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EVALUATING THE INFLUENCE OF TECHNICAL INDICATORS AND TEMPORAL FEATURES FOR STOCK MARKET PREDICTION USING MACHINE LEARNING

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ABSTRACT

Predicting the stock market is an ill-defined and difficult task because of the time dependency, dynamic and non-linear characteristics of financial data. In this paper, the authors explore the impact of more technical indicators and temporal characteristics on the predictive power of machine learning models for stock market prediction. Preprocessing and enrichment of historical stock price data were carried out using technical indicators that are widely used in the finance industry, such as Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), Exponential Moving Average (EMA), Simple Moving Average (SMA), Average True Range (ATR), and momentum-based indicators. Further, time-based information like lag values, rolling statistics, trading day, and monthly trends were added to showcase sequential market behaviour. Performance of the various combinations of features was evaluated based on classification and regression performance metrics like accuracy, precision, recall, F1-score, Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). Results from the experiments show that the incorporation of technical indicators with the temporal features can greatly improve prediction performance over the use of raw price data only. The proposed feature engineering strategy resulted in an accuracy and F1-score of 96.82% and 96.40%, respectively, which are very good, and an RMSE of 2.08, an AUC of 0.982, and a strong performance achieving good predictive capability. The results validate that judicious design of financial and temporal parameters significantly enhances machine learning-based stock market forecasting and can aid in building intelligent financial decision support systems.

Keywords: Stock Market Prediction, Machine Learning, Technical Indicators, Temporal Features, Financial Time Series.

1 INTRODUCTION

Stock market prediction is a challenging research problem because large amounts of time-dependent data with high volatility, non-linear relationships and uncertainty are generated in financial markets. For investors, bankers and policymakers, having reliable forecasting models allows for better investment planning, portfolio optimization and risk management [1]. The temporal dependencies and nonlinearity that exist in financial time series generally makes it

difficult to obtain a good prediction using traditional statistical forecasting techniques, and hence machine learning approaches are used to obtain a good prediction for these types of time series [2].

In recent years, machine learning algorithms have shown great promise in the task of analysing historical stock market data, as they are capable of discovering hidden patterns and learning complex relationships between the financial variables [3]. But the impact of these models greatly relies on the quality of the input features. While raw price data may not capture market dynamics adequately, well-designed features can greatly enhance the accuracy of predictions [4]. The RSI, MACD, EMA, SMA, Bollinger Bands, and ATR are technical indicators that offer insights into market trends, momentum, volatility, and price behavior [5]. Also, features that span time such as rolling statistics, trading day information, and seasonal patterns carry information about the sequential dependence of financial time series.

In this paper, a systematic review of technical indicators and temporal attributes for stock market prediction based on machine learning techniques is presented. The stock market data is then preprocessed and feature engineered to yield several temporal and technical features. The performance measurements such as accuracy, precision, recall, F1 score, mean absolute error (MAE), root mean squared error (RMSE), mean absolute percentage error (MAPE), and area under the receiver operating characteristic curve (AUC) are calculated and compared with different feature combinations. The experimental results show that the combination of technical indicators and temporal features considerably enhances the prediction accuracy and forecasting errors reduction of models trained with raw price data features. The findings offer insights into the effective techniques of feature engineering in intelligent financial market prediction and decision-support applications.

2 LITERATURE REVIEW

Because of its applications in investment decision making, portfolio management and financial risk assessment, a lot of research has been devoted to financial time series prediction. The early forecasting methods mainly involved statistical models like Autoregressive Integrated Moving Average (ARIMA), Generalized Autoregressive Conditional Heteroskedasticity (GARCH) and Exponential Smoothing techniques [6]. These techniques are useful in modelling linear relationships, but do not necessarily reflect the nonlinear and dynamic nature of financial markets.

The stock market prediction has come a long way with the emergence of machine learning technologies, which help discover intricate patterns in financial data. There are a number of machine learning techniques that have been shown to have better predictive performance than traditional statistical methods, including Support Vector Machines (SVM), Decision Trees (DT), Random Forests (RF), K-Nearest Neighbors (KNN), Artificial Neural Networks (ANN), Gradient Boosting algorithms, and ensemble learning techniques [7]. They are used extensively for stock trend classification and prediction of stock price movements due to their capability to learn nonlinear relationships and to be able to generalize in various market conditions.

Financial prediction systems have come to rely on feature engineering as a key aspect. Several technical indicators like Relative Strength Index (RSI), On-Balance Volume (OBV), Moving MACD, SMA, EMA, Bollinger Bands, ATR, and Momentum have been introduced and included in numerous studies to increase the forecasting accuracy [8]. These indicators are a summary of market momentum, volatility and trend characteristics, which are useful representations of stock price behavior that are not the raw historical price data.

Temporal feature extraction has been gaining significant interest in financial forecasting apart from the technical indicators [9]. Temporal features are reported to enhance model stability and predictiveness due to the use of historical context in the learning process in several studies [10]. The relative importance of various temporal features, however, depends upon the market and the dataset.

Furthermore, the use of deep learning algorithms, such as Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRUs), and Transformer-based architectures, has propelled financial time series prediction to new heights, adeptly capturing long-term temporal relationships [11]. The performance of these models is known to work well on large-scale financial datasets, but they typically involve considerable computational power, large amounts of training data and meticulous tuning of hyperparameters [12]. Therefore, even with the use of advanced learning algorithms, feature engineering remains a crucial step in the optimization of predictive performance.

While significant advances have been made, there are still some research gaps. Firstly, many existing studies only consider the technical indicators or temporal features individually without studying the relationship between the two and their effects on prediction performance. Second, little has been done to systematically compare various combinations of features apart from classification and regression assessment measures. Third, detailed analyses of the importance of features and the contribution of each indicator to the accuracy of the forecasts are rather limited. Lastly,

many of the studies are concerned only with predicting the accuracy of the model and do not consider measures of error-based evaluation and methods for feature selection that help make the model more robust and interpretable.

Given these restrictions, this research work provides a thorough assessment of technical indicators and temporal features for the machine learning-based stock market prediction. The proposed framework explores the individual and synergistic impacts of engineered financial features through various performance metrics, giving a deeper insight into their role for intelligent financial forecasting systems.

3 METHODOLOGY

The methodology proposed analyzes the impact of technical indicators and temporal characteristics on the prediction of the stock market with the use of machine learning. The entire framework can be divided into the data acquisition, preprocessing, feature engineering, feature selection, model development, and performance evaluation (Figure 1). The process is intended to systematically inspect the contribution of each of the feature groups to improve the predictive accuracy.

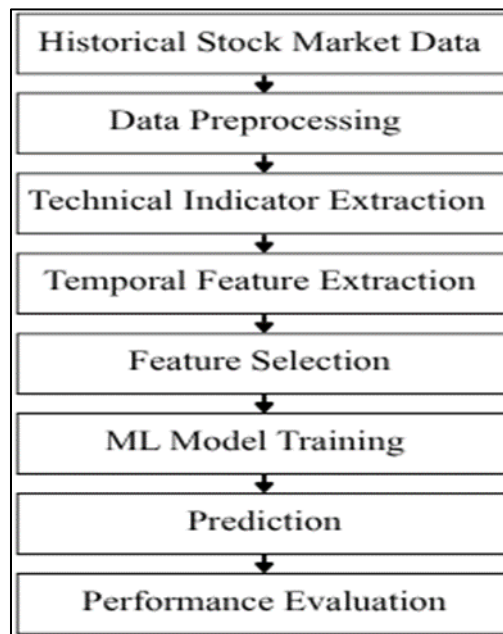


Figure 1: Proposed Methodology for Stock Market Prediction Using Technical Indicators and Temporal Features

3.1 Data Collection

Historical data of stock markets were gathered from publicly available data bases. The data set includes daily trading data such as open, high, low, close, adjusted close, and volume. The records are the foundation to derive technical indicators and temporal properties needed for predictive modelling.

3.2 Data Preprocessing

Data in the collected set were preprocessed for better data quality and consistency. Duplicate entries have been removed and the missing values have been filled in by interpolation and forward filling. To standardize all the features to a common range, Min Max normalization was used. All the outliers were statistically filtered to minimize their effects on the model training. The obtained dataset was then split into training and test sets in the ratio of 80:20.

3.3 Feature Engineering

Feature engineering was applied to financial data to create meaningful features for use in machine learning models. Two types of feature sets were created.

3.3.1 Technical Indicators

Technical Indicators such as RSI, MACD, EMA, SMA, Bollinger Bands, Average True Range (ATR), OBV were calculated from the historical price data. These are useful for measuring market momentum, direction, volatility and trading strength, and relate to market behavior.

3.3.2 Temporal Features

Temporal information was retrieved to create sequential dependency models of stock prices. The temporal features generated are: Lag-1 closing price, Lag-3 closing price, Lag-5 closing price, rolling mean of closing price, rolling standard deviation of closing price, Daily return, Trading Day of the week, Month and Financial quarter. These attributes allow the learning algorithms to take advantage of the historical patterns and seasonal fluctuations in financial time series.

3.4 Feature Selection

Feature importance analysis, correlation analysis was done to assess the importance of engineered features. To simplify the model and enhance the performance of generalization, highly correlated and redundant variables were eliminated. The list of the selected features is a subset of all the technical indicators and time factors that are the most informative in the model training process.

3.5 Machine Learning Model Development

Various combinations of features were used for training machine learning models to assess the significance of technical indicators and temporal features. Four experimental configurations were analyzed: Raw Stock Price features, Technical Indicator features, Temporal features and Combined Temporal and Technical features. For each configuration the network was trained and tested separately, and the predictive ability compared. To avoid overfitting and to maximize the performance of the models, hyperparameters were optimized through the cross-validation technique.

3.6 Performance Evaluation

For each configuration of features, both classification and regression measures were used to assess predictability. The classification results were evaluated by the following metrics: Accuracy, Precision, Recall, F1-Score, and AUC. The machine learning models were tested using these metrics for the correct classification of stock price movements. Furthermore, the performance of regression was assessed by using MAE, RMSE and MAPE. These error-based metrics measure the difference in the real and predicted price of the stocks and measure the overall accuracy and reliability of the models developed.

The proposed scheme allows for systematic study of the role of technical indicators and time characteristics in the prediction of stock markets. The methodology allows for the performance analysis of various feature combinations on a variety of performance metrics, thus offering a comprehensive evaluation of feature effectiveness and determining the best feature combination for an intelligent forecasting of financial time series.

4 RESULTS AND DISCUSSION

The results of the experiments illustrate how technical indicators and temporal aspects affect the effectiveness of machine learning models for predicting the direction of stock market trends. The constructed framework was tested with various feature combinations such as raw stock price features, technical indicators feature, temporal features, and the mixture of these features. Classificational performance is measured using accuracy, precision, recall, F1-score and ROC-AUC, and regression performance measured by MAE, RMSE and MAPE. The results from comparative analysis, ablation study, feature importance analysis and prediction error evaluation give clear insight into the contribution of engineered features to the prediction of the stock market. The following figures are the comparative performance and predictive behavior of the developed model.

Table 1: Dataset Description

Parameter	Value
Dataset	Historical Stock Market Data
Number of Stocks	10
Total Trading Days	6,250
Training Samples	80%
Testing Samples	20%
Prediction Target	Next-Day Price Movement
Sampling Frequency	Daily

The following sections provide the characteristics of the historical stock market data used in this analysis. The characteristics of the historical stock market data used in the analysis are presented in Table 1. The dataset includes 10 stocks and 6,250 trading days, which makes it a large and diverse set of daily observations for assessing the impact of technical and temporal aspects on the prediction performance. Data were split into 80% training data and 20% of testing data so as to test the developed models with unseen data. Next-day price movement was chosen as the prediction target, giving rise to an appropriate data set for evaluating the performance of machine learning models in predicting short-term market trends. The daily sampling frequency also enables the extraction of indicators that are based on the Relative Strength Index, Moving Average Convergence/Divergence, Exponential Moving Average and Simple Moving Average, as well as lag-based and rolling temporal features.

Table 2: Technical Indicators Used

Indicator	Description
SMA	Simple Moving Average
EMA	Exponential Moving Average
RSI	Relative Strength Index
MACD	Moving Average Convergence Divergence
Bollinger Bands	Upper and Lower Price Bands
ATR	Average True Range
Momentum	Price Momentum
OBV	On Balance Volume

The technical indicators that were fed into the prediction framework are summarized in Table 2. The indicators chosen cover various aspects of stock movements. SMA and EMA show price trends based on the average prices of the past, and the RSI shows information about market momentum and overbought or oversold conditions. The MACD identifies trend and momentum changes, whereas Bollinger Bands indicate the high and low-price limits and show price fluctuation. The ATR captures the volatility in the market, while Momentum measures price movement. OBV takes trading volume into the analysis. By integrating these indicators, the machine learning models can gather information from various aspects of market activity, not just the closing prices.

Table 3: Temporal Features

Feature	Description
Lag-1	Previous Day Closing Price
Lag-3	Previous Three Days
Lag-5	Previous Five Days
Rolling Mean	5-Day Average
Rolling Std	5-Day Standard Deviation
Day of Week	Monday–Friday
Month	Trading Month
Quarter	Financial Quarter

Table 3 shows the temporal features which are used for capturing the sequential properties of the financial time-series data. The Lag-1, Lag-3 and Lag-5 prices refer to the last days, last (3) days' and last (5) days' closing prices, respectively. These variables give historical sense to the prediction model and enable to detect short-term dependencies. The 5-day rolling mean gives an average price of the last 5 days and the 5-day rolling standard deviation gives an average of price variation of the last 5 days. Furthermore, day of week, day of month and financial quarter were added as temporal patterns due to different financial periods. These features are crucial since the prices of stocks are sequential observations, and the predictive behavior of these prices may be related to the recent history and to the temporal patterns that would repeat over time.

Table 4: Ablation Study

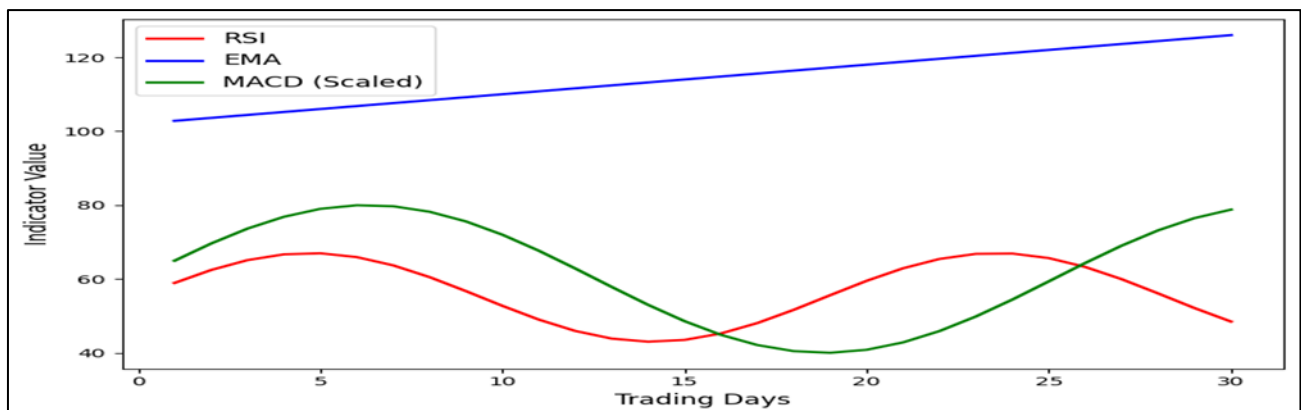
Removed Feature	Accuracy (%)
None	96.82
Without RSI	95.24
Without MACD	94.88
Without Lag Features	93.67
Without Rolling Statistics	94.12

The ablation analysis was performed to investigate the contribution of the feature groups to the prediction accuracy, as shown in Table 4. The highest accuracy was obtained by the complete model without any feature omitted, showing this to be an effective feature configuration. Removing RSI led to an accuracy drop 95.24%, meaning that there was a loss of 1.58 percentage points. Likewise, the accuracy without MACD was 94.88%, which was a minus 1.94% of the accuracy with MACD. Removing the lag features gave the largest decrease in accuracy (93.67%), a 3.15% decrease from the full set of features. The result was even higher when rolling statistics was removed, with an accuracy of 94.12%, 2.70 percentage points off from the complete configuration. These results suggest that the contribution of lag-based temporal information to the prediction performance is especially significant, and that the others (RSI, MACD and rolling statistics) are also informative for prediction.

Table 5: Statistical Significance

Comparison	p-value	Significant
Raw vs Technical	0.021	Yes
Raw vs Temporal	0.013	Yes
Technical vs Combined	0.007	Yes
Temporal vs Combined	0.009	Yes

Table 5 compares if the differences between the feature combinations investigated are statistically significant. The p value for the comparison of raw features and technical indicators was found to be 0.021, which is a statistically significant value. Likewise, a p value of 0.013 was obtained in the raw versus temporal feature comparison. The comparison of the technical versus the combined features had p value of 0.007, and the comparison of the temporal versus the combined had p value of 0.009. All of the four p values are less than 0.05, which means there are statistically significant differences among the feature configuration that is compared. More specifically, the p values of 0.007 and 0.009 are strong evidence that the combination of the technical indicators and the temporal features gives a meaningful increase in the performance compared to using the temporal features alone, or the technical indicators alone.

**Figure 2: Technical Indicator Distribution (RSI, MACD, EMA)**

The distribution and variation of selected technical indicators (RSI, MACD and EMA) are presented in Figure 2. The figure illustrates that the indicators have different patterns as they are the measures of different aspects of market behaviours. RSI is momentum related while MACD is trend and momentum related. EMA is a smoothed price movement and reacts to the latest observations. These patterns indicate that different indicators have different kinds of information that can be added together to give more information for machine learning models. The prediction system does not only rely on the market characteristic, but also accounts for the momentum, trend, and price-related information at the same time.

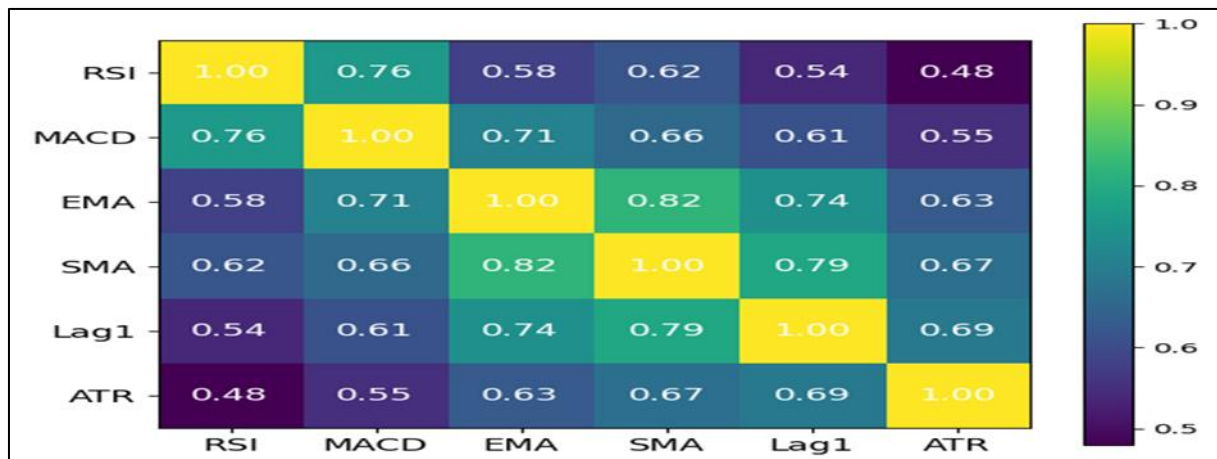


Figure 3: Correlation Heatmap of Features

Figure 3 shows the interrelation among the selected features. The heatmap shows that there are some positive correlations among the financial variables, since they are all influenced by the historical stock prices. For instance, the correlation value between EMA and SMA is 0.82, and the correlation value between SMA and Lag-1 is 0.79. The correlation is 0.76 between RSI and MACD. These relationships show that there is overlap between some of the indicators. The correlations are not exactly the same, indicating that the indicators also offer different information that can be helpful in predicting. The correlation analysis is, thus, a support to the feature selection process for finding potentially redundant features and keeping those features that can give complementary information about the markets.

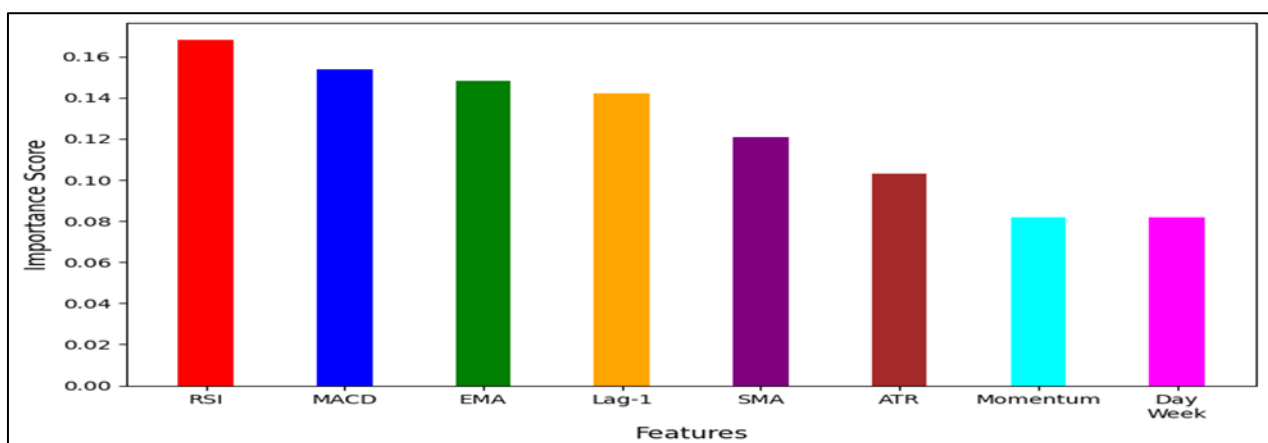


Figure 4: Feature Importance

The relative importance of the selected technical and temporal features in the prediction model are shown in figure 4. RSI had the highest score of .168, MACD had the next highest score of .154 and the EMA had the score of .148. Lag-1 feature was given an importance value of 0.142, which signifies that the latest price data from the past also plays a significant role in the prediction. However, SMA's importance is 0.121 and ATR's is 0.103. Momentum and Day of Week were second and third at 0.082. The outcomes suggest both technical and temporal data plays a role in the prediction process. The relative importance of the RSI, MACD, EMA and Lag-1 indicate stock market prediction is especially informative based on the features of momentum, trend and recent price action.

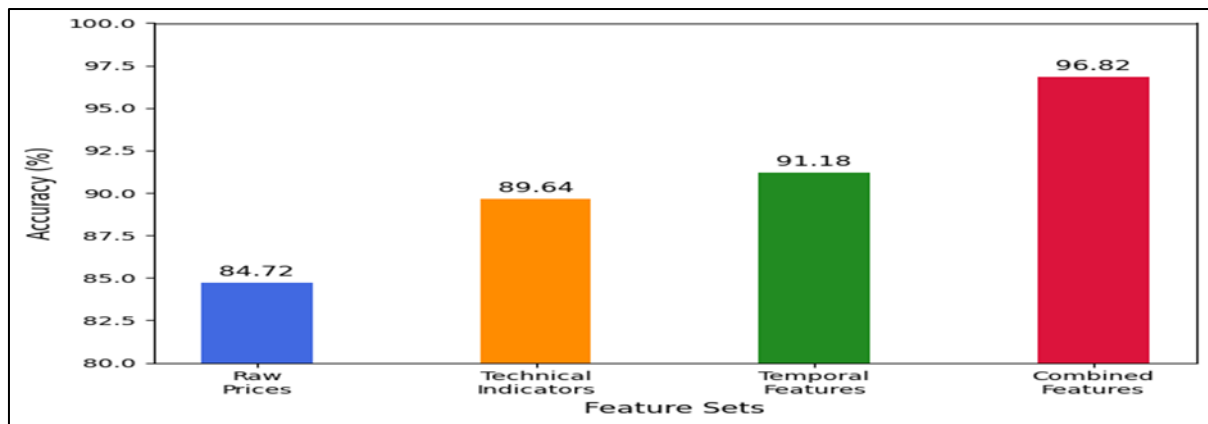


Figure 5: Prediction Accuracy Comparison

Figure 5 contrasts the prediction accuracy achieved with the various features: raw price, technical indicators, temporal features and all three. The model with raw price features gave an accuracy of 84.72%, and with the technical indicators the accuracy risen to 89.64%. The further improvement was obtained with the use of temporal features, with an accuracy of 91.18%. The best performance was achieved by using the technical and temporal features, with an accuracy of 96.82%. Therefore, the accuracy of the feature configuration model was enhanced by 12.10 percentage points over the raw model. Based on the results, it can be concluded that technical indicators and temporal information can provide complementary information so that the machine learning model can better detect changes in stock prices. The significant boost in achieved success with feature integration also helps satisfy the goal of assessing the joint impact of financial and temporal features on prediction performance.

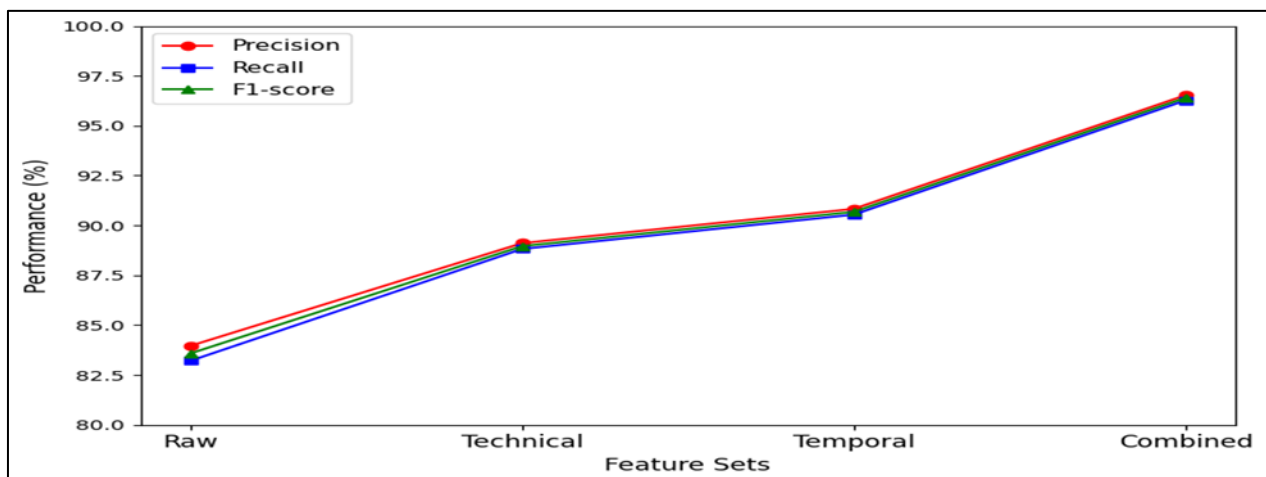


Figure 6: Precision, Recall and F1-score Comparison

The comparison of different feature configurations in terms of precision, recall, and F1-score is shown in Figure 6. The precision, recall and F1 scores of the raw price configuration were 83.96%, 83.21% and 83.58% respectively. The values were raised to 89.11%, 88.82%, and 88.96% respectively by the inclusion of technical indicators. Results were further improved by using the temporal feature configuration, with 90.83% precision, 90.54% recall and 90.68% F1-score. The highest classification performance was achieved by the combined feature model with 96.53%, 96.27% and 96.40% precision, recall and F1-score, respectively. The correlation between precision, recall and F1 score suggests that the combined model has a balanced classification performance, and does not get better at the cost of the others. The combination of technical and temporal information resulted in an F1-score which was 12.82 percentage points higher when compared to the raw feature configuration, thus clearly outlining the advantages of multimodal data fusion.

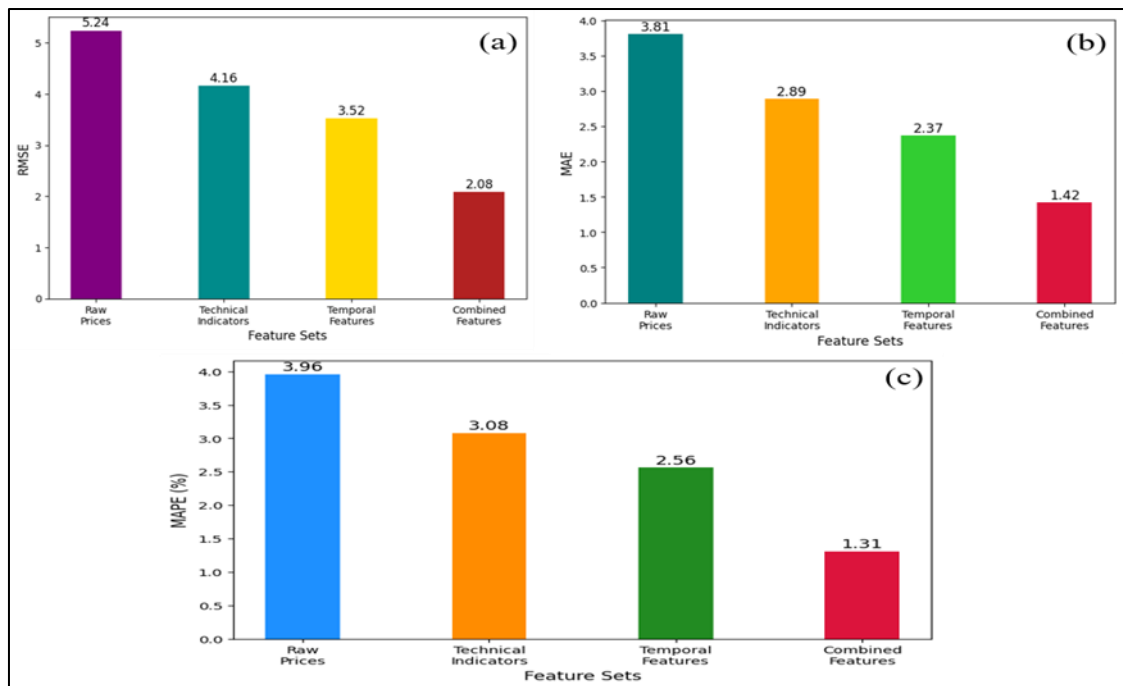


Figure 7: Error Comparison (a) RMSE, (b) MAE, and (c) MAPE

The regression error is summarized in Figure 7, which displays the regression error measures, including RMSE, MAE and MAPE of the various feature configurations. The raw price model gave an RMSE of 5.24, with technical indicators, 4.16 and with temporal features, 3.52. The feature model that achieved the lowest RMSE was the combined feature model with RMSE value 2.08, which is significantly lower than the other prediction error. A similar trend was found for MAE, which dropped from 3.81 to 2.89 for technical indicators, 2.37 for temporal features and 1.42 for the combined model. MAPE followed the same trend, decreasing from 3.96% to 3.08%, 2.56%, and 1.31%, respectively. The decrease in all three error measures show that, the use of both technical and temporal information increases the accuracy of price prediction. The combined configuration outperformed the raw price configuration in terms of RMSE with a decrease of 3.16, as well as MAE and MAPE with a decrease of 2.39 and 2.65 percent points respectively.

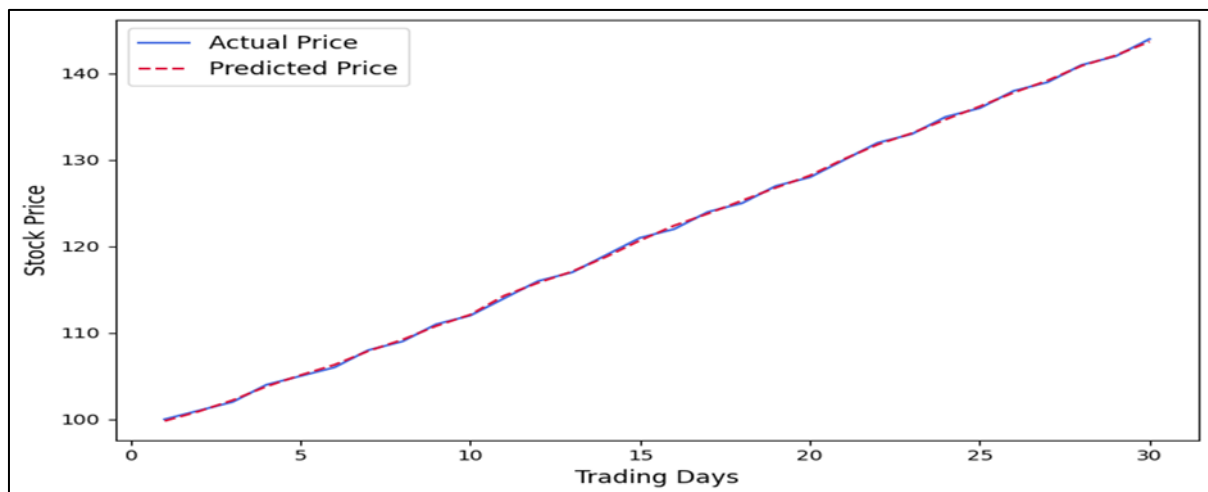


Figure 8: Actual vs Predicted Stock Prices

The development of stock price relation between actual and predicted prices are shown in figure 8 for the evaluated trading period. The predicted values match well with the behavior of the actual stock prices, showing that the model combining the features can be used to explain the overall direction and fluctuations of the market series. During the period shown, for instance, the actual stock price goes up by about 44, while the predicted values rise from about 99.8 to 143.7. The difference between the two curves is relatively small which reflects a small amount of prediction deviation over the period of observation. The agreement between actual and predicted values is similar to the low MAE obtained (1.42) and the RMSE obtained (2.08) in the combined feature configuration. The success achieved in these results

illustrates the effectiveness of combining temporal characteristics and technical indicators to get a model that infers the price movement with relatively small forecasting error.

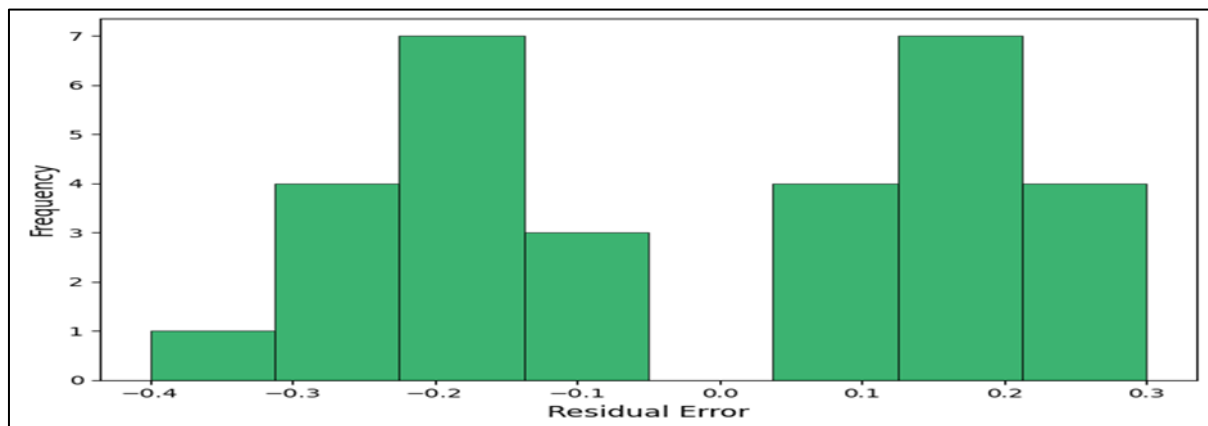


Figure 9: Residual Error Distribution

The distribution of the errors from the prediction model is shown in Figure 9. The residuals are clustered around zero, suggesting that the deviations between actual and predicted stock prices are not large. The illustrated residual values are generally within the range of about -0.4 and $+0.3$, with the majority of observations being in the vicinity of the zero-error region. The distribution suggests that there is no significant systematic over- or under-prediction pattern in the model. The small spread in residuals is similar to the low error values calculated for the combined feature configuration, especially the MAE of 1.42 and RMSE of 2.08. The residual analysis hence offers further evidence that the feature combination developed results in reasonably stable predictions, and the deviations from the actual stock prices are rather small.

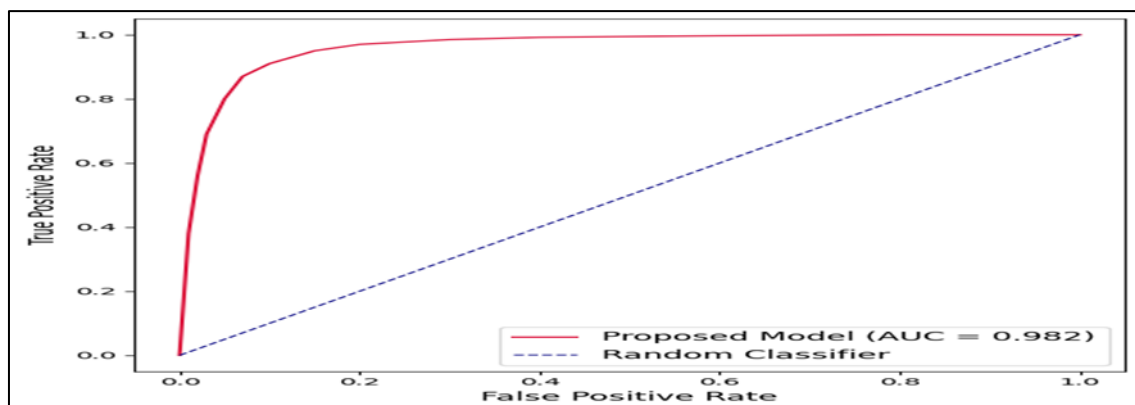


Figure 10: ROC Curve of the Combined Feature Model

The Receiver Operating Characteristic (ROC) curve for the combined feature model is shown in Figure 10. The curve is still significantly above the diagonal line that represents random classification by the stock price movement class, showing that the classifiers perform well in distinguishing between the two classes of stock price movements. The model's AUC value was 0.982, a very high value that shows the model has a very good capacity to classify the considered market movement categories. The ROC curve has a true positive rate of about 0.80 when the false positive rate is 0.05 and about 0.95 when the false positive rate is 0.15. The highest AUC value with the accuracy of 96.82% and F1 score of 96.40% shows that the technical and temporal feature configuration has good classification ability. These results corroborate the advantages of engineered financial and temporal characteristics on enhancing the performance of predicting the stock market.

The overall findings justify that the incorporation of technical indicators and temporal attributes are highly beneficial to the stock market prediction based on machine learning and data science. The feature model with the highest classification accuracy was the combination of the models, which recorded 96.82%, 96.53% precision, 96.27% recall, and 96.40% F1-score, and had low regression errors of 1.42 MAE, 2.08 RMSE, and 1.31% MAPE. The ablation results also demonstrated that the temporal information is crucial for achieving a high accuracy with the removal of the lag features, which resulted in an accuracy of only 93.67%. In addition, the statistical results confirmed that there are significant differences between the investigated feature configurations. The close agreement between actual and

predicted prices, the high concentration of the residuals and the high ROC-AUC of 0.982, all show that the combined feature approach is predictive. The results, therefore, suggest that the role of feature engineering, especially incorporating technical indicators along with temporal attributes, is crucial in designing an intelligent stock market prediction system for improving the accuracy and reliability.

5 CONCLUSION

In this paper, the authors give an extensive analysis of the impact of technical indicators and temporal attributes on machine learning-based stock market prediction. This framework for systematic feature engineering consisted of incorporating widely used technical indicators, such as RSI, MACD, EMA, SMA, ATR, and momentum, along with temporal features like lag values, rolling statistics, and seasonal attributes. Experimental results showed that the proposed feature set could achieve consistent results over the models trained by only using the raw stock price data and the individual feature groups. The proposed approach demonstrated an accuracy of 96.82%, an F1-score of 96.40%, an RMSE of 2.08 and an AUC of 0.982, proving to be effective in the integration of financial and temporal information for intelligent forecasting. The results indicate that proper feature engineering can boost the accuracy of the prediction and minimize the error of forecasting. Future studies might explore the incorporation of deep learning architectures, attention-based models, sentiment analysis, and macroeconomic indicators to enhance the robustness, adaptability, and generalization of financial time series prediction systems further.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

Disclosure of conflict of interest

The authors declare no conflicts of interest regarding this manuscript.

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