Revenue Time Series Forecasting Comparison ARIMA, LSTM & Hybrid (ARIMA/LSTM)

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Abstract*—Accurately forecasting corporate revenue is crucial for strategic planning and decision-making in large organizations. This study focuses on predicting Walmart's quarterly revenue for the next six quarters, utilizing a combination of historical data, and forecasted exogenous variables, including GDP, unemployment rate, and industrial production. Given Walmart's vast scale and influence, precise revenue predictions are essential for optimizing operations, managing resources, and maintaining competitive advantage. The exogenous variables were first forecasted using the Autoregressive Integrated Moving Average (ARIMA) model. Subsequently, Walmart's revenue was predicted using three distinct approaches: ARIMA, Long Short-Term Memory (LSTM) neural networks, and a hybrid ARIMA-LSTM model. Each model was evaluated based on error metrics such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The study found that the hybrid ARIMA-LSTM model demonstrated superior accuracy in revenue forecasting compared to the individual ARIMA and LSTM models. This suggests that combining the strengths of traditional statistical methods with advanced neural networks can enhance predictive performance. The findings offer valuable insights for improving revenue forecasts, which are critical for effective financial planning and long-term business success.

***Keywords*— Time series, Forecasting, Arima, LSTM, Hybrid modelling**

I. Introduction

Time series forecasting is a critical tool in predictive analytics that projects future values of sequential data based on previous observations. It has applications in a variety of fields, including economics, retail, and finance, where it can help with decisions like as stock price prediction, demand forecasting, and sales revenue estimation. The primary issue in time series forecasting is effectively capturing the temporal relationships, seasonality, and trends encoded in previous data and projecting them ahead. In this project, we focus on forecasting Walmart's quarterly revenue by utilizing multiple exogenous variables, including GDP, unemployment rate, consumer price index, and national income. Our aim is to predict Walmart's revenue from Q3 2023 to Q4 2024 by employing three distinct forecasting models: ARIMA, LSTM, and a hybrid approach combining both ARIMA and LSTM. The goal of this project is to compare these models based on residual analysis and key performance metrics, such as RMSE, MAE, and MAPE, to determine which method yields the most accurate forecasts. ARIMA (Autoregressive Integrated Moving Average) is a statistical model designed to handle linear correlations and seasonal patterns in time series data. It is frequently utilised due to its ease of use and efficacy in capturing trends and autoregressive tendencies found in financial and economic time series data. LSTM (Long Short-Term Memory networks) are neural network models that can manage more complicated and non-linear dependencies in sequential data. LSTMs excel at learning from data with long-term relationships, making them excellent for datasets with sophisticated patterns and non-linearity. To fully take advantage on the merits of both approaches, a hybrid model was created, combining ARIMA's capacity to model linear components and seasonality with LSTM's ability to capture nonlinear interactions and complicated temporal patterns. This hybrid technique seeks to provide a more comprehensive and accurate forecast by considering both types of data dependencies.

The steps involved in the project began with forecasting the exogenous variables using ARIMA, extending the dataset beyond Q2 2023. Following this, we applied ARIMA, LSTM, and the hybrid model to predict Walmart's future revenue. Several challenges emerged during the process, particularly in ensuring data quality, as missing values or inconsistencies could introduce significant errors in forecasting. Another major hurdle was the creation of the hybrid model, which required aligning the architectures of two fundamentally different models—ARIMA for capturing linear patterns and LSTM for non-linear dependencies. This integration is complex, as ARIMA operates on statistical principles, while LSTM involves neural networks, making it challenging to synchronize the flow and representation of data across the two models. Additionally, aligning the data for the hybrid model required careful processing to ensure that the residuals from ARIMA were compatible with the LSTM inputs. Model selection and tuning were especially challenging, particularly in balancing computing economy with prediction accuracy for both linear and nonlinear patterns in the data. Various strategies were utilised throughout the process to improve model performance, such as hyperparameter tuning and statistical validation testing. Managing seasonality and trends, while assuring accurate forecasts of exogenous variables, added to the complexity. The models' performance was then extensively examined using residual analysis and comparisons of error metrics such Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). Residual analysis was also useful in identifying problems such as underfitting or overfitting during model selection. Finally, the forecasted revenue values for the six quarters were visualized and analysed to assess the predictive accuracy of the models. Through this process, we aimed to identify the most reliable model for Walmart's revenue forecasting, ensuring that both linear and non-linear dependencies were adequately addressed for improved prediction accuracy.

II. LITERATURE REVIEW

Several studies [1] have investigated the challenges and benefits of revenue prediction, particularly for businesses that rely on precise sales projections to manage inventories, prevent waste, and maximise cash flow. A recent study discovered that Long Short-Term Memory (LSTM) networks are extremely successful in capturing complicated temporal patterns in sales data, outperforming standard models such as ARIMA in some cases. The study emphasised the relevance of data quality and careful tuning of LSTM architectures for effective prediction. It also shown how refining machine learning models, particularly neural networks, may significantly enhance revenue prediction accuracy. The study also emphasised the importance of including external factors, such as economic data, and investigating ensemble approaches to improve forecast accuracy. The results therefore indicate that deep learning techniques have potential for business applications, and that a hybrid strategy combining statistical and neural network models may provide a more reliable solution for revenue forecasting. This is consistent with our methodology of comparing ARIMA, LSTM, and hybrid models to forecast Walmart's future revenue, with a focus on improving these models through hyperparameter tuning and statistical testing.

In this paper [2], we presented a hybrid forecasting strategy that included Kalman filtering, ARIMA, and LSTM models to predict air compressor flow rates. The hybrid model performed admirably in managing flow data, with comparative analysis demonstrating that it had a higher prediction accuracy than other models. However, this analysis focused primarily on the hybrid model's predicting accuracy and did not include its operational efficiency. Future study should focus on improving the hybrid model's running efficiency while preserving its predictive accuracy.
This study [3] investigates the merging of SARIMAX and LSTM models using a simple yet effective back-propagation neural network. This hybrid technique, which combines SARIMAX for linear patterns and LSTM for nonlinear dynamics, improves short-term demand forecasting at the meter level, typically leading to more accurate energy projections. The paper gives an abstract implementation of the method and emphasises its potential for increased accuracy. However, the hybrid model can produce uneven results, with LSTM sometimes underperforming SARIMAX, and there is a risk of overfitting. Still, performance measurements show that this combination method is generally more accurate than using either model alone. Future study should extend this strategy to other domains, such as stock price forecasting, to test its efficacy.
According to the study [4], LSTM achieved an impressive 99.73% accuracy rate. However, the quality and number of training data had a significant impact on prediction success. The enormous computer resources necessary for the research, including large RAM and powerful CPUs, necessitated a reduction in the original dataset. Despite these limitations, LSTM remains a viable model for cryptocurrency forecasting, with future upgrades potentially include more granular minute-by-minute data to improve predictive precision.
A study [5] concluded that while traditional statistical methods for time series forecasting remain very relevant, advances in machine learning have offered a variety of new models and hybrid approaches. Despite machine learning models' outstanding prediction potential, ARIMA is still the favored choice in many applications because to the unique properties of certain datasets. Machine learning models, while strong, demand far more computer resources than traditional statistical methods such as ARIMA. As a result, the choice of forecasting approach should consider the nature of the forecasting problem, resource availability, and past research in the subject.
This paper [6] describes the LMD-SD-ARIMA-LSTM hybrid model, which combines Local Mean Decomposition (LMD), ARIMA, and LSTM to improve crude oil price predictions. The model beats five other methods, notably for medium- and long-

term forecasts, by distinguishing stationary and non-stationary IMFs as stochastic or deterministic components. The study also found that classical econometric models, when combined with decomposition approaches, can improve forecast accuracy. The model's precise forecasts provide useful information for educated decision-making in related industries. Classical models, such as ARIMA, frequently outperform deep learning methods, especially when dealing with linear and univariate datasets, due to their simplicity and portability. However, ARIMA and LSTM have shown efficient in forecasting univariate time series. This work [7] emphasises the benefits of using LSTM deep learning models in financial forecasting, but there is still significant potential for future research to investigate and develop the coupling of deep learning with classical methods such as ARIMA for improved forecasting accuracy.
This work [8] addresses the difficulty of short-term time series forecasting by predicting four days in January with LSTM and SARIMAX models. Following extensive pre-processing, the models were trained using hourly solar PV and weather data from South Asia. Their performance was measured using key metrics such as MAE, MSE, and RMSE. The results show that the SARIMAX model outperformed the LSTM in predicting solar PV power generation. Future research could broaden the use of these algorithms to additional areas, allowing for more accurate predictions across multiple domains.
This research [9] investigates the usefulness of deep learning models in solving real-world multistep forecasting issues, particularly when paired with the MIMO method. The findings confirm that deep learning approaches are well-suited for multistep forecasting problems, particularly when dealing with seasonal variations. These insights can help with the selection of relevant models for various forecasting scenarios.
The research [10] compares the accuracy of various models for time series forecasting using financial data, including ARIMA, LSTM, Linear Regression, and Random Forest. Linear Regression outperformed the other methods by lowering errors more successfully than ARIMA, Random Forest, and LSTM.
Experimental comparisons [11] show that the ARIMA-LSTM parallel model, reinforced by the CRITIC weighting approach, has the best prediction accuracy for HIV/AIDS trends. Future research will investigate multi-factor prediction models to increase accuracy.
This work [12] examines electricity load forecasting for a European region, using an ARIMA-LSTM hybrid model to improve prediction accuracy. The ARIMA model was initially used to forecast power load time series, with climatic data serving as a key influencing element. To further optimise the ARIMA model's residuals, the LSTM model was used, yielding a hybrid forecasting method. The hybrid model outperformed the independent ARIMA and LSTM models, with an RMSE of 0.7835MW, indicating a considerable reduction. This method demonstrates the potential for combining models to handle the issues of accurate power demand forecasting, with future research attempting to account for additional influencing factors such as holiday consumption habits.

III. METHODOLOGY

This project employs a systematic approach to forecasting Walmart's revenue through several predictive models. Data preparation entails cleaning, preprocessing, and extending the dataset with projected exogenous factors to make it suitable for analysis. ARIMA modelling is then utilized to identify linear correlations and forecast future quarters. LSTM modelling follows, taking use of its ability to manage long-term dependencies and complicated patterns. Finally, a Hybrid Modelling technique improves prediction accuracy by combining ARIMA's linear forecasting with LSTM's nonlinear pattern recognition.

i. Data Prepration

The data preparation method included several critical processes to assure the dataset's quality and readiness for modelling. Initially, we checked the dataset for missing values and treated them with appropriate imputation methods. Outlier detection was used to discover and correct anomalies that could affect the results. Data scaling was then used to normalize the features and improve model performance.

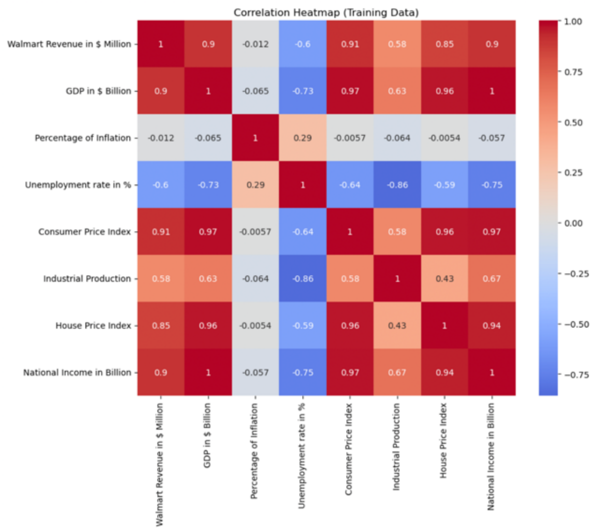

Fig 3.1: Correlation heatmap of features and the target variable i.e., Walmart revenue

Additionally, we examined the correlation between each exogenous variable and the target variable. Variables showing minimal impact on the target were removed to streamline the dataset. Specifically, the Percentage of Inflation, with a correlation coefficient of -0.011682, as shown in fig 3.1 was found to have negligible impact and was excluded from the dataset.

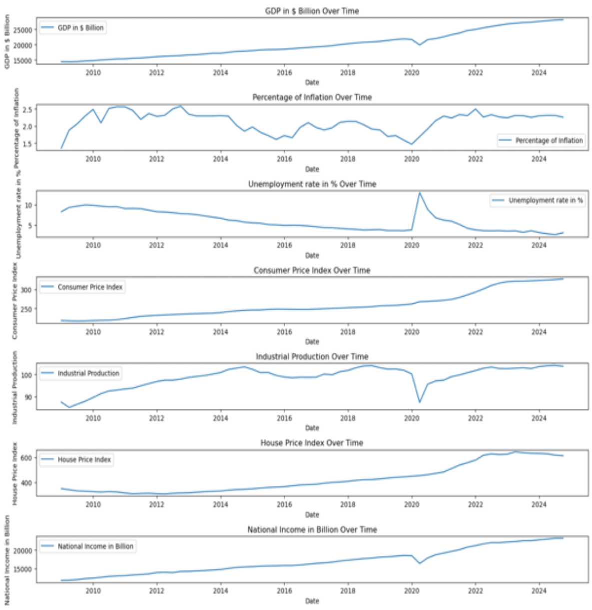

Fig 3.2: Plot of all exogeneous features against the year wise date up till Q4 of 2024

In addition to basic data cleaning, all features were plotted against the year to observe historical trends. It was noted that during the 2020-2021 period, there was a noticeable dip in Industrial Production, GDP, and National Income, while Inflation and House Prices showed an increase it can be seen in fig 3.2, this pattern is likely attributable to the economic impact of the COVID pandemic.

Once the dataset was cleaned and optimized, we forecasted the exogenous variables from Q3 2023 to Q4 2024 using the ARIMA model, extending the dataset beyond its original coverage of up to Q2 2023. These forecasted values were then integrated into the original dataset, providing a comprehensive basis for future predictions of Walmart's revenue based on the updated exogenous features.

ii. ARIMA Modelling

In the first step of ARIMA modeling, seasonal decomposition was performed to break the Walmart Revenue time series into trend, seasonality, and residual components refer fig 3.3. This helps identify long-term patterns and periodic fluctuations, ensuring that the ARIMA model can appropriately capture the underlying structure of the data for more accurate forecasting. Understanding these components allows for better adjustments in the model.

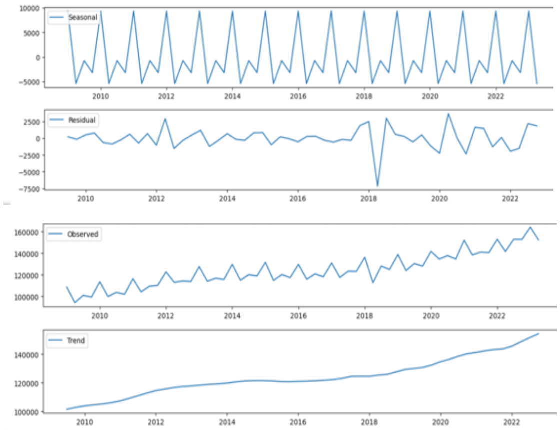

Fig 3.3: Seasonal decomposition of a time series, breaking it down into trend, seasonal, and residual components up till Q2 of 2023(training data)

The decomposition plot of the time series reveals valuable insights into its underlying components: trend, seasonality, and residuals. The trend shows a clear upward trajectory, indicating a consistent increase in Walmart's revenue over time. The seasonal component, although subtle, suggests periodic fluctuations, possibly due to recurring economic cycles or retail patterns. Importantly, the residuals appear random, suggesting that the model effectively captures both the trend and seasonality, leaving minimal unexplained variance.

These observations confirm that the data follows a regular pattern with a rising trend, which is crucial for improving forecasting accuracy.

For the ARIMA modelling process, ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) plots were analyzed as shown in fig 3.4 The ACF plot revealed a gradual decay in the autocorrelation coefficients, suggesting a potential AR (AutoRegressive) process, with significant spikes at the initial lags indicating a strong correlation between current and past values. The PACF plot exhibited a sharp cutoff after the first lag, indicating a probable AR(1) process. Based on these plots, an AR(1) model appears to be appropriate, as it suggests that the value at time t depends primarily on the value at time t−1. The equation with respect to this would be:

$$yt = c + \phi 1yt - 1 + \epsilon t$$

Where: yt is the value at time t, c is a constant (often referred to as the intercept), ϕ1 is the coefficient of the first lag (i.e. yt−1), εt is the white noise error term at time t , with εt~ N(0,σ2)

The term ϕ1yt−1 indicates that the value at time t is primarily influenced by the value at time t−1 and the ACF's gradual decay and the sharp cut-off in the PACF at lag 1 support the selection of an AR (1) model.

Additionally, the absence of a significant moving average (MA) component was noted, implying that no MA terms are necessary for the model.

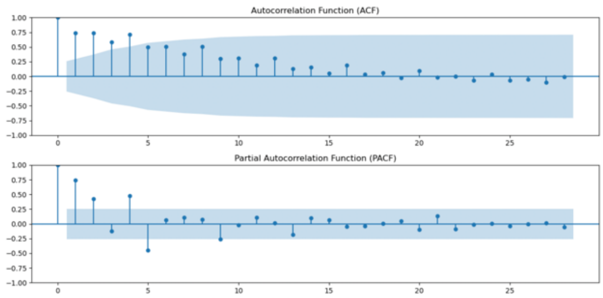

Fig 3.4: ACF & PACF Plots before differencing the dataset

A stationarity test confirmed that the time series was not stationary (ADF Statistic: 1.5848, p-value: 0.9978), indicating that differencing or other transformations are required to achieve stationarity before finalizing the ARIMA model. To address the original time series' non-stationarity, differencing was applied to the data.
The equation is represented below:

$$yt' = yt - yt - 1$$

Where: yt is the original value at time t, yt−1 is the value at the previous time point t−1, yt′ is the differenced series at time t.The differenced series yt′ often exhibits stationarity even if the original series yt does not. The Augmented Dickey-Fuller (ADF) test performed on the differenced series yielded a statistically significant result (ADF Statistic: -3.5857, p-value: 0.0060), confirming stationarity and suitable for ARIMA modelling.
Following this the ACF and PCAF plots were plotted again as can be seen in fig 3.5 for the differenced data, and after differencing it shows better results for ARIMA modelling as the data fits the assumptions of ARIMA model.

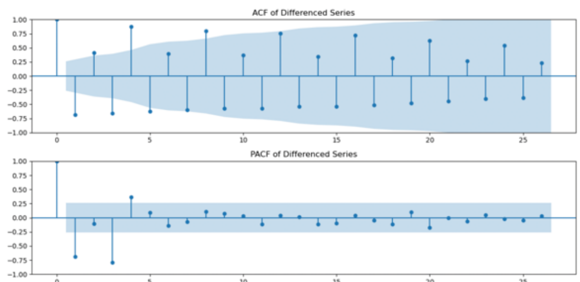

Fig 3.5: ACF &PACF plot after differencing the dataset.

The SARIMAX model equation is an extension of the ARIMA model, incorporating both seasonal and exogenous components. Given the configuration of ARIMA (1,1,0) with a seasonal order (0,1,0,4), the equation can be expressed as follows:

$$(1 - \phi 1L)(1 - L)yt = (1 - \text{L}^\wedge 4)\, \varepsilon t + \beta 1X1, t + \beta 2X2, t + \cdots + \beta nXn, t$$

Where :yt is the dependent variable (Walmart Revenue at time t), L: is the lag operator, ϕ1 : is the AR(1) coefficient, εt is error term or residual at time t, Xi,t : is the i-th exogenous variable at time t (e.g., Consumer Price Index), βi: is coefficient for the i-th exogenous variable, (1−L)is the first difference operator, representing differencing to remove trend and achieve stationarity and (1 - L^4) is the seasonal differencing operator with a seasonal period of 4 (e.g., quarters in a year). This equation encapsulates the model's ability to capture both the autoregressive and seasonal characteristics of the data, while also integrating the impact of exogenous variables.
The model summary shows that the AR coefficient is significant, while most exogenous variables, except the Consumer Price Index, show less impact on the Walmart revenue. The model achieved a log likelihood of -495.383, an AIC of 1006.766, and a BIC of 1022.528, suggesting a good fit given the complexity of the model.
After fitting the model, ACF and PACF plots were generated for the residuals shown in fig 3.6, and the residuals are calculated as:

$$\text{Residual} = \text{yt} - \text{y}^{\text{t}}$$

Where: yt is the actual observed value at time t (e.g., Walmart revenue at time t) and y^t is the predicted value at time t generated by the ARIMA model.
The ACF plot showed no significant autocorrelation coefficients outside the confidence bands, indicating that the residuals are random and lack significant correlations with their past values.
Similarly, the PACF plot revealed no significant partial autocorrelation coefficients, reinforcing the notion that the residuals are effectively white noise.

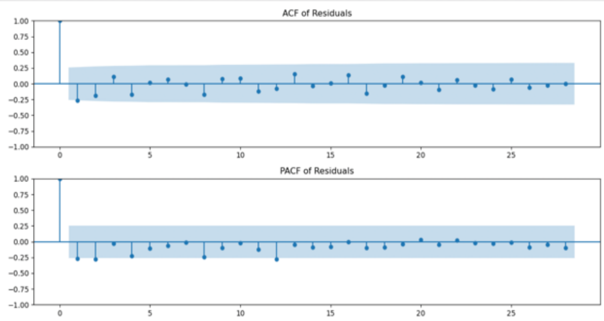

Fig 3.6: ACF &PACF of residuals after model training

These findings indicate that the ARIMA model accurately caught the underlying trends in the data. The absence of considerable autocorrelation in the residuals shows that the model is well-specified, and the AR and MA variables do not require rapid refinement or change. Overall, the model appears to be effective in describing revenue variability at Walmart, and the residuals back up the model's validity.

After fitting the SARIMAX model, it was tested for performance and used to forecast the next six values in the series. A Ljung-Box test was used to detect any remaining autocorrelation in the residuals, validating the model's adequacy. The details of the model evaluation and forecast outcomes will be discussed later in the paper.

iii. LSTM Modelling

The LSTM (Long Short-Term Memory) modelling approach was used to capture complex temporal relationships between various macroeconomic indicators and Walmart's revenue.

a. Data Preparation:

The data, which comprised Walmart's income and other macroeconomic variables (such as GDP, unemployment rate, consumer price index, and so on), was preprocessed. All exogenous variables were standardised with a 'StandardScaler', whereas Walmart's revenue was normalised with a 'MinMaxScaler' that maps values between 0 and 1. This scaling guaranteed that the variables were on a similar scale, which is essential for steady training in deep learning models.

The data was prepared for LSTM input by creating sequences using a sliding window method. Each series had four quarters of historical macroeconomic data, which were used to forecast Walmart's revenue for the next quarter. This strategy enabled the LSTM model to learn from sequential patterns in the data.

b. LSTM Model Architecture:

The architecture of the LSTM model used for forecasting is depicted in Figure 3.7.

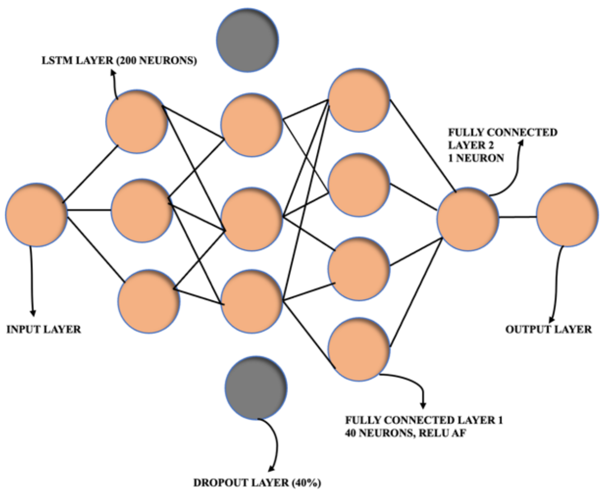

Fig 3.7: LSTM architecture with 6 layers – input, lstm layer, dropout layer, 2 fully connected layer with Relu function and output layer

It begins with an input layer that processes sequences of exogenous variables from the previous four quarters. This is followed by a single LSTM layer containing 200 hidden units, which captures temporal dependencies in the data. To prevent overfitting, a dropout layer with a 40% dropout rate is applied. The output from the LSTM layer is then passed through two fully connected layers with ReLU activation—first reducing to 40 neurons and finally to a single neuron in the output layer, which predicts the revenue for a given quarter.

c. Model Training:

The LSTM model was trained using the Adam optimizer, with a learning rate of 0.008. The learning rate was dynamically adjusted using a learning rate scheduler, which reduced the learning rate when the validation loss plateaued, ensuring better convergence.

The model was trained for 2000 epochs. During training, early stopping was employed to prevent overfitting, with patience set at 150 epochs. This means if the validation loss didn't improve for 150 consecutive epochs, training would stop early. The validation loss was monitored continuously, and the best model (with the lowest validation loss) was saved for further evaluation. After training, the model was evaluated on the validation set, which consisted of the last quarters of data.

d. Evaluation & forecasting

After training, the model was evaluated on the validation set, which consisted of the last 6 quarters of data. Here's a critical point: the actual revenue data for these last 6 quarters was not available. Therefore, the validation metrics (RMSE, MAE, MAPE) could not be computed accurately for this period. Instead, the validation metrics were computed based on available data prior to these last 6 quarters, where actual values were present. Once the model was trained and validated, it was used to forecast Walmart's revenue for the next 6 quarters, covering the period from Q3 2023 to Q4 2024. The forecasting process was iterative:

- The model was initially fed the last available historical data.
- After each forecast, the predicted revenue was fed back into the model along with the subsequent exogenous variable values to generate the next quarter's forecast.
- The forecasted revenue values were scaled back to their original units for interpretation. These forecasts provided Walmart's anticipated revenue trends for the upcoming quarters, assisting in business planning and strategy.

The evaluation and forecasting results will be discussed further.

iv. Hybrid Modelling

The hybrid ARIMA-LSTM model combines the strengths of ARIMA (AutoRegressive Integrated Moving Average) and LSTM (Long Short-Term Memory) to forecast Walmart’s revenue by integrating temporal patterns with sequential dependencies. The data preparation is same as done for the LSTM modelling. Here’s a step-by-step explanation of the process and architecture:

a. ARIMA Model Application:

ARIMA Model Fitting: An ARIMA model was fitted to the historical data to capture linear relationships and seasonal effects. The auto_arima function from the pmdarima library was used to identify the optimal ARIMA configuration. It considered the seasonal nature of the data (quarterly) and adjusted model parameters accordingly.

Residuals Calculation: The ARIMA model provided in-sample predictions and residuals (the difference between actual values and ARIMA's predictions). These residuals were then used as inputs for the LSTM model.

Forecasting Future Values: The ARIMA model also generated forecasts for the next 6 quarters, using the most recent data.

b. LSTM Model Architecture:

The hybrid forecasting approach, illustrated in Fig. 3.8, integrates ARIMA and LSTM models to predict Walmart's revenue more effectively. Initially, the ARIMA model is applied to the historical data to address linear trends and seasonal effects, providing both in-sample forecasts and residuals (the discrepancies between actual data and ARIMA predictions). These residuals, along with additional exogenous variables, are then utilized as inputs for an LSTM model.

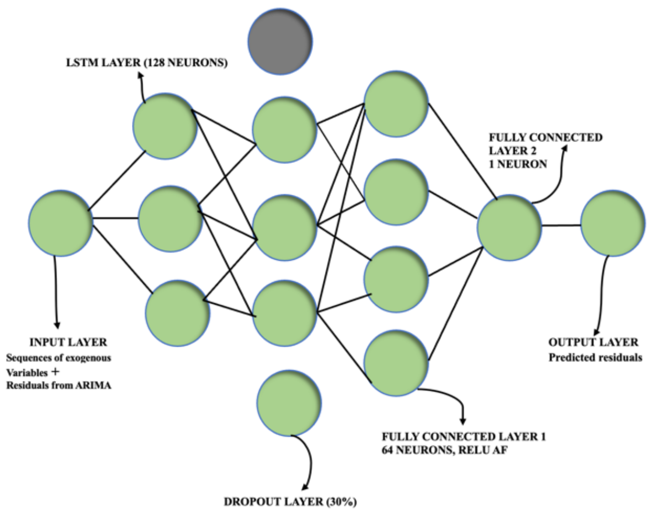

Fig: 3.8: LSTM architecture with 6 layers having ARIMA residuals at the input layer and with Relu in 4th layer

The LSTM network, through its layers, captures any complex patterns not accounted for by ARIMA. The final step combines the ARIMA forecasts with the LSTM-predicted residuals to generate comprehensive revenue predictions for future periods.

Training: The model was trained using the Adam optimizer with a learning rate of 0.001 and a dynamic learning rate scheduler. Early stopping was employed to prevent overfitting, with patience set at 150 epochs. Gradient clipping was applied to manage large gradients and ensure stable training.

c. Evaluation & forecasting

Following training, the model was verified against a hold-out dataset, and the best-performing model was stored. The trained LSTM model was then used to forecast the residuals for the next six quarters. The final revenue estimations were generated by combining the LSTM-predicted residuals with the ARIMA model forecasts. The aggregated forecasts were then inverse translated back to their original scale using the MinMaxScaler. The final output was created by combining these expected values into a Data Frame that detailed Walmart's predicted revenue for the next six quarters.

IV. RESULTS & COMPARISON

In this section, the performance of the ARIMA, LSTM, and hybrid ARIMA-LSTM models is evaluated and compared based on three key metrics: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). These metrics provide insights into the accuracy and effectiveness of each model in forecasting Walmart's revenue.

The evaluation results of the three models are presented in Table 4.1 and shown in fig 4.2.

Model	RMSE	MAE	MAPE (%)
ARIMA	3325.92	2669.36	1.74
LSTM	5536.80	4792.69	3.14
Hybrid	1991.57	1407.86	1.13

Table 4.1: Evaluation metric results

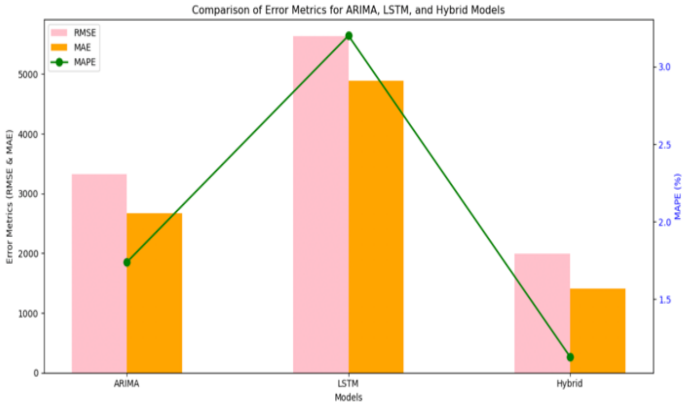

Fig 4.2: Evaluation metric visual comparison, the pink bar represents RMSE scores, the orange bar represents MAE score, and the green line represents MAPE scores.

The ARIMA model demonstrates a moderate error rate with an RMSE of 3325.92 and MAE of 2669.36. Its MAPE of 1.74% reflects a reasonable percentage error relative to the actual values, indicating that while ARIMA is effective, it is not the most accurate model in this comparison.

The LSTM model shows higher RMSE and MAE values compared to ARIMA, with an RMSE of 5536.80 and MAE of 4792.69. Its MAPE of 3.14% indicates a larger percentage error relative to the actual values. This suggests that while LSTM captures complex patterns in the data, it does not perform as well as ARIMA or the Hybrid model in terms of accuracy.

The Hybrid model significantly outperforms both ARIMA and LSTM with the lowest RMSE of 1991.57, MAE of 1407.86, and MAPE of 1.13%. This model combines ARIMA's ability to capture linear correlations with LSTM's ability to predict complicated temporal dependencies, yielding higher accuracy and fewer forecasting errors. ARIMA and LSTM models produce larger error rates, with LSTM performing the least well of the three. This implies that, while LSTM can capture complex data patterns, it may not always be the most accurate option when used alone.

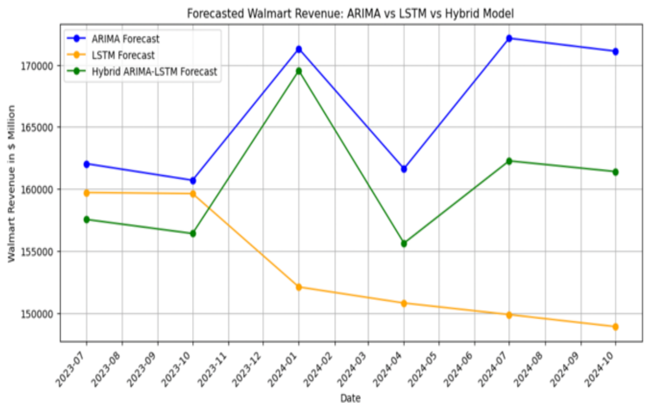

Fig 4.3: Plot of 6 forecasted revenue values by all three models blue line (ARIMA), Yellow line (LSTM) & Green line (Hybrid) Vs Date

The Hybrid model clearly outperforms both ARIMA and LSTM in all metrics, demonstrating its effectiveness in reducing both absolute and relative errors. It achieves the lowest RMSE, MAE, and MAPE, highlighting its robustness in forecasting.

The comparison between future forecasted values by all the three models is shown in fig 4.3, it clears depicts that LSTM perform poorly, whereas ARIMA and Hybrid predictions follows a trend.

Several crucial observations and inferences emerge from the examination of predicted values. To begin, the ARIMA model and the Hybrid ARIMA-LSTM model generate forecasts that follow similar patterns, demonstrating that the ARIMA model's framework efficiently captures the data's underlying trends. This resemblance shows that the LSTM component in the hybrid model may not have provided considerable value in this case. In contrast, the LSTM forecasts depart significantly from the ARIMA and Hybrid projections, particularly in later periods, showing that the LSTM identifies alternative trends or patterns that the ARIMA-based models do not capture. Despite this variance, the ARIMA model performs well as a baseline, producing results equivalent to the hybrid model and demonstrating its usefulness in projecting Walmart's revenue. Although the LSTM did not outperform the other models in this study, it may be more useful in circumstances with complicated, nonlinear data patterns, where standard models may struggle. The hybrid model's resemblance to the ARIMA forecasts in this case suggests that the LSTM's contribution may be minimal in this context, but hybrid approaches generally have the advantage of combining various modelling strengths, potentially improving forecasting capabilities in different situations.

V. CONCLUSION

Finally, the assessment metrics and anticipated values show that the ARIMA and Hybrid models outperformed the LSTM model. This closeness in results clearly implies that the underlying data primarily follows linear relationships and patterns. The ARIMA model, with its strong capacity to capture linear trends and seasonal components, performed well on its own and remained dominant even in the hybrid model. The Hybrid ARIMA-LSTM model's forecasts closely matched those of the ARIMA model, indicating that the linear component of ARIMA was the primary driver in this context. The LSTM model, which is intended to capture complicated, nonlinear patterns, showed no significant advantages, implying that the data's linear properties may have hampered its efficacy. This study emphasises the necessity of selecting the appropriate model based on the intrinsic structure of the data, and it implies that hybrid approaches can be effective, but their effectiveness is dependent on how much value the nonlinear component provides to the linear models. Overall, the ARIMA model's performance demonstrates its applicability for datasets with dominating linear trends, whereas the LSTM's less noticeable influence highlights the importance of cautious model selection in predicting tasks.

VI. REFERENCES

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