PAKISTAN STOCK MARKET PRICE PREDICTION USING MACHINE LEARNING

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Candidate of **Master of Science in Software Engineering (MSSE)** at the National University of Modern Languages do hereby declare that the thesis **Pakistan Stock Market Price Prediction using Machine Learning** submitted by me in partial fulfillment of MSSE degree, is my original work, and has not been submitted or published earlier. I also solemnly declare that it shall not, in future, be submitted by me for obtaining any other degree from this or any other university or institution. I also understand that if evidence of plagiarism is found in my thesis/dissertation at any stage, even after the award of a degree, the work may be cancelled and the degree revoked.

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ABSTRACT

PAKISTAN STOCK MARKET PRICE PREDICTION USING MACHINE LEARNING

The stock market is a regulated marketplace where companies raise capital by selling shares of stock, or equity to investors. The stock market is the backbone of a country because it is essential for country's development, corporate governance, capital formation, investment, and economic growth. However, due to various factors such as company performance, financial crises, political instability, and pandemic outbreaks, the stock market is very challenging to predict. This study uses a dataset from different sectors of Pakistan Stock market, carefully processed by adjusting sizes, normalizing, and fixing errors. Initially, Moving Average (MA) and Exponential Moving Average (EMA) are used to identify crisis points in stock market. Afterward, the Stochastic Relative Strength Index (Stoch RSI) is applied to predict the stock market. The novel part comes in the third step, where an advanced transformer model is used for better predictions of stock market prices. The model's performance is thoroughly assessed using standard measures like Root Mean Square Error (RMSE), Mean Squared Error (MSE), and Mean Absolute Error (MAE). The Average evaluation scores for all indices of Pakistan stock Market Sectors are RMSE=0.052865, MSE=0.002866, and MAE=0.071720. The results now improve understanding of the Pakistan stock market and also highlight the effectiveness of transformer models in predicting stock prices by tunning different parameters and hyperparameters. The transformer layers used in the proposed studies for extracting the most effective features which outperforms as compared to the techniques used in previous studies for Pakistan stock market price predictions.

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PSX	Pakistan Stock Exchange
KSX	Karachi Stock Exchange
LSE	Lahore Stock Exchange
ISE	Islamabad Stock Exchange
LSTM	Long-Short Term Memory
SVM	Support Vector Machine
NB	Naïve Bayes
RNN	Recurrent Neural Network
ANN	Artificial Neural Network
CNN	Conventional Neural Network
GRU	Gated Recurrent Unit
XGBOOST	Extreme Gradient Boosting
LR	Logistic Regression
RSI	Relative Strength Index
UBL	United Bank Limited
ABL	Bank Alfalah Limited
HBL	Habib Bank Limited
MA	Moving Average
EMA	Exponential Moving Average
MACD	Moving Average Convergence Divergence
RMSE	Root Mean Squared Error
MAE	Mean Absolute Error
MSE	Mean Squared Error
YF	Yahoo Finance
MAPE	Mean Absolute Percentage Error
AMAPE	Adjusted Mean Absolute Percentage Error

STOCHRSI	Stochastic Relative Strength Index
Bi-LSTM	Bidirectional Long Short-Term Memory
IPO	Initial Public Offering
ML	Machine Learning
ReLU	Rectified Linear Unit
DL	Deep Learning
MTL	Millat Tractors
INDU	Indus Motors
ALTH	Altus Honda
KOHT	Kohat Cement
MLC	Mapel Leaf Cement
FCCL	Falcon Co and Cement Limited
BOS	Break of structure
CHoCH	Change of character

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DEDICATION

This thesis serves as a testament to the enduring influence of my family, the bedrock of my aspirations. Gratitude fills my heart as I acknowledge my parents, whose unwavering support and countless sacrifices have illuminated my academic path. Their belief in my potential has been the propulsive force guiding me through the challenges of academia. To my siblings, whose unwavering encouragement has been a perpetual source of motivation, I express heartfelt appreciation.

In dedicating this work, I extend profound gratitude to my friends and mentors, whose guidance and camaraderie have been indispensable. Their insights and shared experiences have enriched my academic journey, molded not only my intellectual growth but also contributed to the ultimate realization of this research endeavor. To those who believed in my capabilities and offered encouragement, your influence has been truly transformative.

As this thesis takes its place on the academic stage, I dedicate it to the cherished individuals who have played pivotal roles in my life. May this dedication stand as a humble acknowledgment of the profound impact each of you has had in shaping my academic pursuits. Additionally, I extend appreciation to the broader academic community, whose collective wisdom and resources have been instrumental in the development and completion of this research.

CHAPTER 1

INTRODUCTION

The stock market is a place or platform where people can buy and sell shares of companies that are on the stock market. Companies can get money by selling these shares, and people can try to make money by buying and selling them. The prices of the shares go's up and down because of some factors like the geopolitical tensions, pandemics, financial instability, economic stability, company's reputations etc [1]. Stock market is a complex and challenging task, as stock markets are influenced by various factors, including economic indicators, company performance, geopolitical events, and investor sentiment [2].

1.1 Stock

A stock is like a special kind of ownership certificate in a company. An individual who has stocks, it means they own a piece of that company and have a claim on its money and profits. Stocks are also called shares or equity. If an individual own shares, they can vote in meetings where decisions about the company are made, they may get a share of the profits as dividends, and they can sell their shares [3].

1.2 Stock Market

Stock market describes a number of different sectors where share of publicly different traded companies can be sold and purchased. Stock market plays an important role for the country development and economic growth. An effective and efficient stock market helps to raise capital, country economy and attract investors to invest their money on stock market and promoting long-term development and overall prosperity [4].

One of the most efficient and successful ways to generate passive income is the stock market. The closing price is like a common reference point for how stocks did each day. It's expected and easy for traders, investors, and the market to use when figuring out how stock prices are changing [5].

Considering the backbone of current financial systems, the stock market is essential in determining the direction of the world economy. It acts as an interface for the successful movement of capital and as a representation of the state of the economy [6].

1.2.1 Structure of Stock Market

Stocks or Shares

Stocks are a symbol of ownership in a business. When you have shares or stocks in a company, it means you own a piece of that company. Companies create shares to get money, and people can buy these shares on the stock market. It's like owning a part of the company, and if the company does well, the value of your shares may go up. People buy and sell these shares on the stock market [7].

Stock Exchange

Stock exchange is centralized market for the buying and selling of stock shares. The London Stock Exchange (LSE), Nasdaq, New York Stock Exchange (NYSE), Pakistan Stock Exchange PSX and Karachi Stock Exchange KSX and numerous other stock exchanges are major stock exchanges. This is basically a platform where broker and trader can buy and sell stock shares [8].

Stock Indices

A certain set of stocks make up stock indices such as the Dow Jones Industrial Average and the S&P 500, Karachi Stock Exchange (KSX-100) and NASDAQ. They offer a quick overview of the general performance of a certain stock market sector [9].

Stockbrokers

These are the professionals working in the centralized market or financial industry that help investors purchase and sell stock shares. A stockbroker serves as a representative or entity who charge fee or commission for carrying out the buying and selling instructions on behalf of an investor [10].

Bull and Bear Markets

Rising stock prices define a bull market, while declining stock prices define a bear market. These terms are used to describe direction of the overall financial market.

Figure 1.1: Stock Market Representation Using Bull and Bear [11]

Dividends

In the stock market, a dividend is a share of a company's earnings that is distributed to its shareholders. Some companies distribute a portion of their earnings to shareholders in the form of dividends [12].

Market Capitalization

The total value of a company's outstanding shares of stock is known as its market capitalization. It is computed by taking the number of outstanding shares and multiplying it by the stock price [13].

Earnings Reports

Reports on a publicly traded company's financial performance must be released on a quarterly and annual basis. Stock prices may be significantly impacted by these reports.

Figure 1.2: Stock Market Earning Report [14]

1.2.2 Stock Sectors

The division of publicly traded corporations into groups according to the characteristics of their businesses or industries is known as the "stock sector," sometimes referred to as the "industry sector" or the "equity sector" [15].

The listed companies are distributed amongst thirty-seven sectors/groups of industries. These classifications aid in the comprehension and analysis of the performance of businesses with comparable economic features and modes of operation by academics, analysts, and investors. Every sector has its own distinct set of opportunities and challenges and represents a distinct area of the economy.

Figure 1.3: Stock Market Sectors Representation [16]

1.2.3 Stock Market Interpretations

Candlestick diagram serve as a widely employed instrument in technical analysis for the interpretation and anticipation of stock market price movements. Each individual candlestick corresponds to a specific time frame, and the configuration and color of the candle furnish details about the opening, closing, high, and low prices within that timeframe [17]. The following are essential factors to take into account when analyzing stock market information through candlestick charts:

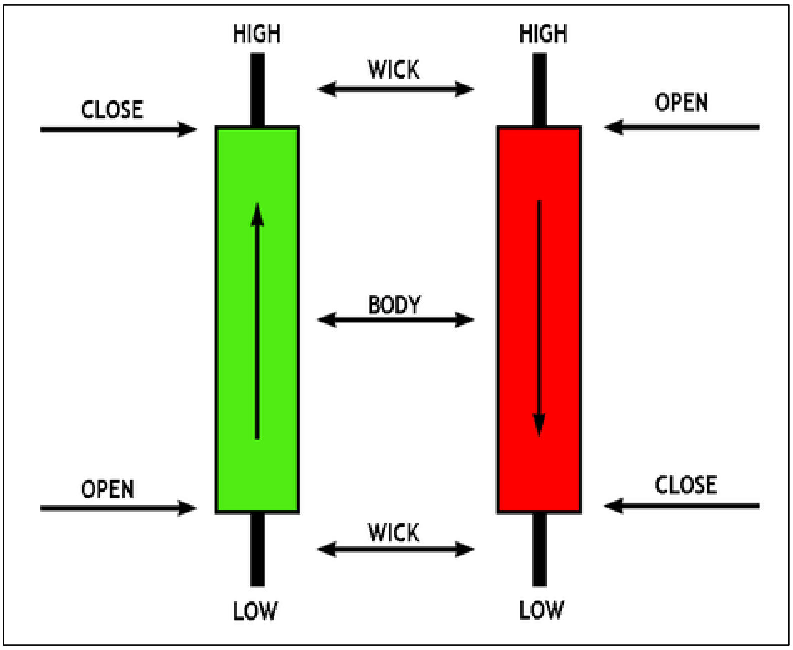


Figure 1.4: Stock Market Interpretation Using Candle Stick [18]

1.2.4 Candlestick Components

There are multiple components of the candles sticks which are discuss below:

Body

The rectangular section of the candlestick denotes the opening and closing prices during the designated time period. A filled (black or red) body signifies a bearish (downward) movement, while a (white or green) body indicates a bullish (upward) movement [19].

Wicks (or Shadows)

The lines extending above and below the body portray the highest and lowest prices observed during the timeframe.

Bullish Trend

Sequential white or green candles suggest an upward trend.

Bearish Trend

Consecutive black or red candles indicate a downward trend.

Hammer

Characterized by a small body and a long lower wick, often signaling a potential reversal after a downtrend.

1.3 Stock Market Price Analysis

Stock market interpretation is discussed above in detail, one candle shows the full day analysis of the stock market price. This below diagram figure 1.4 shows the detail description of the candle with time to price. In the given graph x-axis show the time while y-axis shows the price of the stock days. As the green color indicate the highest stock price while red color shows the lowest price of the stock price during analyzing, which makes a full candle of the day, the starting point in the given diagram shows the market opening time, with passage of time the stock goes down and at the same day before closing the stock jumped (green color) which shows that the market is up and then close. The next day of the stock market starts from the closing price of the previous day, in the graph the stock price is gone up with respect to time but with the passage of time the market price is down (red color) and closed.

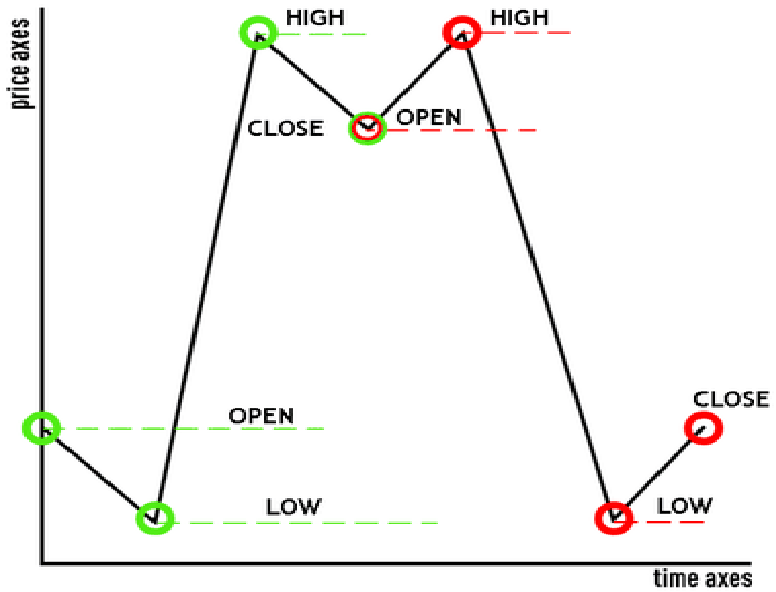


Figure 1.5: Stock Market Price Analysis [20]

1.3.1 Financial Market

Financial market is the place where assets such as stocks, bonds, and other alternatives like foreign exchange, and shares are being traded. A financial market is like a bridge connecting people who have extra money with those who need money (borrowers). It helps transfer money from those with a surplus to those who want to invest or borrow [21]. Usually, the people with extra money are called investors, and the ones in need of money are businesses. So, the financial market brings these two groups together, making it easier for people who want to lend or invest money to find those who need it [22].

Money Market

This is the chosen region for short-term borrowing or finance. The money market allows for the short-term holding of assets roughly less than a year. It is for overnight funds, and banks and other financial institutions share the majority of it [23].

Capital Market

A capital market refers to a financial market where long-term debt (exceeding one year) or securities backed by equity are traded, distinguishing it from a money market where short-term debt transactions occur.

Figure 1.6: Classification of Capital Market [24]

A secondary market is a market that facilitates the buying and selling of both newly issued and used securities. A broker acts as an intermediary between the two parties so that the securities can be exchanged for cash. Some of the features of Capital Market are given below:

Acts As a Bridge Between Server and Investor: A capital market plays a vital role in connecting those who save money with those who want to use that money for business or investments. It helps move money from people who save to those who want to start businesses.

Focuses on Long-Term Investments: A capital market provides funds for plans that need money for a medium or long period. It doesn't handle savings meant for less than a year.

Involves Intermediaries: In a capital market, various go-between entities like underwriters, brokers, and depositories play important roles. These intermediaries are like the working parts of the capital market, making them essential elements [13].

Follows Government Rules: While a capital market operates with some freedom, it operates within the rules set by the government. The capital market works under the guidance of government policies and regulations [25].

1.4 Initial Public Offering (IPO)

When a company that was privately owned decides to sell its shares to the public for the first time, it's called an initial public offering (IPO). Essentially, during an IPO, a company is changing from being owned by private individuals to being owned by the public. That's why people also call it going public [2].

Figure 1.7: Initial Public Offering [2]

When you join an IPO, it means you agree to buy shares of a stock at a set price before it starts trading on the regular market. This price is decided by the lead underwriter and the company based on different factors, including the interest shown by potential investors.

Before you can take part in an IPO, you have to check if your brokerage allows access to new stock offerings and what the conditions are [5].

1.5 Types of Stock Trading

There are generally two types of trading methods the one is long-term and the other is short-term. Long-term investing in stable stocks is less time-consuming and effort-intensive for traders [26]. On the other hand, short-term trading aims to capitalize on small changes in stock prices. This could happen within seconds, known as intra-day stock trading, or over a day to a few days, known as short move trading. Short-term trading, especially when done manually, can be quite demanding.

1.6 Stock Analysis Methods

The two main types of stock market analysis are:

1.6.1 Fundamental Analysis

Examines the intrinsic value of a stock by analyzing financial statements, earnings reports, management, competitive advantages, and economic indicators. To determine the underlying value of a stock and it's potential for long-term growth. Earnings per share (EPS), Price-to-Earnings (P/E) ratio, debt levels, and overall financial health [27].

1.6.2 Technical Analysis

Analyzes historical price and volume data using charts, graphs, and technical indicators to identify trends and predict country's future movements. To make short-term predictions based on historical market data and patterns. Candlestick charts, moving averages, (RSI), (EMA), Moving average (MA) and trendiness [28].

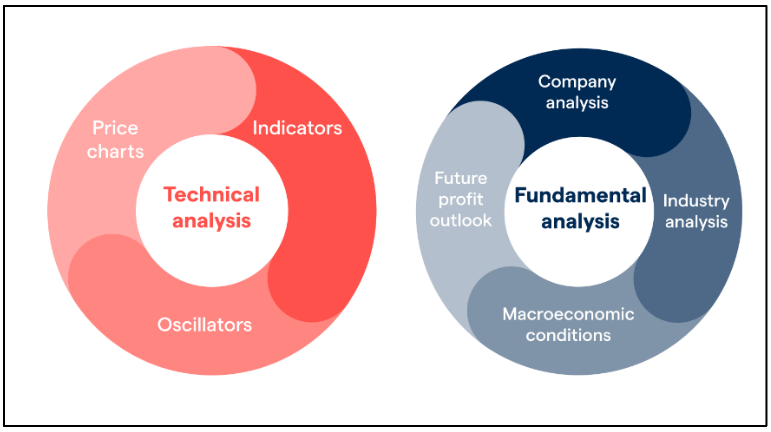


Figure 1.8: Stock Market Analysis [29]

These two approaches represent the fundamental comparison in the stock market analysis. Fundamental analysis is about understanding the basic values of a company, while technical analysis is focused on studying historical price movements and patterns to predict future market direction. Investors often use a combination of these methods to make well-informed decisions.

1.7 Pakistan Stock Market

All stock markets of Pakistan to unite the nation's three major exchange markets located in Karachi, Lahore, and Islamabad into a single market in January 2016 by the government of Pakistan, combine we called the Pakistan Stock Exchange (PSX) [30]. The Karachi Stock Exchange, Lahore Stock Exchange, and Islamabad Stock Exchange integrated to form the PSX on January 11, 2016. There are more than 530 indices are listed on the PSX as of January 2023 [31].

Figure 1.9: Pakistan Stock Market Graph [23]

1.7.1 Karachi Stock Exchange

Karachi Stock Exchange Limited (KSE) was established on September 18, 1947, and it was registered in Pakistan. It was situated at the Stock Exchange Building (SEB) on Stock Exchange Road, in the center of Karachi's commercial sector [32]. It was the biggest stock exchange in Pakistan and one of the top 10 stock exchanges in the world in 2015.

1.7.2 Lahore Stock Exchange

The Lahore Stock Exchange (LSE) was established in October 1970 under the Securities and Exchange Ordinance of 1969 by the Government of Pakistan [33].

1.7.3 Islamabad Stock Exchange

The latest of Pakistan's three stock markets, the Islamabad Stock Exchange (ISE), was founded in Islamabad, the country's capital. On October 25, 1989, ISE was established as a guarantee-limited corporation [34].

1.8 Stock Market Challenges

Financial market is one of the markets which have most effective and significant effect in many areas like in education, political, health, economy, business, technology and jobs [35]. With the passage of time people are interested in prediction and analysis of stock market where investors invest money for making profits but this is one of the difficult and most challenging tasks because of different type of data exist like chaotic, ambiguous, nonlinear, stationary, non-stationary and blurring data so that’s why the prediction of an accurate stock market is very difficult and challenging [36].

1.8.1 Factors Influencing Stock Market Volatility

Due to the interrelated factors in the stock market, it may include economic, technical, educational political and business which are highly effected. Many companies trade publicly throughout the world which help in increasing the stock market and by day-to-day investment and trading publicly may have the challenging factors which is very difficult task for the prediction and stock market analysis.

To understand how macroeconomic factors impact stock markets is of significant interest to both academic researchers and investors, can help well-informed investment decisions [37]. Currency Exchange Rates consider how exchange rate variations may impact the profitability and competitiveness of international corporations listed on the stock market [38]. Government Policies examine the potential effects of financial policies, tax changes, and governmental regulations on certain markets or market sectors.

Trade Policies and Global Economic Conditions examine how global economic conditions, such as trade conflicts and geopolitical events, might affect stock markets, particularly in nations that are highly dependent on international trade. Item Prices examine the connection between stock market fluctuations and commodity prices (such as those for agricultural products, gold, and oil), especially in sectors where these prices are tightly correlated [39].

1.8.2 Globalization Crisis and Its Impact on the Stock Markets

The dynamic and corelated factors that changes in the market and the growing complexity it’s a very difficult and challenge task because of the non-linear nature of the stock market [40]. A range of variables, such as business outcomes, geopolitical unrest, financial crises, and pandemic outbreaks, can cause stock prices to decline [41]. A stock forms a bubble before it crashes. Crash prediction has been applied extensively in the banking industry, investment, business, and other sectors. The significance of crisis prediction in the financial industry has captured the interest of numerous scholars and investigators. One of the proposed work's most important contributions is the ability to predict crisis [42].

The recent drop in the stock market has a number of causes like the price of the company's shares, the company's loss, the trade war's impact on the global market, geopolitical tensions, and pandemics like the Corona Virus viral infection covid-19 [37].

1.9 Problem Statement

It is very challenging and difficult to predict the stock market due to its complex and non-linear nature. This problem is addressed in various studies using different traditional and machine learning techniques [28-43]. The primary problem in the existing studies is the low accuracy of the stock market. Hence a study is needed which can use modern technique to enhance the existing prediction results.

1.10 Research Questions

The research questions are:

RQ1: How does the statistical techniques help for identifying stock crash points and stock bubble prices?

RQ2: How does the latest model can increase the prediction accuracy of the stock market?

1.11 Research Objectives

The research objectives are:

OBJ1: To find the technical indicators for identifying stock market crash point and stock bubble price.

OBJ2: To propose a model using latest technique for better accuracy of the stock market predictions.

1.12 Motivation

It is very crucial for investors and governments to understand and identify stock market natural disasters in the ever-changing world of global finance. Pakistan, one of the largest contributors in the developing market economies, is stuck between economic growth and financial instability [7]. The variations observed on the Pakistan Stock Exchange (PSX) are significant for investors both locally and internationally, since it reflects the complexities of the country's economic situation. This study aims to contribute to the ongoing discussion about financial stability and tackle the difficult task of understanding the complicated structure of the Pakistan stock market by using advanced prediction models to identify future crises. This study aims to provide investors, policymakers, and financial analysts with useful knowledge by exploring the complexities of the market. The proposed study be more capable and effective in managing Pakistan's complicated financial environment as a result. Getting such knowledge is not just a necessary research task in a day where financial crises have a worldwide impact, but it is also an essential initial step in increasing financial stability as well as profession decision-making.

1.13 Scope of the Study

The proposed studies are mostly focus on handling big amounts of data, understanding complicated patterns, and adjusting to the market's changes. The goal of the study is to focus on the latest and State-of-the-Art techniques for solving non-linear nature of Pakistan stock market. The finding of the study is to contribute to predict the non-linear and complex nature of the stock market.

Predicting stock market is difficult, where complex relationships and interrelated factors are significantly impact outcomes therefore, latest state-of-the-art machine learning models becomes essential. Traditional approaches were used in the existing study to solve regression problems in stock market analysis often struggle to capture the non-linearity of the stock but still need a latest model to find out the root of the stock crisis and bubble price where to predict the accuracy of the market. In light of this challenge, the integration of advance models, notably the Transformer model, emerges the latest to elevate predictive accuracy. Different layers of the models use for getting accurate results like 1D layer is used 2 times for extraction of useful and important features.

1.14 Contribution and Significance

This study makes a significant contribution which are given below:

- **i.** Modern techniques: State-of-the-Art Transformer model is used for the sequential data taken from different sectors of Pakistan, for the stock market price prediction using different layers like multiheadattention layer, CNN 1D layer for relevant feature extractions, Convolution 1D layer again, Normalization layer, Dense layer and output layer.
- **ii.** Identification of the stock crisis: Different Statistical techniques are used for the identification of the stock crisis identifications (Moving average and Exponential moving average).
- **iii.** Stock Bubble Price Predictions: Stochastic Relative Strength Index used for the stock up and down movement called stock price bubble identification.
- **iv.** Evaluation Scores of better prediction of Model: Different evaluation models used for the model best performance like (MAE, MSE, RSME).

1.15 Summary

A brief review of the Pakistan Stock Market and their subtypes is given in this chapter. We have discussed the different analysis methods of Stock market, their features, Sectors, challenges and the reasons crisis behind them. A brief discussion is given of the many methods used in the identification and management of Pakistan Stock Market, particularly Transformer. I gave a quick explanation of the task's objective and its purpose. Lastly, I gave an easy-to-understand description of the structure and contribution of the thesis.

CHAPTER 2

LITERATURE REVIEW

In the previous studies, different methods and classifications were used to identify stock market crisis and to improve stock market accuracy using different methods of ML and deep learning Model. Over time, in the field of stock crisis prediction has experienced significant changes, shifting from traditional methods to more advanced computational models. Initially, the focus was on time-series analysis, where methods like ARIMA (Autoregressive Integrated Moving Average) dominated the scene [44].

2.1 Challenges

The non-linear and volatile nature of the financial market often caused these models, which were based on historical price movements, to face challenges in their attempts to predict future market behaviors. Parallel to these were the practices of fundamental and technical analysis. Fundamental analysis looks deeply into a company's financial statements, industry conditions, and wider economic factors to draw predictions about stock performance. A technical indicator is use for prediction the direction of financial markets. It is based on historical data on price, volume, or open interest. Econometric models also played a role, incorporating various economic indicators in regression analyses to predict the market movements.

Minimal spanning trees and threshold networks are mathematical representations of the connections between the stocks in the PSX, using cross-correlations. To explore how the stock market's structure changed before, during, and after the 2008 global financial crisis, the study divides the data into three subsamples in addition to the complete sample analysis. Shannon entropy was used to calculate the volatility in the stock market [45].

It has been observed that the crisis may start in a developed country and then extend to developing nations. Similar to how the subprime mortgage crisis started in the US and developed into the European sovereign debt crisis. The crisis also had an impact on the Asian market [46].

The PSX (Pakistan Stock Exchange) had a tough time after reaching its highest point in six years, crossing 49,000 points in July. This increase was due to Pakistan securing a new IMF loan of $3 billion in late June 2023. However, things took a downturn as the currency lost value, decreasing by 5%, which is equal to Rs17, during the first two weeks of the caretaker government.

High political instability in the entire nation is also dissolving the capital markets, creating uncertainty about the timing of the upcoming general elections, which were previously irrationally scheduled for November 2023 [47].

Uncertainty in economic policy has significant effects on how an economy is shaped as a whole. Due to its potential impact on numerous economic activities, economic policy uncertainty (EPU) has become one of the most hotly disputed topics in recent years among academics, decision-makers, and financial experts. Recent studies examine how stock market volatility, unemployment, real estate returns, and exchange rate fluctuations are affected by economic policy uncertainty [40].

Terrorism, political unrest, conflict, and natural calamities have all negatively impacted Pakistan's economy over the past few decades. These indicators take into account things like terrorist attacks, political unpredictability, fluctuating exchange rates, the food in 2010, and the IMF program [38].

Changes in macroeconomic data and market economic policy on the local, national, and international levels might lead to a stock market crisis. For instance, a financial market slowdown in 2008 that started in the United States (US) eventually had an impact on the economies of other nations. It has been noted that a major economy may be the source of the crisis and that smaller economies will also be affected by its effects. As an illustration, the US-based subprime crisis developed into a European sovereign debt crisis. Additionally, the Asian market was impacted by this crisis. The banking industry, business, investments, and other fields have employed crisis prediction. The importance of crisis prediction for the financial sector has drawn numerous academics and researchers [28].

The hybridized Feature Selection (HFS) technique was used to create a model for stock crisis prediction. The model makes use of the Naïve Bayes technique to categorize strong fundamental stocks, the Stochastic Relative Strength Index (Stoch RSI) to detect bubbles in stock prices, and moving average statistics to pinpoint the time at which stock prices reach a crisis. Deep learning algorithms like the Gated Recurrent Unit (GRU) and

Long-Short Term Memory (LSTM) are used to predict market crises. When it came to stock crisis prediction, the HFS-based GRU approach performed better than the HFS-based LSTM method [43].

As stock values are irregular identifying stock crisis movements is difficult. A significant drop in the stock price of more than 10% in a short period as a result of heavy selling is considered a stock price crisis. For this, the author uses the hybridized model to prediction the stock closing price and fined the stock bubble using different machine learning and deep traditional models [28].

Over 6.3 million individuals traveled abroad during the Chinese New Year's holidays in 2019, according to a survey by the China Overseas Tourism Research Institute, although the number has recently dropped sharply. The returns transmission and volatility spillover pattern of these markets over the standard and COVID-19 eras were ascertained by the study using the VAR-DCC-MEGARCH model. The findings show that, under typical conditions, returns produced in Pakistan's financial markets have a major influence on SSEC's return movements. In terms of returns, Chinese stock markets' dominance over Pakistan's stock markets, however, remained minimal. According to the analysis, there was little volatility spillover between the (SSEC) Shanghai Stock Exchange Composite and the Karachi stock exchange (KSE-100) index when things were stable [48].

The progression into deep learning further enhanced predictive capabilities. Models like Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNN), Gated Neural Network (GRU), XGBoost, Support Vector (SVM) given their capacity to identify complex patterns and temporal connections in time-series data, machine learning became very useful [49].

The field also saw the emergence of hybrid models that amalgamated traditional statistical approaches with cutting-edge machine learning techniques, aiming to harness the strengths of both worlds for superior prediction accuracy. Moreover, the integration of Natural Language Processing (NLP) to analyses financial news, reports, and social media has become increasingly prevalent. This shift acknowledges the growing importance of market sentiment, which is often influenced by qualitative information and can significantly impact stock movements [46].

However, the limitations of these traditional methods, especially their inadequacy in handling complex market dynamics, led to the exploration of advanced and latest computational models. A new age in stock prediction was established in with the development of machine learning, which allowed algorithms like Random Forest, Support Vector Machines, and Neural Networks to learn from massive datasets and provide a more accurate knowledge of market trends.

Table 2.1: Existing Studies on Stock Market Prediction Using Different Classification

Year	Author	Techniques	Dataset	Accuracy
2023	Muhammad Ali et al [50]	EMD-LSTM hybrid Model	Pakistan Stock Market (KSX-100)	The evaluation matrices scores MAE=234.3 and MAPE = 0.59
2022	Irfan Javid et al [43]	GRU and LSTM	Pakistan Stock Exchange (KSX-100)	GRU perform better than LSTM
2021	Mazhar Hameed et al [51]	ANN, LSTM and LR	Karachi Stock Exchange	The evaluation metric scores are RMSE = (0.42), MAPE = (0.77) and MAE = (0.013).
2019	Bilal Ahmed Memon et al [45]	Minimum Spanning Tree and Shannon Entropy	Pakistan Stock Exchange	Shannon Entropy having the evaluation metrics score is up to 1.699%
2020	Wasiat Khan et al [52]	Machine Learning (Sentiment analysis, SMO, ASC and Bagging)	Pakistan Stock Exchange	Sentiments features accuracy up to 0-3% while political accuracy improved up to 20%.
2020	Suhui Lia et al [53]	Recurrent Convolution Neural Kernal	Chinese Stock Exchange	The proposed model performs having accuracy 56.9%
2022	Leeanne Lindsay et al [54]	Nonlinear Autoregressive Moving Average Model (NAMRAX)	Five stocks (Nike, Pfizer, Goldsmith Sachs, JP Morgan, Johnson & Johnson)	Johnson & Johnson have best MAPE score of 0.78% other than 4 datasets
2021	Nagaraj Naik et al [28]	XGBoost and DNN	Bombay Stock Exchange	XGBoost perform better than DNN

Year	Author	Techniques	Dataset	Accuracy
2021	Nadeem Malibari et al [8]	Vision Transformer	Saudi Stock Exchange	By using the latest Method, the accuracy achieved up to 88%
2023	Shuzhen Wang et al [55]	BiLSTM-MTRAN-TCN	Shanghai Stock Exchange	Hybrid model of BiLSTM-MTRAN-TCN perform better than other single methods
2022	Qazi Mudassar Ilyas et al [24]	Hybrid model (Fully Modified Hodrick Prescott)	Apple dataset	Achieve prediction accuracy of 70.88%
2022	Dian Angga Prasetyo et al [56]	Bidirectional-LSTM Model	Indonesia Stock Market	Average of 5 stock MAPE = 1.886% and SMAPE=1.837%
2020	Salah Bouktif et al [57]	Deep Learning (Finer-grained and Sentiment Analysis)	NASDAQ-100	Accuracy up to 60%
2022	Diaa Salama Abd Elminaam et al [58]	KNN, Linear Regression, Random Forest, Gradient Boosting	Bank of New York, HP Inc, Pfizer dataset.	Linear Regression perform better than all other methods having RMSE=0.489 and MAE= 0.388.
2020	Mehar Vijh et al [59]	ANN and Random Forest	Nike, Goldman Sachs, Johnson and Johnson, Pfizer and JP Morgan Chase and Co.	ANN performs better than RF having RMSE = (0.49), MAPE= (0.77) and MBE = (0.13).
2022	Saurabh Kamal et al [60]	CNN, LSTM, SVM, RF and Naïve Bayes classification	London Stock Exchange	BERT = 90% while ROBERT a = 88% perform better than CNN =80% and LSTM =84%
2023	AGUS TRI HARYONO et al [61]	Transformer encoder GRU	Indonesia Stock Market	The evaluation matric Accuracy Mean Absolute Percentage Error = 1.24%

Year	Author	Techniques	Dataset	Accuracy
2022	CHANG LIU et al [62]	ML and DL Methos (NMC-BERT-LSTM-DQN-X)	Chinese Stock Market	Evaluation Matric scores MSE = 0.095, RMSE = 0.0739, MAE = 0.104 MAPE = 15.1%
2019	Bilal Ahmed Memon et al [63]	Correlation based Minimum Spanning Tree comparison	Karachi Stock Exchange (KSX-100)	MST Perform better than other methods having accuracy is up to 62%.
2020	Sondo Kim et al [64]	Integration of ETE (Effective Transform Entropy) with ML	US Stock Market Dataset	MLP and LSTM perform better having accuracy is 67%.
2020	M Nabipour et al [65]	Machine learning and Deep Learning different methods	Tehran Stock Exchange	LSTM perform better than other methods.
2020	Xiongwen Pang et al [66]	Deep Learning (Embedded LSTM)	Shanghai A-Composite Index dataset.	The average accuracy based on ELSTM for 3 stocks is 53.5%

2.2 Stock Market Analysis

The stock market is like a marketplace where people buy and sell shares of companies that are available to the public. This is important for companies because it helps to get money, and for people to own a part of a company and share in its profits. The stock market is also a way to understand how well the economy is going, as it shows how the companies in the market are performing.

2.3 Technical Indicators

Different technical indicators are used in the previous study to predict stock market some of them are given below:

1.3.1 Moving Average

A Moving Average (MA) is a statistical technique commonly applied in data analysis, especially in finance and time-series analysis. Its purpose is to reduce irregularities and emphasize patterns within a dataset by calculating an average value across a specific timeframe or set period [43].

1.3.2 Exponential Moving Average (EMA)

The Exponential Moving Average (EMA) is a type of moving average frequently applied in time-series and financial market technical analysis. For potential entry or exit in the financial market to identify stock the traders or investors always use Exponential moving average indicators. Short-term EMAs, being more sensitive to price changes, are often utilized for short-term trading strategies, while longer-term EMAs offer a more comprehensive perspective on market trends [44].

$$\mathrm{EMAt} = \alpha * (\mathrm{Pt} - \mathrm{EMAt} - 1) + \mathrm{EMAt} \qquad 2.1$$

t is time of EMA

Pt is price at time of t

α is constant smoothing factor between 0 and 1

EMAt-1 show previous time periods

1.3.3 Simple Moving Average

A popular technical analysis indicator in finance, the Simple Moving Average (SMA) is computed by adding up the closing prices of an asset over a selected period and dividing by the total number of periods. By offering a smoothed average, it enables traders in understanding market movements and future turning points. When comparing short- and long-term SMAs to produce buy or sell signals, investors can use both as useful indicators to determine the general direction of the price of an asset movement [67].

$$\mathrm{Sum} = \frac{\text{sum of values over time period}}{\text{number of observations in that time periods}} \qquad 2.2$$

1.3.4 Momentum

Momentum is a technical indicator used to evaluate how quickly the price of a financial instrument changes over a given period of time. It is computed, usually as a percentage or ratio, by comparing the closing price of the current period to the closing price of a prior period. While negative momentum suggests a downward trend and declining price performance, positive momentum indicates an upward trend and suggests that the price of an asset is gaining strength. Traders frequently utilize momentum to validate the strength of an established direction and identify possible market turning points [44].

1.3.5 Relative Strength Index

The Relative Strength Index (RSI) is a momentum indicator extensively used in technical analysis, especially in financial markets. It gauges the speed and magnitude of price changes by calculating the ratio of recent gains to losses. The resulting RSI value falls within a range of 0 to 100. RSI assists traders and analysts in determining if an asset is either overbought or oversold. When the RSI surpasses a certain level, it may suggest that the asset is overbought, hinting at a potential reversal or correction. Conversely, if the RSI drops below a specific level, it could indicate that the asset is oversold, implying a potential upward correction [68].

$$\text{StockRSI} = \frac{\text{sum of over gain over specfic time periods}}{\text{Number of periods}} \qquad 2.3$$

1.3.6 Moving Average Convergence Divergence

The Moving Average Convergence Divergence, commonly known as MACD, is a popular momentum indicator used in technical analysis to identify potential trends and reversals in the price movements of a financial asset. The MACD is calculated by subtracting the 26-period Exponential Moving Average (EMA) from the 12-period EMA [69].

$$\text{MACD Line} = 12 - \text{Period EMA} - 26 - \text{Period EMA} \qquad 2.4$$

2.4 Classification Models

Many classification models are discussed in the previous studies for prediction of the stock market crisis prediction. The progression into deep learning further enhanced predictive capabilities. Models like Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNN), Gated Neural Network (GRU), XGBoost, Support Vector Machine (SVM) were particularly effective, given their ability to capture dependencies and complex patterns in time-series data. In order to combine the best features of both fields for increased prediction accuracy, hybrid models that combined conventional statistical methods with state-of-the-art machine learning techniques also emerged in the sector. Moreover, the integration of Natural Language Processing (NLP) to analyses financial news, reports, and social media has become increasing.

2.4.1 Artificial Neural Network

Artificial Neural Network, is a computational model inspired by the functioning of biological neural networks found in the human brain. It comprises interconnected nodes, often referred to as neurons, organized in layers. These layers include the Input Layer, which receives initial data, Hidden Layers situated between the input and output layers, and the Output Layer, responsible for producing the final output [69]. The connections between nodes have associated weights, adjusted during training based on the error between predicted and actual output. This adjustment is typically achieved through a process known as backpropagation. Artificial neural networks are widely used in machine learning and artificial intelligence for tasks such as image and speech recognition, natural language processing, and various other pattern recognition tasks [70].

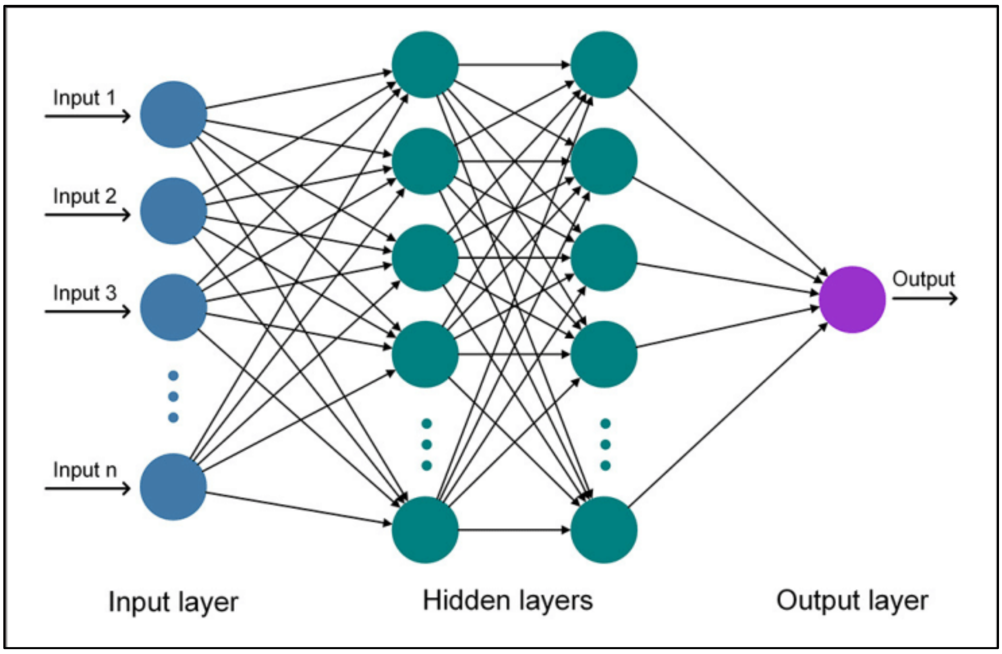


Figure 2.1: Artificial Neural Network [70]

There are several types of ANN designed to address specific task and challenges. Some of the types of Artificial Neural Networks are Feedforward Neural Networks (FNN), Radial Basis Function Neural Networks (RBFNN), Recurrent Neural Networks (RNN), Convolutional Neural Networks (CNN), Modular Neural Networks (MNN), Long Short-Term Memory Networks (LSTM) [69].

2.4.2 Convolutional Neural Network

CNN, or Convolutional Neural Network, is a specialized type of artificial neural network crafted for the analysis and processing of visual data. Specifically tailored for tasks like image recognition and computer vision, CNNs draw inspiration from the human brain's visual processing mechanisms [71].

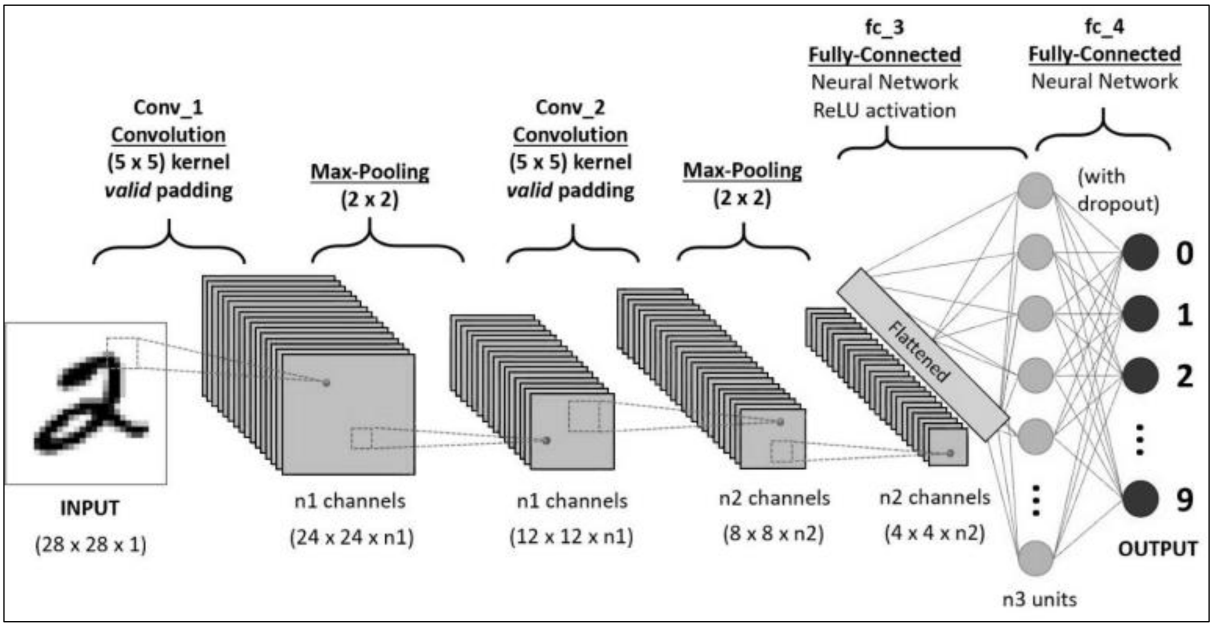


Figure 2.2: Convolutional Neural Network Model [72]

CNN architecture includes convolutional layers, where filters are applied to input data through convolutional operations, facilitating the learning of spatial hierarchies. Pooling layers then down sample the input, reducing spatial dimensions to enhance computational efficiency and robustness. Activation functions, such as ReLU, introduce non-linearity, allowing the network to grasp intricate data relationships.

Fully connected layers establish connections between every neuron in one layer and every neuron in the subsequent layer, enabling the network to make final predictions based on the learned features [73].

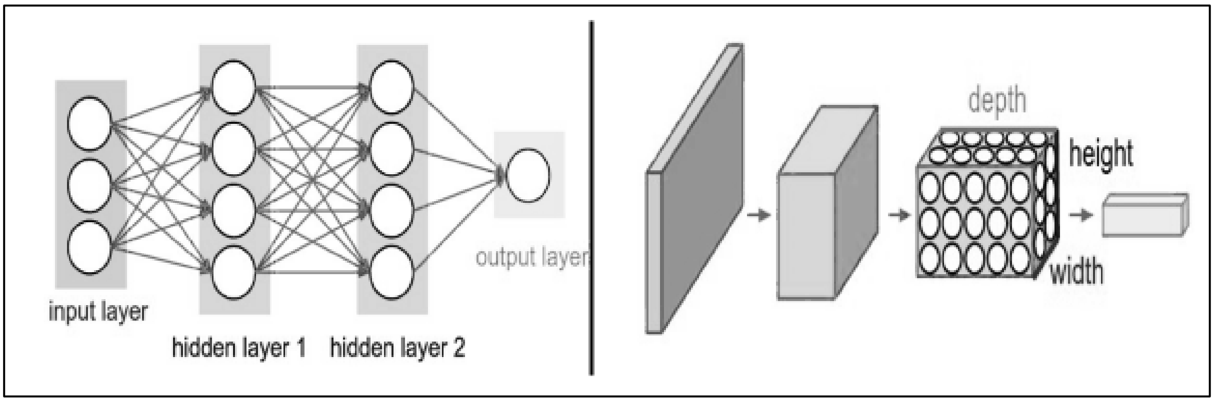


Figure 2.3: CNN and Simple Neural Network [71]

In the above diagram, the left side shows a regular 3-layer neural network. On the right side, neurons arranged in 3 dimensions that is height, width, and depth.

Convolution operation

In Convolutional Neural Networks (CNNs), a convolution operation is a mathematical process applied to input data. This operation involves combining two functions, represented as "a" and "b", to generate a third function. Mathematically denoted as "a * b", convolution is computed by integrating the product of the two functions after flipping and shifting one of them [71].

$$(F * I)(x, y) = \sum_{i=0}^{F\text{rows}-1} \sum_{j=0}^{F\text{col}-1} F(i, j) \cdot I(x - i, y - j) \qquad 2.5$$

(F*I) (x, y) represent value at (x, y) position in the resulting feature map.

F is the filter having dimension x and y.

I represent input.

Summation on the input data values.

(x-i, y-j) represent input applied filter position.

Foundational Element of CNN Model

CNN model is composed of three main layers, each employing a differentiable function to convert one set of activations into another. These layers fall into three main categories, contributing to the building of CNN architectures. CNNs are structured with various layers, each designed for specific functions in processing and feature extraction from input data [3].

The key layers in CNN architectures include:

Input Layer

The initial layer that receives raw input data, such as images or sequences [73].

Convolutional Layer

Applies convolutional operations using learnable filters to identify patterns and features in localized regions of the input. It performs a process called convolution on the input image by using a group of filters or kernels [73].

Activation function: Activation functions in Convolutional Neural Networks (CNNs) are pivotal for introducing non-linearity to the model. Below are some commonly utilized activation functions in CNNs.

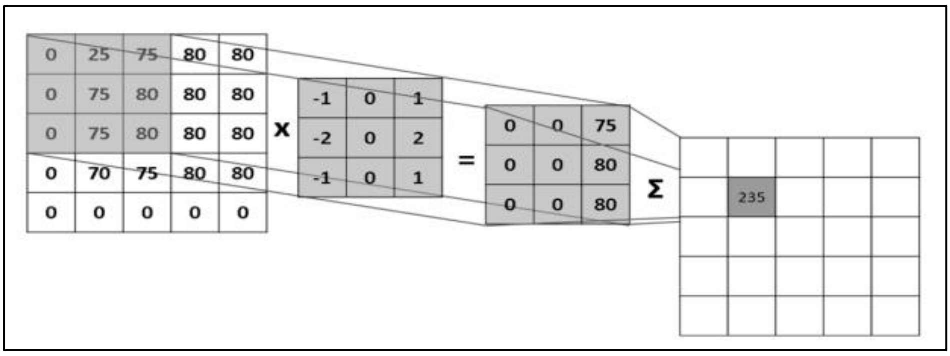


Figure 2.4: CNN Convolutional Operations [74]

Rectified Linear Unit Layer

By introducing non-linearity, the ReLU activation function enables the network to learn and express more complex connections in the data. In neural networks, the output of a convolutional layer connects to the Rectified Linear Unit (ReLU) activation function to introduce non-linearity, allowing the model to capture complicated relationships in the data. This element-wise activation function increases computational efficiency by substituting zero for negative values.

The formula used for ReLu is as followed;

$$f(x) = max(0, x) \qquad 2.6$$

x represent input

Max (0, x) maximum of either 0 or x.

Output will be 0 if the input is negative.

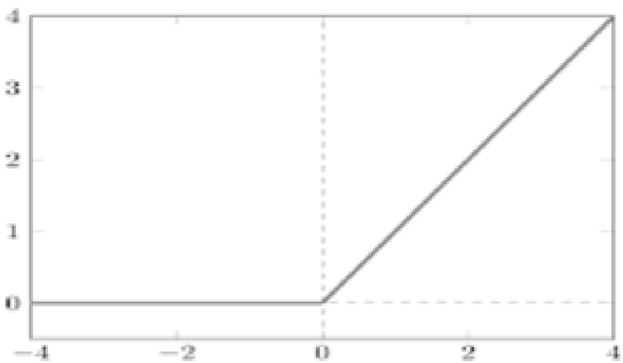


Figure 2.5: ReLu Function Curves [73]

SoftMax: The SoftMax activation function extends the concept of the logistic function to handle multiple classes. When applied to an input vector, this function generates a probability distribution across all potential classes. This proves valuable in scenarios involving multi-class classification, where the objective is to assign an input to one of several available classes. In the output layer of multi-layer neural networks tailored for classification tasks, the SoftMax function is commonly utilized. It computes the probability for each class, ensuring that the sum of all SoftMax results in the output layer equals 1. SoftMax aids in predicting the class to which the input is most likely associated, providing a probability distribution rather than a definitive choice between classes [71].

$$\mathrm{SoftMax}(x) = \frac{e^{x_k}}{\sum_{i=1}^{m} e^{x_i}} \qquad 2.7$$

Sigmoid: The sigmoid function, also called the logistic function, is a mathematical tool often used in machine learning. It has a special curve that looks like the letter 'S.' This function takes any number and gives an output between 0 and 1 [71].
Formula for sigmoid function is;

$$S(A) = \frac{1}{1+e^{-a}} \qquad 2.8$$

The input to the activation function is represented by (x). The sigmoid function is characterized by a smooth transition, gradually changing its output from 0 to 1. This smoothness is beneficial for the neural network, enhancing its ability to converge effectively during the training process [71].

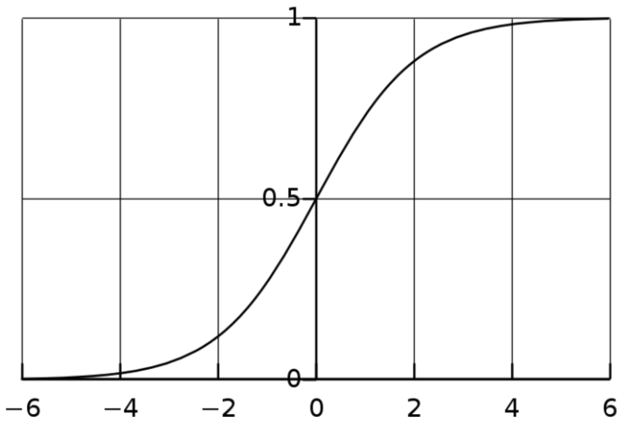


Figure 2.6: Sigmoid Function Curves [71]

In the context of binary classification tasks, the sigmoid function is commonly chosen as the activation function for the output layer when employing a Convolutional Neural Network (CNN).

Pooling Layer

Executes down-sampling to reduce spatial dimensions, aiding in feature selection and computational efficiency. Common pooling methods include max pooling and average pooling.

Various types of pooling functions include the following:

Max Pooling: This operation yields the maximum value within a specified region.
Average Pooling: It computes the average value within a defined region and returns the result.
Weighted Average Pooling: This method assigns weights to pixels based on their distance from the center, determining the neighborhood weight.
L2 Norm Pooling: It produces the square root of the sum of squares within the neighborhood's rectangles.

Max Pooling is commonly employed in the majority of ConvNet architectures to decrease computational costs [71].

Fully Connected Layer

Also known as a dense layer, establishes connections between each neuron and every neuron in preceding and succeeding layers, facilitating global feature learning and classification [3].

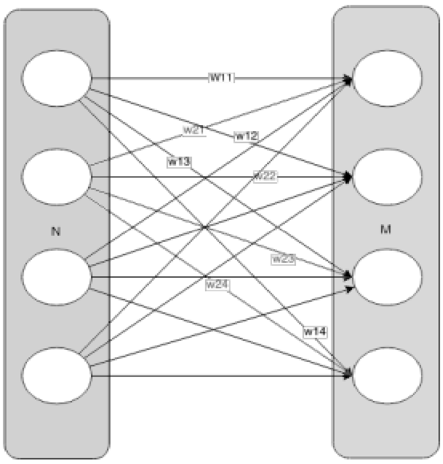


Figure 2.7: CNN Fully Connected Layers [3]

Flatten Layer

Converts the multi-dimensional output from the previous layer into a one-dimensional vector, preparing it for input into fully connected layers.

Dropout Layer

A regularization technique that randomly omits a percentage of neurons during training to prevent over fitting.

Batch Normalization Layer

Normalizes network activations, fostering quicker training and enhancing generalization.

Output Layer

The output layer of a convolutional neural network (CNN) is in responsibility for generating the final predictions based on the input data. The output layer's architecture is determined by the particular purpose for which the CNN was designed for, such as segmentation, object detection, or image categorization.

1.4.3 Long-short Term Memory LSTM

Recurrent neural network (RNN) architecture known as Long Short-Term Memory (LSTM) was designed to get rid some of the drawbacks of conventional RNNs while handling long-term dependencies in sequences. LSTM was introduced in 1997, by Jürgen Schmid Huber and Sepp Hochreiter [43].

The vanishing gradient issue, which commonly happens when training conventional RNNs, is the main difficulty that LSTMs attempt to solve. Due to the vanishing gradient issue, RNNs perform poorly on tasks requiring the comprehension of long-range dependencies since they have trouble capturing and propagating information over lengthy sequences. Long-term storage and access of information is made possible by LSTMs through the employment of a complex structure known as a memory cell [50].

Working of LSTM Model

Recurrent neural networks with long short-term memory (LSTM) were designed specifically to manage long-term dependencies in sequential input. A memory cell with gates is used by LSTMs to regulate the information flow. The input is analyzed at each time step, and the model determines what data to output, forget, and retain. Because of the memory cell's assistance in storing and retrieving data across longer sequences, LSTMs are useful for tasks where capturing long-range dependencies is essential, such as time series prediction and natural language processing. Through parameter adjustments during training, the network can be trained to handle complicated temporal patterns by minimizing the difference between expected and actual outputs [43].

Input gate

The input gate in an LSTM (Long Short-Term Memory) network acts like a gatekeeper, deciding which information from the new input should be remembered for the long term. It uses a smart system with two parts – one to decide the importance of each piece of new information and another to generate potential new memories. This way, the input gate filters and stores only the important things, helping the LSTM cell remember what's necessary for future tasks [27].

Forgot gate

Think of the forget gate in an LSTM (Long Short-Term Memory) network like a memory manager. It decides what old memories to keep and what to let go of. The gate uses a smart system to figure out which memories are important and which ones are not so important. This helps the LSTM cell remember the important stuff and clear out what it doesn't need, making its memory more efficient [27].

Output gate

Imagine the output gate in an LSTM (Long Short-Term Memory) network as a decision-maker. It decides what information from the memory should be shared as the final output. Using a smart system, picks important parts from the long-term memory and adjusts them to create the output. This way, the output gate ensures that the LSTM cell shares only the important and useful information for the task it's working on [27].

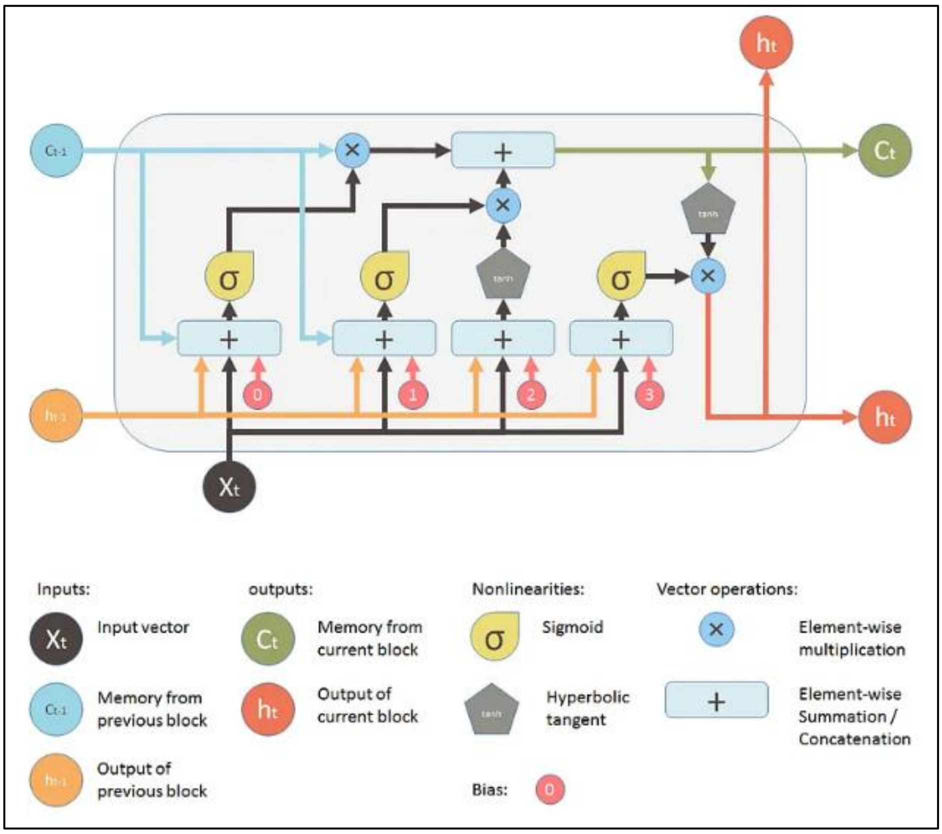


Figure 2.8: Long-Short Term Memory [62]

Advantages of LSTM

- LSTMs are better at remembering information for a long time compared to regular neural networks.
- They use smart gates to decide what information to remember, add, and use in their final answers, giving them better control over data.
- LSTMs are effective in solving the problem of forgetting important details during learning, making them more reliable.
- These networks are versatile and can handle various tasks, such as understanding language, recognizing speech, and identifying patterns in data.
- LSTMs excel at predicting things over time, like forecasting stock prices or predicting future weather conditions.
- Their flexibility and intelligence make LSTMs valuable for different types of information and complex pattern learning in the field of computer science.

Disadvantages of LSTM

- LSTMs, pose challenges in terms of computational complexity, leading to longer training times and increased resource needs.

- Their effectiveness may be limited when dealing with smaller datasets, requiring a substantial amount of training data to perform well.
- The intricate architecture of LSTMs makes it difficult to understand their decision-making process, resulting in a lack of transparency.
- Overfitting is a risk, particularly when the model becomes too complex, potentially memorizing training data instead of generalizing from it.
- Configuring optimal hyperparameters for LSTMs can be challenging, necessitating extensive experimentation.
- LSTMs face constraints in efficient parallelization due to their sequential nature, potentially impacting performance on parallel processing hardware.

1.4.4 Support Vector Machine SVM

Support Vector Machines (SVM) are handy for solving problems related to regression and classification. They work by creating decision boundaries called hyperplanes. In a two-dimensional space, this hyperplane is like a line. When building the model, SVM develops algorithms to assign new points to different classes by placing a hyperplane between them. SVM aims to create models that have the maximum separation between classes [75]. Using a five-fold cross-validation method for assessment, SVM proves to be effective and accurate, especially when dealing with a higher number of dimensions. The algorithm becomes powerful in machine learning, especially when the quantity of measurements exceeds the number of tests. SVM's accuracy is enhanced by parameters like gamma, which influences the impact of training data, and regularization parameters, controlling misclassification [76].

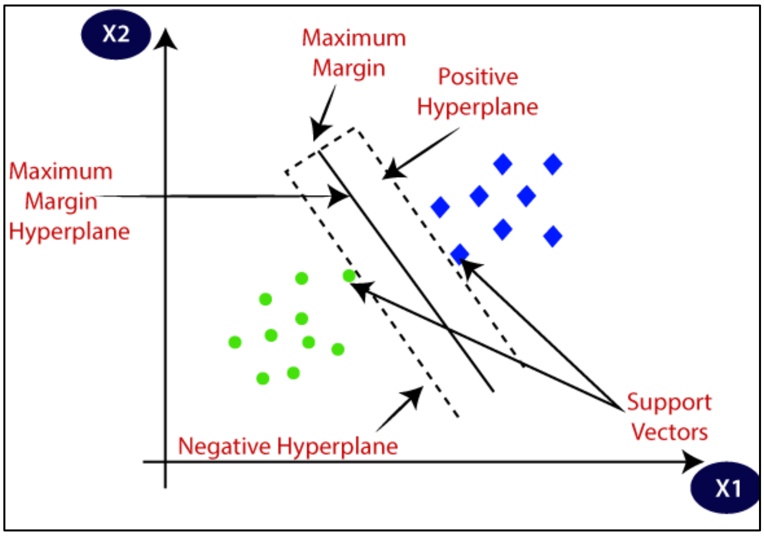


Figure 2.9: Support Vector Machine [75]

Advantages of SVM

- Adaptable to diverse data types.
- Resilient against information overload.
- Applicable across various tasks.
- Handles scenarios with more details than examples.
- Employs an intelligent approach to delineate distinctions.
- Demonstrates consistent accuracy.
- Effective with moderate-sized datasets.
- Maintains stability in the presence of unusual data points.
- Tolerant of errors in the information [76].

Disadvantages of SVM

- Inefficient for extensive datasets.
- Susceptible to the impact of noisy or irrelevant data.
- Computationally demanding, especially for complex models.
- Challenges in parameter tuning, requiring careful selection.
- Limited interpretability, providing less insight into predictions.
- Originally designed for binary classification, necessitating modifications for multi-class tasks.
- Memory-intensive, scaling with the size of the training dataset.
- Not well-suited for continual learning with a constant influx of new data points [75].

2.4.5 Naïve Bayes Classifier

The Naive Bayes classifier is a probabilistic machine learning model rooted in Bayes' theorem, commonly employed for tasks like text classification and spam filtering. It assumes feature independence, albeit often unrealistic, by calculating probabilities for features based on labeled training data [77]. During training, the model establishes the likelihood of each feature occurring within each class. When applied to new data, the classifier estimates class probabilities for a given set of features, ultimately assigning the observation to the class with the highest probability [28].

Advantages of Naïve Bayes

- Quick and straightforward, suitable for large datasets.
- Easy to implement with minimal hyper parameter tuning.
- Performs well in scenarios with numerous features.
- Despite assumptions, often performs well in various classification tasks [43].

Disadvantages Naïve Bayes

- Assumes features are independent, which may not hold.
- May struggle with continuous features and non-normal distributions.
- Assigns zero probability to unseen categories, impacting classification.
- Can be sensitive to irrelevant features, affecting performance [43].

2.4.6 Logistic Regression

Logistic regression is a statistical model utilized for binary classification, predicting the likelihood of an instance belonging to a specific category. Despite its name, it serves classification purposes, applying the logistic function to convert the linear combination of input features into a probability value between 0 and 1. This probability determines whether the instance is classified as the positive or negative class based on a threshold (usually 0.5). Logistic regression is valued for its simplicity, interpretability, and effectiveness in binary classification tasks [78].

Advantages of LR

- Logistic regression is simple and easy to interpret.
- It performs well on large datasets and is computationally efficient.
- Logistic regression provides probability scores, aiding in likelihood assessment.
- It is less sensitive to outliers compared to some other models.

Disadvantages of LR

- Logistic regression assumes a linear relationship between variables.
- It may struggle with capturing complex relationships in the data.
- Unsuitable for datasets with non-linear decision boundaries.
- Performance depends heavily on feature quality, struggling with irrelevant features.

2.5 Summary

In this section, a comprehensive analysis of 23 research papers is presented, focusing on various technical indicators like the Relative Strength Index (RSI), Exponential Moving Average (EMA), Moving Average (MA), and Momentum and classification models Artificial Neural Network (ANN), Convolutional Neural Network (CNN), Support Vector Machine (SVM) and Long-Short Term Memory (LSTM) for stock market prediction. This chapter also provides a concise overview of the classification models used for the prediction of stock market price and crisis prediction. Some important indicators were discussed above that were used previously for the identifications of the stock market which shows the market up and down. Some of the evaluation metrics (RMSE, MSE, AMAPE, MAPE) are discussed which show the evaluation scores of each model used previously. As a result, a research gap was found in the literature.

CHAPTER 3

METHODOLOG

In this study, the main focus is on the methodology of the stock market price prediction using the latest and updated state-of-the-art technique. The dataset of different sectors of Pakistan stock market was download from the Yahoo finance and then dataset was preprocessed. Once the dataset is preprocessed and prepared, then for training and testing is done by using transformer model different layers. The stock crisis was identified first then stock overbought and oversold called bubble were also identified using stochastic RSI techniques. Finally, the latest transformer model was applied on the dataset for stock market price prediction that perform better prediction accuracy as compared to the traditional techniques.

3.1 Datasets

Datasets play a vital role in the development and evaluation of algorithms for Stock market price prediction and classification. The dataset for this study is sourced from the yahoo finance website which provides a comprehensive and detailed of the stock market, reflecting the diverse sectors of the Pakistan economy. The collection of this data involves a systematic approach focusing on historical stock prices, trading volumes, and other relevant financial indicators (P/E, sell, market capitalization, dividend yield, etc.) Of companies listed under the automobile assembler, cement, and banking sectors.

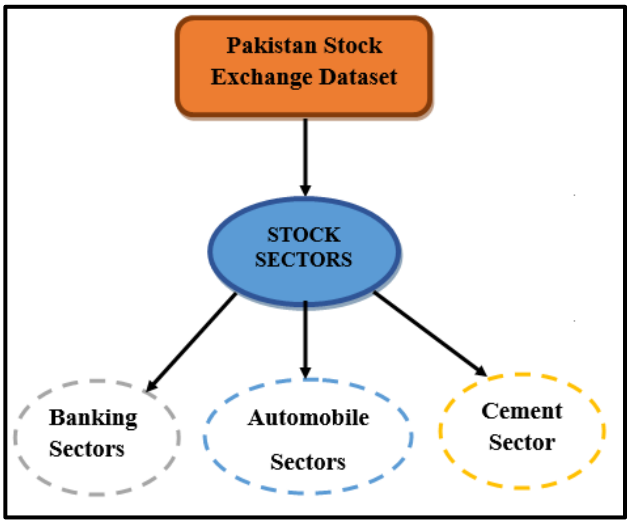
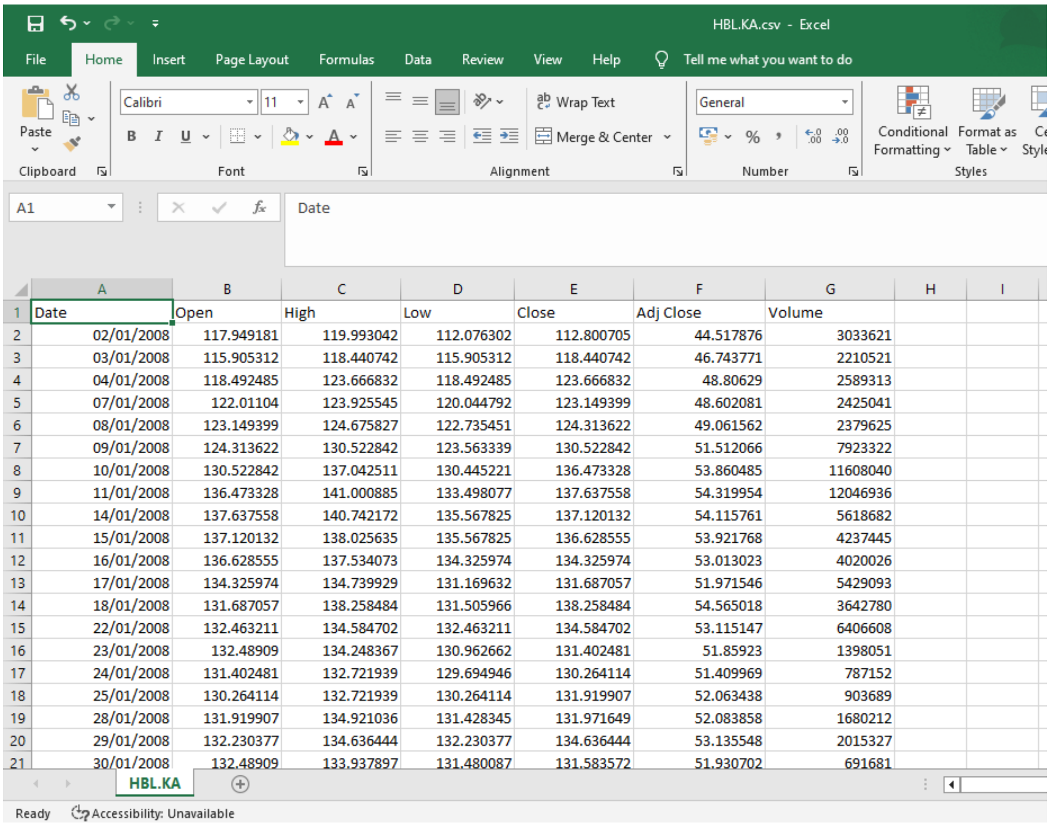


Figure 3.1: Pakistan Stock Market Selected Sectors

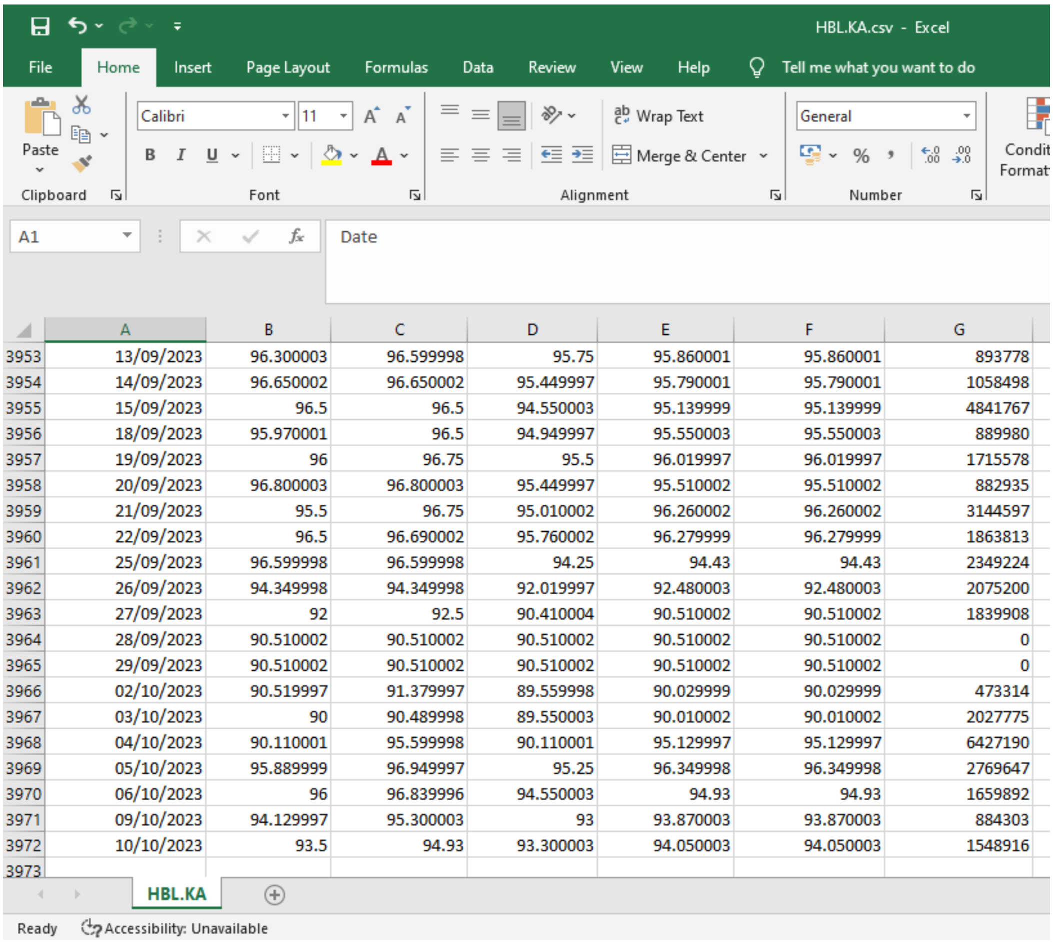
The methodology for data collection starts with the extraction of historical stock price data, including opening, closing, high, and low prices, along with trading volumes. The time frame for the data collection is carefully selected to ensure a comprehensive representation of different market cycles, including periods of growth, stability, and decline. This temporal diversity is crucial for training the model to recognize and predict various market conditions.



Date	Open	High	Low	Close	Adj Close	Volume
02/01/2008	117.949181	119.993042	112.076302	112.800705	44.517876	3033621
03/01/2008	115.905312	118.440742	115.905312	118.440742	46.743771	2210521
04/01/2008	118.492485	123.666832	118.492485	123.666832	48.80629	2589313
07/01/2008	122.01104	123.925545	120.044792	123.149399	48.602081	2425041
08/01/2008	123.149399	124.675827	122.735451	124.313622	49.061562	2379625
09/01/2008	124.313622	130.522842	123.563339	130.522842	51.512066	7923322
10/01/2008	130.522842	137.042511	130.445221	136.473328	53.860485	11608040
11/01/2008	136.473328	141.000885	133.498077	137.637558	54.319954	12046936
14/01/2008	137.637558	140.742172	135.567825	137.120132	54.115761	5618682
15/01/2008	137.120132	138.025635	135.567825	136.628555	53.921768	4237445
16/01/2008	136.628555	137.534073	134.325974	134.325974	53.013023	4020026
17/01/2008	134.325974	134.739929	131.169632	131.687057	51.971546	5429093
18/01/2008	131.687057	138.258484	131.505966	138.258484	54.565018	3642780
22/01/2008	132.463211	134.584702	132.463211	134.584702	53.115147	6406608
23/01/2008	132.48909	134.248367	130.962662	131.402481	51.85923	1398051
24/01/2008	131.402481	132.721939	129.694946	130.264114	51.409969	787152
25/01/2008	130.264114	132.721939	130.264114	131.919907	52.063438	903689
28/01/2008	131.919907	134.921036	131.428345	131.971649	52.083858	1680212
29/01/2008	132.230377	134.636444	132.230377	134.636444	53.135548	2015327
30/01/2008	132.48909	133.937897	131.480087	131.583572	51.930702	691681

Fig 3.2: Pakistan Stock Market Dataset Timeframe From 2008

The dataset is available in the CSV file having size 5000 × 7 and is compiled for the training and testing of prediction algorithms. The chosen time frame for training and testing is from January 2008 to 2023. Some attributes of the historical data are given below:



	A	B	C	D	E	F	G
3953	13/09/2023	96.300003	96.599998	95.75	95.860001	95.860001	893778
3954	14/09/2023	96.650002	96.650002	95.449997	95.790001	95.790001	1058498
3955	15/09/2023	96.5	96.5	94.550003	95.139999	95.139999	4841767
3956	18/09/2023	95.970001	96.5	94.949997	95.550003	95.550003	889980
3957	19/09/2023	96	96.75	95.5	96.019997	96.019997	1715578
3958	20/09/2023	96.800003	96.800003	95.449997	95.510002	95.510002	882935
3959	21/09/2023	95.5	96.75	95.010002	96.260002	96.260002	3144597
3960	22/09/2023	96.5	96.690002	95.760002	96.279999	96.279999	1863813
3961	25/09/2023	96.599998	96.599998	94.25	94.43	94.43	2349224
3962	26/09/2023	94.349998	94.349998	92.019997	92.480003	92.480003	2075200
3963	27/09/2023	92	92.5	90.410004	90.510002	90.510002	1839908
3964	28/09/2023	90.510002	90.510002	90.510002	90.510002	90.510002	0
3965	29/09/2023	90.510002	90.510002	90.510002	90.510002	90.510002	0
3966	02/10/2023	90.519997	91.379997	89.559998	90.029999	90.029999	473314
3967	03/10/2023	90	90.489998	89.550003	90.010002	90.010002	2027775
3968	04/10/2023	90.110001	95.599998	90.110001	95.129997	95.129997	6427190
3969	05/10/2023	95.889999	96.949997	95.25	96.349998	96.349998	2769647
3970	06/10/2023	96	96.839996	94.550003	94.93	94.93	1659892
3971	09/10/2023	94.129997	95.300003	93	93.870003	93.870003	884303
3972	10/10/2023	93.5	94.93	93.300003	94.050003	94.050003	1548916
3973							

Figure 3.3: Pakistan Stock Market Dataset Timeframe Till 2023

- **Date:** Stock data collection date
- **Open:** Stock opening values
- **Closed:** Values on which stock is closed on that day
- **High:** The highest values noted in stock on that day
- **Low:** Lowest values of the stock on that day
- **Price:** Price of the specific stock
- **Volume:** How much volume of that stock
- **Adj close:** How much the stock value is close to the next day on which the market is open.

3.2 Sector-Wise Data Description

Dataset from different sectors is collected from yahoo finance. Each sector plays an important role in the development of Pakistan’s economic growth. Different indices are selected from each sector of PSX for further stock market prediction and analysis.

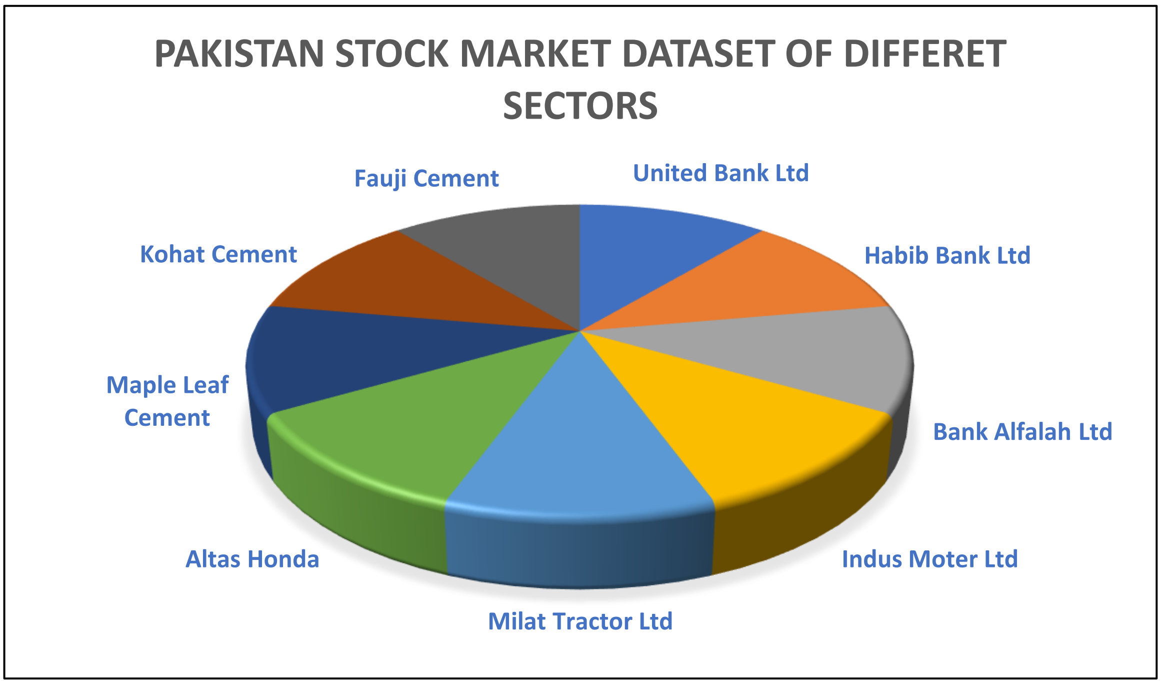


Figure 3.4: Pakistan Stock Market Indices of Different Sectors

3.2.1 Automobile Assembler

The automobile assembler sector is an integral part of the Pakistan economy and the PSX. This sector's data typically includes stock prices of leading automobile manufacturers and assemblers. The characteristics of this data often reflect the economic cycles, consumer demand, and policy changes impacting the automotive industry. Given the sector's sensitivity to economic policies, consumer preferences, and import regulations, its stock prices can exhibit significant volatility, making it a compelling sector for predictive analysis. The relevance of this sector to the Pakistani economy is underscored by its substantial contribution to the country's GDP, employment, and technological advancement.

3.2.2 Cement

The cement sector represents a crucial segment of Pakistan's industrial and construction landscape. An overview of this sector reveals its cyclic nature, closely tied to the country's construction and infrastructure development activities. The data specifics for this sector encompass stock prices of major cement companies, which are influenced by factors like construction demand, raw material costs, and export opportunities. The cement sector's data, thus, provides insights into the industrial growth and infrastructure development in Pakistan, making it a significant area for stock price prediction.

3.2.3 Banking

The banking sector is a cornerstone of any stock market, including the PSX. The significance of this sector lies in its role in reflecting and influencing the overall economic health of a country. The stock prices of major banks, which are impacted by a variety of factors such interest rate changes, inflation, and economic stability, are among the banking sector data analysis used in this study. The banking sector data is crucial not only due to its direct impact on the financial markets but also because it acts as an indicator for nation’s overall economic circumstances.

3.3 Training and Testing Dataset

To present the predictive model to past market data, the training dataset helps it learn patterns and correlations that are useful for stock market price prediction. On the other hand, the model's performance on fresh, untested market data is assessed using the testing dataset, which is separate from the training data. The training dataset usually consists of data on stock prices, volumes, and other attributes over a predetermined period. The testing dataset is used to evaluate the model's capacity to generalize to new situations, ensuring that its predicted accuracy overtakes the training data and prevents overfitting. Having a distinct division between training and testing datasets is crucial for producing solid and trustworthy stock market forecasts. The stock market price data has been collected from historical data from Yahoo Finances for the following 3 sectors:

- **AUTOMOBILE ASSEMBLER:** (Millat Tractors, Atlas Hondas, Indus Motors Ltd)
- **CEMENT:** (Kohat cement, Maple cement, Fauji cement co)
- **BANKING:** (Bank Alfalah, Habib Bank, United Bank)

The training and testing periods are chosen from January 2008 to 2023, avoiding periods of sudden jumps or down in prices which we call Bubble, such as those seen during the 2008-2023 financial crisis. Yahoo Finance's Historical Database is utilized and split datasets for training and testing.

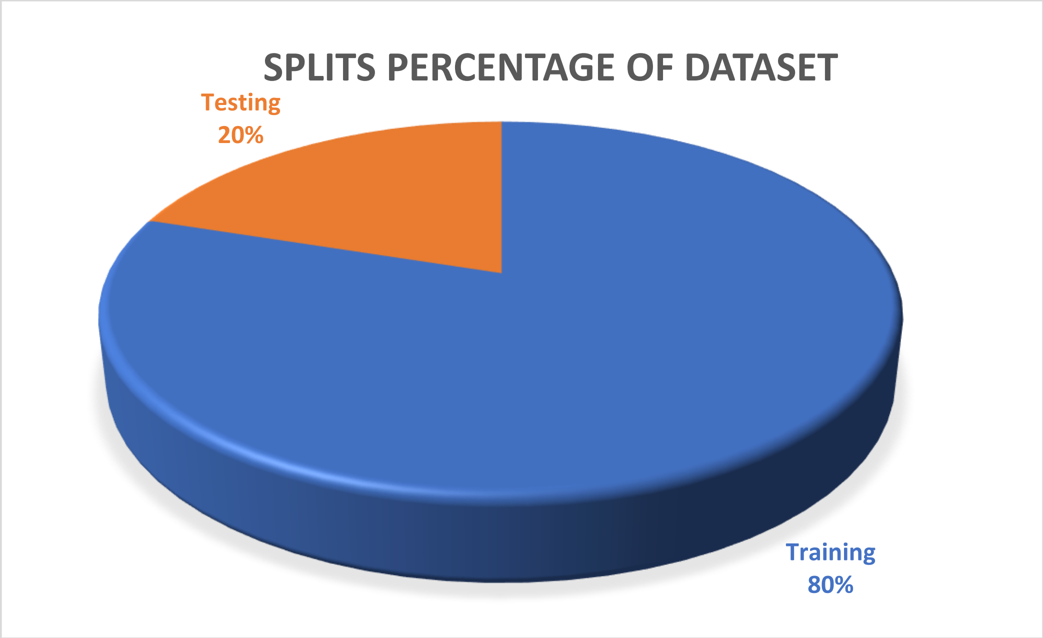


Figure 3.5: Training and Testing Dataset

3.3.1 Training Process

The training process for the stock crisis prediction model using transformers is thoughtfully structured to ensure the model effectively learns to predict stock prices with high accuracy. The dataset used for training comprises stock data up to the year 2020, providing a comprehensive range of market behaviors, including periods of growth, stability, and decline. This historical data serves as the foundation upon which the model learns the complex patterns and relationships inherent in stock market movements. This historical information helps the model understand the complex patterns and connections that how the stock market works.

Some of the advantages of the training dataset is as followed:

- Splitting the dataset, it guards against the model memorizing the training data excessively, preventing overfitting issues.
- The division dataset ensures an impartial evaluation of the model's effectiveness, as it assesses its performance on unseen data, and minimizes bias.
- The separation enables the fine-tuning of the model's hyperparameters, optimizing its configuration for better performance without compromising the evaluation's integrity.
- It allows to generalize of new, unseen data that can be effectively gauged, providing insights into its real-world applicability beyond the training set.

```python
def train(ticker, start='2000-01-01', end='2023-12-10'):

  df = yf.download(ticker,start, end)
  df = df.reset_index()

  year = list()

  for date in df['Date']:
      year.append(str(date).split("-")[0])

  df['Year'] = year

  df['Close'] = df['Close'].astype(float)
  df['Year'] = df['Year'].astype(int)
  df_train = df[df['Year']<2020]
  df_test = df[df['Year']>=2020]

  spots_train = df_train['Close'].tolist()
  spots_test = df_test['Close'].tolist()

  scaler_train = MinMaxScaler()
  spots_train = scaler_train.fit_transform(np.array(spots_train).reshape(-1,1))

  scaler_test = MinMaxScaler()
  spots_test = scaler_test.fit_transform(np.array(spots_test).reshape(-1,1))

  spots_train = [i[0] for i in spots_train]

  spots_test = [i[0] for i in spots_test]

  #print("Training set has {} observations.".format(len(spots_train)))
  #print("Test set has {} observations.".format(len(spots_test)))

  SEQUENCE_SIZE = 11
  x_train,y_train = to_sequences(SEQUENCE_SIZE,spots_train)
  x_test,y_test = to_sequences(SEQUENCE_SIZE,spots_test)
```

Figure 3.6: Code of Training and Testing Dataset

3.3.2 Training Methodology

The training methodology involves several key steps:

Data Preparation: The data is first pre-processed, which includes normalizing the values, handling missing data, and potentially creating additional derived features that could aid in prediction. The data is then split into features (such as historical prices, trading volumes, etc.) and labels (future stock prices).

Sequence Creation: Given the sequential nature of stock data, the dataset is transformed into a series of sequences that the model can process. This typically involves creating 'windows' of data, where each sequence consists of a fixed number of time steps.

Model Feeding: The prepared sequences are fed into the model. Here, the transformer architecture, with layers like MultiHeadAttention and Conv1D, processes the data.

Backpropagation and Optimization: The model uses backpropagation to update the weights during training. An optimizer, typically Adam or a similar advanced optimizer, is used to adjust the weights in a way that minimizes the prediction error.

3.3.3 Parameters and Hyperparameters

The training process involves careful tuning of various parameters and hyperparameters:

Learning Rate: This is a crucial hyperparameter that determines the step size at each iteration while moving toward a minimum of the loss function. A learning rate scheduler may be used to adjust the rate over epochs.

Batch Size: This defines the number of samples that will be propagated through the network in one pass. A balance is sought to ensure efficient training without overloading memory resources.

Epochs: This refers to the number of complete passes through the training dataset. The number of epochs is set to ensure sufficient training without causing overfitting.

Loss Function: For a regression task like stock price prediction, Mean Squared Error (MSE) or Mean Absolute Error (MAE) are commonly used as loss functions.

Regularization Techniques: Techniques like dropout or L2 regularization are applied to prevent overfitting, ensuring the model generalizes well to unseen data.

3.4 Important Libraries and Software Tools

Python has been used in this research study that enable to preprocess and analysis Pakistan Stock Market Data, as well as to visualize the final results. Python, recognized for its readability and simplicity, stands as a versatile high-level programming language. Supporting diverse programming paradigms such as procedural, object-oriented, and functional programming, Python boasts an extensive standard library and a robust ecosystem of third-party packages. Consequently, it has emerged as a favored option for a various application, spanning from web development and data analysis to machine learning, and artificial intelligence. Python is extensively used in stock market prediction and financial analysis.

i. Libraries like Pandas facilitate efficient data retrieval, cleaning, and preprocessing of financial data.

ii. Matplotlib and Seaborn are popular for creating informative visualizations of historical price trends and correlations.

iii. Machine learning libraries like Scikit-learn, TensorFlow, and PyTorch enable the development of predictive models for analyzing historical data and making future price predictions.

iv. Python's stats model library is employed for statistical analysis in finance, including regressions and time series analysis.

v. Python allows easy integration with financial APIs, providing access to real-time market data and news sentiment.

Many PYTHON libraries are commonly used for the analysis of financial data and visualization, such libraries which are used in this research are the Pandas, Pandas_dataereader, NumPy, Matplotlib, TensorFlow, Keras, and Json Library.

1. Pandas

Pandas is a versatile open-source library for Python, specializing in data manipulation and analysis. It introduces essential data structures like Data Frames and Series, tailored for effortless handling and analysis of structured data. Widely applied in data science, finance, and statistics, Pandas simplifies tasks such as cleaning, transforming, and exploring datasets. With features like data alignment, effective handling of missing data, and robust manipulation tools, Pandas is a foundational resource for efficiently working with structured data in the Python programming language.

2. Keras

Keras is an open-source high-level neural networks API that simplifies the creation, training, and deployment of machine learning models. Recognized for its user-friendly syntax and abstraction, Keras enables the construction of intricate neural network architectures with minimal coding effort. Initially developed as a standalone library, Keras has seamlessly integrated into TensorFlow, offering a convenient interface for building neural networks atop the TensorFlow framework. Its widespread use stems from its adaptability and ease of use, appealing to both newcomers and seasoned practitioners in the realm of deep learning.

3. TensorFlow

TensorFlow stands as an open-source framework designed for the development and deployment of machine learning algorithms. Known for its scalability, it allows computations to be efficiently distributed across multiple CPUs and GPUs, enhancing performance. Python and Java, among various other programming languages, provide straightforward access to and management of TensorFlow. Widely acclaimed for its user-friendly interface, accessibility, and robust performance, TensorFlow has emerged as one of the most popular machine-learning libraries. Furthermore, Keras, a high-level neural networks API integrated with TensorFlow, serves as a foundation for building additional libraries.

4. NumPy

NumPy stands as an open-source Python library dedicated to numerical operations and the effective management of extensive, multi-dimensional arrays and matrices. Offering a comprehensive range of functions for mathematical operations, NumPy is a crucial package for scientific computing and data analysis. Widely employed in disciplines such as machine learning, data science, physics, and engineering, NumPy is indispensable for tasks involving linear algebra, statistical analysis, and mathematical computations. Renowned for its efficiency and versatility, NumPy serves as a foundational element for numerical computing within the Python environment.

3.5 Model Architecture

The model architecture designed for stock crisis prediction using Pakistan Stock Data is a sophisticated blend of various layers, each serving a distinct purpose to enhance the predictive accuracy of the model. The architecture is built upon the foundation of a transformer model, primarily leveraging its MultiHeadAttention mechanism, known for its efficiency in handling sequential data like time-series stock prices. The model's construction is a deliberate choice, integrating layers that specialize in processing, analyzing, and extracting meaningful patterns from complex financial data.

3.6 Implementations of the proposed study

In the implementations phase each step of the proposed studies is explained here. The dataset of Pakistan Stock market was collected and then preprocessed by applying some steps like by removing inconsistencies from data scaling and data was prepared. After data preparation then training and testing performed on the prepared data performed.

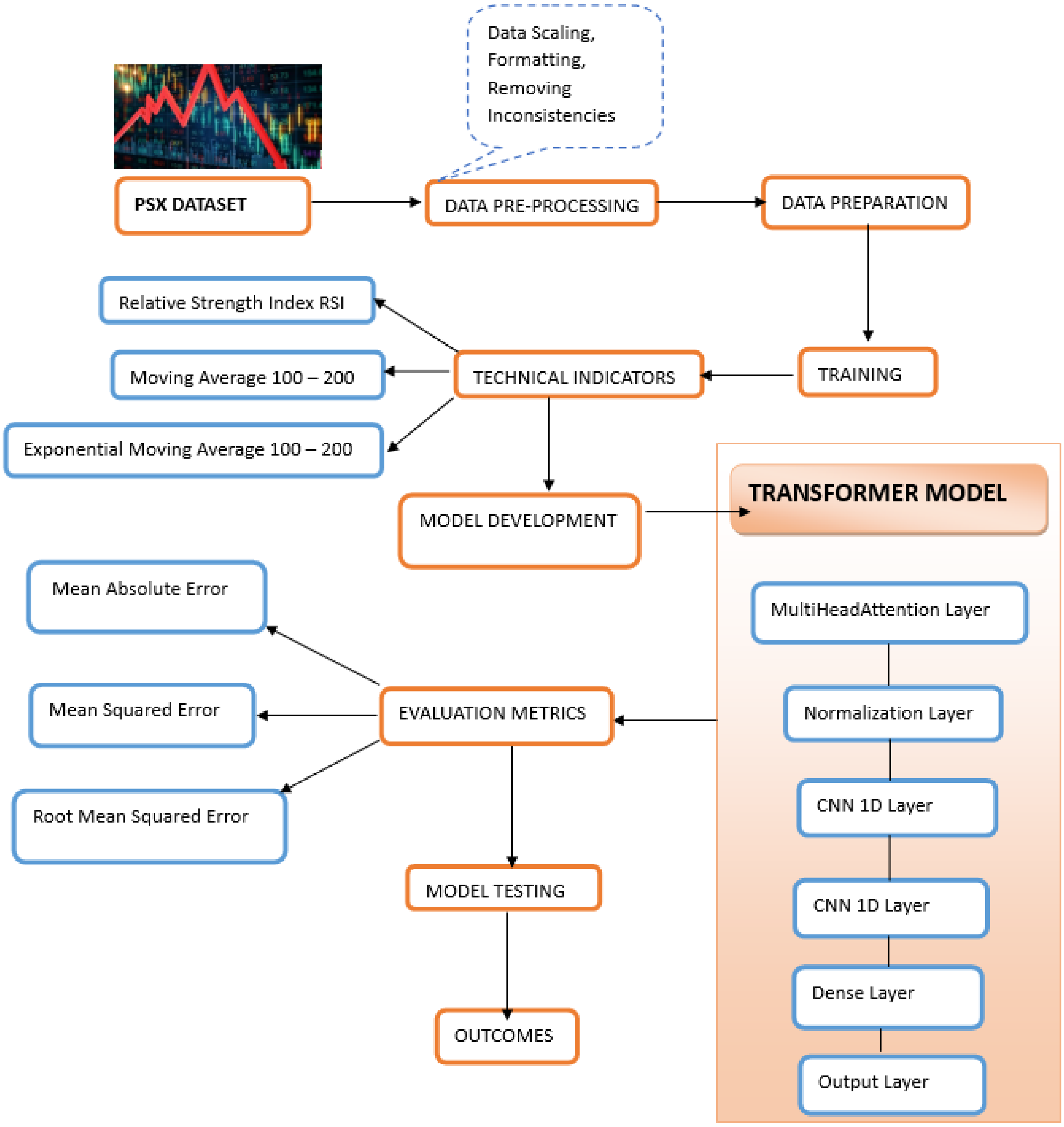


Figure 3.7: Proposed Methodology

3.6.1 Preprocessing steps

Preprocessing the data is a critical step in the methodology. It involves cleaning the data to remove any inconsistencies or missing values, normalizing the data to a common scale, and potentially engineering additional features that could aid in the prediction process. Features like moving averages, percentage changes, and relative strength index (RSI) might be considered to enhance the model's understanding of market trends.

1. **Maintain sequence of data**

As historical dataset of Pakistan Stock Exchange is download from PSX website and Yahoo Finance. The dataset is spilt into a specific range for training and testing like from 2008 – 2020 for training and onwards till 2023 for testing, so maintaining pattern or sequences of dataset is very important especially in time-series data. As in the introduction part the candle concept is discussed in detail where current day candle depends on the pervious candle, so dataset is maintained and format in sequences to avoid inconsistencies of pattern of the dataset.

Date
02/01/2008
03/01/2008
04/01/2008
07/01/2008
08/01/2008
09/01/2008
10/01/2008
11/01/2008
14/01/2008
15/01/2008
16/01/2008
17/01/2008
18/01/2008
22/01/2008
23/01/2008
24/01/2008
25/01/2008

Figure 3.8: Maintaining Pattern or Sequenced

2. **Scaling Data**

Scaling a dataset is an important procedure in handling stock market data, ensuring uniformity in the magnitude of features and preventing the dominance of specific variables. As price of the stock change with time so it is difficult for model to train the dataset accurately so data scaling is performed on the dataset to scale down the dataset in certain range for better understanding of model training.

```
scaler_train = MinMaxScaler()
spots_train = scaler_train.fit_transform(np.array(spots_train).reshape(-1,1))

scaler_test = MinMaxScaler()
spots_test = scaler_test.fit_transform(np.array(spots_test).reshape(-1,1))

spots_train = [i[0] for i in spots_train]

spots_test = [i[0] for i in spots_test]
```

Figure 3.9: Scaling Dataset in Preprocessing

3. Sequence of Chunks

Once the dataset is prepared and normalized in a specific pattern and in a certain format, inconsistencies are removed then data is ready to feed for training. Then sliding windows of eleven months are prepared to feed for model training and at the twelve months data is predicted base on the closing price of the stock market.

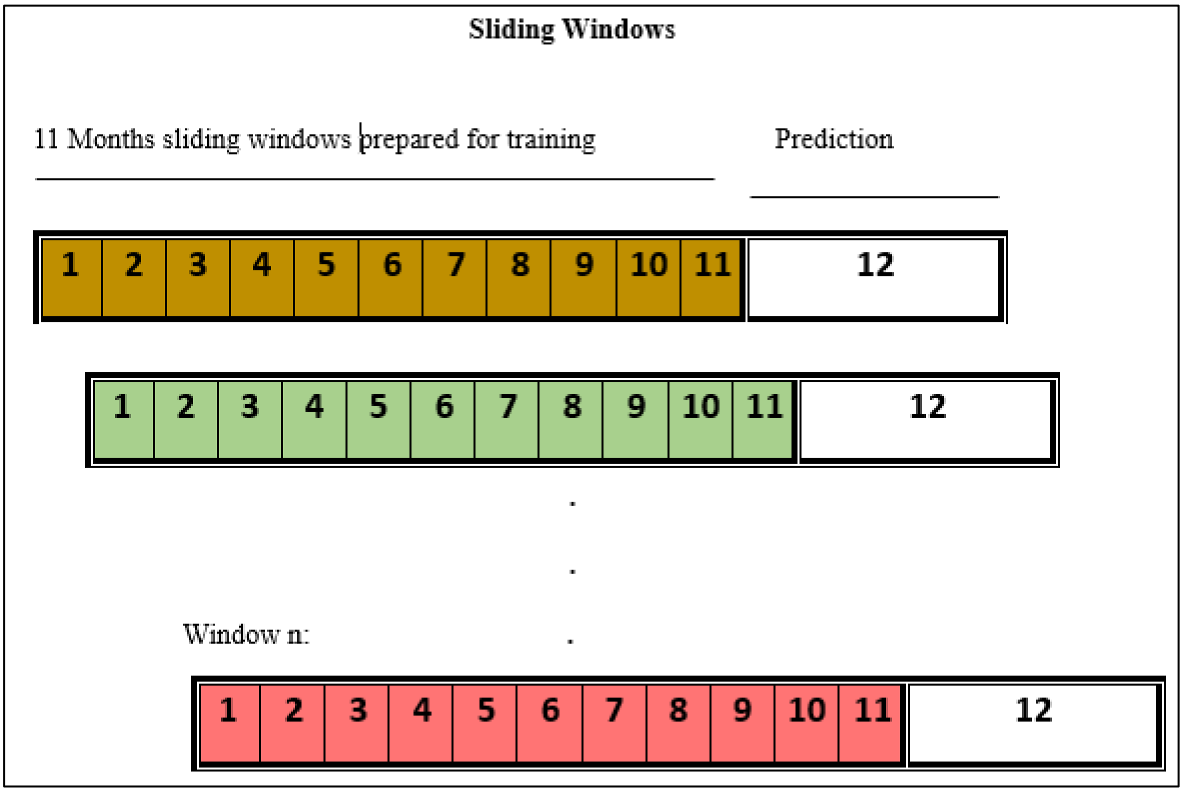


Figure 3.10: Sliding Window Prepared for Training Dataset

3.7 Transformer Model

The development of transformer model marks a revolutionary moment in the field of machine learning, particularly in natural language processing (NLP) and, increasingly, in other areas like time-series analysis for stock prediction. Transformers were introduced in a landmark paper titled "Attention Is All You Need" by Vaswani [79]. This model represented a departure from the then-dominant recurrent neural networks (RNNs) and long short-term memory (LSTM) networks, which processed data sequentially and thus were limited in handling long-range dependencies within the data.

The key feature of the transformer model is as it dependent on the attention mechanism, specifically the self-attention mechanism, which allows the model to weigh the significance of different parts of the input data relative to each other. Unlike RNNs and LSTMs, transformers process all parts of the input data simultaneously (in parallel), which significantly speeds up training and improves the model's ability to learn from large datasets [80].

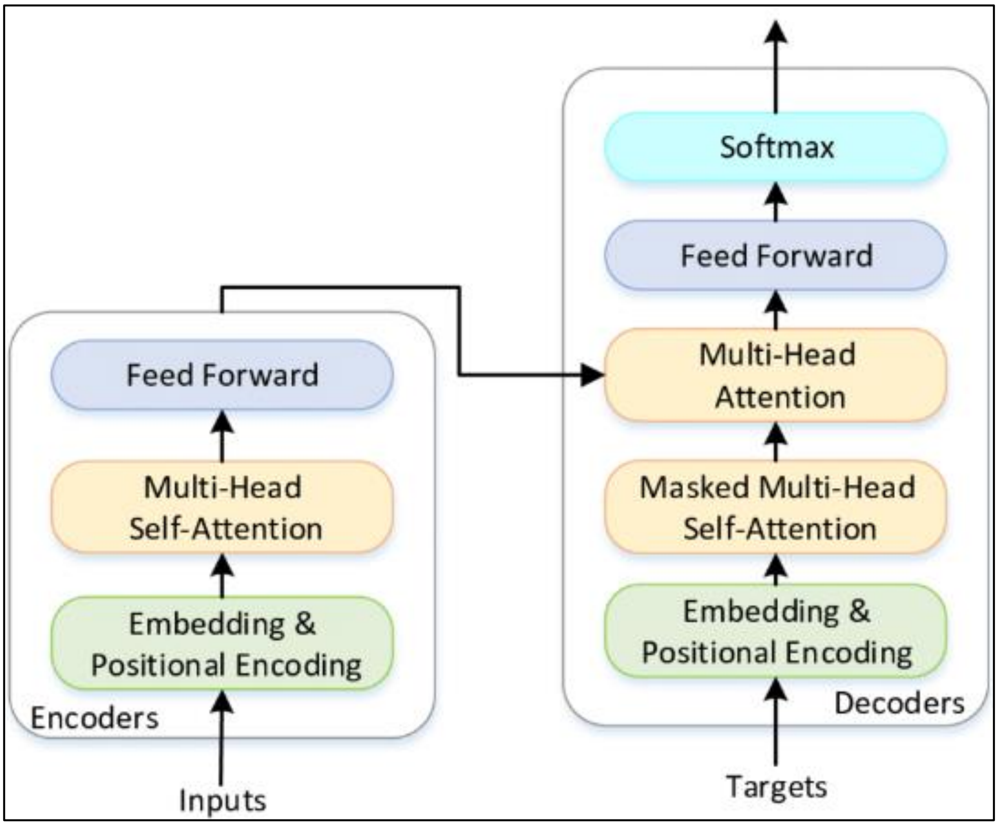


Figure 3.11: Structure of Transformer Model [81]

One of the primary advantages of transformers over previous models is their ability to handle long-range dependencies in data. Additionally, the parallel processing nature of transformers makes them highly efficient and scalable, especially when training on large datasets. The attention mechanism of the model helps to focus on the most significant portions of the input data, which further improves efficiency.

3.7.1 MultiHeadAttention in Transformers

The MultiHeadAttention mechanism is a critical component of the transformer architecture and represents an evolution of the basic attention concept. In simple terms, attention mechanisms allow a model to focus on different parts of the input sequence when producing each part of the output sequence, akin to how human attention works when reading a text or analyzing a scene.

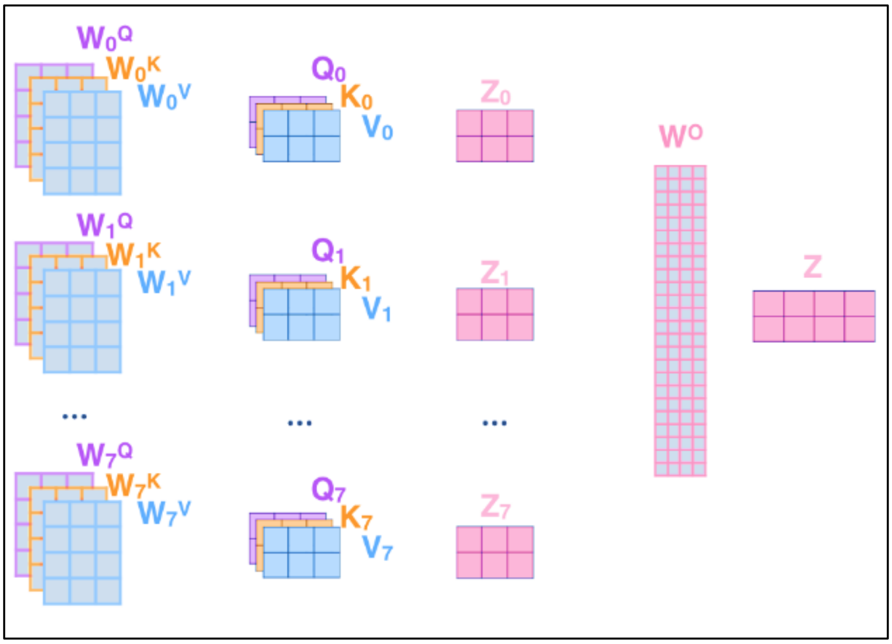


Figure 3.12: MultiheadedAttention Layer [82]

MultiHeadAttention, as the name suggests, involves multiple 'heads' of attention. In essence, it splits the input into several parts and applies the attention mechanism to each part separately. This design allows the model to capture different types of relationships in the data simultaneously. For example, in language processing, one head might focus on the syntactic structure, while another might focus on semantic meaning.

In the context of stock price prediction, MultiHeadAttention is particularly relevant because of its ability to capture complex patterns and relationships in time-series data. Stock market data is inherently noisy and non-linear, with many influencing factors. The MultiHeadAttention mechanism can attend to different aspects of such data – for instance, one head might focus on short-term price fluctuations, while another might concentrate on longer-term trends influenced by broader economic indicators. This ability to simultaneously process and integrate diverse information makes transformers with MultiHeadAttention highly suitable for predicting stock prices, where understanding the interplay of various market factors is crucial.

The relevance of this mechanism in stock price prediction also lies in its adaptability and generalizability. Unlike models that require manual feature engineering or are specifically tailored to certain market conditions, transformers with MultiHeadAttention can automatically learn to identify and prioritize the most relevant features from the data. This capability is particularly valuable in the volatile and unpredictable domain of stock markets, where the factors influencing prices can change rapidly and are often interdependent.

```
[ ] def transformer_encoder(inputs, head_size, num_heads, ff_dim, dropout=0):
        # Normalization and Attention
        x = layers.LayerNormalization(epsilon=1e-6)(inputs)
        x = layers.MultiHeadAttention(
            key_dim=head_size, num_heads=num_heads, dropout=dropout
        )(x, x)
        x = layers.Dropout(dropout)(x)
        res = x + inputs

        # Feed Forward Part
        x = layers.LayerNormalization(epsilon=1e-6)(res)
        x = layers.Conv1D(filters=ff_dim, kernel_size=1, activation="relu")(x)
        x = layers.Dropout(dropout)(x)
        x = layers.Conv1D(filters=inputs.shape[-1], kernel_size=1)(x)
        return x + res

[ ] def build_model(input_shape, head_size, num_heads, ff_dim, num_transformer_blocks, mlp_units, dropout=0, mlp_dropout=0,):

        inputs = keras.Input(shape=input_shape)
        x = inputs
        for _ in range(num_transformer_blocks):
            x = transformer_encoder(x, head_size, num_heads, ff_dim, dropout)

        x = layers.GlobalAveragePooling1D(data_format="channels_first")(x)
        for dim in mlp_units:
            x = layers.Dense(dim, activation="relu")(x)
            x = layers.Dropout(mlp_dropout)(x)
        outputs = layers.Dense(1)(x)
        return keras.Model(inputs, outputs)
```

Figure 3.13: Code of Transformer Model

3.7.2 Detailed Description of Layers

The detail description of the transformer layers is given below:

1. **Input Layer**

The input layer is the entry point of the model, where the stock data, comprising historical prices and other relevant financial indicators, is fed into the model. This layer's role is to format the input data correctly so that it can be efficiently processed by subsequent layers. In the context of stock data, this involves structuring the data into a sequence that represents the chronological order of stock prices and associated indicators, enabling the model to recognize and learn from temporal patterns in the data.

2. MultiheadAttention Layer

The MultiHeadAttention layer is at the heart of the model, designed to process the input data by focusing on different parts of the sequence simultaneously. This mechanism allows the model to weigh the importance of different aspects of the stock data, such as short-term price movements and long-term trends. The use of multiple 'heads' in this layer enables the model to capture a diverse range of relationships in the data, enhancing the model's ability to discern complex patterns that are indicative of potential stock crises. This layer significantly impacts prediction accuracy by providing a nuanced understanding of the stock data.

3. Layer Normalization

Following the MultiHeadAttention layer is the LayerNormalization layer, which plays a crucial role in stabilizing the learning process. Normalization is essential in deep learning models to ensure that the scale of inputs to different layers does not hinder the model's training. In the context of stock data, where the range of values can be quite diverse (e.g., stock prices versus trading volumes), normalization ensures that no particular feature dominates the learning process, leading to a more balanced and effective model.

4. Conv1D Layers

The Conv1D (Convolutional 1D) layers are used to extract local features from the sequential data. Unlike their 2D counterparts used in image processing, 1D convolutions are ideal for time-series data as they slide across the temporal axis, detecting patterns over time. These layers are particularly adept at identifying short-term trends and anomalies in stock prices, which are crucial for predicting sudden market changes or crash.

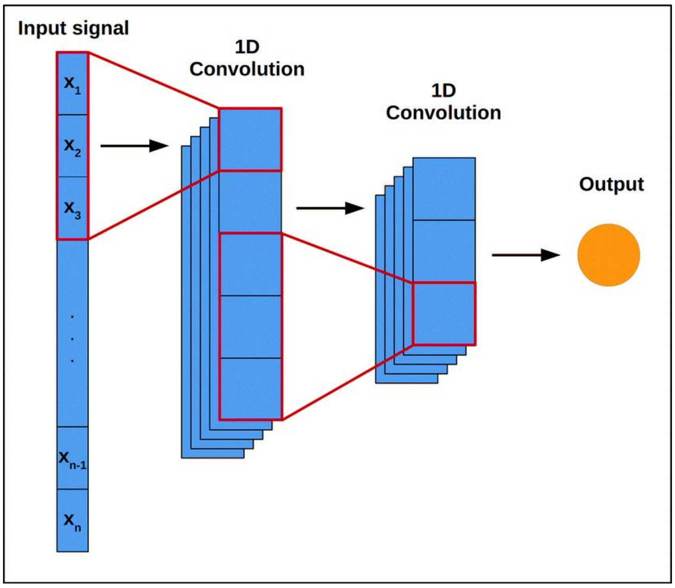


Figure 3.14: Convolution 1D Layer for Feature Extraction [83]

5. GlobalAveragePooling1D

The GlobalAveragePooling1D layer serves to reduce the dimensionality of the data coming from the Conv1D layers. This layer simplifies the output by calculating the average of each feature map. This process helps in reducing the computational load and also in preventing overfitting by summarizing the key features extracted from the previous layers. It distils the essential information needed for the final prediction, ensuring that the model focuses on the most salient features of the data.

6. Dense Layer (Output)

The final layer in the model is the dense layer, which outputs the predicted stock prices. This layer takes the simplified and processed information from the GlobalAveragePooling1D layer and transforms it into a final prediction. The Dense layer's role is to integrate the learned features and relationships in the stock data to make a coherent prediction about future stock prices. It's where all the preceding layers' processing and analysis culminate into a tangible output, representing the model's best prediction based on the learned patterns from the historical data.

3.8 Stock Crash Point Identifications Based On MA/EMA 100-200

Moving Average and Exponential moving are two techniques used in the proposed study for the identification of stock crisis occurrence point throughout the selected range of the stock market dataset.

```
def ma_ema(df):

    data = df.copy()

    data['MA100'] = data['Close'].rolling(window=100).mean()
    data['MA200'] = data['Close'].rolling(window=200).mean()

    data['EMA100'] = data['Close'].ewm(span=100, adjust=False).mean()
    data['EMA200'] = data['Close'].ewm(span=200, adjust=False).mean()

    return data
```

Figure 3.15: Code of MA and EMA 100-200days

3.8.1 EMA100-EMA200 Crossover

The use of EMA (Exponential Moving Average) 100-EMA 200 cross-over in this research serves as a critical indicator for predicting stock crashes. EMA is a type of moving average that places a greater weight and significance on the most recent data points. It is more responsive to recent price changes compared to a simple moving average (SMA), making it a valuable tool in volatile markets.

$$\mathrm{EMAt} = \alpha * (\mathrm{Pt} - \mathrm{EMAt} - 1) + \mathrm{EMAt} \qquad 3.1$$

t is time of EMA

Pt is price at time of t

α is constant smoothing factor between 0 and 1

EMAt-1 show previous time periods

Strategies involves in EMA (100 – 200): A shorter 100-day EMA and a longer 200-day EMA. When the EMA100 crosses below the EMA200, it is typically considered a bearish signal, indicating a potential stock crash. This crossover is seen as a shift in market momentum and is often used by traders to identify possible downturns in the market.

In the context of the research, this EMA crossover strategy was used to enhance the predictive accuracy of the model. By integrating these EMA indicators into the dataset, the model could incorporate additional information about potential shifts in market trends. When combined with the transformer model's capabilities, this allowed for a more complex and timely prediction of stock crashes, capturing not only the smaller changes in price movements but also the broader shifts in market sentiment.

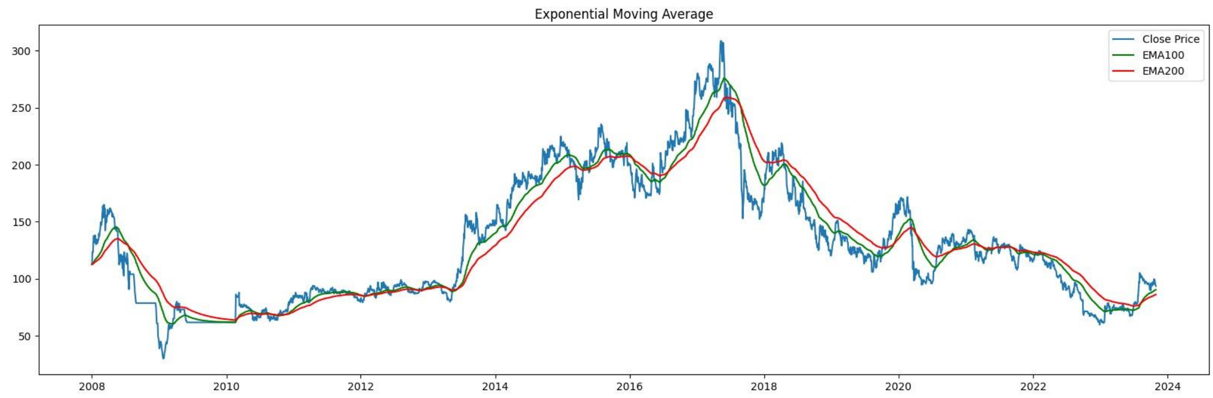


Figure 3.16: Exponential Moving Average 100-200 Crossover

The above graph shows the EMA 100-200 crossover on Pakistan stock dataset which basically helps to identified the crash points that occurs over a specific time periods. The blue line in the graph shows the closing price of the stock price, the red line shows EMA 100days moving average while green line shows EMA 200days moving average. Once the 100 and 200-days EMA line cross each other the crash occurs at that point.

3.8.2 MA (100-200) Crossover

Similar to the EMA crossover, the MA100-MA200 crossover was utilized, but with the purpose of identifying bubble prices, which often precede a market crash. Moving Averages (MAs) are fundamental tools in financial analysis, used to smooth out price trends by filtering out the “noise” from random short-term price fluctuations.

$$MA = C1 + C2 + C3 \ldots . Cn / N \qquad 3.2$$

C1, C2…. Cn is for the closing numbers, prices

N is the number of periods for which the average requires to be calculated [44].

The MA100-MA200 crossover strategy involves monitoring the interaction between a shorter 100-day MA and a longer 200-day MA. In this strategy, a crossover of the MA100 above the MA200 can signal an overvaluation of stocks, often termed as a 'bubble'. This condition suggests that stock prices are significantly higher than their true value, indicating a potential correction or crash.

By analyzing these crossover points, the model was able to predict not just the likelihood of a crash, but also identify the peak prices from where a potential crash could start. This added a layer of predictive power to the model, allowing for more strategic and informed decisions about when a stock might be entering a dangerously overvalued state.

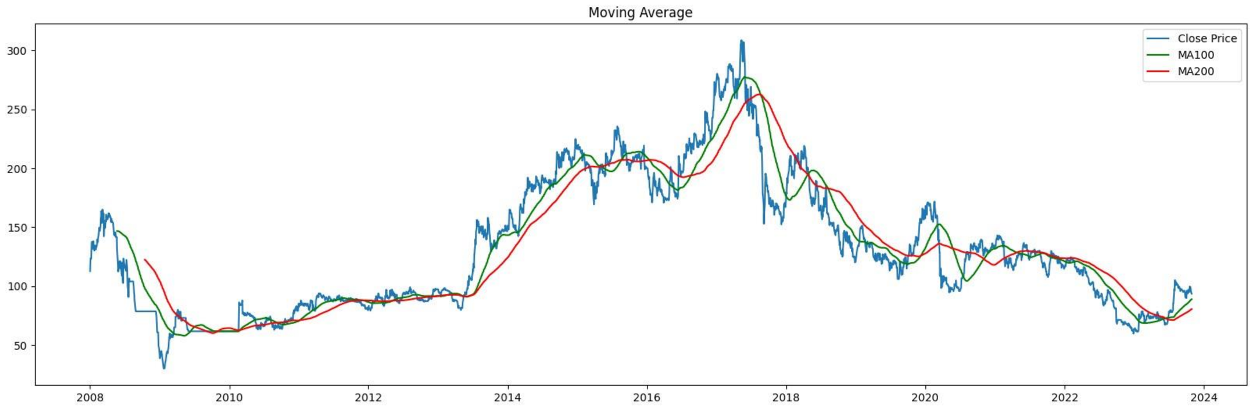


Figure 3.17: Moving Average 100-200 Crossover

The above graph shows the MA 100-200 crossover on Pakistan stock dataset which basically helps to identified the crash points that occurs over a specific time periods. The blue line in the graph shows the closing price of the stock price, the red line shows MA 100days moving average while green line shows MA 200days moving average. Once the 100 and 200-days MA line cross each other the crash occurs at that point.

3.9 RSI Indicator for Stock Bubble Price Prediction

The Relative Strength Index (RSI) is a momentum oscillator that measures the speed and change of price movements. The RSI oscillates between 0 and 100 and is typically used to identify overbought or oversold conditions in trading assets. In this research, the standard RSI threshold of 70 and 20 was used as an indicator of an impending stock crash. An RSI value above 70 suggests that the stock is significantly overbought, indicating that a reversal or downturn in prices might be tackled, when 20 is significantly use for oversold. Using historical stock price data from the Pakistan stock exchange (PSX), the Stochastic RSI value was computed. We looked at historical stock data from 2008 to December 2023. Next, ascertain the stochastic RSI value based on the stock price using the following calculation.

$$\text{StochRSI}\ (\#\ \text{Days}) = \text{RSI} - \min\ [\text{RSI}]/\max[\text{RSI}]\ - \min\ [\text{RSI}] \qquad 3.3$$

Relative strength index (RSI) can be expressed as follows: max [RSI] is equal to the highest RSI reading over the last number of days, min [RSI] is equal to the lowest RSI reading over the last number of days, and the current RSI reading. For 200 days, we employed StochRSI to identify the stock price bubble in our method. This is justified by the fact that intraday trading lasts for 14 days as opposed to long-term trading. An overvalued stock is all that constitutes a stock price bubble. The statistics of StochRSI are employed to capture the bubbles.

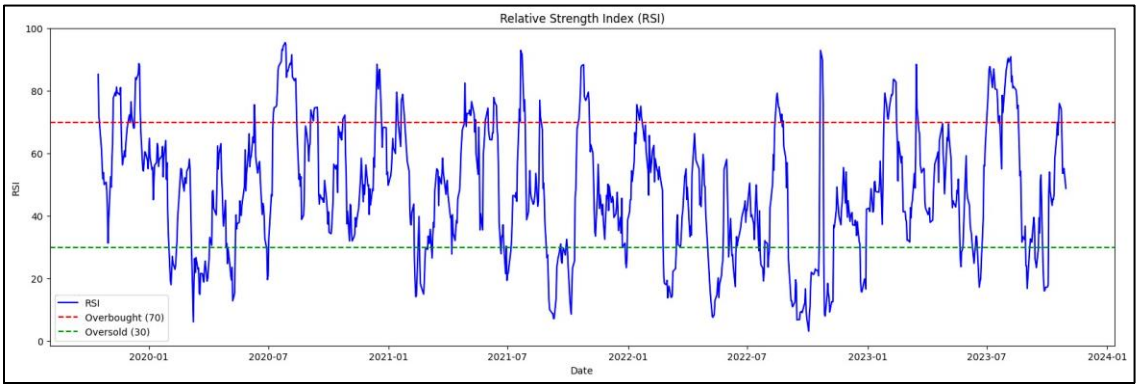


Figure 3.18: Relative Strength Index (RSI)

Incorporating the RSI into the model added an important dimension to the prediction process. By monitoring when the RSI crossed above the critical threshold of 85, the model could flag stocks that were at a high risk of crashing due to being overbought. This served as a complement to the other indicators (EMA and MA crossovers), providing a more comprehensive approach to identifying potential stock market crashes. The integration of RSI helped in refining the model's predictions, ensuring that the signals for potential crashes were backed by a momentum-based indicator, which is crucial in volatile and rapidly changing markets like stocks.

3.10 Fake Trap Analysis Prediction

The term fake trap is also known as false breakout or bull/bear trap which involves analyzing various technical indicators and market conditions to identify when a price movement is likely to be deceptive. Combining technical indications with analytical methods is how fake traps are predicted. Through continuous observation of several indicators such as volume, MACD, RSI, Bollinger Bands, candlestick patterns, moving averages, support and resistance levels, and chart patterns, traders can enhance their ability to detect possible false breakouts and escape fraudulent schemes. Effective risk management and well-informed trading decisions are facilitated by this methodical approach.

Table 3.1: Fake Trap Analysis in Stock Market Using Different Technical Indicators

Technical Indicators	Explanation	Fake trap prediction
Volume Analysis	Examining trading volume accompanying price movements.	Low volume on breakout might indicate a fake trap. High volume confirms the breakout.
Support and Resistance Levels	Identifying key price levels where price tends to reverse.	Breakout beyond these levels with weak follow-through suggests a fake trap.
Candlestick Patterns	Analysing specific formations like Doji, Hammer, and Engulfing patterns.	Reversal patterns near breakout levels indicate potential fake traps.
Moving Averages (MA, EMA)	Comparing short-term and long-term moving averages.	Quick reversion to the mean after breakout indicates a fake trap.
Relative Strength Index (RSI)	Measuring momentum and identifying overbought/oversold conditions.	RSI divergence from price movement suggests a fake trap.
Bollinger Bands	Using bands to measure price volatility and identify overbought/oversold conditions.	Price returning inside bands after breakout indicates a fake trap.
MACD (Moving Average Convergence Divergence)	Analysing the relationship between two moving averages.	MACD divergence from price movement can signal a fake trap.
Chart Patterns	Identifying patterns like Head and Shoulders, Double Tops/Bottoms.	Failed patterns or premature reversals suggest a fake trap.

3.11 Candle Formation

The picture below shows different trend situation in the stock market. Every candle shows the specific information regarding the bearish and bullish trend in the stock market. Each candle like green and red is used for up and downward trend in the market. The following happens for a specific time period (e.g., 1 minute, 5 minutes, 1 hour, 1 day):

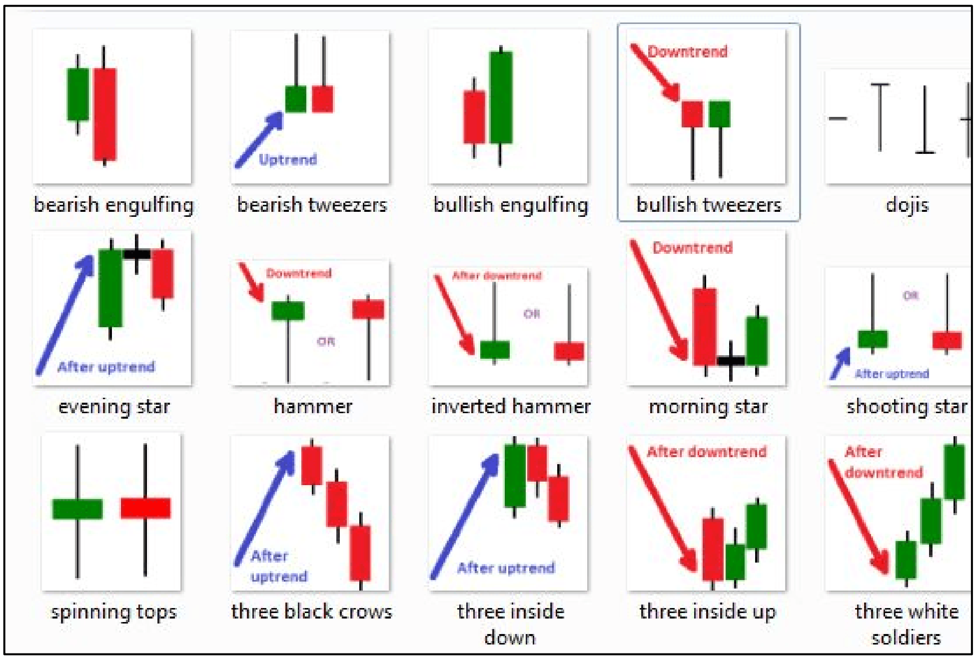


Fig 3.19: Candle Formation in Stock Market [18]

Candlesticks typically consist of two wicks on each end in addition to a body. The opening price is represented by the bottom of the white/green body, and the closing price is represented by the top of the body. The greatest and lowest prices of the day are indicated at the top and bottom tips of each wick, respectively.

3.11 Break of Structure and Change of Character

Break of Structure: Traders utilize BOS to verify the beginning of a new trend. For example, the beginning of a new uptrend can be signalled by a break over a strong resistance level in a downtrend. Traders may wait for a retreat to the broken level as a possible entry point after spotting a break of structure.

Change of Character: Before a BOS, traders can identify possible reversals using Change of Character. This bears a higher risk because of the possibility of false signals, but it can be very helpful for obtaining a better entry price. It is common to look for additional confirmation using other signs or signals from price activity.

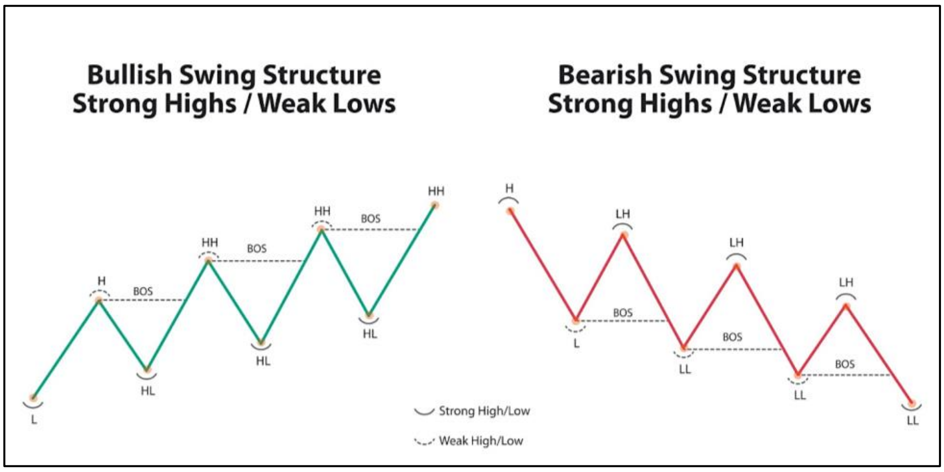


Fig 3.20: Break of Structure and Change of Character in Stock Market [20]

A Change of Character happens when the market breaks a critical swing point in the opposite direction of the current trend, potentially signalling the start of a new trend or reversal. Break of Structure indicates trend continuity by providing new highs or lows.

3.12 Stock Market Price Prediction Using Transformer Models

In the field of financial market analysis, particularly in the context of predicting stock crises, the integration of advanced technical indicators with cutting-edge machine learning models offers an exact and powerful approach. This research not only employs a sophisticated transformer-based model for predicting stock prices but also incorporates well-established technical indicators - EMA100-EMA200 crossover, MA100-MA200 crossover, and the Relative Strength Index (RSI) to enhance prediction accuracy and reliability.

Technical indicators are essential tools in financial analysis, used for decades by traders and analysts to interpret market trends and predict future movements. These indicators are based on historical price data and trading volumes, and they provide insights into market momentum, trends, and potential reversals. The rationale behind integrating these indicators into a machine learning model for stock crisis prediction lies in their proven ability to signal key market events, such as bubbles and impending crashes.

By combining these time-tested technical indicators with a transformer model, the research aims to capture the complex interplay of factors that influence stock prices. This integration adds technical analysis insights into the analysis while also utilizing the model's capacity to analyze large datasets and identify trends. Such a multifaceted approach is particularly pertinent in the volatile and unpredictable domain of stock markets, where the integration of various factors can lead to rapid changes in stock prices.

The following segments elaborate on the particular technical indicators employed in this research, namely the RSI, the MA100-MA200 crossover, and the EMA100-EMA200 crossover, explaining their functions and importance within the overall framework of stock crisis forecasting. This comprehensive approach provides a more effective strategy for managing the complicated workings of stock markets and illustrates the integration of modern machine learning techniques with classic financial market analysis.

3.10.1 Pakistan Stock Price Prediction

The latest model used in the proposed study for the prediction of stock market price. Different layers of Transformer used for different purpose. Each graph below shows the index graph of each sector. The graph below shows the stock data, x-axis in the given graph shows the volume of the dataset while y-axis shows the closing price of that stock.

1. Automobile Sectors

Automobile is one of the sectors of Pakistan stock market. In the proposed study Automobile sector dataset is selected from different stock indices the graph below shows the actual vs predicted values of the stock market sectors which are given below:

Figure 3.21: Indus Motors Ltd Graph

The above graph is Indus motor of the stock index where x-axis show the day/months/year while y-axis show volume of the stock market closing price.

Figure 3.22: Atlas Honda Motors Ltd Graph

The above graph is Atlas Honda motor of the stock index where x-axis show the day/months/year while y-axis show volume of the stock market closing price.

Figure 3.23: Millat Tractors Ltd Graph

The above graph is Milat tractor motor of the stock index where x-axis show the day/months/year while y-axis show volume of the stock market closing price.

2. Banking Sectors Graphical Representations

Bank is one of the sectors of Pakistan stock market. In the proposed study bank sector dataset is selected from different stock indices the graph below shows the actual vs predicted values of the stock market sectors which are given below:

Figure 3.24: Habib Bank Ltd Graph

The above graph is Habib Bank Limited of the stock index where x-axis show the day/months/year while y-axis show volume of the stock market closing price.

Figure 3.25: United Bank Ltd Graph

The above graph is United Bank Limited of the stock index where x-axis show the day/months/year while y-axis show volume of the stock market closing price.

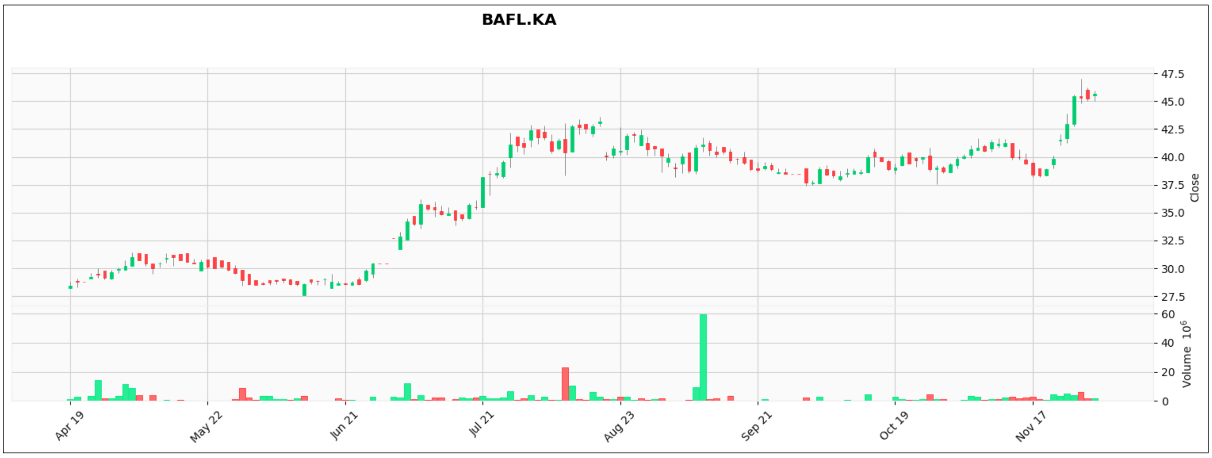


Figure 3.26: Bank Alfalah Ltd Graph

The above graph is Bank Alfalah Limited of the stock index where x-axis show the day/months/year while y-axis show volume of the stock market closing price.

3. Cement Sectors Graphical Representations

Cement is one of the sectors of Pakistan stock market. In the proposed study cement sector dataset is selected from different stock indices the graph below shows the actual vs predicted values of the stock market sectors which are given below:

Figure 3.27: Kohat Cement & Co Graph

The above graph is Kohat Cement of the stock index where x-axis show the day/months/year while y-axis show volume of the stock market closing price.

Figure 3.28: Falcon Cement & Co Graph

The above graph is Falcon and Co Cement of the stock index where x-axis show the day/months/year while y-axis show volume of the stock market closing price.

Figure 3.29: Maple Leaf Cement Graph

The above graph is Maple Leaf Cement of the stock index where x-axis show the day/months/year while y-axis show volume of the stock market closing price.

The above diagram shows different sectors of Pakistan stock dataset having different indices, in the given diagram the x-axis shows the total volume of the specific stock where y-axis shows the closing price of that index. The red line in the above diagram shows that the stock price of the specific index is going down while green shows that's stock price is going upward. Each candle in the given diagram shows a specific day closing price and have volume of the stock.

3.11 Metrics for Evaluating Prediction Accuracy

MAE, MSE, and RMSE are widely employed metrics to assess the effectiveness of a machine learning model, especially in regression tasks that involve predicting numerical values. Several metrics are used to evaluate the model's prediction accuracy:

Mean Absolute Error (MAE): This metric measures the average magnitude of errors in a set of predictions, without considering their direction. MAE calculates the average absolute difference between actual and predicted values. It is derived by computing the mean of the absolute differences for each data point:

$$\mathrm{MAE} = \frac{1}{\mathrm{n}} \sum_{\mathrm{i=1}}^{\mathrm{n}} \quad |\mathrm{Yi} - \mathrm{Xi}| \qquad 3.4$$

n shows number of datapoint
Yi shows the actual values
Xi shows the predicted values

Mean Squared Error (MSE): MSE gauges the average squared difference between actual and predicted values. The calculation involves finding the mean of the squared differences for each data point:

$$MAE = \frac{1}{n} \sum_{i=1}^{n} 0 \quad (|Yi - Xi|)^{2} \qquad 3.5$$

Root Mean Squared Error (RMSE): RMSE is a quadratic scoring rule that measures the average magnitude of the error. It’s particularly useful when large errors are particularly undesirable. RMSE is the square root of the Mean Squared Error. It provides a measure of the average magnitude of errors in predicted values:

$$\mathrm{RMSE} = \sqrt{}\mathrm{RMSE} \qquad 3.6$$

R-squared (R^2): This statistic measures how close the data are to the fitted regression line. It indicates the proportion of the variance in the dependent variable that is predictable from the independent variables.

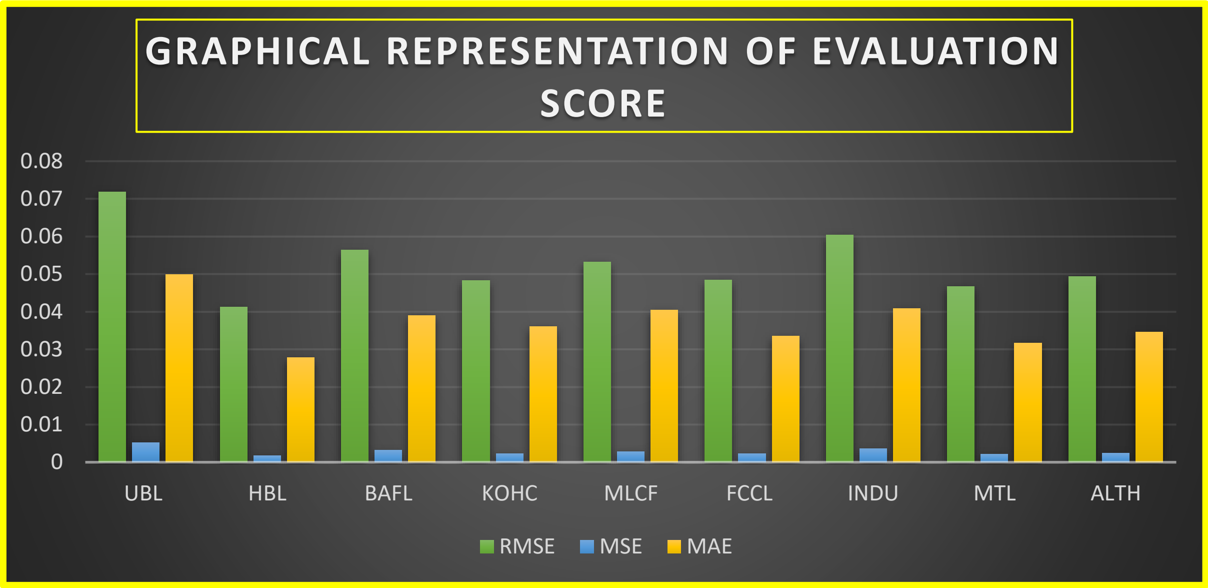


Figure 3.30: Graphical Representation of Evaluation Scores

3.12 Challenges and Solutions

Conducting research on stock crisis prediction using transformer models on Pakistan Stock Data presented a range of challenges, each necessitating specific solutions to ensure the study's validity and effectiveness.

3.12.1 Data Quality and Completeness

Challenge: Financial data, particularly from emerging markets, often suffers from issues like missing values, outliers, and inconsistencies. This is especially true for Pakistani stock data, where recording practices might not always align with international standards.

Solution: Rigorous data preprocessing was essential. This involved employing statistical methods for outlier detection and correction, and sophisticated imputation techniques for handling missing data. The data normalization process was also crucial, standardizing the range of different financial indicators to a common scale, thus mitigating the issue of inconsistent data formats and scales.

3.12.2 Model Complexity and Overfitting

Challenge: The inherent complexity of transformer models, while beneficial for capturing complex patterns, posed a significant risk of overfitting, particularly due to the noisy and volatile nature of financial data.

Solution: Implementing regularization techniques such as dropout and L2 regularization helped mitigate overfitting. Dropout randomly deactivates certain neurons during training, preventing the model from becoming overly reliant on specific data features. L2 regularization adds a penalty to the loss function based on the weights' magnitude, encouraging the model to maintain smaller weights. Additionally, extensive cross-validation was employed, where the model was trained and validated on different subsets of the data to ensure it could generalize well to new, unseen data.

3.12.3 Interpretability of Model Predictions

Challenge: Given the complexity of transformer models and the opaque nature of deep learning mechanisms, achieving interpretability in model predictions was challenging. This interpretability is crucial for trust and practical application in financial contexts.

Solution: The use of post-hoc explanation tools like LIME and SHAP provided insights into how different features influenced the model's predictions. These tools break down predictions to a level where the contribution of each feature can be understood, offering a window into the model's decision-making process. This step was vital for ensuring that the model's outputs were interpretable and justifiable.

3.12.4 Handling Non-Stationary Time Series Data

Challenge: Stock data is inherently non-stationary, with its statistical properties like mean and variance changing over time, posing a significant challenge for predictive modelling.

Solution: Techniques such as differencing, where the difference between consecutive data points is computed, were applied. This method helped in mitigating the issue of non-stationarity, as differencing can stabilize the mean of a time series. Additionally, transformation techniques like logarithmic or exponential transformations were considered to stabilize the variance.

3.12.5 Computational Resources

Challenge: The computational demand for training sophisticated models like transformers is substantial. This posed a challenge, especially in scenarios with limited access to high-performance computing facilities.

Solution: The model's architecture was optimized for computational efficiency. This included fine-tuning the number of layers and parameters to balance between model complexity and computational feasibility. Additionally, leveraging cloud computing resources emerged as a vital solution. Cloud platforms provided the necessary computational power, enabling the use of more sophisticated models without the constraint of local hardware limitations.

These preprocessing processes were important in controlling the financial data's noisy and unstable characteristics. The preprocessing stage made sure that the data input into the transformer model was as clean and dependable as possible by resolving problems with overfitting and data quality, which improved the model's predicted accuracy and robustness.

3.13 Summary

This chapter serves as the cornerstone of the research, detailing the methodologies employed in predicting stock crises using state-of-the-art transformer models on Pakistan Stock Data and identified bubble using RSI indicator. The primary focus here is on three major sectors: automobile assembler, cement, and banking. This chapter aims to provide a comprehensive understanding of the approach taken, starting from the conceptual background of the existing work in stock crisis prediction and transformer models, leading to the specifics of the dataset and the intricate details of the model architecture.

CHAPTER 4

RESULT AND ANALYSIS

The results of this study on predicting stock market crises through transformers and identifying bubbles using RSI, MA, and EMA demonstrates promising findings. The transformer model exhibits robust performance in crisis prediction, supported by favorable MAE, RMSE, and MSE scores. Additionally, the application of RSI, MA, and EMA proves effective in bubble identification. Comparative analysis against baseline models emphasizes the superiority of the transformer approach. In summary, the results highlight the potential of advanced models to improve stock market prediction and inform financial decision-making.

4.1 Data analysis and results

Datasets play a crucial role in the development and evaluation of algorithms for stock market price prediction and classification. The proposed study used historical dataset of Pakistan stock market from yahoo finance website which provides a comprehensive and detailed array of stock market data, reflecting the diverse sectors of the Pakistani economy. The dataset is available in the csv file having size 5000 × 7 and the is compiled for the training and testing of predictive algorithms. This database is selected to minimize deviations and reflect normal stock market behavior. The dataset was scaled, normalized and set in a certain format and then the data was prepared and preprocessed for further the process like training and testing.

4.2 Training and testing output

In the proposed study the training dataset helps it learn patterns and correlations that are very helpful for stock market price prediction and accuracy. On the other hand, the model's performance on fresh, untested market data is assessed using the testing dataset, which is separate from the training data. The dataset used in this study for training and testing for achieving good result or stock market better performance as compared to the previous study to overcome the limitations.

As the stock market prediction is a regression problem so in this case prediction can be done by minimizing the error called loss function. Different evaluation scores are used for better performance and prediction of stock market. The graph below in pictures shows the loss function for each selected stock sector of Pakistan.

1. **Loss Function:** For a regression task like stock price prediction, Mean Squared Error (MSE), Root Mean Squared Error and Mean Absolute Error (MAE) are commonly used as loss functions.

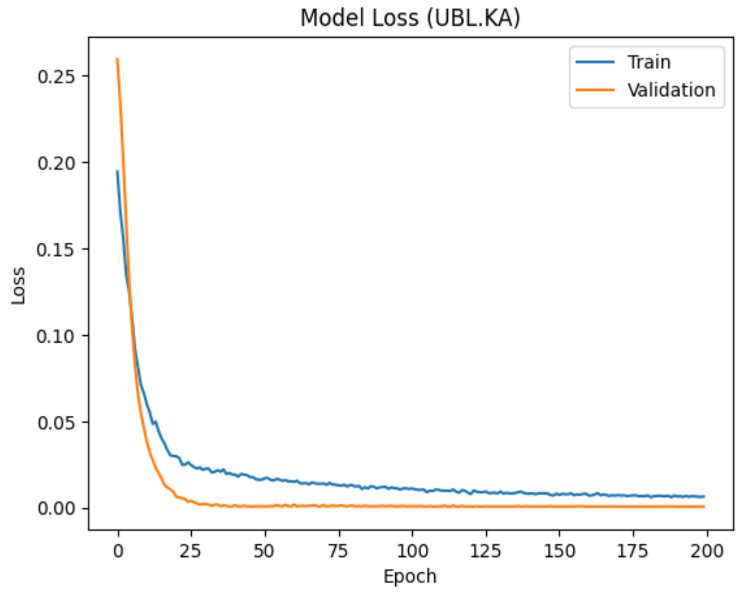


Figure 4.1: Model Loss Function of United Bank Ltd

The graph above shows the loss function of the United Bank Limited using different evaluation matrices like Mean Absolute Error (MAE), Mean Squared Error (MAE) and Root Mean Squared Error (RMSE) for the training and validation of the stock market dataset where blue line shows the training of the dataset and red line shows validation of the dataset.

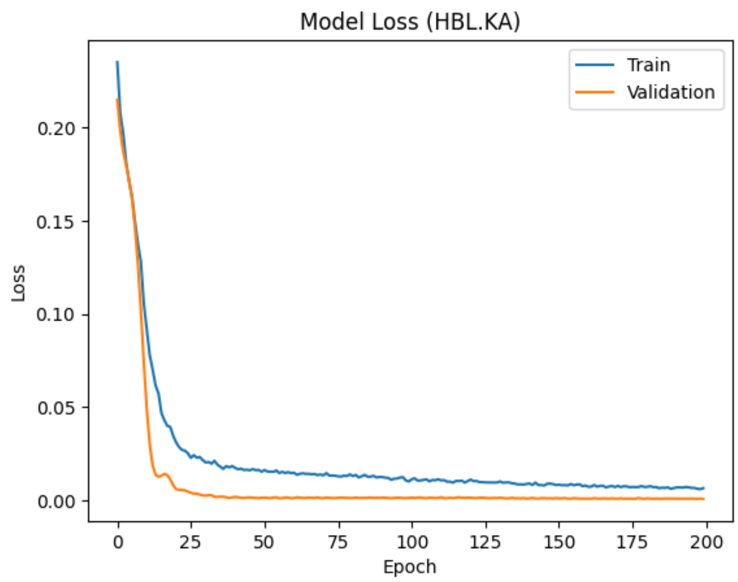


Figure 4.2: Model Loss Function of Habib Bank Ltd

The graph above shows the loss function of the Habib Bank Limited using different evaluation matrices like Mean Absolute Error (MAE), Mean Squared Error (MAE) and Root Mean Squared Error (RMSE) for the training and validation of the stock market dataset where blue line shows the training of the dataset and red line shows validation of the dataset.

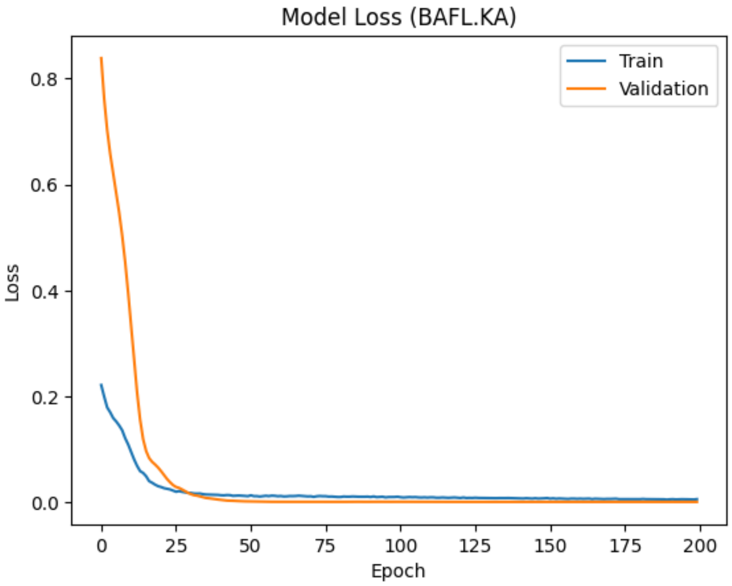


Figure 4.3: Model Loss Function of Bank Alfalah Ltd

The graph above shows the loss function of the Bank Alfalah Limited using different evaluation matrices like Mean Absolute Error (MAE), Mean Squared Error (MAE) and Root Mean Squared Error (RMSE) for the training and validation of the stock market dataset where blue line shows the training of the dataset and red line shows validation of the dataset.

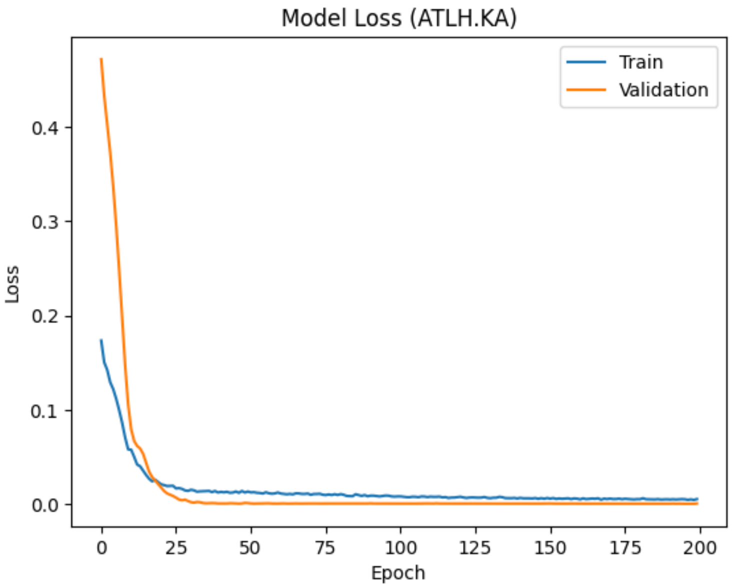


Figure 4.4: Model Loss Function of Atlas Honda Motors

The graph above shows the loss function of the Atlas Honda Motors using different evaluation matrices like Mean Absolute Error (MAE), Mean Squared Error (MAE) and Root Mean Squared Error (RMSE) for the training and validation of the stock market dataset where blue line shows the training of the dataset and red line shows validation of the dataset.

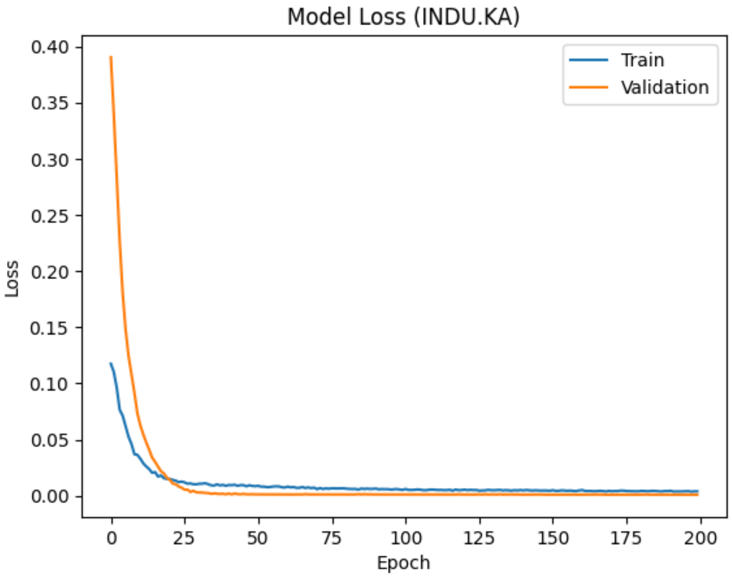


Figure 4.5: Model Loss Function of Indus Motors

The graph above shows the loss function of the Indus Motors using different evaluation matrices like Mean Absolute Error (MAE), Mean Squared Error (MAE) and Root Mean Squared Error (RMSE) for the training and validation of the stock market dataset where blue line shows the training of the dataset and red line shows validation of the dataset.

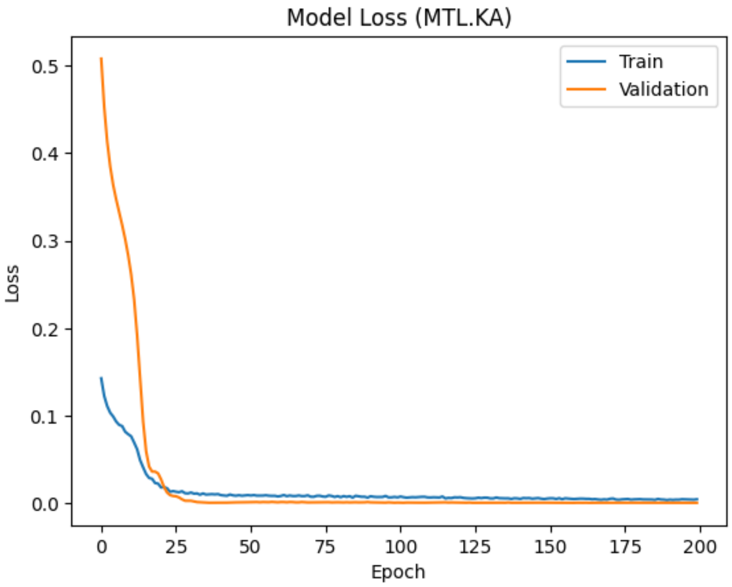


Figure 4.6: Model Loss Function of Millat Tractors Motors

The graph above shows the loss function of the Milat Tractors using different evaluation matrices like Mean Absolute Error (MAE), Mean Squared Error (MAE) and Root Mean Squared Error (RMSE) for the training and validation of the stock market dataset where blue line shows the training of the dataset and red line shows validation of the dataset.

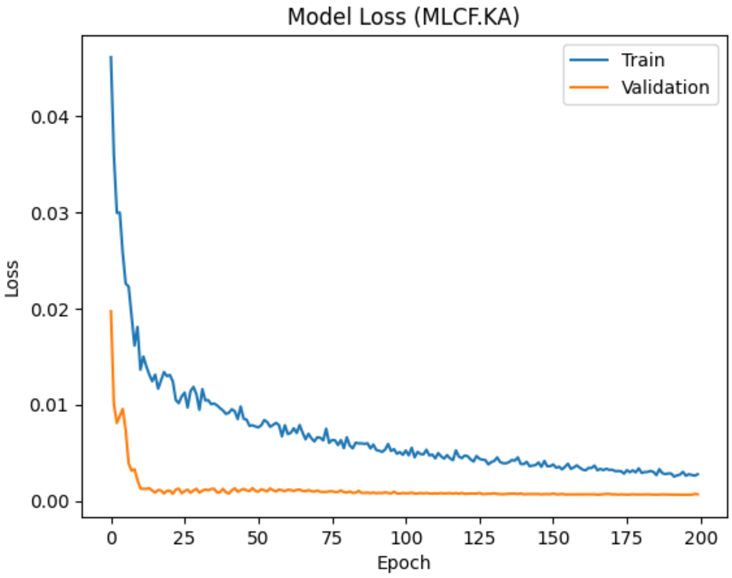


Figure 4.7: Model Loss Function of Maple Leaf Cement and Co

The graph above shows the loss function of the Maple Leaf Cement & Co using different evaluation matrices like Mean Absolute Error (MAE), Mean Squared Error (MAE) and Root Mean Squared Error (RMSE) for the training and validation of the stock market dataset where blue line shows the training of the dataset and red line shows validation of the dataset.

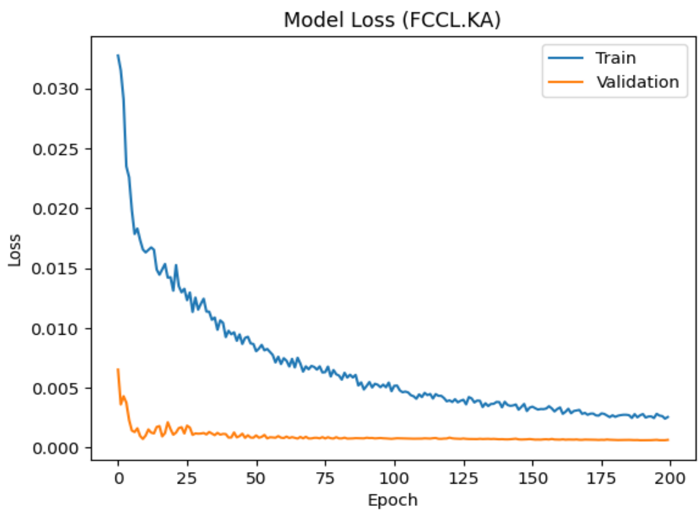


Figure 4.8: Model Loss Function of Falcon Cement and Co

The graph above shows the loss function of the Falcon Cement & Co using different evaluation matrices like Mean Absolute Error (MAE), Mean Squared Error (MAE) and Root Mean Squared Error (RMSE) for the training and validation of the stock market dataset where blue line shows the training of the dataset and red line shows validation of the dataset.

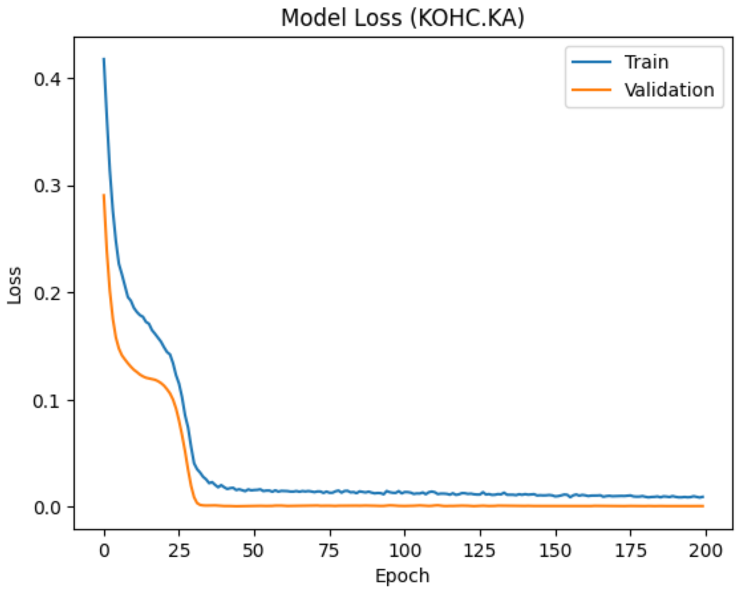


Figure 4.9: Model Loss Function of Kohat Cement and Co

The graph above shows the loss function of the Kohat Cement & Co using different evaluation matrices like Mean Absolute Error (MAE), Mean Squared Error (MAE) and Root Mean Squared Error (RMSE) for the training and validation of the stock market dataset where blue line shows the training of the dataset and red line shows validation of the dataset.

4.3 EMA and MA (100-200) Crossover Results

Moving Averages (MA) and Exponential Moving Averages (EMA) play crucial roles in stock market analysis by smoothing out price data, identifying trends, and assisting in decision-making. In the proposed research based on the Moving Average Statistics and Exponential Moving Average Stock Market Crises are predicted. As the 100 days and 200 days Moving Average line intersect each other than the crise occurs.

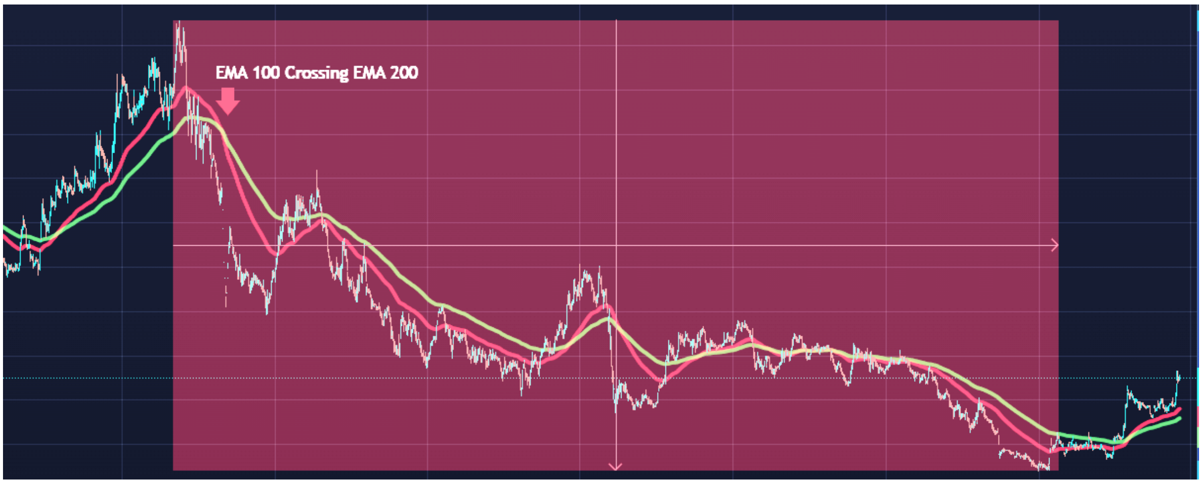


Figure 4.10: EMA 100-200 Crossover Points

The given graph above is an example of EMA100-200 days which predict the stock market crises points in the Pakistan Stock Market. Here some of the values for the values in tabular form which shows the stock crisis points for all indices of the Pakistan stock Market Sectors. The red line shows Moving Average (100-200) while green line shows Exponential Moving Average (100-200).

Table 4.1: Stock Crash Point Identification Using ME and EMA

Ticker	Date	Crash Price	MA100	MA200	EMA100	EMA200
ATLH	15/05/2017	544.583313	488.815666	457.770042	482.091846	453.883585
ATLH	30/04/2018	532.875	454.385918	451.598501	459.519155	456.508007
ATLH	01/07/2021	516	467.036599	473.64405	473.855373	462.71533
BAFL	24/04/2015	27.81818	27.979272	27.099272	26.863762	26.713873
BAFL	09/11/2018	51.5	49.980509	48.068481	49.39741	47.450162
BAFL	03/03/2020	48.970001	46.8592	44.48215	47.206372	46.039019
FCCL	24/05/2017	47.5	39.775822	36.666666	38.768878	37.469055
FCCL	26/07/2021	22.950001	20.749422	20.184133	20.624953	19.98945
HBL	11/05/2017	310	273.738399	250.12465	269.744502	253.287474
HBL	06/04/2018	229.720001	189.4355	197.68435	198.889373	203.670191
HBL	01/06/2021	137.75	127.2444	129.67395	126.120608	126.761611
INDU	07/08/2015	1299.98999	1184.0195	1060.545651	1184.750696	1058.291301
INDU	24/01/2018	1967.98999	1736.987101	1783.081801	1747.41134	1721.557035
INDU	25/04/2022	1430	1305.776602	1269.1347	1310.071181	1275.450918
KOHC	19/06/2017	184.615387	202.068614	203.623307	198.552156	200.8612
KOHC	02/11/2018	113.5	94.179684	105.513841	97.077823	105.086417

KOHC	06/07/2021	238.5	211.4235	209.6544	208.827852	199.55887
MLCF	21/04/2017	108.258064	103.74331	94.186895	100.899441	94.749253
MLCF	20/08/2021	46.75	45.2042	44.35225	44.956941	43.120221
MTL	31/08/2018	1133.333374	1076.203111	1094.981508	1070.154719	1081.520916
MTL	30/08/2021	1119.880005	1088.584729	1049.510555	1080.550178	1025.463631
UBL	08/05/2017	275.380005	240.1744	222.3015	235.831173	222.381627
UBL	12/04/2018	208.449997	191.8485	194.3884	196.463957	198.703176
UBL	23/02/2022	150.899994	137.5198	131.3384	137.398394	133.481931

4.4 Results of Stock RSI for Bubble Identification

Using historical stock price data from the Pakistan Stock Exchange (PSX) webpage and yahoo finance, the Stoch RSI value was computed. Historical stock data from 2008 to December 2023 has been examined in the proposed study. Earlier RSI computations used a 14-day period, but in our method, we found the stock price bubble by using Stoch RSI for 100 and 200 days. This is justified by the fact that intraday trading takes place every 14 days, as opposed to long-term trading. An overvalued stock is all that constitutes a stock price bubble. Table below illustrates that how the bubbles are captured using Stoch RSI statistics. Finding stock crisis zones based on the stock price bubble is the next step.

Ticker	Date	Crash Price	RSI	Stochastic RSI
ATLH	15/05/2017	544.583313	76.09	91.19
ATLH	30/04/2018	532.875	77.41	89.77
ATLH	01/07/2021	516	62.56	31.97
BAFL	24/04/2015	27.81818	67.88	99.83
BAFL	09/11/2018	51.5	55.78	64.13
BAFL	03/03/2020	48.970001	45.75	57.86
FCCL	24/05/2017	47.5	66.01	76.32
FCCL	26/07/2021	22.950001	41.89	51.09
HBL	11/05/2017	310	72.5	93.13
HBL	06/04/2018	229.720001	60.41	45.6
HBL	01/06/2021	137.75	61.37	54.09
INDU	07/08/2015	1299.98999	68.02	100
INDU	24/01/2018	1967.98999	78.02	100
INDU	25/04/2022	1430	56.96	55
KOHC	19/06/2017	184.615387	46.21	73.45
KOHC	02/11/2018	113.5	70.55	100
KOHC	06/07/2021	238.5	73.36	87.53
MLCF	21/04/2017	108.258064	58.8	84.26
MLCF	20/08/2021	46.75	57.25	65.18
MTL	31/08/2018	1133.333374	69.61	93.13
MTL	30/08/2021	1119.880005	62.64	97.7
UBL	08/05/2017	275.380005	80.24	98.7
UBL	12/04/2018	208.449997	58.92	54.26
UBL	23/02/2022	150.899994	76.77	80.4

Figure 4.11: Stock Price Bubble Prediction Using RSI and StochRSI

4.5 Cross-Check Analysis of MA, EMA, RS and RSI.

Here the cross-check analysis has been done between MA, EMA, RS and RSI. By doing the cross-check analysis it can easily identify that which indicators perform the best in the given scenario.

Table 4.2: Cross-check Analysis between MA, EMA, RS and RSL

s

Ticker	Date	Crash Price	RSI	Stochastic RSI	MA100	MA200	EMA100	EMA200
ATLH	15/05/2017	544.583313	76.09	91.19	488.815666	457.770042	482.091846	453.883585
ATLH	30/04/2018	532.875	77.41	89.77	454.385918	451.598501	459.519155	456.508007
ATLH	01/07/2021	516	62.56	31.97	467.036599	473.64405	473.855373	462.71533
BAFL	24/04/2015	27.81818	67.88	99.83	27.979272	27.099272	26.863762	26.713873
BAFL	09/11/2018	51.5	55.78	64.13	49.980509	48.068481	49.39741	47.450162
BAFL	03/03/2020	48.970001	45.75	57.86	46.8592	44.48215	47.206372	46.039019
FCCL	24/05/2017	47.5	66.01	76.32	39.775822	36.666666	38.768878	37.469055
FCCL	26/07/2021	22.950001	41.89	51.09	20.749422	20.184133	20.624953	19.98945
HBL	11/05/2017	310	72.5	93.13	273.738399	250.12465	269.744502	253.287474
HBL	06/04/2018	229.720001	60.41	45.6	189.4355	197.68435	198.889373	203.670191
HBL	01/06/2021	137.75	61.37	54.09	127.2444	129.67395	126.120608	126.761611
INDU	07/08/2015	1299.98999	68.02	100	1184.0195	1060.545651	1184.750696	1058.291301
INDU	24/01/2018	1967.98999	78.02	100	1736.987101	1783.081801	1747.41134	1721.557035
INDU	25/04/2022	1430	56.96	55	1305.776602	1269.1347	1310.071181	1275.450918
KOHC	19/06/2017	184.615387	46.21	73.45	202.068614	203.623307	198.552156	200.8612
KOHC	02/11/2018	113.5	70.55	100	94.179684	105.513841	97.077823	105.086417
KOHC	06/07/2021	238.5	73.36	87.53	211.4235	209.6544	208.827852	199.55887
MLCF	21/04/2017	108.258064	58.8	84.26	103.74331	94.186895	100.899441	94.749253
MLCF	20/08/2021	46.75	57.25	65.18	45.2042	44.35225	44.956941	43.120221
MTL	31/08/2018	1133.333374	69.61	93.13	1076.203111	1094.981508	1070.154719	1081.520916
MTL	30/08/2021	1119.880005	62.64	97.7	1088.584729	1049.510555	1080.550178	1025.463631
UBL	08/05/2017	275.380005	80.24	98.7	240.1744	222.3015	235.831173	222.381627
UBL	12/04/2018	208.449997	58.92	54.26	191.8485	194.3884	196.463957	198.703176
UBL	23/02/2022	150.899994	76.77	80.4	137.5198	131.3384	137.398394	133.481931

The above table shows values of different indicators for identifying the stock crash points and stock bubble prices using multiple indicators like Moving Average (100-200), Exponential Moving average (100-200), Relative strength Index and Stochastic Relative Strength Index. By using these multiple indicators, a cross-check between theses indictors which shows that which of the indicators shows the best results of different stock index in the respective timeframe.

4.5 Transformer Model for stock crisis prediction

The importance of exploring this area is manifold. Firstly, these markets offer a realm of unexplored potential for academic and practical insights into stock prediction. The economic significance of such research is substantial, considering the pivotal role of the PSX in Pakistan's financial landscape. For investors and policymakers, understanding the nuances of this market could lead to more informed decision-making and better economic outcomes. Moreover, research in this domain contributes to a more diversified and holistic understanding of global financial markets, challenging the predominance of research focused on developed economies. The application of state-of-the-art models like transformers to Pakistan Stock Data not only fills a crucial research gap but also serves as a testament to the adaptability and effectiveness of these models in diverse market conditions. Additionally, the development of better prediction models for such markets is imperative for enhanced risk management strategies, which are vital for investors and companies operating within these economies.

4.5.1 Actual vs Predicted Results using Transformer model

Stock price of different sectors of Pakistan stock market was predicted using transformer model. The latest state-of-the-art transformer model on the dataset of Pakistan stock market shows best prediction results. The errors were minimized using different evaluation scores matric. The given diagram below shows the graphs of different sectors and having their actual vs predicted values.

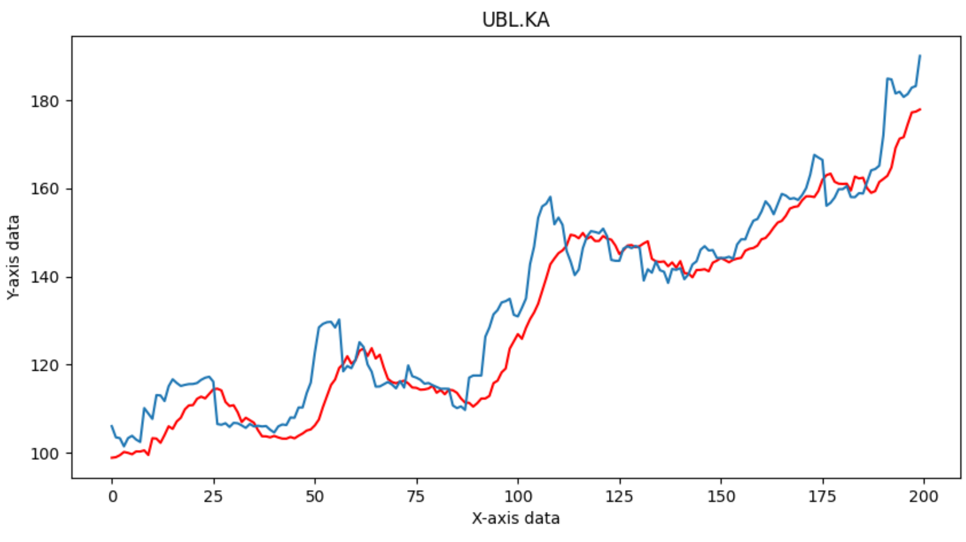


Figure 4.12: Actual Vs Predicted Graph of UBL.KA Sector

The graph above shows the actual vs predictive values of the United bank limited where the x-axis shows time and y-axis shows the price. There are two lines in the graph blue and red which shows the actual vs predicted stream of the price.

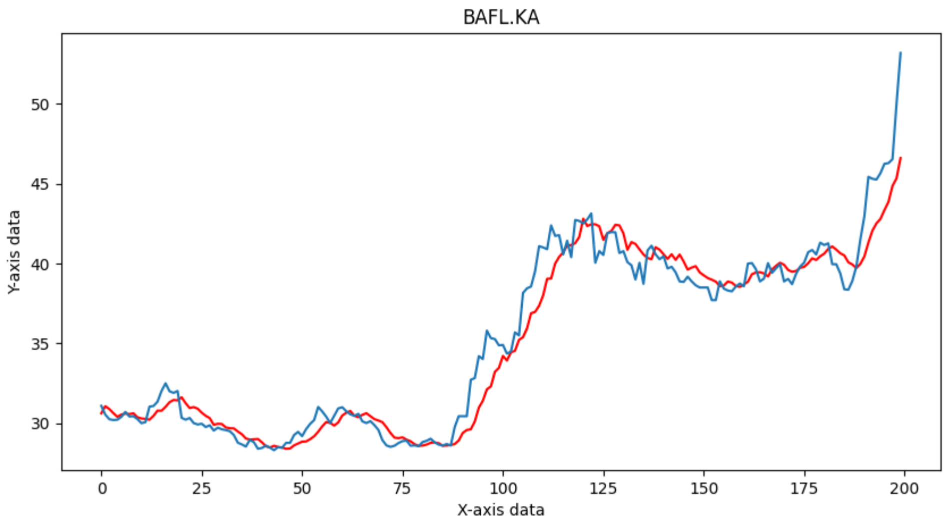


Figure 4.13: Actual Vs Predicted Graph of BAFL.KA Sector

The graph above shows the actual vs predictive values of the Bank Alfalah limited where the x-axis shows time and y-axis shows the price. There are two lines in the graph blue and red which shows the actual vs predicted stream of the price.

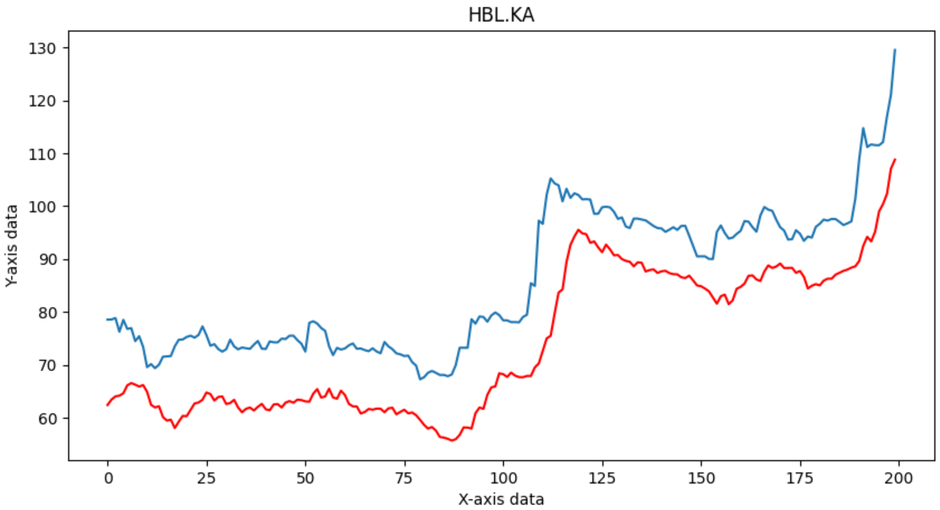


Figure 4.14: Actual Vs Predicted Graph of HBL.KA Sector

The graph above shows the actual vs predictive values of the Habib bank limited where the x-axis shows time and y-axis shows the price. There are two lines in the graph blue and red which shows the actual vs predicted stream of the price.

1	BANKING SECTOS					
2	UBL BANK		BANK ALFALAH		HABIB BANK	
3	actual	predicted	actual	predicted	actual	predicted
4	180.83	180.83	51.27	52.54091	165.083	166.7327
5	178.08	180.4889	52.97	51.82764	168.01	168.331
6	178.99	180.8414	52.33	52.44943	168.45	169.2779
7	178.22	181.0133	52.77	52.92473	169.93	168.3134
8	178.89	181.0285	52.22	52.94345	169.02	170.4104
9	178.99	182.1809	52.23	53.09028	169.95	169.1428
10	177.48	181.3131	51.77	53.01725	167.87	167.9168
11	174.67	181.3279	51.9	53.15313	164.03	168.0768
12	172.81	181.44	51.4	52.98136	164.83	165.8764
13	169.93	179.842	49.98	52.98618	163.12	165.4814
14	167.23	179.5377	47.74	52.24856	157.08	166.1802
15	171.37	177.4738	49.47	51.25765	156.6	161.8572
16	170.63	175.6489	50.49	50.69171	159.28	160.3897
17	169.08	175.521	48.9	51.34362	156.61	162.2751
18	166.9	175.1006	47.52	51.33323	155.94	158.3347
19	166.71	173.8815	48.39	50.28291	154.6	154.8502
20	168.79	172.8977	49.43	49.32784	156.73	155.296
21	169.4	172.841	49.66	49.54647	159.35	154.7445

UBL.KA excel

Figure 4.15: Actual Vs Predicted Prices of Banking Sector

The above diagram shows the graphs of the banking sector of stock market price prediction using transformer model the actual vs predicted values are given above which shows better prediction results.

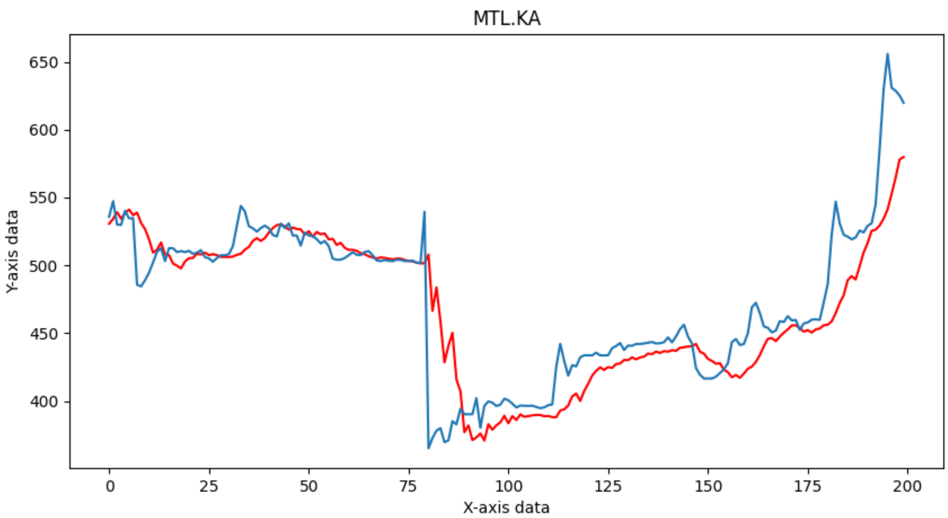


Figure 4.16: Actual Vs Predicted Graph of MLT.KA Sector

The graph above shows the actual vs predictive values of the Milat Tractor where the x-axis shows time and y-axis shows the price. There are two lines in the graph blue and red which shows the actual vs predicted stream of the price.

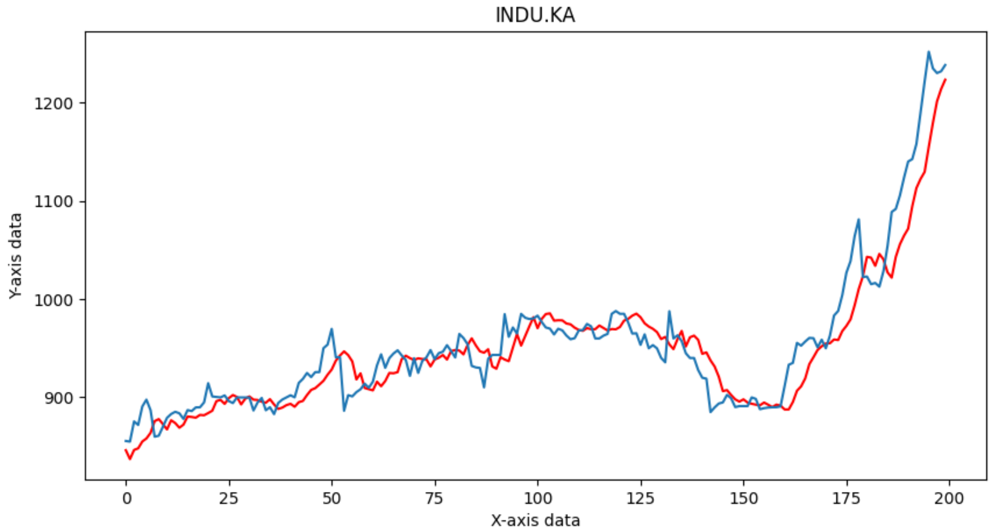


Figure 4.17: Actual Vs Predicted Graph of INDU.KA Sector

The graph above shows the actual vs predictive values of the Indus motor sector where the x-axis shows time and y-axis shows the price. There are two lines in the graph blue and red which shows the actual vs predicted stream of the price.

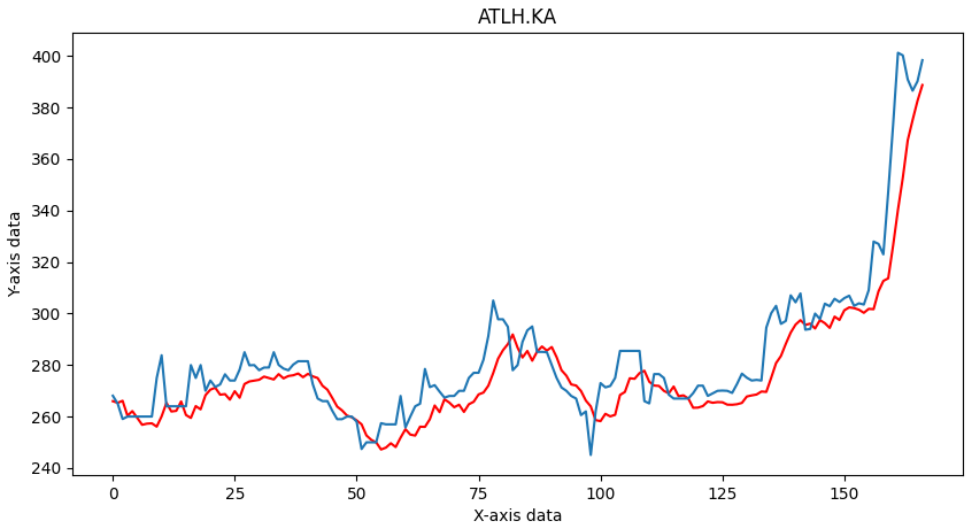


Figure 4.18: Actual Vs Predicted Graph of ATHL.KA Sector

The graph above shows the actual vs predictive values of the Atlas Honda sector where the x-axis shows time and y-axis shows the price. There are two lines in the graph blue and red which shows the actual vs predicted stream of the price.

1	Automobile sector					
2	Millat Tractors		Atlas hondas		Indus Motors	
3	Actual	Predicted	Actual	Predicted	Actual	Predicted
4	730.91	725.6844	399	385.6356	1046.2	1068.844
5	726.12	731.8284	380	391.0881	1049.25	1069.905
6	728.08	729.4619	380	385.9812	1048	1058.885
7	730.48	736.4287	380	384.5482	1043.88	1054.992
8	737.28	736.3862	392.85	385.6225	1046.22	1059.254
9	735.52	739.9754	382.51	386.2946	1046.85	1055.611
10	729.98	740.9347	401.39	383.3451	1072.47	1054.233
11	729.23	742.93	392.5	391.5888	1070.06	1056.295
12	731.98	742.9453	392.5	391.2938	1065.13	1063.037
13	729.96	742.8274	394	392.7882	1073.97	1068.862
14	707.99	740.7506	394	394.8791	1058.49	1064.761
15	715.11	738.8392	394	398.4269	1049.94	1072.229
16	715.93	741.6998	399	391.4704	1044.54	1076.269
17	702	736.9667	399	398.4482	1040.57	1069.504
18	673.43	731.3257	399	395.6904	1000	1062.829
19	680.66	727.0908	380	398.6859	1004.47	1061.51
20	685.32	727.5492	380	394.3993	1022.08	1047.695

MTL.KA excel

Figure 4.19: Actual Vs Predicted Prices of Automobile Sector

The above diagram shows the graphs of the automobile sector of stock market price prediction using transformer model the actual vs predicted values are given above which shows better prediction results.

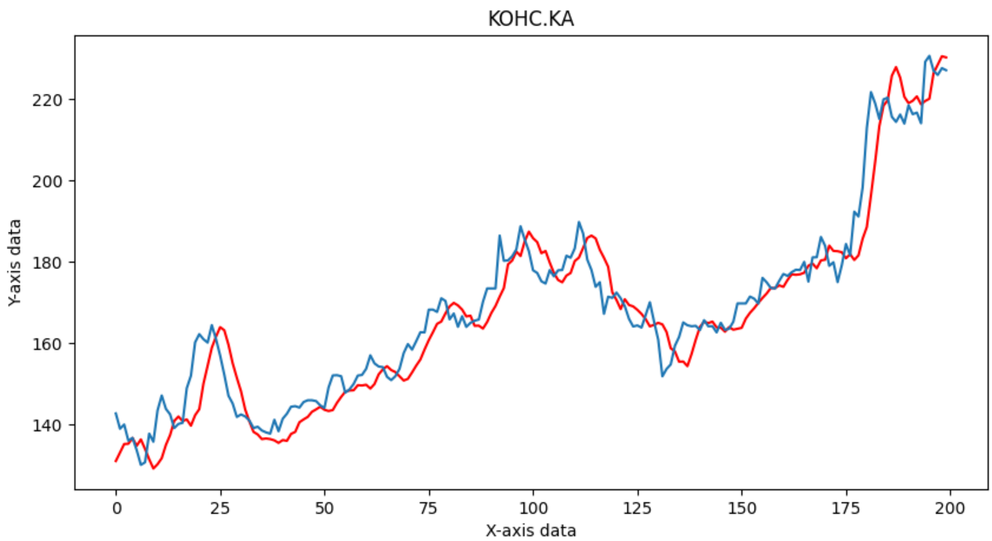


Figure 4.20: Actual Vs Predicted Graph of KOHT.KA Sector

The graph above shows the actual vs predictive values of the Kohat Cement sector where the x-axis shows time and y-axis shows the price. There are two lines in the graph blue and red which shows the actual vs predicted stream of the price.

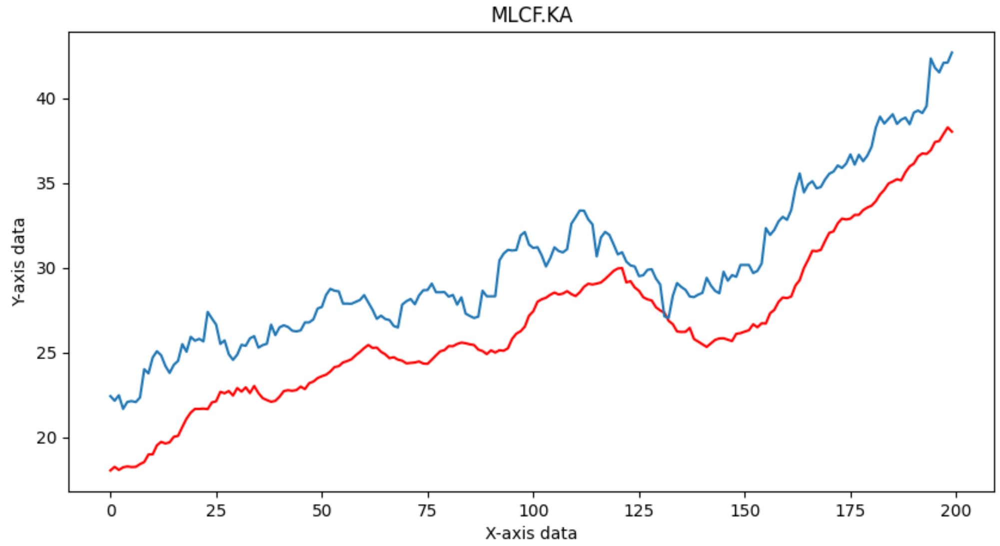


Figure 4.21: Actual Vs Predicted Graph of MLCF.KA Sector

The graph above shows the actual vs predictive values of the Maple Leaf cement and Co sector where the x-axis shows time and y-axis shows the price. There are two lines in the graph blue and red which shows the actual vs predicted stream of the price.

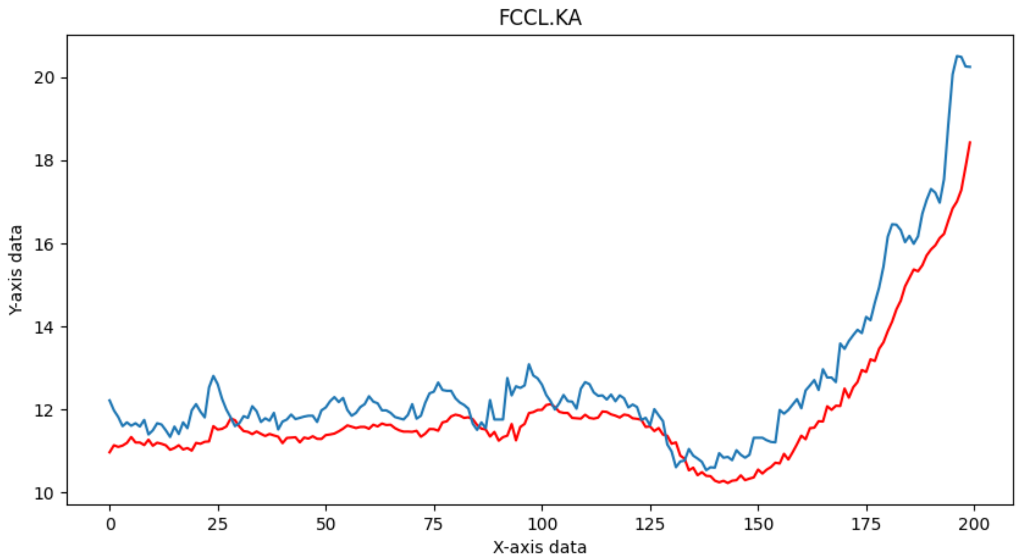


Figure 4.22: Actual Vs Predicted Graph of FCCL.KA Sector

The graph above shows the actual vs predictive values of the Falcon Cement and Co sector where the x-axis shows time and y-axis shows the price. There are two lines in the graph blue and red which shows the actual vs predicted stream of the price.

1	cement sector					
2	Kohat cement		Maple leaf cement		falcon cement	
3	Actual	Predicted	Actual	Predicted	Actual	Predicted
4	79.95	69.13567	23.05	19.53993	16.97	16.15909
5	77.13	71.32819	21.81	19.66266	16.47	16.16792
6	79.35	71.97231	22.25	19.17326	16.51	15.94432
7	78.7	71.55868	22.92	19.26828	16.6	16.12242
8	83.02	71.52254	23.54	19.1477	16.86	16.18268
9	87.58	71.54737	24.83	19.48389	17.25	16.28761
10	90.19	73.85641	24.99	19.9025	16.98	16.28198
11	88.67	75.8888	24.18	20.2666	16.6	16.27343
12	89.96	78.55766	24.26	20.00149	16.64	16.25082
13	89.59	80.26784	23.71	20.22856	16.64	16.40552
14	87.23	82.42872	22.45	19.91753	16.29	16.34835
15	87.06	83.94893	22.96	19.76736	16.87	16.10044
16	85.1	83.54884	23.04	20.10665	16.91	16.24716
17	83.92	82.33135	21.81	20.27307	15.93	16.20266
18	80.9	79.90504	21.37	20.27003	15.02	15.92808
19	84.39	78.50577	22.57	20.44562	15.47	15.70834
20	89.38	76.30202	23.38	20.33036	15.75	15.89503

KOHC.KA excel

Figure 4.23: Actual Vs Predicted Price of Cement Sector

The above given diagram shows the stock market different sectors price on y-axis and volume of the data at x-axis. The above diagram shows the predicted vs actual values using transformer model. The given graph shows better results using transformer model which is the latest and updated state-of-the-art model as compared the traditional model used in the existing studies.

4.5.2 Sectors wise evaluation score results

As compared to the previous study the evaluation scores (Mean Squared Error, Root Mean Squared Error, Mean Absolute Error) of the proposed study are more less given in the below graph. The Mean Squared Error (MAE) score for each stock indices are very low as compared to other Evaluation scores. The evaluation scores for Banking Sectors having 3 indices Scores are 1) UBL bank are (RMSE=0.071885, MSE=0.005167, MAE=0.049879), 2) HBL bank scores are (RMSE=0.041255, MSE=0.001702, MAE=0.027830), 3) Bank Alfalah Scores are (RMSE=0.056351, MSE=0.003175, MAE=0.038994). Second is the Cement Sectors which also consist of 3 indices 4) Kohat Cement Scores are (RMSE=0.048259, MSE=0.002328, MAE=0.036131), 5) Maple Leaf Cement Scores are (RMSE=0.053193, MSE=0.002829, MAE=0.040515), 6) Fauji Fertilizer & co Scores are (RMSE=0.048383, MSE=0.002340, MAE=0.033476). Third last is the Automobile sectors having 3 indices and their evaluation scores are 7) Indus Motors Scores are (RMSE=0.060429, MSE=0.003651, MAE=0.040801), 8) Millat Tractors Scores are (RMSE=0.046659, MSE=0.002177, MAE=0.031720), 9) Atlas Honda Scores are (RMSE=0.049333, MSE=0.049333, MAE=0.034614). The graphical representation of evaluation scores for each sector is given below. The Mean Squared Error (MSE) scores for each index show very low score and having perform best and compared to others evaluation scores.

Table 4.3: Evaluation Scores of Each Stock Sector Index.

Sr no.	Stock Indices	Model	RMSE	MSE	MAE
1	United Bank Ltd	Transformer	0.071885	0.005167	0.049879
2	Habib Bank Ltd	Transformer	0.041255	0.001702	0.027830
3	Bank Alfalah Ltd	Transformer	0.056351	0.003175	0.038994
4	Kohat Cement	Transformer	0.048259	0.002328	0.036131
5	Maple Leaf Cement	Transformer	0.053193	0.002829	0.040515
6	Fauji Fertilizer & co	Transformer	0.048383	0.002340	0.033476
7	Indus Motors	Transformer	0.060429	0.003651	0.040801
8	Millat Tractors	Transformer	0.046659	0.002177	0.031720
9	Atlas Honda	Transformer	0.049333	0.002433	0.034614

4.6 Comparison of the existing vs Proposed Model

The table below shows the comparative study of both the existing Model vs Proposed Model based on national and international level.

Table 4.4: Comparison of Existing Vs Proposed Model.

Descriptions	Year and Author	Methods/Model	Dataset	Evaluation Scores
Pakistan base comparison	Irfan Javid et al.[43] (2022)	Hybrid Model GRU and LSTM	PSX Dataset	GRU perform better than LSTM. The evaluation scores RMSE Values are 14.5877, 6.437014, 6.63871, and 6.806898,
	Muhammad Ali et al.[50] (2023)	EMD-LSTM hybrid Model	PSX Dataset	Evaluation matric scores MAE=234.3 and MAPE = 0.59
	Mazhar Hameed et al [51] (2021)	ANN, LSTM and LR	Karachi Stock Exchange KSX-100	Evaluation scores RMSE = (0.42), MAPE = (0.77) and MAE = (0.013).
Proposed Model	2023	Transformer Model	PSX Dataset	The Average evaluation scores for all indices of Pakistan stock Market Sectors are RMSE=0.052865, MSE=0.002866, and MAE=0.071720

4.7 Summary

The main focus of this study is to predict stock market accuracy while using the latest approach. This study uses the latest approach (Transformer Model) for the prediction of stock market accuracy. As the data were successfully prepared by using scaling and formatting data. After that MA and EMA used for stock crisis point identification and the Stochastics RSI for stock price bubbles prediction. Then different layers were applied for stock market prediction using transformer model as a result good scores of the evaluation scores were achieved of RMSE, MSE, and MAE for model better performance.

CHAPTER 5

CONCLUSION

The conclusions drawn from this research have the potential to significantly influence how decisions are made in the ever-changing stock market, where accurate forecasts are critical to minimizing losses and maximizing gains. The significance of this study within the broader financial context emphasizes how the stock market serves as an essential indicator of economic health and plays a key role in encouraging investment, economic growth, and financial stability.

5.1 Contribution

In conclusion, this study aims to make a meaningful contribution to the realm of stock market prediction in the context of the Pakistan stock market through the utilization of a transformer model. The dataset was collected from Pakistan Stock Market. The dataset was from three sectors having 3, 3 indices of the PSX. The dataset was inconsistent, irregular so first dataset was preprocessed using formatting, scaling process. The outcomes of this research underscore the efficacy of the transformer model in forecasting stock prices, outperforming conventional methods like Moving Averages (MA) and Exponential Moving Averages (EMA). The incorporation of StochRSI to detect crisis points and bubble prices further enhances the model's adaptability to capture market intricacies. While the results are promising, it is imperative to recognize inherent limitations, including data constraints and assumptions made during the modeling process. Evaluation score like Root Mean Squared Error (RMSE), Mean Squared Error (MSE), and Mean Absolute Error (MAE) used in this this for model improvement.

5.2 Conclusion

The conclusion of this research underscores the efficiency of the transformer model in predicting the stock prices, outperforming conventional methods like Moving Averages (MA) and Exponential Moving Averages (EMA) and RSI to predict the stock crash points and bubbles. The technical indicators used to check the behavior of the stock market. While, the results are promising, it is imperative to recognize inherent limitations, including data constraints and assumptions made during the modeling process. Evaluation score like Root Mean Squared Error (RMSE), Mean Squared Error (MSE), and Mean Absolute Error (MAE) used in the studies for model improvement and evaluation scores as compared to the traditional models used in previous studies.

The proposed study used these evaluation scores for each sectors index. For Banking sector, the evaluation score for United Bank limited is (RMSE=0.071885, MSE=0.005167, MAE=0.049879) for Habib Bank Limited, bank scores are (RMSE=0.041255, MSE=0.001702, MAE=0.027830) and for Bank Alfalah Scores are (RMSE=0.056351, MSE=0.003175, MAE=0.038994). Second is the Cement Sectors which also consist of 3 indices the first one is Kohat Cement which Scores are (RMSE=0.048259, MSE=0.002328, MAE=0.036131) second is Maple Leaf Cement having Score are (RMSE=0.053193, MSE=0.002829, MAE=0.040515) and last one of the cement sectors is Fauji Fertilizer & co having evaluation Scores are (RMSE=0.048383, MSE=0.002340, MAE=0.033476). Third and last sector is the Automobile sectors having 3 indices the first one is Indus Motors index having Scores are (RMSE=0.060429, MSE=0.003651, MAE=0.040801), second is Millat Tractors having Scores are (RMSE=0.046659, MSE=0.002177, MAE=0.031720), while third and last index of the last sector is Atlas Honda have evaluation Scores are (RMSE=0.049333, MSE=0.049333, MAE=0.034614).

The practical implications of these findings extend to investors, financial analysts, and policymakers, providing valuable insights for decision-making in the ever-evolving stock market landscape. Similar to any research endeavor, there exist areas for enhancement, and future inquiries could delve into refining the model, integrating additional indicators, and applying the approach to diverse financial markets. This study not only advances the comprehension of stock market prediction but also lays the groundwork for ongoing exploration and improvement of predictive models in financial forecasting.

5.3 Future Work

For improving accuracy more as compared to the proposed study need to consider more stock market indices dataset from different sectors of Pakistan stock market. Stock can be predicted more efficiently by considering more factors other than geopolitical, economical and pandemic etc.

By applying more technical indicators for identifying the behaviour of the stock market. If more evaluation matrices are considered then the model may perform more precision. Apply the model to other emerging markets of the stock markets using transfer learning to test generalizability. Use ensemble learning techniques to combine multiple models for better accuracy.

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