Engineering and Technology Journal e-ISSN: 2456-3358

Volume 11 Issue 06 June-2026, Page No.- 10339-10345

DOI: 10.47191/etj/v11i06.09, I.F. – 8.595

Deep Learning-Based Solutions for Business Enterprise Demand Prediction and Analytics

Bhalchandra Bapat
Independent researcher

ABSTRACT: Sales forecasting is crucial to business strategy, which affects inventory, finance and customer satisfaction. The conventional demand forecasting approaches cannot cope with complicated and dynamic data and with new changes. However, the present paper explores how deep learning (DL) can enhance the accuracy of sales forecasting in various industries. It is analyzed using a dataset of retail sales that had sales data, product categories and consumer profiles. Preprocessing and feature engineering of the data were conducted before being used in the creation of CNN and BiLSTM architecture-based forecasting models. Conventional methods like ARIMA, LR, were used to assess and compare the models. As indicated by the findings, deep learning methods worked much better than conventional models; that is, CNN was slightly better than the BiLSTM in error reduction. The two models generated a high R^2 value of 0.94, and both models had a good predictive ability, though the CNN model had lower prediction error (RMSE 239.10, MAE 157.10) than BiLSTM (RMSE 242.52, MAE 154.58). Finally, the findings demonstrate that deep learning techniques are the best approach to demand planning and inventory management in the real-world retail sector, as they yield more reliable and valid sales predictions.

KEYWORDS: Retail Sales Forecasting, Demand Prediction, Supply Chain Management, Predictive Analytics, Business Intelligence, Deep Learning.

I. INTRODUCTION

Nowadays, businesses are using more targeted marketing strategies to stay afloat and preserve or increase their profit margins [1][2][3]. Supply chains have now been more interdependent and intricate as a result of the fast changing globalization and digital transformation. The enterprises must now not only be able to react to the changing market conditions but also organize the resources effectively at many levels, such as procurement, production and distribution [4]. Supply chain management (SCM) has become a key operation in this dynamic environment, which directly affects the efficiency of operations and the performance of business [5]. SCM helps an organization to make optimum use of its resources, minimize inventory expenses, enhance the efficiency of its logistics and quickly adjust to evolving market dynamics thus gaining a competitive edge [6][7].

An essential component of supply chain management is demand forecasting, which is the ability to predict the future customer demand using previous sales and demand information [8]. Proper forecasting assists organizations to maximise inventory levels, reduce operational expenses and maximize customer satisfaction. But standard forecasting methods which predominantly depend on statistical models, tend to fail to reflect complicated trends and abrupt market changes. Supply Chain Management 4.0 (SCM 4.0) has a new perspective whereby advanced technologies are incorporated to counter these challenges and enhance demand planning processes [9][10].

As a subset of machine learning (ML), deep learning (DL) models particularly those designed for time series analysis can uncover hidden patterns, adapt to real-time changes, and significantly improve forecasting accuracy. Using AI-based predictive analytics, organizations can shift to proactive supply chain management, minimize uncertainties, and improve decision-making, thereby making ML and DL a prominent component in the current demand forecasting system of an enterprise [11][12]. DL solutions have become an important component of enterprise demand forecasting and business analytics due to their capacity to handle substantial amounts of unstructured and organized data from many sources [13].

Modern supply chain systems are increasingly dependent on accurate and efficient demand forecasting, which is the motivation behind this study. Complex, dynamic, nonlinear sales trends are the order of the day in the current ruthless economic environment, and most of the time, standard statistical methods fail to handle them. Digital transformation and Supply Chain Management 4.0 are becoming increasingly common, which is why intelligent forecasting models are in high demand. These models are designed to improve decision-making and operational efficiency. DL methods are the best for accurate, reliable forecasting of retail demand due to their ability to extract latent trends from large datasets. The following are some of the most important contributions made by this study:

- Developed a retail sales forecasting framework using advanced deep learning models (CNN and BiLSTM) for improved prediction accuracy.
- Performed comprehensive data preprocessing and feature engineering, enhancing data quality and temporal pattern extraction.
- Demonstrated that DL models outperformed traditional methods including Decision Trees, ARIMA, and LR
- Achieved high predictive accuracy with strong R^2 values and reduced error metrics (RMSE and MAE), ensuring reliable forecasting.
- Provided a scalable and efficient approach for real-world retail demand prediction to support inventory and business decision-making.

The novelty of this study lies in integrating DL models, such as CNNs and BiLSTMs, for retail demand forecasting, while combining extensive feature engineering with temporal feature extraction from transactional data. In contrast to conventional statistical and ML methods, the framework proposed is useful in capturing nonlinear trends and seasonality of sales data. The rationale behind this move lies in the fact that increased forecasting accuracy and reliability is required, with the traditional models demonstrating inferior performance in dynamic retail settings. The findings indicate that DL offers a more powerful and scalable solution to the current retail analytics.

A. Organization of the Paper

The paper is organized as follows: Section II is Reviews of related work, and Section III describes dataset, preprocessing and model implementation. Section IV presents experimental findings with comparative analysis, and Section V concludes the study by providing a set of key findings and future research directions.

II. LITERATURE REVIEW

An overview of several studies on demand forecasting is provided in this section. Automatic demand forecasting techniques have a wide range of applications in literature. Table I provides an overview of recent studies by showing suggested models, datasets, key findings, and challenges.

Singla and Lad (2026) determine the opportunities of AI in reducing demand-supply gap and enhancing the accuracy of forecasting and production planning of retail organisations. A massive amount of data was utilized in the creation and experimentation of a highly complex AI system and included approximately 6,000 transactions of multivariety products with multiple geographical locations. The proposed model resulted in an accuracy of 91.7%, which outperformed the benchmark value of 35.3% for the industry. The model yielded a state-of-the-art performance of 94.0% for the F1-score, 94.2% precision, and 93.8% recall for retail optimization. It considers seasonality, competitive dynamics, consumer behavior, and operational constraints. The enterprise impact analysis presents that the model will be able to bring in around 58.67 million every year for medium-scale enterprises [14].

Mir *et al.* (2025) present the Attentive Bayesian Multi-Stage predictions Network (ABMF-Net), a revolutionary DL model intended for reliable electricity price (USD/MWh) and demand (MW) predictions. Additionally, a multi-objective Salp Swarm Algorithm (MSSA) is employed to maximize stability and forecasting accuracy. ABMF-Net outperforms LSTM, GRU, and Transformer models with a MAPE as low as 1.89%, MAE of 0.67, RMSE of 0.98, and FICP of 0.98, according to experimental assessment on four real-world datasets from Australian energy market. Seasonal assessments validate model's resilience in high-variability scenarios [15].

Kumar et al., (2025) Introduce a novel hybrid deep learning architecture, termed LSCN-Att, was developed to enhance the precision of demand forecasts by leveraging supply chain data. The statistics indicate that the proposed LSCN-Att model significantly outperforms traditional predictive approaches, achieving a success rate of 96.42%. The results indicate that the approach facilitated cost reduction and enhanced customer service by addressing demand unpredictability and optimising inventory management [16].

Verma, Baby and Vaish, (2025) utilized three models-Random Forest, XGBoost, and Stacked Ensemble-to predict critical business metrics. The Stacked Ensemble model outperformed XGBoost (accuracy: 93.4%) and Random Forest (91.2%) for the highest prediction performance with an accuracy of 94.6%, RMSE of 0.251, and an R^2 of 0.94. The model achieved a 12-18% efficiency increase in resource allocation and a 20 percent decrease in forecast error in companies that were tested [17].

Lei *et al.*, (2025) proposes a complete demand forecasting system based on Variational Mode Decomposition (VMD) and attention. Empirical findings indicate that the suggested methodology is much more accurate in prediction than traditional methods, and that the Mean Absolute Error (MAE) decreases by 37% compared to conventional models. This significant increase in the accuracy of demand forecasts can offer actionable insights to decision-makers, allowing them to better manage inventory and plan production and the optimization of the supply chain overall [18].

Zhang and Niu, (2024) provide a novel convolutional neural network (LICNN) framework for hotel demand prediction based on lengthy short-term memory interactions. The results demonstrate that adding online review functions reduces MAE by a minimum of 3.2% and a maximum of 44.8, RMSE by a minimum of 2.2% and a maximum of 46.6, and the MAPE by a minimum of 3.5% and a maximum of 44. In addition, when compared to baseline models, their LICNN model has the lowest RMSE, MAE, and MAPE. The ablation research emphasizes how important it is to determine feature interactions for demand forecasting [19].

TABLE I. COMPARATIVE ANALYSIS OF RECENT DEMAND FORECASTING MODELS AND TECHNIQUES

Author	Dataset	Method	Key Findings	Limitations / Future Scope
Singla and Lad (2026)	~6,000 retail transactions across multiple products and regions	AI-based demand forecasting model	Achieved 91.7% accuracy, 94% F1-score; improved production planning and reduced demand-supply gap; estimated annual benefit of 58.67 million	Limited discussion on model generalization across industries; scalability to real-time systems not explored
Mir et al. (2025)	Australian electricity market datasets	ABMF-Net with MSSA optimization	Achieved MAPE 1.89%, RMSE 0.98; outperformed LSTM, GRU, Transformer; robust across seasonal variations	High computational complexity; applicability to other domains not validated
Kumar et al. (2025)	Supply chain demand dataset	Hybrid deep learning (LSCN-Att)	Achieved 96.42% accuracy; improved inventory management and cost efficiency	Model interpretability not addressed; requires large-scale structured data
Verma et al. (2025)	Business metrics dataset	RF, XGBoost, Stacked Ensemble	Stacked model achieved 94.6% accuracy; improved resource allocation by 12–18%	Ensemble complexity increases training time; lacks real-time deployment analysis
Lei et al. (2025)	Demand forecasting dataset	VMD with attention mechanism	Reduced MAE by 37%; improved supply chain decisions	Limited comparison with deep learning baselines; computational overhead
Zhang and Niu (2024)	Hotel demand with online reviews	LICNN (LSTM + CNN hybrid)	Significant reduction in RMSE, MAE, MAPE; effective feature interaction modeling	Domain-specific (hotel industry); may not generalize to other sectors

A. Research Gap

Research on demand forecasting thus far has mostly used complicated deep learning models trained on large-scale or domain-specific datasets, which can make generalizability difficult, computationally expensive, and difficult to understand. Despite the importance of accurate predictions, many methods fail to address issues including class imbalance, feature relevance, and deployment limits in the actual world. Consequently, models that are efficient, interpretable, and scalable are required, as are models that can retain excellent predictive performance for real-world commercial applications on datasets of intermediate size.

III. METHODOLOGY

In order to developed a reliable model for predicting retail sales, the study follows to a systematic pipeline shows in Figure 1. Before being processed, retail sales data is organized according to data categories, categorical variables were encoded, and time aspects including month, day, and quarter were extracted. In order to more accurately portray the data and identify sales trends, feature engineering is used. A training set and a testing set are then developed from the processed dataset to ensure accurate assessment. DL models like CNN and BiLSTM were developed and trained to find complex patterns in the data. To assess the effectiveness of the model, performance of model is compared to that of traditional forecasting techniques and is evaluated through such measures as R^2, RMSE, and MAE.

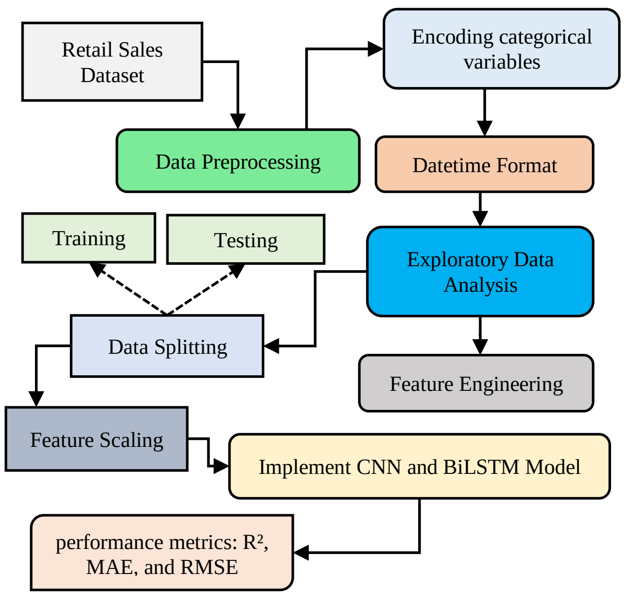

Fig. 1.Proposed flowchart for demand forecasting.

The detailed description of every step that of the proposed methodology presented in the following section:

A. Data Gathering and Pre-Processing

The research is based on retail sales data, which consists of 1,000 transactions of 9 key criteria such as demographics of buyers, product details, and purchase details. Repeatedly checking the data to ensure that there are no duplicates of either item or value and that the data is complete also allowed us to verify that there are no repetitions or gaps in the data at any point in time during data collection. Some preparations that were done included the normalisation and the encoding of the categorical variables, such as Gender and Product Category, in an appropriate manner. The Date column is converted to the datetime form in order to analyse the data based on time. To have more analytical capacity, it derived more temporal variables out of date. The numerical columns like quantity, price per unit and total amount are kept in correct integer format which ensures that dataset is clean, organized, and ready to be analyzed and modeled regarding exploratory data.

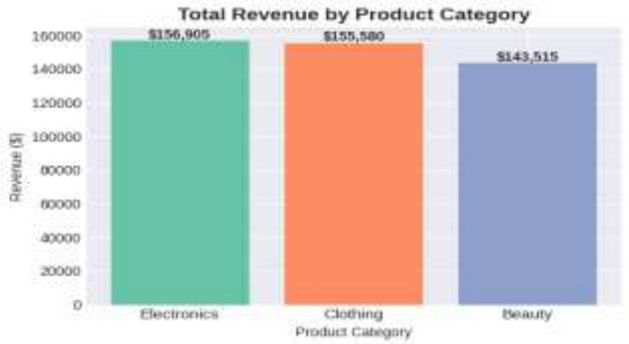

Fig. 2. Bar graph of Total Revenue by Product Category

The bar graph in Figure 2 shows the total income made by three different types of products. The Electronics has the highest income as per the statistics followed by Clothing and Beauty.. They all perform well but according to the graphic analysis, Electronics slightly beats Clothing and significantly beats Beauty in relation to total contribution to the revenue.

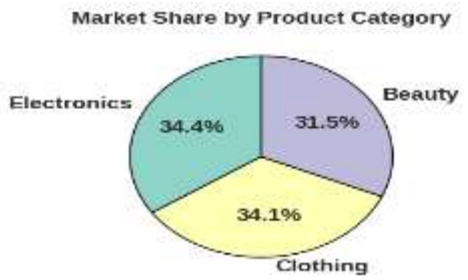

Fig. 3.Pie chart for Market Share By Product Category

Figure 3 shows market share distribution of three product categories. Electronics has the highest share at 34.4%, closely followed by Clothing with 34.1%, and Beauty with 31.5% of the total market. The relatively equal percentages show that all three categories have a significant contribution to the total sales, with a minor dominance of Electronics. The above distribution implies diversification in market demand, which businesses can watch to strategically target all categories with a slight emphasis on high performing segments such as Electronics.

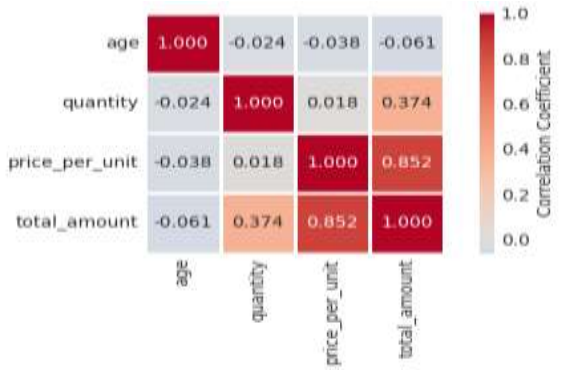

Fig. 4.Correlation Heatmap for Numercal Features

The correlations between the numeric variables of the dataset are shown in a simple visual way in Figure 4. The diagonal cells are self-correlated perfectly and the off-diagonal values emphasize the pair-wise dependencies. The highest level of positive correlation is seen between *price_per_unit* and *total_amount* (0.852) which highlights the direct influence of unit price on total transaction value. Conversely, the correlations between age and quantity are weak, indicating little linear effects. The color gradient assists in making quick differences between strong and weak association, aiding feature selection and interpretability of the subsequent analysis.

B. Feature Engineering

This results in the creation of 25 new features, which increase the dataset to 344 samples x 27 variables. These engineered variables are used to capture temporal change, cyclical seasonality, categorical differences and lagged or rolling trends. Combining time-based signals with historical measurements, which were aggregated, the data has become more informative about customer behavior and revenue trends. Such an elaborate structure is more interpretable and has a superior predictive power of the models.

C. Data Splitting

A rigorous assessment is ensured by dividing the dataset with 25 distinctive features into training and testing sets. A total of 275 samples (79.9%) made up the training set, but only 69 samples (20.1%) made up the test set. This chronological divide allows for fair appraisal of generalizations while preserving the integrity of the original timeline.

D. Feature Scaling

The min-max scaling technique is used to normalise the records to ensure that the values of features fall within the 0-1 range. This has been done in order to improve the performance of classifiers as well as eliminate the impact of outliers. The process of normalization is done using the following mathematical expression Equation (1):

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Where X is feature's initial value, X' is its normalized value, X_{min} is its lowest value, and X_{max} is its highest value.

E. Propose Convolutional Neural Network (CNN) Model

CNNs' superior performance (accuracy) makes them a popular DL architecture for classification applications. A CNN's input, convolution, activation, pooling, fully linked, and output layers make up its basic structure. The input layer of CNN is where raw image data is first received. Every pixel in the image has an input neuron. The CNN's fundamental building blocks are convolutional layers. By using convolutional operations, these layers extract local features from input image. Multiple filters, also known as kernels, are slid over the image during the convolution process to compute dot products with local patches. Equation (2) yields another image matrix y, which is convolution of image X with filter H. X_{ij} is regarded as 0 for i and j that are outside range.

$$y_{ij} = \sum_{a=1}^{n} \sum_{b}^{n} H_{ab} x_{(i+a)(j+b)} \quad □□□$$

In addition to filter size, two typical parameters, padding and stride, both regulate specific dimensions of output image and the sliding action of the filter over the input image. CNN creates a feature map that highlights textures or edges. A ReLU activation removes negative values, followed by pooling (max or average) to down sample the feature map, reducing dimensionality while retaining important information. Equation (3, 4) provides dimensions of output received following a pooling layer for a feature map with dimensions $q_h \times q_w \times q_c$.

$$ya_{ij} = f\,(y_{ij}) = max\,(0, y_{ij}) \quad (3)$$

$$r_h \times r_w \times r_c = \left(q_p - p + 1\right)/s \times (q_w - p + 1)/sxq_c \quad (4)$$

where q_p is feature map's height, q_w is its width, q_c is its number of channels, p is the pooling filter size, s is pooling layer's stride, and r_h is the downsampled feature map's height, r_w is its width, and r_c is its number of channels. Following the convolutional, activation, and pooling layers, a fully connected (FC) layer is used for classification. Every neuron in the preceding layer is connected to every other neuron in FC layer. Lastly, SoftMax activation units, which provide class probabilities, make up the output layer.

F. Bidirectional Long Short-Term Memory (Bi-LSTM)

Bi-LSTM employs two distinct hidden layers: the forward hidden layer conveys information from the past to the future, while the backward hidden layer conveys information from the past to the future. When compared to traditional LSTM, Bi-LSTM exhibits improved data representation capabilities in deep learning systems. The Bi-LSTM output is explained as follows Equations (5) to (7):

$$h^f{}_t = LSTM(x_t, h^f{}_{t-1}) \quad (5)$$

$$h^b{}_t = LSTM(x_t, h^b{}_{t-1}) \quad (6)$$

$$y_t = W_o h_t + b_o \quad (7)$$

The output layer's bias vector is represented by b_o, the weights from the forward layer to the output layer are represented by $W^f{}_{hy}$, and the weights from the backward layer to the output layer are represented by $W^b{}_{hy}$. Combining $h^f{}_t$ and $h^b{}_t$ results in h_t. Bi-LSTM integrates previous and future data at time t in order to learn.

G. Evaluation Metrics

Model evaluation is an important stage because it helps interpret model performance and present the outcomes properly. Regression activities cannot always predict precise values, the emphasis is on the aspect of determining the degree to which the predicted results compare to the real results. The models in this study are assessed based on three major performance measures: R^2, MAE and RMSE.

1) *R-Squared*

The model's overall fit in the regression task is measured by R^2. Additionally, it is employed to describe the level of correlation between the model's actual and anticipated values. Equation (8) to calculate R^2 is:

$$R^2 = \frac{\sum_{i=1}^{n}(y_i - y_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \quad (8)$$

2) RMSE (Root Mean Squared Error)

The RMSE quantifies how much the model's predictions deviate from actual values. Reduced RMSE values indicate improved model performance. The Equation (9) to calculate RMSE is:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_i^{\acute{P}})^2} \quad (9)$$

3) Mean Absolute Error (MAE)

MAE is a common way to measure how well a predictive model performs. It looks at the average magnitude of the error across a group of predictions, but not its direction. The Equation (10) to calculate MAE is:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|(y_i - y_i^P)| \quad (10)$$

Where n is the number of observations, y_i is the actual value, and $y_i^{\acute{P}}$ is the projected value.

IV. RESULTS AND DISCUSSION

The experimental environment is run on a Windows 11 operating system that has an Intel i7 processor, 16 GB of RAM, and NVIDIA graphics card to enable deep learning calculations. It is implemented in a Python 3.10 environment, using scikit-learn, stats models, Prophet, TensorFlow/Keras, Pandas, and Matplotlib.

A. Result Demonstrations

This section summarises experiment and evaluates proposed model's performance during testing phases, demonstrating its efficiency and effectiveness. The R^2 of both models is similar 0.94 and this shows that they have a high predictive power, as well as fit the data well. Table II shows that the CNN model is marginally better than the BiLSTM in terms of RMSE (239.10 vs 242.52), whereby the CNN model is slightly more accurate at reducing large errors. The performance of both models in general is similar and effective in terms of forecasting.

TABLE II. RESULTS OF PROPOSED MODELS FOR DEMAND FORECASTING

Model	RMSE	MAE	R^2
BiLSTM	242.52	154.58	0.94
CNN	239.10	157.10	0.94

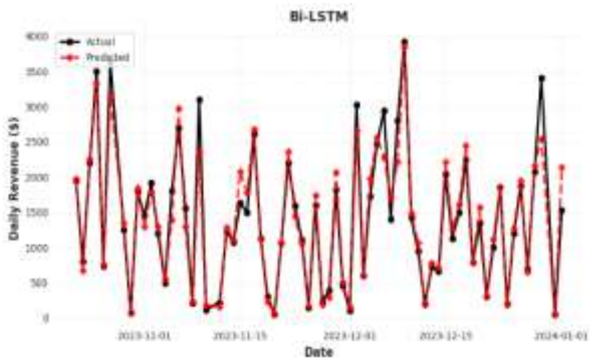

Fig. 5.Actual and Predited Sales using BiLSTM Model

The BiLSTM model's predicted and actual daily income are compared in Figure 5. The model can in most instances pick out broad tendencies and follow a number of data highs and lows. On the other hand, there are a few discrepancies when there are rapid increases and decreases. All said and done, the results indicate that the BiLSTM model can be relied upon and sufficient to predict sales.

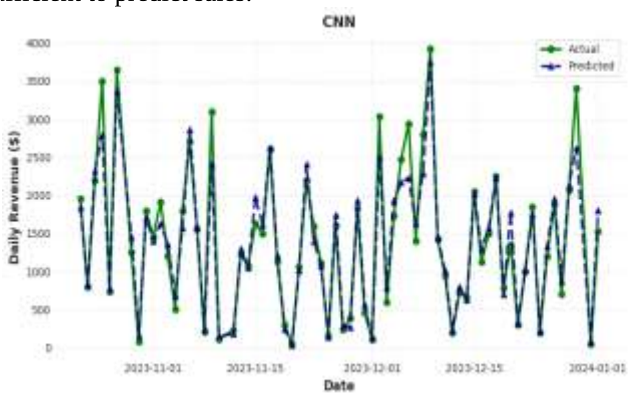

Fig. 6.Actual and Predited Sales using CNN Model

Figure 6 compares the predicted and actual income of CNN model in terms of daily income (not annual) between November

2023 and January 2024. The actual values are plotted in a green line, and the predicted values are plotted in a blue line, both lines closely follow each other over time. Trends in sales are also expected to be related to the real sales trends, as observed in the graphic that shows the model is able to capture changes in revenues. It confirms that the CNN model can be used to predict the short-term dynamics of revenue, and that it can be used to predict it accurately.

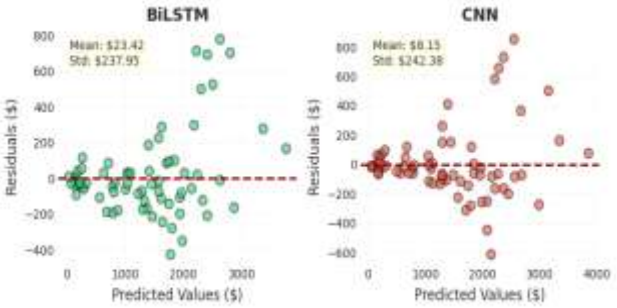

Fig. 7.Residual Analysis for Bi-LSTM and CNN model

Figure 7 has provided the residual analysis of the BiLSTM and CNN models, which illustrates the distribution of errors in predictions versus the predicted values. The BiLSTM model has a comparatively more distributed residual values with some of the highest deviation values being large positive values and this means that the model sometimes overestimates. However, the CNN model exhibits a more even distribution around the zero line, but it also has a few outliers and negative residuals. Both models exhibit growing variance of residuals when predicted values increase and this is indicative of heteroscedasticity. On the whole, the prediction errors in both models are similar, with the CNN model being a bit more stable, and the BiLSTM being able to capture patterns with a bit more variability.

B. Comparative Analysis

In order to determine efficacy of the proposed models, it compared to current models. As indicated in Table III, the traditional models like the ARIMA, Linear Regression (LR) and Decision Tree (DT) have lower accuracy as they have an R^2 value of 72, 82 and 86 respectively. The deep learning models, CNN and BiLSTM, achieve significantly higher R^2 values (0.945 and 0.943), indicating better predictive accuracy compared to other models. Overall, the results show that DL models are better at finding complicated patterns in retail sales data than traditional methods.

TABLE III. COMPARISON OF ML AND DL MODELS FOR DEMAND FORECASTING USING RETAIL SALES DATASET

Model	R^2	RMSE	MAE
ARIMA[20]	72	215.7	185.4
LR[21]	82	1608.78	1250.34
BiLSTM	0.943	242.52	154.58
CNN	0.945	239.10	157.10

The study enhances retail demand forecasting by utilizing deep learning models like CNN and BiLSTM, which are better at capturing complicated patterns compared to more conventional methods. Model accuracy and data quality are both improved by careful feature engineering and data preparation. The models consistently and reliably produce accurate predictions, with CNN displaying slightly higher stability. In overall, the method provides a scalable and effective answer to the problems of poor planning and ill-informed decision-making in retail settings.

V. CONCLUSION AND FUTURE STUDY

The contemporary world has witnessed business intelligence (BI) as the most important element in the development of strategies and facilitation of data-driven decision-making in businesses. The paper offers a detailed method of retail sales forecasting using sophisticated DL methods. The use of CNN and BiLSTM in comparison with traditional forecasting methods, such as ARIMA, LR enabled us to visualize the effectiveness of the proposed models. DL models can oftentimes more effectively capture nonlinear associations in retail sales data when compared to more traditional methods. R^2 values of 0.94 show that both CNN and BiLSTM performed quite well in terms of prediction, suggesting a good match between the two models. The RMSE values for CNN and BiLSTM are slightly different at 239.10 and 242.52, respectively, while the MAE values are comparable for both models. CNN demonstrated marginally higher performance in terms of error metrics. Companies may benefit from his study in three areas: preparing for demand, managing inventories, and making strategic decisions. These areas contribute to operational efficiency and profitability. Some drawbacks of the study include its use of a limited dataset and failure to account for external variables, such as promotions and economic conditions, that might affect prediction accuracy. The models also require more computing resources, which might make real-time deployment difficult in certain situations. Improving performance can be the subject of future study by including external factors and employing greater, multi-source datasets. Better accuracy and efficiency in real-world applications can be achieved by exploring hybrid and lightweight models.

REFERENCES

1. Z. You, Y.-W. Si, D. Zhang, X. Zeng, S. C. H. Leung, and T. Li, "A decision-making framework for precision marketing," *Expert Syst. Appl.*, vol. 42, no. 7, pp. 3357–3367, May 2015, doi: 10.1016/j.eswa.2014.12.022.
2. Z. X. Guo, W. K. Wong, and M. Li, "A multivariate intelligent decision-making model for retail sales forecasting," *Decis. Support Syst.*, vol. 55, no. 1, pp. 247–255, Apr. 2013, doi: 10.1016/j.dss.2013.01.026.
3. J.-T. Wei, M.-C. Lee, H.-K. Chen, and H.-H. Wu, "Customer relationship management in the hairdressing industry: An application of data mining techniques," *Expert Syst. Appl.*, vol. 40, no. 18, pp. 7513–7518, Dec. 2013, doi: 10.1016/j.eswa.2013.07.053.
4. S. Satyanarayana, S. Kilaru, and K. Venkatrao, "An Integrated Deep Learning and Reinforcement Learning Framework for Profit Maximization in Perishable Food Supply Chains," in *Proceedings of the 1st Engineering Data Analytics and Management Conference (EAMCON 2025)*, 2025, pp. 156–171. doi: 10.2991/978-94-6463-978-0_15.
5. R. V. Prabhu, S. Amsa, and C. J. Murthy, "Integrating IoT Data in Retail: Challenges and Opportunities for Enhancing Customer Engagement," *J. Artif. Intell. Res.*, vol. 3, no. 2, 2023.
6. M. S. Almahairah1, "Enhancing Supply Chain Decision-Making through Machine Learning and Mathematical Modelling Approaches," vol. 10, no. Ml, 2025.
7. H. Gholizadeh, A. Tajdin, and N. Javadian, "A closed-loop supply chain robust optimization for disposable

appliances," *Neural Comput. Appl.*, vol. 32, no. 8, pp. 3967–3985, Apr. 2020, doi: 10.1007/s00521-018-3847-9.

8. K. Dixit, "Artificial Intelligence-Driven Prediction of Hotel Booking Demand for Revenue Optimization," *Int. J. Curr. Eng. Technol.*, vol. 14, no. 6, 2024, doi: 10.14741/ijcet/v.14.6.20.
9. E. Hofmann and E. Rutschmann, "Big data analytics and demand forecasting in supply chains: a conceptual analysis," *Int. J. Logist. Manag.*, vol. 29, no. 2, pp. 739–766, 2018.
10. K. Zekhnini, A. Cherrafi, I. Bouhaddou, Y. Benghabrit, and J. A. Garza-Reyes, "Supply chain management 4.0: a literature review and research framework," *Benchmarking An Int. J.*, vol. 28, no. 2, pp. 465–501, Sep. 2020, doi: 10.1108/BIJ-04-2020-0156.
11. G. Baryannis, S. Validi, S. Dani, and G. Antoniou, "Supply chain risk management and artificial intelligence: state of the art and future research directions," *Int. J. Prod. Res.*, vol. 57, no. 7, pp. 2179–2202, Apr. 2019, doi: 10.1080/00207543.2018.1530476.
12. F. Naz, A. Kumar, A. Majumdar, and R. Agrawal, "Is artificial intelligence an enabler of supply chain resiliency post COVID-19? An exploratory state-of-the-art review for future research," *Oper. Manag. Res.*, vol. 15, no. 1–2, pp. 378–398, Jun. 2022, doi: 10.1007/s12063-021-00208-w.
13. J. A. Guajardo, "How Do Usage and Payment Behavior Interact in Rent-to-Own Business Models? Evidence from Developing Economies," *Prod. Oper. Manag.*, vol. 28, no. 11, pp. 2808–2822, Nov. 2019, doi: 10.1111/poms.13067.
14. L. Singla and M. Lad, "AI-Powered Demand-Supply Matching: Enhancing Forecast Accuracy and Production Planning," in *2026 7th International Conference on Mobile Computing and Sustainable Informatics (ICMCSI)*, IEEE, Jan. 2026, pp. 991–997. doi: 10.1109/ICMCSI67283.2026.11412650.
15. N. H. Mir, A. K. Biswas, M. S. A. Bhuiyan, G. R. Abir, M. F. Mridha, and J. J. M. Hossen, "ABMF-Net: An Attentive Bayesian Multi-Stage Deep Learning Model for Robust Forecasting of Electricity Price and Demand," *IEEE Open J. Comput. Soc.*, 2025, doi: 10.1109/OJCS.2025.3579522.
16. B. R. Kumar, S. R. M. Ali, R. V. S. Praveen, A. Thangam, N. Malik, and G. Kalra, "A Novel Optimized Hybrid LSTM-Based Dynamic Demand Forecasting Model for Resilient Supply Chains," in *2025 International Conference on Information, Implementation, and Innovation in Technology (I2ITCON)*, IEEE, Jul. 2025, pp. 1–6. doi: 10.1109/I2ITCON65200.2025.11210705.
17. A. Verma, S. Baby, and P. C. Vaish, "Predictive Business Strategy Formulation Using Machine Learning: An Ensemble Learning Approach for Operational Forecasting and Decision Optimization in Indian Enterprises," in *2025 World Conference on Cutting-Edge Science and Technology (WCCEST)*, IEEE, Sep. 2025, pp. 1–6. doi: 10.1109/WCCEST66994.2025.11389987.
18. C. Lei, H. Zhang, Z. Wang, and Q. Miao, "Deep Learning for Demand Forecasting: A Framework Incorporating Variational Mode Decomposition and Attention Mechanism," *Processes*, vol. 13, no. 2, Feb. 2025, doi: 10.3390/pr13020594.
19. D. Zhang and B. Niu, "Leveraging online reviews for hotel demand forecasting: A deep learning approach," *Inf. Process. Manag.*, vol. 61, no. 1, p. 103527, Jan. 2024, doi: 10.1016/j.ipm.2023.103527.
20. N. Himanshu and D. D. Patil, "International Journal of Research Publication and Reviews Sales Forecasting Using Machine Learning Approaches : A Comparative Study," vol. 6, no. 7, pp. 596–598, 2025.
21. K. M. Reddy, K. Ravikanth, N. K. Penjarla, and S. Poola, "International Journal of Research Publication and Reviews Sales Forecasting using Predictive Analytics : A Machine Learning and Time-Series Approach," vol. 6, no. 8, pp. 5476–5483, 2025.