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Forecasting Modeling of Day of the Week Calendar Anomalies in Pakistan Stock Exchange: An Artificial Intelligence Perspective

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Abstract
Stock price forecasting provide valuable insight to the investor to facilitate well-informed investment decision making. The aim of this study is to examine the calendar anomalies i.e. DOW in Pakistan stock exchange though Artificial intelligence techniques. For this purpose, Support vector machine (SVM), Decision Tree (DT) and Artificial Neural Network is used to forecast the daily stock prices. The daily stock prices data of KSE100 index ranges from May,1994 to August 2023 is used as out variable while stock open, close, high and low prices are used as features/input variables. The training and testing ratio was 80:20 means 80% of the data was used in training and the 20% values were utilized for forecasting. To evaluate the accuracy of predictions, mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE)/mean absolute deviation (MAD), mean absolute percent error (MAPE), and R-squared (R^2) are taken as decision criteria. The daily forecasted stock prices show the almost zero error on Tuesday, Wednesday and Thursday in SVM. Decision tree show very low error in actual and forecasted stock prices. Therefore, it is concluded that, the DOW anomalies exist in KSE100 index of PSX. Results show that, SVM can better predict the stock prices than DT and ANN. These results conclude that the forecasted stock prices are much closer to actual daily stock price means the daily stock prices can be forecast in KSE100 index. These finding contradicts the Efficient market hypothesis and conclude that the Pakistan stock exchange (PSX) is weak-form inefficient market.
Keywords: Calendar anomalies, ANN, Decision Tree, SVM, EMH, Forecasting

1. Introduction

The forecasting of stock market fluctuations has been a subject of considerable discourse within the field of finance, as shown by the works of Fender (2020) and Said et al. (2021). A recurring and very significant inquiry pertains to the fundamental determinant of fluctuations in stock values, for which a definitive and precise answer remains difficult. One perspective is that the task of properly forecasting stock prices and comprehensively understanding the overall state of the stock market may provide a formidable challenge. However, an alternative viewpoint suggests that by the use of historical market data and the discovery of patterns within it, it is feasibly to possibly predict stock values and anticipate market trends.

The primary objective of stock market prediction is to provide investors with valuable insights to facilitate well-informed investment decisions. Additionally, it aims to minimize the possible adverse effects of market volatility on the overall stability of the capital market, said Wen et al. (2019). In order to attain these aims, scholars have focused their efforts on constructing models that provide insight into the correlation between historical stock price patterns and subsequent market fluctuations. Within the domain of financial prediction, two predominant approaches have emerged, namely technical analysis and fundamental analysis (Harikrishnan et al., 2021). The practice of technical analysis involves using previous price data and technical indicators to make predictions about future patterns in financial time series. In contrast to the Efficient Market Hypothesis, which posits the rapid assimilation of all available information into stock prices, proponents of technical analysis argue that evaluating previous price patterns may provide significant forecasting insights. In contrast, fundamental analysis delves into a wider range of elements, embracing both internal and external impacts on the success of an organization. External factors include several elements, such as interest rates and currency rates, which have influence on a company's operations. On the other hand, internal factors entail the examination of a company's press releases and financial statements (Nti et al., 2020).

Investment refers to the deliberate allocation of one's financial resources with the expectation of obtaining future benefits. Nevertheless, due to the inherent volatility of the future, the realm of investing is renowned for its fluctuating trends, whereby not all prognostications materialize as anticipated. Financial theory posits that using scientific research techniques and adhering to basic economic principles might potentially mitigate volatility and enhance the likelihood of attaining favorable results for investors. Hussain et al. (2022) propose that financial theory is predicated on the premise that investors, acting in a rational manner, endeavor to achieve their targeted returns by making logical and well-reasoned investment decisions. The stock exchange serves as a marketplace where people may participate in the purchase and sale of shares, bonds, and other securities issued by diverse firms. Within the PSX, it is noteworthy that individual investors have a substantial degree of power, as they account for more than 25% of the total capitalization. Conversely, these investments possess the capacity to provide profits or incur financial losses Riaz et al.(2019). Hence, it is important for individual investors to consider a multitude of aspects that might influence their decision-making process. Numerous variables have effect on the investment choices undertaken by individual investors (Mumtaz et al., 2023).

Investors should give due consideration to the prospect of investing in stock exchanges, as it presents them with opportunities to augment their money, get dividend payments, and safeguard against the adverse effects of inflation and currency depreciation. Stocks are renowned for their high level of liquidity and the inherent potential they provide for individuals to acquire partial ownership in firms. The possession of this ownership confers upon people the capacity to receive dividends and have influence over the administration of corporations. Stock markets also provide firms the benefit of capital raising. Hussain et al. (2022) believe that stock markets fulfill several functions, such as transmitting signals to managers and exerting influence on corporate governance. Irregularities are rare events that occur infrequently in non-investing contexts. Discrepancies within the realm of commerce manifest when securities deviate from the prevailing consensus of the market, hence presenting a formidable obstacle to its overall efficiency

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(Alvi et al., 2021). Investors depend on projected stock prices to guide their decision-making process. Gemici & Polat (2018)and (Erdas, 2019; Munir et al., 2024) argue that in an efficient market, there is a correspondence between the projected prices and the present prices. This phenomenon might be attributed to the fact that all pertinent information has already been assimilated into the prevailing stock prices.

Market efficiency is a concept that pertains to the extent to which asset prices accurately represent the entirety of the information that is currently accessible. The efficient market hypothesis posits that prices should promptly and precisely respond to new information, hence eliminating any opportunities for investors to regularly achieve superior performance relative to the whole market. Nevertheless, the concept of market anomalies poses a challenge to this assumption since it points out consistent trends or deviations from anticipated market behavior. Investors have the potential to capitalize on such anomalies with the aim to achieve extraordinary profits, indicating that market efficiency may not always be consistently upheld in practical contexts(Irtiza et al., 2021; Xiong, 2024).

The efficient market hypothesis, introduced in 1970, has been a focal point of discussion among economists. It posits that financial asset prices continuously reflect all available information, guiding investors accurately (Fama, 1970). In an efficient stock market, stock prices serve as unbiased estimators of their intrinsic values, with occasional deviations being essentially random and unrelated to observable factors (Damodaran, 2003; Cizakca, 2024). The market naturally adjusts over the medium and long term, preventing any consistent outperformance by investor groups employing specific strategies. Even if some investors achieve excess profits, this is largely a matter of luck. In such markets, earning excess returns without taking on greater risks is challenging due to the strong correlation between stock returns and long-term risk (Malkiel, 2000; Karim & Said. 2024). Efficient stock markets provide more accurate share value assessments and transmit clear signals (Andrei Shleifer, 2000). Investors can allocate their resources wisely, choosing profitable firms and reallocating funds from less profitable sectors because stock prices incorporate all relevant information. This efficient resource allocation promotes economic growth through profit maximization (Pagano, 1993).

1.1. Calendar Anomalies

Identifying anomalies presents a significant intellectual challenge due to their unexpected and irregular nature. Anomalies are unique or infrequent occurrences in a non-conforming context. These irregularities conflict with the Efficient Market Hypothesis (EMH), which posits that stock market returns cannot be predicted through regular patterns. However, empirical evidence suggests the existence of such patterns that impact market efficiency, giving rise to what we term as market anomalies (Anjum, 2020). Market anomalies in the stock market create discrepancies among different categories of stocks, challenging the principles of the EMH. Achieving and maintaining efficient markets can be daunting due to the continuous release and rapid dissemination of new information. These anomalies deviate from the norms of market efficiency and may result in investors receiving unusually substantial financial gains (Irtiza et al., 2021).

The quest for novel anomalies not only enhances our understanding of asset price trends across various financial markets but also has the potential to improve investment outcomes and provide greater incentives for asset managers (Zaremba & Nikorowski, 2019). Building on these findings, certain stock market anomalies exhibit long-term patterns, while others display transient tendencies. For example, the "day of the week effect" suggests that specific days tend to yield the highest market returns. The "month of the year effect," particularly the January effect, indicates that profits are often more pronounced in January. According to the monthly effect, average stock returns tend to be more favorable and higher in the first half of the month compared to the second (Irtiza et al., 2021).

The anomaly known as the day-of-the-week effect bears considerable significance for traders in financial markets due to its implications for predicting swings in returns and related trading risks over several days. The effective identification of tactics that result in financial gains is contingent upon the ability to discern periods during which stock prices and associated risks are at their minimum levels. The aforementioned phenomenon is particularly widespread in mature security markets, characterized by the vigorous trading of equities on days that exhibit significant price surges (Sakalauskas & Krikščiūnienė, 2007).

The notion of market efficiency, which was first introduced by Fama in 1970, has had further developments and refinements. The outcome is contingent upon several aspects, including the ease of accessing information, the quantity of individuals involved in the market, and the extent to which prices effectively represent pertinent information. The degree of efficiency within a market can vary throughout a continuum, ranging from low levels of inefficiency to high levels of efficiency, contingent upon a multitude of variables. Numerous scholarly investigations have been conducted to examine the evaluation of market efficiency in various marketplaces, time periods, and categories of pertinent information (Alekneviciene et al., 2018; Bowman & Buchanan, 1995; Goss, 1983).

1.2. Problem statement and Research Gap

Market efficiency has always been a fascinating topic among researchers and practitioners and examined through several calendars anomalies such as day of the week effect, week of the month and moth of the year etc. Yardımcı & Erdem, (2020) investigated the 19 Muslim countries using GARCH method to examine DOW effect and conclude that, different days shows significant DOW effect in different countries. These results neglect the concept of market efficiency in MENA and GCC regions. Sahoo (2021) empirically examined daily closing data of Nifty50 index, Nifty50 Mid-cap, Nifty100 index and Nifty100 Mid-cap index. The study has applied GARCH model on both before and after covid-19 crises data and found that the Monday returns are negative during covid-19 and positively significant before covid-19 while Tuesday stock returns found positively significant during the crises of covid-19. Aggarwal & Jha (2023) investigated weak form efficiency in six Asian countries using different ARCH and GARCH models including OLS method. The finding revealed that daily and monthly returns of almost all countries found significant that neglect the existence of Market efficiency. Miss et al. (2020) revisited the Monday effect in Germany. The study examined the data from DAX ranges from year 2000-2017 and applied the GARCH model. The study disclosed that the DAX is an efficient and most liquid market as market affirmed the non-existence of Monday effect.

The above mentioned studies has found the presence of calendar anomalies using different Box-Jenkins's model such as ARMA, ARCH or family of GARCH models but none of the study as per the author's knowledge has used machine learning and deep learning techniques to investigate calendar anomalies especially in the context of Pakistan stock exchange (PSX). This study is intended to fill this gap. The current study will increase the insight of efficient market hypothesis in Pakistan under different machine learning and deep learning techniques such as Artificial Neural Network and Support Vector machine and Decision Tree to test the calendar anomalies. The study is important for the investors because the techniques used in this study will provide the evidence of stock price and predictions of each day of the week. So that, the investors will be able the make rational decision to choose best day and for their investment in PSX. This study will also help the investors to reduce their investment risk and to make better portfolio optimization.

1.3. Contribution

This study has contributed in literature by using Machine learning and deep learning techniques to predict stock prices of KSE100 index using 29 years of data. Prior study has used different classical regression models like OLS, ARIMA, ARCH and GARCH models. Classical models only test the effect of DOW anomalies and concluded that which day has effect on returns either positive or negatively significant but the accuracy level of stock price prediction was missed in the literature especially in KSE100 index. For this purpose, the data was taken from April, 1994 to August, 2023. The data was consisting of Daily stock prices, Closing Price, High Price, Low Price and Stock returns. This study was intended to predict the daily closing price of each day of the week so the closing price of the stock along with its features were bifurcated into Monday, Tuesday, Wednesday, Thursday and Friday. Two machine learning techniques such as SVM and Decision Tree and Deep learning technique Artificial neural network were used to predict the closing prices of each day of the week. The accuracy of prediction was further analyzed though five evaluation criteria like MSE, RMSE, MAE/MAD, MAPE and R-square. The range of these parameters is 0 to ∞. The value closed to zero means high level of accuracy. In other words, lower value of error means more accurate prediction. The results of this study proved that Artificial neural network shows the best accuracy as compared to SVM and Decision tree techniques.

This study is further organized as section 2 belongs to Literature review, material and methodology of the study is presented in section 3, the results will be discussed in section 4 and section 5 will encompasses the study conclusion, implication and future research directions.

2. Literature Review

Gayaker, Yalcin, and Berument (2020) studied the day of the week effect in Turkey ISE100 index using the daily closing prices. The study reveals that, as compare to Monday, the stock returns on Friday decrease with the decrease of interest rate. The reason behind this phenomenon is that, if the payment settlement date is after two days, then on Friday, investor have four days to invest his money in financial markets or elsewhere. This empirical investigation revealed that, day of the week is not an anomaly and this anomaly can be reducing if the settlement period is reducing to one day or less. Market participants can tackle the day of the week effect's impact on market anomalies by adjusting settlement dates and adjusting monetary policy to alter risk-free interest rates. The day of the week anomaly was examined by Yang and Nemlioğlu (2023) in the capital markets of china and America. Eleven years of data from Gem-composite index of China and Russell-1000 index from America was observed in the study. To investigate the week day effect anomaly, two classical models such as GARCH and ARMA-GARCH were used. The statistics proved that, there is no evidence found with respect to DOW anomaly in both markets even the author cross checked the both markets by separating Covid-19 period and re-examined through OLS method but the results were robust with the former statistics.

On the contrary, Samaniego, Salgado, and Pérez (2022) examined two calendar anomalies i.e.; DOW as well as Holiday effect anomaly. The data ranges from January, 2000 until September 2018 from Mexican stock exchange. The data set include large capitalization, Small capitalization and medium capitalization data (sub-indices of MSE) and Price & Quotation index data. The investigation concludes that, DOW anomaly was present in all-time series with respect to Volatility and stock returns along with holiday effect however the holiday effect was only found in Medium Cap sub-index return series. Another study of Mohamad Shariff and Yusof (2021) has revealed the mixed evidence of calendar anomalies. The study intended to explore three calendar anomalies i.e.; DOW, MOY and Quarterly anomalies in KLCI index of Malaysia. For this purpose, the data was collected from January, 2015 to December, 2018. To examine these anomalies, Results of GARCH model spot insignificant DOW effect. According to the argument of investigation, insignificant DOW effect might be occurred due to small time series. While, the results show that, stock returns of the month of May, November and the month of December significantly proved the presence of MOY anomaly. For the third under considered anomaly, only first Quarter was found significant in Malaysian capital market. Further investigation to unveil DOW anomaly was performed by Afrilianto and Daryanto (2019) in the Indonesia. Daily stock returns of twenty-two companies listed in LQ45 index from 2013 until 2018 was taken for the examination of DOW anomaly. After the multiple regression model, two statistical parameters such as T-test and F-test were used. The research consequent that, both simultaneous and partial effect found significant in all twenty-two firms listed in LQ45. It is also claimed that, this study would be beneficial for investment decision making Indonesia.

The DOW, MOY, and TOM are commonly used as benchmarks to assess the overall performance of stock markets. These indices represent different sectors or groups of stocks, and their variations in returns can be attributed to various factors such as economic conditions, geopolitical events, or investor sentiment. Understanding the reasons behind these inconsistencies is crucial for investors to make informed decisions and manage their portfolios effectively. Gharaibeh (2021) examined DOW, MOY and TOM anomaly is Gulf Co-operation Countries using data from 2012 until 2017. The GARCH (1,1) and OLS results unveiled that Monday returns are significant in Bahrain, Thursday is significant in Dubai, Saudi Arabia and in Bahrain too while only GARCH (1,1) exposed Monday significance in only in Kuwait. Wednesday is significant in Dubai on the basis of GARCH (1, 1) and OLS too. In Kuwait, only January found significant under GARCH (1, 1) and OLS statistics while Dubai, Qatar and Abu Dhabi found the present of MOY effect anomaly. GARCH (1, 1) statistics proved TOM in Dubai and Qatar only and on the flipside, TOM anomaly found significant only in Oman with respect to GARCH (1, 1) and OLS results. The behavior of investors is crucial in the stock markets. They apply their past experience in the following investment.(Aleknevičienė et al., 2022) examined the three most famous calendar anomalies to test "Adaptive market hypothesis" in Baltic capital markets. The time frame used for this investigation was from year 2000 to 2017 and applies three statistical techniques such as 1) GARCH (1, 1) model, 2) Kruskal-wallis, and 3) rolling window for the examination of DOW, MOY and TOM anomaly. The outcomes proved the existence of DOW (Friday), MOY (January & July) and TOM in all three markets. This examination also concludes that, these three proven anomalies has shown more time varying trend and disappeared in Global Financial Crises from 2007 to 2009.

Ferrouhi et al. (2021) investigated DOW and MOY with respect to both Islamic and Gregorian calendar in African capital market. The data collection period ranges from start of 2009 until end of 2019. Egypt, Namibia, Kenya, Botswana, BRVM, Tunisia and Zambia were the sampled countries in this study. The results of OLS statistics provided the evidence that, Monday is significant in Namibia & BRVM and in Namibia & Kenya, Friday found significant. For MOY effect anomaly, in Zambia and Botswana, January found significant and December found significant only in Botswana as well as in Tunisia stock market only Ramadan found significant. These results negate the theory of efficient market hypothesis in African stock markets. Financial markets cannot be predicted on the basis of a single theory because capital markets are cross sectional in nature. To test the daily and monthly calendar anomalies, Dutta and Das (2021) explored NSE-Nifty and utilized the data from 2001-2015. The data of every certain point was taken and averaged to get the value of Monday. This procedure kept following for entire period for both daily and monthly data. The results of Least-square method show that, Monday and Friday effect exist in NSE-Nifty as well as March returns and October anomalies were present too while rest of the months were not visible that shows the inefficiency of stock NSE-Nifty capital markets. The Dhaka Stock Exchange is experiencing rapid growth, attracting both domestic and international investors. The government's efforts to improve regulatory frameworks and promote transparency have contributed to its expansion, ensuring investor protection and minimizing market manipulation. Continuous monitoring helps identify potential risks and issues, enabling timely intervention and corrective measures. Ahmed (2021) collected the daily and monthly data of DSE-all-share price index from 1987 to 2020. Different analytical models were applied to these data set such as ARIMA model with lag values, Auto-correlation, Momentum Effect and Run test. The result findings exposed that Stock price trends and predictability patterns alter with the change of above mentions test which exhibits the weak form inefficiency of Dhaka Stock exchange. Dinesh, Jyothi, and Ramyashree (2021) Explored the BSE-Sensex index using the daily data from year 2000 to 2020 and divided the whole data into sub-sample period of 5 years i.e.; 2000-2005, 2006-10, 2011-15 and 2016-20. The study only applies descriptive statistics and realized that the values of t-test not proven significant evident that, BSE-Sensex is in efficient stock exchange in Weak form.

It is observed by several researchers that the stock return on Monday are relatively lower than other days of the week. To confirm this fact, Khan et al. (2023) considered to examine Asian stock market including Pakistan, Chine, Taiwan, Indonesia, India and South Korea. The examination undergone through three statistical models as OLS, Kreskas Wallis test and GARCH (1, 1) model. The daily stock returns and trading volume data was used for the analysis. In India and Malaysia there is no evidence found for DOW effect however trading volume volatility found significant in all stock exchanges except in Malaysia. On Monday, it was observed that, trading activities is comparatively less. Further, facts reveled that, stock returns and trading volume does not follow the same pattern. In conclusion, these markets are weak form inefficient.

3. Material and Methods

The primary purpose of this study is to predict the closing price of each day of the week to test the market efficiency of KSE100 index. For this purpose, the following procedure was adopted as shown in figure1.

- The data was collected from Investing.com for the purpose of predicting daily closing prices to test Market Efficiency of KSE100 index. The data ranges from July, 1994-August, 2023.
- In data pre-processing, the outliers were deleted. The data was segregated into days of the week i.e; Monday, Tuesday, Wednesday, Thursday and Friday.
- The data was then split into training, validation and testing. Here the two major statistical analysis were performed.
- First the descriptive analysis which contain mean, median, Standard deviation, skewness, kurtosis, Quartile 1,2 and 3. The second analysis was performed to predict the closing prices of each day of the week by using opening prices, high prices low prices and daily stock returns as features to predict closing prices under two machine learning techniques such as Decision tree and Support Vector Machine and one deep learning techniques as Artificial Neural Network.
- The comparison was also performed to evaluate the prediction results of Machine learning techniques i.e; Decision Tree(DT) and Support Vector Machine(SVM) and Deep Learning Techniques Artificial Neural Network(ANN). After comparison, it is concluded that the performance results of ANN were quite appropriate than SVM and DT.
- The prediction output of these techniques were evaluated under five performance evaluation criteria i.e.; MSE, RMSE, MAE/MAD, MAPE % and R-Square.

3.1. Dataset Collection

This research is intended to predict the stock prices of KSE100 index. For this purpose, daily KSE100 index data including Stock opening price, Closing price, High price, Low price, trade volume and stock returns data was downloaded from Investing.com. the data comprises 29 years from May,1994 to August 2023. Pakistan stock exchange is a dynamic capital market. Initially there were three stock exchanges in Pakistan i.e.; Islamabad stock exchange, Lahore stock exchange and Karachi stock exchange. Karachi stock exchange was established in 1947 right after Pakistan independence. In 2016, all stock exchange merged into Karachi stock exchange and known as Pakistan stock exchange(PSX). In May 2017, the Pakistan Stock Exchange (PSX) achieved a significant milestone by becoming a constituent of the MSCI Emerging Market Index, marking its recognition and inclusion on the global investment stage. With this inclusion, it garnered attention from international investors seeking opportunities in emerging markets. The PSX is supported by a robust financial ecosystem, boasting nearly 400 brokerage houses and 21 asset management companies as members.

These institutions play a pivotal role in facilitating trading and investments, contributing to the growth and dynamism of Pakistan's stock market, making it an increasingly attractive destination for both domestic and foreign investors.(Anjum, 2020).

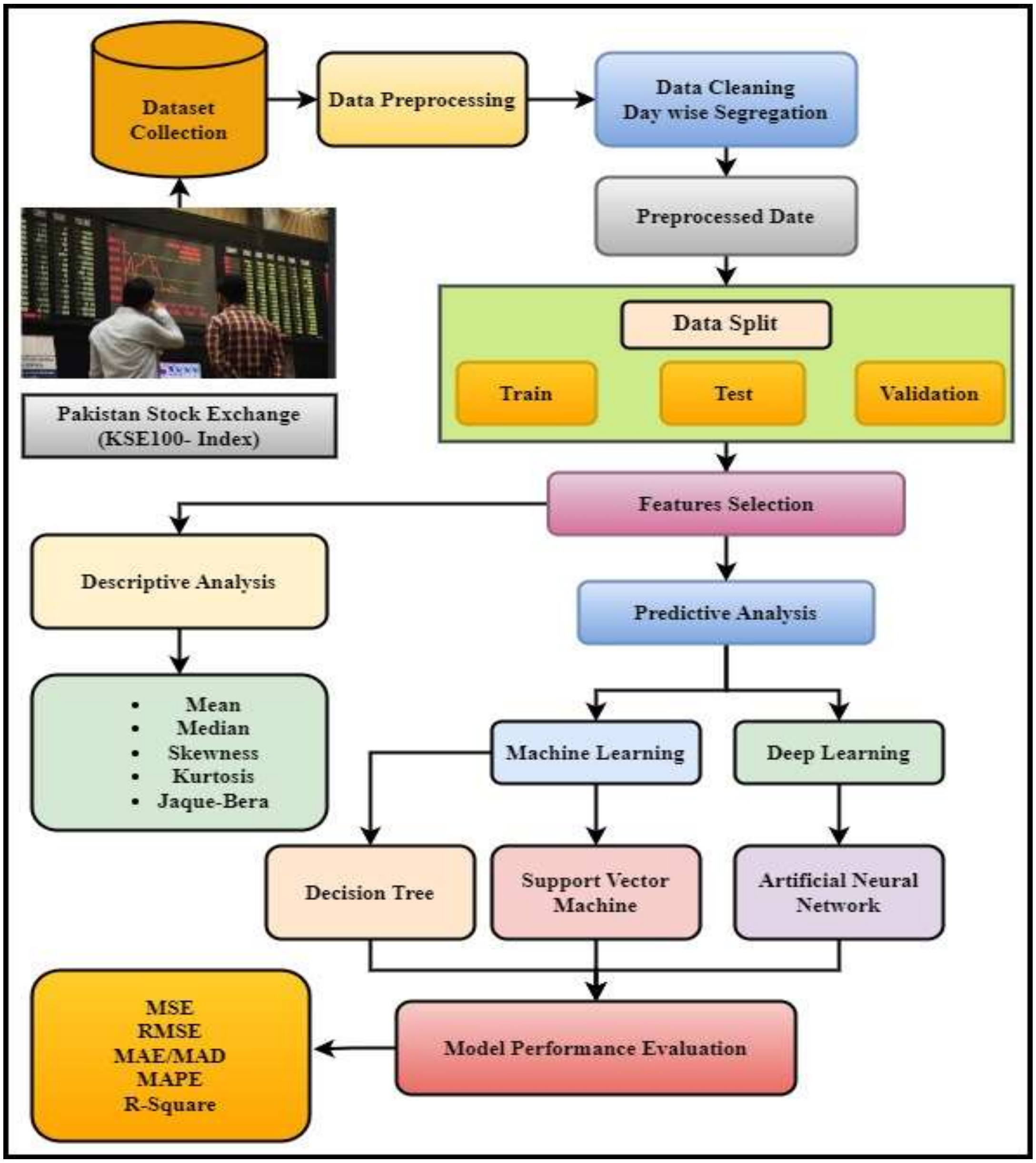

Figure 1: Proposed pipeline model for stock price prediction

3.2. Data Preprocessing and Data Split

In the begging days of KSE100 index, Friday was the public holiday and after few years the government change the public holiday on Saturday. To coordinate with the world trading days, the government again changed the public holiday on Sunday that is continued till date. The values of Saturdays and Sundays were less in number, so the study removed the values of these days as outlier and the rest of the data was consisting of Monday, Tuesday, Wednesday, Thursday and Friday along with opening price, high price, low price and daily stock returns were the features selected to predict closing price of each day of the week. Then the data was split for training, testing and validation. The ratio of training and testing data was 80:20.

3.3. Types of Analysis

3.3.1. Descriptive Analysis

Prior to predict the closing prices of each day of the week, it is necessary to test the descriptive statistics of predictor and predicting variables. The main variable is the closing price of each day of the week while opening price, high price, low price and stock return of specific day were predicting variables. The descriptive statistic shows that the mean value of Monday ranges from 17444.92 to 17698.93, Tuesday ranges from 17445.13 to 17683, Wednesday 17399.52 to 17513.30, Thursday 17685.70 to 17788.96 and mean values of Friday ranges from 19076 to 19196.36. This means that the mean results of predicting and predictor variable are about close to each other shows that the high price, low price, opening price and stock return are best feature to predict stock closing prices. The ranges of skewness and kurtosis values of Monday, Tuesday, Wednesday, Thursday and Friday are also between -3 to +3 which shows that the data of predictor and predicting variables are normally distributed. The results of descriptive statistics present in table 4.1 are appropriate and allow us to proceed further to perform prediction of each day of the week.

3.3.2. Predictive Analysis

First technique used in stock price prediction in this study was Artificial neural network(ANN). The target variable was closing price and the other time series such as opening price, high price, low price, trading volume and stock returns used as feature to predict closing stock price on a particular day. All the time series data were segregated into Monday, Tuesday, Wednesday, Thursday and Friday and ANN applied on all the days separately. Eighty percent of the data was used to trained the ANN and twenty percent data was used to validate and predict the closing stock price. The activation function was "Hyperbolic tangent function" because the linear, Gaussian and ReLu function overestimate the model and results were quite haphazard. The evaluation criteria for ANN were MSE, RMSE, MAE/MAD, MAPE and R-square were used. The second technique was Decision tree to predict the daily closing price of Monday, Tuesday, Wednesday, Thursday and Friday. Similar as ANN, eighty percent data were used for training the model and 20 percent data was used to validate and predict the closing price. In Support vector machine techniques, the linear algorithm was used with degree = 3, Gamma =1 and constraint violation = 1, "tolerance of termination criteria = 0.001 and Epsilon = 0.01.

3.3.3. Decision Criteria

Different metrics are often used in different fields to evaluate the accuracy of predictions. These include mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE)/mean absolute deviation (MAD), mean absolute percent error (MAPE), and R-squared (R^2). included. While MSE and RMSE measure the mean squared difference between expected and actual values, RMSE provides a more easily understood scale. MAE and MAD represent mean absolute error and can account for outliers. MAPE expresses inaccuracy as a percentage and allows comparisons between different datasets. R-squared quantifies the proportion of variation revealed by the model, with higher values indicating better fit. As the predictions improve, the values of these metrics decrease, demonstrating the efficiency of the model. The accuracy criteria defined by (Jierula et al., 2021) and utilized by Kahraman & Akay, (2022); Zhang et al., (2022) is used in this study. The range of errors explained above have range from 0 to ∞. Smaller the value of above errors the prediction accuracy will be high. The range of R^2 is explained by Ozili (2023) is defined as the value of R^2 from 0-0.09 is not acceptable, from 0.10 to 0.50 is acceptable when few independent variable are found significant and the value from 0.50-0.99 is acceptable when most of the independent variables found significant.

4. Results and Discussion

4.1. The Study was intended to test the market efficiency of KSE100 index

4.1.1. Descriptive Analysis

The Table.1 explain the descriptive analysis of predictor and predicting variables of days the week. In descriptive analysis, the study includes mean, median, standard deviation, skewness, kurtosis, quartile 1, 2 and 3. The value of mean for Monday, Tuesday, Wednesday, Thursday and Friday are near to each other represents that the predicting and predictor variables move in a same direction. The median values are also proves showing the co-movement of features and target variable. the values of skewness and kurtosis are also in the range of -3 to +3 exhibits the data normality of all days of the week. The co-movement of features and predicting variable can be observed in figure.2.

4.2. Predictive Analysis

4.2.1. Artificial Neural Network

The table 3.1 provides a detailed assessment of an Artificial Neural Network (ANN) machine learning model's performance in predicting stock prices across different weekdays using various evaluation criteria. From Monday to Friday, the model's Mean Squared Error (MSE) ranges from 0.421 to 1.007, with Monday showcasing the lowest error. Root Mean Squared Error (RMSE) values range from 0.649 to 1.003, again with Monday exhibiting the most accurate predictions. Mean Absolute Error/Mean Absolute Deviation (MAE/MAD) values vary from 0.079 to 0.188, with Friday having the lowest error. Mean Absolute Percentage Error (MAPE) fluctuates significantly, from 10.29% to 51.31%, with the lowest on Monday. The correlation coefficient (R) ranges from 0.604 to 0.733, with Tuesday having the highest correlation. In summary, the ANN model displays variable performance across weekdays, performing best on Monday and Tuesday, but facing challenges on Wednesday and Thursday, where errors and MAPE are notably higher. The graphical representation of model prediction can be seen in figure 2.

4.2.2. Decision Tree

The table provides a detailed assessment of a Decision Tree machine learning model's performance in predicting stock prices on different weekdays, with metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error/Mean Absolute Deviation (MAE/MAD), Mean Absolute Percentage Error (MAPE), and R-squared (R2) for each day. From Monday to Thursday, the model demonstrated robust and consistent performance. MSE values were consistently low, ranging from 0.004 to 0.006, indicating that the model's predictions closely aligned with actual stock prices. RMSE values were also low, varying from 0.063 to 0.077, showing minimal error in the model's predictions in the same units as stock prices. MAE/MAD values were consistently low as well, ranging from 0.041 to 0.046, suggesting that the model's predictions were, on average, close to the actual prices. MAPE, representing the percentage error, remained relatively low, with values ranging from 52.21% to 72.3%, indicating good predictive accuracy. Furthermore, R2 values were consistently high, varying from 0.995 to 0.996, indicating that the model explained nearly all the variance in stock prices on these days.

However, on Friday, the model's performance diverged significantly. MSE increased to 0.204, RMSE rose to 0.452, and MAE/MAD increased to 0.068, indicating less accurate predictions and higher errors compared to the previous days. MAPE also increased to 63.27%, signifying a larger percentage-wise difference between predicted and actual prices. Notably, the R-square value dropped to 0.738, suggesting that the model struggled to explain the variance in stock prices on Fridays, potentially due to unique market dynamics on that day. In summary, the Decision Tree model demonstrated strong and consistent predictive capabilities for stock prices from Monday to Thursday, but its performance faced challenges on Fridays, likely necessitating further model refinement or the incorporation of additional factors to better capture the dynamics of the market on that specific day.

Table 1: Descriptive Analysis of Predictor and Predicting Variables

Days	Descriptive	Price	Open	High	Low	Return
Monday	Mean	17550.703	17592.181	17698.929	17444.92	17450.703
	Median	11002.435	11036.805	11146.775	10913.49	10902.435
	SD	16373.763	16411.022	16503.148	16048.29	12684.234
	Skewness	0.6115	0.6101	0.6107	0.6114	0.6115
	Kurtosis	-1.2204	-1.224	-1.2225	-1.2205	-1.2204
	Q1	1984.6125	1995.2875	2002.8375	1979.518	1884.6125
	Q2	11002.435	11036.805	11146.775	10913.49	10902.435
	Q3	33860.878	33943.983	34097.85	33732.3	33760.878
Tuesday	Mean	17567.754	17560.366	17683.004	17445.13	17467.754
	Median	10932.875	10948.64	11066.07	10853.22	10832.875
	SD	16411.823	16407.75	16510.122	16311.81	16411.823
	Skewness	0.6123	0.6131	0.6119	0.6133	0.6123
	Kurtosis	-1.2229	-1.2211	-1.2234	-1.2214	-1.2229
	Q1	1966.9925	1973.0025	1996.5325	1940.333	1866.9925
	Q2	10932.875	10948.64	11066.07	10853.22	10832.875
	Q3	33899.138	33861.963	34055.075	33756.48	33799.138
Wednesday	Mean	17513.297	17504.444	17626.857	17399.52	17413.366
	Median	10941.94	10956.96	11059.62	10879.27	10841.94
	SD	16408.898	16401.489	16502.553	16315.75	16408.834
	Skewness	0.6205	0.6211	0.6198	0.6212	0.6205
	Kurtosis	-1.2116	-1.2095	-1.2119	-1.2101	-1.2116
	Q1	1968.4	1968.28	2003.06	1956.32	1868.4
	Q2	10941.94	10956.96	11059.62	10879.27	10841.94
	Q3	33932.81	33917.85	34111.5	33786.96	33832.81
Thursday	Mean	17785.696	17788.961	17910.315	17671.35	17685.696
	Median	11264.95	11264.85	11326.14	11158.91	11164.95
	SD	16462.293	16467.84	16572.423	16365.21	16462.293
	Skewness	0.5903	0.5917	0.5909	0.591	0.5903
	Kurtosis	-1.2541	-1.2501	-1.2523	-1.2521	-1.2541
	Q1	1996.995	1990.615	2011.68	1973.385	1896.995
	Q2	11264.95	11264.85	11326.14	11158.91	11164.95
	Q3	34098.69	34184.655	34332.865	33924.87	33998.69
Friday	Mean	19196.36	19188.373	19312.701	19076.85	19096.36
	Median	12000.03	11974.17	12086.58	11938.24	11900.03
	SD	16417.507	16412.928	16506.224	16328.27	16417.507
	Skewness	0.4775	0.4776	0.4769	0.4783	0.4775
	Kurtosis	-1.3628	-1.3627	-1.3633	-1.3612	-1.3628
	Q1	4463.04	4486.31	4495.56	4455.06	4363.04
	Q2	12000.03	11974.17	12086.58	11938.24	11900.03
	Q3	35973.68	35936.31	36048.52	35758.52	35873.68

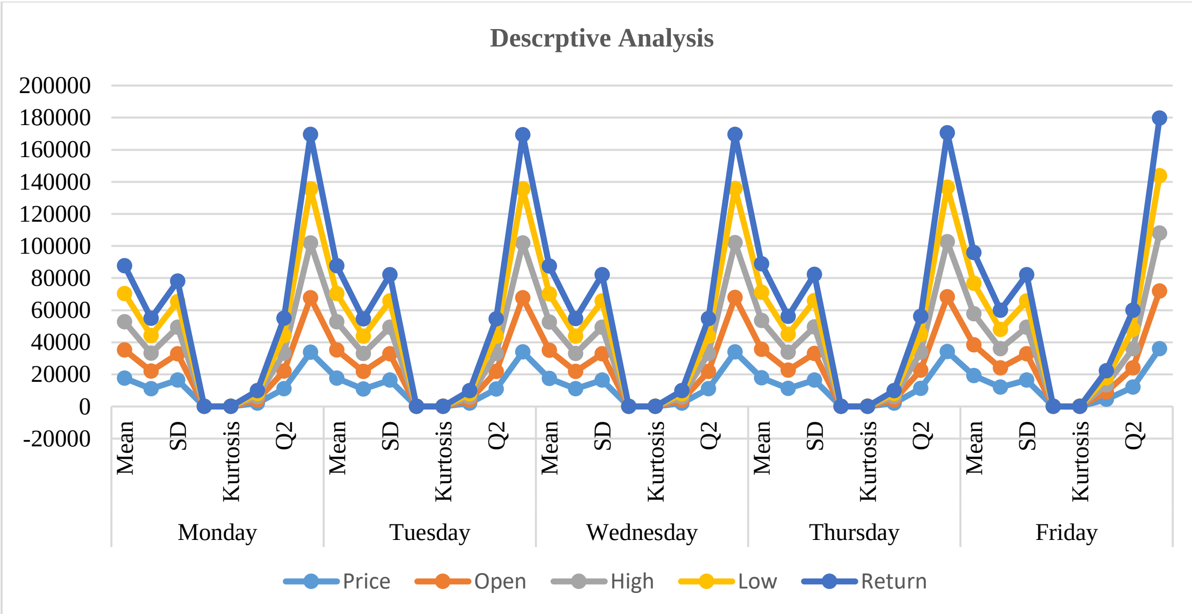

Figure 2: Descriptive Analysis of the Features and target variable of all days of the week

Table 2: Tabular Results of Artificial Neural Network

Machine Learning Techniques	Evaluation Criteria	Monday	Tuesday	Wednesday	Thursday	Friday
Artificial Neural Network	MSE	0.421	0.726	0.861	1.007	0.459
	RMSE	0.649	0.852	0.928	1.003	0.677
	MAE/MAD	0.084	0.129	0.164	0.188	0.079
	MAPE	11.4	11.31	51.31	27.21	10.29
	R-square	0.604	0.733	0.421	0.72	0.639

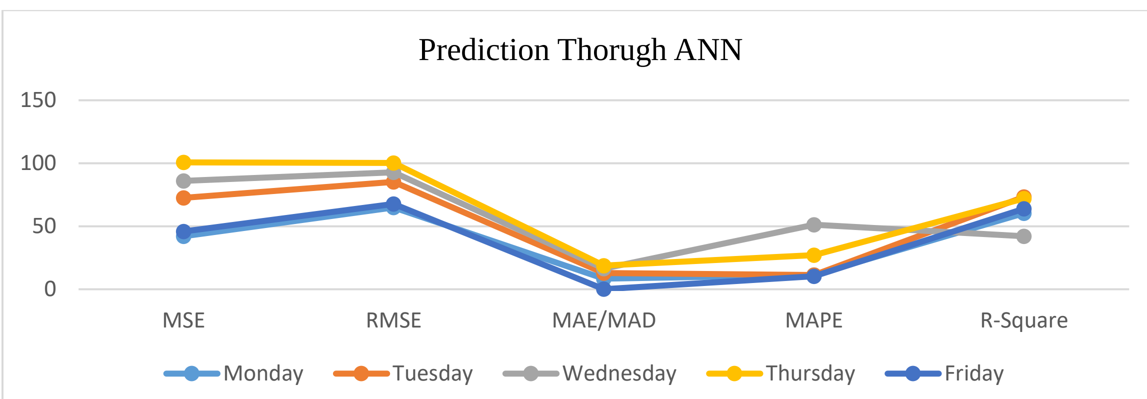

Figure 3: Prediction Through ANN

Table 3: Tabular results of Decision Tree

Machine Learning Techniques	Evaluation Criteria	Monday	Tuesday	Wednesday	Thursday	Friday
Decision Tree	MSE	0.004	0.004	0.004	0.006	0.204
	RMSE	0.063	0.063	0.063	0.077	0.452
	MAE/MAD	0.041	0.044	0.044	0.046	0.068
	MAPE	52.21	72.3	61.06	60.46	63.27
	R-square	0.996	0.995	0.996	0.996	0.738

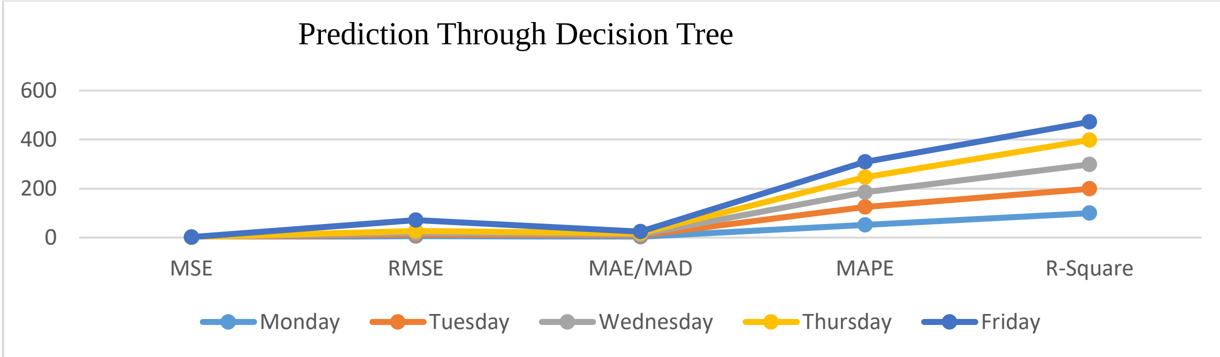

Figure 4: Graphical Representation of Prediction through DT

4.2.3. Support Vector Machine

The table presents a comprehensive evaluation of a Support Vector Machine(SVM) model's performance in predicting stock prices throughout a trading week. Several key metrics were used to assess the model's accuracy and consistency. Mean squared error of Monday is 20% but 23% of Friday but rest of the days shows zero percent error means 100% prediction that is not valid and same pattern was sown by Root mean square error the values of mean absolute errors are also very small. Mean absolute errors and MAPE percentages are also quite small shows the high level of prediction accuracy. The values of R-square for Tuesday, Wednesday and Thursday are 100 percentages. These statistics are also not appropriate because the predicting prices does not 100 percent depends upon their historical prices. These haphazard results show that the SVM overestimate the predicting values of stock closing prices.

Table 4: Tabular Results of Support Vector Machine

Machine Learning Techniques	Evaluation Criteria	Monday	Tuesday	Wednesday	Thursday	Friday
	MSE	0.205	0.000	0.000	0.000	0.238
	RMSE	0.453	0.000	0.000	0.000	0.488
SVM	MAE/MAD	0.036	0.008	0.009	0.007	0.037
	MAPE	8.81%	11.43%	12.18%	5.86%	17.34%
	R-square	0.714	1	1	1	0.704

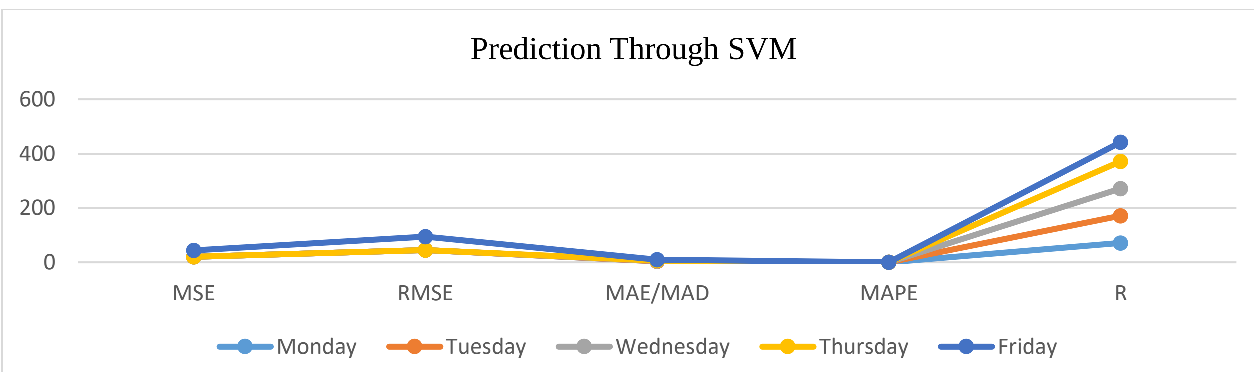

Figure 5: Graphical Representation of Prediction through SVM

4.2.4. Self-Comparison of the Proposed Model

This study aimed to test the market efficiency of KSE100 index though calendar anomalies DOW using two machine learning techniques such as SVM and Decision tree and one deep learning technique i.e; ANN. The accuracy of stock price prediction is very important and fascinating for investors. The prediction results of SVM shows that as per the decision criteria like MSE, RMSE, MAE/MAD, and MAPE, the values should be between 0-∞. Smaller values of these errors means higher rate of prediction accuracy.

4.3. Support vector machine

The range of MSE and RMSE values is relatively narrow, 0.205–0.238 and 0.453–0.488, respectively, indicating consistently low prediction errors. The MAE/MAD range is also narrow, between 0.007 and 0.009, reflecting the small absolute error. The MAPE value fluctuates widely from 5.86% to 17.34%, with the highest value on Friday. The R-squared value is in the moderate range between 0.704 and 1.0, indicating good prediction accuracy.

4.4. Decision tree

MSE and RMSE: The range of MSE and RMSE values is narrow and consistent across all data, indicating that the predictions are highly accurate with values between 0.004 and 0.452. The range of MAE/MAD values is also narrow from 0.041 to 0.068, indicating a low absolute error. The MAPE value fluctuated widely from 52.21% to 72.3%, with the highest value on Tuesday. The R-squared values show a very high range of 0.738 to 0.996, indicating good predictive performance, especially for decision trees.

4.5. Artificial Neural Network (ANN)

ANN has a larger range of MSE and RMSE values, 0.421–1.007 and 0.649–1.003, respectively, and a larger prediction error. The MAE/MAD range for these values is relatively wide from 0.079 to 0.188, meaning the absolute error is moderate to high. The MAPE value fluctuates widely between 10.29% and 51.31% and reached its highest value on Wednesday. The R-squared values varied between 0.421 and 0.733, indicating different levels of predictive accuracy for each date.

In summary, decision trees consistently have the narrowest range of error metrics (MSE, RMSE, MAE/MAD) and highest R-squared values, meaning better predictive accuracy. On the other hand, SVM and ANN show high performance across the days.

5. Conclusion

Stock price predictions provide investors with valuable insights that help them make informed decisions in their investment activities. This study seeks to apply artificial intelligence (AI) to investigate calendar anomalies within the Pakistan Stock Exchange (PSX), specifically day of the week (DOW) and month of the year (MOY) anomaly techniques. The purpose is Predict daily and monthly stock prices using support vector machines (SVM), decision trees (DT), and artificial neural networks (ANN) techniques. Using data of KSE100 index from May 1994 to August 2023, daily and monthly stock prices are used as dependent variables, and the characteristics/input variables include stock price opening price, closing price, highest price, and lowest price. Contains values. The ratio of training and testing data is set to 80:20, with 80% of the data used for training and the remaining 20% for prediction.

Forecast accuracy uses various metrics such as mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE)/mean absolute deviation (MAD), mean absolute percent error (MAPE), and R-squared. will be evaluated. (R^2). SVM had very low error rates on Tuesday, Wednesday, and Thursday, and Decision Tree had very low error rates for both actual and predicted stock prices. Additionally, the study also confirmed the presence of a DOW anomaly in the KSE100 index of PSX. The results show that SVM outperforms DT and ANN in stock price prediction and the daily stock price prediction is close to the actual stock price, suggesting the feasibility of daily stock price prediction within the KSE100 index. These results question the efficient market hypothesis and argue that a weak form of inefficiency exists in the Pakistan Stock Exchange (PSX).

This study is unique in its nature. Previous studies have used GARCH, ARIMA and other classical models. These studies were not being able to forecast the daily stock price with higher certainty and accuracy. The techniques used in this study were state of the art technique and provide better insights to the investor for decision making than prior techniques. This study can be used by investors, fund managers, potential investors and investment companies to minimize their risk and better yield. This study has only incorporate DOW calendar anomalies, future studies can examine other calendar anomalies. Machine learning and deep learning techniques are most emerging techniques now a days, further work can be done with other technique like Random forest, CNN and can predict the time series using mentioned techniques.

References

Afrilianto, A., & Daryanto, W. M. (2019). Market Anomaly Testing: The Day of The Week Effect on LQ45 Stocks in Indonesia Stock Exchange. *International Journal of Business, Economics and Law*, *19*(1), 74–82.

Aggarwal, K., & Jha, M. K. (2023). Stock returns seasonality in emerging asian markets. *Asia-Pacific Financial Markets*, *30*(1), 109–130.

Ahmed, F. (2021). Assessment of Capital Market Efficiency in COVID-19. *European Journal of Business and Management Research*, *6*(3), 42–46.

Aleknevičienė, V., Klasauskaitė, V., & Aleknevičiūtė, E. (2022). Behavior of calendar anomalies and the adaptive market hypothesis: evidence from the Baltic stock markets. *Journal of Baltic Studies*, *53*(2), 187–210.

Alekneviciene, V., Kviedaraitiene, L., & Alekneviciute, E. (2018). Semi-strong form efficiency in the baltic stock markets under changing economic situation. *Engineering Economics*, *29*(5), 495–506.

Alvi, J., Rehan, M., & Mohiuddin, I. (2021). Calendar Anomalies or illusions? Evidence from Pakistan Stock Market. *Ege Academic Review*, *21*(3), 285–298.

Andrei Shleifer. (2000). Are Markets efficient? No, arbitrage is inherent risky. *A10*, *236*(125).

Anjum, S. (2020). Impact of market anomalies on stock exchange: a comparative study of KSE and PSX. *Future Business Journal*, *6*(1), 1–11.

Bowman, R. G., & Buchanan, J. (1995). The Efficient Market Hypothesis—A Discussion of Institutional, Agency and Behavioural Issues. *Australian Journal of Management*, *20*(2), 155–166.

Cizakca, M. (2024). Understanding the Determinants of Foreign Trade Volume in Turkiye: An Empirical Analysis. *Journal of Business and Economic Options*, *7*(1), 19-28.

Damodaran, A. (2003). *Investment philosophies: successful strategies and the investors who made them work.*

Dinesh, K., Jyothi, J., & Ramyashree, D. (2021). Examination of Monday effect in Indian stock Market Examination of Monday effect in Indian stock Market. *International Research Journal of Management Sociology & Humanity*, *12*(4), 260–268.

Dutta, A., & Das, S. (2021). Day-of-the-Week and Month of the Year Anomalies in the Indian Stock Market using Multiple Regression Technique. *International Journal of Management (IJM)*, *12*(5), 101–111.

Erdas, M. L. (2019). Validity of Weak-Form Market Efficiency in Central and Eastern European Countries (CEECs): Evidence from Linear and Nonlinear Unit Root Tests. *Review of Economic Perspectives*, *19*(4), 399–428.

Fama, E. F. (1970). Session Topic: Stock Market Price Behavior Session Chairman: Burton G. Malkiel Efficient Capital Markets: A Review Of Theory And Empirical Work. *The Journal of Finance*, *25*(2), 383–417.

Fender, J. (2020). Beyond the efficient markets hypothesis: Towards a new paradigm. *Bulletin of Economic Research*, *72*(3), 333–

351.
Ferrouhi, E. M., Kharbouch, O., Aguenaou, S., & Naeem, M. (2021). Calendar anomalies in African stock markets. *Cogent Economics and Finance*, *9*(1).
Gayaker, S., Yalcin, Y., & Berument, M. H. (2020). The day of the week effect and interest rates. *Borsa Istanbul Review*, *20*(1), 55–63.
Gemici, E., & Polat, M. (2018). *MIST Borsalarında Rassal Yürüyüş Hipotezi*. 129–142.
Gharaibeh, O. K. (2021). Calendar anomalies in the GCC equity markets. *Jordan Journal of Business Administration*, *17*(2), 161–176.
Goss, B. A. (1983). The semi-strong form efficiency of the London Metal Exchange. *Applied Economics*, *15*(5), 681–698.
Harikrishnan, R., Gupta, A., Tadanki, N., & Berry, N. (2021). Machine Learning Based Model to Predict Stock Prices : A Survey. *IOP Conf. Series: Materials Science and Engineering*, *1084*(1), 1–9.
Hussain, M., Sadiq, S., Rasheed, M. H., & Amin, K. (2022). Exploring the Dynamics of Investors' Decision Making in Pakistan Stock Market: A Study of Herding Behavior. *Journal of Economic Impact*, *4*(1), 165–173.
Irtiza, M. S., Khan, S., Baig, N., Tirmizi, S. M. A., & Ahmad, I. (2021). The turn-of-the-month effect in Pakistani stock market. *Future Business Journal*, *7*(1), 1–11.
Jierula, A., Wang, S., Oh, T. M., & Wang, P. (2021). Study on accuracy metrics for evaluating the predictions of damage locations in deep piles using artificial neural networks with acoustic emission data. *Applied Sciences (Switzerland)*, *11*(5), 1–21.
Kahraman, E., & Akay, O. (2022). Comparison of exponential smoothing methods in forecasting global prices of main metals. *Mineral Economics*, *2010*.
Karim, A., & Said, F. (2024). Discussion on Malaysia's Globalization Journey From Resource-Based Economy to Global Player. *Journal of Business and Economic Options*, *7*(1), 29-38.
Khan, B., Aqil, M., Alam Kazmi, S. H., & Zaman, S. I. (2023). Day-of-the-week effect and market liquidity: A comparative study from emerging stock markets of Asia†. *International Journal of Finance and Economics*, *28*(1), 544–561.
Malkiel, B. G. (2000). Are markets efficient. *The Wall Street Journal*, *28*.
Miss, S., Charifzadeh, M., & Herberger, T. A. (2020). Revisiting the monday effect: a replication study for the German stock market. *Management Review Quarterly*, *70*(2), 257–273.
Mohamad Shariff, N. S., & Yusof, N. A. (2021). Stock Market Anomalies: a Case of Calendar Effects on the Malaysian Stock Market. *Malaysian Journal of Computing*, *6*(1), 772.
Mumtaz, A., Munir, N., Mumtaz, R., Farooq, M., & Asif, M. (2023). Impact Of Psychological & Economic Factors On Investment Decision-Making In Pakistan Stock Exchange. *Journal of Positive School Psychology*, *7*(4), 130–135.
Munir, Q., Akram, B., & Abbas, S. A. (2024). Understanding Stock Price Dynamics with Dividend-Related Metrics and Financial Indicators in Pakistan's Non-Financial Sectors. *Journal of Business and Economic Options*, *7*(1), 1-9.
Nti, I. K., Adekoya, A. F., & Weyori, B. A. (2020). A systematic review of fundamental and technical analysis of stock market predictions. In *Artificial Intelligence Review* (Vol. 53, Issue 4). Springer Netherlands.
Ozili, P. K. (2023). The acceptable R-square in empirical modelling for social science research. *Social Research Methodology and Publishing Results: A Guide to Non-Native English Speakers*, *January 2023*, 134–143.
Pagano, M. (1993). Financial Markets and the Macroeconomy Financial markets and growth An overview. *European Economic Review*, *37*(2–3), 613–622.
Riaz, S., Xu, Y., & Hussain, S. (2019). Workplace ostracism and knowledge hiding: The mediating role of Job Tension. *Sustainability (Switzerland)*, *11*(20), 1–16.
Sahoo, M. (2021). COVID-19 impact on stock market: Evidence from the Indian stock market. *Journal of Public Affairs*, *21*(4), 1–13.
Said, B., Rehman, S. U., Ullah, R., & Khan, J. (2021). Investor overreaction and global financial crisis: A case of Pakistan stock exchange. *Cogent Economics and Finance*, *9*(1).
Sakalauskas, V., & Kriksčiūnienė, D. (2007). the Impact of Daily Trade Volume on the Day-of-the- Week Effect in Emerging Stock Markets. *Information Technology and Control*, *36*(1), 152–157.
Samaniego, J. D. V., Salgado, R. J. S., & Pérez, M. A. L. (2022). Are there "day-of-the-week" and "holiday" anomalies in the mexican stock market? *Contaduria y Administracion*, *67*(3), 111–134.
Wen, F., Xu, L., Ouyang, G., & Kou, G. (2019). Retail investor attention and stock price crash risk: Evidence from China. *International Review of Financial Analysis*, *65*, 101376.
Xiong, L. (2024). Driving Growth for SMEs in Laos' Commercial Sector Challenges and Opportunities. *Journal of Business and Economic Options*, *7*(1), 10-18.
Yang, X., & Nemlioğlu, İ. (2023). Investigation of Monday Effect in the American and Chinese Stock Markets. *Bulletin of Economic Theory and Analysis*, *8*(May), 93–109.
Yardımcı, B., & Erdem, S. (2020). The day of the week effects in stock markets of countries with predominantly Muslim populations. *International Journal of Islamic and Middle Eastern Finance and Management*, *13*(2), 195–218.
Zaremba, A., & Nikorowski, J. (2019). Trading costs, short sale constraints, and the performance of stock market anomalies in Emerging Europe. *Economic Research-Ekonomska Istrazivanja* , *32*(1), 403–422.
Zhang, C., Sjarif, N. N. A., & Ibrahim, R. B. (2022). Decision Fusion for Stock Market Prediction: A Systematic Review. *IEEE Access*, *10*(August), 81364–81379.

Table 5: Descriptive Analysis of Days of The Week

	Monday						**Tuesday**				
	Price	Open	High	Low	Return		**Price**	**Open**	**High**	**Low**	**Return**
Mean	17550.7	17592.18	17698.93	17444.92	17450.7		17567.75	17560.37	17683	17445.13	17467.75
Median	11002.44	11036.81	11146.78	10913.49	10902.44		10932.88	10948.64	11066.07	10853.22	10832.88
SD	16373.76	16411.02	16503.15	16048.29	12684.23		16411.82	16407.75	16510.12	16311.81	16411.82
Skewness	0.6115	0.6101	0.6107	0.6114	0.6115		0.6123	0.6131	0.6119	0.6133	0.6123
Kurtosis	-1.2204	-1.224	-1.2225	-1.2205	-1.2204		-1.2229	-1.2211	-1.2234	-1.2214	-1.2229
Q1	1984.613	1995.288	2002.838	1979.518	1884.613		1966.993	1973.003	1996.533	1940.333	1866.993
Q2	11002.44	11036.81	11146.78	10913.49	10902.44		10932.88	10948.64	11066.07	10853.22	10832.88
Q3	33860.88	33943.98	34097.85	33732.3	33760.88		33899.14	33861.96	34055.08	33756.48	33799.14

	Wednesday						Thursday				
	Price	Open	High	Low	Return		Price	Open	High	Low	Return
Mean	17513.3	17504.44	17626.86	17399.52	17413.37		17785.7	17788.96	17910.32	17671.35	17685.7
Median	10941.94	10956.96	11059.62	10879.27	10841.94		11264.95	11264.85	11326.14	11158.91	11164.95
SD	16408.9	16401.49	16502.55	16315.75	16408.83		16462.29	16467.84	16572.42	16365.21	16462.29
Skewness	0.6205	0.6211	0.6198	0.6212	0.6205		0.5903	0.5917	0.5909	0.591	0.5903
Kurtosis	-1.2116	-1.2095	-1.2119	-1.2101	-1.2116		-1.2541	-1.2501	-1.2523	-1.2521	-1.2541
Q1	1968.4	1968.28	2003.06	1956.32	1868.4		1996.995	1990.615	2011.68	1973.385	1896.995
Q2	10941.94	10956.96	11059.62	10879.27	10841.94		11264.95	11264.85	11326.14	11158.91	11164.95
Q3	33932.81	33917.85	34111.5	33786.96	33832.81		34098.69	34184.66	34332.87	33924.87	33998.69

	Friday				
	Price	Open	High	Low	Return
Mean	19196.36	19188.37	19312.7	19076.85	19096.36
Median	12000.03	11974.17	12086.58	11938.24	11900.03
SD	16417.51	16412.93	16506.22	16328.27	16417.51
Skewness	0.4775	0.4776	0.4769	0.4783	0.4775
Kurtosis	-1.3628	-1.3627	-1.3633	-1.3612	-1.3628
Q1	4463.04	4486.31	4495.56	4455.06	4363.04
Q2	12000.03	11974.17	12086.58	11938.24	11900.03
Q3	35973.68	35936.31	36048.52	35758.52	35873.68