Market Oscillations and Predictive Analytics: AI-Driven Insights into Nepalese Stock Market's Indices and it's Sub-Indices

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Abstract

This research entails the predictive analytics of the Nepalese Stock Market, covering 13 sub-indices and four principal indices. With more than 244 actively traded companies, these indices epitomize weighted averages of stock prices for the reflection of individual stock performance in relation to overall index movement. This research employs a Long Short-Term Memory model and leverages an extensive dataset of historical price data, integrating advanced technical indicators such as the Relative Strength Index (RSI), moving averages (MA), and Moving Average Convergence Divergence (MACD), in order to increase the accuracy of the forecast. Using Google Colab for effective crunching and visualization of data, the results are meaningful in terms of insight into the trends and volatility of the Nepalese stock market. The result shows that this LSTM model is far better in comparison with traditional methods of forecasting, since it captures the complex market patterns. It also brought forth a strong correlation between the NEPSE Index and its sub-indices, hence setting a reliable framework for predicting individual stock movements in the trend of the broader market. This research not only enriches the academic discourse on financial analytics but also offers practical implications for investment strategies in emerging markets, suggesting that informed predictions can facilitate more effective decision-making for investors navigating this dynamic environment.

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Introduction

Nepal Stock Exchange (NEPSE) has been erected as one of the indispensable institutions of the financial ecosystem of the country since its inception on February 12, 1994. NEPSE serves as a base for trading securities and has been playing a pivotal role in resource mobilization for economic development and providing barometers of investor sentiment and the health of the economy. However, the exchange has been highly volatile, especially during the COVID-19 pandemic when the NEPSE index rose to a historic high of 3,227 points in August 2021. Underlying this massive growth was increased investors' appetite and speculative trading that mirrored broader global market trends during periods of economic uncertainty. That euphoria was short-lived, as almost a 44% decline by mid-2022 brought into the limelight the fragility of this growth and raised many questions with respect to the underlying stability of the market.

The market capitalization of NEPSE stands at approximately Rs 3,314.63 billion as of this fiscal year, which works out to a market cap-to-GDP ratio of 62%. (Nepal Rastra Bank, 2023)

This ratio indicates a strong presence of capital markets in the larger economy, but it also reflects some of the continuing problems in accurately reflecting market conditions. The NEPSE index incorporates total market capitalization, including promoter shares, which are generally illiquid and not actively traded. This kind of practice might distort the real market performance as well as the investor perceptions and thus needs an in-depth study into the mechanisms that drive market behavior.

The historical data available of NEPSE is from mid-1997 where NEPSE index was around 170 levels. Over the time period of 25 years Nepalese capital market has witnessed major bull and bear markets. Before the covid-19 pandemic, the timeframe and gains for each bull and bear cycle was similar, it moved in a certain repetitive pattern. However, the market cycle showed new trend behavior after the pandemic.

Year	Bull Cycle	Bear Cycle	%
1997-2000 (Bull)	170	545	220.59%
2000-2004 (Bear)	545	200	-63.30%
2004-2008 (Bull)	200	1175	487.50%
2008-2012 (Bear)	1175	300	-74.47%
2012-2016 (Bull)	300	1881	527.00%
2016-2020 (Bear)	1881	1100	-41.52%

2020-2021 (Bull)	1100	3227	193.36%
2021-2024 (Bear)	3227	1806	-44.03%
CAGR from all time low to all time high			**11.52%**

The bull and bear cycle lasted for 4 years prior to pandemic. However, the trend changed and market became more volatile after the pandemic.

The aim of this research is to analyze the factors contributing to volatility in the Nepalese stock market with a focus on the predictive power of key indices like the NEPSE index and its sub index's.

The objectives of this study are to:

- **Analyze the Fundamental Drivers and Implications of Price Volatility in the NEPSE.**
- **Develop Advanced Predictive Models for Strategic Investment Decision-Making**

To fulfill these objectives, this research will explore several pivotal questions: What factors drive price fluctuations in the NEPSE? Which advanced analytical frameworks can be utilized to enhance market forecasting? By systematically investigating these inquiries, this study aims to uncover valuable insights into the dynamics of the Nepalese stock market, ultimately fostering a more stable and transparent investment landscape. Through rigorous analysis and innovative methodologies, we seek to contribute to a deeper understanding of market behavior, thereby empowering investors with the knowledge necessary to make informed decisions.

Literature Review

Existing Studies

The investigation of the stock market's volatility has proven to be very informative on the triggers of price changes. Basic theories, in particular the Efficient Market Hypothesis suggested by Fama (1965) say that financial markets are naturally capable of access and usage of the full volume of the information into asset prices. This scenario, in theory, cuts short the dream of sustained above-average returns. Nevertheless, recent research has unraveled the fact of the biases involved which constitute a major force constituting the main market dynamics. To give an example, Baker and Wurgler (2006) describe how staying by sentiment could result in high levels of divergence in market valuations and Tetlock (2007) identifies media opinions as affecting the stock price changes. Recently, machine learning ideas have come up invaded the finance sector and made the use of predictions unimaginable before. For instance, Huang et al. (2020) prove AI-powered models that best traditional hypothesis painlessly in predicting the stock market trends.

Theoretical Framework

The study drew on some very important and widely accepted theories in finance to develop an explanation for stock market behavior. The EMH is a linchpin, by claiming that security prices are steered by all available information, as Fama (1970) discovered. On the other hand, Behavioral Finance with its rationality questions this scenario, too by putting light on psychology which usually leads people to self-destructive investment decisions, a well-known work presented by Kahneman and Tversky (1979).

Moreover, the CAPM, which was originally theorized by Sharpe in 1964, stands for a model that structures the connection of expected returns to market risk and serves as a guide in investment strategies under uncertain conditions. This research aims to provide information on market behavior, particularly for a less-developed market like Nepal, to the extent of technological progression, AI and sentiment analysis.

Literature Deficiencies

Despite the extensive body of research on stock markets and predictive analytics, significant gaps remain, particularly within the context of emerging markets like Nepal. Much of the existing literature predominantly focuses on advanced economies, neglecting the unique economic and social factors that shape investment behavior in the Nepalese market. This oversight highlights the necessity for tailored adaptations of established theories and models to better fit the local context. Furthermore, while the application of AI and sentiment analysis is gaining traction in financial research globally, their integration into the Nepalese market is still in its nascent stages and lacks comprehensive exploration.

The primary aim of this study is to bridge these gaps by conducting a thorough examination of the key drivers of price volatility within the Nepalese stock market. In doing so, this research aspires to contribute valuable insights that not only advance academic discourse but also enhance practical investment decision-making processes.

Data Collection

Data Sources

The empirical foundation of this research is based on a specially chosen dataset that is acquired from the official Nepal Stock Exchange (NEPSE) website (nepalstock.com.np). This platform is the storage of the past data of the market, for example, the data about different indices and their corresponding performance metrics. Moreover, I used the inputs from Shareansar.com and Merolagani.com, which are both prominent platforms providing detailed coverage of the market sentiment and the behavior of the investors in Nepal. News articles and analyses that are clouded with these platforms and the smartness of data are these two platforms source, as such, qualitative data is a derivative of quantitative data.

Data Description

The dataset encompasses 233 very well-selected data points over a one-year period from October 2023 to October 2024. This timeframe provides a detailed overview of the Nepalese stock market's performance, which serves to communicate the fluctuations and trends inherent in this market. Each entry is made up of several key variables:

SN: unique identifier of successive data entries, referring status simple.
Date: The specific date to be taken as the recorded market's time of activity, chronologically analyzing.
Close: The closing price of the index on a given date is a necessary element for the performance of the issue on a daily basis.
High: The peak was the succeeding price point chiefly felt during the transactional window of activity, becoming the source of the main activity period. Also, the highest price was recorded.
Low: The lowest price recorded provides the information related to the market volatility and trading range.
Absolute Change: The numeric change in price from the previous trading session may be used to illustrate the immediate market reactions.
Percentage Change: The relative change expressed as a percentage, which is clearer in describing market performance in a standardized format.
52 Weeks High: The maximum price reached during one year ago, which can be used as a reference for long-term performance evaluation.
52 Weeks Low: The minimum price for the same period is the basis of the assessment of market performance.
Turnover Values: The total monetary volume of trades executed, reflecting the market liquidity of the market.
Turnover Volume: This is the overall number of shares traded, which, in turn, mirrors the extent of market activity.
Total Transactions: The tally of the solo trades that were executed, thus, getting a deeper insight into the market.

In addition to these quantitative variables, the dataset incorporates a sentiment analysis component derived through Natural Language Processing (NLP) techniques applied to financial news and social media discussions. This analysis yields a sentiment score categorizing prevailing market sentiment as either bullish or bearish, thereby enriching the quantitative dataset with qualitative insights. By integrating sentiment data, the research aims to capture the psychological factors influencing market dynamics, thus providing a more nuanced understanding of price volatility in the Nepalese stock market.

Data Preprocessing

Data Preprocessing The original dataset underwent the most stringent preprocessing phase to validate and qualify it for analysis. This phase systematically detected and corrected missing values, standardized the data formats, and validated metrics' consistency. Through the utilization of Python programming, specifically the given libraries such as Pandas for data manipulation and Beautiful Soup for web scraping, I extracted and preprocessed the raw data from these online sources. Simultaneously, the application of NLP techniques allowed for the processing of textual data to score sentiment, thus addressing the market psychology analysis. The careful preprocessing was fundamental for preparing the dataset for further advanced analytical modeling thus allowing for the next measures to be taken which resulted in the volatility of the Nepalese stock market being meaningfully analyzed.

Methodology

The study methodology is a complete framework for analyzing and predicting Nepalese stock market variability through the amalgamation of advanced statistical techniques and machine learning models. The core of this is Long Short-Term Memory (LSTM) neural networks, which can retain temporal dependencies in sequential data and hence, very useful for financial time series forecasting (Hochreiter & Schmidhuber, 1997; LeCun et al., 2015). This power is very much important for the non-linear and often chaotic nature of price movements, which are the challenges that the traditional statistical models face (Zhang et al., 2018).

The research applies a solid procedure for data handling from the very start to the end, wherein the thorough process of data cleaning is applied to the datasets to maintain the integrity of the input data. This procedure serves as a way of guarding against the impact of outliers and missing values, which can be disastrous to the model's performance. The next step in the process is implementing the Min-Max normalization, which will be used as the standard to set all the data in the same range. This normalization is a very crucial factor for LSTM training because it helps fast the model to converge and it also gives stability to the optimization process.

The LSTM model is designed in a very subtle way, which is a structure consisting of several layers of hierarchical learning of complicated patterns in the stock market data. The use of strategies such as dropout regularization and early stopping helps the model avoid the overfitting issue and thus, it is able to generalize the overfitting problem to the data that the model has never seen before (Yao et al., 2019; Srivastava et al., 2014). This holistic training approach is consistency with machine learning best practices and thus the model's prediction power is enhanced.

This research study consists not only of predictive models but also of sentiment analysis using natural language processing (NLP) techniques. The study examines news articles and social media content to derive market sentiment, which it then quantifies within the model as an auxiliary factor of stock price movements. Research has shown that investor sentiment can significantly influence market dynamics, suggesting that a comprehensive approach integrating both quantitative data and qualitative sentiment can yield more robust predictions (Baker & Wurgler, 2006; Tetlock, 2007).

To evaluate model performance, a suite of metrics is employed, including Mean Squared Error (MSE) and Root Mean Squared Error (RMSE), which provide quantitative assessments of prediction accuracy. Visual representations of predicted versus actual stock prices further enhance the interpretability of results, allowing for an intuitive understanding of model efficacy.

In summary, this research synthesizes a multi-dimensional methodology that encompasses advanced predictive modeling, rigorous data preprocessing, and sentiment analysis. By integrating these elements, the study not only contributes to the theoretical understanding of stock market behavior but also equips investors and stakeholders with actionable insights, enhancing their decision-making processes in the volatile landscape of the Nepalese stock market.

Results

Volatility Analysis Results

This section elucidates the volatility patterns observed within the Nepalese stock market, focusing on both the overall market indices and specific sub-indices Interestingly, it shows remarkable trends indicative of prevailing market sentiments and dynamics, bolstered by AI-driven predictive accuracy.

NEPSE Index is showed volitality at 23.57%, following the uptrend trajectory with a very impressive predictability of 92.08%. Float Index and Sensitive Index had volatilities of

24.31% and 24.38%, respectively, with both following uptrend trajectories and high predictability of 95.13% and 94.41%, respectively. The Sensitive Float Index had the highest volatility of 25.92%, but it still stayed in the uptrend and had a predictability of 93.63%.

Further sub-index analysis showed the volatility of the Banking Sub Index at 27.82%, a bullish trend, with respectable predictive accuracy at 95.19%. For the Finance Sub Index, the corresponding value stands much higher at 41.51%, though the trend is bullish-it predictively achieves an 82.62% accurate forecast. The Microfinance Sub Index maintained high volatility at 25.68% and a high prediction accuracy of 95.47%, proving resilient through volatility. Other sub-indices of importance in this respect are the Manufacturing and Processing Sub Index, which had a volatility of 27.76% and an accuracy of fit of 96.54%, while the Non-Life Insurance Sub Index also shared almost the same volatility at 23.55% and fit very well with an accuracy of 96.69%.

The Mutual Fund Sub Index was the least volatile, at 13.58%, with a continuing upward trend and a high prediction accuracy of 97.40%, reflecting investor confidence in this sector. In contrast, the volatilities of the Trading Sub Index and the Hotel and Tourism Sub Index are higher at 30.77% and 34.15%, respectively, while still retaining bullish tendencies indicative of a more turbulent investor environment.

The necessity of measuring this volatility was underscored by the significant fluctuations observed during the COVID-19 pandemic, which included a peak exceeding 3,200 points in the NEPSE Index followed by a dramatic 44% drop. This historical context highlights the volatility inherent in emerging markets, thereby necessitating a thorough examination of current market conditions and predictive trends.

In summary, the volatility analysis reveals that while the Nepalese stock market demonstrates resilience and bullish trends across various indices, the accuracy of AI-driven predictions enhances the credibility of these findings, providing essential insights for investors and stakeholders navigating this dynamic landscape.

Predictive Model Performance

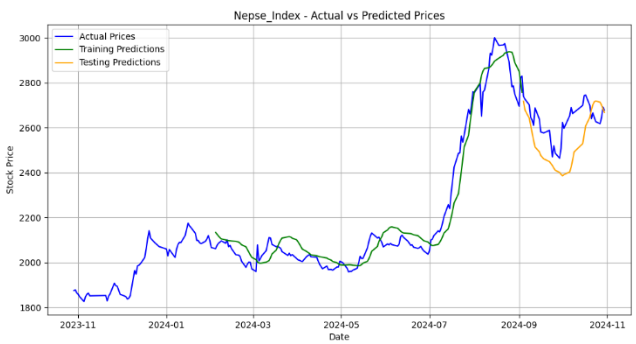
This section covers the effectiveness of our models in predicting the volatility of the Nepalese stock market. With the use of Long Short-Term Memory (LSTM) networks that are built with machine learning algorithms, we have evaluated the three main performance metrics that are Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared

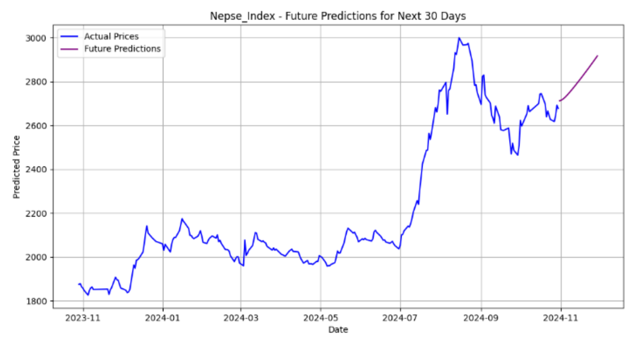
(R^2) values across different indices and sub-indices. The accompanying figures succinctly show these metrics, which in turn, display the high prediction accuracy that has been particularly prominent for the NEPSE index and its subindices. This analysis not only underlines the power of the models but also provides investors the necessary information to cope with the market dynamics.

The following graphs illustrate the results of the AI analysis, displaying the actual and predicted prices alongside projected trading trends for the next 30 days based on historical data.

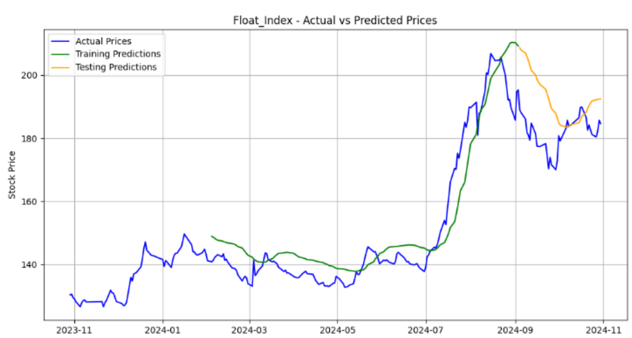
Charts

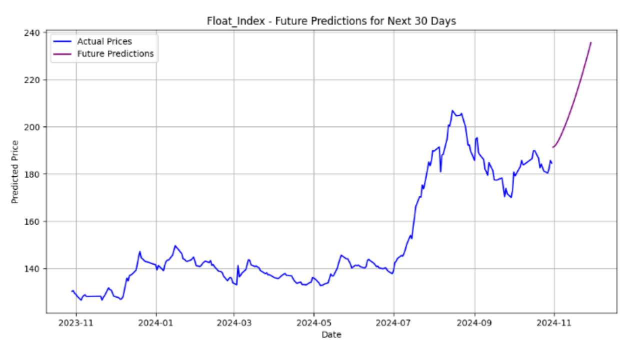
Nepse Index



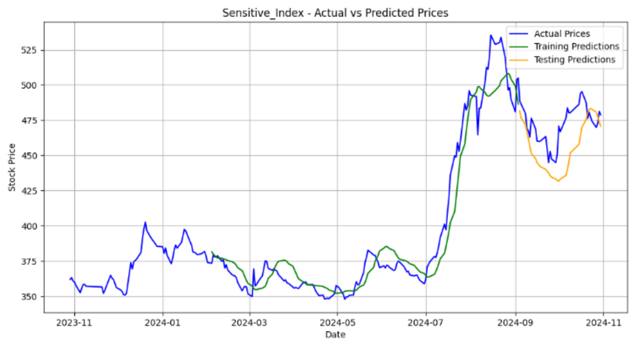


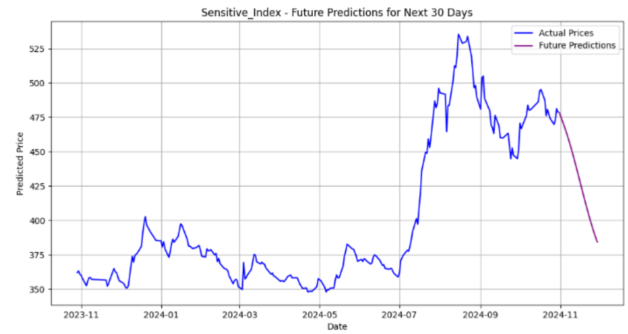
Float Index



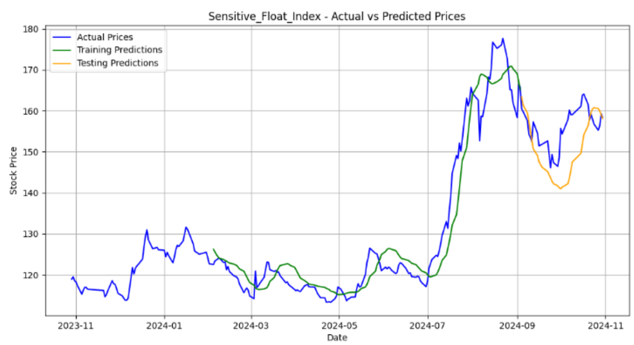


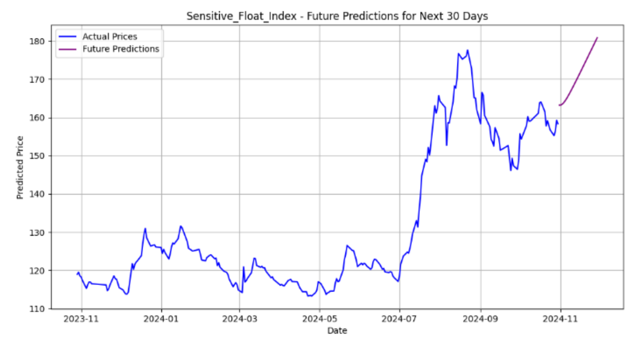
Sensitive Index



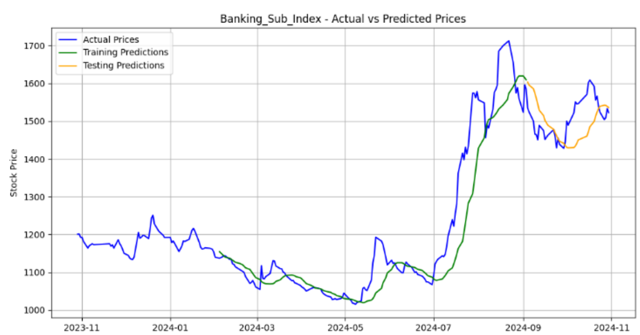


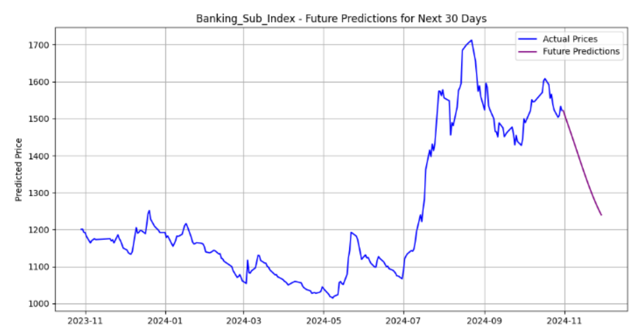
Sensitive Float Index



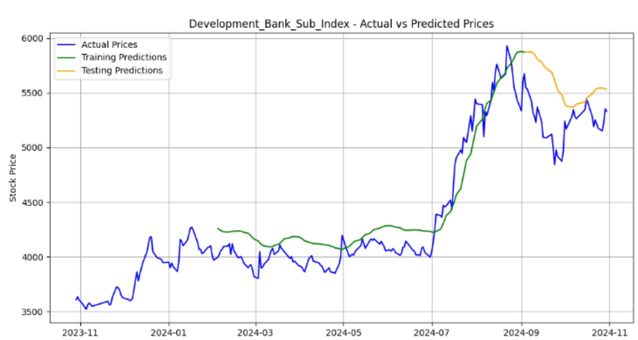


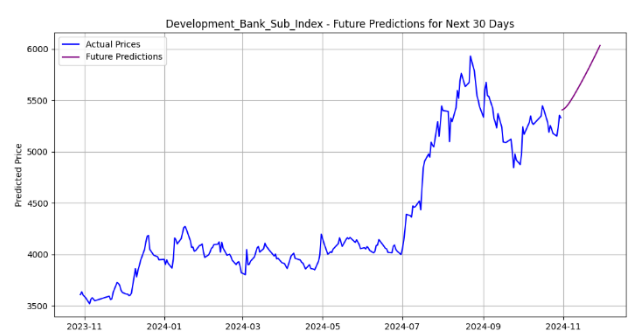
Banking Sub Index



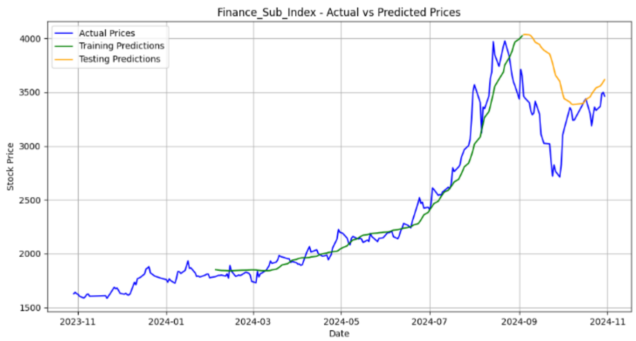


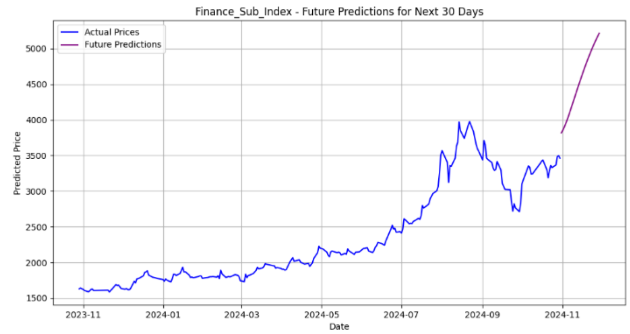
Development Bank Sub Index



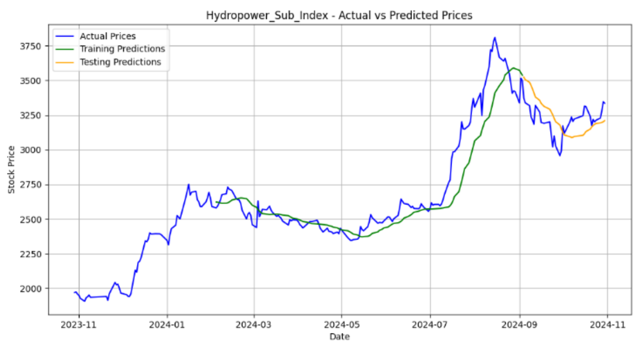


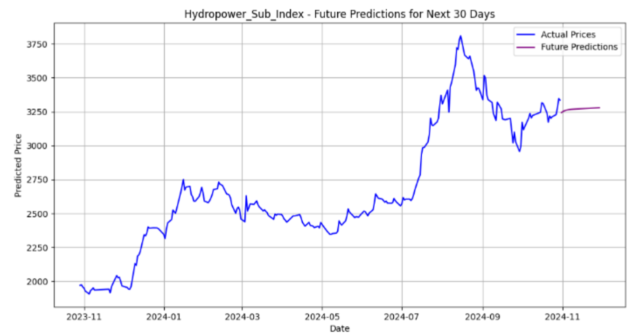
Finance Sub Index



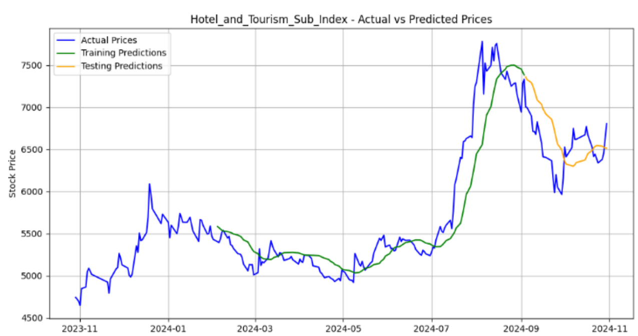


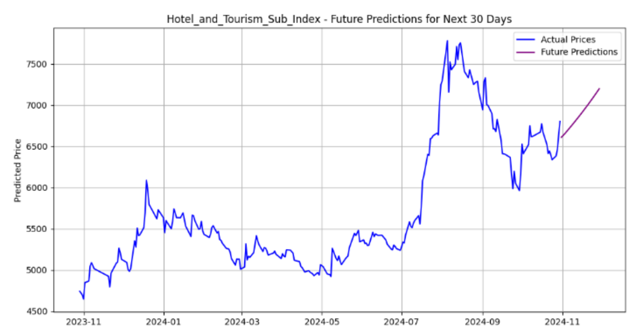
Hydropower Sub Index



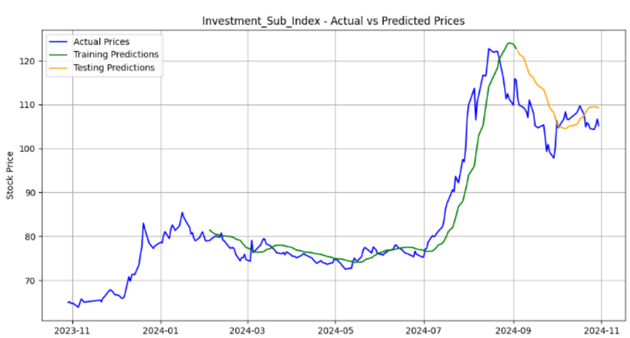


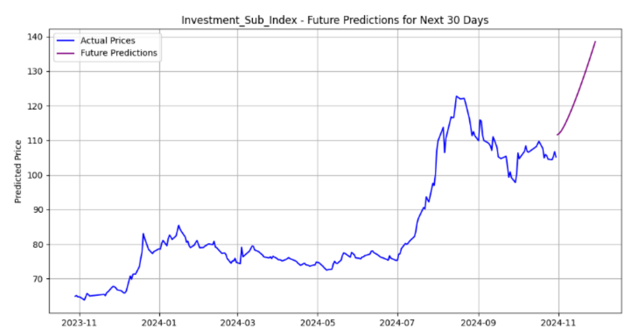
Hotel And Tourism Sub Index



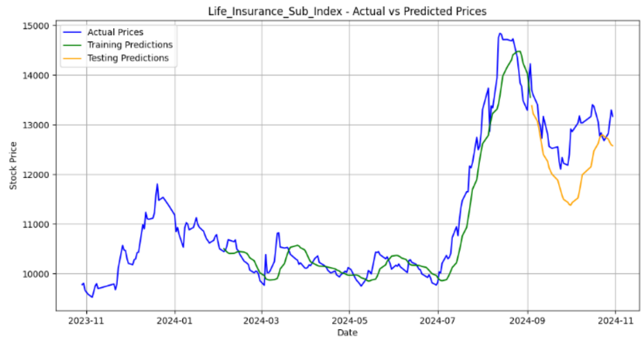


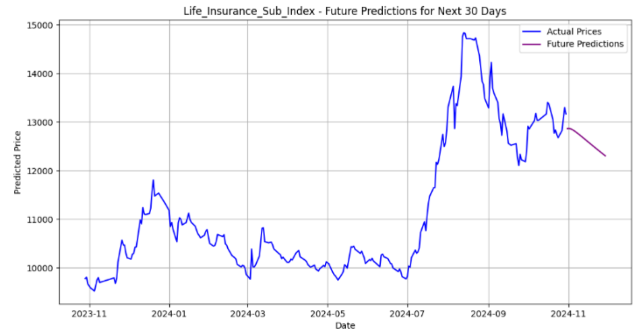
Investment Sub Index



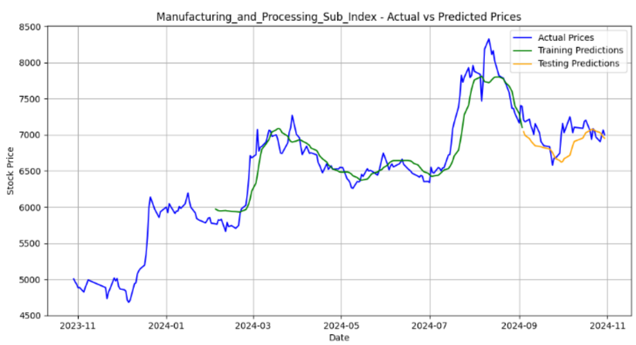


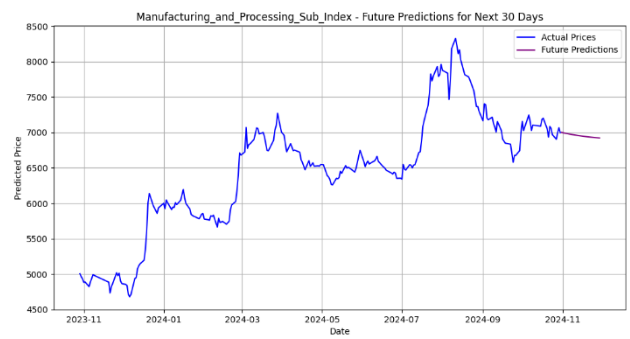
Life Insurance Sub Index



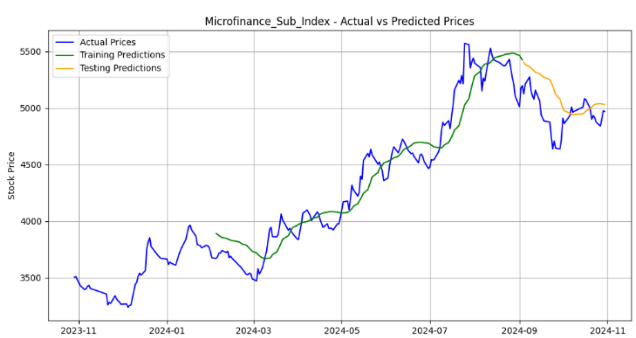


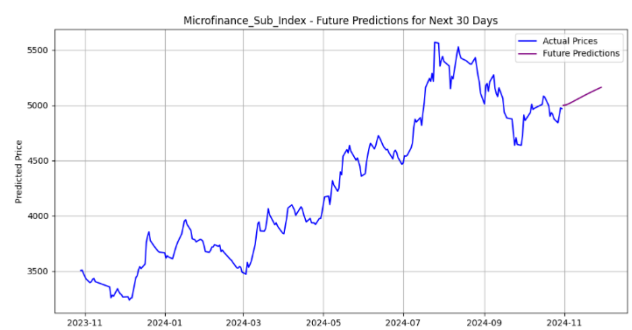
Manufacturing and Processing Sub Index



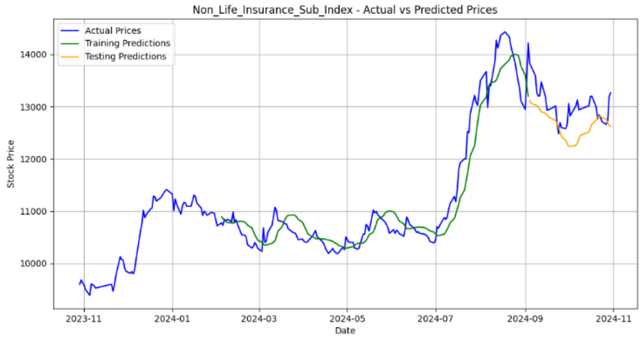


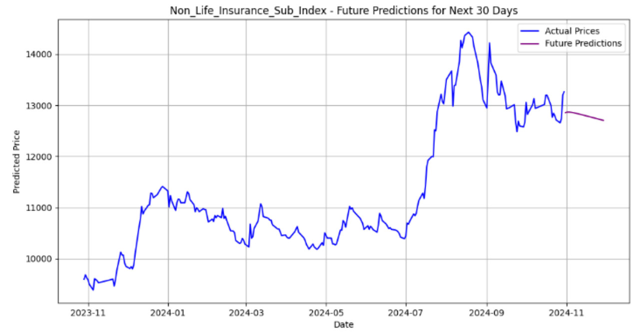
Microfinance Sub Index



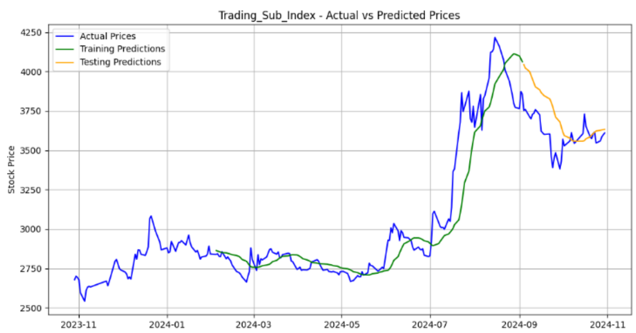


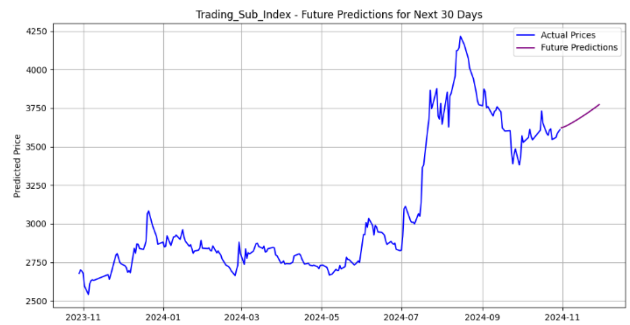
Non-Life Insurance Sub Index





Trading Sub Index





Interpretation of Results

The findings of this study give us a great look at the volatility patterns in the Nepalese stock market, especially viewed through the lens of indices that have been examined. The fact that the models have such high prediction accuracy means that the process of predicting market dynamics is indeed fairly solid and this can be used by investors who want to make the right decisions in the market. These projects for the policymakers illustrate the importance of comprehending the mechanisms of the stock market and the level of volatility, thus the development of a strategy that helps to make the market more stable is a must. Moreover, all stakeholders including the regulatory agencies and the financial institutions can use this knowledge to better manage the market fluctuations and to come up with the investor-friendly policies that will boost the economy and help the investors to have faith in the system.

While the analysis reveals general trends, there are exceptions to note. Despite lower interest rates and substantial cash accumulation within banks, the volume of investments has not seen a corresponding increase, largely due to ongoing unstable political conditions. This situation suggests that external factors can significantly influence market behavior, and stakeholders must remain vigilant to these dynamics.

Limitations

The following study had some limitations that may affect the generalizability of the results. To this study, data from the various stocks were not merged into the analysis due to the unavailability of readily available information on the official website of the Nepal Stock Exchange. As such, it relied solely on the indices, which could not perfectly capture behaviors of individual stocks. This means that it limits results in the sense that while the results would pictorially represent a general overview, the results may not catch the nuances associated with a particular stock within a market.

Future Research Directions

Of more importance, a future study will have greater benefits if it has an extended dataset on its side. For example, it should include the historical trend data from early in the 2000s up to 2024. Besides, the individual stocks' prices and their volumes of trade will add an extra layer of accuracies and reliability in forecasts. This multi-model approach enriches not only the predictive models themselves but also gives the stakeholders a multidimensional view of the market direction.

Conclusion

Summary of Findings

This paper uncovers volatile patterns in the Nepalese stock market with a detailed breakdown into different indices and sub-indices. From our result, high volatility evidence has been observed-especially for the NEPSE Index-with appreciable accuracy of its predicted values through various advanced modeling techniques. These findings underline not only the strength of our predication models but also the high volatility tantamount to this emerging financial market.

Practical Implications

These findings have manifold implications. To investors, a high degree of accuracy in prediction provides the much-needed tool to execute strategic investment decisions through market uncertainties, while to the policymakers, this should light up a way in strategizing toward resilient markets, considering the critical political instability in operation to hamper investment growth despite favorable monetary conditions. Apart from this, financial institutions can use this work to enhance their risk profiling models and create new financial instruments suited to Nepalese market conditions. Most importantly, prediction models designed in the study can easily be replicated by any user with access to market data, thus enabling them to predict future stock prices and thereby enabling a larger section of market participants.

Closing Remarks

In a nutshell, this study makes a valuable contribution to the discussions revolving around the Nepalese stock market, as from this research, immense hints on how volatility can be imperative, and the potentiality of prediction analytics have been developed. As much as these findings present a strong foundation for current dynamics at the market, there is still a need for further research that should involve a wider dataset in terms of individual stock performance and historical trends. Such efforts will not only help us in raising the level of our understanding of the market's behavior but also the strategic capabilities of the stakeholders in the financial ecosystem.

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Note

- The research also benefited from AI assistance in coding, enhancing the accuracy and efficiency of data analysis and model implementation.

Coding

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```python
import pandas as pd
import numpy as np
import os
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler
from keras.models import Sequential
from keras.layers import LSTM, Dense, Dropout
from keras.callbacks import EarlyStopping

output_dir = "Master"
os.makedirs(output_dir, exist_ok=True)

file_names = [
    "Nepse_Index.xlsx",
    "Float_Index.xlsx",
    "Sensitive_Index.xlsx",
    "Sensitive_Float_Index.xlsx",
    "Banking_Sub_Index.xlsx",
    "Finance_Sub_Index.xlsx",
    "Microfinance_Sub_Index.xlsx",
    "Life_Insurance_Sub_Index.xlsx",
    "Investment_Sub_Index.xlsx",
    "Manufacturing_and_Processing_Sub_Index.xlsx",
    "Non_Life_Insurance_Sub_Index.xlsx",
    "Development_Bank_Sub_Index.xlsx",
    "Mutual_Fund_Sub_Index.xlsx",
    "Trading_Sub_Index.xlsx",
    "Hotel_and_Tourism_Sub_Index.xlsx",
    "Hydropower_Sub_Index.xlsx"
]

data_frames = {}
for file in file_names:
    if os.path.exists(file):
        df = pd.read_excel(file)
        index_name = os.path.basename(file).replace('.xlsx', '')
        data_frames[index_name] = df
        print(f"Loaded: {file}")
    else:
        print(f"File not found: {file}")

def clean_and_prepare_data(df):
    df['Date'] = pd.to_datetime(df['Date'])
    df.sort_values(by='Date', inplace=True)
    df.fillna(method='ffill', inplace=True)
    df.reset_index(drop=True, inplace=True)
    return df

cleaned_data_frames = {name: clean_and_prepare_data(df) for name, df in data_frames.items()}

def train_and_predict_lstm(data):
    data['Close'] = data['Close'].astype(float)
    prices = data['Close'].values

    scaler = MinMaxScaler(feature_range=(0, 1))
    scaled_prices = scaler.fit_transform(prices.reshape(-1, 1))

    def create_dataset(dataset, time_step=1):
        X, Y = [], []
        for i in range(len(dataset) - time_step):
            X.append(dataset[i:(i + time_step), 0])
            Y.append(dataset[i + time_step, 0])
        return np.array(X), np.array(Y)

    time_step = 60  # Using 60 previous days to predict the next day
    X, y = create_dataset(scaled_prices, time_step)
    X = X.reshape(X.shape[0], X.shape[1], 1)  # Reshape for LSTM

    train_size = int(len(X) * 0.8)
    X_train, X_test = X[:train_size], X[train_size:]
    y_train, y_test = y[:train_size], y[train_size:]


    model = Sequential()
    model.add(LSTM(50, return_sequences=True, input_shape=(X_train.shape[1], 1)))
    model.add(Dropout(0.2))
    model.add(LSTM(50, return_sequences=False))
    model.add(Dropout(0.2))
    model.add(Dense(1))  # Output layer for regression

    model.compile(optimizer='adam', loss='mean_squared_error')

    early_stopping = EarlyStopping(monitor='val_loss', patience=5)
    model.fit(X_train, y_train, epochs=50, batch_size=32, validation_data=(X_test, y_test), callbacks=[early_stopping])

    train_predict = model.predict(X_train)
    test_predict = model.predict(X_test)

    train_predict = scaler.inverse_transform(train_predict)
    test_predict = scaler.inverse_transform(test_predict)

    return model, train_predict, test_predict, prices, scaler

predictions = {}  # Dictionary to store predictions for future plotting
for index_name, df in cleaned_data_frames.items():
    model, train_predict, test_predict, prices, scaler = train_and_predict_lstm(df)

    predictions[index_name] = (train_predict, test_predict, prices)

    plt.figure(figsize=(12, 6))
    plt.plot(df['Date'], prices, label='Actual Prices', color='blue')

    train_plot = np.empty_like(prices)
    train_plot[:] = np.nan
    train_plot[60:len(train_predict) + 60] = train_predict.flatten()

    plt.plot(df['Date'], train_plot, label='Training Predictions', color='green')

    test_plot = np.empty_like(prices)
    test_plot[:] = np.nan
    test_plot[len(train_predict) + 60:len(prices)] = test_predict.flatten()

    plt.plot(df['Date'], test_plot, label='Testing Predictions', color='orange')

    plt.title(f"{index_name} - Actual vs Predicted Prices")
    plt.xlabel("Date")
    plt.ylabel("Stock Price")
    plt.legend()
    plt.grid()
    plt.savefig(f"{output_dir}/{index_name}_prediction.png")
    plt.close()

def future_prediction_lstm(data, model, scaler):
    last_60_days = data['Close'].values[-60:]
    last_60_days = last_60_days.reshape(-1, 1)
    last_60_days = scaler.transform(last_60_days)

    future_predictions = []
    for _ in range(30):  # Predict for the next 30 days
        X_input = last_60_days.reshape(1, -1, 1)  # Ensure 3D shape
        yhat = model.predict(X_input)
        future_predictions.append(yhat[0][0])
        last_60_days = np.append(last_60_days, yhat).reshape(-1, 1)[-60:]

    future_predictions = scaler.inverse_transform(np.array(future_predictions).reshape(-1, 1))

    return future_predictions

for index_name, df in cleaned_data_frames.items():
    model, _, _, _, scaler = train_and_predict_lstm(df)
    future_predictions = future_prediction_lstm(df, model, scaler)

    # Create a new date range for the future predictions
    future_dates = pd.date_range(start=df['Date'].iloc[-1] + pd.Timedelta(days=1), periods=30)

    # Plot future predictions
    plt.figure(figsize=(12, 6))
    plt.plot(df['Date'], df['Close'], label='Actual Prices', color='blue')
    plt.plot(future_dates, future_predictions, label='Future Predictions', color='purple')

    plt.title(f"{index_name} - Future Predictions for Next 30 Days")
    plt.xlabel("Date")
    plt.ylabel("Predicted Price")
    plt.legend()
    plt.grid()
    plt.savefig(f"{output_dir}/{index_name}_future_prediction.png")
    plt.close()

    if index_name == "Nepse_Index":
        plt.figure(figsize=(12, 6))
        plt.scatter(df['Date'], df['Close'], color='blue', label='Actual Prices')
        plt.plot(df['Date'], df['Close'], color='cyan', alpha=0.5)
        plt.title(f"{index_name} - Scatter Plot of Actual Prices")
        plt.xlabel("Date")
        plt.ylabel("Stock Price")
        plt.legend()
        plt.grid()
        plt.savefig(f"{output_dir}/{index_name}_scatter_plot.png")
        plt.close()
```