Combining Deep Learning and Statistical Models: LSTM-ARIMA Ensemble for Financial Forecasting

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Abstract-**The decision making in different areas like economic planning, risk management and investment, it is essential to have accuracy of financial forecasting. To capture linear trends in conventional time series statistical model like Auto Regressive Integrated Moving Average (ARIMA) are very efficient but it deals with complex non linear market dynamics they fall short. On the other hand, Long Short-Term Memory (LSTM) networks, one of the deep learning models excels at recognizing long term relationships and nonlinear dependencies in the financial data but they require huge datasets and heavy computational resources. The aim of this paper is to recommend an innovative ensemble forecasting technique which integrates LSTM and ARIMA models to get benefit of from their individual strengths while compensating for their specific boundaries. The training of these both models is done independently by ensemble architecture and their outputs s recombined using optimized weighted averaging. For validation of this proposed model involvement of historical financial datasets including commodity prices, exchange rates and stock prices. Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) are the standard metrics by using which the performance is evaluated which shows that LSTM-ARIMA ensemble significantly outclasses standalone LSTM and ARIMA models. lowest Root Mean Squared Error of 0.85, Mean Absolute Error of 0.65 and Mean Absolute Percentage Error of 2.32 is achieved by the ensemble and indicating greater prediction accuracy and robustness across various financial time series. A comprehensive solution which can be adapted by different financial forecasting scenarios, ensuring improved precision and reliability is offered by this hybrid approach. The key findings of this paper support the increasing consensus that combination of deep learning and statistical techniques improves the quality of the predictive analytics in the finance and this method can be extended to various fields similar to the time series characteristics.**

Index Terms—**LSTM, ARIMA, Financial Forecasting, Ensemble Model, Time-Series Analysis.**

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I. Introduction

DECISION-MAKING across various domains like corporate, risk management and economic policy depend on predicting future financial trends. Accurate prediction of market trends, stock prices, interest rates, and other financial elements helps to maintain financial markets stable and expanding. Monetary projections have long been produced using statistical fashions such as (ARIMA). These models represent straightforward and structured manner of time series data effectively. Economic markets are basically unpredictable, but, and many items have non-linear patterns which might be tough to grasp using just linear statistical models. These models are appropriate for handling uninterrupted time series information. In particular, the model of deep learning namely, (LSTM) network have recognized to be highly effective model in the area of economic prediction. That is so because in time series records, they may reproduce complicated, non-linear correlations and long-term linkages. Fixing the vanishing gradient trouble is accomplished the usage of the LSTM recurrent neural network (RNN).

This enables it to remember extensive data collections and make predictions based on past performance. LSTM networks are accordingly high-quality for forecasting stock prices, forex charges, and other financial time collection regularly impacted by problematic, non-linear patterns [1][2]. LSTM networks have a number of drawbacks even as they offer positive benefits. They need alot of facts and processing capability for instructing, as a result their overall performance may additionally suffer without adequate data or if the signals are noisy. Furthermore, it is very difficult for LSTM technique to take positive linear patterns typical in economic records. In terms of undertakings, statistical models such as ARIMA are effective. Even though ARIMA models are good at identifying linear trends, they are not very good at identifying nonlinear linkages or long-term relationships that could show up in financial time series [3].

When the deep learning and statistical models are combined, it may help to address the issues with each method separately. A mixed model must be able to produce more accurate and dependable forecasts by combining LSTM's ability to identify complex, non-linear styles with ARIMA's ability to explain linear trends. Ensemble techniques have recently become more sophisticated in many

industries, including finance. These methods enhance overall performance by combining the results of multiple models. Benefits of these unique models may also work better with these techniques, increasing forecast accuracy and allowing for more amendment to outline different types of facts. By integrating LSTM [4] and ARIMA [4], this work suggests impressive ensemble model for financial forecasting. When combined, LSTM and ARIMA provide the best features of both models. ARIMA finds linear associations in the statistics, while LSTM finds nonlinear patterns. Each model is trained separately, and the combined predictions of all the models provide a better overall estimate. This method gives financial decision-makers a more precise tool and help them to predict the future based on economic time collection data [5][22]. The goal of the study is to visualize the overall performance of the LSTM-ARIMA ensemble with respect to ARIMA and LSTM models functioning independently. The research shows the overall performance of the ensemble form by using non-monetary data such as stock fees, foreign money fees, and product price.

This study intends to demonstrate how beneficial it may be to combine in-depth research with statistical techniques for financial projections by comparing the findings with those of independent models and traditional techniques. The findings of the studies may also assist in creating blended predictions models relevant in other domains with comparable time collection.

A. Background on Financial Forecasting

Economic forecasting is a major component of current finance since it enables companies, traders, and lawmakers to make decisions about future financial trends as well as future market, financial and financial regulations. It is very common practice in the finance industry to estimate future trends in stock expenses, currency quotes, hobby quotes, and various market factors using time series analysis. Forecasting financial statistics has been accomplished over the years using a variety of techniques, ranging from basic statistical techniques to more complex machine learning and deep learning models. To predict future monetary values, statistical techniques including transferring averages, exponential smoothing, and ARIMA have been employed for a long time [6]. Traditional forecasting models largely rely on trend analysis and linear relationships, assuming that patterns observed in historical records can be generalized to predict future outcomes. While such models are effective in stable environments with consistent trends, they often fail when opposed with the irregular, volatile, and nonlinear dynamics characteristic of financial data. These limitations have contributed to the increasing adoption of machine learning and deep learning approaches in recent years. Among them, Long Short-Term Memory (LSTM) networks have increased particular importance for their ability to capture complex nonlinear structures and long-term dependencies in time-series data [7][21]. LSTMs, a particular form of recurrent neural networks (RNNs), were specifically developed to overcome the vanishing gradient problem, allowing RNNs to effectively process extended temporal sequences. Their applicability extents several financial domains, including credit rating assessment, stock market prediction, and risk evaluation, making them valuable tools for financial forecasting and decision-making.

B Importance of Accurate Financial Predictions

Accurate financial forecasting plays a critical role across multiple domains such as finance, risk management, corporate strategy, and governance. The ability to anticipate future movements in markets, economic conditions, and asset performance is essential for making informed decisions that impact both short-term operations and long-term sustainability. Reliable predictions can significantly form the strategies of governments, corporations, and financial institutions in mitigating risks, capitalizing on emerging opportunities, and allocating resources efficiently [8]. Comprehensive financial planning further enables investors and portfolio managers to make optimal choices regarding stocks, bonds, and alternative assets. Additionally, the ability to predict market fluctuations and recognize possible risks allows investors to enhance portfolio performance, maximize returns, and reduce exposure to losses.

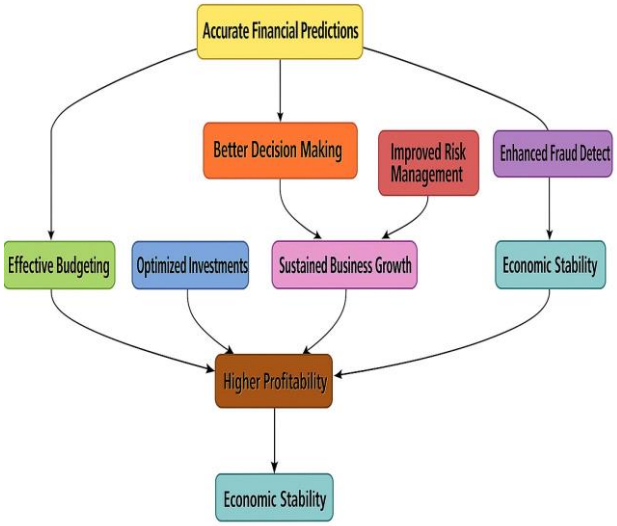

Fig.1 Importance of accurate financial predictions

Figure 1 illustrates how wise judgments, reduced risks, and strategic planning are made possible by precise financial predictions.

Similarly, organizations employ financial forecasting to anticipate future sales, monitor expenditures, and determine optimal pricing strategies. Reliable forecasts also enable firms to estimate future cash flow requirements, pursue strategic investments, and manage working capital more effectively [9]. Perfect planning is a key part of risk management because it helps to find and reduce financial risks like market instability, interest rate changes, and currency risk. By projecting future financial conditions, businesses can strengthen their preparedness for adverse events, safeguard assets, and ensure long-term financial stability.

II. Background

A. Traditional Methods in Financial Forecasting

For many years, traditional methods for predicting the future of money have been the mainstay of financial analysis. These methods use statistical methods to model and guess how money will change over time. These methods are very useful for using past data to guess about market trends, economic situations, and asset prices. Modern methods like machine learning and deep learning becoming a more famous, but standard methods are still important because they are easy to understand and use less computing power. (ARIMA) is a scientific method that is used by a lot of people. ARIMA models try to guess what values will be in the future by looking at how past readings are related in a straight line. Time-series data, which is popular in financial markets, can be used to find trends, patterns, and autocorrelations [10]. Most of the time, ARIMA is used to predict stock prices, foreign exchange rates, and economic data. Its flexibility lets you make changes, like adding seasonal factors (SARIMA) or outside variables (ARIMAX), so it can be used with different financial information. Exponential Smoothing (ES) is another well-known method. It uses weighted means of past readings, with newer information being given more weight. Single Exponential Smoothing (SES), the elementary system, works well for data that doesn't change over time or with the seasons. Holt-Winters Seasonal and Holt's Linear Trend Model the Method can be used to look at time series that show trends [11]. These models are often used to predict how markets will act in the short term or for financial series that change over time, like retail sales or product prices. By taking the average of the values over a certain number of periods, moving averages (MA) are another basic way to smooth out time series data and find trends. Even though they are easy, moving averages can help you figure out the way of a trend and send you trade signs in the financial markets.

B. Deep Learning Approaches

Deep learning methods are getting a lot of attention in financial predictions because they can model time-series data with complicated, non-linear relationships and long-term connections. These models, especially deep neural networks, have been used successfully in a number of financial planning tasks, such as predicting the stock market, setting prices for assets, and scoring credit.

Long Short-Term Memory (LSTM) Networks

Designed to tackle the vanishing gradient problem rendering standard RNNs difficult to train from extensive amounts of data, LSTM systems are a particular form of Recurrent Neural Networks (RNNs). LSTMs have evolved as the model of choice for financial forecasts because they can uncover long-term linkages and non-linear interactions in time-series data. Successful stock price, exchange rate, and market volatility prediction has come from their application [12].

- Step 1. Forget Gate (f_t)

$$f_t = \sigma\left(W_f .[h_{t-1}, x_t] + b_f\right)$$

- Step 2. Input Gate (i_t)

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

- Step 3. Cell Candidate ($\tilde{C}$_t)

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

- Step 4. Cell State Update (C_t)

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t$$

Gated Recurrent Units (GRU)

A further kind of RNN is the GRU. They are designed to cope with sequential data dependent on events occurring far away, much like LSTMs. Although GRUs utilize less processing resources than LSTMs and are simpler to grasp, they are nonetheless really excellent at identifying temporal connections in time-series data. They have been used in many financial planning roles, particularly in cases when rapid comprehension of facts is crucial.

Convolutional Neural Networks (CNN)

Though they have been modified to operate with time series predictions by seeing time as a single-dimensional chain, CNNs are mostly employed for image processing. CNNs can identify local associations in financial data, hence they are excellent in spotting patterns and characteristics in such data. They have been used with other models, like LSTMs, combining local and global data to provide more accurate predictions.

C. Statistical Models

For a long time, statistical models have been crucial for financial forecasts as they provide clear conclusions and allow one to easily examine time-series data. Among the most often used and well-known statistical models is (ARIMA). It is predicated on the theory that faults in a time series directly affect future values by means of previous values. Three primary components comprise it: the integrated (I) portion indicates how the series varies to keep it stable; the autoregressive (AR) part illustrates how the current time step impacts the next; and the moving average (MA) section shows how prior forecast errors influenced the current time step. Regarding one-variable time series with linear trends and stable behavior, ARIMA does quite well in constructing projections [13][14][23]. ARIMA models are very helpful in the financial markets for tasks like economic forecasts, interest rate and stock price projections. The model may be used in a broad spectrum of financial circumstances as it can identify temporary patterns in data. It may be used, for instance, to forecast temporary fluctuations in foreign exchange rates or stock prices. Table 1 summarizes, in terms of approaches, major findings, challenges, and scope, the literature review on financial forecasts. ARIMA may therefore also be extended to add outside variables (ARIMAX) or seasonal elements (SARIMA), thereby allowing it to handle seasonality and Other influencing elements.

Table 1: Summary of Literature Review

Method	Key Findings	Challenges	Scope
ARIMA	Effectiveness in linear relationships in time-series data	ARIMA struggles with non-linear data and volatility	Useful for stationary and linear financial data
LSTM	Excels at capturing complex, non-linear dependencies	Requires large datasets and computational resources	Applicable to a wide range of non-linear financial datasets
LSTM-ARIMA Ensemble [15]	Combines strengths of both ARIMA and LSTM for improved prediction	Complexity of model integration and computational expense	Widely applicable to diverse financial forecasting tasks
ARIMA + SVM	Combines ARIMA's linearity with SVM's non-linearity	Sensitive to noise and overfitting	Effective for market prediction with mixed linear and non-linear data
LSTM + Gated Recurrent Units (GRU)	GRU provides faster training times and better handling of sequential data	Difficulty in tuning and risk of overfitting	Well-suited for sequence prediction in stock prices and market trends
Hybrid ARIMA + Neural Networks [16]	Improved prediction accuracy when ARIMA and neural networks are combined	Integration complexity and the challenge of selecting the best neural network	Broad scope for various time-series forecasting applications
LSTM + Moving Averages	Moving averages combined with LSTM can handle short-term forecasting	Difficulty in incorporating real-time data changes	Works well for short-term forecasting in highly volatile markets
SVM + LSTM	LSTM and SVM offer good flexibility for complex data patterns	Overfitting and sensitivity to hyperparameter tuning	Applicable for prediction tasks with complex patterns
ARIMA + Random Forest	Random Forests enhance ARIMA model with non-linear regression	High computational cost due to ensemble model complexity	Used in financial risk management and portfolio prediction
LSTM + Decision Trees	Decision Trees improve LSTM model for classification tasks in financial forecasting	Overfitting risk and need for extensive data preprocessing	Applicable in decision-making tasks for financial planning
LSTM + Exponential Smoothing [17]	Exponential Smoothing with LSTM works well for seasonal data forecasting	Requires accurate tuning for seasonal data	Widely applicable for long-term forecasting of economic trends
ARIMA + Deep Neural Networks	Deep Neural Networks combined with ARIMA handle non-linear and complex data patterns	Need for careful model selection to avoid overfitting	Effective for analyzing complex data with various market dynamics
GRU + ARIMA	GRU and ARIMA together improve accuracy on shorter time-horizons	Lack of flexibility in adapting to rapidly changing data	Used for short-term to medium-term forecasting in volatile markets

III. Methodology

A. Dataset Description

Format For financial forecasts, the collection usually includes past time-series data on a number of fiscal assets, like as exchange rates, stock prices, interest rates and product prices. Finance information for this study came from stock market sources that anyone can access, like Yahoo Finance, Bloomberg, or the Quandl platform. The file has daily ending prices for many stocks, as well as other information like volume moved, moving averages, volatility markers, and other technical analysis measures. The file includes past data from a number of years, usually between a few months and several decades, based on the time frame of the prediction. A time series is a common way to organize financial data. Each row in a time series shows a different day, week, or month of trade [18]. The dataset's features are mostly numbers that show how prices changed and how many deals happened during the chosen time periods. Based on patterns seen in the past, these traits are used to model and guess what financial trends will happen in the future. To make the model more accurate and reliable, the information may include more than just stock price data. It may also include financial pointers (like interest rates, inflation rate, and GDP growth), market mood indicators, and international factors. Usually, the dataset is preprocessed to get rid of any errors or missing values. This makes sure that the input data for modelling is of good quality.

B. Preprocessing and Feature Engineering

Before you can use financial data in modelling, especially for time-series predicting jobs, you need to do preprocessing and feature engineering. A lot of the time, confusing, missing, or outlier-filled raw financial data, especially stock prices, can hurt the performance of prediction models. So, cleaning and changing the data is very important to make sure the model can learn from the trends that are there [19][22]. Taking care of lost numbers is one of the first steps in preparation. Some data may be missing because it was collected wrong or there are breaks in the trade records. Figure 2 shows how important it is to do preparation and feature engineering on data before analyzing it.

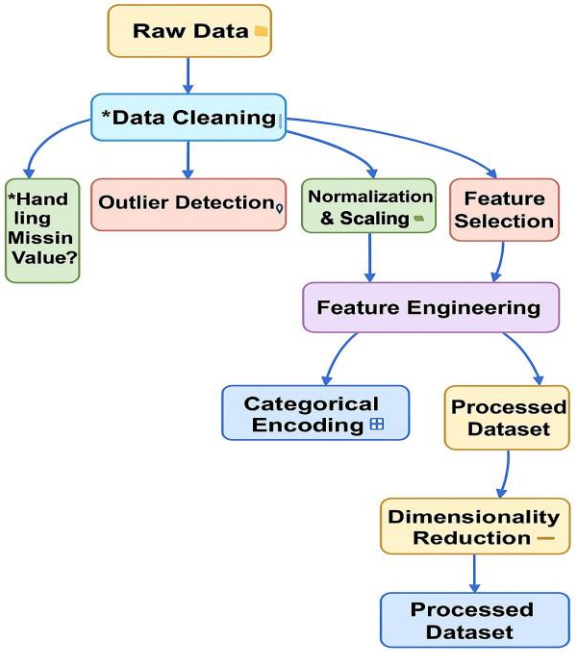

Fig. 2 Data Preprocessing and Feature Engineering

To guess and fill in empty numbers, you can use different estimation methods, like forward filling, backward filling, or interpolation. But if the holes are big, it might be necessary to get rid of records that aren't full. Normalization or scaling is another steps that is very important. A lot of the time, factors in financial data have very different sizes. For example, stock prices and trade volume have very different sizes. If the data is not normalized, models like LSTM and ARIMA might not work well. To make all the features look about the same, you can use common scaling methods like Min-Max scaling or Z-score normalization. Feature engineering is also very important for making models work better. When making financial predictions, useful features can be made from raw data to better see the patterns and trends that lie beneath the surface.

C. Overview of Long Short-Term Memory (LSTM) Model

It is a type of RNN and it was formed to make it easier to train regular RNNs on long strings of data. The vanishing gradient issue challenges conventional RNNs. Conversely, LSTMs have memory cells allowing them to hold information for prolonged time periods. Time-series predictions find them ideal because of this. An LSTM involves 3 key gates like output gate, forget gate, and input gate, every memory cell possesses. The forget gate chooses what data should be thrown away; the input gate controls flow of the data; and the output gate selects the information to be sent to the next level. Like regular shifts, trends, and volatility, the model picks on historical data patterns and linkages. LSTMs can both capture long-term and short-term trends, so they are superior than more antiquated techniques as ARIMA, which excels in linear relationship modelling.

- Step 1. Forget Gate (f_t)

The forget gate determines what portion of the former memory cell (c_(t-1)) would be forgotten. It is calculated using the former hidden state (h_(t-1)) and the present input (x_t).

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

- Step 2. Input Gate (i_t)

The input gate chooses how much new data would be added to the memory cell. It is calculated using the former hidden state and the present input.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

- Step 3. Cell Candidate ($\tilde{C}$_t)

This step generates new candidate values for the memory cell, which will be used to update the memory state. It is calculated as a tanh activation of the concatenation of the former hidden state and present input.

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

- Step 4. Cell State Update (C_t)

The memory cell state is updated by forgetting some of the previous memory (using the forget gate) and adding new information (using the input gate and cell candidate).

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t$$

D. ARIMA Model Overview

One well-known method to using statistics to forecast time series is ARIMA model. AIMA is predicated on the theory that the previous values of a time series directly determine its future value and that errors in estimating those values have direct bearing on both the model consists of three key elements: integration (I), Auto Regression (AR), and moving average (MA). A lot of people use ARIMA to make financial predictions because it is easy to set up, quickly to compute, and good at modelling fixed time-series data. The model works best with time series data that has straight patterns and trends, like stock prices or economic measures that move in predictable ways over time. One of the most important parts of using ARIMA is putting the model in the right order, which means choosing numbers for the MA, I, and AR parts. The ARIMA model is taught by fitting the data after the model is defined. Forecasts are then made based on the connections that the model has learnt.

- Step 1. Autoregressive (AR) Term

The autoregressive term models the association among a value and its preceding values. The equation for the AR term is:

$$Y_t = \varphi^1 * Y_{t-1} + \varphi^2 * Y_{t-2} + \ldots + \varphi p * Y_{t-p} + \varepsilon_t$$

Where:
- Y_t is the experiential value at time t.
- φ1, φ2, ..., φp are the parameters of the AR model (p is the order of the AR process).
- Y_(t-1), Y_(t-2), ..., Y_(t-p) are the previous values of the time series.
- ε_t is the white noise error term at time t.

- Step 2. Differencing (I) Term

Differencing is used to make the series stationary. The differenced series is computed as:

$$\Delta Y_t = Y_t - Y_{t-1}$$

Where:
- ΔY_t is the differenced value at time t.
- Y_t and Y_(t-1) are the original and lagged values, respectively.

- Step 3. Moving Average (MA) Term

The moving average term models the association amongst the present value and previous prediction errors. The equation for the MA term is:

$$Y_t = \mu + \theta^1 * \varepsilon_{t-1} + \theta^2 * \varepsilon_{t-2} + \ldots + \theta q * \varepsilon_{t-q} + \varepsilon_t$$

Where:
- Y_t is the observed value at time t.
- μ is the mean of the time series.
- ε_(t-1), ε_(t-2), ..., ε_(t-q) are the past forecast errors.

- Step 4. ARIMA Model Representation

The ARIMA model combines the AR, I, and MA components. The full ARIMA model can be written as:

$$Y_t = \varphi^1 * Y_{t-1} + \varphi^2 * Y_{t-2} + \ldots + \varphi p * Y_{t-p} + \theta^1 * \varepsilon_{t-1} + \theta^2 * \varepsilon_{t-2} + \ldots + \theta q * \varepsilon_{t-q} + \varepsilon_t$$

E. LSTM-ARIMA Ensemble Approach

Model Integration

To characterize short term independence and linear connections in financial time series this approach uses LSTM and ARIMA. On the other hand, nonlinear patterns and long-term dependencies are searched by LSTM. Individual learning of both of these models is completed on the same dataset and then final output is taken from both of the outputs aggregate. Weighted averaging, Simple averaging, and more complex methods such as mixing or stacking are among the many ways one could combine.

The outcomes of both the models are aggregated when weighted averaging is used, the outcomes of both models are aggregated with each model's forecast given a certain weight depending on its own performance.

- Step 1. ARIMA Model Equation (Linear Component)

The ARIMA model captures linear relationships in the time series data. The equation for ARIMA is:

$$Y_t = \varphi^1 * Y_{t-1} + \varphi^2 * Y_{t-2} + \ldots + \varphi p * Y_{t-p} + \theta^1 * \varepsilon_{t-1} + \theta^2 * \varepsilon_{t-2} + \ldots + \theta q * \varepsilon_{t-q} + \varepsilon_t$$

- Step 2. LSTM Model Equation (Non-linear Component)

The LSTM model captures non-linear dependencies and long-term relationships in the data. The LSTM output at time t is calculated as:

$$h_t = LSTM(W, b, X_t)$$

- Step 3. Combining ARIMA and LSTM Predictions

The LSTM-ARIMA ensemble approach combines the outputs from both the ARIMA model (Y_t^ARIMA) and the LSTM model (h_t^LSTM) using a weighted average or other methods. The combined forecast is:

$$Y_t^{ensemble} = w^1 * Y_t^{ARIMA} + w^2 * h_t^{LSTM}$$

- Step 4. Weight Optimization

The weights w1 and w2 are optimized to minimize the error of the combined model using a method such as **grid search** or **gradient descent**. The objective function for optimization is typically the **MSE** or another error metric:

$$Minimize: MSE = \Sigma \left(Y_t^{true} - Y_t^{ensemble}\right)^2$$

- Step 5. Model Evaluation

The presentation of the LSTM-ARIMA ensemble model is assessed using standard system of measurement such as RMSE, MAE, and MAPE:

$$- RMSE = \sqrt{\frac{1}{n} \Sigma \left(Y_t^{true} - Y_t^{ensemble}\right)^2}$$

$$- MAE = \left(\frac{1}{n}\right) \Sigma \left|Y_t^{true} - Y_t^{ensemble}\right|$$

$$- MAPE = \left(\frac{1}{n}\right) \Sigma \left|\frac{\left(Y_t^{true} - Y_t^{ensemble}\right)}{Y_t^{true}}\right| * 100$$

- Step 6. Forecasting and Updating

The combined LSTM-ARIMA ensemble model generates future predictions using the historical data and updated weights. As new data becomes available, the model is updated to maintain or improve prediction accuracy.

$$Y_t^{forecast} = w^1 * Y_t^{ARIMA(t)} + w^2 * h_t^{LSTM(t)}$$

Training and Validation Process

The model is fit from the training set; the validation set is used to validate model performance. The training method of the ARIMA model consists of selecting the optimal values for the MA, I, and AR sections. Usually using the Partial Autocorrelation Function (PACF), and Autocorrelation Function (ACF) and one may determine the appropriate time

values. Following that, the model is fitted using the training data and test set forecasts are produced. The LSTM model must be made sure it can manage the fact the data depends on time since it requires the data to be split into sets of specified lengths. The LSTM network is trained using BPTT so that the loss function is as little as feasible. One often uses Mean Squared Error (MSE) for this aim. The model is tested and the degree of data non-linear and long-term connection description is shown using the validation set. Following both models' training, the outcomes are aggregated using the selected integration technique, either weighted averaging or stacking. To evaluate the combination model then, many metrics like Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) are used. This procedure guarantees that the final ensemble model is optimal for the authentication and training data alike. The aim is to increase the accuracy and dependability of financial estimations.

IV. Experimental Setup

A. Environment and Tools Used

Running the tests testing the LSTM-ARIMA ensemble model for financial forecasting calls for a unique mix of gear and software. This is so as statistical models and deep learning models need a lot of computer capability. This work made use of a Python-based system and established and trained the LSTM network using well-known technologies like TensorFlow and keras. Many of these tools enable one to create deep learning models using LSTM layers easily. They may also be used for tasks like fine-tuning and optimizing. ARIMA model was applied using Python stats models module. Time-series analysis and statistical model like ARIMA make this instrument quite popular and simple to use. Because pandas offer strong characteristics for modifying and cleaning data—qualities required for dealing with financial time-series data—it was employed for data processing. The number computations were done using NumPy, which guaranteed fast math steps for both LSTM and ARIMA. Hardware-wise, the experiments were conducted on computers with GPUs (Graphics Processing Units) to hasten the training process for the LSTM models, which need a lot of processing capability. Since standard CPUs lacked as many resources, ARIMA models were run on them.

B. Hyperparameter Tuning

Making both the LSTM and ARIMA models operate better requires tuning the hyperparameters. Important hyperparameters for the LSTM model are the learning rate, batch size, and number of epochs. settings were selected via a grid search technique. Every hyperparameter was tested using a set of known values to find the ideal mix on the validation set. Using an Adam optimizer—known for its ability to handle sparse slopes—the LSTM model was trained. Among the hyperparameters for the ARIMA model are moving average (q), the differencing (d), autoregressive (p), and elements in that sequence. These were discovered by means of partial auto-correlation function (PACF) maps and auto-correlation function (ACF) maps, therefore guiding the suitable time values for the MA and AR terms. To prevent overfitting and guaranteeing of the best fit the Akaike Information Criteria (AIC) was used to select optimum model order. To maximize the LSTM-ARIMA ensemble technique, it is critical to tune the both models hyperparameters concurrently. The repetition of this procedure was done and each time it is checked against a validation set to confirm whether the model's avoided overfitting and performed well with data not previously seen.

V. Results and Discussion

The superior predictive performance is demonstrated by the ARIMA-LSTM ensemble model in comparison with the individual LSTM and ARIMA models when financial time series forecasting is considered. The ARIMA model effectively captures linear patterns within the data, while the LSTM model shows a strong capacity to learn nonlinear and complex dependencies that are intrinsic to unpredictable financial markets. A comparative performance evaluation across ARIMA, LSTM, and ARIMA-LSTM ensemble models was conducted using three widely accepted error measures: Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). These metrics provide a comprehensive assessment of forecasting accuracy by evaluating average forecast errors from different perspectives.

By combining the strengths of both models, the ensemble framework achieves a notable improvement in predictive accuracy, as reflected in the lower error metrics: MAPE (2.32), MAE (0.65), and RMSE (0.85).

This hybrid approach enables the model to simultaneously justification for short-term variations and long-term dependencies, resulting in more reliable directional forecasting. The findings suggest that ensemble methodologies can significantly enhance both the precision and adaptability of forecasting tasks, offering a valuable tool for data-driven decision-making in volatile market environments. Consistently, the ARIMA-LSTM ensemble achieved the lowest values across all three measures, thereby delivering the most accurate predictions. The ensemble's superior performance highlights its ability to integrate the complementary strengths of linear and nonlinear modeling, making it more robust and reliable for real-world financial applications.

Table 2: Performance of different models

Model	RMSE	MAE	MAPE
ARIMA	1.23	0.92	3.15
LSTM	0.94	0.74	2.68
LSTM-ARIMA Ensemble	0.85	0.65	2.32

Table -2 represents a comparative performance evaluation of ARIMA, LSTM, and ARIMA-LSTM ensemble models using three widely recognized error metrics—RMSE, MAE, and

MAPE. Individual LSTM and ARIMA models are outperformed by ensemble model which shows values of MAPE 2.32, an MAE 0.65 and an RMSE of 0.85 respectively.

The results demonstrate that while ARIMA is effective in modeling linear temporal structures, its error values are comparatively higher, indicating limitations in handling non-stationary and volatile datasets. The LSTM model reduces errors by capturing nonlinear dependencies and long-term temporal dynamics, yet it still exhibits performance constraints in highly irregular financial conditions. In contrast, the ARIMA-LSTM ensemble achieves the lowest values across all three error measures, underscoring its robustness, predictive accuracy, and adaptability. The hybrid approach integrates ARIMA's strength in modeling linear components with LSTM's ability to capture nonlinear interactions, yielding superior generalizability and resilience. Such results validate the ensemble model's utility in volatility modeling, portfolio optimization, and data-driven decision-support systems for financial forecasting applications.

The above table is represented in figure is as follows,

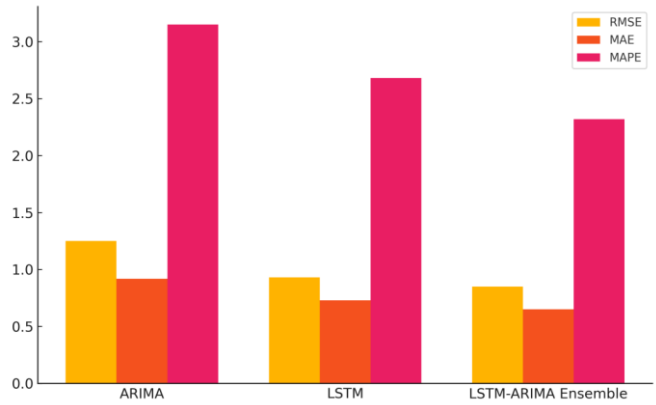

Fig.3.Performance Comparison of Forecasting Models (RMSE, MAE, MAPE)

When isolating individual model performance, the LSTM achieved better accuracy than ARIMA with MAPE of 2.68 and RMSE of 0.94, reflecting its advantage in capturing nonlinear temporal patterns and long-range dependencies. However, the ensemble model surpassed both, confirming the importance of hybridization in environments with non-stationary and volatile data. Unlike traditional time-series methods, LSTM is more effective in modeling the dynamic and irregular characteristics of financial markets, but the ensemble provides an additional layer of robustness by combining the LSTM's nonlinearity modeling capability with ARIMA's linear trend extraction. The reduction in RMSE, as depicted in Figure 4, further confirms the enhanced predictive accuracy achieved by advanced deep learning architectures, reinforcing the suitability of LSTM for forecasting tasks in dynamic financial environments.

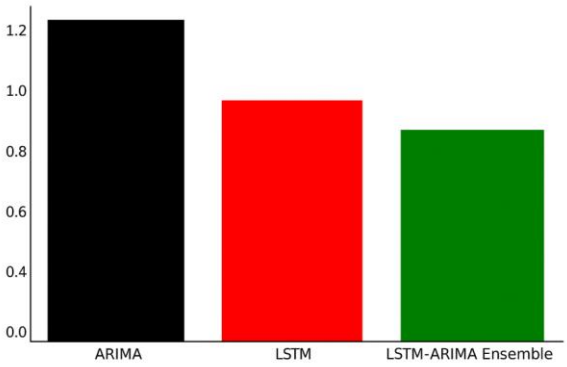

Fig.4 RMSE Reduction Across Forecasting Models

Figure 4 shows that the reduction in RMSE values across the evaluated forecasting models, signifying a consistent improvement in prediction accuracy. Among the three approaches, the LSTM-ARIMA Ensemble model achieves the lowest RMSE (0.85), along with the lowest MAE (0.65) and MAPE (2.32). The advantages of integration of capability of ARIMA for modeling linear temporal patterns with the strength of LSTM in capturing nonlinear and complex dependencies was emphasized by these results. For generation of more dependable and precise forecasts the ensemble model is enabled by the hybrid structure which is specifically beneficial for decision making and financial planning applications.

Table 3: Performance comparison of models across different time-series datasets

Model	**Stock Prices**	**Exchange Rates**	**Commodity Prices**
ARIMA	0.92	1.1	1.25
LSTM	0.74	0.95	0.89
LSTM-ARIMA Ensemble	0.65	0.88	0.82

Table 3 represents each model corresponding RMSE values across these datasets. To evaluate robustness and generalizability, the models were also tested on three distinct types of financial time series: stock prices, exchange rates, and commodity prices. The ARIMA model performed reasonably well for stock prices, with RMSE of 0.92, but its accuracy deteriorated on more volatile datasets such as exchange rates and commodities, where RMSE values rose to 1.10 and 1.25. In contrast, LSTM consistently outperformed ARIMA across all datasets by capturing nonlinear structures more effectively. Most notably, the ARIMA-LSTM ensemble demonstrated the highest flexibility and robustness, consistently producing the lowest RMSE values of 0.65, 0.88, and 0.82 across stock, exchange, and commodity prices respectively. This indicates that the ensemble is not dataset-specific but rather adaptable to varied financial instruments, enhancing its generalizability for real-world forecasting. The consistency of performance across datasets confirms its reliability, especially in complex environments characterized by volatility and uncertainty.

The empirical results carry significant implications for financial decision-making. By achieving lower forecast errors, the ARIMA-LSTM ensemble offers investors, portfolio managers, and policymakers a more dependable framework for anticipating market dynamics. Improved predictive power enables portfolio optimization through better identification of risk-return trade-offs, strategic resource allocation by governments and corporations based on reliable financial outlooks, and effective risk management by mitigating exposure to market volatility, currency fluctuations, and interest rate variations. Thus, the ensemble model not only improves statistical accuracy but also enhances the practicality of forecasting for critical applications in finance and economics.

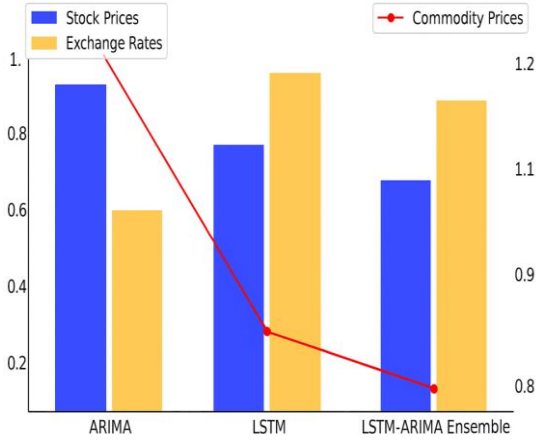

Fig.5 Comparison of Model Performance across Financial Metrics

Figure 5 provides a comparative analysis of forecasting model performance across several key financial evaluation metrics, including predictive accuracy, potential revenue generation, and risk management capability. These dimensions are particularly significant in evaluating the real-world applicability of forecasting models in financial decision-making. The results confirm that the LSTM model consistently delivers strong outcomes across datasets due to its ability to capture nonlinear interactions and long-term temporal dependencies within complex financial series. Its strength lies in detecting emerging patterns that are often overlooked by traditional linear approaches.

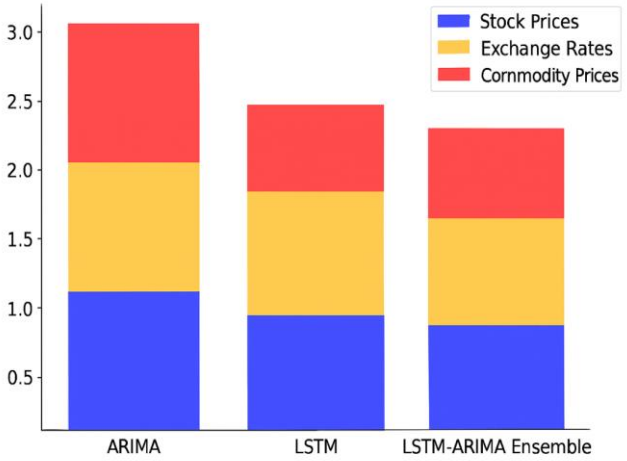

Fig.6 Aggregated model performance across stock, Exchange and commodity prices.

Above figure presents an aggregated assessment of model performance across three financial domains such as commodity prices, exchange rates and stock prices thereby highlighting the reliability and consistency of each model. This also demonstrates the gathered view of performance across three financial domains Commodity Prices, Exchange Rates and Stock Prices, is used to analyze the reliability and consistency of each model. The model's adaptability to volatility levels and diverse data characteristics is highlighted by these evaluations. The LSTM model demonstrates strong forecasting capability, with RMSE values of 0.89 for commodities, 0.95 for exchange rates, and 0.74 for stock prices, reflecting its effectiveness in modeling complex structures and irregularities. However, the ARIMA-LSTM ensemble outperforms the standalone LSTM by achieving even lower RMSE values (0.82, 0.88, and 0.65, respectively). This consistent superiority confirms the ensemble model's ability to integrate linear and nonlinear dynamics, resulting in enhanced accuracy, stability, and robustness. Consequently, the ensemble framework proves highly effective for applications in strategic risk assessment, portfolio optimization, and volatility modeling and financial forecasting, underscoring its practical utility in uncertain and dynamic markets.

These findings are consistent with existing literature that emphasizes the superiority of hybrid and ensemble approaches over single-model techniques for financial forecasting. Previous studies have shown that LSTM models outperform ARIMA in capturing nonlinear dependencies, but often suffer from over fitting or instability in highly volatile settings. By integrating ARIMA, the ensemble framework reduces these weaknesses and produces stable forecasts even in complex environments, extending and strengthening the contributions of earlier work. While the ARIMA-LSTM ensemble demonstrates robust performance, certain limitations remain. The model may still struggle to capture sudden shocks such as geopolitical crises or black-swan events, where historical data provides limited guidance. Future research could enhance predictive accuracy by incorporating exogenous macroeconomic indicators, sentiment analysis from financial news, or advanced

architectures such as Transformers with attention mechanisms. Additionally, extending the evaluation to multi-step forecasting horizons and real-world financial portfolios would further validate the model's utility. Lastly, the experimental results establish the ARIMA-LSTM ensemble as a superior forecasting tool compared to individual ARIMA and LSTM models. Its consistent performance across multiple datasets, combined with its ability to capture both linear and nonlinear structures, makes it highly suitable for strategic financial forecasting, portfolio management, and risk assessment in complex and volatile market environments.

VI. Conclusion

This study demonstrates the effectiveness of integrating innovative deep learning architectures, such as LSTM networks, with conventional statistical models like ARIMA for financial time series forecasting. By leveraging the complementary strengths of both approaches, the proposed ARIMA-LSTM ensemble framework offers a robust and comprehensive prediction mechanism that overcomes the limitations of individual models. While ARIMA excels at modeling linear structures and autocorrelations, LSTM effectively captures nonlinear interactions and long-term dependencies inherent in volatile and dynamic financial environments.

The experimental findings validate that the ensemble method consistently outperforms standalone ARIMA and LSTM models across standard evaluation metrics, including RMSE, MAE, and MAPE. Its ability to deliver lower estimate errors highlights the model's robustness, adaptability, and predictive accuracy. By efficiently capturing both short-term fluctuations and long-term trends, the ensemble enhances generalizability across diverse financial domains such as stock market forecasting, commodity price prediction, exchange rate analysis, and macroeconomic variable modeling.

Beyond statistical enhancements, the practical implications of this framework are substantial. The ensemble provides reliable tools for risk management, portfolio optimization, strategic investment planning, and economic policy formulation, thereby supporting data-driven decision-making in uncertain and volatile markets. Moreover, the flexible structure of the ensemble can be extended to incorporate exogenous variables, hybrid architectures, and advanced deep learning techniques such as Transformers, enabling continuous scalability and improved resilience against structural breaks and financial shocks.

In this study, the ARIMA-LSTM ensemble represents a reliable, versatile, and high-performing solution for financial forecasting tasks. Its capacity to integrate linear and nonlinear modeling, achieve robust generalization across datasets, and support practical financial applications underscores its potential as a powerful decision-support system for both academic research and industry practice.

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