04
03	Opened	20	08	-12
	Total	**100**	**100**	

Source: Field Survey, 2019

Table 3 indicates that the people of the study area use three different types of toilets. Among the total households of the sample area, the use of modern (permanent) toilets increased by 8 percent after the project, and the use of kachchi (temporary) toilets increased by 4 percent. Meanwhile, the number of households practicing open defecation decreased by 12 percent after the project. The project conducted various consciousness programs on sanitation and environmental conservation for households in the surrounding area. As a result, the overall number of households using toilets increased, which is a positive impact of the project.

4.4 Energy Used for Cooking Purposes

The main source of energy for cooking in the study area is firewood. However, there has been a slight change in the energy consumption pattern after the implementation of the project. The number of consumers using biogas and electricity for cooking has increased in the project area, as shown in the table below.

Table: 4

Energy Used for Cooking Purpose (%)

S. No.	Source of Energy	Before Project	After Project	Percent Change
01	Fire wood	90	74	-16
02	Bio-gas	02	12	+10
03	Kerosene	08	06	-02
04	Electricity	00	08	+08
	Total:	**100**	**100**	

Source; Field Survey, 2019

Table 4 indicate that the number of families using firewood as a source of energy for cooking has decreased by 16 percent, and the use of kerosene has also decreased by 2 percent. In contrast, the number of users of biogas and electricity has increased by 10 percent and 8 percent, respectively, after the completion of the project. Previously, no households used electricity for cooking, but now 8 percent of the 95 households use electric heaters for this purpose. This indicates that electricity and biogas have become the main alternative sources of energy for cooking in survey times.

4.5 Housing Condition in the Sample Area

In the hilly and mountainous regions of Nepal, houses are typically made of stone, mud, and wood. Most of the houses in the study area are two-storied and constructed using stone and mud. However, there are also some cemented houses in the area. The shift from traditional stone-mud-wood houses to cemented houses is another indicator used to measure the socio-economic impacts. The changes in housing conditions in the project area due to the Panauti Small Hydroelectricity Project are presented below.

Table: 5

Housing Condition in the Sample Area (%)

S. No.	Particulars	Before Project	After Project	Percentage Change
01	Kachchi (Stone)	80	68	-12
02	Pakki (Cement)	20	32	+12
	Total	**100**	**100**	

Source: Field Survey, 2019

Table 5 shows that before the project, 80 percent of the houses were kachchi (stone/mud) and 20 percent were pakki (cemented). However, after the project, the number of kachchi houses has decreased to 12 percent, while pakki houses have increased correspondingly. Following the construction of the access road, many people replaced their kachchi houses with cemented ones. As a result, the area is gradually beginning to take on an urban appearance.

Additionally, the number of local contractors has increased after the project. Therefore, the project has had a positive effect on the housing conditions of the local people in the study area.

4.6 Price of Agro Products

The most important profession of the households in the sample region is agriculture. The prices of agricultural products influence their income and living standards. After the hydroelectricity project, the market expanded due to the construction of the project's link road. The situation of agricultural product prices before and after the project is shown in the table below.

Table: 6

Agro Products Price in the Sample Area (Rs)

S. No.	Agro Products	Unit	Before Project	After Project	Change
01	Rice (Mota)	P/Pathi	65	140	+ 75
02	Maize	P/Pathi	50	100	+ 50
03	Wheat	P/Pathi	65	120	+ 55
04	Kodo	P/Pathi	35	80	+ 45
05	Tori	P/Pathi	150	250	+ 100

Source: Field Survey, 2019

Table 6 expresses that the main agricultural products in the study area are rice, maize, wheat, kodo, and tori. The table indicates that the price of each product has approximately doubled over the past five years. The project has had a direct impact on the prices of agricultural products.

During and after the construction of the Panauti Small Hydroelectric Project (PSHP), many people lost interest in agriculture as they found alternative sources of income, such as jobs and small businesses. Some individuals even changed their profession from agriculturists to contractors after the project. Additionally, the loss of cultivable land due to the project contributed to the rise in agricultural product prices.

4.7 Meat Products Price

Milk and meat production are supplementary occupations to agriculture for the people in the sample area. Specifically, local people raise various animals and birds for meat.

The hydroelectric project has affected the prices of these meat products, which has helped increase the income of the local people in the sample area. The prices of meat products in the study area before and after the project are shown in the table below.

Table: 7

Meat Product of the Sample Area (Rs)

S. No.	Meat Products	Unit	Price (BP)	Price (AP)	Change
01	Goat	P/Dharni	500	800	+ 300 (60%)
02	Chicken (Local)	P/Kg.	250	400	+ 150 (60%)
03	Buffalo	P/Dharni	300	500	+ 200 (67%)
04	Pigs	P/Dharni	300	500	+ 200 (67%)
05	Chicken (Boiler)	P/Kg	150	250	+100 (67%)

Source: Field Survey, 2019

Table 7 presents that the prices of goat, local chicken, broiler chicken, buffalo, and pig meat have increased by approximately 65 percent after the project. In the study area, the unit of measurement for goat, buffalo, and pig meat is Dharni, while for other types of meat, it is measured in kilograms. People's interest in animal husbandry has increased, as dairy products now provide them with better returns. This indicates that the hydroelectric project has had a positive effect on the income and living standards of the people in the sample area.

4.8 Effect on Cottage and Small Industries

Changes in cottage and small industries such as water mills, rice mills, bakeries, furniture making, tailoring, gold-smithing, and blacksmithing are important indicators to measure the socio-economic effects of the project. The following table represents the situation of these industries before and after the Panauti Hydroelectricity Project.

Table: 8

Industrial Status of the Sample Area

S. No.	Type of Industries	Before Project	After Project	Change
01	Water Mills (Ghattas)	10	04	-06
02	Rice Mills	01	03	+02
03	Bakery	01	02	+01
04	Furniture	02	04	+02
05	Tailoring	05	08	+03
06	Goldsmith	01	01	No change
07	Blacksmith	01	01	No change

Source: Field Survey, 2019

Table 8 expresses the development of the industrial sector in the PHEP area due to the hydroelectricity project. Except for water mills (Ghattas), other industries such as rice mills, bakeries, furniture making, and tailoring have increased in the sample area. After the project, six out of ten Ghattas have closed due to the hydro project. The remaining four Ghattas operate only during the months of Asadh, Shrawan, Bhadra, and Aswin.

Thus, the project has had a negative impact on Ghattas. However, other industries like rice mills, bakeries, and furniture workshops have benefited positively from the project. The table indicates that the PHEP has had a positive effect on increasing industries in the surrounding area, which has, in turn, created employment opportunities and improved the income and living standards of the local people.

5. Conclusion

The Small Hydroelectricity Project is very important in terms of investment, construction capital, and the technology used. Nepalese technology and capital are sufficient for implementing such projects. This research is based on the Panauti Small Hydroelectricity Project, located in Panauti Municipality of Kavrepalanchok District, Nepal.

With more than 6,000 small and large rivers in Nepal, there is vast potential for constructing many small hydroelectricity plants. However, all small hydroelectric projects do not have the same socio-economic impact on the people living in the surrounding areas. This study analyzes the socio-economic impact of the Panauti Small Hydroelectricity Project and compares its results with those of other similar projects.

The main objective of this research was to study the socioeconomic impact of the Panauti Small Hydroelectricity Project on the local population. As suggested in the summary above, the local people have gained much more than they have lost from the project. After the completion of the project, all the sampled households started using electricity for lighting in their daily lives. This made their lives more comfortable, helped extend the learning hours for children, and improved school education.

The project has had a positive socio-economic impact on the sample area by providing safe drinking water, improving sanitation, and introducing modern toilet systems. Similarly, the project contributed to market expansion through the construction of link roads. These roads facilitated the transportation of agricultural products and supported the growth of small and cottage industries, thereby creating employment and self-employment opportunities.

Furthermore, the link roads improved transportation facilities, giving local people better access to higher education and health services. The Panauti Small Hydroelectricity Project has played a vital role in increasing income, improving living standards, raising awareness, and enhancing access to health and education facilities, transportation, market expansion, agro-based production, trade, and industries in the study area. These are the positive socioeconomic impacts of the project.

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Impact of Social Media on Teenage Girls of Nepal

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Abstract

Social media encompasses internet-based platforms that facilitate the formation of online communities and networks, enabling the real-time exchange of information, ideas, and perspectives. Through electronic content, including text, images, audio, and video, users interact and communicate via web-based applications on devices such as smartphones, tablets, and computers (Dollarhide, 2019). With platforms catering to both global and region-specific audiences, the scope of social media continues to expand. According to Chand and Zuckerman (2021), there are more than 500 social media sites worldwide, with 39 of the top 100 originating in the United States. Globally, social media is becoming an increasingly primary source of information (Newman, 2025). From an anthropological standpoint, it also plays a vital cultural role in the construction, deconstruction, and transmission of culture, from local traditions to global narratives and across generations. This study examines the impact of social media on teenage girls in Nepal, with a specific focus on a sample of 120 females aged 13 to 19 from Tarakeshwor Municipality, located in Kathmandu. The findings show that while a majority of participants perceive social media as a positive influence in their lives, nearly 70% reported encounters with fake profiles, and approximately 30% experienced some form of blackmail. These insights highlight the nature of social media: its potential to empower and connect, but also to expose users to harmful and predatory behavior, underscoring the urgent need for targeted interventions to safeguard vulnerable groups.

Keywords: *Social media, teenage females, cyber harassment, anthropology of social media, Nepal*

1. Introduction: Anthropological Study of Mass Media

The anthropological study of mass media began in the United States and Europe during the post–World War II period. Mass media were referenced in Benedict's (1946) analysis of Japanese popular culture, while U.S. anthropologists, such as Bateson (1942), explored topics like film and national character, and Mead (1964) analyzed cross-cultural media communication. Although these pioneers investigated media phenomena, their focus tended to be peripheral, using media as a means to explore broader societal issues. An exception was Powdermaker's (1950) ethnography of Hollywood, which received special attention for its concentrated examination of media production (Pardo, ErkenBrack, & Jackson, 2012).

Meanwhile, Sapir and Whorf contributed significantly to linguistic anthropology. Sapir (1985) argued that all social behavior is fundamentally communicative, involving symbolic acts such as gestures, imitation, and social suggestion, which are essential to maintaining social cohesion. Sapir emphasized that specific technologies often mediate these forms of communication.

In the anthropological framework, culture is essential for human continuity—transmitted not through mere movement, but across time. Culture is memory. Culture is heritage. According to Osorio (2001), media serve as a mechanism for cultural transmission, intertwining memory, time, and identity. Mass media anthropologists study the processes by which media represent and reconfigure identity (e.g., gender, ethnicity, nationhood), often using symbolic rather than discursive tools (Coman, 2005). Today, media are no longer just outlets for representation—they are dynamic, interactive spaces that produce, challenge, and redistribute culture. Anthropologists now investigate not just "media content" but also media production, reception, and use across digital spaces. Scholarly attention increasingly turns to the impact of mass communication on identity construction, community formation, and cultural circulation (Pardo et al., 2012).

2. Study Area and Sources of Data

This study focuses on Tarakeshwor Municipality Wards no. 8, 9, and 11 in Kathmandu, Nepal. The area was selected due to its accessibility, diverse social makeup, and increasing internet penetration. A mixed-method approach was used, combining a structured interview schedule with in-depth interviews. The sample includes 120 female teenagers aged 13 to 20 from educational institutions, college, and the workforce.

3. Mass Media: Global to Local Context

Mass media includes print, electronic, and digital forms, offering users tools for communication, networking, and self-representation (Editorial Office, 2024). Globally, digital media, especially social media, has overtaken traditional forms of news and communication. Kemp (2024) reports that over 62.6% of the global population uses social media, with users spending an average of 2 hours and 20 minutes daily (Chaffey, 2025). Globally, social media is increasingly becoming the primary source of information (Newman, 2025).

Table 1:

Global and Local Social Media

Social media	**Global (Global Social Media Statistics, 2025)**	**Nepal (Kemp, 2024 February 23: Nepal)**
Facebook	3.07 billion	17 million (51.8% of the Total population)

YouTube	2.53 billion	0.85% of the total population
Instagram	2.00 billion	3.60 million
WhatsApp	2.00 billion	-
TikTok	1.59 billion	2.2 million (before ban)
WeChat	1.38 billion	-
Messenger	970 million	10.85 million
Snapchat	850 million	-
X	586 million	466.1 thousand
LinkedIn	1 billion	1.50 million

Source: Digital 2024 Global Overview Report

In the last decade, the swift rise of social networking platforms such as Facebook, Twitter, Instagram, and others has brought about notable shifts in the ways individuals connect and communicate. Currently, more than one billion people are active on Facebook, the largest social networking platform, and this figure is expected to increase significantly over time, particularly in developing nations. Facebook fulfills both personal and professional roles, leading to various benefits in connectivity, the sharing of ideas, and online learning. Additionally, the total number of social media users worldwide in 2019 reached 3.484 billion, marking a 9% year-on-year growth (Khalaf, Alubied, Khalaf, et al., August 05, 2023). Similarly, Last ten years, social media users in the world have significantly increased. The Pew Research Center published a report in 2015, which mentioned that 71% of individuals aged 13 to 17 were using Facebook, 52% were on Instagram, and 41% engaged with Snapchat. Furthermore, teenage girls are engaging more often with image-centric social media platforms than boys; 61% of girls utilize Instagram compared to 44% of boys. This rise in social media engagement, especially on Facebook and Instagram, may have adverse effects on the self-esteem and body image satisfaction of adolescent girls and young women (Lenhart, 2015). This data indicates the use of social media by teenage girls and boys around the globe.

While a significant segment of Nepal's population falls beneath the poverty line, a household survey carried out in 26 districts in 2070 BS indicates that 40% of people live in poverty (Gyanwali, 2020). However, a growing number of citizens are recognizing the benefits of the Internet, leading to substantial improvements in Internet accessibility throughout Nepal. Over the past five years, the rate of internet penetration in Nepal has improved by seven percentage points each year. As reported by the Nepal Telecom Authority, 2.25 million individuals connected to the internet in 2017, averaging about 250 new users every hour. The rise in internet adoption in Nepal is fueled by the growing influence of social media and online communication channels, a surge in mobile phone connections and smartphone usage, as well as a rise in various applications, including entertainment, music streaming, and online shopping. This access to digital facilities also promotes digital journalistic media. Registration of 66% of the total national number of mass media in Bagmati Province (Dhungel, 2020) is an indicator of the concentration of access to digital platforms. The surging interest in social media significantly contributes to the increasing internet usage in Nepal. In South Asia, Nepal ranks just behind Bhutan in terms of social media user penetration. As of 2025, 49.6% of Nepal's population had access to the internet (Kemp, 2024). Facebook remains the dominant platform with over 95% market share among Nepali social media users (StatCounter, 2025). A significant number of users reside in Kathmandu Valley, highlighting urban digital centrality (Acharya, 2021).

Table 2:

Distribution of Social Media Users in Nepal

Date	*Facebook* (%)	X (%)	*YouTube* (%)	*Instagram* (%)	*LinkedIn* (%)
2024-03	93.09	4.92	1.32	0.37	0.14
2025-01	91.34	5.59	2.03	0.43	0.4
2025-02	95.53	2.96	0.75	0.36	0.22
2025-03	95.14	3.42	0.76	0.33	0.19

Source: Stat Counter, 2025

Drawing from Acharya's (2022) survey, social media use has become deeply embedded in the everyday experiences of Nepali people, shaping both social interaction and patterns of communication. According to the Center for Media Research, Nepal, the survey covered 403 respondents from 63 districts, revealing that a large majority—over 92%—turn to social media to pass the time and access news and information. Similarly, above 90% engage with these platforms to connect with friends, and nearly 88% use them to express personal feelings and opinions. Platforms such as Facebook and Twitter remain particularly popular, with most participants maintaining accounts on both, typically accessed through mobile devices. Multiplicity of accounts, including many anonymous profiles, was a distinct feature among younger users. Acharya's findings further show that for much of Nepali society, social media now functions not only as a tool for communication and self-expression but also as an engine for social and political transformation. At the same time, concerns about misinformation and the platform's influence on public attitudes are growing, highlighting the complex role of social media in contemporary Nepal.

These trends illustrate the influence of global digital infrastructures on local identities, behavior, and social interaction. Social media has not only introduced new communication forms but also reshaped how culture and gender intersect in real-time.

4. Socio-Demographic Characteristics of Respondents

4.1 Age Group of Respondents

Younger generations tend to prefer engaging with newer and different forms of communication rather than traditional methods. This trend is a global occurrence and is not limited to Nepal. The age demographic of the respondents is significant in this study. The age distribution of the respondents is shown in the following table.

Table 3:

Distribution of the Respondents by Age

Age Group	Number of Respondents	Percentage
12-14	8	6.67
15-16	36	30
17-18	52	43.33
19-20	24	20
Total	**120**	**100**

Source: Field Study, 2024.

Table 3 displays the ages of the respondents. The average age of participants was 17.03 years. Among all respondents, 6.67% belonged to the 12–14 age group. The 15–16 age category comprised 30% of respondents. Around 43.33% of respondents were in the 17–18 age group, while 20% were from the 19–20 age group. The majority of respondents were from the 17–18 age range, who are +2 students studying in different higher secondary schools. Regardless of age, all respondents were female students who fell within the teenage category. As shown, most respondents (43.33%) are aged 17–18, aligning with higher secondary schooling. The mean age is 17.03 years, indicating that the sample represents the teenage population effectively.

4.2 Educational Level

Social media and the use of social media in daily activities are also aspects of education. Due to modern technology, today's education system is increasingly guided by smart learning. Since education is considered the backbone of any country, the level of education determines the delivery of knowledge and its utility. The main educational levels of respondents are categorized into two groups: school-level education and higher education. According to the education system of Nepal, "illiterate" refers to individuals unable to read and write their name; "school level" refers to those who can read and write their name and are enrolled in school, specifically at the primary and secondary levels. It is now categorized as primary (classes 1–8), secondary (classes 9–12), and higher education (bachelor's to master's level). The following table shows the education levels of the respondents.

Table 4:

Distribution of Respondents According to their Education

Level of Education	**Number of Respondents**	**Percent**
Primary Level (class 1-8)	8	6.67
Secondary Level (class 9-12)	60	50
Higher education (Bachelor +)	52	43.33
Total	**120**	**100**

Source: Field Study, 2024.

Table 4 shows that most respondents were literate, with 50% belonging to the secondary education level. Secondary-level respondents are those students who have completed primary education. 6.67% of respondents were at the primary level, and 43.33% were at the higher education level. This data indicates that secondary-level students are mostly involved in social media.

4.3 Caste and Ethnic Composition

Social, religious, cultural, and geographical diversity, along with variations in caste and ethnicity, are significant features of the context of Nepal. Caste and ethnic groups are crucial social classifications within Nepali society, influencing lifestyle, professional status, living standards, educational attainment, and various other aspects of society. The caste and ethnic groups of respondents are shown in the following table.

Table 5:

Distribution of Respondents According to the Caste/Ethnicity

Caste/Ethnicity	**Respondents**	**Percentage**
Brahman	28	23.33
Kshatri	48	40
Ethnic groups	24	20
Dalit	20	16.67
Total	**120**	**100**

Source: Field Study, 2024

The Kathmandu district serves as a hub for various castes and ethnicities. Similarly, Tarakeshwor Municipality Ward No. 8 reflects this diversity found throughout the Kathmandu district. The table presented indicates that 23.33% of the respondents identified as Brahman, while 40% were Chhetri. Additionally, 20% and 16.67% of respondents were from ethnic groups and Dalit communities, respectively. The ethnic group primarily consists of individuals from the Matawali community, and Dalit individuals are often categorized as members of the untouchables in Nepalese society. Among these groups, 40% of Chhetri individuals engage with social media, the highest percentage compared to the rest.

4.4 Duration of Social Media Experience

Social media has become an integral part of life for people in general, and teenage students in particular. The time span from when respondents first opened their social media accounts to the date of the interview is considered the duration of social media use. Students reported varying durations of use, as shown in the table below.

Table 6:

Duration of Using Social Media

Duration	**Respondents**	**Percent**
For a month	8	6.67
For one year	28	23.33
For more than a year	84	70
Total	120	100

Source: Field Study, 2024

Table 6 shows that 70% of the respondents have been utilizing social media for over a year. Additionally, 6.67% have started using it within the last month, while 23.33% indicated usage for approximately one year. Based on this data, we can conclude that a significant proportion of teenage students in this area have been active on social media for over a year, suggesting long-term engagement with digital platforms.

5. Results and Discussion

5.1 Purpose of Social Media Use

The use and purpose of social media vary depending on the youth's time, situation, and circumstances. Young people use social media for different purposes, as reported in the table below.

Table 7:

Purpose of Use of Social Media

Purpose	**Number of Respondents**	**Percent**
Entertainment/Chat	72	60
Time pass	20	16.67
For knowledge	28	23.33
Total	120	100.0

Source: Field Study, 2024

The table indicates that 60 percent of participants use social media for entertainment or chatting. Meanwhile, 16.67% reported using it to pass the time, and 23.33% use it for gaining knowledge. This data shows that, primarily, social media serves as a source of amusement or a way to pass the time. Only a smaller portion uses it in an intentional, educational manner. Notably, no respondents reported using platforms like Gmail for communication. One X (formerly Twitter) user mentioned that the platform helps them access academic knowledge, while the majority described their use as casual and social. Most respondents talked about social media as a space to connect with friends and enjoy shared content, whereas only a minority viewed it as a tool for knowledge production. Social media platforms allow users to create profiles, upload photos and videos, send messages, and keep in touch with friends, family, and colleagues. The research shows that 60% of social media users spend most of their time chatting. Respondents reported using the platform for news and information (20%) and photo/status uploads (16.67%) in nearly equal numbers, while only 3.33% use it for practical apps like e-banking or accessing e-books. This suggests that among teenagers, the chat feature is the most frequently used functionality on social media platforms. As seen in Table 7, most respondents (60%) use social media for entertainment and chatting. Only 23.33% use it for knowledge or education, indicating its primary use as a recreational tool.

5.2 Types of Social Media Used

In today's digital world, a wide range of social media platforms is available. Each serves specific purposes and user needs. Academics and professionals frequently utilize email and LinkedIn, whereas younger people tend to favor platforms such as YouTube, Instagram, and X. The wider public generally exhibits a greater usage of Facebook.

Table 8:

Types of Social Media (multiple answers)

Types	Frequency	Percentage
Facebook/Messenger	92	76.67
Viber	12	10
X	4	3.33
WhatsApp	12	10

FB/Messenger and Viber	12	10
FB/Messenger, Viber, and WhatsApp	28	23.33

Source: Field Study, 2024

According to the study, 76.67% of respondents reported using Facebook or Messenger as their primary social media platform. Only 10% were using Viber, and another 10% were using WhatsApp. X was used by 3.33% of respondents. In addition, 10% used both Facebook/Messenger and Viber, while 23.33% of total respondents used a combination of Facebook/Messenger, Viber, and WhatsApp. Interestingly, the results show that rural girls are generally less likely to use platforms like X.

5.3 Common Features Used

Chatting (60%) is the most-used feature, followed by news access and photo/status sharing (Table 8). Very few respondents use social media for banking or educational tools, despite the platforms' capabilities.

Table 8:

Features of Social Media

Feature	**Frequency**	**Percent**
News and Information	24	20
Photo/Status upload	20	16.67
Chat	72	60
e-banking and e-book	4	3.33
Total	120	100

Source: Field Study, 2024

5.4 Social Media and Abuse

Today, social media is used not only for entertainment and educational purposes but also for harmful activities such as sexual harassment, hacking, and cybercrimes. The following table outlines the types of social media abuse experienced by teenage girls.

Table 10:

Abuses Faced by Respondents

Abuses	**Frequency**	**Percentage**
Harassment	28	23.33
Domination	64	53.33
Love Propose	20	16.67
Bad Comments	8	6.67
Total	120	100

Source: Field Visit, 2024

According to the findings, 23.33% of respondents reported experiencing harassment. The majority (53.33%) said they had been dominated by male colleagues during social media interactions. Additionally, 16.67% of respondents received romantic proposals—often with implications of marriage—through social media. Another 6.67% were victims of inappropriate or offensive comments posted on their statuses or photos. These results suggest that many teenage girls face issues such as domination, harassment, and unsolicited romantic advances in digital spaces.

Teenage students may also misuse social media for immoral purposes, including the use of inappropriate language, threats, and unethical hacking. These behaviors contribute to broader social problems such as sexual harassment, substance abuse, performative lifestyles, impulsive elopements, feelings of frustration, and in extreme cases, suicide.

Table 11:

Respondents' Perception of the Abuse of Social Media

Problems of social media	Respondents	Percentage
Black mailing	38	31.66
Fake account	82	68.34
Total	120	100

Source: Field Study, 2024

Further analysis reveals that fake accounts are a significant issue in the study area. Data shows that 68.34% of participants have encountered fake accounts, and 31.66% have experienced blackmail. These figures underline how social media can pose serious risks for teenage girls—even as new laws and security policies are introduced. This persistence of misbehavior shows that for many adolescents, social media remains a vulnerable space, often exploited for illegal and damaging activities.

5.5 Language in Social Media

English has become the dominant language in global academic and digital communication, comprising 75% of editorial teams and 70% of authorship in key journals. However, contributions from low-income countries remain minimal (Andersen & Hellman, 2021). In the study area, most respondents prefer using Roman Nepali on social media. Roman Nepali refers to the use of the English alphabet to write in the Nepali language.

Table 12:

Distribution of Respondents According to Language in Social Media

Languages	Frequency	Percentage
Roman Nepali	96	80
Pure Nepali	8	6.67
Pure English	16	13.33
Total	120	100

Source: Field Study, 2024

The findings show that 80% of respondents primarily use Roman Nepali. Meanwhile, 6.67% reported using only the Nepali language, and 13.33% use pure English to communicate on social media. Those using English generally come from English-speaking households or have studied in private schools. Similarly, respondents from more educated family backgrounds showed a higher likelihood of using English.

Most respondents prefer Roman Nepali (Table 12). This hybridized digital communication style blends global form with local meaning. Romanized scripts serve as a linguistic bridge for Nepali youth in digital spaces (Androutsopoulos, 2015).

5.6 Impacts of Social Media

Every phenomenon has two sides—positive and negative—and social media is no exception. With increasing digital connectivity, social media has become deeply embedded in the everyday lives of people, especially teenagers. Many people use it for business activities, learning opportunities, accessing news, and staying connected. At the same time, it is also a space filled with privacy risks, cyberbullying, digital addiction, disinformation, and morally questionable content. Unethical hacking, online scams, fraud, and emotional distress are part of the growing problems associated with social media use. When examining education, social media plays a pivotal role—from early years to higher education—by facilitating learning, sharing resources, and promoting engagement. Positive effects also include global connections, marketing opportunities, stress relief, and awareness-building. However, negatives such as violent content, intrusive ads, superficial relationships, time wastage, and exposure to harmful themes are equally significant—particularly for teenagers whose mental health is still developing.

There is extensive research on the impacts of social media on teenagers. A report published by Common Sense Media (2022) regarding the impact of social media on teenagers found that nearly half of the 1,500 adolescents surveyed indicated that social media plays a significant role in providing support and advice, reducing feelings of loneliness, fostering creativity, and maintaining connections with friends and family. Additionally, 43 percent mentioned that engaging with social media helps alleviate feelings of depression, stress, or anxiety. One-third of teenagers experiencing depression reported frequent social media usage, in contrast to 18 percent of those without depressive symptoms. Another study carried out by University College London monitored the social media habits of 13,000 adolescents over a period of three years, beginning when they turned 13. The teenagers also provided self-reports on their social media experiences alongside their emotional states and overall well-being. The findings highlighted three primary consequences for teenagers: insufficient sleep, encounters with cyberbullying, and reduced physical activity. Consequently, these factors led to missed opportunities for the positive effects that exercise can have on both mental and physical health. (Rideout, Peebles, Mann, & Robb, 2022). There are different types of impacts of social media on teenage girls. The following two are explained here.

5.6.1 Cyberbullying

According to McAfee (August 2022), cyberbullying is defined as bullying that occurs through digital devices such as cell phones, computers, and tablets. It encompasses the act of sending, posting, or sharing negative, harmful, untrue, or hurtful content about another person. This behavior can manifest across various social media platforms. Facebook reports the highest prevalence of cyberbullying among children, with 53% having witnessed it and 50% having experienced it, while Instagram follows with 40% witnessing and 30% experiencing. YouTube has 31% witnessing and 27% experiencing, TikTok has 30% witnessing and 23% experiencing, and Twitter shows 20% witnessing and 18% experiencing cyberbullying on a global scale.

Cyberbullying leads to emotional distress and can worsen the symptoms of anxiety, depression, and feelings of isolation among teenagers. According to the Pew Research Center (2022), 46 percent of teenagers in the US, aged 13 to 17, have faced bullying or harassment online. The report indicated that 54% of girls between the ages of 15 and 17 have encountered at least one of six types of cyberbullying, whereas 44% of boys aged 15 to 17 and 41% of boys and girls aged 13 to 14 have experienced similar situations (Newport Academy, 2025). Sam Cook (2024), in "Cyberbullying data, facts and statistics for 2018 – 2024," stated that 60 percent of parents with children aged 14 to 18 reported their kids being bullied in 2019, with 59.9% falling within the 14-18 age range and 56.4% in the 11-13 age group (Bischoff, 2022). Of those bullied, 82.8% reported being targeted at school, 32.5% on the bus, 19.2% on social media platforms, 11% via text messages, and 7.9% through online video games (Bischoff in Comparitech, 2022). Furthermore, a study by the United Nations Children's Fund (UNICEF) discovered that 19.7% of college students had engaged in cyberbullying at least once during their lifetime, while 54.4% reported having experienced it at least once (Ozden and Icellioglu, 2014).

5.6.2 Positive and Negative Impacts of Social Media

Social media offers both benefits and harm. Positively, it enables access to information, connection, peer learning, and psychological support (Boyd, 2014). Negatively, it enables trolling, misinformation, addiction, and identity-based violence.

Table 13:

Impacts of Social Media

Positive aspects of social media	**Negative aspects of social media**
Staying Connected	Distraction and Loss of Productivity
Access to News and Current Events	Spread of Misinformation
Platform for Personal Branding	Compromise Privacy and Data Vulnerabilities
Business and Marketing Opportunity	Promotes Superficial Connections
Convenience and Ease of Access	Social Media Addiction
Fosters Innovation and Learning	Enables Bullying and Harassment
Provides Entertainment	Promotes Social Isolation
Platform for Societal Change	Causes Depression and Anxiety
Promotes Skill Development	Promotes Obsessive Self-Presentation
Supplement to Education	Helps Spread Scams and Frauds

Source: Raghavan, 2024

According to field data, 76.67% of participants perceived social media as a positive influence in their day-to-day lives. They reported benefits such as increased knowledge, better communication, and broader social awareness. On the other hand, 23.33% described its consequences as negative, citing time-wasting, sexual abuse, emotional distress, depression, and cybercrime. These results show that social media is both a beneficial and troubling force—its impact depends largely on intent, usage habits, and user awareness. The data show that 76.67% of girls see its advantages, but a significant 23.33% associate it with various harms—highlighting its dual nature (Table 14). Especially worrying is how such spaces become zones of performative pressure, often leading to deteriorated self-esteem among teens (O'Reilly et al., 2018).

Table 14:

Distribution of Respondents about the Impact of Social Media

Impacts	Descriptions	Frequency	Percentage
Positive	Health/quality of life	48	40
	Education/sharing of knowledge and information	44	36.67
Negative	Wasting time	8	6.67
	Victims of wrong users	20	16.67
	Total	120	100

Source: Field Visit, 2024

6. Conclusion

Social media has become one of the most widely used and deeply embedded forms of communication in contemporary life, extending far beyond casual conversation to shape daily practices of expression, education, identity, and social interaction. It operates through a complex system of electronic texts, images, videos, and sounds that allow users to engage with content across mobile devices, computers, and internet-based platforms. This interactivity, combined with immediate access and global reach, has made social media central not only to personal communication but also to education, entertainment, marketing, and civic engagement. Its technological framework affects both the quantity and quality of information available and the speed at which it is accessed and shared.

In the context of Nepal, and specifically among teenage girls in Tarakeshwor Municipality, social media plays a powerful yet contradictory role. Data from the field show that 60% of the respondents use social media primarily for entertainment and chatting, 16.67% to pass the time, and only 23.33% for seeking or sharing knowledge. This highlights that while social media holds educational potential, its usage among teenagers is largely recreational. However, the study also reveals notable benefits: approximately 76.67% of teenage girls consider social media to be a positive influence in their lives, often using it to stay informed, connected, and engaged with peers.

At the same time, social media presents serious risks. A significant portion (23.33%) reported experiences of harassment, including verbal abuse, unwanted advances, and negative comments. More than half of these incidents were perpetrated by male peers, underlining the persistence of gendered power dynamics in digital spaces. Additionally, 68.34% of respondents had encountered fake accounts and 31.66% had been victims of blackmail—exposing how online platforms can become fertile ground for exploitation, misinformation, and emotional manipulation.

From an anthropological perspective, social media serves as both a tool and a site of cultural production, reproducing norms, shaping identities, and mediating behavioral change. It reflects and reinforces social structures such as caste, education, ethnicity, and gender. Interactions on platforms like Facebook, through likes, friend counts, and comments, affect how teenage users perceive themselves and others, with measurable effects on self-esteem, social belonging, and emotional well-being.

This study affirms that social media is a double-edged space: it empowers, connects, and entertains, but it can also isolate, manipulate, and harm. For teenage girls navigating educational, social, and emotional transitions, the digital world mirrors real-world tensions, offering opportunities for growth along with exposure to risk. These findings underscore the urgency for digital literacy initiatives, gender-sensitive cyber safety policies, and ongoing community engagement to ensure that the digital future is inclusive, safe, and empowering for all.

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Stock Prediction Based on Transformer Model

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Abstract

Stock price forecasting is a critical tool for investors and traders to manage risks and make informed financial decisions in volatile markets. Traditional models often struggle with the non-linear and unpredictable nature of stock prices, leading to the adoption of advanced deep-learning techniques. In this study, we propose a LASSO-regularized Transformer model for stock price prediction, focusing on the encoder component to capture long-term dependencies in historical stock data. We evaluate the model's performance using MAPE across five Nepalese commercial banks and analyze the impact of different look-back periods on prediction accuracy. Our results show that the LASSO-Transformer achieves low MAPE values, with the best performance observed for shorter look-back periods (2-5 days). The model demonstrates robustness across different stocks, with the lowest MAPE of 1.4140% for SCB. This study highlights the effectiveness of combining feature selection (LASSO) with self-attention mechanisms (Transformer) for accurate stock price forecasting, offering practical insights for future applications in financial markets.

Keywords: stock price prediction, transformer model, lasso regularization, look-back period

1. Introduction: Stock Prediction Based on Transformer Model

Stock price forecasting is vital for making wise financial decisions and helping investors and traders manage risks in unpredictable markets. Accurate predictions can improve investment strategies and economic stability. However, forecasting is challenging because many factors like economic trends, global events, and investor behaviors influence stock prices (Fama, 1970). Traditional statistical methods, such as ARIMA, are helpful but often struggle to capture the complex, non-linear patterns of the stock market (Box, 1976) (Shiller, 1981). This has led to the use of advanced techniques like deep learning, which can improve accuracy and provide better insights into market trends (Fischer, 2018).

Deep learning models have become popular tools for predicting stock prices in recent years. Models like LSTM and GRU have performed well in understanding patterns and relationships in time-series data (Hochreiter, 1997). However, these models have their drawbacks, such as difficulty with long-term dependencies, a tendency to overfit, and a lack of interpretability, which is essential for making financial decisions (Fischer, 2018). To overcome these issues, researchers have looked into more advanced models like Transformers, which use self-attention mechanisms to capture long-term dependencies better (A. Vaswani, 2017).

Even though Transformer models have been successful in NLP, they haven't been widely used for stock price forecasting, especially when combined with regularization methods like LASSO. LASSO is helpful because it helps prevent overfitting and improves model interpretability by encouraging simplicity in the model's coefficients (Tibshirani, 1996). Combining LASSO with Transformer models is a promising way to enhance the accuracy and understanding of stock price predictions.

In this study, we propose a new approach by integrating LASSO regularization into a Transformer model for forecasting stock prices. We focus on using only the encoder part of the Transformer architecture to predict the next day's closing price. Unlike the standard Transformer, which uses both an encoder and a decoder for sequence-to-sequence tasks, our approach takes advantage of the encoder's ability to identify meaningful patterns and dependencies from past stock price data. The encoder's self-attention mechanism helps the model concentrate on the most relevant parts of the input sequence, making it ideal for time-series forecasting. Additionally, we perform a novel analysis of the Look-back period used with the Transformer model.

2. Literature Review/ Related Works

Stock price forecasting has come a long way, evolving from traditional statistical methods to advanced deep-learning models. Early methods, like the ARIMA, worked well for capturing linear patterns but struggled to handle the non-linear and unpredictable nature of financial markets (Box, 1976). With the rise of deep learning, models like LSTM and GRUs became popular for predicting stock prices. For example, (Hochreiter, 1997) Found that LSTMs performed better than traditional methods due to their ability to capture non-linear relationships in data. Similarly, (Junyoung Chung, 2014) showed that GRUs, with simpler structures, performed similarly to LSTMs but were more efficient. However, these models are often criticized for being hard to interpret and prone to overfitting, especially when working with large, complex datasets (Fischer, 2018).

To address these issues, researchers have explored regularization techniques like LASSO (L1 regularization) and L2 regularization. For instance, (Saud, 2021) showed that adjusting the L2 regularization hyperparameters could significantly improve stock price predictions. Additionally, (Gao, 2021) optimized LSTM and GRU models for stock forecasting, emphasizing the role of hyperparameter tuning in enhancing performance. These studies highlight the potential benefits of combining deep learning models with regularization techniques to boost forecasting accuracy and interpretability.

Recently, Transformer models have gained attention due to their ability to capture long-term dependencies more effectively than traditional recurrent models. By using self-attention mechanisms, Transformers can focus on the most relevant parts of the data, making them a good fit for time-series forecasting tasks (A. Vaswani, 2017). For example, (Tashreef Muhammad, 2023) proposed a Transformer-based model for stock prediction in the Bangladesh stock market, demonstrating its ability to handle complex market dynamics. However, using Transformers for stock price forecasting, especially in combination with LASSO regularization, remains relatively unexplored. This presents a unique opportunity to improve stock forecasting accuracy and interpretability.

This study aims to fill this gap by proposing a LASSO-regularized Transformer model for stock price prediction. We analyze the optimal look-back period for the Transformer to achieve the lowest MAPE, providing practical insights into the best configuration for stock price forecasting tasks.

3. Methodology

This section describes data collection, feature engineering and selection, data preprocessing, model implementation, training and optimization, performance evaluation, and experimental setup.

Data Collection

This research used historical stock data from NEPSE. We collected daily trading data for five major commercial banks from October 20, 2019, to October 7, 2024. The selected banks were: Citizens Bank International Limited (CZBIL), Everest Bank Limited (EBL), Sanima Bank Limited (SANIMA), Nepal SBI Bank Limited (SBL) and Standard Chartered Bank (SCB). These institutions represent some of the most actively traded stocks on NEPSE.

We collected the historical stock data using Nepal Paisa's API, which provided structured daily records containing:

- Opening, high, low, and closing prices (OHLC)
- Trading volume (number of shares traded)
- Total transaction amount
- Number of transactions executed
- Daily price change (both absolute and percentage values)

The dataset's five-year span covers significant market periods including the pre-COVID bull market, the 2020 pandemic crash, and subsequent recovery phases, providing a diverse set of market conditions for model training and evaluation. The raw data was stored in CSV format and systematically organized by bank and date for further processing.

Feature Engineering and Selection

To improve the predictive power of our model, we expanded the original dataset by computing 46 technical indicators using the TA-Lib Python library. These indicators spanned multiple categories of market analysis:

1. Trend Indicators: Including moving averages (SMA, EMA) and trend strength metrics

2. Momentum Oscillators: Such as Relative Strength Index (RSI) and Stochastic Oscillator
3. Volatility Measures: Including Average True Range (ATR) and Bollinger Bands
4. Volume-based Indicators: Like On-Balance Volume (OBV) and Volume Weighted Average Price (VWAP)

Following feature generation, we implemented LASSO (Least Absolute Shrinkage and Selection Operator) regression for feature selection. The LASSO method applies L1 regularization, which effectively shrinks less important feature coefficients to zero, resulting in automatic feature selection. The regularization strength parameter (α) was tuned separately for each bank's dataset through cross-validation to optimize model performance

This process yielded distinct sets of selected features for each financial institution, reflecting their unique price movement characteristics. For instance, while some banks' predictions relied heavily on momentum indicators, others showed greater dependence on volume-based features. The feature selection phase typically retained 15-20 of the most predictive technical indicators per stock, significantly reducing dimensionality while maintaining model accuracy.

Data Preprocessing

At first, the unnecessary column date was removed from the dataset. Then the close price was shifted back by one position. This is done because we intended to predict the close price for the next day using historical data. The data was split into training and testing sets in an 80:20 ratio. To ensure consistency in model training, Z-score normalization was applied to standardize the features. Once the models generated predictions, the results were transformed back to their original scale for evaluation.

$$z = \frac{x - \mu}{\sigma}$$

Equation 1: Z-score Normalization

where μ and σ represent the mean and standard deviation calculated exclusively from the training set. This approach prevented information leakage from the test set during model training. The normalization parameters (μ, σ) were stored and later reapplied to transform the model's predictions back to the original price scale for interpretability and evaluation.

Historical stock prices in this study were not adjusted for corporate actions such as bonus shares or stock splits due to data constraints. While this may introduce minor discontinuities in price series, the model's focus on short-term look-back periods (2–5 days) reduces the impact of such structural breaks, as most trading signals were derived from recent, unadjusted price movements. Future work will incorporate adjusted prices for improved robustness.

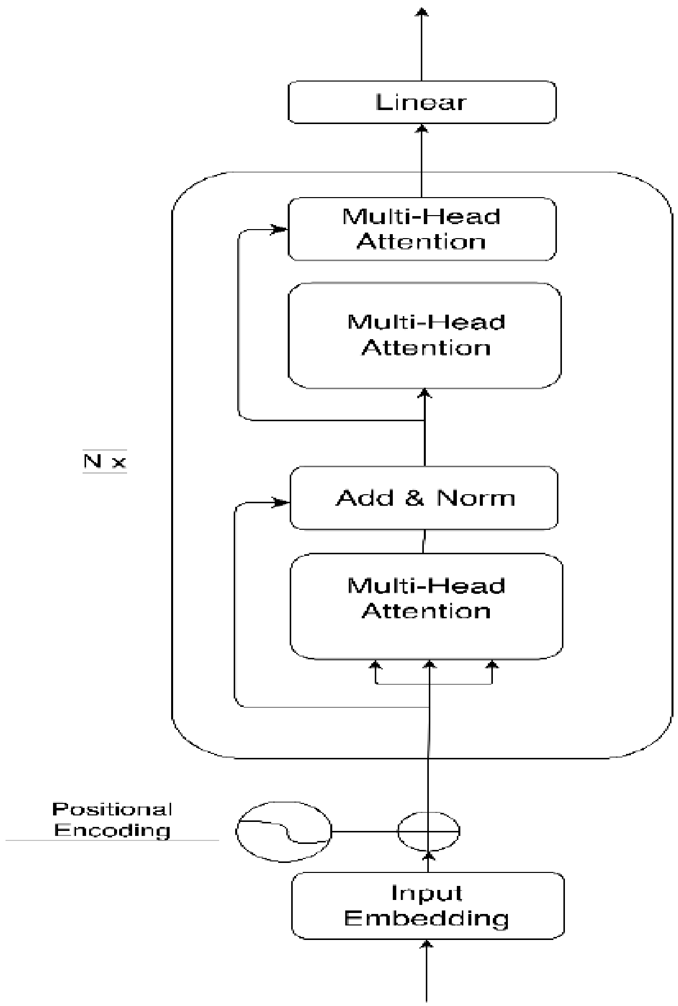
Model Implementation

The proposed encoder-only Transformer model is shown in the figure. The Transformer model, introduced by (A. Vaswani, 2017), consists of an encoder and a decoder. However, only the encoder component is necessary for tasks like stock price prediction, where the output is a single value rather than a sequence (Bryan Lim, 2021) (Wu, 2020). The Transformer model consisted of six layers, an embedding dimension of 512, eight attention heads, and a dropout rate of 0.3. The self-attention mechanism in the Transformer model helped capture complex dependencies in financial time-series data.

The encoder is responsible for processing the input sequence and extracting relevant features using its self-attention mechanism. This allows the model to capture long-term dependencies and temporal patterns in the historical stock data, which are critical for accurate predictions.

Figure 1:

Encoder-only Transformer



The encoder is composed of the following key components:

1. **Input Embedding**:

   The input sequence (e.g., historical stock prices, technical indicators) is first passed through an embedding layer, which maps the input features to a higher-dimensional space. This step ensures that the model can effectively process the input data.

2. **Positional Encoding**:

   Since the Transformer does not inherently understand the order of the input sequence, positional encodings are added to the input embeddings. These encodings provide information about the position of each data point in the sequence, allowing the model to capture temporal relationships.

3. **Multi-Head Self-Attention**:

   The core of the encoder is the multi-head self-attention mechanism, which allows the model to focus on different parts of the input sequence. Each "head" in the multi-head attention mechanism learns to attend to different aspects of the data, enabling the model to capture complex dependencies and patterns.

4. **Feed-Forward Neural Network**:

   After the self-attention mechanism, the output is passed through a position-wise feed-forward neural network. This network applies a non-linear transformation to the data, further enhancing the model's ability to extract relevant features.

5. **Layer Normalization and Residual Connections**:

Each sub-layer in the encoder (e.g., self-attention, feed-forward network) is followed by layer normalization and residual connections. These components help stabilize the training process and improve the model's performance.

The encoder's final output is passed through a fully connected layer, which maps the encoded representation to a single value (e.g., the predicted stock price). This output layer is trained to minimize the difference between the predicted and actual stock prices using a loss function such as MAPE.

Training and Optimization

The training process utilized the AdamW optimizer with a learning rate of 0.0001 and a weight decay of 1e-5 to prevent overfitting. The model was trained for up to 100 epochs, with early stopping applied using a patience value of 20 epochs to avoid unnecessary training and reduce overfitting. MSE was chosen as the loss function for optimization. Mean Squared Error (MSE) served as the loss function during training due to its favorable properties for regression tasks and stable gradient behavior.

Performance Evaluation

The predictions were evaluated using MAPE on both the training and testing datasets to assess the model's effectiveness. Additionally, we explored the optimal look-back period for the transformer model to achieve the lowest MAPE, providing insights into the best configuration for stock price forecasting tasks.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|$$

Equation 2: MAPE

where,

At = Actual Closing Price

Ft = Predicted Price

Being percentage-based, MAPE allowed direct comparison of prediction quality across different bank stocks with varying price ranges.

Look-Back Period Selection

To determine the most suitable look-back period for each stock, we adopted a data-driven approach rather than relying on arbitrary or fixed values. Specifically, we tested a wide range of look-back window sizes from 2 to 25 days across five Nepalese stocks.

This was done by running an automated evaluation loop that applied the LASSO-regularized Transformer model to each stock at every look-back interval in the given range. For each run, we recorded key performance metrics such as prediction accuracy, train MAPE, and test MAPE. The results were systematically saved in a CSV file for later analysis. After compiling all results, we selected the look-back period with the lowest test MAPE for each stock as the optimal window. This approach ensured that the chosen sequence length was empirically the best performer, minimizing overfitting while capturing the most relevant historical price patterns.

Such dynamic tuning also revealed insights about how different stocks respond to historical data, some favored very short look-back periods (e.g., 2–3 days), while others performed better with slightly longer sequences (up to 5 days), depending on their volatility and market behavior.

Experimental Setup

The experimental setup utilized a workstation running Windows 10 Pro 64-bit with an AMD Ryzen 7 3750H processor (4 cores, 8 threads at 2.30-4.0 GHz), Radeon Vega Mobile Graphics, and 16GB DDR4 RAM (13.9GB usable). All coding was implemented in Visual Studio Code using Python 3.8 through Anaconda, with key dependencies including PyTorch 1.9.0 for model development, TA-Lib 0.4.24 for technical indicators, Scikit-learn 0.24.2 for preprocessing and LASSO, Pandas 1.3.0 for data handling, and NumPy 1.21.0 for numerical operations. The implementation leveraged PyTorch's DataLoader for efficient batch processing, with fixed random seeds across all libraries (PyTorch, NumPy, random) to ensure reproducibility. Model training was conducted sequentially for different banks and look-back periods (2-25 days), with each configuration taking approximately 45-60 minutes to complete, typically converging within 50-70 epochs through early stopping (patience=20) while monitoring validation loss. Memory optimization techniques were applied to manage the computational load from the 46 technical indicators across varying sequence lengths.

5. Results & Findings

The performance of the LASSO-Transformer model was evaluated using historical stock data from five Nepalese commercial banks: CZBIL, EBL, SANIMA, SBI, and SCB. The results are presented in the table below, which compares the model's performance based on different look-back periods (sequence lengths) and the corresponding MAPE for both training and testing datasets.

Table 1:

Performance of LASSO-Transformer Model Across Different Look-back Periods

Stock	Sequence	Train MAPE	Test MAPE
CZBIL	2	3.175693	2.06383
CZBIL	3	2.360033	2.17688
CZBIL	4	1.955477	1.756503
CZBIL	5	2.460421	2.067583
Stock	Sequence	Train MAPE	Test MAPE
CZBIL	10	1.991811	1.991861
CZBIL	20	1.825003	2.470844
CZBIL	25	3.327166	3.197488
EBL	2	1.691775	1.523527
EBL	3	1.650168	1.784886
EBL	4	1.545254	1.636649
EBL	5	1.693527	1.751041
EBL	10	2.066812	1.992358
EBL	20	1.749597	1.685832
EBL	25	1.623769	1.982144

SANIMA	2	2.306483	1.791901
SANIMA	3	1.829239	1.652578
SANIMA	4	2.533196	2.043615
SANIMA	5	2.428951	1.882755
SANIMA	10	2.804272	1.827777
SANIMA	20	2.222166	1.739917
SANIMA	25	2.773545	1.90227
SBI	2	1.528741	1.63772
SBI	3	1.695598	1.744858
SBI	4	1.503927	1.677454
SBI	5	1.870215	1.741539
Stock	Sequence	Train MAPE	Test MAPE
SBI	10	1.912466	1.795523
SBI	20	1.685932	1.866993
SBI	25	1.793036	1.892668
SCB	2	1.872641	1.779297
SCB	3	1.917815	1.4292
SCB	4	2.121629	1.436706

SCB	5	2.420458	1.414048
SCB	10	2.268671	2.053399
SCB	20	2.581698	2.215344
SCB	25	2.5699	2.602314

From the above table, we can see that CZBIL achieved its best performance with a 4-day look-back period with an MAPE of 1.75%, indicating that recent data (4 days) is most relevant for accurate predictions. The model's performance degraded significantly with longer look-back periods, such as 25 days, where the MAPE increased to 3.1975%. This suggests that CZBIL's stock prices are influenced by short-term trends, and longer historical data may introduce noise.

A similar pattern can be seen where EBL achieved its lowest MAPE (1.5235%) with a 2-day look-back period, the shortest among the five banks. This indicates that EBL's stock prices are highly influenced by very recent data. The model's performance remained relatively stable across different look-back periods, with the worst MAPE (1.9821%) still below 2%, demonstrating the model's robustness for this stock. If we look at SANIMA, it also performed best with a 3-day look-back period, achieving a MAPE of 1.6526%. Interestingly, the model's performance degraded slightly with a 4-day look-back period, suggesting that SANIMA's stock prices are sensitive to very recent trends. The worst performance occurred with a 25-day look-back period, but the MAPE remained relatively low (2.0436%), indicating that the model handles this stock well across different periods.

SBI achieved its best performance with a 2-day look-back period, similar to EBL, indicating that recent data is crucial for accurate predictions. The model's performance degraded slightly with longer look-back periods, but the worst MAPE (1.8927%) was still below 2%, demonstrating the model's consistency for SBI.

SCB achieved the lowest MAPE (1.4140%) among all five banks, with a 5-day look-back period. This suggests that SCB's stock prices benefit from a slightly longer historical context compared to the other banks. However, the model's performance degraded significantly with longer look-back periods, such as 25 days, where the MAPE increased to 2.6023%. This indicates that while SCB benefits from a slightly longer look-back period, very long periods introduce noise and reduce accuracy.

The prediction graphs for SANIMA, SCB, and EBL show noticeable deviation between actual and predicted prices during the period from August 24 to October 24, 2024. This period typically overlaps with increased corporate activity in Nepal’s financial sector, including dividend announcements and bonus share distributions, which can introduce short-term volatility in stock prices. These factors were not considered during experimentation, and the model was trained on raw closing prices without adjustment for such events. As a result, the model may have misinterpreted structural price shifts such as ex-dividend or bonus listing effects as normal fluctuations.

Additionally, the use of a short look-back window (2–5 days) limits the model’s ability to contextualize abrupt movements driven by external announcements. While these deviations led to temporary drops in predictive accuracy, overall model performance remained strong across other time periods. Future iterations can address this by incorporating event-aware inputs or adjusting prices for corporate actions to improve robustness during such volatility.

Analysis of the Look-Back period

The results indicate that the look-back period significantly influences the model's performance. Shorter look-back periods (2-5 days) consistently yielded lower MAPE values compared to longer periods (10-25 days). This suggests that recent stock price data is more relevant for accurate predictions, as it captures the most recent market trends and fluctuations. The bank-specific results reveal important nuances in how different stocks respond to historical data:

For Everest Bank Limited (EBL) and Nepal SBI Bank Limited (SBL), the optimal prediction accuracy was achieved with the shortest tested look-back period of just 2 days. This indicates that these particular stocks are predominantly influenced by immediate market movements and recent trading activity. The superior performance at 2 days suggests that price patterns for these banks exhibit strong momentum characteristics, where recent trends tend to persist in the very short term. Citizens Bank International Limited (CZBIL) and Sanima Bank Limited (SANIMA) showed slightly different behavior, performing best with 4-day and 3-day look-back periods, respectively. This marginal extension of the optimal historical window implies that these stocks may incorporate additional factors beyond pure momentum, possibly including:

- Delayed market reactions to news or events
- Slightly longer-term trend patterns
- Institutional trading behaviors that unfold over multiple days

Standard Chartered Bank Nepal (SCB) presented the most distinctive pattern, achieving peak accuracy with a 5-day look-back window. This extended optimal period compared to other banks suggests SCB's price movements may be influenced by:

- More gradual incorporation of market information
- Different investor composition and trading behaviors
- Possible international market linkages affecting price discovery
- Weekly patterns or cycles in trading activity

The consistent degradation in model performance with look-back periods beyond 5 days across all banks indicates that:

1. Older price data contains diminishing predictive value
2. Longer historical windows introduce noise that outweighs any additional signal
3. Nepal's market conditions favor short-term trading strategies
4. Mean-reversion effects may become stronger over longer time horizons

These findings have important implications for both financial analysts and algorithmic trading systems operating in Nepal's market. The results suggest that prediction models should:

- Prioritize very recent price data (2-5 days)
- Avoid excessive historical windows that reduce accuracy
- Be customized based on each stock's unique temporal characteristics
- Potentially incorporate different look-back periods for different banking stock

Predicted vs Actual Close Price Graph

Figure 2:

CZBIL Actual Price vs Predicted Price

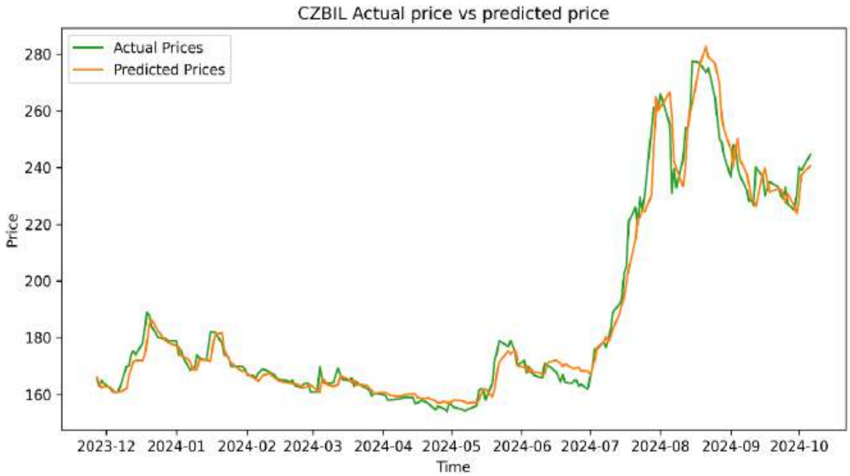


Figure 3:

MA Actual Price vs Predicted Price

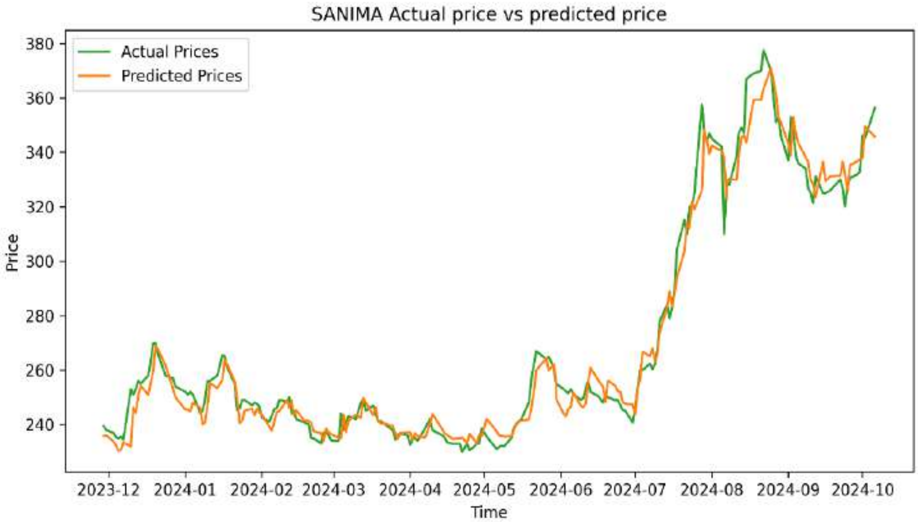


Figure 3: SANI

Figure 4:

SCB Actual Price vs Predicted Price

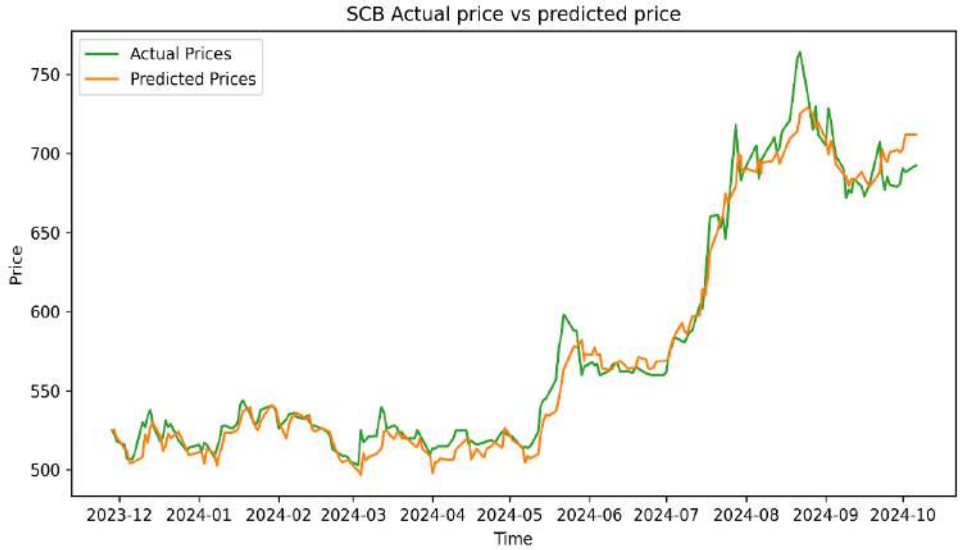


Figure 5:

EBL Actual Price vs Predicted Price

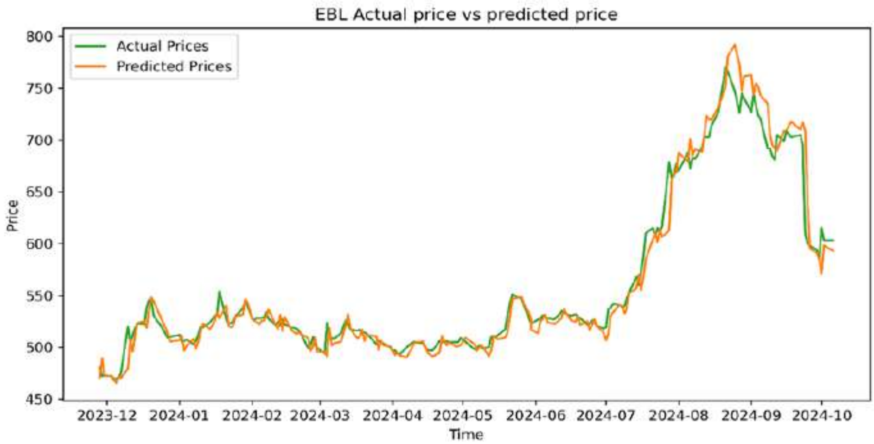
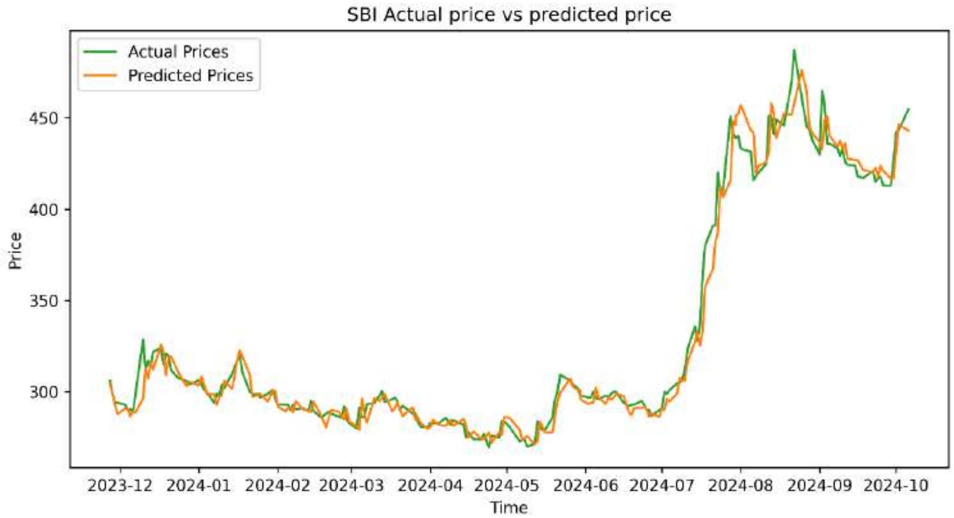


Figure 6:

SBI Actual Price vs Predicted Price



The predicted vs. actual price graphs (Figures 2-6) provide visual evidence of the model's performance. The graphs show that the LASSO-Transformer's predictions closely follow the actual stock prices, with minimal deviations during periods of stability. However, during high market volatility, such as the mid-2020 COVID-19 market crash, the model shows some prediction errors. It slightly underestimates sharp price drops and overestimates recovery speed. These errors lead to small increases in MAPE values during these periods.

Each bank's graph provides useful insights:

- Everest Bank Limited (EBL) and Nepal State Bank of India (SBI) show very accurate predictions, even during moderate price changes. The predicted prices closely match actual values, explaining their low MAPE scores. This suggests their price movements are easier for the model to learn.

- Citizens Bank International Limited (CZBIL) and Sanima Bank Limited (SANIMA) have slightly larger gaps between predicted and actual prices during market shocks. The graphs highlight moments when sudden price spikes or drops are not fully captured. These mismatches align with their slightly higher MAPE values.
- Standard Chartered Bank Nepal (SCB) has the best prediction accuracy. The predicted prices match the actual prices so well that their lines almost merge in the graphs. This strong alignment holds in both stable and volatile markets.

The graphs also reveal that prediction accuracy slightly decreases during:

- Major economic announcements
- Unexpected political events
- Sudden trading volume changes
- Extreme market sentiment shifts

Overall, the graphs confirm that the LASSO-Transformer model works well under normal conditions but struggles with sudden, extreme market movements. These visual findings support the MAPE results and highlight areas for improvement in handling market shocks.

5. Conclusion

This study introduced a LASSO-regularized Transformer model for stock price forecasting, focusing on the encoder component to predict the next day's closing price. The model was evaluated using historical stock data from five Nepalese commercial banks, and its performance was assessed based on the MAPE across different look-back periods. The results demonstrate that the LASSO-Transformer is highly effective for stock price prediction, achieving low MAPE values across all five banks. The optimal look-back period varied by stock, with shorter periods (2-5 days) generally yielding the best results, indicating that recent data is more relevant for accurate predictions.

The study underscores the importance of feature selection (via LASSO) and self-attention mechanisms (via Transformer) in improving stock price forecasting accuracy. The LASSO-Transformer's ability to generalize across different stocks, regardless of their volatility, makes it a promising tool for financial markets. Future work could focus on expanding the dataset to include other industries, incorporating real-time data feeds, and exploring hybrid models to enhance prediction accuracy further. This research contributes to the growing body of work on Transformer-based models in financial forecasting, offering practical insights for investors and traders in volatile markets.

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Knee Osteoarthritis Severity Classification Using CNN and Image Enhancement Filters

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Abstract

CNNs for the classification of knee osteoarthritis is a promising avenue to assist in clinical decision making. Our study examined the influence of several image enhancement filters on CNN performance for KOA severity classification using X-rays. The KOA dataset contained 8,260 labelled X-ray images of five KL grades (0-4) divided into three datasets (training, validation, and test). As we assessed the effects of the different image enhancement preprocessing filters on labelled X-ray images, we applied several typical image enhancement preprocessing filters such as the Sobel, Gaussian, CLAHE, Gabor, and Entropy filters in order to evaluate the effect they had on classification performance. The best classifier for KOA classification, using the CLAHE filter, had the best performance for the 5-layered CNN model with the best accuracy (85%), F1-score (0.72), and AUC score of (0.83). This exemplifies the usefulness of contrast enhancement in medical image classification. Findings from our study can demonstrate that image enhancement techniques contribute to the reproducibility of CNN based KOA grading systems and offer one more step towards more reliable and automated KOA assessment.

Keywords: convolutional neural networks, image enhancement filters, Knee Osteoarthritis Classification, X-Ray image processing.

1. Introduction: Knee Osteoarthritis Severity Classification Using CNN and Image Enhancement Filters

Knee osteoarthritis (KOA) is a common joint disease that causes pain, stiffness, and difficulty moving. It affects millions of people worldwide and can significantly reduce their quality of life (Antico et al., 2020). Detecting KOA early and correctly assessing its severity is very important for effective treatment. Doctors usually use the Kellgren-Lawrence (KL) grading system, which classifies KOA into five levels based on X-ray images (Schiphof et al., 2008). However, this method is not always reliable because different doctors may interpret X-rays differently, leading to inconsistent results. It is also time-consuming, which can delay treatment (Mohammed et al., 2023). As a result, there is a growing need for automated systems that can assist in accurate and efficient KOA diagnosis.

With the advancement of artificial intelligence, deep learning techniques like Convolutional Neural Networks (CNNs) have been widely used in medical image analysis. CNNs are powerful at detecting patterns in images and can help automate the process of diagnosing and classifying KOA (Guida et al., 2021). However, one major challenge is that the early stages of KOA (KL grades 0 and 1) are difficult to differentiate because the features in X-ray images often overlap. This makes it hard for the model to classify them accurately. To overcome this, researchers have explored the use of image enhancement techniques to improve the quality of X-ray images, making it easier for the model to detect key features (Ahmed & Mstafa, 2022).

In this study, we aim to develop an automated KOA severity classification system using CNNs and image enhancement techniques. Our goal is to improve the model’s accuracy in detecting different KOA stages, especially the early ones. By enhancing X-ray images before feeding them into the model, we hope to increase its ability to identify key features and make more reliable predictions. This system has the potential to support doctors by providing quick and consistent KOA diagnosis, reducing errors, and speeding up the decision-making process. The rest of the paper is organized as follows: Section 2 reviews existing studies on KOA classification using deep learning. Section 3 explains the methodology, including how the CNN model works and the image enhancement techniques used. Section 4 presents the results and discusses key findings. Finally, Section 5 concludes the study and provides directions for future research.

2. Literature Review/ Related Works

The diagnosis of Knee Osteoarthritis (KOA) from X-ray images has long been a challenging task due to the complexity of the condition and the need for expert interpretation. Traditional methods rely heavily on manual grading, which is time-consuming and often subjective. Machine learning, particularly Convolutional Neural Networks (CNNs), has emerged as an effective solution for automating KOA detection. Guida et al. (2021) applied 3D CNNs to MRI sequences for classifying KOA severity and demonstrated superior accuracy compared to traditional CNNs used on X-ray images. Their study showed an improvement in multi-class and binary classification accuracy, suggesting that 3D CNNs combined with MR imaging could improve clinical diagnosis. However, their focus was on MRI, and the challenge of applying such methods to X-ray images remains underexplored.

Mohammed et al. (2023) used CNNs to classify KOA severity from X-ray images, with a focus on early-stage detection. Despite achieving a 69% accuracy, their study highlighted significant challenges, including the limited availability of early-stage data and the difficulty in distinguishing between KL grade0, KL grade1 and KL grade2 which exhibit subtle radiographic differences. This points to the need for more robust datasets and improved model architectures that can handle such complexities in X-ray images.

To address these challenges, recent studies have explored image enhancement techniques to improve the quality of X-ray images. Image enhancement plays a vital role in medical image analysis, particularly in improving the contrast and visibility of key features in X-ray and ultrasound images. One study critically evaluated the effects of Histogram Equalization, Contrast Limited Adaptive Histogram Equalization, and Fuzzy Enhancement on X-ray images from the MURA dataset, highlighting the potential of these techniques to enhance diagnostic accuracy in clinical practice (Htun & Tun, 2024). These methods significantly improved contrast and edge detection, which are critical for successful image analysis and classification. By making hidden details more visible, such enhancement techniques can improve the performance of downstream machine learning models. However, the integration of such enhancement methods with CNNs for KOA detection remains underexplored, particularly regarding their impact on classification accuracy.

In this study, we propose a novel approach that integrates image enhancement filters with CNNs to improve KOA classification accuracy from X-ray images. By addressing the challenge of poor-quality images and enhancing critical features, our approach aims to improve the model's ability to differentiate between different KOA grades more effectively, especially in the early stages of the disease where subtle differences are often difficult to distinguish. This will ultimately enhance diagnostic accuracy and efficiency in clinical settings, providing a reliable and automated tool that can assist medical professionals in making quicker and more accurate diagnoses. Through this approach, we aim to contribute to the ongoing development of deep-learning-based diagnostic tools that can be used in clinical practice to support physicians and healthcare providers in making informed decisions regarding KOA treatment and management.

3. Methodology

This section describes data collection, feature engineering and selection, data preprocessing, model implementation, training and optimization, performance evaluation and experimental setup.

Data Collection

The knee X-ray images utilized in this study were obtained from the publicly available "Knee Osteoarthritis Dataset with Severity Grading" curated by Falah Gatea and hosted on Kaggle (https://www.kaggle.com/datasets/falahgatea/knee-osteoarthritis-dataset-with-severity-grading). The dataset comprises a total of 8,260 grayscale anterior-posterior knee X-ray images, each labeled according to the Kellgren-Lawrence (KL) grading scale, ranging from Grade 0 (normal) to Grade 4 (severe osteoarthritis). All images were resized to a standardized resolution of 224x224 pixels to maintain uniformity during preprocessing. The dataset was divided into training (70%), validation (10%), and testing (20%) subsets to facilitate model development and performance evaluation. Acknowledging the source of the dataset not only credits the original contributor but also supports reproducibility and transparency in research, allowing future studies to build upon the same data foundation.

Data Preprocessing

All X-ray images were first resized to a standardized resolution of 224x224 pixels to ensure uniform input dimensions for the CNN model. As part of the image enhancement process, the CLAHE (Contrast Limited Adaptive Histogram Equalization) filter was initially applied during preprocessing to improve the local contrast of grayscale images, making critical anatomical structures more distinguishable. Although multiple image enhancement filters were later applied and compared individually during experimentation (as discussed in Section 4), CLAHE was selected as the base filter for early-stage preprocessing to evaluate its baseline impact before introducing additional transformations. This initial use of CLAHE was not mandatory for all experiments, hence earlier noted as "optional," but served as a controlled starting point for performance benchmarking.

In addition, data augmentation techniques were employed to increase the diversity and size of the training dataset and reduce overfitting. Augmentation steps included random horizontal flipping, brightness and contrast adjustments, and slight rotations. These transformations aimed to simulate variability in real-world clinical imaging conditions and enhance the model's generalization ability. Finally, pixel values were normalized to ensure numerical stability during training and to speed up convergence of the optimization process.

Model Implementation

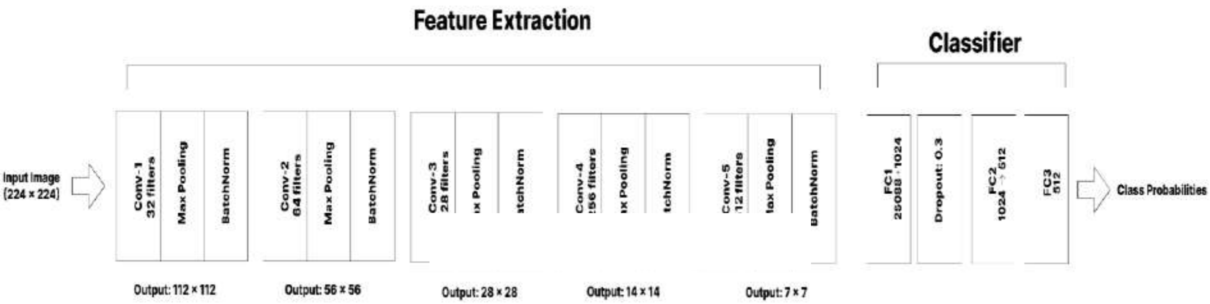
The proposed CNN model is shown in figure 1. The CNN model consists of convolutional and fully connected layers. The architecture begins with five convolutional layers, each followed by batch normalization and max-pooling operations to progressively reduce the spatial dimensions of the input images. The convolutional filters start at 32 and gradually increase to 512 as the layers deepen, effectively capturing complex features at various levels of abstraction. These operations reduce the input image size from 224x224 pixels to a smaller 7x7 feature map. After passing through the final convolutional layer, the resulting 7x7x512 feature map is flattened into a 25088-dimensional vector.

This vector is then passed through three fully connected layers designed to process and extract high-level features. The first fully connected layer reduces the feature dimensions to 1024 units, which helps retain key information while reducing computational complexity. To mitigate overfitting, several dropouts specifically 0.25, 0.3, 0.4, and 0.5 are applied after the first fully connected layer and 0.3 consistently yields the best validation performance, providing an effective balance between model generalization and learning capacity.

The second fully connected layer further reduces the dimension to 512 units. Finally, the last layer outputs the classification probabilities for each class, effectively generating the final predictions for the input images. This architecture enables the model to learn meaningful patterns while controlling overfitting, thereby improving prediction accuracy on complex image classification tasks.

Figure 1:

Architectural Diagram of the CNN Model



The image enhancement filters are applied to the input images to highlight important features, such as edges and textures, that are crucial for accurate classification. These filters help the model better capture critical details and improve its ability to learn relevant patterns, leading to enhanced performance in the classification task. These filters were chosen based on their individual strengths in handling noise reduction, edge detection, contrast enhancement, and texture extraction. Each filter contributes differently to emphasizing certain aspects of the image that are crucial for accurate feature learning and classification. For instance, some filters focus on enhancing boundaries, while others improve contrast or preserve structural textures.

a) **Sobel Filters:**

   The Sobel filter algorithm works by detecting edges in an image through convolution with two predefined Sobel kernels: one for detecting horizontal edges (Sobel X) and another for vertical edges (Sobel Y). The image is first converted into a tensor, and a batch dimension is added to prepare it for convolution operations.

b) **Gaussian Filter:** The Gaussian blur algorithm smooths an image by averaging pixel values with their neighbors using a Gaussian kernel, reducing noise and detail. The degree of blurring is controlled by the kernel size, with larger kernels producing stronger blurs. This process results in a softened image, useful for noise reduction or pre-processing in tasks like edge detection.

c) **Bilateral Filter:** The bilateral filter is a widely used edge-preserving smoothing technique that reduces noise in images while maintaining sharp edges. Unlike traditional filters that consider only spatial proximity, the bilateral filter also accounts for differences in pixel intensity, which helps preserve edge information. The filtering process involves a weighted average of nearby pixels, where weights are determined by both the spatial distance and the intensity difference between neighboring pixels. The behavior of the filter is controlled by three key parameters: the neighborhood diameter, which defines the spatial extent of the filter; the intensity sigma, which controls how strongly intensity differences influence filtering; and the spatial sigma, which determines how much influence neighboring pixels have based on their distance. This combination allows the bilateral filter to smooth homogeneous regions while retaining important edge details.

d) **Entropy Filter:** Entropy Filter is implemented as a custom transformation for preprocessing images in the dataset. This filter is designed to enhance the features of the images by highlighting regions of high complexity, which can be particularly useful for distinguishing between different classes of bone conditions in knee osteoarthritis. The Entropy Filter class inherits from object and overrides the call method, which allows it to be used in a pipeline of image transformations.

e) **CLAHE Filter:** CLAHE (Contrast Limited Adaptive Histogram Equalization) is applied to enhance the contrast of the images in the dataset. After reading each image , the CLAHE filter is initialized with specific parameters to limit contrast amplification and define the grid size for processing. The filter is then applied to the grayscale image, improving its visual quality by enhancing local contrast while avoiding over-amplification of noise.

f) **Bidirectional Filter:** The bidirectional filter applies smoothing in two orthogonal directions, such as horizontal and vertical. This helps reduce noise while preserving important features in an image by considering both axes of variation.

g) **Laplacian Filter:** The Laplacian filter is used for edge detection and image enhancement by computing the second spatial derivative of an image. It highlights regions of rapid intensity change.

h) **Gabor Filter:** Gabor filters are used for texture analysis, combining a Gaussian envelope with a sinusoidal carrier. They effectively detect edges and patterns at different orientations and scales, making them useful for feature extraction.

i) **Histogram Equalization:** Histogram equalization improves image contrast by redistributing intensity values. It enhances features that are too dark or light, making the image more visually balanced and revealing more details.

Training and Optimization

The training process began by addressing class imbalance, which can negatively impact model performance by causing it to favor majority classes. To counter this, class weights were calculated and incorporated into the CrossEntropyLoss function, which measures the dissimilarity between the predicted class probabilities and the true class labels, penalizing incorrect predictions more when the model is confident about the wrong class. This helped in improving prediction accuracy across all categories. For optimization, the Adam optimizer was selected due to its efficiency in handling sparse gradients and its adaptive learning rate. A learning rate of 0.0001 was used to facilitate stable learning, while weight decay of 1e-5 was applied to prevent overfitting by regularizing the model's parameters. The training process was set to run for a maximum of 150 epochs, but to avoid unnecessary computations and overfitting, an early stopping mechanism was implemented. If the validation loss failed to improve for 12 consecutive epochs, training was halted to preserve the best-performing model.

Each epoch processed data in mini batches of 32 images, which improved computational efficiency and model convergence. Throughout training, the model's progress was closely monitored using training and validation loss, along with their corresponding accuracy metrics. These evaluations ensured that the model was learning effectively and not overfitting to the training data. At the end of training, the best-performing model determined by the lowest validation loss was saved for further testing and deployment. This approach ensured that the final model had strong generalization capabilities, making it reliable for real-world applications.

Performance Evaluation

The model was evaluated using several performance metrics including the confusion matrix, classification accuracy, precision, recall, F1-score, and Area Under the Curve (AUC) to assess its effectiveness on validation data.

- **Confusion Matrix**: This tabulates the number of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), helping visualize misclassification patterns.
- **Accuracy**:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

This measures the overall correctness of the model's predictions.

- **Precision:** Precision evaluates the proportion of correctly predicted positive samples out of all predicted positives.

$$\text{Precision} = \frac{TP}{TP + FP}$$

- **Recall:** Recall measures how well the model identifies actual positive cases.

$$\text{Recall} = \frac{TP}{TP + FN}$$

- **F1-Score:** This harmonic mean of precision and recall ensures a balanced evaluation, especially in imbalanced datasets.

$$\text{F1-Score} = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

- **AUC:** AUC quantifies the model's ability to distinguish between classes by measuring the area under the Receiver Operating Characteristic (ROC) curve. A higher AUC indicates better class separation.

These metrics collectively provide a comprehensive understanding of the model's strengths and weaknesses, particularly in handling class imbalance and distinguishing between KOA severity levels.

Experimental Setup

The experiments were conducted on a system equipped with an Intel Core i5 processor and an MX 550 graphics card, along with 16 GB of RAM. The implementation leveraged the PyTorch framework along with supporting libraries like Seaborn and Scikit-learn for data preprocessing, visualization, and model development.

4. Results & Findings

The performance of the model was analyzed through a series of experiments using various combinations of preprocessing filters and dropout values. The experiments were structured around two primary conditions: those conducted with image preprocessing filters such as Contrast Limited Adaptive Histogram Equalization and histogram equalization and those conducted without any filters. The objective was to evaluate how these preprocessing steps affected the model's ability to classify the severity of knee osteoarthritis (KOA).

A dropout rate of 0.3 was used in the majority of the experimental combinations. This particular value was chosen based on its consistent and stable performance during preliminary trials. It effectively balanced the risks of overfitting and underfitting, making it a reliable baseline for further comparisons. However, to understand the sensitivity of the model to dropout changes, additional experiments were selectively conducted with dropout values of 0.25, 0.4, and 0.5. These alternative values were not applied across all filter conditions. The reason for this selective testing was twofold: first, combinations with very high dropout rates (such as 0.4 and 0.5) yielded poor performance during initial testing, indicating a loss of important features; and second, the study aimed to maintain computational efficiency and feasibility, so only promising configurations were explored further.

To ensure diversity while maintaining experimental control, specific combinations were chosen. For the filtered input condition, experiments were performed with dropout rates of 0.25, 0.3, and 0.4. In contrast, for the unfiltered input condition, only dropout values of 0.3 and 0.5 were tested. This decision was made because extending all dropout values across both conditions was not practical due to time and resource limitations. Moreover, earlier results suggested that certain combinations were unlikely to perform well, so they were intentionally omitted. Although a complete matrix of experiments would be ideal, the selected combinations were sufficient to demonstrate the general trend and impact of both filters and dropout on model performance.

All the trained models were evaluated on a separate test dataset. This ensured that the reported performance metrics accuracy, precision, recall, F1-score, and AUC reflected the model’s ability to generalize beyond the training and validation data. The use of this test set provided a robust and unbiased assessment of each experimental setup. The results from these combinations were then compared to identify the most effective configuration for classifying KOA severity. By focusing on meaningful experimental designs and justifying the exclusion of unpromising combinations, the study maintained a balance between comprehensive analysis and practical constraints.

Table 1:

Performance of CNN Model with Different Dropout and Image Enhancement Filters

Model	Dropouts	Filters	Classification Accuracy for Test Data	Metrics
5-layer Convolutional Neural Network	0.25	-	Class 0:0.79 Class 1:0.77 Class 2:0.80 Class 3:0.93 Class 4:0.97	Precision:0.62 F1 score:0.65 AUC:0.78
5-layer Convolutional Neural Network	0.3	-	Class 0:0.81 Class 1:0.76 Class 2:0.84 Class 3:0.95 Class 4:0.98	Precision:0.72 F1 score:0.71 AUC:0.81
5-layer Convolutional Neural Network	0.3	ENTROPY	Class 0:0.79 Class 1:0.73 Class 2:0.82 Class 3:0.95 Class 4:0.97	Precision:0.69 F1 score:0.66 AUC:0.77

5-layer Convolutional Neural Network	0.3	HISTOGRAM EQUALIZATION	Class 0:0.76 Class 1:0.74 Class 2:0.80 Class 3:0.95 Class 4:0.97	Precision:0.69 F1 score:0.70 AUC:0.79
5-layer Convolutional Neural Network	0.3	BILATERAL	Class 0:0.77 Class 1:0.72 Class 2:0.80 Class 3:0.93 Class 4:0.96	Precision:0.64 F1 score:0.66 AUC:0.76
Model	Dropouts	Filters	Classification Accuracy for Test Data	Metrics
5-layer Convolutional Neural Network	0.3	SOBEL	Class 0:0.78 Class 1:0.80 Class 2:0.81 Class 3:0.94 Class 4:0.98	Precision:0.68 F1 score:0.68 AUC:0.80
5-layer Convolutional Neural Network	0.3	DIRECTIONAL	Class 0:0.75 Class 1:0.77 Class 2:0.84 Class 3:0.93 Class 4:0.98	Precision:0.70 F1 score:0.66 AUC:0.77

5-layer Convolutional Neural Network	0.3	LAPLACIAN	Class 0:0.76 Class 1:0.77 Class 2:0.79 Class 3:0.91 Class 4:0.99	Precision:0.65 F1 score:0.63 AUC:0.77
5-layer Convolutional Neural Network	0.3	GABOR	Class 0:0.75 Class 1:0.66 Class 2:0.83 Class 3:0.94 Class 4:0.99	Precision:0.70 F1 score:0.69 AUC:0.80
5-layer Convolutional Neural Network	0.3	GAUSSIAN	Class 0:0.78 Class 1:0.73 Class 2:0.78 Class 3:0.92 Class 4:0.99	Precision:0.68 F1 score:0.69 AUC:0.78
5-layer Convolutional Neural Network	0.3	CLAHE	Class 0:0.82 Class 1:0.76 Class 2:0.85 Class 3:0.95 Class 4:0.99	Precision:0.72 F1 score:0.72 AUC: 0.83
Model	Dropouts	Filters	Classification Accuracy for Test Data	Metrics
5-layer Convolutional Neural Network	0.4	-	Class 0:0.81 Class 1:0.72 Class 2:0.83 Class 3:0.95 Class 4:0.99	Precision:0.71 F1 score:0.72 AUC:0.80

5-layer Convolutional Neural Network	0.5	-	Class 0:0.78 Class 1:0.71 Class 2:0.83 Class 3:0.94 Class 4:0.99	Precision:0.73 F1 score:0.70 AUC:0.80

The confusion matrices for different dropout rates and image enhancement filters are provided below, illustrating the detailed classification performance across all categories.

Figure 2:

Confusion Matrix for 0.25 Dropout

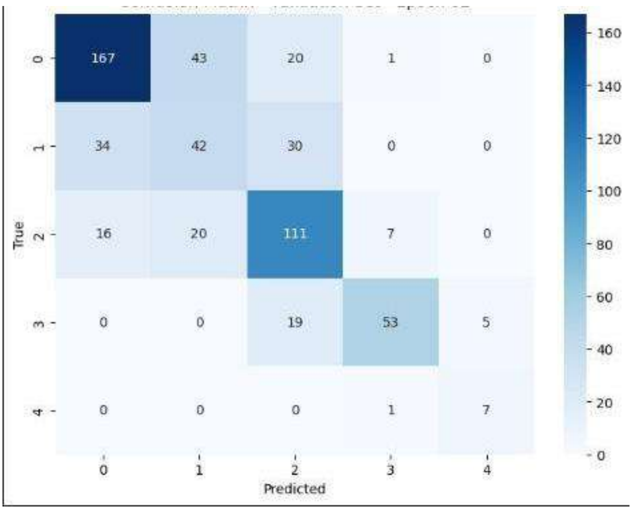


Figure 3:

Confusion Matrix for 0.30 Dropout

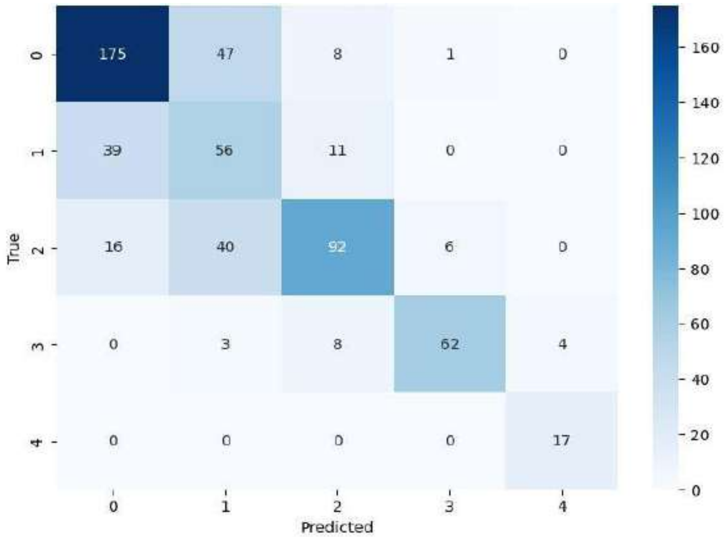


Figure 4:

Confusion Matrix for 0.40 Dropout

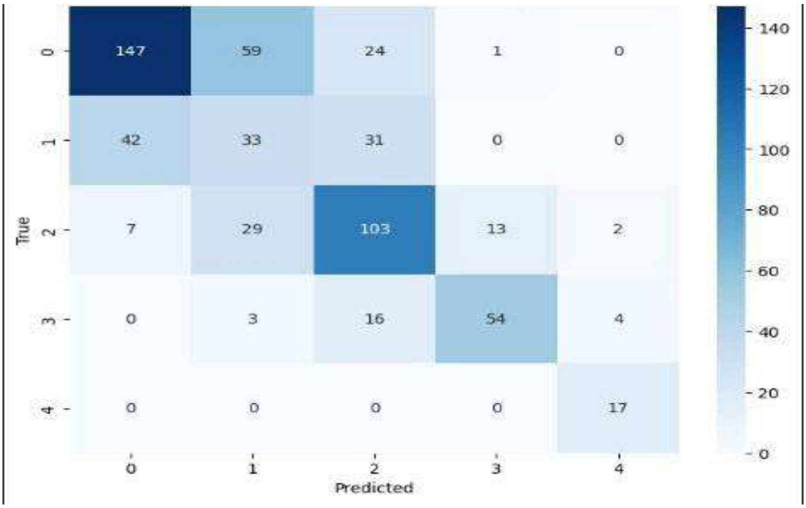


Figure 5:

Confusion Matrix for Sobel Filter

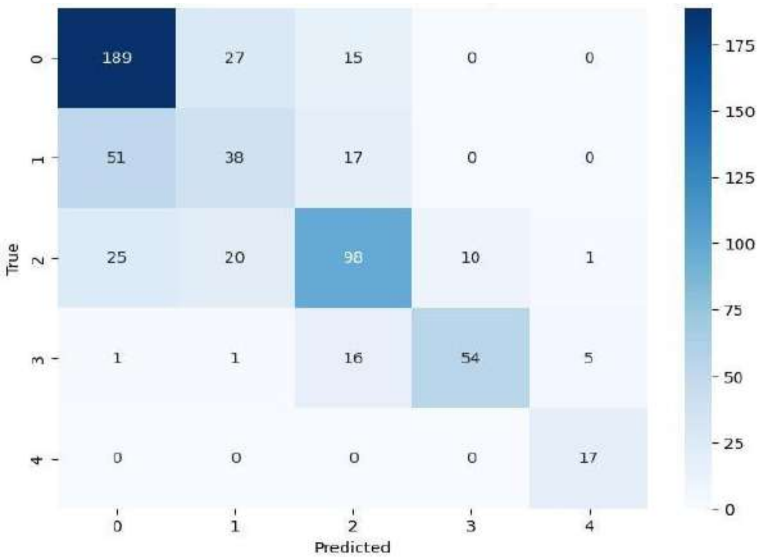


Figure 6:

Confusion Matrix for Gaussian Filter

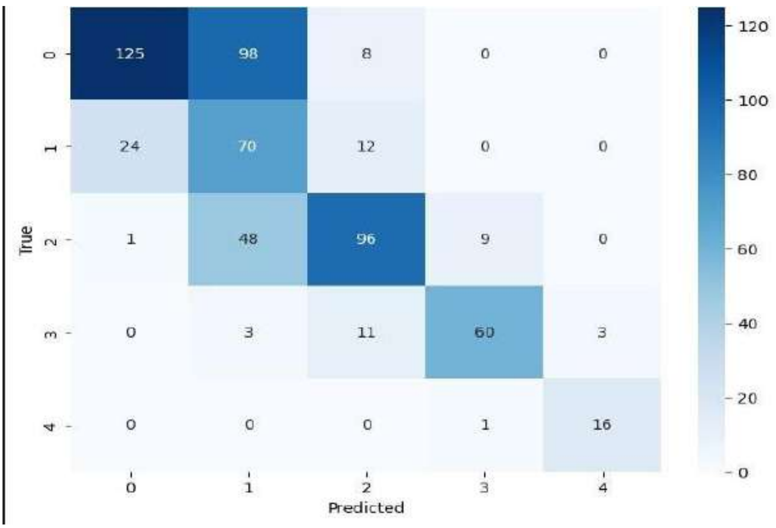


Figure 7:

Confusion Matrix for Entropy Filter

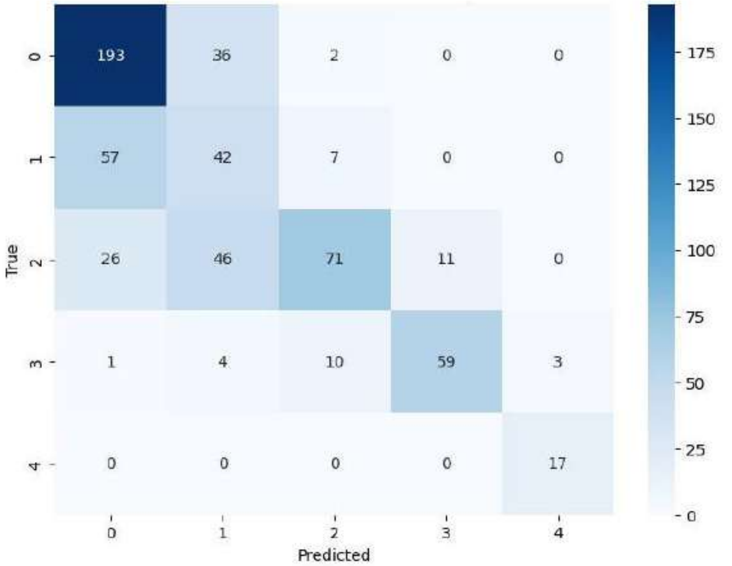


Figure 8:

Confusion Matrix for Directional Filter

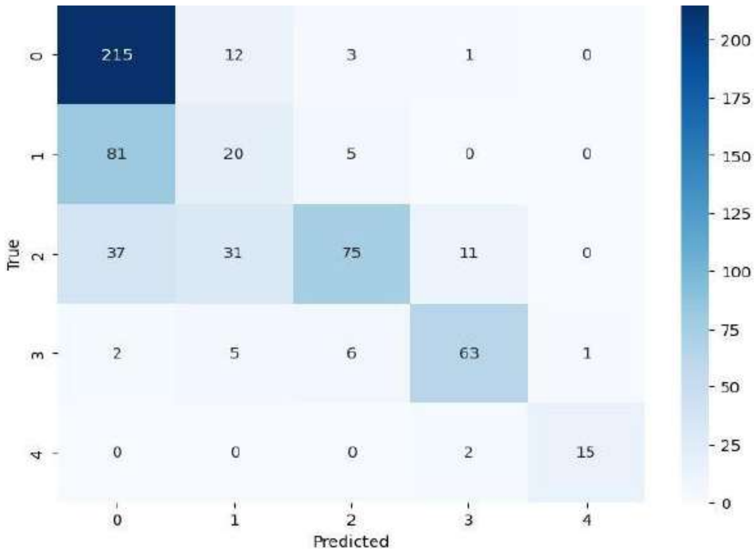


Figure 9:

Confusion Matrix for Histogram Equalization Filter

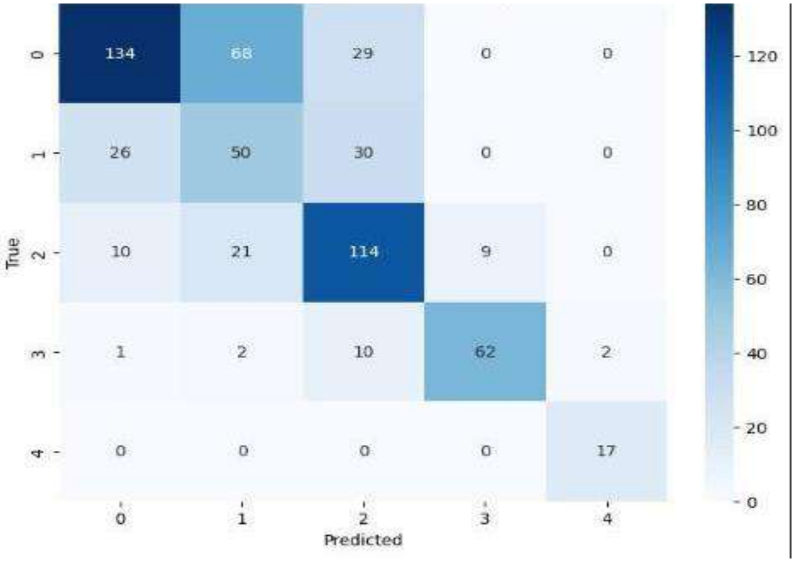


Figure 10:

Confusion Matrix for Laplacian Filter

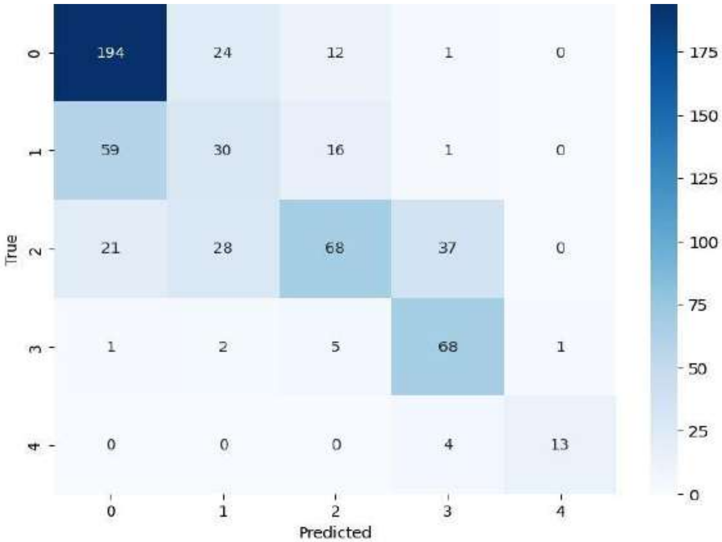


Figure 11:

Confusion Matrix for Gabor Filter

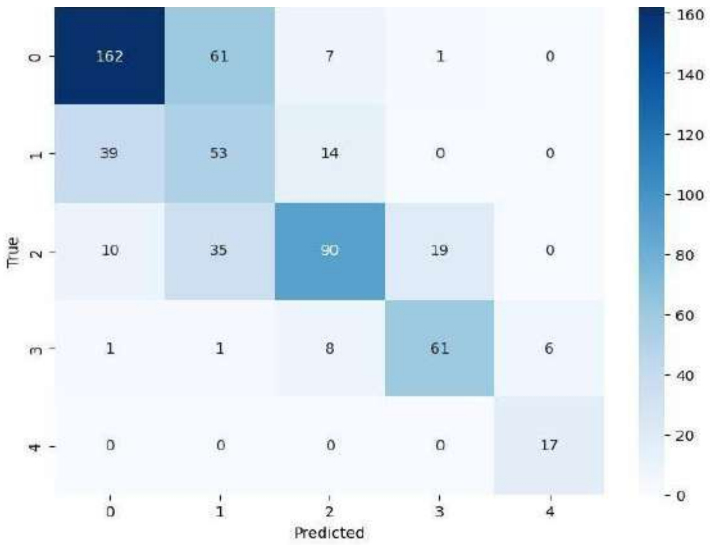


Figure 12:

Confusion Matrix for Bilateral Filter

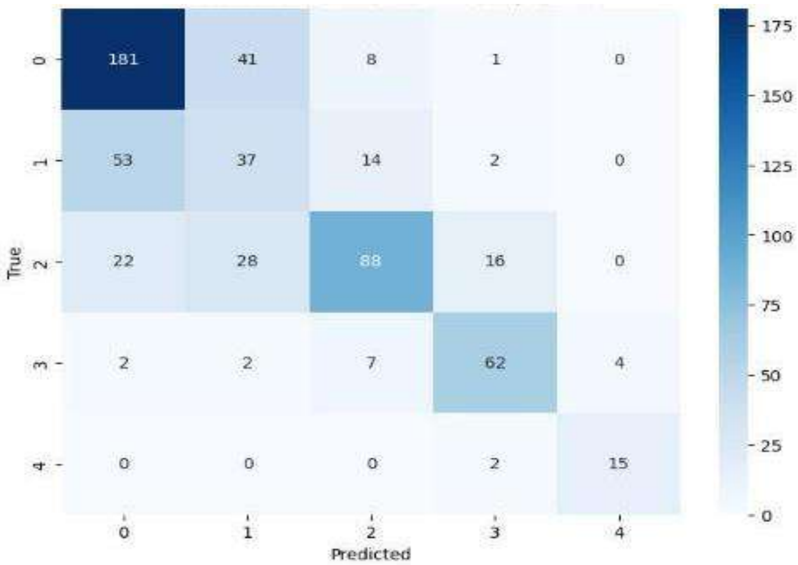
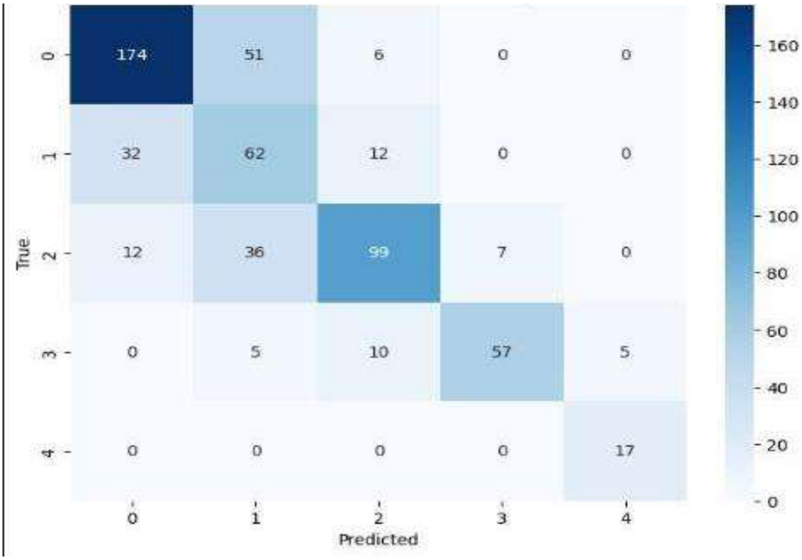


Figure 13 :

Confusion Matrix for Clahe Filter



Based on the analysis of the confusion matrices, the CLAHE (Contrast Limited Adaptive Histogram Equalization) filter demonstrated improved performance, particularly in distinguishing between overlapping classes in Knee Osteoarthritis (KOA) detection. The model showed significant improvements in accuracy, especially for Class 4 (moderate KOA) with an accuracy of 0.95 and Class 5 (severe KOA) with an accuracy of 0.99. These results suggest that CLAHE effectively enhanced the contrast of key features, enabling the model to better identify and classify the more advanced stages of KOA.

The model's overall performance, measured by the AUC score of 0.83, indicates a strong ability to differentiate between the stages of KOA. This demonstrates that CLAHE not only improved the accuracy for later stages but also contributed to better classification overall. The results confirm that CLAHE is a valuable preprocessing technique, particularly for enhancing the detection of advanced KOA stages.

5. Conclusion

This study implemented a CNN-based Knee Osteoarthritis (KOA) classification system, integrating various enhancement filters to improve classification accuracy, particularly for advanced KOA stages (KL grades 3 and 4). The model was rigorously evaluated based on its ability to address class imbalance, which is a common issue in medical image datasets, and to enhance feature extraction, with Contrast Limited Adaptive Histogram Equalization (CLAHE) emerging as the most effective preprocessing technique. The results demonstrate that image enhancement filters significantly improve KOA classification, particularly for later-stage cases (Moderate (3) and Severe (4)), leading to more reliable and accurate predictions. By refining the quality of X-ray images, the system is able to more effectively capture key features that distinguish between different severity levels. However, distinguishing between early KOA stages (KL grades 0, 1, and 2) remains a challenge due to overlapping features, which makes it difficult for the model to differentiate subtle differences in the early stages of the disease.

The study underscores the importance of image preprocessing in medical image classification, emphasizing that proper data enhancement is crucial for improving the performance of deep learning models. It also highlights how enhancement techniques, such as CLAHE, influence deep learning model performance by allowing the model to better recognize and interpret features that would otherwise be overlooked. The findings suggest that incorporating advanced preprocessing methods and optimizing feature extraction strategies can significantly enhance the model's ability to differentiate between various KOA stages and thus further refine KOA severity grading. Moreover, this study contributes to the ongoing development of deep-learning-based diagnostic tools, which hold great potential for transforming clinical practice by providing more accurate and automated assessments.

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Impact of Operational Risk on the Insurance Industry of Nepal

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Abstract

This paper discusses the impact of operational risk in the insurance industry. The risk related to operational cost represents a financial challenge to the insurance companies in Nepal and beyond. The primary objective of this article is to explore variables that cause operational risk in financial institutions in general and in the insurance industry in Nepal in particular. The risk of high operational costs impacts insurers' financial performance. The finding of the study reflects in the risks and their impact on Nepalese insurance companies associated to claims management costs, technology infrastructure, fraud and risk management, customer acquisition and retention, and disasters and losses. The research paper centers on only five arenas wherein the risk is faced by almost all the insurance institutions in Nepal. The researcher has used secondary sources of information in order to meet the objective. The mixed research design method has been employed to analyze the data. The exploration reveals that most of the insurance companies in Nepal suffer high risk when operating the cost for technology infrastructure and disasters and losses out of numerous operational costs.

Keywords: Operation cost, risk, insurance industry, technology infrastructure, customer retention, claims management

1. Introduction

The paper examines the risks that insurance companies face in Nepal regarding operational costs. The companies need to boost their competencies to mitigate the risks. Meanwhile, they get to accept the obvious risks posed to every sort of financial institution, including insurance organizations. The contribution of insurance companies to society as a whole is commendable. However, Nepalese insurance companies are mostly under suspicion by the common insurers when buying the policies because of the rumors spread. Both insurers and prospects lack ideas about how much insurance companies pay for mitigating risks.

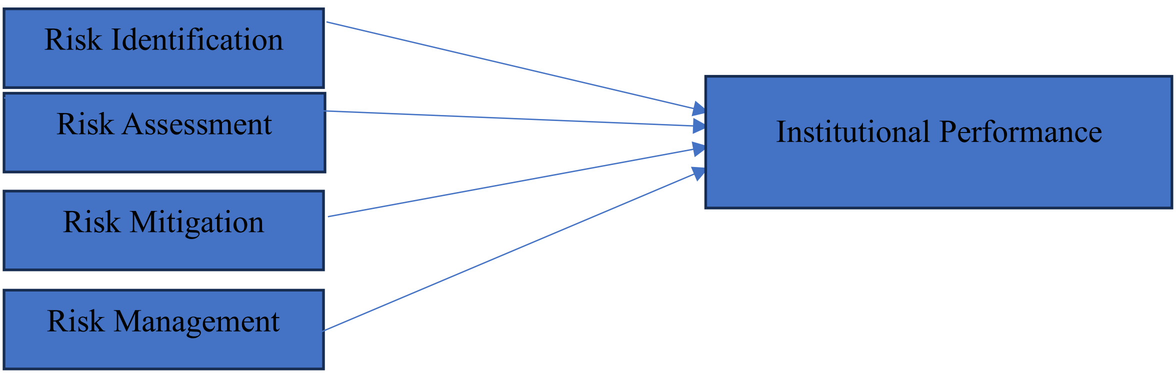
Operational risk is becoming more critical in the governance and management of insurance firms in Nepal. Insurance companies are facing greater consequences and interactions with other risks, such as credit or market risks. The management and assessment of operational risk is an essential task for insurers. The insurance industry offers numerous growth opportunities and serves as a significant area of social service through financial security. Nevertheless, its operational risk is unavoidable. The recent Nepalese regulation inevitably heightens the demand for efficient management of operational risks and the creation and execution of organized approaches for its evaluation. The traditional method of modeling, Value at Risk (VaR), along with other approaches for analyzing and quantifying operational risk for insurance companies, is also examined. The boards of directors in different insurance companies are concerned about the risk. The operational risk management identifies, analyzes, and mitigates the different risks business operations are exposed to. Two things are intertwined: the presence and integrity of management and operational controls of the insurance companies, and the capacity to keep the promise made to clients that the companies are committed to serving customers and meeting with the stakeholders, such as employees and suppliers of services. This paper assesses five different types of operational risk, such as claims management costs, technology infrastructure, fraud risk management, customer acquisition and retention, and disasters and losses that insurance companies in Nepal face.

2. Research Method

This paper has employed a descriptive and causal-comparative research design to discuss the operational risk in the insurance companies in Nepal. The descriptive research design has been adopted for fact-finding and adequate information gathering about the core issues associated with claims management costs, technology infrastructure, fraud and risk management, customer acquisition and retention and disasters and losses in the insurance companies in Nepal. It explains the real and actual conditions, situations, and facts. Causal-comparative research design has been used to demonstrate the cause-and-effect relationship among the areas of operational risk in Nepalese insurance companies. More specifically, the paper analyzes the impact of operational risk on the business of insurance companies in the current competitive business world. The article largely relies on secondary sources of information for analysis and conclusion.

Theoretical Framework

Independent Variables Dependent Variable



Source: *Altuntas et al., 2021, Altanashat et al., 2019, Mahat et al., 2023*

3. Review of Literature

Operational risk refers to the danger of loss, direct or indirect, resulting from insufficient internal procedures and/or incorrect individuals and systems or due to external events. In particular, for the insurance industry, operational risk, according to Solvency II standards, refers to the potential loss stemming from insufficient or unsuccessful internal processes, personnel, or systems, as well as from external incidents, encompassing legal risks, but excluding risks that emerge from strategic choices and reputational dangers. This concept of operational risk emphasizes the effects of operational losses. In this regard, there have been numerous studies, and some of them have been highlighted in this paper to clarify the concept of operational risk and its relevant core issues.

Kamal Gyawali and Dhan Bahadur Pun Thapa (2024) have opined that risk management in the insurance industry is serious but imperative for the sustainability of the companies. It is critical because it impacts on both performance and sustainability of the institutions. Financial institutions have to reduce the risk by analyzing all the variables that can help to discourage risk (p. 63). Additionally, insurance companies can safeguard themselves only through effective risk management for sustainable development. In most of cases, insurance companies suffer risks in terms of finance, regulation, operation, and marketing (Gyawali & Thapa, 2024). Provided that the risk in these areas is not managed effectively, the companies cannot meet the corporate objective.

A. Sayaju & K. Dhakal (2024) investigated the opinions and knowledge of employees about operational risk management in the banking sector. Their study shows that female employees have better knowledge of operational risk management than male employees because the former are closer to the issue than the latter. Their findings imply that there has been a huge impact of identification, management, and mitigation of operational risks on operational risk reduction in commercial banks of Nepal. The researchers have explored some of the major causes of operational risk, including "systems failure, inability to use new technologies, and lack of management support" as obstacles to performing better. Effective and timely reduction of operational risks in the banking sector can help to foster morale and performance of the employees. To accelerate the growth of the banks, the proper management of operational risks has been imperative. The banks need to stay committed to the management of operational risk for collective benefits. For doing so, employees must be made aware and trained through numerous development programs related to system management and operational risk management. Ensuring the security and efficient and effective management of the operational risk, along with other problems such as organizational conflicts in the financial institutions, can help to boost the corporate culture.

V.K. Kaishev, D.S. Dimitrova, and Z.G. Ignatov (2008) have investigated the finite time probability of (non) ruin that can be used as an operational risk measure to mitigate risk in a financial institution. In their view, this approach can help to discourage the operational loss frequency. In their terms, "it allows for inhomogeneous operational loss frequency (dependent inter-arrival times) and dependent loss severities which may have any joint discrete or continuous distribution". The linkage shown between inhomogeneous operational loss frequency and dependent loss severities is reflected in operational cost management.

Bhupal Jaishi (2020) has focused on the correlation between independent variables and dependent variables. In his terms, "return on assets and earnings per share are the dependent variables. Independent variables are the total debt ratio, the equity to total assets ratio, size, liquidity and tangibility. The finding of the research demonstrates that insurance companies with a high debt ratio can have better financial performance. Jaishi has emphasized the interdependent situation in which there is an increase in debt ratio and tangibility increases return on assets, and an increase in equity, size, and liquidity decreases return on assets in the financial institutions, especially in insurance companies of Nepal. The debt ratio and tangibility on earnings per share have garnered positive results, whereas equity, size and liquidity ratios on earnings per share have caused negative implications. Jaishi has concluded that the total debt ratio, equity to total assets ratio, leverage, size, liquidity, and tangibility significantly affect the financial performance of insurance companies in Nepal. Besides, these companies do not seem interested in enhancing financial performance that can foster their "total debt ratio and tangible assets and decrease equity, firm size, and liquidity ratio" (ibid). Jaishi has added that there has been a close connection between capital structure and the financial performance of insurance companies, although this case is disputable in both advanced and growing economies of the globe (2020). The capital structure variables, including debt and equity, along with firm-specific factors such as size, liquidity, and tangibility, have played a crucial role in shaping the financial performance of the insurance sector in Nepal. Decisions regarding capital structure directly on both investment and operational choices within the organization. Therefore, determining the optimal level of capital structure is essential since it significantly impacts the investment and operational strategies of the insurance companies.

Ganesh Sharma, in his research, found out that the size of a firm impacts financial return on equity, while it adversely affects return on assets. This implies that an increase in firm size correlates with a reduction in return on assets and an enhancement in return on equity. Similarly, leverage positively affects return on assets but negatively impacts return on equity, which indicates that greater leverage is associated with higher returns on assets and diminished returns on equity. Besides, the age of a firm positively affects return on equity and negatively influences return on assets, which further suggests that as a firm ages, its return on equity increases, whereas its return on assets decreases. Furthermore, liquidity negatively impacts both return on assets and return on equity, which signifies that higher liquidity of assets corresponds to lower returns on both metrics. In a related context, the leverage ratio negatively affects return on equity, while it positively influences return on assets, which implies that an increase in the liquidity ratio results in higher returns on assets and lower returns on equity. In Sharma's observation, financial institutions represent a diverse array of business activities within the financial services industry, which includes entities such as banks, trust companies, insurance firms, brokerage houses, and investment dealers. These institutions are pivotal to the socio-economic advancement and development of a country. The insurance sector, in particular, holds a crucial position within the financial services landscape across both developed and developing nations. It contributes to economic growth, enhances resource allocation efficiency, lowers transaction costs, generates liquidity, enables economies of scale in investment, and mitigates financial losses (2024). The role of insurance companies in the growth of finance in a country is reflected in the engagement of other financial institutions, including commercial banks, with the insurance industry.

The business strategy emphasizes the importance of insurance for the entire community. Due to ongoing economic advancement and technological progress, the growth of public infrastructure systems, a rising number of cultural and artistic public facilities, population increases, heightened population density, and the accumulation of economic values per unit area, along with production and service capabilities, the population, industries, and infrastructure face greater exposure to various risks and damaging events that lead to financial losses for the involved entities (Bosiljkal, Adamovic, & Milosevic, 2025).

Insurance does not stop losses from happening nor lessen them for separate individuals. Nonetheless, it reduces their effect on the economy, since the occurrence of damage can interrupt economic networks and unsettle economic relationships. Insurance provides prompt reimbursement for losses, facilitates recovery, and supports the rehabilitation of economic entities that have experienced damage, thus allowing for a quick restart of economic operations. Nonetheless, insurance may also produce adverse effects, possibly motivating economic agents to overlook precautions that prevent negative outcomes and losses, resulting in the development of unfavorable trends (Bosiljkal, Adamovic, & Milosevic, 2025). They focused on risk management that depends on the arrangement of structures, tools, and techniques for risk metrics and control, along with the regulatory framework and oversight of insurance. Reducing risk exposure is additionally reinforced by creating a specific department in the organizational framework, focusing on specialized staff capable of effectively managing risks (2025).

Nikki et al. (2023) have stated that contemporary statistical and machine learning methods are utilized predominantly (65%), with supervised (37%) and unsupervised (28%) strategies. This extensive model family encompasses algorithms grounded in statistical learning theory that examine and identify patterns in historical (and often higher-dimensional) data to draw inferences or forecasts about unobserved (future) data (Hastie et al., 2009). Supervised learning, in contrast to unsupervised learning, is directed by a dependent variable and typically suits prediction tasks. Decision trees and artificial neural networks (ANNs) are commonly employed to forecast the occurrence, type, or intensity of micro risks, especially in ENR.

Within these challenges, operational risk emerges as a vital element affecting the financial stability, profitability, and market value of these firms. Operational risk includes possible losses arising from internal procedures, personnel, systems, and external occurrences (Basel Committee on Banking Supervision, 2004). For insurance firms in Nigeria, grasping the effects of these risks on business performance is crucial, as efficient risk management safeguards the company's worth and fosters confidence among stakeholders, such as shareholders, regulators, and policyholders (Olaiya et al., 2025).

Operational risk in insurance firms stems from breakdowns in internal processes, personnel, and systems, alongside external occurrences that may hinder business operations. Within the Nigerian insurance sector, where economic instability and operational difficulties are common, leverage significantly influences how operational risks convert into financial results. Elevated leverage can limit a company's capacity to handle unforeseen operational losses efficiently, possibly resulting in financial difficulties. On the other hand, careful management of leverage can reduce the negative impacts of operational risks on financial outcomes, allowing companies to sustain stability and profitability (Olaiya et al., 2025).

4. Results and Discussion

This paper particularly discusses five major areas of operational risk in the insurance companies of Nepal. The first is claims management costs that get higher due to inefficiencies in handling claims. When processing claims is delayed, administrative expenses increase. Consequently, profit margins decrease in the companies. The second is technology infrastructure, which is reflected in the installation of the latest technological devices that can ensure protection from cyber-attacks and hacking. For cybersecurity and data analysis, the companies are under pressure to invest a large amount in buying technologies, including Artificial Intelligence (AI) and data analytics, and digital platforms in the competitive business environment. In the beginning, the installation of such technologies becomes expensive, and the companies usually fear the risk of losing the invested amount if the profit is not made accordingly. There are two kinds of risks: the first is that the companies may fail to generate business, but the investment in the installation is high, and the second is that the maintenance expenses for proper operation have to be covered. Meanwhile, the companies are expected to update their technologies or buy the latest technologies to cope with the ongoing changes in the world of science and technology. Otherwise, the companies can go out of business.

The third is fraud and risk management, which most of the insurance companies in Nepal face now. The insurers get pressured to conduct investigations into fraudulent claims, which pose a risk to operational costs. Besides, insurers and even the companies are obliged to detect fraud and prevent their systems from any wrongdoing. Some of the insurance companies have been found incapable of managing fraud effectively. As a result, such companies get pressured to adopt more advanced fraud detection systems. This obligatory act increases the ongoing operational costs in the respective companies.

The fourth cause of the operational risk is customer acquisition and retention. How to increase the number of customers in the insurance companies is a kind of pressure on the part of the insurance agents and the executive management. Even the employees experience this pressure as they are the coordinators between the management body and the freelance agents for the insurance companies. Customer acquisition demands marketing and advertising to draw the attention of the prospects. Besides, when a new product is launched, it demands a lot of attention from new customers. The investment in customer acquisition does not always bring about the expected results. Meanwhile, to retain the business, customer retention becomes essential. Most of the insurance companies in Nepal suffer from the crisis of customer retention, especially in rural areas, because when customers stop generating income or getting salaries from their workplace, they do not even pay the premium. In some cases, without maturing the policy, the insured stops paying the premium. This customer retention gets worse when the customers do not show any interest in new products. In both cases, the insurance companies face the risk. Customer acquisition and retention become costly and sometimes more expensive than the budget allocated for marketing and advertising.

The fifth cause of the operational risk is disasters and losses. When natural disasters, including the earthquake of 2015 in Nepal and pandemics worldwide, occur, the claims volumes and operational burdens increase unexpectedly. Most of the insurance companies in Nepal had to face a terrible crisis in addressing the claims. Mostly, claims were obvious in a crisis, but some of the claims were fraudulent. Such disasters aggravated the operation of the insurance companies due to a hike in the payment to the claimants. The insurers come under pressure to allocate additional resources to address the claims in the aftermath of the disasters. Most of the insurance companies had to compensate the public for losses. On one hand, there had been the casualties due to earthquakes and pandemics, and on the other, the insured had lost their properties. The insurance companies in such crises had to allocate more resources to the operational risk in Nepal. The figure below presents the major challenges that operational risk management faces.

Table 1:

Major Challenges and Their Impact on Insurance Companies

Challenges	*Impact*
Claims management costs	Reduction of profitability
Technology infrastructure	Operational Efficiency
Fraud risk management	Financial Losses
Customer acquisition and retention	Revenue Growth and High Premium Collection Ratio
Disasters and losses	Increased Claims Volume

Nepalese insurance companies experience challenges of different types when maintaining operational costs. The risk management practices directly affect performance and delivery of services. The correlation between performance and risk identification in Nepalese insurance companies is positive. However, due to poor regulation and lack of integrity in the financial institutions, the correlation has become weak. The implementation of risk identification measures fosters performance. Managing operational risk in the insurance companies in Nepal reflects the positive correlation with performance. Both risk examination and risk reduction display this positive correlation that eventually affects the performance of the insurance industry.

There are three different approaches to mitigating operational risk, such as the Basic Indicator Approach (BIA), the Standardized Approach (TSA), and the Advanced Measurement Approach (AMA). The Advanced Measurement Approach underscores using both internal and external loss information. The lost data can be retrieved through the Loss Distribution Approach (LDA). The AMA modelling framework helps mitigate the operational risk in Nepalese insurance companies. Dutta and Perry (2006) used the LDA to fit appropriate loss distributions to operational loss data.

Insurance companies in Nepal, in terms of operational risk management, experience diverse challenges, and the top management personnel have difficulty managing risks in insurance companies. A shift in investor risk-taking behavior emerged in risk management during the financial crisis (Aren & Nayman Hamamci, 2023). Operational risk occurs when external events affect insurance company employees, systems, and procedures. The study demonstrates that operational risk has been one of the main causes of financial losses in both the insurance industry and the commercial banking sector. Therefore, roles and duties in developing operational risk patterns need to be revised (Tuncel & Alpan, 2010; Zango et al., 2015). The current tendency of operational risk in the insurance industry in Nepal needs to be understood, and according to its pattern, the solution should be explored.

Bishnu Prasad Bhattarai (2020) has opined that in an insurance company, performance is typically measured by net premiums earned, profitability from underwriting operations, yearly revenue, investment returns, and return on equity. These metrics can be categorized as profit performance metrics and investment performance metrics. The connection between capital structure and profitability has been a notable focus of significant progress over the last ten years (p. 35). The focus on the relation between the performance of the insurance companies and their premium earning reflects the core principle of the insurance industry. Pertaining to risk identification and its assessment, Nishwarth Mahat, Surendra Pandey, and Bharat Singh Thapa (2023) have explored the positive impact of risk identification, risk assessments, and risk mitigation on insurance companies' performance. Nevertheless, the impact of risk reduction is scientifically crucial. Nepalese insurance companies need to emphasize risk reduction to boost up their performance. The first thing the companies gets to do is risk identification; the second thing is the risk assessment; the third thing they must focus on risk reduction; the final thing they must do is selection and implementation of the apt risk reduction techniques. Despite the high importance of all these four steps, the impact of risk mitigation on the performance of the insurance companies is high. The performance of life insurance companies in Nepal has been negatively affected by risk management and implementation. However, there have been very few companies that showed serious concern for resolving the problem.

The performance of insurance companies in Nepal can be improved if they focus on risk identification and mitigation, as reflected in the management of the operational costs that usually increase due to the pressures of claims management costs, the need for updated technology infrastructure, fraud and risk management, customer acquisition and retention, and disasters and losses. In fact, the goal of the insurance companies, under the pretext of social service and financial security for their customers, is to make profits.

Insurance risk pertains to the probability that a covered event happens, necessitating the insurance company to settle a claim, exceeding either its initial anticipation during the cost of the insurance offering, or its willingness to take on risk, like in situations involving natural disasters. Certain insured occurrences in Nepal carry a significantly reduced insurance risk. The anticipated claim experience from insurance in Nepal is relevant. Claims involving greater quantifiable losses are not as risky. For instance, the harm caused to a car under an auto insurance policy is easier to quantify (and therefore less hazardous) than the medical expenses or other obligations. Claims that have a high probability of being settled over an extended timeframe carry more risk compared to personal accident insurance. For life insurance, a critical illness rider poses a greater risk than endowment insurance. The comparative dangers are evidenced by the different amounts of capital that the Nepalese insurance companies need to maintain. The greater the risk, the larger the volume of capital needed to back those risks. Insurance risks can emerge from any of the fundamental functions of an insurance business: costing, risk assessment, claim processing, and retrocession, as they affect the frequency and quantity of risk.

5. Conclusion

This paper has studied the intertwined relationship between risk management of operational cost and the performance of the insurance companies in Nepal. The major finding of the study is that the impact of operational risk costs has been on most of the insurance companies of Nepal in the aftermath of the earthquake of 2015 and the worldwide pandemic. Because of the casualties and property losses due to the natural calamities, claim volumes increased unexpectedly, which forced almost all Nepalese insurance companies to allocate additional resources, including employees and capital for operational risk cost management. The installation of technology infrastructure became imperative in every Nepalese insurance company for cybersecurity. Due to the digitized financial institutions across the country, even insurance companies came under pressure to adapt to the digital world. The digital culture became costly, and therefore, operational risk management proved the top priority over the years. Only risk management of the operational cost helped the financial institutions, especially Nepalese insurance companies, to modernize their operational systems for effectiveness and efficiency.

By identifying, assessing, and mitigating possible risks, Nepalese insurance companies avoided unexpected financial losses and eventually fostered profitability. The overall impact of the risk management is reflected in customers' trust in the insurance companies. The researcher, by employing the descriptive and analytical approach based on the secondary data, successfully explored the significant impact of operational risk management on Nepalese insurance companies. One of the recent explorations has been that the relationship between risk management of operational costs and the performance, effectiveness, and efficiency of the insurance companies is unavoidable.

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Growth and Climate Sensitivity of *Pinus roxburghii* (Chir pine) from Melamchi Region of Nepal Himalaya: Research through Education

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Abstract

Climate change is affecting multiple sectors in Nepal including its diverse forests. Tree-rings data have many applications including the growth of species, and climate change impacts on tree species, among others. The Melamchi region has witnessed rapid climate change and extreme events and associated environmental hazards in recent years. In this context, a dendrochronological educational research field work was carried out in the Melamchi region of Nepal with the objective to assess the growth and regeneration of trees in different forests including the climatic response of chir pine (*Pinus roxburghii* Sarg.). Tree-core samples were collected and analyzed by following the standard dendrochronological method. The average diameter at breast height (DBH) of pine was 29.62 cm while the average annual radial growth was 2.71 mm per year and the average basal area increment was 1153.92 mm^2 per year. We observed many false ring bands in tree rings likely due to intra-annual climatic variability and or due to anthropogenic disturbances in the studied forest stands. An 83 years long tree-ring width site chronology of chir pine spanning from 1941 to 2023 AD was developed which shows long-term growth variability. The study found a significant positive relationship (based on correlation coefficient) between the pine chronology and precipitation in current year February, negative relationship with May month precipitation and February month temperature (average and maximum). The study also highlights that growth climate response of the chir pine is stable to changing over time i.e. the response to the February and May month precipitation and February month temperature is persistent over time while response with May month temperature is positively intensified but response to June and previous year October precipitation is weakening during recent years. The study also indicated that pine trees are sensitive and responsive not only to the climate change but also to the prevailing disturbances events, and growth of which can be affected by both of the phenomena. Educational research field studies are effective means in transferring theoretical knowledge to practical research aspects.

Keywords: Climate change, tree-ring, dbh, basal area, dendrochronology, forest growth

1. Growth and Climate Sensitivity of the *Pinus roxburghii* (Chir pine) from Melamchi Region of Nepal Himalaya: Research through Education

Dendrochronology, the science of tree-ring dating, has several applications in ecology, forestry, climatology, among others (Speer, 2010). Annual tree-ring can be used not only to study the climatic sensitivity and response but also to assess the impacts of climate change in the forests (Gaire et al., 2023a; Speer, 2010). Similarly, tree-ring data have been widely used to study past centennial to millennial-scale local, regional to hemispheric scale temperature, precipitation, drought conditions and streamflow (Cook et al., 2003; Gaire et al., 2022, 2024; PAGES 2k Consortium, 2013; Rao et al., 2020; Shah et al., 2014, 2019). Nepal Himalaya is experiencing rapid climate change with diverse impacts on multiple sectors (Chaudhary et al., 2023; ICIMOD 2023; IPCC 2022; MOFE 2021). Knowing the climatic sensitivity of the forest species is very essential to understand the possible fate of the different forest species in response to climate change as forests respond to climate change in diverse ways (IPCC, 2022; MOFE, 2021).

Located in the central part of the Himalaya, Nepal holds multiple tree species that can be used to assess the climate change impacts in the forests and biodiversity sectors using a dendrochronological approach (Gaire et al., 2023a; Gautam et al., 2020). Dendroecological studies already revealed the impacts of climate change on treeline ecotone of Nepal which indicated stable to changing treeline position in response to climate change (Chhetri and Cairns, 2015; Gaire et al., 2023a; Sigdel et al., 2024; Tiwari et al., 2023). Diverse tree species found in the country may respond to and adapt to the changing climate in their own ways. Growth-climate response analysis indicated that there is species- and site-specific climatic sensitivity and response of the tree species (Baral et al., 2022; Dawadi et al., 2013; Gaire et al., 2023a; Panthi et al., 2020). Therefore, it is very essential to know how the growth of tree species is controlled by different climatic factors. Are there any changes in the growth-limiting climatic factors over time? How are diverse tree species adapting in changing climate? Answering these questions enables us to assess how the ecosystem services provided by forest can be change in future.

Pine forests occupy sub-tropical to temperate regions of Nepal (DFRS, 2015; Stainton, 1972). Pine forest is very important socio-economically and ecologically (DFRS, 2015). They provide different ecosystem services to the people, and hence pine forests are under human pressure in most of the accessible areas of the country. A study from the Koshi River Basin of Eastern Nepal found that disturbance events evident in pine ring-width data are largely asynchronous, indicating these forests have been historically perturbed by human influences rather than large-scale climatic or ecological influences (Thapa & George, 2019). Pine trees are widely used in dendroclimatic study across Himalaya (Ahmed et al., 2009; Bhattacharya et al., 1992; Shah and Bhattacharyya, 2012). *Pinus wallichiana* and *Pinus roxburghii* are the two major native pine tree species distributed across the Himalaya including Nepal (FRTC 2015). These pine species produce annual rings that can be used to analyze quantitative growth, their climatic sensitivity and response to climate change (Aryal et al., 2023, 2024; Bhattacharya et al., 1992; Gaire et al., 2019; Gautam et al., 2022). Considering the significance of *Pinus roxburghii* (chir pine), some tree-ring studies have been conducted from Nepal using their annual tree-rings and associated features. Previous studies on chir pine have covered different aspects like wood anatomy (Joshi & Chalise, 2022), growth and plantation history (Bhuju & Gaire, 2012; Tiwari et al., 2020), growth-climate response (Aryal et al., 2018; Bhandari et al., 2024; Sigdel et al., 2018; Verma et al., 2018), forest health (Speer et al., 2017; Thapa & George, 2019), impacts of resin tapping (Bhattarai et al., 2025), impacts of invasive species in growth (Dyola et al., 2020), intra-annual growth dynamics (Aryal et al., 2023) and tree-ring stable isotopes (Aryal et al., 2024). Studies have been carried out from far-east to far-west of Nepal. Pine forest occupies large fraction of the forest in the Sindhupalchok district, however previous tree-ring studies have not covered the Melamchi watershed of the district which is experiencing rapid climate change, extremes and climate induced disasters (Adhikari et al., 2023; Baniya et al., 2024). Realizing this research gap and considering the importance of dendro-study, an educational research field visit was carried out in the Melamchi region in Nepal with the aim to understand the climate change situation, the growth of chir pine, and the climatic sensitivity of the pine growth.

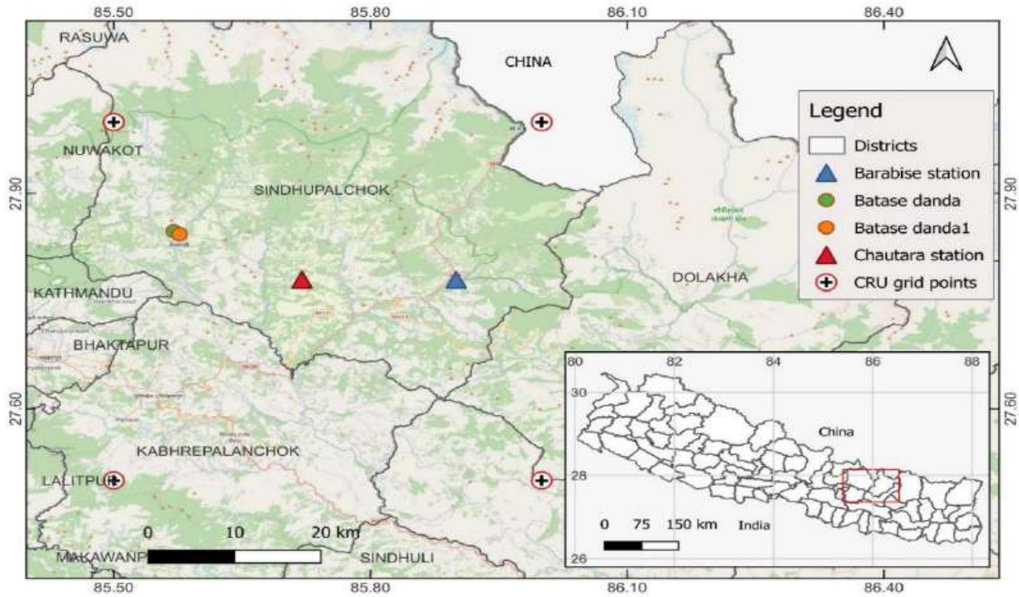
2. Materials and Methods

Study Area and Climate

Melamchi Municipality was selected as the study area (Figure 1). Melamchi Municipality is situated in Sindhupalchok District in the Bagmati Province of central Nepal. Of the total 160.04 km^2 area of the municipality, 37.4% was covered by forest in 2017 (DFRS, 2018; GGGI, 2018). Most of the area's forests are community forests, being sal, asna, khayar, katus, chilaune, gobre salla, thingre salla and gurans major tree species (GGGI, 2018).

Figure 1

Location of two Sampling Sites (circle) in Batase Danda of Melamchi Municipality and Local Climatological Stations (triangle) and CRU Grid (crossed circle) Used in This Study



The Melamchi watershed region is monsoon-dominated with majority of annual precipitation being received during the summer monsoon season (Figure 2). According to the Köppen–Geiger classification (Karki et al., 2016) it falls in Cwa (Temperate climate with dry winter and hot summer) and Cwb (Temperate climate with dry winter and warm summer). The lower part of Melamchi valley has a sub-tropical climate, while the upper part has a cool temperate climate (GGGI, 2018). The upper part of the valley receives more rainfall than in the lower part. According to the CRU gridded climate data (Harris et al., 2020), the average annual temperature was 16.2 °C while annual total precipitation was 2041 mm during the period of 1950 to 2022. Autumn and winter season are relatively dry (Figure 2). There is a significant increasing trend in the annual minimum (slope = 0.015), maximum (slope = 0.01) and average (0.013) temperature while no significant trend observed in the annual CRU and local station (Barabise) rainfall data (Figure 3). Previous studies also indicated that Sindhupalchok district is experiencing a non-significant decreasing trend in the annual and seasonal precipitation but a significant positive trend in the maximum seasonal and annual temperature and monsoon season minimum temperature (DHM 2017). The district is experiencing significant changes in climatic extreme events like Extremely wet days, Warm days, Cool days, Warm spell duration and Warm nights (DHM, 2017). But, no long-term trend in the scPDSI data (van der Schrier et al., 2013) was observed though extreme drought events have been increasing in recent years. The scPDSI data analysis revealed that years 2015, 2014, 1995, 1921, 1994, 1908, 1992, 1958, and 1993 experienced severe to extreme droughts while years 2011, 1945, 1949, 1987, 1913, 1946 and 1986 were very wet (Figure 3b).

Figure 2

Walter-Leith Climograph of the Melamchi area based on CRU grid climate data. In the X-axis, Abbreviations of the Month are Presented Starting from January (J) to December (D)

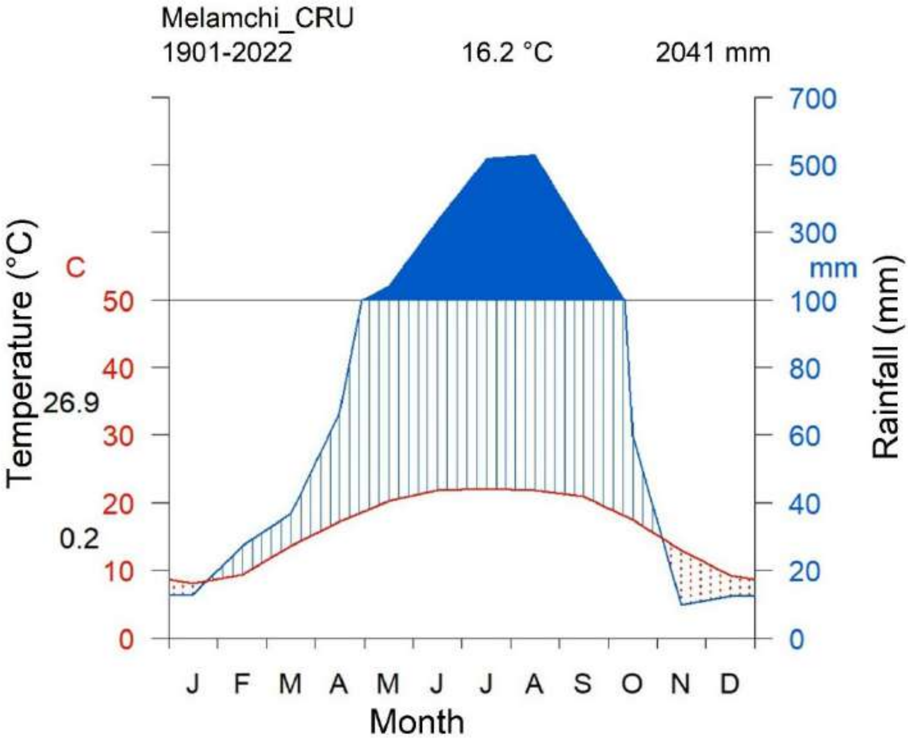
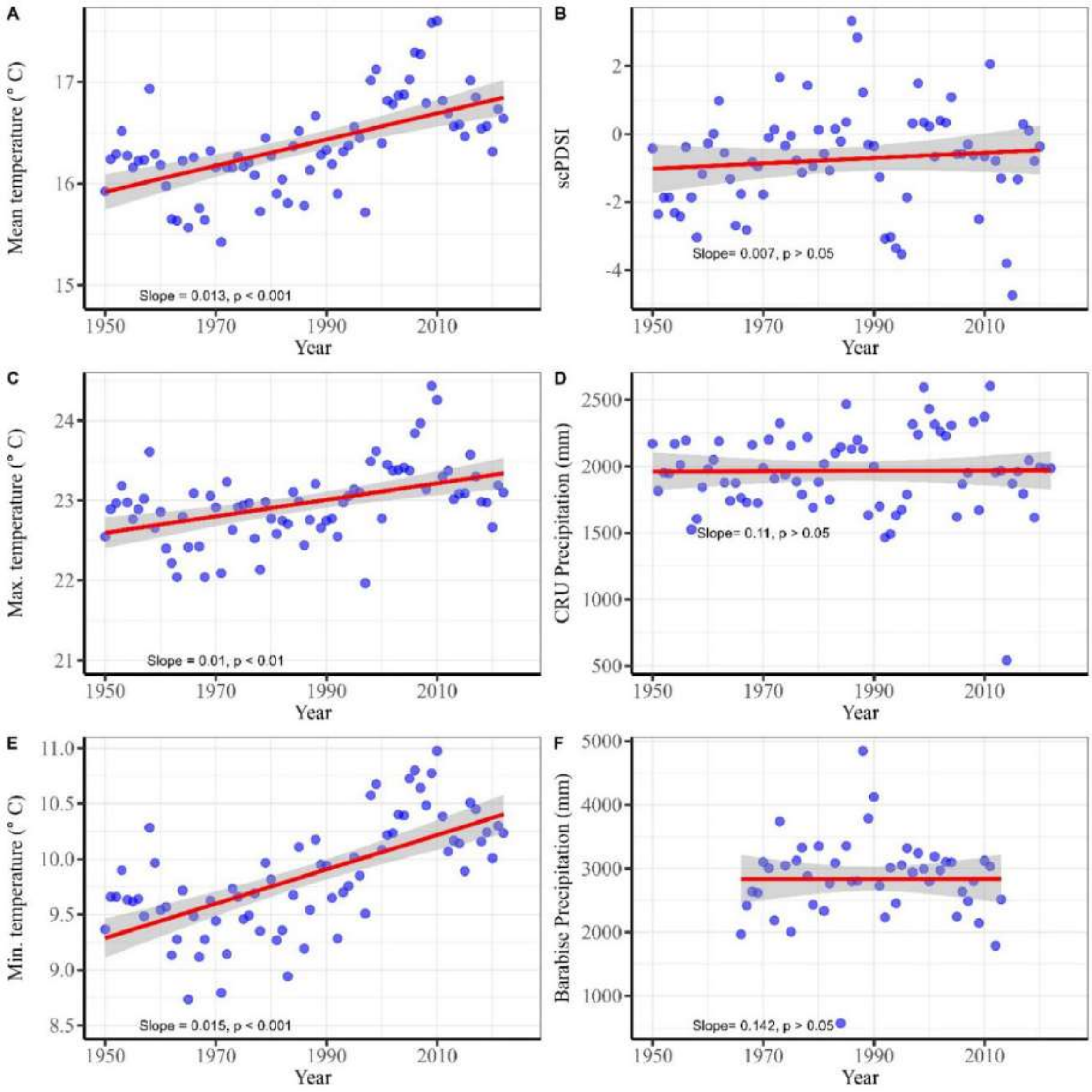


Figure 3

Trend in the Annual Maximum, Minimum, Average Temperature, Annual Total Precipitation and scPDSI Based on CRU and Barabise Station Data



Field Visit, Data and Sample Collection and Analysis

An educational field visit was carried out in the Melamchi Municipality during March-April month of 2024. We carried out forest surveys in the different locations of the Melamchi for educational research field study purposes targeting species richness of the area and growth of pine trees. During the visit students also learned different aspects of dendrochronological research including how to collect tree cores for different study purposes, and how to analyze samples to estimate their age and growth. Pine forest of Batasedanda of Melamchi Municipality was selected for the study site. Tree cores were collected using an increment borer following standard sampling procedures (Fritts, 1976; Speer, 2010). One to two cores per tree were collected from the breast height of the selected healthy appearing trees. Sampling location was recorded using the GPS. Collected tree cores were carefully packed in the plastic straw with proper labelling and brought to the laboratory for further analysis.

In the laboratory, tree cores were left for a few days for the air dry and then mounted in the wooden frame with the transverse surface facing up (Speer, 2010). Then they were again left for a week to air dry of the glue. The air-dried core samples were sanded and polished using different grits of sandpaper until the cellular levels' visibility of the tree-rings under the microscope. Then, each ring in the cores was counted and dated to their calendar year. As the sampling year's growth was just started with incomplete growth rings, its width was not measured and measurements were done until 2023 AD's rings. After counting and dating of each ring, measurement of the ring width was carried out by using the LINTAB measuring system attached to the computer having TSAP-win software (Rinn, 2010). Crossdating was carried out in the TSAP-win program by using different crossdating statistics (Rinn, 2010). Crossdating was challenging due to the presence of asynchronous false ring bands within tree rings; however, we were able to accomplish it by careful re-checking of samples. Further error in the crossdating was corrected using the quality control program COFECHA (Holmes, 1983).

Crossdated samples were proceeded for standardization and chronology development. Standardization was carried out in the dplR package (Bunn, 2008). Detrending was done by using modified negative exponential growth curve or spline curve or using both. Finally, a different version of the chronologies was developed. The quality of the chronology was assessed by using commonly used chronology statistics like R-bar, EPS, etc. (Wigley et al, 1984). The running R-bar and EPS value were calculated in the RCSSigFree program (http://www.ldeo.columbia.edu/tree-ring-laboratory/resources/software). To assess the long-term growth of trees, a BAI chronology was developed by using dplR package (Bunn, 2008).

The climate data of meteorological stations closer to the sampling site were collected from the Department of Hydrology and Meteorology. Since, stations data covers only short time span with many missing values, CRU gridded climate data (0.5 X 0.5° resolutions) was extracted by using KNMI climate explorer (Harris et al., 2020; Trouet & Oldenborgh, 2013) for further analysis as majority of the previous dendrochronological studies from Nepal have also used them in growth-climate response analysis. The CRU data used in the study includes monthly minimum, maximum and average temperature, monthly precipitation and monthly scPDSI. To assess the growth-climate relationship, simple and bootstrapped correlation was carried out by using the "treeclim" R package (Zang & Biondi, 2015). A 14-month's climatic window starting from previous year September to current year October was used for response analysis and to identify growth limiting climatic factors. Temporal stability of the response was assessed by using the "treeclim" R package using a 30 years climatic moving window with one-year time offset (Zang & Biondi, 2015).

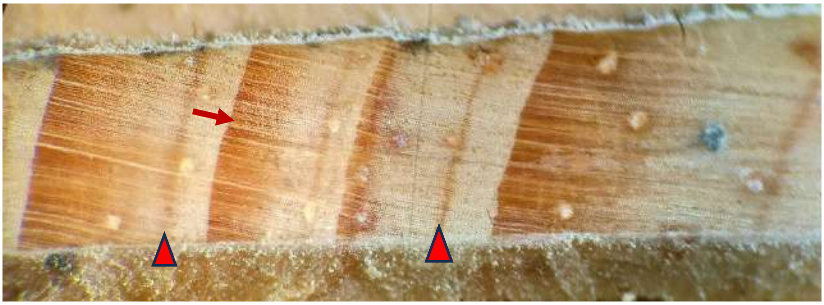
3. Results and Discussion

Growth Characteristics of Chir Pine from the Melamchi Area

We sampled trees having different diameter sizes. The average DBH (diameter at breast height) of trees in the sampling area was 29.86 cm. In the sampled trees there is a distinct ring boundary (Figure 4) in most of the years; however, diffused ring boundaries as well as false ring bands (Figure 4) were also recorded in many samples. Only a few series had zero flag in COFECHA though the majority of the series have shown high (>10) CDI value in TSAP-win software with moderate interseries correlation r-bar (> 0.4). Similar situation was obtained in the pine samples from Nagarkot area where only three sampled series showed zero flag in COFECHA (Speer et al., 2017). Presence of false rings is common observations for this species in previous studies too (Aryal et al., 2018, 2024; Bhattacharya et al, 1992; Bhattarai et al., 2025; Speer et al., 2017; Thapa & George, 2019). Similar to our observations, the chir pine trees sampled from the Nagarkot region in Kathmandu valley where false rings were observed in several consecutive years (Speer et al., 2017). The chir pine trees in the study sites of Melamchi were 25 to 83 years old with an average age of 60 years (Table 1). The overall average radial growth of all sampled trees was 2.71 mm per year with individual tree's average growth ranging from 1.89 mm to 4.69 mm, while the maximum growth of the individual trees ranges from 5.33 mm to 13.48 mm per year (Table 1). Even in the same tree growth was different in the different radial directions of a stem. Radial growth of the species in Kathmandu Valley was observed to be 0.25±0.05 cm/yr, 0.31±0.08 cm/yr, and 0.32 ±0.03 cm/yr at Sallaghari (Bhaktapur), Singh Durbar and Thapathali (Kathmandu), respectively (Bhuju & Gaire, 2012). The growth rate of the trees varies with size and age in addition to the influence of topo-climatic factors (Fritts, 1976).

Figure 4

Picture showing True Annual Tree Ring (horizontal arrow) and False Rings Band (triangle)



Eighty-three years long tree-ring width site chronology of chir pine spanning from 1941 to 2023 AD was developed in the present study which revealed growth fluctuations over time with some low and high growth periods (Figure 5). There is a slide decline in the growth during recent few years. Previous studies developed 50 yrs to ~300 years long chir pine chronologies in different regions of Nepal (Aryal et al., 2018; Bhattacharyya et al., 1992; Bhuju & Gaire, 2012; Sigdel et al., 2018; Verma et al., 2018). The chronology statistics (Table 1) of our chronology revealed moderate mean sensitivity (0.33) and r-bar, but a high EPS value compared to commonly used

EPS threshold value of 0.85 (Fritts, 1976; Wigley et al., 1984). As the EPS value was different in the different detrending options and program, here we used a running R-bar and EPS value obtained from the RCSSigfree program as it was highest among different options we tried. The statistics obtained in the chronology are comparable to that obtained in the pine from Nagarkot region but relatively low compared to the data of the same or other conifer species in the different studies in Nepal (Aryal et al., 2018; Bhattarai et al., 2025; Bhuju & Gaire, 2012; Chhetri & Cairns, 2015; Sigdel et al., 2018; Speer et al., 2017).

Since many chronology statistics like EPS are also dependent in the sample depth, age and shared response captured in trees, a low EPS values could be the result of the low sample depth, incorporation of young trees in the samples, individualistic growth pattern of young trees and or poor crossdating resulted from false rings. In a study in the Nagarkot region, pine stands at a heavily impacted site also resulted in the poor crossdating with the encounter of the several false rings (Speer et al., 2017). Similar to the pine samples from Nagarkot, our study site was also close to a mountain road, a picnic spot and often used for cattle grazing by local peoples.

Figure 5

Tree-ring width standard (blue) and residual (red) chronology of chir pine from Melamchi region with sample depth (shaded area) (a), and running EPS and R-bar with EPS threshold value (b)

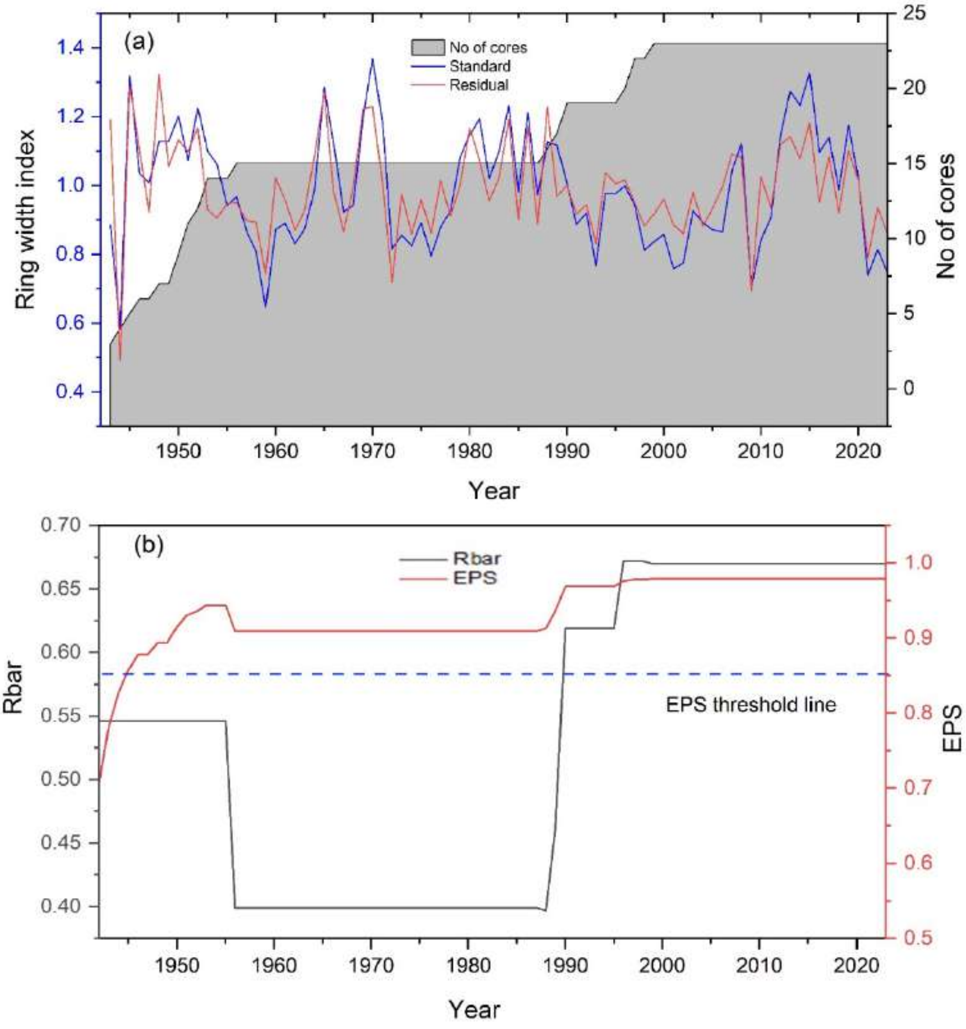


Table 1

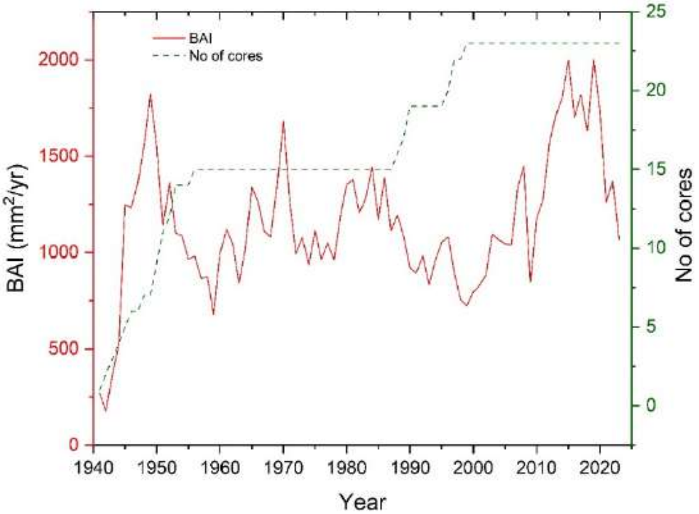
Chronology statistics of Pinus roxburghii from the Melamchi region of Nepal

Parameters	Value
Average DBH (cm)	29.62
No of samples	23
First year	1941
Last year	2023
Period	83
Mean age (yr)	60
Average radial growth rate (mm/yr)	2.71
Standard deviation (SD)	1.83
Skew	1.20
Mean Sensitivity in COFECHA	0.33
First order autocorrelation (AC1)	0.67
R-bar	0.43
Expressed Population Signal (EPS) (using RCSsigfree)	0.97

The basal area increment of the pine trees was also calculated. The average annual BAI was found to be 1153.92 mm^2 per year (Figure 6). The BAI chronology of the chir pine revealed an overall growing stage of the forest with growth suppression during some period (Figure 6) which indicates that the forest is in a growing stage. We don't have previous literature to explain exactly how the BAI curve of the chir pine follows. However, previous studies indicated that BAI of many species follow a sigmoid growth curve (Baral et al., 2022; Gaire et al., 2023b; Tiwari et al., 2020).

Figure 6

Basal Area Increment (BAI) chronology of the Chir pine from the Melamchi Area in Nepal



Growth-Climate Response of Chir Pine

Different detrending options was tried to develop various versions of the chronologies. The chronologies using the spline growth curve or double detrending using modified negative exponential and age dependent spline curve captured more climatic signals. Therefore, here we present the response of the residual tree-ring width chronology developed using the double detrending. The study found a significant positive relationship (Pearson's correlation coefficient) between the pine chronology and precipitation during current year February and significant negative with May month precipitation and average temperature of February Month (Figure 7). Similarly, we obtained a negative relationship between pine growth and monthly maximum temperature during the current year February (Figure 8). The climate graph shows dry periods during late autumn and winter (November, December and January) months (Figure 2) which may explain a positive response with precipitation and negative with temperature during February month.

The result indicated that favorable climate in February is very critical for chir pine growth in the study area as it is the beginning period of the annual growth. Negative relation with May month's precipitation could be related to the high precipitation (cloud cover) related temporary cooling during peak growth period leading to a growth retardation or less growth, as the study area receives more than 2000 mm annual precipitation majority being received during subsequent monsoon season (June to

September). There is no persistent pattern in the climatic response of chir pine growth across entire Nepal Himalaya rather it varies with site condition and climatic regime of the region and prevailing disturbance events (Aryal et al., 2018, 2023, 2024; Bhandari et al., 2024; Bhattarai et al., 2025; Chauhan et al., 2017; Sigdel et al 2018; Speer et al., 2017; Thapa & George, 2019; Tiwari et al., 2020; Verma et al., 2018).

However, spring season moisture stress to tree growth is most widely observed growth-climate response in the Nepal and India Himalaya in the pine and other conifer and broadleaved species (Dawadi et al., 2013; Gaire et al., 2019, 2022; Panthi et al., 2020; Sigdel et al., 2018; Tiwari et al., 2020). The positive relationship with precipitation in February and the negative response with spring season's February month temperature (average and maximum) is a shared response to the previous studies (Aryal et al., 2018; Sigdel et al., 2018; Tiwari et al., 2020).

Study on chir pine from Nagarkot region obtained a positive relationship with precipitation during the current year March and November month (Speer et al., 2017). Similar to our observation, the chir pine growing in the Chure region of Makwanpur district has displayed a weaker relationship with CRU precipitation during growing seasons (Aryal et al., 2024). Chir pine chronology from the Nagarkot area showed significant negative correlations with precipitation during previous and current September but positive correlations with current March and November (Speer et al., 2017). We don't have exact growth phenology of chir pine from Melamchi area to say scientifically when the growth starts and when the growth ends for which monitoring using dendrometer data and quantitative wood anatomy in future will shed a light on exact cycle of pine growth and their climatic sensitivity (Aryal et al., 2023).

Figure 7

Relationship between the tree-ring residual chronology of chir pine with monthly average temperature (Tmean) and precipitation (PPT). The solid bar indicates significant relation which dashed bar indicates statistically insignificant correlation

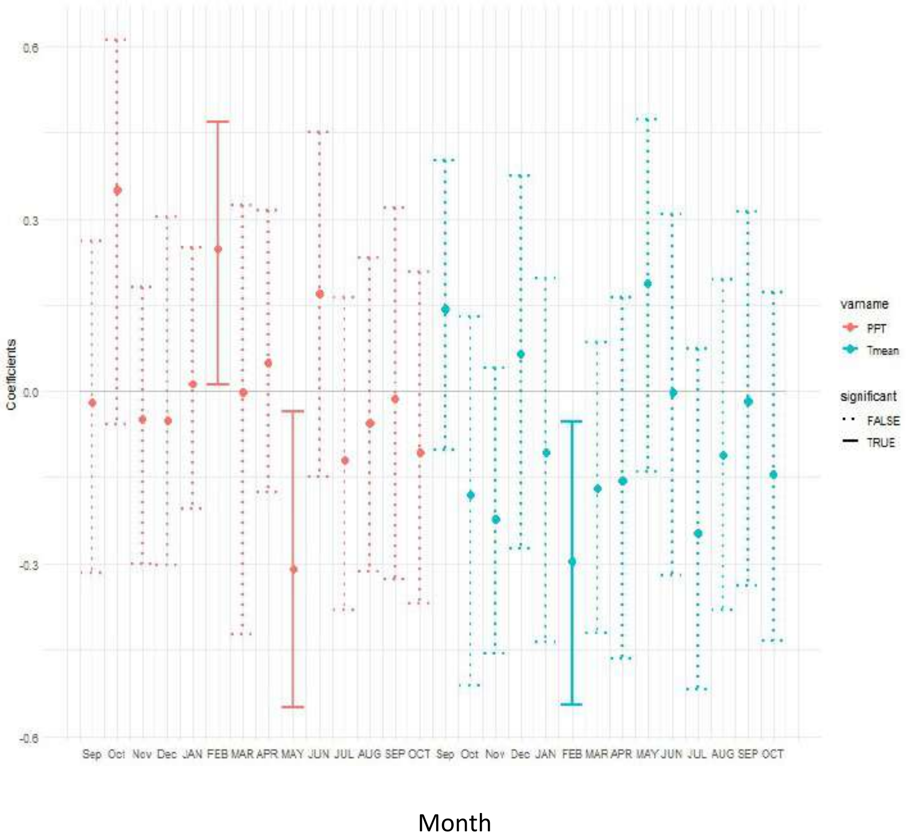
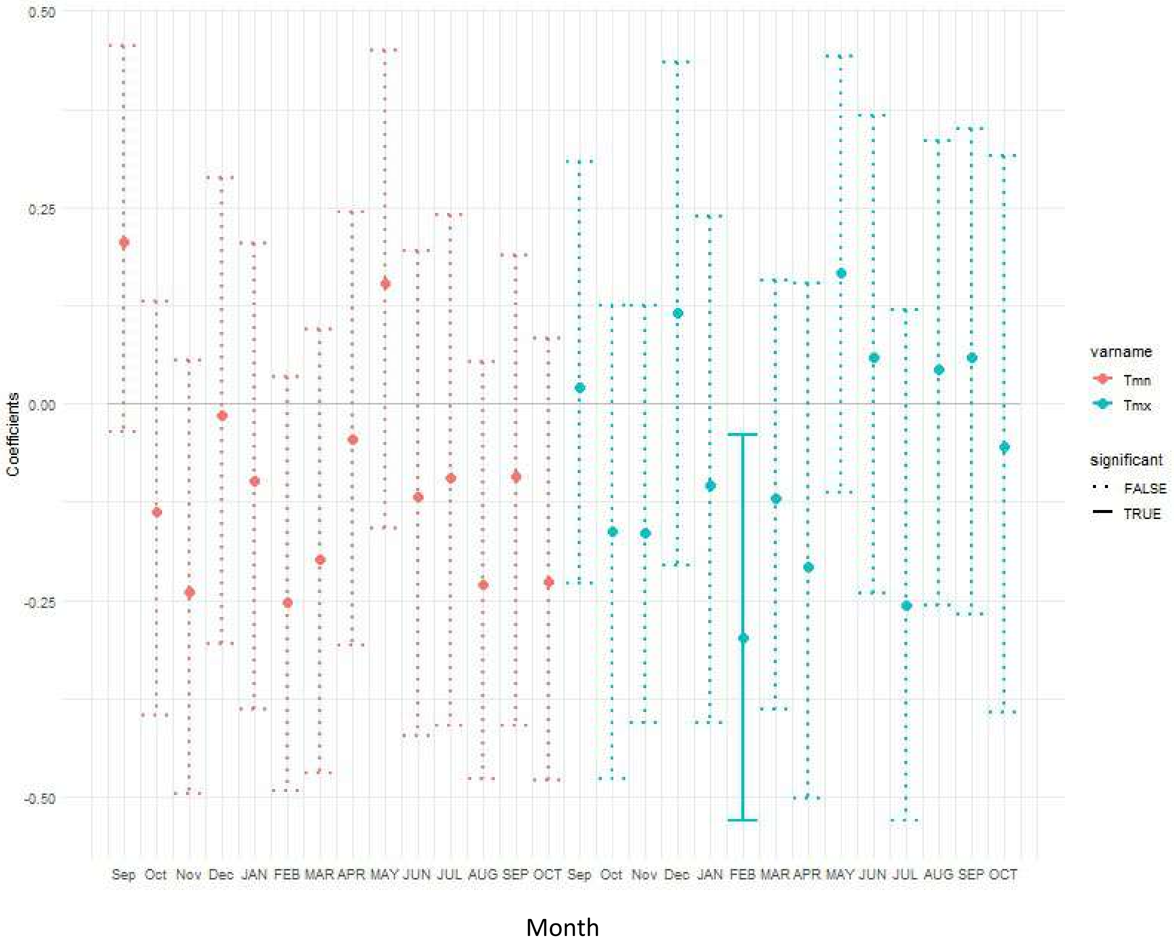


Figure 8

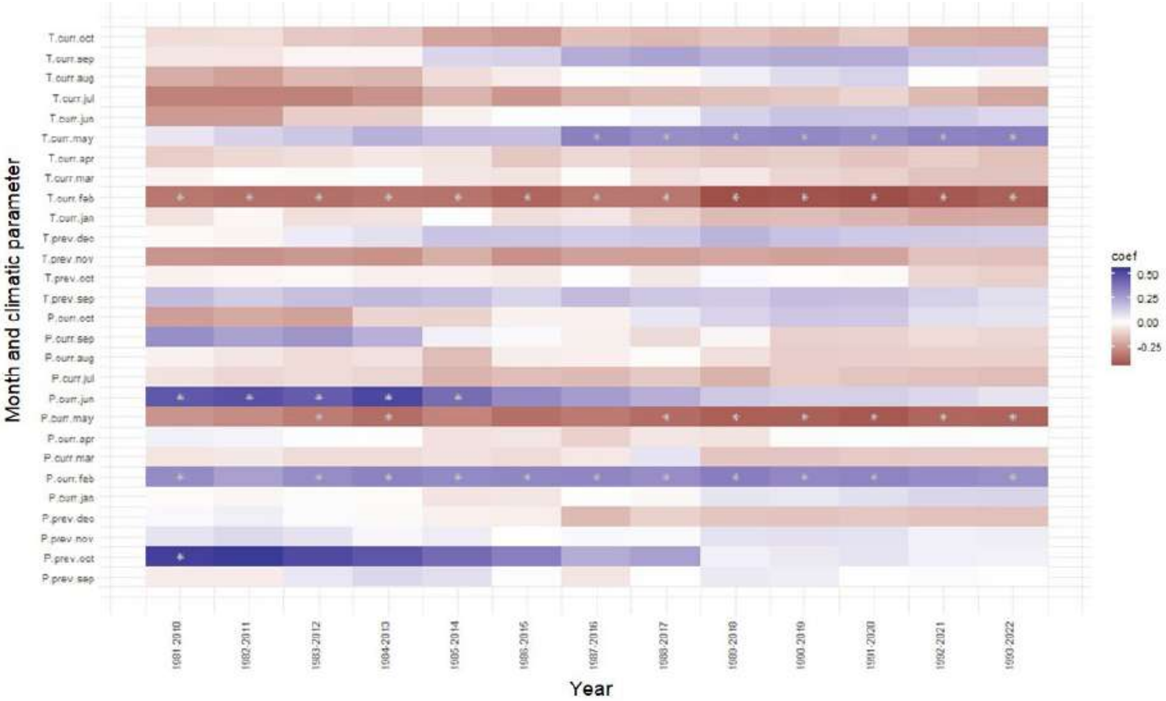
Relationship between the tree-ring residual chronology of chir pine with monthly maximum (Tmx) and minimum (Tmn) temperature. The solid bar indicates significant relation which dashed bar indicates statistically insignificant correlation



The present study analyzed the temporal stability of the growth-climate response of the chir pine. The result indicated that the response is stable to changing over time (Figure 8). The response of pine growth to the February and May month precipitation and February month temperature is persistent over time (Figure 9). Looking at the temporal stability of the growth response to seasonal average climate, there is no obvious shift in the response, though there are changes in the strength of association between the tree growth and climatic parameters. Response of growth with May month temperature is positively intensified. The response of growth to current year June and previous year October is weakening during recent years. Though there are limited studies in the temporal response of pine growth to climate in the Nepal Himalaya, studies on the *Abies spectabilis* (Gaire et al., 2020; 2023b; Schwaab et al., 2018) and *Shorea robusta* (Baral et al., 2022) have reported temporally stable to changing response of growth to climatic parameters. A study from the Gaurishankar Conservation Area observed temporal shift in the growth limiting factor in *Abies spectabilis* (Schwab et al., 2018).

Figure 9

*Temporal (Moving correlation) variation in climatic response of pine growth in Melamchi Area. The filled color indicates correlation coefficient and * symbol indicates significant response, P and T denotes temperature and precipitation*



4. Conclusion

A dendroecological educational field research work successfully developed an 83 years long tree-ring width site chronology of chir pine from the Melamchi region of Nepal spanning from 1941 to 2023 AD. The quantitative radial growth analysis revealed that the species is growing radially at a rate of 2.7 mm per year on an average.

Despite the presence of some false rings, study found that chir pine of the region has huge dendrochronological potential and hence can be used for multi-aspect tree-ring research especially to explore the impact of climate change on forest and forest health. The basal area increments chronology of the species indicating a growing stage of the pine forest. Both temperature and precipitation in different months and seasons are acting as major growth-limiting climatic factors for the pine. Studies incorporating more samples as well as sampling from multiple sites can provide a robust picture on long-term pine growth and their climatic sensitivity along environmental gradients in the Himalayas. Future education field studies can extend the scope of the research incorporating multiple tree species and focusing on contemporary environmental issues.

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Change in Country-Related Emotions in Nepal from 2021 to 2024: A Trend Study

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Abstract

Emotion-related longitudinal studies are rare in Nepal. This study aimed to track changes in various emotions, including basic and country related emotions, over four years. Data were collected from 286 individuals over four years in four time periods using the survey method. The data were processed in trend analysis and time series regression analysis. This trend study showed that basic emotions did not change consistently over time. Some country-related emotions like country pride and country love showed a consistent decline/incline. Moreover, anger toward leaders was also seen consistently rising. The conclusion is that tracking changes in basic emotions may not be useful in the future. However, tracking changes of country-related emotions can give insights to modify the government's behaviors, programs, policies, and decisions.

Keywords: basic emotions, country-related emotions, anger, jealousy, love

1. Change in Country-Related Emotions in Nepal from 2021 to 2024: A Trend Study

Emotion is strong feeling with complex reactions (Baron & Misra, 2016) that include physiological responses (e.g. variations in blood pressure and heart rate), subjective experiences/cognitive evaluation (Feldman, 2019a) we label as joy, happiness, fear, anger, sorrow, and disgust, and expressive behaviors (e.g. facial expressions or changes in posture) that convey these internal states. Emotions play a vital role in various aspects of behavior, including personal well-being and psychological disorders. Moreover, they significantly impact cognition, shaping or even dictating our judgments and decisions in meaningful ways. Emotions help us prepare for action, plan for the future, and behave with others (Feldman, 2019b). Emotions can be negative (such as anger, sadness, and fear) or positive (such as joy, love, and pride). Emotions have feelings and intentionality, which consist of evaluation, cognition, and motivation (Ben-Zeev, 1987). Emotions have a mental, behavioral, and neurophysiological basis. Ben-Zeev considers it a mental state. Emotions are object-directed. Emotions are not isolated internal entities but ongoing attitudes of the whole agent with public and private features. Intentions, goals, and social context shape emotional experiences (Campos et al., 1994). Emotions and the mind have evolved through natural selection to increase fitness or adaptation (Plutchik, 2001).

Anger, fear, disgust, sadness, and enjoyment are basic emotions with universal facial expressions and changes in voice (Ekman, 2003, 2016). Surprise may not be a basic emotion. Our brains rapidly and unconsciously assess situations for their emotional relevance. Emotions are short-lived, intense reactions, whereas moods are longer-lasting, less intense emotional states. Basic emotions are universal, evolved for basic life tasks, and have distinct physiological patterns (Ekman, 1999). They are fleeting in duration and quick to start. They occur unbidden and are associated with specific thought patterns, memories, and mental images.

Emotions may be felt with little or no consciousness (Feldman, 2019a).

Emotions also play a role in rational/non-emotional decisions.

In 2020, a pandemic-induced lockdown caused positive, negative, and changing emotions (Adhikari, 2020). Fear, sadness, and frustration were common but were counterbalanced by hope, happiness, and personal growth. The nature of emotions changed from moment to moment.

Emotional expression or regulation is contributed by social and cultural factors. For example, Brahman and Chhetri children in Nepal could express and hide negative emotions more than Tamang children. Tamang children discovered this on their own, but Brahman and Chhetri children were taught emotion regulation (Cole & Tamang, 1998). Nepali mothers reacted punitively to children's emotions (Cho et al., 2022). They also showed distress reactions.

Emotions have a social nature. Emotions are elicited by, expressed toward, and regulated to influence others or comply with social norms (Van Kleef et al., 2016). Van Kleef et al. have showed the need for further research into the social nature of emotion. So, this research, which mostly focuses on changes in emotions toward countryrelated aspects, is justified.

Theoretical Framework

Affective adaptation theory (or hedonic adaptation) is a theory relevant to this study. It says that despite vicissitudes in life, people tend to return to their normal level of feeling emotions after a rise or dip of emotions for some time. Speeds of adaptation to positive or negative emotions differ (Lyubomirsky, 2012).

People adapt quickly to positive emotions/events but slower to negative emotions/events.

2. Methods

Participants

A total of 286 participants participated in the study. The aim was to stop at 300, but for unexplained reasons, Google removed the Forms. A possible reason is the removal (by reporting to Google) from my earlier college with which I had shared the form as editor and forgot to remove the editorship after I terminated my affiliation with it. The participants were the college students who had come to college(s) to pursue their bachelor's degrees and the participants they shared the link of Google Forms with. Participants ranged from 15 to 55 years. The mean age was 23.18 (SD=5.72), with 86% being emerging adults (18-29 years; Arnett, 2014).

Measures

A Google Forms was created. In the sociodemographic section, participants were asked their age. In the Emotions section, they were asked about 19 emotions they felt in the last 24 hours. The emotions were basic emotions and the emotions about country (love, pride) or related aspects (e.g., anger toward leaders) as shown in the Appendix 1. Since the Nepali people have been exposed to the international scenario in a daily basis in the last decade, the emotions related to foreigners and neighboring countries were also included (e.g., jealousy towards foreigners, negative feelings toward China/India). Cronbach's alpha for negative emotions was 0.82, and for positive emotions was 0.62.

McDonald's Omega for them was 0.82 and 0.65, respectively. Alpha and Omega for country-related emotions (country pride, fear because of political reasons, country love, worry about country's future, and guilt of not contributing enough to country) were both 0.79 in this sample.

Procedure

An online survey was created. The implied consent was shown at the introduction of the form. The participation was informed to be voluntary. Students in three colleges were asked to fill out the survey and distribute the link among people with an age similar to theirs. The privacy and confidentiality of participants were regarded.

The data were collected beginning in 2021. The new participants were approached each year till the end of 2024. In other words, the trend study continued for four consecutive years. The project had to be terminated after Google Forms disappeared from Google Drive for reasons that Google did not provide. Table 1 gives the duration of time points in the trend study.

Table 1

Four Timepoints of Data Collection

Timepoint	Start	End	f	Mean Age (SD)
T1	2021/11/15	2022/2/6	31	21.74 (6.19)
T2	2023/3/7	2023/4/24	77	22.39 (5.60)
T3	2023/5/6	2023/9/20	34	21.71 (3.65)
T4	2024/1/30	2024/12/17	144	24.26 (5.92)

Data Analysis

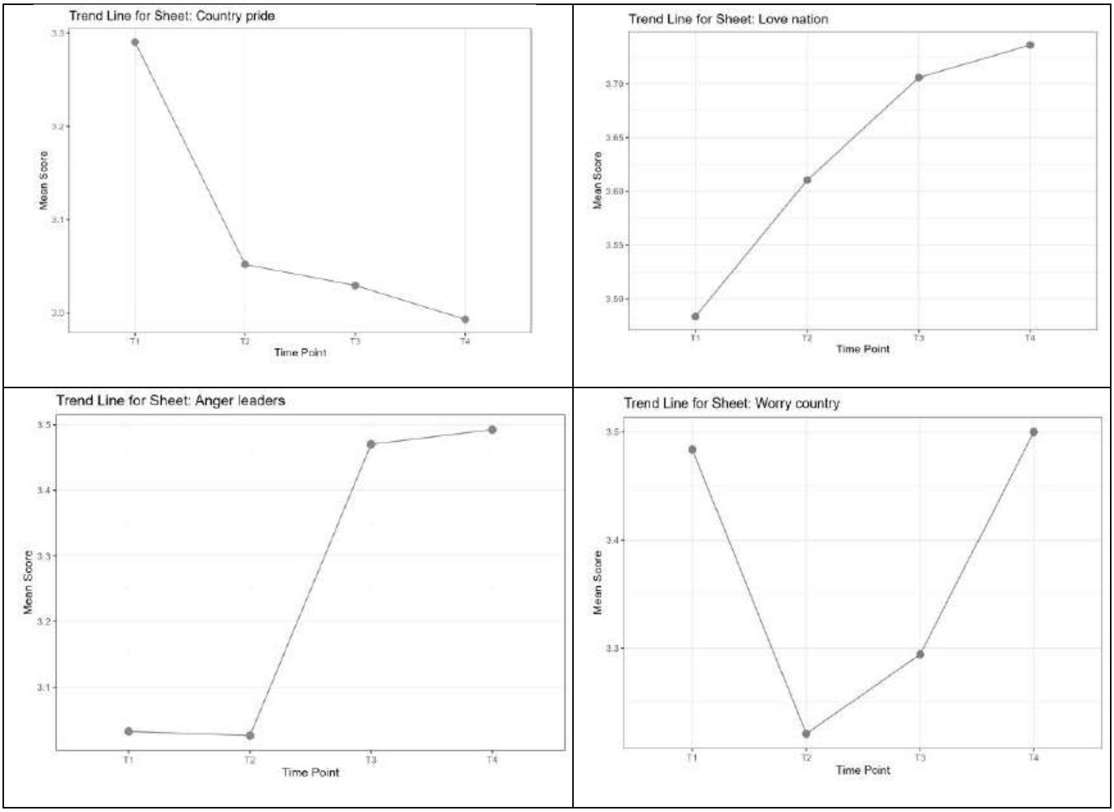
With the help of Gemini and ChatGPT, scripts were created for R to plot graphs. Time series regression analysis (in JASP) was used to see if there were significant changes in emotions across the years. Jamovi was used to calculate reliability statistics.

3. Results

The descriptives for all emotions (and their four time periods) are given in Appendix 2. The emotions that showed a consistent pattern were anger toward the leader, love toward the country, and pride toward the country. The last emotion was in a decreasing trend, and the former two were in an increasing trend. Figure 1 below shows that the first three emotions have consistent trends/patterns, but the last emotion does not. Change in time (at T2 and T4) was not significant.

Figure 1

Trend Lines for Change in Emotions



Note. The data in Excel

Sheets were imported into R to draw trendlines.

Time series regression analysis showed that models with jealousy toward foreigners or other negative feelings (hatred) were significant. As shown in Table 2, the changes were not significant across various timepoints. Insignificant models and their coefficients have not been showed.

Table 2

Time Series Regression Analysis for Two Emotions (df1=3, df2=282)

							Model		ANOVA	
Emotion	Model		b	SE	t	p	R^2	RMSE	F	p
Jealosy Foreigners	M_0	c	2.13	0.08	25.96	< .001	0	1.38	8.26	< .001
	M_1	c	2	0.25	8.16	< .001	0.08	1.33		
		T2	-0.12	0.29	-0.4	0.69				
		T3	0.85	0.34	2.52	0.01				
		T4	0.12	0.27	0.44	0.66				
Hatred India	M_0	c	2.13	0.08	25.96	< .001	0	1.39	4.12	0.01
	M_1	c	2	0.25	8.16	< .001	0.03	1.36		
		T2	-0.12	0.29	-0.4	0.69				
		T3	0.85	0.34	2.52	0.01				
		T4	0.12	0.27	0.44	0.66				

Change in time explained 8% of the variance in jealousy scores.

Change in time explained 3% of variance in hatred scores. These are both small but meaningful effects. There is a notable spike at time point 3 for both emotions. These findings could point to a contextual or historical event around this time point (e.g., political, or social change) that temporarily raised negative emotions. Time in general is not a strong predictor (low R^2), but the specific increase at T3 is statistically and substantively interesting.

4. Discussion

Interpretation of Results

Basic emotions fluctuate in people's lives. However, this collective representation of emotions revealed that they are not significantly different across periods (from 2021 to 2024). This same pattern is expected for the time to come because life is the mixture of good and bad emotions always. As predicted by hedonic adaptation theory, the basic emotions return to set point, and significant changes might not have been noticed. It is the decrement in the emotional intensity of favorable and unfavorable conditions over time (Frederick & Loewenstein, 1999).

Regarding jealousy toward foreigners and negative feelings toward neighboring countries, no consistent trend was observed, but significant differences in emotion were found between specific time points. There might have been nonlinear changes. Moreover, the negative feelings might have come out because of some deals between the neighboring country and Nepal or the contrast between the achievements of Nepal and foreign countries. The Nepali have been exposed to the global scenario of economy and development, and they compare those things related to Nepal. Consequently, negative feelings have emerged because Nepal has not been able to catch up.

The results may indicate that neighboring countries should be balanced in their diplomatic relationship with Nepal, or they should improve the public image, at least if their behaviors are just fine. Negative feelings toward neighboring nations did not show a consistent trend, even though a significant change was noticed. Even significant, the lack of consistent pattern (or fluctuating mean values) does not indicate a clear trend. So, it can be concluded that Nepali people do not hate their neighboring nations, but the changing dynamics between Nepal and these countries overwhelm them with negative emotions sometimes.

It is the right time to catch up with the foreigners' pace of development; the government should be proactive. Doing so may keep country pride in check, country love intact, and placate the anger toward leaders. The findings may be interpreted with reference to the events that happened during the time of data collection. For example, Nepal was fighting with COVID-19 in November 2021, president had dissolved parliament six months before this month, there were protests against MCC, an American corporation in February 2022, Prachanda, the then prime-minister had switched his partners in government in March 2023, there was an uproar about degrading air quality in Nepal in April 2023, there were floods in Koshi in June 2023, Nepal exported electricity for the first time in July 2023, the highest amount of remittance was collected in October 2023, increase in suicide rates was brought to notice in August 2023, Nepal welcomed most number of tourists in 11 months as reported in February 2024, political instability continued in March 2024, there were floods and landslides in many districts in September 2024, and inflation rose very high in December 2024. In the last month of 2024, a strong government with a majority in parliament could not deliver expected outcomes, and a popular politician from the opposition party faced corruption charges.

Comparison With Past Studies

Emotions are caused by specific events or objects (Robbins & Judge, 2024). So, change in country-caused emotions were studied in this research. The study done during the pandemic showed that people have an amazing ability for resilience and they display positive emotions despite sources of distress because they have the adaptational ability (Adhikari, 2020). So, emotions do not last long to bother people. After all, emotions have been defined as cursory feelings. The lack of consistency in most of the emotions may be attributed to the very momentary nature of emotions.

Moods, personality traits, and emotional disorders are related to specific emotions (Ekman, 2016). So, studying emotions is always needed. When they are persistently negative, regulating them is necessary, too. For example, walking in the natural environment (versus walking in an urban area) has been shown to boost positive emotions and decrease negative affect (Bratman et al., 2015).

There are some areas in which further studies are needed. What triggers emotions is unknown. There is disagreement among psychologists on cognitive appraisal and physiology related to emotions (Ekman, 2016).

Limitations and Strengths

The time points were not equidistant. So, the trend should be cautiously considered. The sample was convenient and dominated by young adults. The findings may not be generalizable because of small sample size and unequal sample sizes across time points. The basic emotions should not have been collected to keep the survey short. Undirected emotions should not have been assessed because these keep changing. The basic emotions reset to the set points. In other words, even the people from poor nations learn to be happy over time. If some person transitions to poverty, they may begin to accept and adapt, and gain a set point of emotions.

A strength of the study is that it measured the change in emotions longitudinally. Another strength is that it tested the widespread rumors or claims empirically. For example, the data have supported the widespread claim that anger toward leaders is increasing but refuted the claim that love toward the nation is decreasing. However, the claim that the feeling that 'I am proud to be Nepali' is waning was found to be true.

Implications

The findings showed that general/basic emotions were not significantly changing, but country-related emotions were. Such a finding is important theoretically. In other words, generic or basic emotions keep fluctuating regardless of circumstances. People have the set point of feeling them. However, a consistent pattern is found in country-related emotions because they are very much affected by political, social, and cultural developments in the society.

Practically, the pattern in data should be a wake-up call to stakeholders like the government to adapt their behaviors so that people can have positive emotions. Moreover, circumstances should be created so that people will have the right attitude toward their countries. If the behaviors of stakeholders are just fine, they should introduce interventions to drive people's emotions toward positivity. So, a positive branding is needed.

Future Research

The research of this nature should go on. The country-related emotions should be consistently assessed, and the changes over time should be evaluated in the future also. Moreover, specific event-related emotions can be assessed in the future. For example, emotions related to a particular decision of the government may be assessed. Such assessment may work as systematic feedback for the government.

5. Conclusion

The basic emotions were not found to vary significantly across time. Some country-related emotions showed a consistent pattern of change. For example, country love was steadily increasing, but country pride was steadily decreasing. Moreover, anger toward leaders was in a constant incline. In addition, even though not consistent, there were significant changes in negative emotions toward neighbors and jealousy toward foreigners. These changes in emotions should be a wake-up call for related stakeholders. For example, the government should be aware that country pride is declining. It may utilize the capital of country love incline for some good cause.

Theoretically, tracking changes in emotions may be useful if they are not basic emotions and are country- or any other target/event-related.

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Appendix 1: Questionnaire Used in the Study

Socioeconomic Section

What is your age? तपाईंको उमेर कति हो?

Emotions Section

In the last 24 hours, how much did you feel the emotions given below? Choose one answer in the five-point scale. पछिल्लो २४ घण्टामा, तपाईंले तल दिइएका भावनाहरू कति महसुस गर्नुभयो? पाँच-बिन्दुको मापनमा उत्तर दिनुहोस्।

1= Did not feel at all बिल्कुलै महसुस गरिनँ

5= Felt very much धेरै नै महसुस गरें

1. Anger रिस
2. Happiness खुशी
3. Sadness दुःख
4. Surprise अचम्म
5. Disgust घिन
6. Fear डर
7. Loneliness एक्लोपन
8. Bliss आनन्द
9. Proud of your country देशप्रति गर्व
10. Fear because of political situation राजनितिक कारणले गर्दा डर
11. Anger towards government सरकारसँग रिस
12. Love to this nation यो देशको माया
13. Jealousy of the foreigners विदेशीहरुको ईर्ष्या
14. Hatred toward India भारतसँग घृणा
15. Hatred toward China चीनसँग घृणा

16. Worry about your future आफ्नो भविष्यको चिन्ता
17. Worry about country's future देशको भविष्यको चिन्ता
18. Anger toward leaders नेताहरुसँग रिस
19. Guilt of not contributing enough to country देशलाई उचित सेवा गर्न सकिनँ भनी पश्चाताप

Appendix 2: Descriptives of Each Emotion Table 4

Descriptives Related to Each Emotion in Four Points of Time: T1, T2, T3, and T4

Emotion	Time	Mean	SD	Mdn	Min	Max
Anger	T1	2.23	1.06	2	1	4
	T2	2.61	1.41	3	1	5
	T3	2.91	1.50	3	1	5
	T4	2.72	1.34	3	1	5
Happiness	T1	3.45	0.99	3	1	5
	T2	3.22	1.34	3	1	5
	T3	2.91	1.33	3	1	5
	T4	3.39	1.09	3	1	5
Sadness	T1	2.68	1.33	2	1	5
	T2	2.44	1.49	2	1	5

Emotion	Time	Mean	SD	Mdn	Min	Max
	T3	2.74	1.52	3	1	5
	T4	2.53	1.36	2	1	5
Surprise	T1	2.52	1.34	3	1	5
	T2	2.39	1.38	2	1	5
	T3	2.47	1.26	3	1	5
	T4	2.24	1.37	2	1	5
Disgust	T1	2.23	1.23	2	1	5
	T2	2.03	1.40	1	1	5
	T3	2.15	1.46	2	1	5
	T4	2.01	1.26	1	1	5
Fear	T1	2.48	1.26	2	1	5
	T2	2.17	1.39	2	1	5
	T3	2.71	1.22	3	1	5
	T4	2.44	1.33	2	1	5
Loneliness	T1	2.65	1.31	2	1	5
	T2	2.45	1.43	2	1	5
	T3	2.35	1.52	2	1	5
	T4	2.54	1.45	2	1	5
Bliss	T1	3.32	1.17	3	1	5
	T2	3.09	1.43	3	1	5

	T3	2.85	1.16	3	1	5
	T4	3.10	1.29	3	1	5
	T1	3.29	1.44	3	1	5
	T2	3.05	1.65	3	1	5
	T3	3.03	1.31	3	1	5
	T4	2.99	1.43	3	1	5
Fear Political	T1	2.97	1.38	3	1	5
	T2	2.68	1.67	2	1	5
	T3	3.21	1.55	3	1	5
	T4	2.99	1.50	3	1	5
Anger Government	T1	3.58	1.57	4	1	5
	T2	3.06	1.65	3	1	5
	T3	3.68	1.41	4	1	5
	T4	3.51	1.50	4	1	5

Emotion	Time	Mean	SD	Mdn	Min	Max
Love Nation	T1	3.48	1.52	4	1	5
	T2	3.61	1.47	4	1	5
	T3	3.71	1.38	4	1	5
	T4	3.74	1.39	4	1	5
Jealousy Foreigners	T1	2.58	1.48	2	1	5
	T2	1.83	1.17	1	1	5

	T3	3.12	1.47	3	1	5
	T4	2.14	1.35	2	1	5
Hatred India	T1	2.00	1.26	2	1	5
	T2	1.88	1.25	1	1	5
	T3	2.85	1.64	2	1	5
	T4	2.12	1.38	1	1	5
Hatred China	T1	1.65	1.20	1	1	5
	T2	1.49	0.87	1	1	4
	T3	1.97	1.11	2	1	5
	T4	1.69	1.20	1	1	5
Worry Future	T1	4.29	0.90	5	2	5
	T2	3.69	1.62	5	1	5
	T3	4.24	1.30	5	1	5
	T4	3.99	1.38	5	1	5
Worry Country	T1	3.48	1.39	4	1	5
	T2	3.22	1.63	4	1	5
Emotion	Time	Mean	SD	Mdn	Min	Max
	T3	3.29	1.51	3	1	5
	T4	3.50	1.51	4	1	5
Anger Leaders	T1	3.03	1.45	3	1	5
	T2	3.03	1.66	3	1	5
	T3	3.47	1.58	3	1	5
	T4	3.49	1.55	4	1	5

Guilt of Not Contributing Enough to the Nation	T1	2.65	1.40	3	1	5
	T2	2.27	1.29	2	1	5
	T3	2.85	1.44	3	1	5
	T4	2.46	1.25	2	1	5

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