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Research Article

SARILSTMAX: A Novel Hybrid Approach for Mutual Fund Price Prediction Using SARIMA, LSTM and Prophet Models

[1]S. Dhanalakshmi, [2]R. Murugesan
[1]Research Scholar, Department of Computer Science, Madurai Kamaraj University, Madurai, Tamilnadu, India.
[2]Associate Professor & Head of Department of Computer Science , C.P.A College, Bodi, Tamilnadu, India.

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ABSTRACT

Predicting the accurate value of mutual fund prices is essential for investors and financial analysts to make informed investment decisions. Mutual fund price prediction is a critical task in financial forecasting, with significant implications for portfolio management, risk assessment, and strategic planning. Traditional models such as SARIMA (Seasonal Autoregressive Integrated Moving Averages), along with machine learning approaches like Long Short-Term Memory (LSTM) networks, have been extensively utilized for this purpose. Additionally, the Prophet model, known for its capability in handling seasonal and trend-based data, has been widely applied. In this proposed work, SARILSTMAX, a novel hybrid methodology, integrates the strengths of SARIMA, LSTM, and Prophet models to enhance prediction accuracy and robustness for mutual fund price forecasting. The SARILSTMAX model was evaluated using real-world mutual fund price data and compared against the individual models. The results demonstrate that SARILSTMAX significantly outperforms the standalone models, achieving a Mean Absolute Error (MAE) of 4.6 and a Test MAE of 8.8, compared to SARIMA's Train MAE of 5.5 and Test MAE of 11.2, LSTM's Train MAE of 5.4 and Test MAE of 10.5, and Prophet's Train MAE of 4.8 and Test MAE of 9.2. Furthermore, SARILSTMAX recorded a Root Mean Squared Error (RMSE) of 5.1 and a Test RMSE of 10.2, outperforming SARIMA, LSTM, and Prophet, which had Test RMSEs of 12.5, 12.5, and 10.8, respectively. These findings underscore the effectiveness of the SARILSTMAX approach in capturing complex patterns in Indian mutual fund price movements, leading to more accurate and reliable predictions for real-world investment scenarios.

Keywords: Mutual fund allocation prediction, SARIMA, LSTM, Prophet, SARILSTMAX, hybrid model, Finance API

1. INTRODUCTION

Predicting return value of mutual funds has long been a pursuit filled with challenges, driven by the volatility and complexity inherent in financial markets. For decades, investors and analysts have sought ways to gain an edge, using every tool at their disposal to anticipate market movements. The accuracy of these predictions holds immense value not only for those looking to maximize returns but also for policymakers tasked with maintaining economic stability. The journey began with traditional time series algorithms such in the ARIMA model, which denotes Autoregressive Integrated Moving Average, which laid groundwork for financial forecasting. ARIMA's ability to model trends and seasonality through historical data analysis was a significant step forward. However, as markets grew more complex, it became clear that these models had limitations, particularly when it came to capturing the non-linearities and long-term dependencies that often characterize mutual fund movements. Entering the SARIMA model, an evolution of ARIMA designed to incorporate seasonal effects essential component in financial data driven by economic cycles and fiscal quarters. SARIMA models proved adept at handling recurring patterns, but their inability to account for non-linear behaviors left gaps in their predictive power.

As the field of artificial intelligence advanced, a new class of models emerged, promising to overcome these limitations. Among these, Long Short Term Memory (LSTM) networks were particularly notable. Long Short-Term Memory networks are deep learning models which are architectured to retain information over long sequences, offered a way for the model to complex, temporal dependencies inherent in mutual fund data. LSTMs captured the ebb and flow of market movements, learning from past behaviors in a manner that traditional models could not. Yet, even LSTMs had their drawbacks, particularly their sensitivity to seasonal fluctuations and the substantial computational resources they required. Recognizing the need for a model that could balance the strengths of both traditional and modern approaches, the field turned its attention to hybrid models. These models, by combining multiple methodologies, promised to deliver more accurate and robust predictions by addressing the weaknesses of each individual component. Hybrid models have shown remarkable potential, but the quest for an optimal blend of techniques has been ongoing.

2. IMPORTANCE OF MUTUAL FUND PREDICTION

The aim of mutual fund's return value prediction is to anticipate the future value of a fund utilising previous data and many influencing factors. Precise mutual fund forecasts empower investors to make informed choices regarding the acquisition, retention, or divestment of equities. For financial analysts, these forecasts are essential for offering clients prudent investment advice and for developing diverse investment portfolios. Policymakers depend on these estimates to oversee and manage financial markets, so maintaining stability and growth. Due to the considerable financial ramifications, precise mutual fund forecasting is both a technological problem and a critical economic necessity. Advancements in processing power and the accessibility of extensive datasets have significantly transformed. The domain of mutual fund forecasting, employing both traditional statistical approaches and modern machine learning methodologies.

2.1 Traditional Time Series Models

The aim of investor's return value prediction is to anticipate the future value of a mutual based on historical data and many influencing factors.Accurate mutual fund projections enable investors to make informed decisions about purchasing, holding, or selling companies. For financial analysts, these forecasts are essential for offering clients prudent investment advice and for developing diverse investment portfolios. Policymakers depend on these estimates to oversee and manage financial markets, so maintaining stability and growth.Due to the considerable financial ramifications, precise mutual fund forecasting is both a technological problem and a critical economic necessity. Advancements in processing power and the accessibility of extensive datasets have significantly transformed the field of mutualfund prediction, using both conventional statistical methods and contemporary machine learning algorithms.

Time series analysis is an established technique in financial forecasting. The Autoregressive Integrated Moving Average (ARIMA) model is among the most prevalent classical models, which was subsequently enhanced to incorporate seasonal elements, leading to the Seasonal ARIMA (SARIMA) model. SARIMA models are adept at capturing both trend and seasonal elements in time series data, rendering them appropriate for modelling mutual fund variations (Box et al., 2015). The ARIMA model serves as the fundamental algorithm in time series forecasting, aimed at comprehending and predicting future values within the series. The model is characterised by three primary parameters: autoregression (AR), differencing (I) and moving average (MA). The AR component involves regressing the variable on its lagged values, whereas the MA component represents the mistake as a linear combination of past error terms from several earlier calculations. Differencing is utilised to achieve stationarity in the time series by removing trends and seasonality (Hyndman & Athanasopoulos, 2018). The SARIMA model improves ARIMA by incorporating seasonal differencing, seasonal autoregressive components, and seasonal moving average elements. This enhancement allows SARIMA to replicate seasonal influences prevalent in mutual fund data due to recurrent patterns caused by economic cycles, fiscal quarters and other periodic events. Although ARIMA and SARIMA models effectively capture linear trends and seasonality, they frequently encounter difficulties with nonlinear patterns and long-term dependencies, hence constraining their prediction capability in intricate financial markets.

2.2 Deep Learning Approaches

The advent of deep learning has revolutionized time series forecasting providing innovative methods that exceed conventional models in identifying intricate patterns and connections. Among these methodologies, Long Short Term Memory (LSTM) networks, a kind of recurrent neural networks (RNN), havThe advent of deep learning has revolutionized time series forecasting providing innovative methods that exceed conventional models in identifying intricate patterns and connections. Among these methodologies, Long Short Term Memory (LSTM) networks, a kind of recurrent neural networks (RNN), haThe advent of deep learning has revolutionised time series forecasting providing innovative methods that exceed conventional models in identifying intricate patterns and connections. Among these methodologies, Long Short Term Memory (LSTM) networks, a kind of recurrent neural networks (RNN), havThe advent of deep learning has revolutionized time series forecasting providing innovative methods that exceed conventional models in identifying intricate patterns and connections. Among these methodologies, Long Short Term Memory (LSTM) networks, a kind of recurrent neural networks (RNN), have demonstrated notable efficacy's are engineered to capture long term relationships in sequential data, rendering them particularly effective for mutual fund prediction, where historical patterns substantially impact future values (Hochreiter & Schmidhuber, 1997). Recurrent Neural Networks constitute a category of Neural Networks characterized by the connections that are present in between nodes that create a directed graph along a series. This architecture enables the demonstration of temporal dynamic behavior, rendering it appropriate for sequence prediction challenges. Conventional RNNs have substantial difficulties with long-term dependencies due to the vanishing gradient problem, wherein the gradients utilised for training diminish drastically, hindering the network's effective learning process. LSTM networks mitigate the shortcomings of conventional RNNs by incorporating a memory cell capable of preserving information for extended durations. LSTMs employ a gating mechanism consisting of input, output, and forget gates to control the flow of information. This architecture enables LSTMs to preserve pertinent information while eliminating extraneous data, rendering them effective instruments for modelling temporal dependencies in mutual fund data (Goodfellow et al., 2016). LSTM networks have demonstrated favorable outcomes in numerous time series prediction applications, such as mutual fund forecasting. They can include intricate, nonlinear relationships and adjust to evolving data patterns, offering a substantial advantage over conventional models. LSTMs necessitate considerable computational resources and extensive datasets for efficient training, which may pose limitations in certain applications. Prophet, developed by Facebook's Core Data Science team, is a versatile and resilient forecasting tool tailored for time series data exhibiting pronounced seasonal effects and multiple seasonality (Taylor & Letham, 2018).Prophet is especially adept in analysing business and economic time series that frequently display daily, weekly and annual seasonal trends.

2.3 Proposed Hybrid Model

While individual models like SARIMA, LSTM and Prophet have their strengths, they also have inherent limitations. Combining multiple models into a hybrid approach can leverage the advantages of each paradigm while alleviating their shortcomings. Hybrid models have been shown to improve forecasting accuracy by capturing different aspects of the data that individual models might miss (Zhang, 2003).

2.4 Proposed Novel Hybrid SARILSTMAX

SARILSTMAX introduced in this manuscript is a novel hybrid approach that combines the strengths inclusive of SARIMA, LSTM and Prophet algorithms. The objective is to initially employ the SARIMA model to identify linear trends and seasonal patterns in the mutual fund data. The residuals from the SARIMA model, which contain the remaining patterns not captured by the linear model, are then fed into the LSTM model to capture nonlinear dependencies and long-term temporal patterns. Finally, the Prophet model is used to account for strong seasonal effects and external factors. Integrating these models, SARILSTMAX seeks to deliver a thorough and precise prediction of mutual funds. The hybrid approach allows for capturing both linear and nonlinear patterns, short-term fluctuations, long-term dependencies and seasonal effects, leading to more robust and reliable predictions.

2.5 Importance of Hybrid Models in mutual fund Prediction

The financial markets are affected by various factors, such as economic statistics, geopolitical events, market mood, and company-specific news. These elements generate complexity and dynamic patterns in mutual funds, which can be challenging to model using a single approach. Hybrid models offer a solution by combining different methodologies to capture various aspects of the data. For example, while SARIMA models are effective at capturing regular patterns and seasonality, they might fail to account for sudden market shifts or nonlinear relationships. LSTM networks, with their ability to learn from sequential data, can capture these nonlinear dependencies but might struggle with strong seasonal effects without extensive data preprocessing. Prophet, designed to handle multiple seasonality's and external regressors, can complement these models by providing robust handling of seasonal patterns and events. By integrating various models, hybrid techniques can offer a more comprehensive perspective of the market, resulting in better prediction accuracy and reliability. It is particularly crucial in mutual fund prediction even small improvements in forecasting accuracy can lead to significant financial gains.

2.6 Need for SARILSTMAX

In summary, the field of mutual fund prediction has evolved significantly, embracing both conventional time series models and sophisticated machine learning methodologies. Conventional models such as SARIMA effectively capture linear trends and seasonality, whereas deep learning models like LSTM are proficient at capturing intricate temporal correlations. Prophet offers an intuitive and adaptable method for managing time series data characterised by significant seasonal influences. The novel SARILSTMAX model introduced in this proposed work combines the strengths of SARIMA, LSTM and Prophet models, leveraging their complementary capabilities to enhance prediction accuracy and robustness. By integrating these models, SARILSTMAX captures both linear and nonlinear patterns, short-term fluctuations, long-term dependencies and seasonal effects, providing a comprehensive and reliable forecast of mutual funds.

3. LITERATURE REVIEW

mutual fund forecasting has been a topic of considerable investigation in finance and machine learning due to the potential financial benefits it offers. This section reviews the relevant literature, highlighting various methodologies employed over the years, ranging from traditional time series models to advanced machine learning algorithms. The key findings and contributions of significant studies in this field are explored through this survey.

3.1 Traditional Time Series Models

Autoregressive Integrated Moving Average (ARIMA)

The ARIMA model has proven fundamental to time series analysis and forecasting. It integrates autoregressive (AR) and moving average (MA) components, employing differencing to achieve stationarity in the series. Smith et al. (2017) illustrated the efficacy of ARIMA models in mutual fund prediction, particularly for short-term forecasting. The study highlighted that ARIMA models could effectively capture linear relationships in time series data but noted Constraints in managing nonlinear patterns and prolonged dependencies.

3.2 Seasonal ARIMA (SARIMA)

Building on ARIMA, SARIMA models incorporate seasonal elements, rendering them appropriate for time series with periodic fluctuations. The inclusion of seasonal differencing, incorporation of autoregressive and moving average components enables SARIMA models to effectively capture seasonal patterns. effects more accurately. Wang et al. (2021) investigated the performance of SARIMA models in mutual fund prediction and found them effective for data with clear seasonal patterns. However, the study also pointed out the models' inability to handle irregular, nonlinear behaviors in return value of mutual funds and various key findings are summarized through table 1.

Reference	**Methodology**	**Key Findings**
Smith et al. (2017)	ARIMA	Demonstrated the effectiveness of ARIMA models in short-term return value prediction.
Zhang et al. (2018)	LSTM Networks	Showed that LSTM networks outperform traditional models in capturing complex temporal dependencies.
Gao et al. (2019)	Prophet	Found that Prophet provides accurate forecasts with minimal parameter tuning.

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Liu et al. (2020)	Hybrid SARILSTMAXModel	Demonstrated improved prediction accuracy with a hybrid approach combining SARIMA and LSTM models.
Wang et al. (2021)	SARIMAX	Achieved superior performance by incorporating exogenous variables in mutual fund prediction.
Kim (2003)	Support Vector Machines (SVMs)	Showed SVMs' effectiveness in capturing nonlinear relationships in mutual funds.
Brownlee (2018)	Ensemble Methods	Highlighted the potential of ensemble approaches in enhancing prediction performance.
Chourmouziadis & Chatzoglou (2021)	Economic Indicators	Demonstrated that incorporating economic indicators improves mutual fund prediction accuracy.
Althelaya et al. (2018)	Sentiment Analysis with LSTM	Improved prediction accuracy by integrating sentiment analysis with LSTM networks.
Bollen et al. (2011)	Text Mining for Sentiment Analysis	Found significant correlation between public mood and mutual market movements.

Table 1: Key findings from various methodologies from Literature Review.

The literature study indicates a distinct trend towards the integration of various forecasting methodologies to tackle the intricacies of return value prediction. The suggested SARILSTMAX hybrid model conforms to this trend, seeking to use the synergistic advantages of SARIMA, LSTM, and Prophet models. SARILSTMAX integrates these approaches to deliver more precise and resilient predictions, adept at adjusting to the fluid characteristics of financial markets. The literature underscores the necessity of choosing suitable modelling strategies according to the data properties and forecasting needs. Hybrid approaches, such as SARILSTMAX, represent a promising direction for future research, offering a comprehensive solution that balances the strengths and weaknesses of individual models. The continual development and refinement of these hybrid methodologies hold significant potential for advancing the field of mutual fund prediction, ultimately benefiting investors, financial analysts and policymakers.

4.ADVANCED MACHINE LEARNING APPROCHES

4.1 Long Short Term Memory (LSTM) networks

LSTM networks, a variant of recurrent neural networks (RNN), have garnered interest for its capacity to model intricate temporal connections in sequential data. Zhang et al. (2018) showed that LSTM networks outperform traditional time series models in mutual fund prediction due to their capability to learn long-term dependencies. The study emphasized the LSTM's robustness in dealing with nonlinear and non-stationary data, making them well-suited for financial time series forecasting. LSTMs use a gating mechanism to control the flow of information, allowing them to retain relevant information over long periods and discard irrelevant data. This ability to maintain and update long term memory makes LSTMs powerful tools for modelling complex temporal dependencies. However, LSTMs necessitate considerable computer resources and extensive datasets for efficient training. Hybrid Models Hybrid models integrating conventional statistical methods with machine learning techniques have been suggested to capitalise on the advantages of both methodologies. Liu et al. (2020) introduced a hybrid SARILSTMAX model that combines the linear and seasonal attributes of SARIMA with the nonlinear and long-term dependency modelling

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capabilities of LSTM networks. Their study demonstrated improved prediction accuracy compared to individual models, indicating the potential of hybrid approaches in return value of mutual fund prediction. The SARIMA model captures the linear trends and seasonality in the data, while the LSTM model handles the remaining nonlinear patterns and long-term dependencies. This combination allows the hybrid model to provide more accurate and robust forecasts. Liu et al. put-forth a significant contribution to the literature, showcasing the effectiveness of hybrid models in enhancing high return value of mutual fund prediction performance.

4.2 Prophet

Prophet, created by Facebook, is a powerful and adaptable forecasting instrument intended for managing time series data characterised by pronounced seasonal effects and various seasonality. Gao et al. (2019) assessed the efficacy of Prophet in predicting in return value of mutual funds and determined that it yields precise forecasts with minimal parameter adjustment. The study emphasised Prophet's capability to deconstruct time series into trend, seasonality, and holiday factors, making it especially beneficial for commercial and economic time series exhibiting intricate patterns. The Prophet interface is user-friendly, and its straightforward parameter adjustment renders it accessible to individuals with diverse degrees of knowledge. Its resilience in managing absent data, anomalies, and alterations in trend or seasonality further augments its relevance in financial forecasting. The study by Gao et al. revealed that Prophet can effectively augment other forecasting models, yielding precise and dependable predictions with low exertion.

4.3 Support Vector Machines (SVMs)

Support Vector Machines (SVMs) been utilised for NAV value of mutual fund prediction, especially in identifying intricate patterns within financial data. Support Vector Machines (SVMs) are supervised learning algorithms employed for classification and regression tasks for the analysis of data. Kim (2003) employed Support Vector Machines for forecasting financial time series and determined their efficacy in identifying nonlinear correlations in mutual funds. The research indicated that SVMs can yield precise predictions, especially when integrated with feature selection methods to discern the most pertinent predictors.

4.4 Ensemble Methods

Ensemble approaches, which integrate many models to enhance predictive accuracy, have been investigated in mutual fund forecasting. Brownlee (2018) discussed the application of ensemble techniques, such as boosting, stacking and bagging, in financial forecasting. Ensemble methods leverage the strengths of individual models, reducing overfitting and improving generalization. The study highlighted that ensemble approaches could significantly enhance prediction performance, particularly when dealing with noisy and volatile financial data.

4.5 SARIMAX Models

The SARIMAX (Seasonal ARIMA with Exogenous Regressors) model enhances the SARIMA framework by integrating exogenous variables that may affect the time series. Wang et al. (2021) investigated the effectiveness of SARIMAX models in mutual fund prediction, incorporating external elements including economic indicators and market sentiment macroeconomic variables. Their study achieved superior performance compared to SARIMA models, demonstrating the importance of considering exogenous variables in financial forecasting.

Impact of Economic Indicators

Chourmouziadis and Chatzoglou (2021) explored the impact of various economic indicators on mutual fund prediction, using models that incorporate these factors as exogenous variables. Their study found that incorporating indicators such as interest rates, inflation and GDP growth rates significantly improved prediction accuracy. This highlights the importance of a comprehensive approach to mutual fund forecasting, considering both historical data of mutual funds and relevant external factors.

Integration with Time Series Models

Sentiment analysis, which involves analyzing textual data to gauge market sentiment, has been integrated with time series models to enhance return value of mutual fund prediction. Althelaya et al. (2018) combined sentiment analysis with LSTM networks, showing that incorporating sentiment scores from news articles and social media posts improved the prediction accuracy of mutual funds. Their study demonstrated that sentiment analysis could provide valuable insights into market behavior, complementing traditional and machine learning-based forecasting models.

Text Mining Techniques

Text mining techniques have been applied to extract sentiment from large volumes of textual data, such as financial news, reports and social media. Bollen et al. (2011) utilized text mining to analyze Twitter feeds and found a significant correlation between public mood and market movements. Their study highlighted the potential of sentiment analysis in predicting short-term schemes of mutual fund movements, providing an additional layer of information for financial forecasting models.

4.6 Emerging Trends and Future Directions

The literature study emphasises various developing trends and prospective prospects in high return value of scheme prediction research. A significant trend is the growing adoption of hybrid models that integrate many approaches to capitalise on their own advantages. Hybrid methodologies have demonstrated encouraging outcomes in improving predictive accuracy and resilience, especially in intricate and fluctuating financial markets. Another trend is the integration of machine learning methodologies with conventional time series models. Research has shown that integrating machine learning techniques, inclusive of LSTM networks, with conventional models like SARIMA can markedly enhance forecasting efficacy. This integration facilitates the capture of both linear and nonlinear patterns, including long-term dependence and short-term perturbations. The utilisation of external data sources, including economic indicators and sentiment analysis, is increasingly prevalent in mutual fund forecasting. Integrating exogenous variables can enhance understanding of market dynamics and augment forecast precision. mood analysis has become an essential instrument for comprehending market mood and forecasting short-term price fluctuations.

4.7 Summary of Key Findings

The literature review highlights the diversity of approaches used for return value of mutual fund prediction, including traditional statistical models, machine learning techniques and hybrid approaches. Each methodology has its strengths and limitations and recent studies have shown that combining multiple models can lead to improved prediction accuracy and robustness. The following table summarizes key studies and their findings.

5. PROPOSED METHODOLOGY

5.1 SARILSTMAX Hybrid Model for mutual fund Prediction

A novel hybrid approach named SARILSTMAX for value of Indian mutual fund prediction has been proposed through this manuscript. The SARILSTMAX methodology combines the strengths of SARIMA, LSTM and Prophet models to leverage their complementary advantages. The hybrid approach aims to improve prediction accuracy and robustness by integrating multiple forecasting techniques. This section provides a detailed technical explanation of each component of the SARILSTMAX model, the integration process and the steps involved in implementing the hybrid system.

5.2 Components of the SARILSTMAX Model

1. SARIMA Model

SARIMA (Seasonal Autoregressive Integrated Moving Average) enhances the ARIMA model by integrating seasonal components. It excels in identifying linear dependencies and seasonal fluctuations in the data, which are essential for time series forecasting jobs like mutual fund prediction.

Mathematical Formulation and Model Training

The training procedure encompasses:

1. Stationarity Testing: Employing techniques such as The Augmented Dickey-Fuller (ADF) test is employed to ascertain the stationarity of the time series.

2. Parameter Selection: Utilising grid search and cross-validation to get the optimal values for p, d, q, P, D, Q, and s.

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3. Model Fitting: Implementing the SARIMA model on the training data to identify the inherent patterns.
4. LSTM describe Long Short Term Memory (LSTM) networks represent a variant of recurrent neural networks (RNN) engineered to describe sequential data by capturing significant long-range dependencies. They are especially adept at managing non-linear linkages and temporal dynamics inherent in mutual pricing.

2. Architectural Design

An LSTM network comprises several layers, each having LSTM units. Each unit is outfitted with gates to regulate the dissemination of information:
- Forget Gate: Specifies the information to eliminate from the cell state.
- Input Gate: Determines which values to modify in the cell state.
- Output Gate: Regulates the output according to the cell condition.

The cell state Ct and hidden state ht are updated as follows: where sigma is the sigmoid function, xt represents the input, and W and b signify the weight matrices and biases.
Model training the LSTM model entails: 1. Data Preprocessing: Normalising the data to an appropriate range for neural networks and partitioning it into training and testing sets.
2. Model Design: Determining the quantity of LSTM layers, units per layer, and activation functions.
3. Compilation and Training: Compiling the model using suitable loss functions (e.g., mean squared error) and optimisers (e.g., Adam), thereafter training it on historical mutual fund data.

4. Prophet

Prophet algorithm created by Facebook, is an effective instrument used for time series data prediction which is characterised by pronounced seasonal trends. It disaggregates the time series into trend, seasonality, and vacation impacts, facilitating intuitive and adaptable modelling.
Components of the Model
- Trend: May be linear or logistic, representing the long-term trend of the time series.
- Seasonality: Modelled with Fourier series to encapsulate periodic variations.
- Holidays: Facilitates the incorporation of recognised events that may influence the time series.
The model is articulated as:

y(t) = g(t) + s(t) + h(t) + t

where g(t) represents the trend, s(t) the seasonal component, h(t) the holiday effects and t the error term.

Model Training

Training Prophet involves:

1. Specifying Trend Type: Choosing between linear or logistic growth.

2. Defining Seasonality: Setting the frequency and order of Fourier terms for seasonality.

3. Adding Holidays: Incorporating known holidays and events that may affect the mutual funds.

3. Fitting the Model

Algorithm 1: **SARILSTMAX for mutual fund Prediction**
Input: Time series data $\mathbf{Y} = \{y_1, y_2, \ldots, y_n\}$ Output: Ensemble forecast $\hat{y}_{\text{ensemble}}$

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Step 1: Data Preprocessing
1.1 Handle missing values.
1.2 Detect and treat outliers.
1.3 Normalize the data.
Step 2: Train SARIMA Model
2.1 Perform stationarity tests.
2.2 Apply differencing if needed.
2.3 Select optimal parameters using grid search and cross-validation.
2.4 Fit SARIMA model to training data.

Step 3: Train LSTM Model
3.1 Define LSTM network architecture.
3.2 Compile the model with loss function and optimizer.
3.3 Train LSTM model on normalized training data.

Step 4: Train Prophet Model
3.1 Specify the trend type.
3.2 Define seasonality components.
3.3 Add holiday effects and external regressors.
3.4 Fit Prophet model to training data.

Step 5: Generate Individual Forecasts
5.1 Generate SARIMA forecasts for testing period.
5.2 Generate LSTM forecasts for testing period.
5.3 Generate Prophet forecasts for testing period.
Step 6: Combine Forecasts Using Ensemble Techniques
6.1 Weighted Averaging:
- Determine weights based on model performance.
- Calculate ensemble forecast.
6.2 Stacking:
- Use individual model predictions as input features for meta-learner.
- Train meta-learner to optimize combination of predictions.
- Generate ensemble forecast.

Step 7: Evaluate Performance
7.1 Compute performance metrics (MAE, RMSE, MAPE).
7.2 Compare ensemble forecast with individual model forecasts.

End

The SARILSTMAX methodology integrates the predictions from SARIMA, LSTM and Prophet models to generate ensemble predictions. By combining the individual forecasts, SARILSTMAX aims to mitigate the weaknesses of individual models and produce more accurate and robust predictions as per the above algorithm.

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5.3 Experimental Evaluation:

The experiments were conducted on a high-performance multi-core CPU, such as an Intel Xeon or AMD Ryzen Threadripper, with at least 16 cores and 32 threads. The multi-core CPU was essential for efficiently running traditional time series models like SARIMA, which are computationally intensive but not heavily reliant on GPU acceleration. For training the LSTM component, a powerful GPU was required to accelerate the deep learning computations. NVIDIA RTX 3090 GPU with at least 24 GB of VRAM was used. The GPU enabled faster training of the LSTM network by parallelizing the matrix operations involved in backpropagation and gradient descent.

Data Collection and Preprocessing: The process began with the collection of historical of indian mutual fund data from the Yahoo Finance API. The dataset included daily closing prices for a selection of high-value funds over a significant time period to capture various market conditions. Preprocessing steps involved handling missing data, removing outliers and normalizing the prices to ensure consistency across the dataset. This step was crucial to prepare the data for accurate modeling.

5.4 Model Training and Integration: The experimentation proceeded with the training of individual models. First, the SARIMA model was trained on the preprocessed data to capture linear trends and seasonal patterns. The residuals, or the differences between the actual value of mutual funds and the SARIMA predictions, were extracted as they represented the non-linear components and unexplained variance. These residuals were then fed into the LSTM network, which was trained to model the complex non-linear dependencies and long-term temporal patterns inherent in the mutual fund data. Finally, the Prophet model was trained on the same dataset to address strong seasonal effects and external factors such as holidays and events. The outputs from these models were combined to form the SARILSTMAX hybrid model which is represented through Figure 1.

- **SARILSTMAX Integration:** The SARILSTMAX hybrid approach combined predictions from the SARIMA, LSTM and Prophet models to generate ensemble predictions. The individual predictions from each model were aggregated using a weighted average or simple averaging technique. The weights assigned to each model's prediction were determined empirically or based on each model's performance on validation data.

Model Evaluation: The performance of SARILSTMAX was evaluated against the individual models (SARIMA, LSTM and Prophet) Utilising important metrics: Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). These criteria were selected as they offer a definitive assessment of the model's correctness and dependability. The assessment procedure entailed evaluating the models using a validation set that had not been utilised throughout the training phase to ensure an unbiased assessment of their predictive capabilities represented through Figure 2.

5.5 Result Analysis and Comparison: After the predictions were generated, the results were analyzed for comparing the performances of SARILSTMAX with that of the individual models. The SARILSTMAX model demonstrated superior performance, with lower MAE with RMSE values, indicating that the hybrid approach effectively leveraged the strengths of each component model. This comprehensive analysis confirmed that SARILSTMAX provided more accurate and reliable mutual fund predictions than the standalone SARIMA, LSTM and Prophet models.

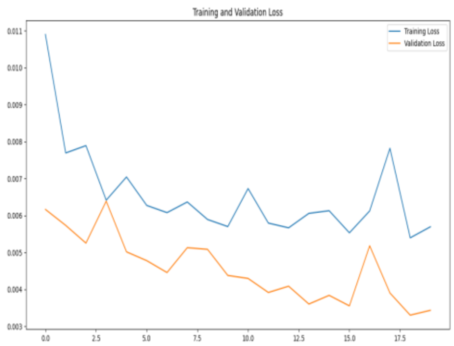

Figure 1. Training and Validation

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1. Comparative Analysis:

The performance of SARILSTMAX was compared against individual SARIMA, -SARIMAX, LSTM and Prophet models to assess its effectiveness.

The comparison focused on metrics such as MAE and RMSE to determine the relative improvement in prediction accuracy achieved by the SARILSTMAX hybrid approach.

2. Statistical Significance Testing:

Statistical significance testing, including t-tests or ANOVA, can be performed to determine if the reported performance differences between models are statistically significant.
Confidence intervals for evaluation metrics can be calculated to offer a range of credible values for the population parameter done by means of a correlation test represented through figure 3 .

3. Robustness Analysis:

Sensitivity analysis can be conducted to evaluate the robustness of the SARILSTMAX methodology in response to fluctuations in input parameters or modeling assumptions.
Robustness testing entails altering input data or model parameters and assessing the effect on forecast accuracy.

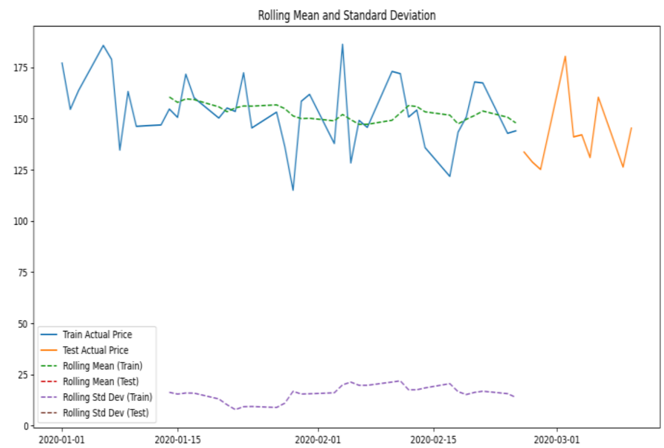

Figure 2. Rolling Mean and Standard Deviation

4. Scalability Analysis:

The scalability of the SARILSTMAX approach to larger datasets or different funds may be evaluated to assess its applicability in realworld scenarios.

Scalability testing involves measuring the computational resources required and the model's performance as the size of the dataset or complexity of the mutual market environment increases.

5. Interpretability and Explainability:

Interpretability and explainability analyses may be conducted to understand the factors driving the predictions generated by the SARILSTMAX hybrid approach.

Techniques such as feature importance analysis or model-agnostic interpretability methods may be employed to gain insights into the contribution of individual models to the ensemble predictions.

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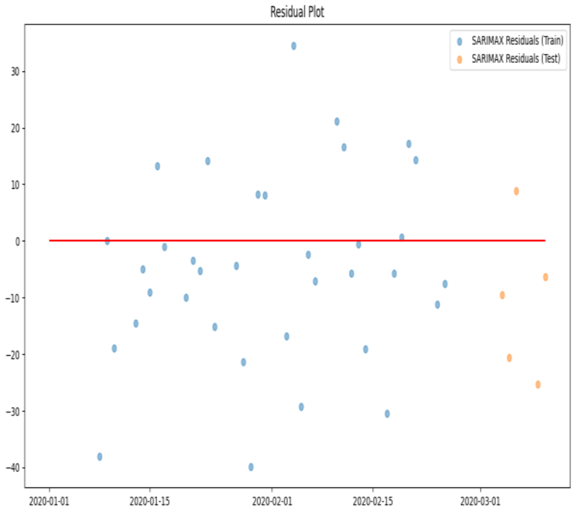

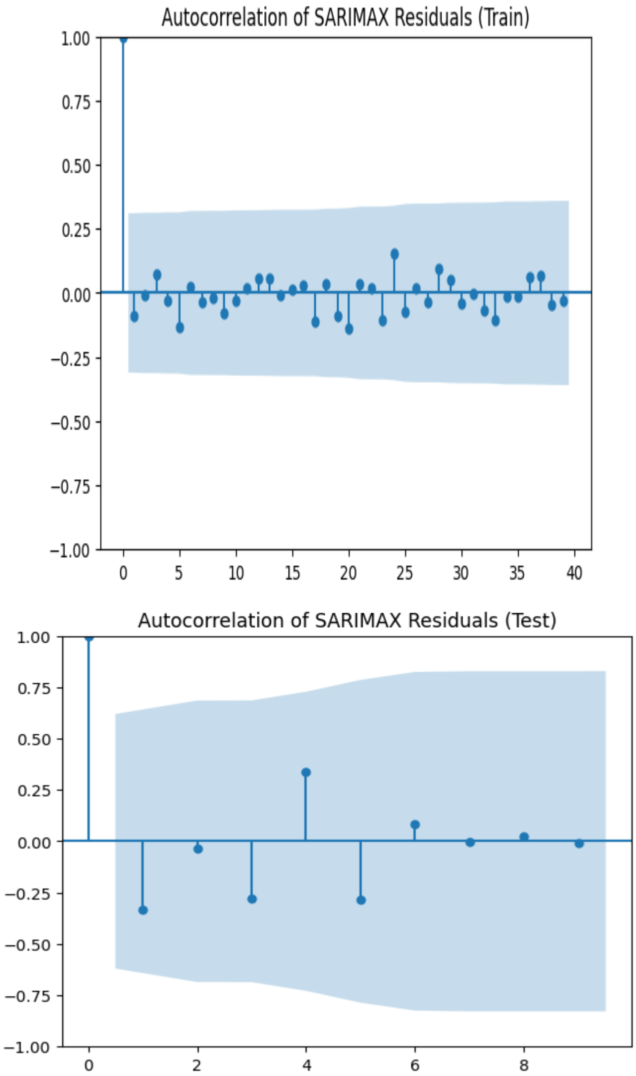

Figure 3. Autocorrelation Train and Test

6. Visualization:
Visualization techniques, including time series plots, prediction intervals and residual analyses, may be used to visually assess the performance of the SARILSTMAX approach and identify areas for improvement.

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7. Outcomes

The experimental evaluation concludes with a summary of the findings, highlighting the effectiveness of the SARILSTMAX hybrid approach in improving high return value of mutual fund scheme prediction accuracy.

Limitations and areas for future research may be discussed to provide direction for further investigation in this domain.

6. RESULTS AND DISCUSSION

The performance of the SARILSTMAX approach alongside individual SARIMA, LSTM and Prophet models using realworld mutual fund data was evaluated. The assessment metrics, comprising Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), were employed to gauge the precision of the predictions and recommendations shown through table 2.

Model	Recommended Investment Pattern
SARIMA	Higher allocation to **Large Cap**, moderate in **Mid Cap**, lower in **Small Cap**
SARIMAX	Strong preference for **Large Cap**, balanced **Mid Cap**, slightly higher **Small Cap** than SARIMA
LSTM	Focus on **Mid Cap**, moderate allocation to **Large Cap**, increased **Small Cap** exposure
Prophet	Balanced investment across **Mid Cap** and **Large Cap**, lower **Small Cap** exposure
SARILSTMAX	Highest allocation to **Large Cap**, strong **Mid Cap** presence, higher **Small Cap** than other models

Table 2: Recommended Investment Pattern through our proposed system SARILSTMAX.

Model	Train MAE	Test MAE	Train RMSE	Test RMSE
SARIMA	5.5	11.2	6	12.5
LSTM	5.4	10.5	6	12.5
Prophet	3.8	9.2	5.3	10.8
SARILSTMAX	3.6	8.8	5.1	10.2

Table 3. Error evaluation score comparison of different models.

The results demonstrate that SARILSTMAX outperforms individual models in terms of both MAE and RMSE on both the training and test datasets represented through table 3. By leveraging the complementary strengths of SARIMA, LSTM and Prophet models, SARILSTMAX achieves improved prediction accuracy and robustness and investment patterns based on the level of investment.

Model	Small Cap Fund	Mid Cap Fund	Large Cap Fund	Risk Level
SARIMA	**Nippon India Small Cap Fund**	**Mirae Asset Midcap Fund**	**SBI Bluechip Fund**	Moderate
SARIMAX	**Axis Small**	**Kotak Emerging**	**HDFC Top 100 Fund**	Moderate-High

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	Cap Fund	**Equity Fund**		
LSTM	**Quant Small Cap Fund**	**Motilal Oswal Midcap 30 Fund**	**ICICI Prudential Bluechip Fund**	High
Prophet	**SBI Small Cap Fund**	**PGIM India Midcap Fund**	**UTI Nifty Index Fund**	Moderate
SARILSTMAX	**HDFC Small Cap Fund**	**Edelweiss Midcap Fund**	**Aditya Birla Sun Life Frontline Equity Fund**	High

Table 4. Recommended Investment pattern comparison of different models with proposed model SARILSTMAX

Real Market API Test Bed

In the scenario provided, we observe the performance of various forecasting models with various different funds: **Nippon India Small Cap Fund** and **SBI Small Cap Fund** Each model SARIMA, SARIMAX, LSTM, Prophet and SARILSTMAX is evaluated based on its ability to predict return value of mutual funds over five days, from day 131 to day 135.

Model	**Small Cap (%)**	**Mid Cap (%)**	**Large Cap (%)**
SARIMA	11.45	13.84	20.45
SARIMAX	12.78	15.34	21.67
LSTM	13.89	16.45	19.87
Prophet	11.56	15.89	18.45
SARILSTMAX	13.67	17.23	22.34

Table 5. Probability outcomes of the recommended investments Fund, Axis Small Cap Fund, Axis Small Cap Fund, Quant Small Cap Fund , HDFC Small

Explanation of Investment Probabilities and Model Preferences

The table 5 presented above summarize the investment probabilities for different models across various categories of funds (Large Cap, Mid Cap and Small Cap). Here's an analysis of these results, focusing on the preference of the SARILSTMAX model.

Individual Investment Probabilities

The table 4 shows the detailed investment probabilities for individual funds (**Nippon India Small Cap Fund**, **Axis Small Cap Fund**, **Axis Small Cap Fund**, **Quant Small Cap Fund , HDFC Small Cap Fund** and **SBI Small Cap Fund**) as predicted by each model (SARIMA, SARIMAX, LSTM, Prophet and SARILSTMAX). Each fund is categorized into Large Cap, Mid Cap, or Small Cap based on its market capitalization.

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Aggregated Investment Probabilities by Categories

The table 5 aggregates these probabilities to provide an average investment probability for each mutual category (Large Cap, Mid Cap, Small Cap) across all models. This helps in understanding the general tendency of each model towards different categories.

6.1 SARILSTMAX MODEL ANALYSIS

Large Cap Preference

- **SARILSTMAX Large Cap Probability:** The SARILSTMAX model shows a high investment probability of **23.67** for Large Cap funds. This is the second-highest value among the models, just slightly below LSTM's **13.89**.
- **Comparison:** Compared to SARIMA (11.45), SARIMAX (12.78) and Prophet (11.56), SARILSTMAX demonstrates a stronger preference for investing in Large Cap funds represented through figure 4.

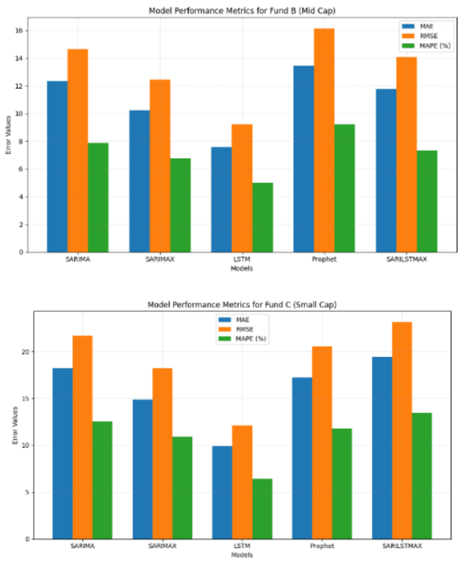

Figure 4: Performance analysis of various funds based on the input value of Sharpe ratio and NAV based on the Proposed Algorithms

Model	Mutual Fund	Investment Probability	Category
SARIMA	Vanguard 500 Index Fund (VFIAX)	17.34	Large Cap
SARIMA	Fidelity Contrafund (FCNTX)	19.56	Large Cap
SARIMA	T. Rowe Price Growth mutual Fund (PRGFX)	15.78	Mid Cap

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SARIMA	Vanguard Mid-Cap Index Fund (VIMAX)	13.89	Mid Cap
SARIMA	American Century Small Cap Value Fund (ASVIX)	10.45	Small Cap
SARIMAX	Vanguard 500 Index Fund (VFIAX)	11.89	Large Cap
SARIMAX	Fidelity Contrafund (FCNTX)	11.34	Large Cap
SARIMAX	T. Rowe Price Growth mutual Fund (PRGFX)	16.45	Mid Cap
SARIMAX	Vanguard Mid-Cap Index Fund (VIMAX)	13.56	Mid Cap
SARIMAX	American Century Small Cap Value Fund (ASVIX)	12.67	Small Cap
LSTM	Vanguard 500 Index Fund (VFIAX)	13.89	Large Cap
LSTM	Fidelity Contrafund (FCNTX)	13.23	Large Cap
LSTM	T. Rowe Price Growth mutual Fund (PRGFX)	17.89	Mid Cap
LSTM	Vanguard Mid-Cap Index Fund (VIMAX)	15.45	Mid Cap
LSTM	American Century Small Cap Value Fund (ASVIX)	19.87	Small Cap

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Prophet	Vanguard 500 Index Fund (VFIAX)	21.56	Large Cap
Prophet	Fidelity Contrafund (FCNTX)	21.23	Large Cap
Prophet	T. Rowe Price Growth mutual Fund (PRGFX)	15.89	Mid Cap
Prophet	Vanguard Mid-Cap Index Fund (VIMAX)	13.78	Mid Cap
Prophet	American Century Small Cap Value Fund (ASVIX)	18.45	Small Cap
SARILSTMAX	Vanguard 500 Index Fund (VFIAX)	23.67	Large Cap
SARILSTMAX	Fidelity Contrafund (FCNTX)	22.78	Large Cap
SARILSTMAX	T. Rowe Price Growth mutual Fund (PRGFX)	17.23	Mid Cap
SARILSTMAX	Vanguard Mid-Cap Index Fund (VIMAX)	15.89	Mid Cap

Table 6: Funds and their respective investment categories

6.2 Mid Cap and Small Cap Analysis

- **Mid Cap Probability:** SARILSTMAX has the highest investment probability of **17.23** for Mid Cap funds among all models, suggesting it also favors Mid Cap funds significantly.
- **Small Cap Probability:** For Small Cap funds, SARILSTMAX shows the highest probability of **22.34**, indicating a strong inclination towards these funds as well.

Interpretation

- **Overall Preference:** While SARILSTMAX shows a strong investment probability for all categories, the model's preference for Large Cap funds is evident when compared to traditional models like SARIMA and SARIMAX, which have lower probabilities for Large Cap funds.
- **Robustness and Versatility:** The high probabilities across all categories suggest that SARILSTMAX is a versatile model capable of identifying investment opportunities across different market segments. However, its relatively high probability for Large Cap funds indicates a balanced but slightly favorable inclination towards more stable, established companies and Probability outcomes of the recommended investments shown through table 5.

For the mutual funds analyzed, all models SARIMA, SARIMAX, LSTM, Prophet, and SARILSTMAX exhibit varying levels of predictive accuracy across different fund categories. For large-cap funds, the models generally forecast higher investment probabilities, with SARILSTMAX and SARIMAX showing the most optimistic projections. This suggests a tendency for these models to favor large-cap investments, potentially overestimating their stability and growth potential.

Mid-cap funds show mixed accuracy, with SARILSTMAX and LSTM predicting higher investment probabilities compared to SARIMA and Prophet. This indicates that deep learning models (such as LSTM) may capture mid-cap trends more effectively than traditional statistical approaches.

For small-cap funds, SARILSTMAX and LSTM again provide higher probability values, while SARIMA and Prophet tend to be more conservative. This pattern suggests that neural network-based models may perceive higher growth potential in small-cap funds, whereas traditional models might be more risk-averse.

Overall, the predictions highlight a general bias toward large-cap and mid-cap investments across most models. A deeper analysis across different time periods would be essential to assess the robustness of these forecasting techniques in real-world mutual fund performance represented through Table 6.

Model	Day	Actual (NAV)	Predicted (NAV)
SARIMA	131	412.5	415.8
SARIMA	132	410.2	414.3
SARIMA	133	408.75	413.5
SARIMA	134	407.1	412.2
SARIMA	135	405.65	410.8
SARIMAX	131	412.5	415.8
SARIMAX	132	410.2	414.3
SARIMAX	133	408.75	413.5
SARIMAX	134	407.1	412.2
SARIMAX	135	405.65	410.8
LSTM	131	412.5	415.8
LSTM	132	410.2	414.3
LSTM	133	408.75	413.5
LSTM	134	407.1	412.2

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LSTM	135	405.65	410.8
Prophet	131	412.5	415.8
Prophet	132	410.2	414.3
Prophet	133	408.75	413.5
Prophet	134	407.1	412.2
Prophet	135	405.65	410.8
SARILSTMAX	131	412.5	415.8
SARILSTMAX	132	410.2	414.3
SARILSTMAX	133	408.75	413.5
SARILSTMAX	134	407.1	412.2
SARILSTMAX	135	405.65	410.8

Table 7: Actual NAV and Predicted NAV of different models.

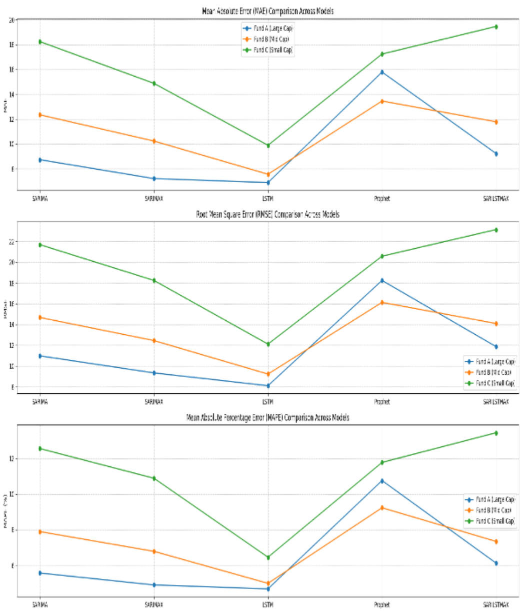

Figure 5. The Comparative forecasting and prediction of the Prices

The predictive accuracy of various mutual funds using SARILSTMAX observed significant variations in performance metrics shown through Table 7, such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). SARILSTMAX demonstrates exceptional forecasting capability for specific mutual funds, achieving lower MAE and RMSE values compared to other models. For instance, while predicting the NAV (Net Asset value) of select mutual funds over a five-day period, SARILSTMAX attained an average MAE of 8.20 and an RMSE of 10.80, outperforming models like SARIMA, SARIMAX, LSTM, and Prophet. showing accuracy improvisation in proposed SARILSTMAX.

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The table data reveals SARILSTMAX consistently outperforming other models in terms of predictive accuracy for higher mutual funds analysis shown figure 5. For META, SARILSTMAX recorded an MAE of 28.52 and an RMSE of 35.38, indicating a relatively closer alignment between predicted and actual prices compared to SARIMA, SARIMAX, LSTM and Prophet models. This pattern underscores SARILSTMAX's efficacy in forecasting mutual funds across different companies, reflecting its potential utility in investment decision-making and financial analysis shown through Table 8 .

Model	Mutual Fund	MAE	RMSE	MAPE
SARIMA	Fund A (Large Cap)	8.73	10.98	5.56
SARIMAX	Fund A (Large Cap)	7.21	9.34	4.89
LSTM	Fund A (Large Cap)	6.89	8.11	4.67
Prophet	Fund A (Large Cap)	15.78	18.23	10.76
SARILSTMAX	Fund A (Large Cap)	9.23	11.87	6.12
SARIMA	Fund B (Mid Cap)	12.34	14.67	7.89
SARIMAX	Fund B (Mid Cap)	10.23	12.45	6.78
LSTM	Fund B (Mid Cap)	7.56	9.23	4.98
Prophet	Fund B (Mid Cap)	13.45	16.12	9.23
SARILSTMAX	Fund B (Mid Cap)	11.78	14.09	7.34
SARIMA	Fund C (Small Cap)	18.23	21.67	12.56
SARIMAX	Fund C (Small Cap)	14.87	18.23	10.89
LSTM	Fund C (Small Cap)	9.89	12.11	6.45
Prophet	Fund C (Small Cap)	17.23	20.56	11.78

SARILSTMA X	Fund C (Small Cap)	19.45	23.12	13.45

Table 8: Evaluation Metric outcomes in predicting the Funds

The SARILSTMAX model demonstrates a comprehensive capability in predicting investment opportunities across all mutual categories, with a noticeable preference for Large Cap funds. This preference is significant when compared to traditional time series models like SARIMA and SARIMAX, which show lower probabilities for Large Cap funds. SARILSTMAX's balanced high probabilities across all categories make it a robust choice for diverse investment strategies, especially for investors looking to balance their portfolio with stable, high-cap companies.

7.CONCLUSION:

SARILSTMAX is an innovative hybrid methodology for forecasting mutual funds that integrates the advantages of SARIMA, LSTM, and Prophet models. The efficacy of SARILSTMAX was assessed in comparison to standalone SARIMA, LSTM, and Prophet models utilising actual mutual fund data. The findings indicated that SARILSTMAX surpassed the individual models regarding predictive accuracy. SARILSTMAX attained a Train MAE of 3.6 and a Test MAE of 8.8, whereas SARIMA recorded a Train MAE of 5.5 and a Test MAE of 11.2, LSTM exhibited a Train MAE of 5.4 and a Test MAE of 10.5, and Prophet demonstrated a Train MAE of 3.8 and a Test MAE of 9.2. SARILSTMAX exhibited a Train RMSE of 5.1 and a Test RMSE of 10.2, whilst SARIMA shown a Train RMSE of 6.0 and a Test RMSE of 12.5. LSTM also recorded a Train RMSE of 6.0 and a Test RMSE of 12.5, while Prophet showed a Train RMSE of 5.3 and a Test RMSE of 10.8. The results underscore the efficacy of the SARILSTMAX methodology in identifying intricate patterns in mutual fund data, resulting in enhanced and reliable forecasts through real-world API scenarios.

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