Time Series Forecasting of KSE-100 Index Using a Hybrid ESN-LSTM Model

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***Abstract*—The volatility and complexity of stock markets, particularly in emerging economies like Pakistan, pose significant challenges for accurate forecasting. This paper aims to improve the predictive accuracy of the Karachi Stock Exchange index (KSE-100) by comparing and combining advanced deep learning models. The research investigates the effectiveness of Echo State Networks (ESN), Long Short-Term Memory (LSTM) networks, and a hybrid ESN-LSTM model in capturing both short-term fluctuations and long-term trends. Daily KSE-100 index prices from September 1, 2019, to September 1, 2024, were used, with scaled closing price, 50- and 200-day moving averages as input features. The models' performances were evaluated using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), R-squared and Directional Accuracy (DA). Results indicate that the ESN-LSTM hybrid model outperformed both individual ESN and LSTM models, achieving the lowest MAE of 513.10 and RMSE of 650.59, along with the highest R-squared of 0.975 and DA of 94.12%. The superior performance of the hybrid model is attributed to its ability to use the efficient temporal feature extraction of ESNs and the long-term memory capabilities of LSTMs. These findings suggest that hybrid approaches can significantly improve stock market forecasting accuracy in emerging markets. Future research should explore the integration of sentiment analysis and macroeconomic indicators to further enhance predictive capabilities.**

***Index Terms*—Stock Market Prediction, Echo State Networks, Long Short-Term Memory, Hybrid Models, KSE-100 Index**

I. Introduction

The Pakistan Stock Exchange (PSX) is an important financial market in the country, playing a vital role in capital formation for corporations [1]. Karachi Stock Exchange index (KSE-100) is one of the important benchmarks of PSX that reflects the overall performance of Pakistani Stock market and it is widely used by investors and analysts around the globe to gauge market trends. Recently, financial time series prediction has received a great deal of interest in recent years due to its ability to aid investment and economic policy decisions, especially the stock market index [2]. The complexity and non-linear nature of stock market data pose challenges for traditional forecasting methods, motivating this research to explore advanced machine learning (ML) techniques such as Long Short-Term Memory (LSTM) networks and Echo State Networks (ESNs) [3]. These approaches have shown promise in capturing the complex dynamics of financial time series, offering more accurate predictions than existing models [4]. The selection of ESN and LSTM models was motivated by their complementary strengths – ESNs excel in capturing immediate temporal patterns with computational efficiency [5], while LSTMs effectively model long-term dependencies that traditional regression models often miss [6]

Stock market prediction is of great value for investors, policymakers, and the overall economy. Accurate forecast can guide investment strategies, help in risk management, and contribute to efficient capital allocation [1]. For investors, both individual and institutional, the reliable predictions would determine the kind of choices they make, which would probably be more informed towards maximizing returns and minimizing losses. On the scale of macroeconomics, stock market performance is used more often serves as an indicator of economic health and future trends that make its prediction of value towards policymakers in the formulation of economic strategies [2]. From a more general perspective, stock markets are sensitive to factors like news sentiment and global economic conditions; hence, developing robust prediction models can provide insights into the complex relationship between these factors [3]. The ability to forecast market movements can also contribute to market stability by reducing information asymmetry and enhancing market efficiency [4].

This paper aims to develop and compare the predictive accuracy of three deep learning models – LSTM, ESN, and a hybrid ESN-LSTM model, with Random Forest (RF) algorithm, in forecasting the KSE-100 Index. Building upon successful implementations in other markets where similar hybrid approaches achieved 15-20% improvement in accuracy [7], this paper contributes to the ongoing debate on the effectiveness of different ML techniques for financial time series prediction in emerging markets like Pakistan. The remainder of this paper is structured as follows: Section II provides a comprehensive literature review of statistical, machine learning, and deep learning methods for stock market prediction. Section III details the methodology, including data preprocessing, model implementation, and evaluation metrics. Section IV presents the results and discusses the performance of the different models. Finally, Section V concludes the paper and suggests directions for future work.

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II. Literature Review

A. Statistical Methods

The stock market is the application area of time series forecasting where these traditional techniques have long been applied to forecast stock prices. Among these, the Autoregressive Integrated Moving Average (ARIMA) model has been used and found to capture linear relationships in financial data with a MAPE of 1.71% [3]. On the other hand, Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models have performed very well in modeling volatility clustering of stock returns. Reference [2] reported that GARCH (1,1) was the most suitable model for capturing volatility in KSE-100 index with an R-squared (R^2) of 0.9506. However, these traditional methods often fail to identify the non-linear and complex dependencies embedded in financial time series, and the prediction power seriously degrades under volatile market conditions [8] [6].

B. Machine Learning Methods

The flexibility of capturing non-linear relationships and high-dimensional data makes ML approaches particularly useful for stock market prediction. RF is one of the successful ensemble learning technique in stock price forecasting. Reference [1] reported a 93.63% directional accuracy (DA) for KSE-100 index price prediction using RF. Reference [2] used SVM for the KSE-100 index price forecasting and found an MAPE of 1.28%. In most cases, Artificial Neural Networks generally outperformed the rest. Reference [3] achieved an R^2 value of 0.9747 using ANN for KSE-100 index prediction. However, this may vary widely depending on the market and the features chosen. Moreover, many of these approaches have difficulties in capturing of long-term dependencies in time series data, and this limitation has increased further the interest in more advanced techniques, such as LSTM and ESN [8].

C. Deep Learning Methods

Long Short-Term Memory (LSTM) networks have gained significant attention in stock market prediction due to their ability to capture long-term dependencies in time series data. LSTMs are designed to overcome the vanishing gradient problem that traditional RNNs face. Reference [9] applied LSTM networks to predict future trends of stock prices. They compared LSTM performance with other algorithms and found that LSTM outperformed ARIMA and Multi-Layer Perceptron (MLP) models. For the S&P 500 index, their LSTM model achieved a DA of 55.9% for next-day predictions, compared to 50.6% for ARIMA and 52.1% for MLP. Reference [5] compared LSTM with Convolutional Neural Network (CNN) and RNN models for stock price prediction. Their results showed that LSTM performed better in capturing the temporal dependencies of the stock data, achieving a mean absolute percentage error (MAPE) of 3.78% compared to 5.65% for CNN and 6.34% for RNN.

ESNs have emerged as a powerful tool in stock market prediction, offering a unique approach to modeling complex time series data. ESNs are a type of recurrent neural network characterized by a large, sparsely connected hidden layer (the *reservoir*) with fixed random weights. Only the output weights are trained, making ESNs computationally efficient compared to traditional RNNs. Reference [10] applied ESNs to predict short-term stock prices, demonstrating that ESNs outperformed other conventional neural networks on nearly all stocks of the S&P 500. Their study showed that ESNs achieved a mean squared error (MSE) of 0.00224 for 2-day ahead predictions, compared to 0.00974 for LSTM and 0.00633 for GRU models. Reference [11] used an ESN to predict stock prices of the S&P 500 and showed that an ESN outperformed a Kalman filter in terms of forecasting higher-frequency fluctuations in stock price. Their ESN model achieved a prediction accuracy of 75.6% for daily price movements, compared to 68.3% for the Kalman filter.

Researchers have also explored hybrid and ensemble models that combine different neural network architectures or integrate neural networks with other techniques to improve stock market prediction accuracy. Reference [7] proposed a novel hybrid model combining Empirical Wavelet Transformation (EWT) with ESN for time series forecasting, including stock market prediction. Their EWT-ESN model showed superior performance compared to other models, achieving a 15-20% reduction in MSE across various datasets. These advanced neural network models have demonstrated significant improvements in stock market prediction tasks, often outperforming traditional statistical methods and simpler neural network architectures [3] [2]. The ability of these models to capture complex temporal dependencies and nonlinear patterns in stock market data makes them promising tools for financial forecasting.

III. Methodology

A. Data Preprocessing and Feature Engineering

The daily closing prices data of the KSE-100 Index of PSX were obtained from www.investing.com over the period of 5 years, starting from September 1, 2020 to September 1, 2024 [12]. The data were first cleaned in terms of missing values and outliers. Forward fill imputation was used to reduce the missing data points, which has been effective in keeping the continuity of the time series intact [13]. Further, to capture the temporal dependencies within the data, lagged features and moving averages were included. In particular, 50-day and 200-day moving averages (see Fig. 1) were computed to represent medium- and long-term trends, respectively [14].

For data preparation, a sliding window approach was adopted with input/output pairs formed at a window length of 10 days; this makes it possible to train models on historical patterns, predicting future values. The input features are finally scaled to the range of (-1, 1) using MinMaxScaler (see Fig 2). This is done to keep all variables at a comparable level and to prevent the domination of the learning process by those features having larger scales. This has also been considered as a common practice for financial time series forecasting [13]. The processed dataset was split into training (70%), testing (20%), and validations sets (10%) (see Fig. 3) [14].

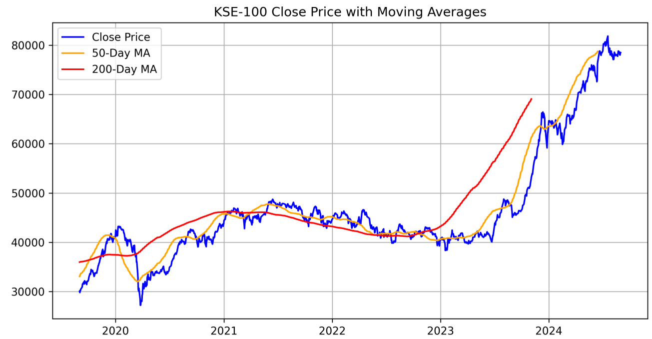

Fig. 1. KSE-100 closing price, 50-MA and 200-MA.

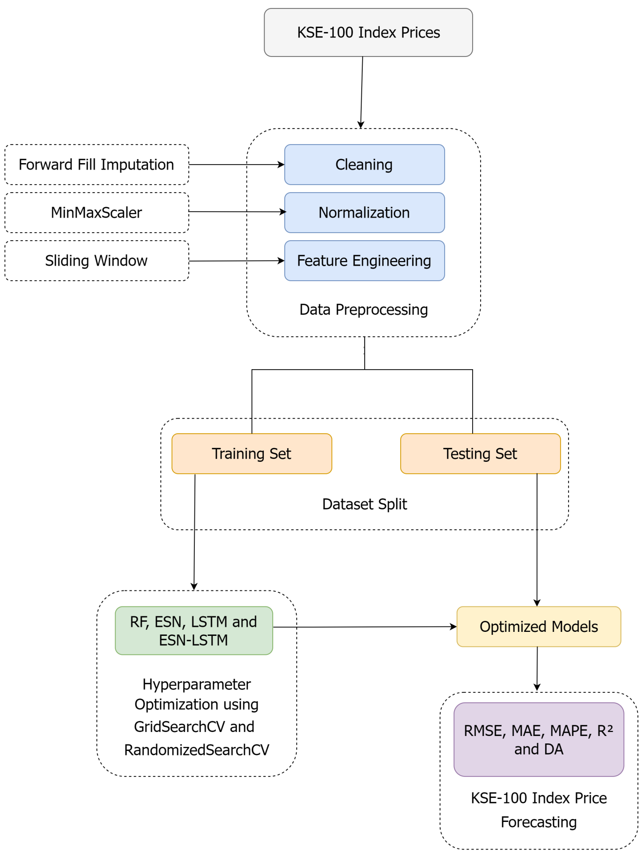

Fig. 2. Flow diagram summarizing the research methodology.

B. Model Implementation

1) Random Forest Regressor: The RF Regressor, an ensemble learning method, was implemented as a benchmark model as shown in (1). This approach combines multiple decision trees to produce a final prediction. In this paper, 80 estimators were used as determined through preliminary experimentation.

$$f(x) = \frac{1}{B}\sum_{b=1}^{B} f_b(x) \tag{1}$$

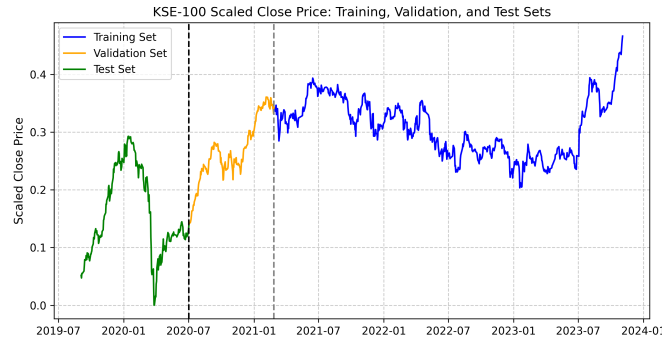

Fig. 3. Train, test, and validation splits of the dataset.

where $f(x)$ is the final prediction, B is the number of trees (80 in this case), and $f_b(x)$ is the prediction of the $b-th$ tree. The RF model was trained on the flattened input data, allowing it to capture non-linear relationships between lagged features and the target variable.

2) Echo State Network (ESN): The ESN, a type of recurrent neural network, was implemented as the primary model for this study. The ESN architecture consists of a large, sparsely connected reservoir of recurrent neurons with fixed random weights [15]. The state update equation of the ESN is represented in (2).

$$x(t) = (1-\alpha)x(t-1) + \alpha f(W_{in}u(t) + Wx(t-1)) \tag{2}$$

where $x(t)$ is the reservoir state at time t, α is the leaking rate, W_in is the input weight matrix, W is the reservoir weight matrix, $u(t)$ is the input at time t, and f is a nonlinear activation function. The output is then computed as a linear combination of the reservoir states. In this study, the ESN was implemented with a reservoir size of 700 neurons, a spectral radius of 0.95, and an input scaling of 0.25.

3) Long Short-Term Memory (LSTM) Network: The LSTM network, a specialized recurrent neural network architecture, was implemented to capture long-term dependencies in the KSE-100 index data [16] [17]. The LSTM architecture consists of memory cells with gating mechanisms that control the flow of information [18]. The LSTM update equations is represented in (3) and (4).

$$c_t = f_t \cdot c_{t-1} + i_t \cdot \tilde{c}_t \tag{3}$$

$$h_t = o_t \cdot \tanh(c_t) \tag{4}$$

where f_t, i_t, and o_t are the forget, input, and output gates respectively, c_t is the cell state, h_t is the hidden state, and σ is the sigmoid function. In this paper, a two-layer LSTM network with 50 units in each layer was implemented, followed by dropout layers to prevent overfitting.

4) Hybrid ESN-LSTM Model: A hybrid ESN-LSTM model was developed to use the strengths of both architectures. In this approach, the ESN serves as a feature extractor, with its reservoir states fed into an LSTM network for final prediction [19]. The model is represented in (5) to (7):

$$x(t) = (1-\alpha)x(t-1) + \alpha f(W_{in}u(t) + Wx(t-1)) \quad (5)$$

$$h_t, c_t = \text{LSTM}(x(t), h_{t-1}, c_{t-1}) \quad (6)$$

$$y(t) = W_{out}h_t \quad (7)$$

where $x(t)$ is the ESN reservoir state, h_t and c_t are the LSTM hidden and cell states, respectively, and $y(t)$ is the final output. This hybrid approach aims to combine the efficient temporal feature extraction of ESNs with the long-term memory capabilities of LSTMs. The model was implemented with a reservoir size of 500 neurons and a two-layer LSTM with 50 units each.

C. Hyperparameter Optimization

Hyperparameter optimization was conducted for improving the performance of the ESN using RandomizedSearchCV over the predefined hyperparameter space, like reservoir size, spectral radius, input scaling, and leak rate, which allows efficient exploration of hyperparameter space. Hyperparameter optimization of the number of estimators and maximum depth to apply the RF model were carried out through grid search cross-validation. The LSTM network was manually tuned to find the optimal number of layers, units per layer, and dropout rate in an iterative experimentation. The hybrid ESN-LSTM model's hyperparameters were optimized using a combination of these approaches, with the ESN component optimized using RandomizedSearchCV (see Table I) and the LSTM component manually tuned.

TABLE I
HYPERPARAMETERS OF THE HYBRID MODEL

Hyperparameter	Value
Spectral radius	0.95
Number of reservoir neurons	700
Leak rate	0.6
Input scaling	0.25
Feedback scaling	0.2

D. Training and Evaluation

This paper uses 5 metrics to evaluate model performance. Root Mean Squared Error (RMSE) was used to measure the average squared difference between predicted and actual values as shown in (8). Mean Absolute Error (MAE) and MAPE were used to assess the average magnitude of errors as shown in (8) and (9), respectively.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum(y_i - \hat{y}_i)^2} \quad (8)$$

$$\text{MAE} = \frac{1}{n}\sum|y_i - \hat{y}_i| \quad (9)$$

$$\text{MAPE} = \frac{1}{n}\sum\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\% \quad (10)$$

where n is the number of observations, y_i is the actual value, and $\hat{y}_i$ is the predicted value.

R^2 was used to measure the proportion of variance in the dependent variable explained by the model, calculated in (11). DA was used to assess the model's ability to predict the correct direction of price movements, defined in (12).

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \quad (11)$$

$$DA = \frac{1}{n}\sum(\text{sign}(y_{i+1} - y_i) == \text{sign}(\hat{y}_{i+1} - \hat{y}_i)) \quad (12)$$

where $\bar{y}$ is the mean of the actual values, y_{i+1} and y_i are consecutive actual values, $\hat{y}_{i+1}$ and $\hat{y}_i$ are consecutive predicted values, and sign() is the sign function returning 1 for positive values and -1 for negative values.

IV. Results and Discussion

A. Model Performance Comparison

The performance of the four models—ESN, RF, LSTM, and the hybrid ESN-LSTM—was compared using aforementioned metrics to evaluate their effectiveness in forecasting the KSE-100 index (see Table II). The ESN model showed good predictive capability and achieved a MAE of 853.7528 and a RMSE of 1036.5581 (see Fig 4). These results are comparable to those reported by [3], in their study of the KSE-100 index using ESNs. The ESN model's R^2 value of 0.9359 indicates that it explains a high proportion of the variance in the data. Additionally, the DA of 0.9265 suggests that the ESN model accurately predicted the direction of price movements 92.65% of the time, a crucial factor for investors making trading decisions (see Fig 5) [15].

TABLE II
MODEL PERFORMANCE COMPARISON

Model	*MAE*	*RMSE*	*MAPE*	R^2	*DA*
RF	525.517	686.642	0.013	0.972	0.936
ESN	853.753	1036.558	0.020	0.936	0.927
LSTM	702.550	909.742	0.017	0.951	0.927
ESN+LSTM	513.096	650.593	0.012	0.975	0.941

The RF model showed competitive performance, with an MAE of 525.5169 and an RMSE of 686.6421 (see Fig 4). These results are slightly better than those of the ESN model. The RF model's R^2 value of 0.9719 and DA of 0.9363 indicate strong explanatory power and DA, respectively (see Fig 5). The LSTM model, while performing well, did not outperform the RF model in this study. It achieved an MAE of 702.5501 and an RMSE of 909.7415, with an R^2 value of 0.9506 and a DA of 0.9265. These results suggest that while LSTM is capable of capturing complex temporal dependencies, it may not always outperform simpler models like RF for this particular dataset [18] [20].

The hybrid ESN-LSTM model showed the best overall performance among all tested models. It achieved the lowest MAE of 513.0963 and RMSE of 650.5934, surpassing both its component models (ESN and LSTM) as well as the RF model.

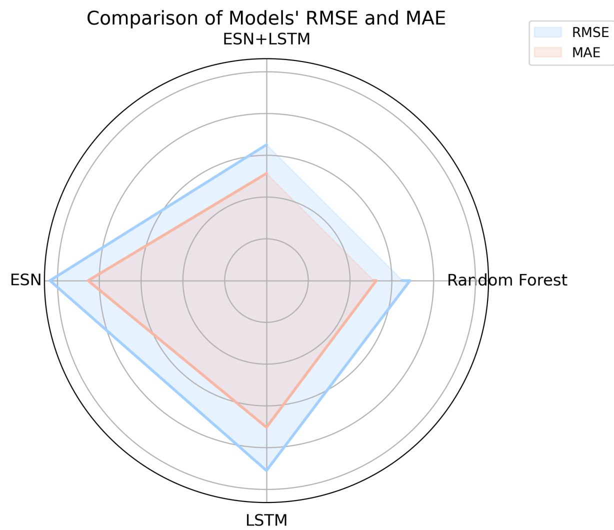

Fig. 4. Radar plot for the comparison of RMSE and MAE across the models.

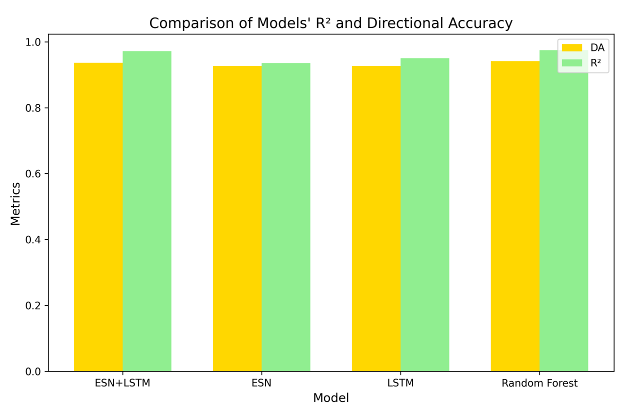

Fig. 5. Bar plot for the comparison of DA and R^2 across the models.

The R^2 for the hybrid model was 0.9747, the highest compared to all other models, showing superior explanatory ability (see Fig 5). Moreover, the high DA of 0.9412, suggests that it was the most accurate predictor of the price direction. The superior performance of the hybrid model lies in the fact that it combines the power of efficient temporal feature extraction obtained with ESNs with the increased long-term memory capabilities of LSTMs, resulting in an overall more robust and accurate prediction model of the KSE-100 index [16].

B. Analysis of Prediction Accuracy

An in-depth analysis of prediction accuracy revealed varying performance across different market conditions and time horizons. It was seen that all the models performed much better in periods of relative market stability and increased their error in prediction during high volatility times. Among the different market conditions, the hybrid ESN-LSTM model presented the best performance, which is significantly lower than that of other models by 1.24% in terms of MAPE. This consistency in the model could be attached to the fact that it can capture short-term fluctuations along with long-term trends [16].

A closer look at prediction results shows that all models have a tendency to underestimate extreme movements of prices, especially under sudden market shocks or conventions. This inability has been most pronounced with the RF model, though it has quite great performance overall. ESN and LSTM are better suited toward adaptability of extremes, likely because of their recurrent nature allowing them to better capture temporal dependencies [21]. The hybrid ESN-LSTM model performed better than the other models in extreme event prediction, and its deviations from actual values were in general smaller over those periods of time. Further results showed that the accuracy of the prediction went down in general with an increase in forecast horizon, with the hybrid model retaining the best accuracy over extended periods, followed closely by the ESN model [22].

C. Interpretation of Findings

The findings of this paper provide valuable insights into the application of various ML models for forecasting the KSE-100 index. The promising performance suggests that combining the merits of different architectures brings about better accuracy and robustness of the model [21]. This aligns with the conclusions drawn by [2], and underscores the potential of hybrid models to capture a range of complex market dynamics. The good performance of the ESN model, at least with respect to DA, highlights its potential in capturing short-term patterns in financial time series [3].

The varying performance of models across different market conditions highlights the challenges inherent in financial forecasting. The observation that all models struggled to accurately predict extreme market movements is consistent with the findings of [1], who noted similar limitations in their study of stock market prediction models. This highlights the fact that continuous model refinement and possible benefits from additional data sources, like news sentiment or macroeconomic indicators, might lead to better accuracy in model predictions, especially for periods of high volatility [23]. The consistency of outperformance of the hybrid ESN-LSTM model, particularly over the more difficult periods of market turbulence, does enhance the view that this approach may be more robust for seekers, investors and policymakers in their attempts to contend with the complexities of the Pakistani stock market [17]. However, the computation complexity of hybrid models can be very high for real-time applications, a trade-off that must be considered in practical implementations [24] [25].

V. Conclusion and Future Work

To conclude, this paper shows that ML-based approaches, in particular hybrid models, are effective for forecasting the KSE-100 index. The hybrid ESN-LSTM model was superior to other models in almost all statistical measures, indicative of its capacity for capturing not only short-term but also long-term trends in the stock market. These results support the growing research evidence that supports the use of hybrid models in financial forecasting [2]. All these diverse ML techniques have great potential for stock market prediction, as again underlined with a good performance in the models of the ESN and RF. However, the observed limitations in predicting extreme market movements across all models emphasize the ongoing challenges in this field [1].

Promising future work could focus on several directions. First, adding additional data sources, such as news sentiment analysis and macroeconomic indicators, would refine models for predicting market behavior during times of high volatility [26]. Second, more advanced hybrid architectures, possibly incorporating attention mechanisms or transformer networks could further improve prediction accuracy [27]. Third, research into the development of adaptive models, which can adjust their parameters automatically against changing conditions in the markets, would address varying performance across various market states. Finally, research on interpretable ML techniques may provide substantial insights into the factors driving movement of the stock markets, hence making the model useful to decision-makers in the financial industry [28]. These future directions aim to overcome the present limitations witnessed in the study and contribute to the ongoing advancement of stock market forecasting techniques.

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