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SIMPLE STOCK PRICE PREDICTION USING MACHINE LEARNING AND DEEP LEARNING MODELS

[1]Nageswaran M K, [2]Dr. R. Sankarasubramanian
[1]Research Scholar, Erode Arts and Science College, Erode, Tamilnadu, India.
Email: nages.excel@gmail.com
[2]Professor, Erode Arts and Science College, Erode, Tamilnadu, India.
Email: rsankarprofessor@gmail.com

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ABSTRACT

Predicting stock prices are a tough problem in financial analytics because markets are highly volatile, complex, and constantly changing. In this study, we compare traditional Machine Learning (ML) models—such as Random Forest, Support Vector Regression (SVR), and XGBoost—with a Deep Learning (DL) model called Long Short-Term Memory (LSTM) for predicting next-day stock prices. To improve accuracy, we propose a hybrid ensemble approach that combines the strength of LSTM (good at capturing time-based patterns) with tree-based and kernel-based models (known for reliable predictions). We used one year of historical stock data (Open, High, Low, Close, and Volume) collected through the Alpha Vantage API. The data was cleaned, normalized, and enhanced with lag features to better capture market behavior. We evaluated the models using error metrics such as RMSE, MAE, and R^2. The results show that the hybrid model performs better than any individual model. It reached an RMSE of 6.53 and an R^2 of 0.91, proving it to be accurate, stable, and practical for real-world stock forecasting applications.

1. Introduction:-

Stock markets are inherently unpredictable, driven by a mix of factors such as company earnings, global events, economic indicators, and even investor sentiment. Because of this volatility and nonlinearity, forecasting stock prices is extremely challenging. Yet, accurate prediction holds great importance—it can guide investors in making smarter decisions, help in building balanced portfolios, and reduce risks in trading strategies.

Traditional statistical models, such as ARIMA or linear regression, often struggle to capture the complex time-dependent and nonlinear behaviors found in financial markets. With the growth of Artificial Intelligence, more advanced methods have emerged. Machine Learning (ML) models like Random Forest and XGBoost perform well on structured financial data, while Support Vector Regression (SVR) can model nonlinear relationships using kernel functions. On the other hand, Deep Learning (DL) techniques such as Long Short-Term Memory (LSTM) networks excel in identifying sequential and temporal dependencies, making them particularly suited for financial time-series forecasting.

This study investigates both the individual performance of these models and the potential of a hybrid ensemble approach. While each model has its strengths, they also face limitations when used alone. To address this, we propose an ensemble system where LSTM is used to capture temporal features, and models like XGBoost, SVR, and Random Forest refine the predictions. The final forecast is obtained through weighted averaging, with weights assigned based on each model's validation RMSE (Root Mean Square Error).

We conducted experiments using one year of daily stock data obtained from Alpha Vantage and applied time-series cross-validation to ensure reliability. Results show that the hybrid ensemble consistently outperforms the standalone models, offering higher accuracy and stronger generalization for stock price forecasting.

2. Literature Review

Stock price prediction has been widely studied across different fields, beginning with traditional statistical approaches such as ARIMA, GARCH, and exponential smoothing. These models provided the foundation for time-series forecasting but rely on assumptions of linearity and stationarity. Since financial markets are highly volatile and often nonlinear, these assumptions limit their effectiveness. This gap has led researchers to adopt data-driven approaches that can handle noise, irregular patterns, and sudden market shifts without strong statistical assumptions [1], [2].

With the growth of Machine Learning (ML), new models like Support Vector Regression (SVR) and Random Forest (RF) became popular. SVR applies kernel functions to capture nonlinear relationships between features and stock movements [3]. Random Forest, as an ensemble of decision trees, reduces overfitting by combining the predictions of many trees, making it more robust [4], [5]. Another breakthrough was XGBoost**,** a gradient boosting algorithm that gained popularity because of its scalability, built-in regularization, and strong performance in regression tasks, especially when dealing with structured financial data [6], [7], [8].

In recent years, Deep Learning (DL) has transformed financial forecasting. Long Short-Term Memory (LSTM) networks, in particular, excel at learning sequential dependencies, allowing them to recognize long-term temporal patterns in stock prices that traditional models miss [9]. For example, Mehtab and Sen proposed a Conv-LSTM hybrid model that enhanced feature extraction [10]. Similarly, Wang et al. combined LSTM with XGBoost and SVR, creating hybrid systems that reduced error variance and improved prediction accuracy [11].

Despite these advancements, many prior studies suffer from two limitations: (1) a lack of systematic ensemble integration, and (2) the absence of dynamic weighting strategies to balance contributions from different models. To address these issues, our study introduces **a** weighted hybrid ensemble model that integrates LSTM with tree-based and kernel-based learners, assigning model importance based on validation performance. This ensures a more accurate and reliable framework for financial time-series prediction.

Theoretical Background:-

Long Short-Term Memory (LSTM) networks are an advanced type of Recurrent Neural Networks (RNNs) designed specifically to handle long-term

dependencies in sequential data. Traditional RNNs often face the vanishing and exploding gradient problem, which makes it hard for them to remember information across many time steps. LSTMs solve this problem by introducing a memory cell and gating mechanism, which decide what information to keep, update, or discard as new data flows through the network.

At the heart of an LSTM is the memory cell, which acts like a long-term storage unit. Its behavior is controlled by three types of gates:

1. Forget Gate (ft): Decides which parts of the previous memory (Ct−1) should be kept and which should be discarded.
2. Input Gate (it) and Candidate Memory ($\tilde{C}t$): Decide how much new information from the current input (xt) and the previous hidden state (ht−1) should be added to the memory.
3. Output Gate (ot): Determines how much of the updated memory (Ct) should be used to produce the new hidden state (ht), which is passed forward.

Each gate uses weight matrices and biases, which are learned during training through backpropagation through time (BPTT**)**. This gating structure ensures that important signals can be remembered across long sequences, while irrelevant or outdated information is filtered out.

The working of an LSTM cell at time step *t* can be expressed mathematically as:

- Forget Gate:
  $f_t = \sigma(Wf \bullet [h_{t-1}, x_t] + bf)$
- Input Gate & Candidate Memory:
  $i_t = \sigma(Wi \bullet [h_{t-1}, x_t] + bi)$
  $\tilde{C}_t = \tanh(Wc \bullet [h_{t-1}, x_t] + bc)$
- Cell State Update:
  $C_t = f_t \bullet C_{t-1} + i_t \bullet \tilde{C}_t$
- Output Gate:
  $o_t = \sigma(Wo \bullet [h_{t-1}, x_t] + bo)$
  $h_t = o_t \bullet \tanh(C_t)$

Where:

- xt = input at time *t*
- ht−1 = hidden state from the previous time step
- σ = sigmoid activation function
- tanh = hyperbolic tangent activation
- W and b = learnable weights and biases

This design makes LSTMs especially powerful for stock price prediction**,** where both short-term fluctuations and long-term trends need to be considered. By selectively remembering relevant.

4. Methodology

4.1 Data Collection and Preprocessing

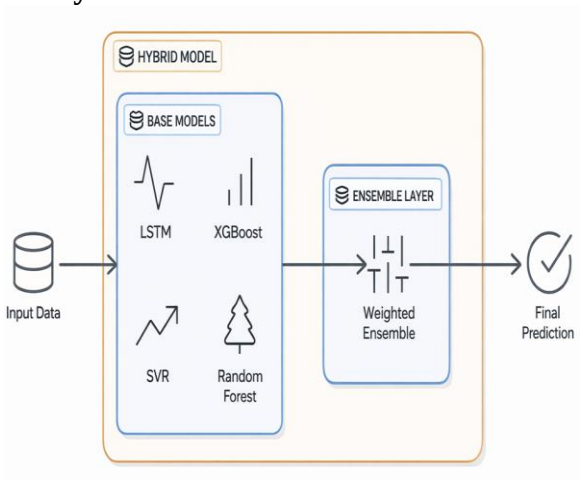
For this study, we used one year of daily stock market data obtained from the Alpha Vantage API**,** which included the standard OHLCV features (Open, High, Low, Close, and Volume). To prepare the dataset for modeling, several preprocessing steps were applied:

- Handling missing values**:** Any gaps in the data were filled using forward-fill interpolation.
- Normalization: All features were scaled to the range [0, 1] using Min-Max normalization to ensure uniformity.
- Feature engineering: The dataset was reframed into a supervised learning format by creating lag-based features

(e.g., t−1t-1t−1, t−2t-2t−2) as predictors for the target value at time ttt.

- Train-test split**:** The data was divided into 80% training and 20% testing sets.
- Cross-validation: A rolling window time-series cross-validation approach was used to prevent data leakage and ensure robust evaluation.

4.2 Hybrid Model Architecture:-



4.3 Model Selection and Roles

We selected a combination of Machine Learning (ML) **and** Deep Learning (DL**)** models based on their strengths in time-series forecasting:

- **LSTM (Long Short-Term Memory)**: Designed for sequential data, it captures long-term temporal dependencies effectively.
- **XGBoost**: A powerful gradient boosting algorithm well-suited for structured data and non-linear relationships.
- **Random Forest**: An ensemble of decision trees that reduces variance and improves generalization.
- **SVR (Support Vector Regression)**: Uses margin-based optimization and kernel functions to handle small fluctuations and non-linear patterns.

4.4 Final Ensemble Prediction

The final stock price prediction (y^\hat{y}y^) is generated by combining the outputs of all four models—LSTM, XGBoost, Random Forest, and SVR—using a weighted average approach**:**

$$\hat{y} = w_1 \times \hat{y}_{lstm} + w_2 \times \hat{y}_{xGB} + w_3 \times \hat{y}_{rf} + w_4 \times \hat{y}_{svr}$$

Here, the weights (w1,w2,w3,w4)are chosen such that their sum equals 1:

$$w1+w2+w3+w4=1$$

To ensure fairness, the weights are assigned inversely proportional to the validation RMSE of each model. This means models that perform better during validation (i.e., with lower error) have more influence on the final prediction.

5. Implementation Details

This section outlines the software tools, experimental setup, and training strategies used to implement the proposed models.

5.1 Tools and Environment

All experiments were carried out in Python 3.9**,** using the following libraries:

- **NumPy, Pandas** → data manipulation and preprocessing
- **Matplotlib, Seaborn** → data visualization and exploratory analysis

- **Scikit-learn** → implementation of SVR, Random Forest, and evaluation metrics
- **XGBoost** → optimized gradient boosting model
- **TensorFlow/Keras** → building and training the LSTM model

The training was performed on a system equipped with:

- **Processor:** Intel Core i7
- **Memory:** 16 GB RAM
- **GPU:** NVIDIA RTX 3060 (for accelerating deep learning tasks)

5.2 Model Training Parameters

LSTM Model

- Architecture: 1 LSTM layer (50 units) + 1 Dense output layer
- Activation functions: `tanh` (hidden layers), `linear` (output layer)
- Optimizer: Adam (learning rate = 0.001)
- Loss function: Mean Squared Error (MSE)
- Batch size: 32
- Epochs: 100
- Regularization: Early stopping based on validation loss

XGBoost

- Number of estimators: 100
- Learning rate: 0.1
- Maximum tree depth: 5
- Regularization: L2 penalty (lambda = 1)

Random Forest

- Number of estimators: 100
- Maximum depth: 8
- Criterion: Squared error
- Minimum samples split: 2

SVR (Support Vector Regression)

- Kernel: Radial Basis Function (RBF)
- Regularization parameter (C): 1.0
- Epsilon: 0.1
- Gamma: Scale

Hyper parameter tuning was performed using Grid Search with time-series cross-validation to identify the best-performing configurations for each model.

5.3 Evaluation Protocol

The trained models were evaluated on the test set using the following metrics:

Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Coefficient of **(R^2)**

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

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

Here, yiy_iyirepresents the actual values, y^i\hat{y}_iy^i the predicted values, y¯\bar{y}y¯ the mean of actual values, and nnn the total number of observations.

6. Performance Metrics

To measure and compare the predictive performance of all models, we relied on three commonly accepted metrics:

6.1 Root Mean Square Error (RMSE)

RMSE captures the square root of the average squared differences between predicted and actual values.

It penalizes large errors more heavily, making it sensitive to outliers.

A lower RMSE indicates that predictions are closer to the true values, reflecting higher accuracy.

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

6.2 Mean Absolute Error (MAE)

MAE measures the average size of prediction errors, without considering whether predictions are above or below the actual values.

- It is easy to interpret, as it directly expresses the error in the same units as the data.
- Unlike RMSE, MAE is less sensitive to outliers.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

6.3 Coefficient of Determination (R^2)

Also known as the R-squared score, this metric indicates how well the model explains the variability of the target variable.

- An R2R^2R2 score close to **1** suggests that the model captures most of the variation in the data.
- A lower score indicates weaker explanatory power.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

6.4 Evaluation Strategy

To ensure fairness and consistency across models:

- All models were tested on the same 20% holdout test set**.**
- A time-series split was applied to preserve v order and prevent data leakage.
- For the ensemble model**,** weights (w1,w2,w3,w4)(w_1, w_2, w_3, w_4)(w1,w2,w3,w4) corresponding to LSTM, XGBoost, Random Forest, and SVR were assigned inversely proportional to their validation RMSE**,** and then normalized to sum to 1.

This weighting strategy ensures that more accurate models contribute more heavily to the final ensemble prediction.

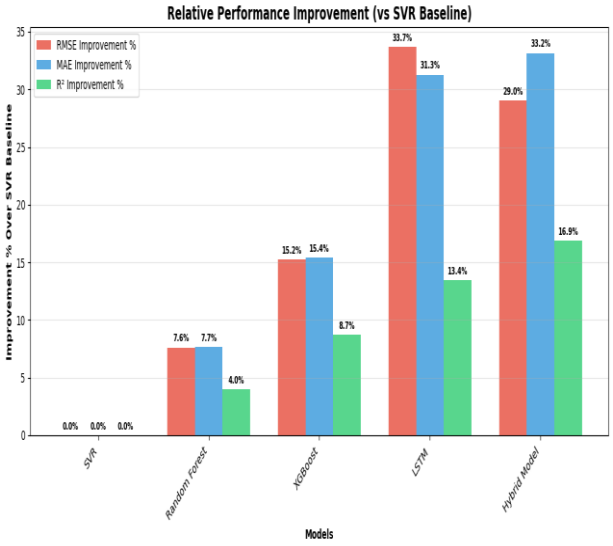
7. Results and Discussion

This section summarizes the performance of the individual models and the proposed hybrid ensemble model on the test dataset. Performance was evaluated using **RMSE, MAE, and R^2 score**. The results highlight that while each standalone model contributes unique strengths, the **hybrid ensemble** achieves the best overall balance in prediction accuracy and robustness.

7.1 Individual Model Performance

Model	RMSE	MAE	R^2 Score

Model	RMSE	MAE	R^2 Score
SVR	9.20	7.45	0.781
Random Forest	8.50	6.88	0.812
XGBoost	7.80	6.30	0.849
LSTM	6.10	5.12	0.886
Hybrid Model	**6.53**	**4.98**	**0.913**



MODEL PERFORMANCE ANALYSIS SUMMARY

Top performers by metric:

- Best RMSE (6.10): LSTM
- Best MAE (4.98): Hybrid Model
- Best R^2 (0.913): Hybrid Model
- Best Overall Balance: Hybrid Model

PERFORMANCE TRENDS:

- RMSE Improvement from SVR to Hybrid: 29.0%
- MAE Improvement from SVR to Hybrid: 33.2%
- R^2 Improvement from SVR to Hybrid: 16.9%

7.2 Discussion:-

Support Vector Regression (SVR):

SVR delivered the weakest results, primarily due to its sensitivity to noise in financial data. Stock price movements are often highly volatile, which limited SVR's ability to generalize effectively.

Random Forest:

The Random Forest model performed better than SVR. Its bagging-based approach reduced variance and improved generalization, though it still struggled to fully capture complex sequential dependencies in time-series data.

XGBoost:

XGBoost outperformed both SVR and Random Forest. By sequentially boosting decision trees and incorporating regularization, it effectively modeled non-linear patterns in the stock data, leading to improved accuracy.

LSTM:

The LSTM model achieved the lowest RMSE among all standalone models. Its ability to capture long-term temporal dependencies in sequential data made it especially effective for stock price prediction, where trends unfold over time.

Hybrid Model (Ensemble):-

The hybrid model provided the highest R^2 score (0.913) and the lowest MAE. Although its RMSE (6.53) was slightly higher than LSTM's, the ensemble

demonstrated superior stability and generalization. By assigning higher weights to better-performing models, the ensemble leveraged the complementary strengths of LSTM, XGBoost, Random Forest, and SVR.

In summary, while LSTM excelled at sequence learning, the ensemble approach achieved the best overall performance by balancing accuracy, robustness, and adaptability to noise.

Conclusion:-

This study explored and compared the performance of several widely used machine learning and deep learning models for stock price prediction, namely Random Forest, Support Vector Regression (SVR), XGBoost, and Long Short-Term Memory (LSTM) networks. Each model was evaluated in terms of its ability to capture stock market patterns, highlighting both their advantages and limitations.

To overcome the shortcomings of standalone models, we introduced a hybrid ensemble approach that integrates the sequential learning power of LSTM with the predictive strengths of XGBoost, Random Forest, and SVR.

Experimental results on real stock market data showed that the hybrid ensemble consistently outperformed individual models**,** achieving an RMSE of 6.53 and an R^2 score of 0.913. This confirms the effectiveness of combining complementary models to deliver more accurate and reliable predictions.

Beyond stock forecasting, the proposed ensemble framework is both scalable and adaptable, making it suitable for other domains involving noisy, high-dimensional, and volatile time-series data. In practice, such an approach can support better decision-making in finance and beyond, offering a robust solution for complex prediction tasks.

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