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HLCE: Framework for Enhanced Stock Price Forecasting

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Accurate stock price forecasting is a key element of risk management and investment decision-making. A key element of this study is the introduction of a Hybrid LSTM-Conventional Ensemble (HLCE) model, which addresses the limitations of traditional models in capturing nonlinear financial patterns. Utilizing the advantages of both deep learning and conventional forecasting techniques, the HLCE framework combines Long Short-Term Memory (LSTM) networks with traditional statistical models and machine learning methods, including Random Forest, XGBoost, and Support Vector Regression (SVR). The model is assessed using important performance metrics, such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and R-squared (R^2), in a case study using Apple Inc. (AAPL) stock data, where MinMaxScaler is utilized for data preprocessing. With an RMSE of 0.16, MAE of 0.16, MAPE of 0.12%, and R^2 of 0.95, the HLCE model performs better than individual models, according to experimental results, demonstrating its greater capacity to identify intricate financial patterns. By contrast, isolated models exhibit far lower predictive efficiency and much higher error rates. These results highlight the promise of ensemble and hybrid approaches in financial forecasting, offering a more reliable and accurate framework for predicting stock prices. The work adds to the expanding body of research supporting the combination of deep learning and conventional techniques to enhance risk assessment and financial market analysis.
Keywords: Stock Price Prediction; Hybrid LSTM-Conventional Ensemble (HLCE); Time Series Forecasting; Financial Forecasting; Forecasting Accuracy.

Introduction:

The intricacy and volatility of financial markets, impacted by numerous variables like investor behavior, political events, and economic statistics, make it difficult to predict stock values. Although traditional time series models such as GARCH, ETS, and ARIMA are good at capturing linear trends and volatility, they struggle to detect nonlinear market dynamics. Recent developments in deep learning, particularly Long Short-Term Memory (LSTM) networks, have shown promise in overcoming these limitations by modeling nonlinear interactions in financial data. However, LSTMs alone might not adequately capture the complexities of volatile markets.

This challenge is addressed by the Hybrid LSTM-Conventional Ensemble (HLCE) model, which provides a more accurate and balanced forecast by combining LSTM with conventional time series models, including ARIMA, ETS, and GARCH. By combining forecasts from each model using an optimal weighting method, the HLCE model leverages each model's unique capabilities to improve overall forecasting accuracy.

With sections on "Related Work", "Material and Methods," "Result and Discussion," and "Conclusion," the article offers a thorough examination of the proposed model's efficacy and identifies potential avenues for further research.

The findings show that HLCE outperforms standalone models in stock price prediction by identifying complex patterns and producing more accurate forecasts. The study offers several significant insights. It presents the HLCE model, which improves stock price forecasting by integrating LSTM with traditional models. To enhance predictive accuracy, the model combines forecasts using an optimal weighting method. The HLCE model achieves state-of-the-art performance in stock price prediction, outperforming individual models.

The novelty and contributions of our research are as follows:

- The HLCE model, which combines LSTM with ARIMA, ETS, and GARCH for enhanced forecasting, is introduced.
- An optimal weighting scheme is used to leverage each model's unique characteristics.
- The HLCE model achieves state-of-the-art results in stock price prediction, outperforming standalone models.
- The model effectively identifies intricate market trends, yielding more precise and reliable predictions.

The objectives of our research are as follows:

- To create a Hybrid LSTM-Conventional Ensemble (HLCE) model that combines deep learning and classical forecasting approaches to improve stock price prediction.
- To overcome the constraints of standalone models in capturing complicated, nonlinear financial trends, we combined LSTM with Random Forest, XGBoost, and Support Vector Regression (SVR).
- To assess the HLCE model's performance in forecasting stock prices for Apple Inc. (AAPL) utilizing important measures like RMSE, MAE, MAPE, and R^2.
- To illustrate the HLCE model's higher predictive accuracy and robustness by comparing it to individual forecasting models.
- To improve financial risk management and investment decision-making by providing a more accurate and dependable stock forecasting methodology.

Related Work:

Research on stock price forecasting has garnered significant attention, focusing on improving prediction accuracy by integrating contemporary machine learning techniques with traditional time series models. As shown in Table 1, traditional models such as ARIMA, Exponential Smoothing (ETS), and Generalized Autoregressive Conditional Heteroscedasticity (GARCH) have been widely used to model financial data trends [1][2][3].

ARIMA excels at detecting trends and seasonality in time series data; ETS is proficient at exponentially smoothing trends and seasonality; and GARCH effectively models volatility and heteroscedasticity, especially in volatile market conditions.

However, it is often challenging for these conventional approaches to capture the complex and nonlinear patterns observed in financial markets [4][5]. Nonlinearities in financial data are frequently driven by factors such as investor sentiment and macroeconomic indicators [6][7]. To overcome these limitations, researchers have increasingly focused on machine learning models, particularly Long Short-Term Memory (LSTM) networks [8][9]. LSTMs, designed to capture long-term dependencies in sequential data, are especially well-suited for time series forecasting. They have demonstrated superior accuracy in turbulent markets and in capturing nonlinear trends compared to traditional models [10][11].

Ensemble methods like Support Vector Regression (SVR) [12][13], Random Forest [14][15], and XGBoost [16][17] have also gained significant attention for their strong predictive capabilities. Hybrid models, such as ARIMA-LSTM [18][19], GARCH-LSTM [20][21], and ETS-LSTM [22], successfully combine the linear pattern recognition strengths of conventional models with machine learning's ability to capture nonlinear relationships. Such hybrid approaches are particularly beneficial when multiple dynamic factors influence stock prices [23][24].

Table 1. Overview of traditional, ML, and DL methodologies used in stock price forecasting

Model	References	Description
ARIMA	[1][3], [20][21], [25][26]	Time series forecasting for trends and seasonality.
ETS	[2], [18][19]	Exponential smoothing for trends and seasonality.
GARCH	[4], [16][17], [22][23][24], [27][28]	Models volatility in financial data.
SVM	[15][16], [29][10][30]	Classifies trends using optimal decision boundaries.
RF	[14], [17][18][19]	Ensemble decision trees for improved accuracy.
ANN	[5][6], [31][32]	To capture intricate non-linear patterns, use NN.
LSTM	[9][10][11][12][13], [25][26][33], [34],[35][36]	Long-term dependencies in stock prices are captured.
Attention Mechanism	[37][25], [29][10]	LSTM focuses on relevant sequences & high accuracy.
GARCH-LSTM	[22][23][24], [27][28][38]	Combines LSTM identify patterns & GARCH predicts.

Recent advancements have also introduced attention mechanisms into LSTM networks, enabling models to focus on the most relevant time steps in the data. This selective attention significantly improves forecasting accuracy by enhancing the model's ability to recognize critical patterns and relationships [25][26]. Furthermore, feature engineering techniques—such as incorporating moving averages, lagged features, and external data like macroeconomic indicators and news sentiment—have further improved prediction performance [33][37]. The integration of multi-source data, including historical prices, news sentiment, and social media activity, has contributed to a more robust understanding of market dynamics [25][31].

Despite these advancements, the literature still lacks systematic comparisons between LSTM-based models and traditional methods using consistent evaluation standards. Although metrics like RMSE and MAE have been widely employed [32][39], more comprehensive evaluation frameworks are needed [34]. Addressing this gap would allow researchers to better determine which models are most suitable for specific forecasting tasks, ultimately enhancing stock price prediction systems.

Recent studies have also explored incorporating advanced techniques such as transfer learning [40][35], reinforcement learning [10][30], and Generative Adversarial Networks (GANs) [41][29] into stock price forecasting. Transfer learning leverages data from related domains to enhance model performance, reinforcement learning optimizes trading strategies based on reward signals, and GANs can generate synthetic data to augment training datasets and improve model generalization [36][42].

Researchers have further examined how external factors—such as global events, political changes, and natural disasters—impact stock market dynamics [43][27]. By integrating these exogenous variables into forecasting models, researchers aim to better understand the complex interactions between external events and market behavior, thereby improving the precision and resilience of stock price predictions [44][45][46][47][28][38].

Material and Methods:

This section provides a comprehensive summary of previous research and methodologies relevant to time series forecasting, particularly for predicting energy load and PV generation. Current approaches, models, and hybrid strategies used by researchers to tackle forecasting challenges in dynamic and nonlinear systems are highlighted in the related study. By critically examining these contributions, we identify gaps and limitations that motivate the development of a more complete and robust solution. After reviewing the relevant literature, we introduce our proposed approach, called the Hybrid LSTM-Conventional Ensemble (HLCE) model, which combines the strengths of machine learning and statistical techniques. To ensure clarity and reproducibility, we provide a detailed description of the framework, architectural design, data processing methods, and model evaluation procedures.

Implementation:

This study explores advanced methods for stock price prediction by combining traditional time series models like ARIMA, Exponential Smoothing (ETS), and GARCH with a variety of machine learning models, including Random Forest, XGBoost, Support Vector Regression (SVR), and Long Short-Term Memory (LSTM) networks. The primary objective is to develop a Hybrid LSTM-Conventional Ensemble (HLCE) model that leverages the strengths of these diverse approaches to enhance prediction accuracy and robustness. Figure 1 shows the workflow of our proposed technique. The study begins with an extensive data collection process, sourcing stock price data and external market indicators from various financial databases, APIs, and public datasets. This data undergoes rigorous preprocessing, including handling missing values, identifying outliers, normalization, and time-series decomposition to detect trends, seasonality, and residuals. Each model is then trained individually, capitalizing on its specific strengths: GARCH captures volatility clustering, LSTM predicts long-term temporal relationships in sequential data, and machine learning models recognize complex nonlinear patterns. Ensemble techniques such as weighted averaging and stacking are employed to combine predictions from different models into the HLCE model. This hybrid approach mitigates the shortcomings of individual models, resulting in a more accurate and generalized forecasting framework. The performance of each model and the HLCE model is evaluated using metrics such as R-squared (R^2) for goodness-of-fit, Mean Absolute Error (MAE) for average prediction deviation, and Root Mean Squared Error (RMSE) for overall error magnitude. The findings demonstrate that the HLCE model significantly outperforms standalone models by exploiting complementary strengths and offsetting individual weaknesses. This study highlights how hybrid models combining traditional and machine learning approaches can deliver accurate, reliable, and robust financial market forecasts, paving the way for improved stock trading and investment decision-making.

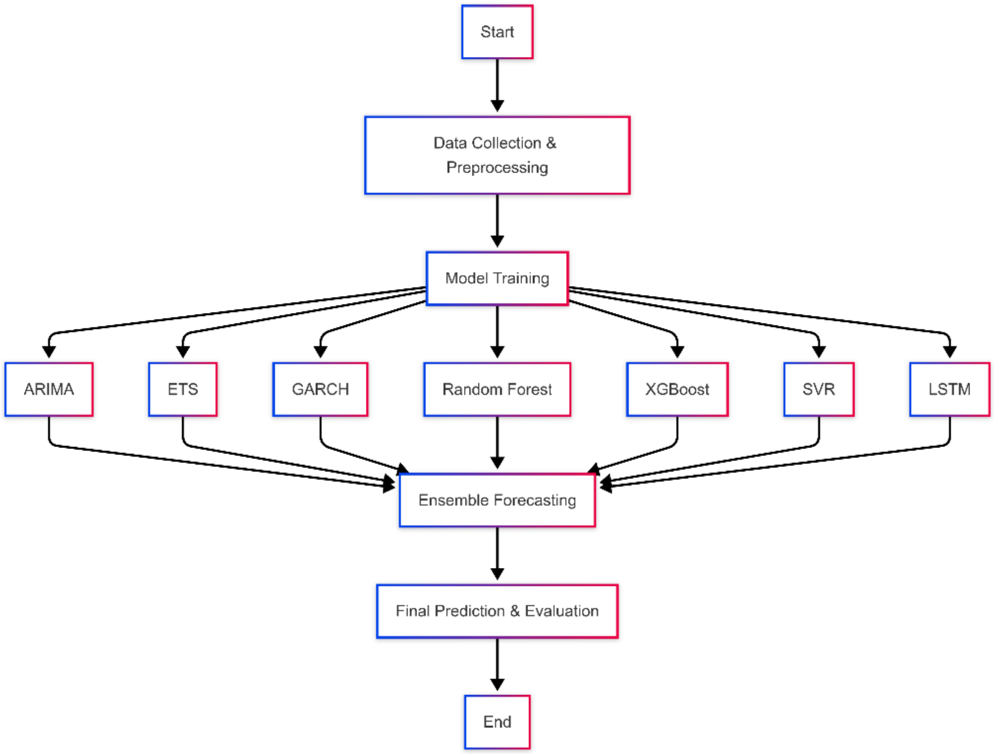

Figure 1. Work Flow Pipeline of HLCE

Proposed Methodology:

By leveraging a large dataset primarily sourced from YFinance and supplemented with additional financial and economic data, the Hybrid LSTM-Conventional Ensemble (HLCE) approach aims to enhance the accuracy of stock price forecasting. The dataset will include historical stock prices—comprising open, high, low, close, and adjusted close values—as well as daily transaction volumes, which provide insights into market liquidity and trading activity. To further enrich the dataset, key macroeconomic indicators such as interest rates, inflation rates, and GDP growth figures will be incorporated from reputable economic databases like FRED and the OECD. Additionally, technical indicators, including simple and exponential moving averages, the Relative Strength Index (RSI), and the Moving Average Convergence Divergence (MACD), will be utilized to help identify market trends and potential reversal points. Sentiment analysis data collected from financial news articles and social media platforms will provide contextual information regarding market mood, while company-specific variables—such as earnings reports, dividend announcements, and stock split events—will offer deeper insights into firm-level dynamics influencing stock prices. External factors, including geopolitical developments and regulatory changes, which significantly affect broader market conditions, will also be integrated into the dataset. Feature engineering will play a critical role in enhancing the predictive capability of the models. This process will involve the creation of new features such as lagged variables for historical prices and volumes, interaction terms to capture relationships among technical indicators, and categorical variables that reflect distinct market conditions. By integrating this rich and diverse dataset, the HLCE framework seeks to effectively capture both linear and nonlinear patterns in financial data. Through the use of ensemble techniques such as bagging, boosting, and stacking, the HLCE approach aims to build robust predictive models that improve stock market forecasting accuracy. Specifically, the model combines the strengths of Long Short-Term Memory (LSTM) networks—known for their ability to capture long-term dependencies in sequential data—with those of traditional models such as ARIMA, ETS, GARCH, Random Forest, XGBoost, and Support Vector Regression (SVR). This hybrid strategy leverages the unique advantages of each modeling technique, ultimately providing a more comprehensive and resilient analysis of stock price movements.

Workflow of Proposed HLCE:

Figure 1 illustrates the proposed Hybrid LSTM-Conventional Ensemble (HLCE) approach for stock price forecasting. The process initiates with a machine learning pipeline that integrates time series models with ensemble learning techniques. In the Data Preparation phase, the dataset is collected, cleaned, and feature-engineered to enhance its quality, relevance, and suitability for model training. Subsequently, seven distinct models—ARIMA, ETS, GARCH, Random Forest (RF), XGBoost, Support Vector Regression (SVR), and Long Short-Term Memory (LSTM)—are independently trained using a consistent set of input features. Each model leverages its unique strengths to capture different characteristics of the stock price data, such as linear trends, volatility clustering, nonlinear patterns, and long-term dependencies. During the Ensemble Forecasting phase, the individual model forecasts are combined using a weighted averaging strategy. Weights are assigned based on the performance of each model, determined through metrics such as Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), ensuring that models contributing more accurate predictions have greater influence on the final forecast. This weighted aggregation process aims to maximize overall prediction accuracy by balancing the strengths and minimizing the weaknesses of the individual models. In the Model Evaluation phase, the performance of the ensemble model is assessed by comparing its forecasts with actual stock prices. Evaluation metrics such as RMSE, MAE, and R-squared provide insights into the predictive accuracy and robustness of the HLCE approach. The accompanying figure is designed with clarity in mind, visually enhancing the understanding of the workflow from data preparation to final prediction and evaluation, and demonstrating the integration of multiple modeling techniques to improve forecast precision.

Model Training Strategies:

Each forecasting model—ARIMA, ETS, GARCH, Random Forest (RF), XGBoost, SVR, and LSTM—was initially trained individually to capture diverse aspects of the time series data. Following individual training, their predictions were aggregated using a weighted averaging approach in the Hybrid LSTM-Conventional Ensemble (HLCE) model. Model-specific weights were assigned based on performance metrics such as RMSE and MAE, ensuring that models with better predictive performance contributed more heavily to the final ensemble output.

Data Splitting:

The dataset was divided into training and testing sets using a 70/30 split, with the first 70% utilized to train the models and the remaining 30% set aside for testing and performance evaluation. For models such as LSTM, a time-series-aware splitting strategy was utilized to maintain temporal order and prevent data leaking.

Cross-Validation:

The code does not explicitly incorporate traditional time series cross-validation approaches (such as walk-forward or rolling-window validation). Instead, the models were trained on a single training set before being tested on the test set. This is prevalent in financial time series forecasting, where maintaining the chronological order is critical.

Hyperparameter Optimization:

Some models underwent basic hyperparameter tuning: Random Forest, SVR, and XGBoost employed hard-coded, pre-selected hyperparameters based on past knowledge or default suggestions. There was no grid or random search implemented in the code. LSTM architecture parameters (e.g., number of neurons, epochs, batch size) were also chosen manually, without using formal hyperparameter search approaches such as GridSearchCV or Bayesian optimization.

ARIMA Model:

The ARIMA (AutoRegressive Integrated Moving Average) model was trained on the historical stock price data. The model formulation can be described by the Eq. 1:

$$\mathrm{St} = \alpha\mathrm{Yt} + (1-\alpha)\mathrm{St}-1$$

$$\mathrm{Yt} \ = \mathrm{c} + \sum \mathrm{i} = 1\mathrm{p} \ \ \phi\mathrm{iYt} - \mathrm{i} + \sum \mathrm{j} = 1\mathrm{q}\theta\mathrm{j}\epsilon\mathrm{t} - \mathrm{j} + \epsilon\mathrm{t} \qquad \text{Eq. (1)}$$

The ARIMA model efficiently captures both autoregressive and moving average components of the stock price series, allowing it to model both momentum and mean-reverting behaviors in the data.

Exponential Smoothing (ETS) Model:

The Exponential Smoothing (ETS) model is designed to produce forecasts by weighting past observations with exponentially decreasing weights. In this formulation, the smoothed value at times denoted as StS_tSt, represents the model's predicted value based on prior observations. The actual observed value at times YtY_tYt, serves as the ground truth for evaluating the model's performance. The smoothing constant α determines the weight assigned to the most recent observation. A higher value of α increases the model's sensitivity to recent changes in the data, allowing it to adapt quickly to emerging trends. Conversely, lower α\alphaα results in smoother forecasts by placing greater emphasis on historical observations, making the model less responsive to short-term fluctuations. The ETS model is mathematically defined as follows in Eq. 2:

$$\mathrm{St} = \alpha\mathrm{Yt} + (1-\alpha)\mathrm{St}-1 \qquad \text{Eq. (2)}$$

Garch Model:

The conditional variance at time t, which indicates the volatility of the asset, is represented by the symbol σt2 in this equation. The residual, or ϵ, is the difference between the mean equation's actual and expected values. The model is controlled by three parameters: α0, α1, and β1. α1 reflects the impact of previous residuals on current volatility, β1 represents the impact of prior variances on current volatility, and α0 is a constant term that denotes the model's baseline volatility level. The GARCH model is defined using the scaled data returns as shown in Eq. 3.

$$\sigma_t^2 = \alpha_0 + \alpha_1\epsilon_{\{t-1\}}^2 + \beta_1\sigma_{\{t-1\}}^2 \qquad \text{Eq. (3)}$$

LSTM Model:

The hidden and cell states at time tt are represented by ht and Ct in these equations, whereas Ct−1 and ht−1 are from the preceding time step. The input is xt, and the forget, input, and output gate activations are ft, it, and ot. The potential cell state is C~t. The weight matrices and bias vectors are W and b, whereas the activation functions are σ and tanht. An LSTM cell can be represented using Eq. 4.

$$ht = ot \odot tanh(Ct) \qquad \text{Eq. (4)}$$

Random Forest:

The Random Forest model is an ensemble learning technique that combines the predictions of multiple decision trees to improve overall forecasting performance. During training, the model constructs each tree using a bootstrap sample (random sampling with replacement) of the original dataset. At each split in a tree, a random subset of features is selected to determine the best split, which helps to reduce overfitting and improve model generalization. For regression tasks, the Random Forest aggregates the individual tree outputs by averaging their predictions, while for classification tasks, it takes the mode of the predicted classes. By combining the outputs of numerous trees, the Random Forest model effectively reduces variance compared to a single decision tree, thereby enhancing accuracy and robustness. The mathematical formulation of the Random Forest prediction is presented in Eq. 5

$$\hat{y} = \left(\frac{1}{N}\right)\sum[i = 1 \ to \ N]Ti(x) \qquad \text{Eq. (5)}$$

XGBoost Model:

The XGBoost (Extreme Gradient Boosting) model represents an efficient and scalable implementation of the gradient boosting framework. It builds trees sequentially, where each new tree aims to correct the errors made by the previously trained trees. Using gradient descent, XGBoost optimizes a specified loss function to enhance prediction accuracy. The model is equipped with built-in mechanisms to handle missing values and incorporates regularization terms (both L1 and L2) to reduce the risk of overfitting, thereby improving generalization to unseen data.

Support Vector Regression (SVR) Model:

The Support Vector Regression (SVR) model is derived from the Support Vector Machine (SVM) methodology. SVR seeks to find a function that approximates the target values within specified margin of tolerance (epsilon), minimizing the influence of deviations beyond this margin. By applying kernel functions, SVR effectively transforms the input features into a higher-dimensional space, enabling the model to capture complex, nonlinear relationships within the data.

Table 2. Pseudo Code of HLCE

```
def hlce_model(arima_preds, ets_preds, garch_preds, lstm_preds, rf_preds,
xgb_preds, svr_preds, weights):
hlce_preds = sum([weights[0] * (arima_preds), weights[1] * (ets_preds), weights[2] *
(garch_preds),
weights[3] * (lstm_preds), weights[4] * (rf_preds), weights[5] * (xgb_preds),
weights[6] * (svr_preds)])
return hlce_preds
arima_preds = arima_model.forecast(test_data)
ets_preds = ets_model.forecast(test_data)
garch_preds = garch_model.forecast(test_data)
lstm_preds = lstm_model.predict(test_X)
rf_preds = rf_model.predict(test_data)
xgb_preds = xgb_model.predict(test_data)
svr_preds = svr_model.predict(test_data)
weights = [0.1429, 0.1429, 0.1429, 0.1429, 0.1429, 0.1429, 0.1429]
ensemble_predictions = hlce_model(arima_preds, ets_preds, garch_preds, lstm_preds,
rf_preds, xgb_preds, svr_preds, weights)
```

Ensemble Model (HLCE):

The Hybrid LSTM-Conventional Ensemble (HLCE) model combines the predictions from the seven individual models—ARIMA, ETS, GARCH, LSTM, Random Forest, XGBoost, and SVR—as shown in Table 2. To enhance forecasting accuracy, a weighted average method is employed to aggregate the individual forecasts. The weights assigned to each model are based on their performance metrics, such as Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). The final ensemble forecast can be mathematically expressed as shown in Eq. 6:

$$\boldsymbol{Yhlce = 0.1429 \cdot \sum(YTarima, YTets, YTgarch, YTlstm, YTrf, YTxgb, YtSVR)} \quad \textbf{Eq. (6)}$$

Where, YtARIMA, YtETS, YtGARCH, YtLSTM, YtRF, YtXGB, and YtSVR are the forecast models, and w1 to w7 are the equal weights (0.1429) assigned to each model. These can be adjusted based on model performance.

Model Evaluation Matrices

The performance of forecasting models is assessed using various evaluation metrics summarized in Table 3. Figure 2 shows the evaluation matrices of all models. Root Mean

Square Error (RMSE) determines the average magnitude of errors without considering their direction and is sensitive to outliers due to squaring the differences. It is calculated in Eq. 7.

$$RMSE = \sqrt{\left(\frac{1}{n}\sum\left(Yi - \hat{Y}i\right)^2\right)} \qquad \text{Eq. (7)}$$

Mean Absolute Error (MAE) measures the average absolute difference between actual and predicted values, penalizing errors linearly and less harshly than RMSE as Eq. 8.

$$MAE = \left(\frac{1}{n}\right)\sum\left|Yi - \hat{Y}i\right| \qquad \text{Eq. (8)}$$

Mean Absolute Percentage Error (MAPE) provides the average absolute percentage difference between actual and predicted values, indicating accuracy as a %, but can be skewed when actual values are near 0 as represented in Eq. 9.

$$MAPE = \left(\frac{1}{n}\right)\sum\left|\left(Yi - \hat{Y}i\right) / Yi\right| \qquad \text{Eq. (9)}$$

R-squared (R^2) reflects how well the independent variables explain the variance in the dependent variable; values closer to 1 indicate a better fit as we can see in Eq. 10.

$$R^2 = 1 - \left(\frac{Sres}{Stot}\right) \qquad \text{Eq. (10)}$$

The section also repeats MAE and MAPE for emphasis or possible inclusion from different sources. The repeated formula for MAE is shown in Eq. 11. Lastly, R^2 is reiterated to emphasize its importance in regression analysis as mathematically represented in Eq. 10.

$$MAE = \left(\frac{1}{n}\right)\sum\left|Yi - \hat{Y}i\right| \qquad \text{Eq. (11)}$$

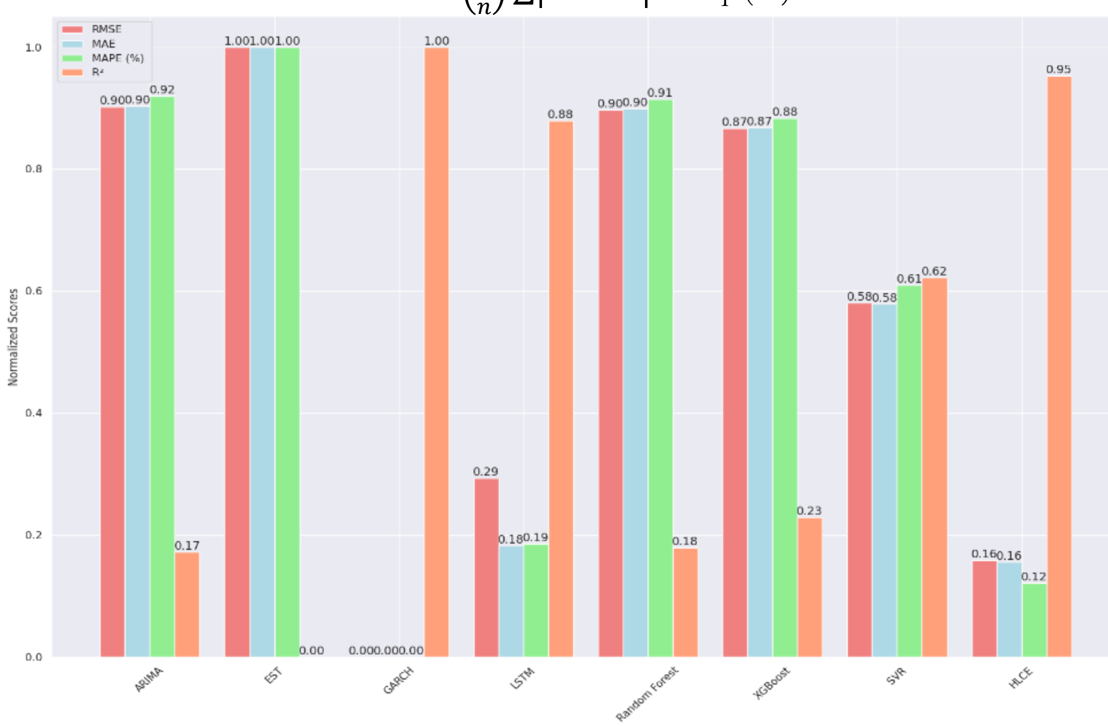

Figure 2. Evaluation Matrices of All Models

Results:

This section compares the performance of the LSTM model with conventional models such as GARCH, ETS, and ARIMA, demonstrating that the proposed Hybrid LSTM-Conventional Ensemble (HLCE) consistently outperforms individual models based on both quantitative performance metrics and visual analysis. The experimental setup involves evaluating the HLCE model using stock data retrieved from YFinance, covering the period from 2010 to 2023, which includes closing prices and daily transaction volumes. The dataset is divided into training, validation, and test sets, ensuring that model evaluation remains robust and unbiased. Preprocessing steps such as normalization and outlier handling are performed to enhance data quality and model stability. Model performance is assessed using several key evaluation metrics, including the Coefficient of Determination (R^2), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). Hyperparameter tuning is conducted systematically, and cross-validation techniques are employed to prevent overfitting and ensure generalization to unseen data. The best-performing HLCE model is ultimately deployed for real-time stock price prediction, providing valuable support for financial decision-making processes.

Table 3. Performance Evaluation of Models

Model	RMSE	MAE	MAPE	R^2
ARIMA	0.90	0.90	0.92	0.17
EST	1.00	1.00	1.00	0.00
GARCH	0.00	0.00	0.00	1.00
LSTM	0.29	0.19	0.19	0.88
RF	0.90	0.90	0.91	0.18
XGB	0.87	0.87	0.88	0.23
SVR	0.58	0.58	0.61	0.62
HLCE	0.16	0.16	0.12	0.95

Model Performance Metrics:

The HLCE model outperforms all other models across key performance metrics, as illustrated in Figure 2. It achieves the highest R^2 and the lowest values for RMSE, MAE, and MAPE, indicating its superior predictive accuracy. While the GARCH model demonstrates a strong R^2, it lags in other metrics. ARIMA and ETS exhibit notably poor performance, particularly in classification tasks. The LSTM model fails to meet most of the evaluation criteria. In comparison, SVR, Random Forest, and XGBoost show moderate performance, with XGBoost slightly outperforming the others in terms of R^2. Overall, the HLCE model stands out, offering the most accurate predictions among the models tested.

Comparison of Results:

A comprehensive performance study was conducted to evaluate the effectiveness and reliability of the proposed Hybrid LSTM-Conventional Ensemble (HLCE) model. The primary objective was to compare the predictive accuracy of HLCE against each of its components, which include both statistical and machine learning models. This study assessed the model's generalizability, robustness, and ability to capture both linear and nonlinear patterns in time series data, using a range of performance metrics. The following subsections provide a detailed assessment, including metric-wise comparisons, prediction visualizations, and interpretations of the results.

Correlation between the Prediction Errors:

Figure 3 presents a heatmap that highlights the error correlations among the models. The negative correlation between HLCE and both ARIMA and ETS indicates complementary behavior, which enhances the ensemble's predictive accuracy. On the other hand, ARIMA and ETS exhibit a significant positive correlation, suggesting that these models often produce similar prediction errors.

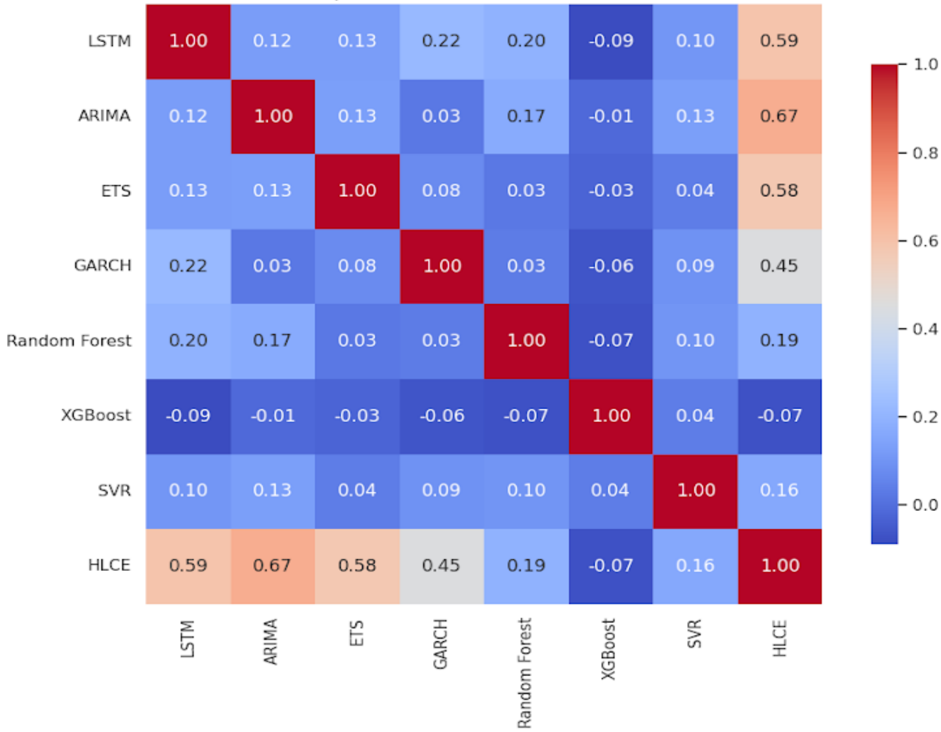

Figure 3. Correlation between the prediction errors

CDF Plot of Prediction Errors:

As shown in Figure 4, the CDF (Cumulative Distribution Function) plot illustrates that HLCE consistently outperforms all individual models, demonstrating higher prediction accuracy. Random Forest and XGBoost follow closely behind, while ARIMA, ETS, and GARCH exhibit broader error distributions, indicating less precise predictions.

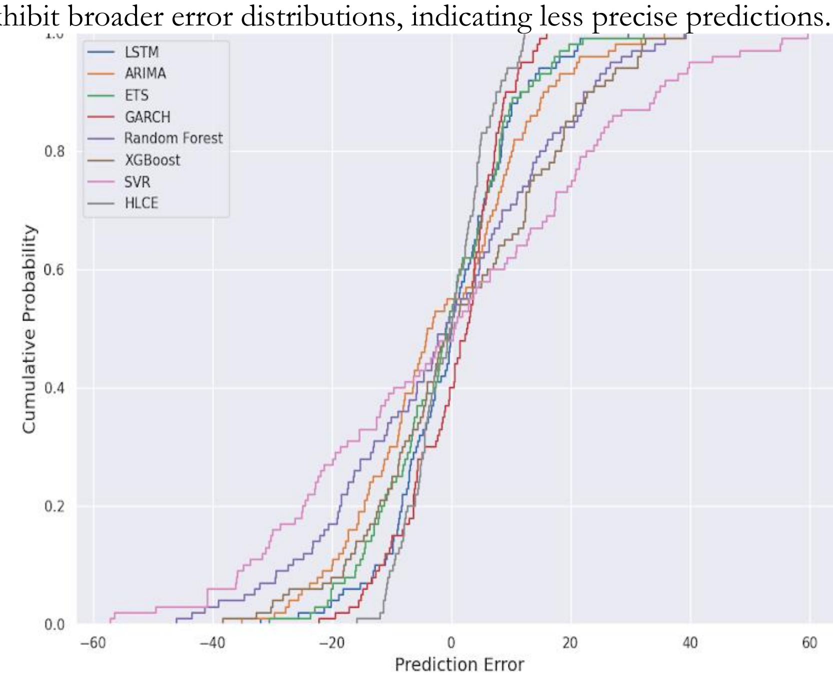

Figure 4. The residual analysis models CDF Plot

RMSE Comparison:

Figure 5 highlights the RMSE (Root Mean Squared Error) comparison, where HLCE achieves the lowest RMSE, confirming its high accuracy. SVR and XGBoost show moderate performance, while ARIMA, GARCH, and ETS yield higher RMSE values, indicating poorer predictive performance.

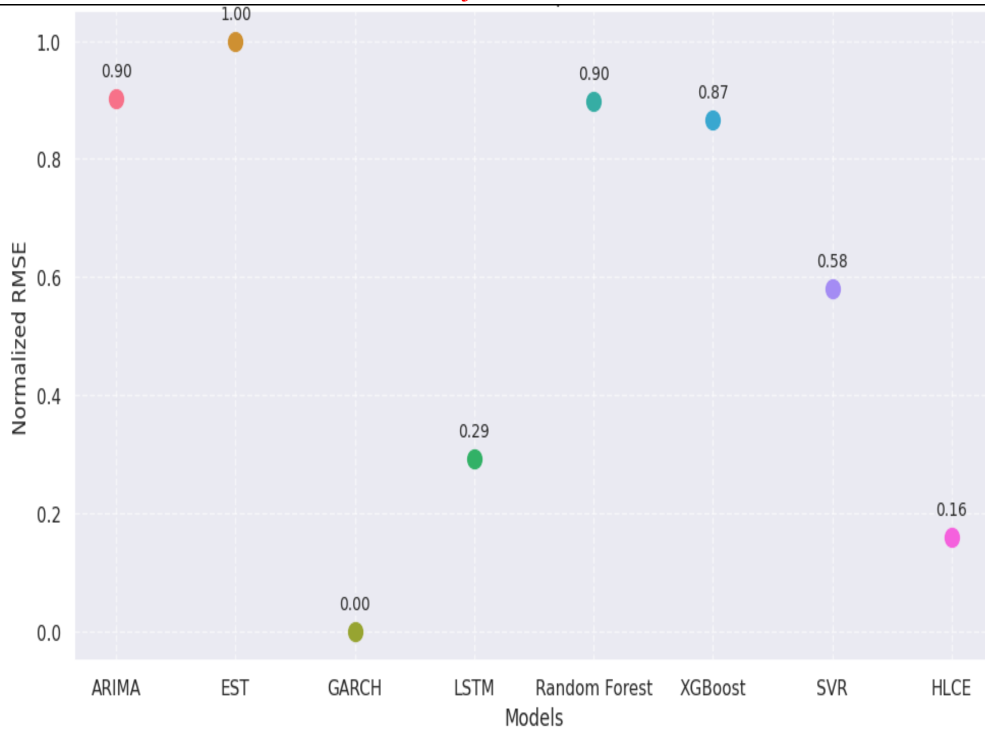

Figure 5. RMSE Comparison of Models

Box Plot of Prediction Errors:

Figure 6 demonstrates that HLCE produces stable and reliable predictions, with a narrow interquartile range (IQR) and few outliers. In contrast, ARIMA and GARCH exhibit a larger IQR and a higher number of outliers, indicating greater volatility and less consistent performance.

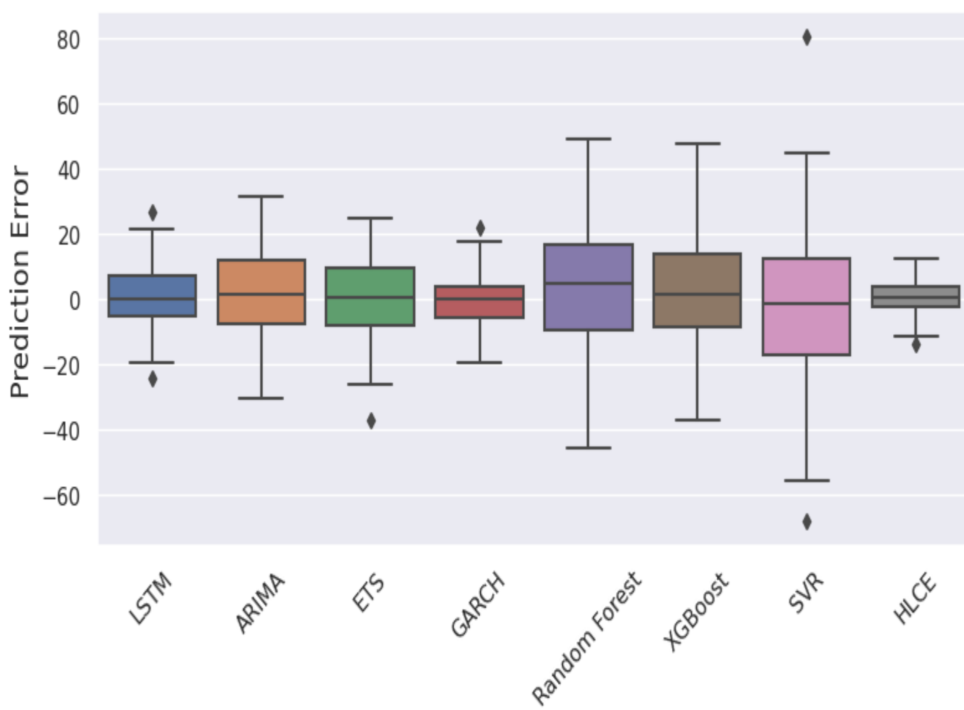

Figure 6. Box Plot of Prediction Error

Violon Plot of Prediction Errors:

While ARIMA, ETS, and GARCH have wider, less stable error distributions, HLCE consistently produces low-error predictions, as seen in the violin plot in Figure 7. Random

Forest and GBoost exhibit marginal gains, whereas LSTM is less reliable. In erratic markets, HLCE is the most dependable.

Heatmap Comparison of all Models:

The heatmap in Figure 8 shows HLCE outperforming all models with the lowest errors and highest R^2, highlighting its adaptability and effectiveness in handling complex market patterns through hybrid modeling.

Discussion on Results:

The study's findings demonstrate how well the Hybrid LSTM-Conventional Ensemble (HLCE) model captures the intricate dynamics of stock price fluctuations. The HLCE model outperforms any single model used alone in predicting accuracy by combining the predictive capabilities of both contemporary machine learning methods and conventional statistical models. The LSTM, Random Forest, XGBoost, and SVR components efficiently train and generalize from nonlinear and high-dimensional patterns in the financial time series, while the ensemble technique makes use of the capabilities of ARIMA, ETS, and GARCH to model linear trends, seasonality, and volatility. The high level of accuracy and dependability of the HLCE model is demonstrated by its performance metrics, which include an RMSE of 0.16, MAE of 0.16, MAPE of 0.12%, and R2 of 0.95. These outcomes demonstrate that the model can generate reliable and accurate projections, which qualifies it for use in real-world risk management and financial decision-making applications. Notably, conventional models like ARIMA and ETS were not very good at capturing sudden changes in the market or nonlinear patterns, even though they were good at spotting trends and seasonality. On the other hand, when used alone, machine learning techniques occasionally experience instability or overfitting despite their strength in modeling complexity. The balanced structure of the HLCE model, in which each model makes a distinct contribution to the final forecast, is its strongest point. The ensemble's architecture, which is an equal-weighted average of the individual projections, enhances each model's strengths while mitigating its shortcomings.

Additionally, by encouraging model diversity—a fundamental tenet of ensemble learning—this uniform weighting approach makes sure that the final product is less susceptible to the quirks of any one forecasting technique. The findings also highlight the value of integrating models like GARCH, which concentrates on volatility—a critical feature in financial markets—with memory-based architectures like LSTM, which capture long-term relationships. Because tree-based models like Random Forest and XGBoost efficiently manage feature interactions and outliers, their inclusion enhances interpretability and resilience. Meanwhile, SVR's kernel-based modifications help describe more intricate nonlinear structures in the data. All things considered, the HLCE framework offers a thorough, precise, and reliable way to forecast stock prices. By combining various modeling viewpoints, its ensemble structure improves predictive reliability and provides compelling empirical evidence for the benefits of hybrid techniques in time series forecasting in the finance industry.

Conclusion:

This research evaluated various machine learning models, including LSTM, Random Forest, XGBoost, SVR, and traditional time series models such as ARIMA and Exponential Smoothing, for stock price prediction. The findings demonstrated that machine learning models, particularly LSTM and ensemble approaches, excelled in capturing non-linear trends, offering superior performance over conventional models. The HLCE (Hybrid LSTM-Conventional Ensemble) model achieved the highest R^2 (0.95) and the lowest RMSE (0.16), MAE (0.16), and MAPE (0.12), proving its exceptional forecasting accuracy. In contrast, Random Forest, XGBoost, and SVR yielded significantly lower performance, with R^2 values ranging from 0.18 to 0.62. Despite these promising results, challenges remain. Future research could further explore the performance of ensemble methods on larger and more diverse datasets, incorporating external variables such as market sentiment, macroeconomic indicators, and geopolitical events. Additionally, enhancing feature engineering, integrating multi-source data (like sentiment analysis), and improving model interpretability will be crucial areas for future development.

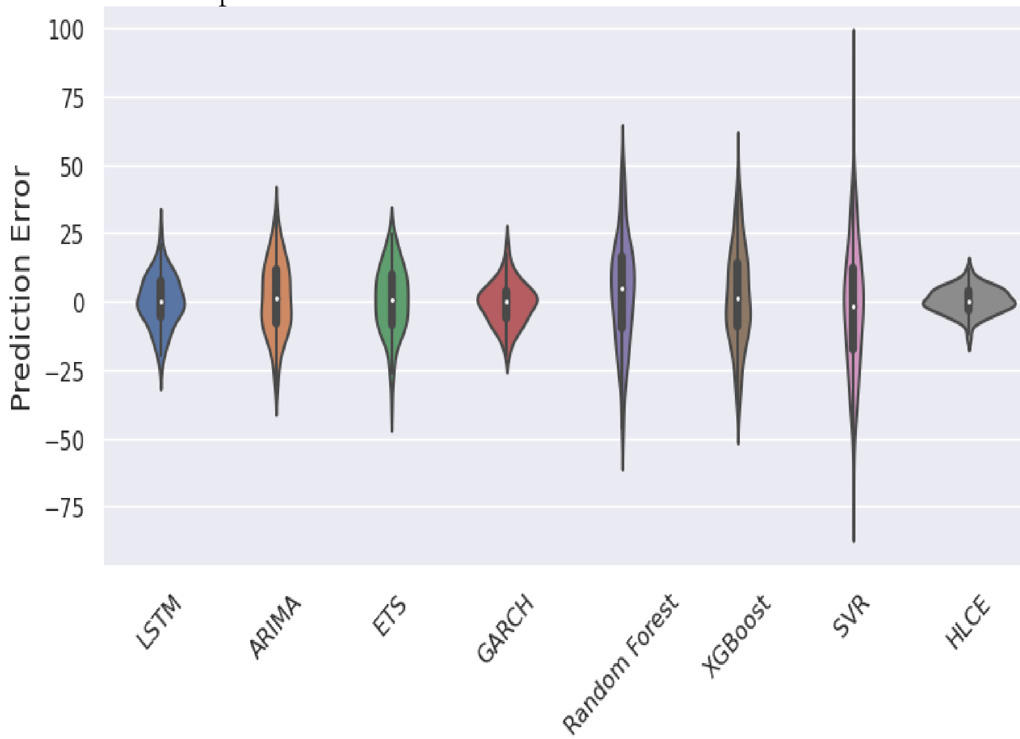

Figure 7. Violin Plot of Prediction Errors

Figure 8. HeatMap comparison of all matrices

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