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FORECASTING THE FUTURE: A COMPARATIVE ANALYSIS OF ML AND DL MODELS IN SUPPLY CHAIN DEMAND PREDICTION

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ABSTRACT
Supply chain demand forecasting is a strategic process aimed at predicting future customer demand for products within the broader framework of a supply chain. This involves forecasting the anticipated quantity of goods or services that customers will purchase and seamlessly integrating this insight into the overall supply chain management. The primary goal is to synchronize production, procurement, and distribution activities with expected demand, thereby optimizing inventory costs, minimizing instances of under stocking or overstocking, reducing waste, and ultimately enhancing overall supply chain efficiency. The emphasis is on leveraging advanced technologies, including deep learning techniques such as CNN, LSTM, CNN+LSTM, GRU, and machine learning techniques like Linear Regression and XGBoost, to achieve accurate predictions. By implementing these algorithms, businesses can construct a robust forecasting system capable of monitoring changes in demand and aligning supply accordingly. This proactive approach empowers retailers to enhance their inventory and planning efficiency, ultimately contributing to increased customer satisfaction.

KEY WORDS: *Machine Learning, Deep Learning, XG Boost, Linear Regression, CNN, LSTM, CNN+LSTM, GRU*

1. INTRODUCTION

Demand Forecasting is the process in which historical sales data is used to develop an estimate of expected customer demand in the future. Supply chain demand forecasting is a critical aspect of supply chain management that involves predicting the future demand for products or services within a supply chain. Forecasting is an essential aspect of business planning and management, as it allows companies to foresee future demand, allocate resources effectively, and reduce costs. Precise sales predictions can result in higher revenue, improved customer satisfaction, and well-informed decision-making. Additionally, supply chain demand forecasting plays a crucial role in strategic decision-making and resource allocation across various sectors. In industries with seasonal demand patterns or volatile market conditions, accurate forecasting enables organizations to optimize production schedules, manage inventory levels efficiently, and minimize the risk of stockouts or excess inventory.

2. LITERATURE SURVEY

LightGBM, an improved GBDT model, was used for Wal-Mart sales forecasting. The experimental results show that the RMSE is 0.641, which is significantly better than Logistic Regression (0.803) and SVM (0.732) [1]

A study utilizes RNN, LSTM, and GRU models for precise power consumption prediction in IoT and big data settings, revealing that the ensemble model combining the three models achieves the highest accuracy rate of 98.43% [2]

The choice of an appropriate forecasting model remains a concerning point. In this context, this research aims to analyse the performance of the CatBoost Gradient boosting model for the prediction of the amount of raw materials required for a meal delivery company that operates in multiple cities having multiple centres [3]

This model showed a better performance of up to 3.2% over a statistical benchmark (the quantile autoregressive model with exogenous variables, QAR-X), being better than the MQ-DRNN without temporal scaling by 6% [4]

Directed Acute Graph Neural Network, consisting of a layer of Convolutional Neural Networks and BiLSTM, showed high predictive performance as a revenue prediction method for e-commerce [5

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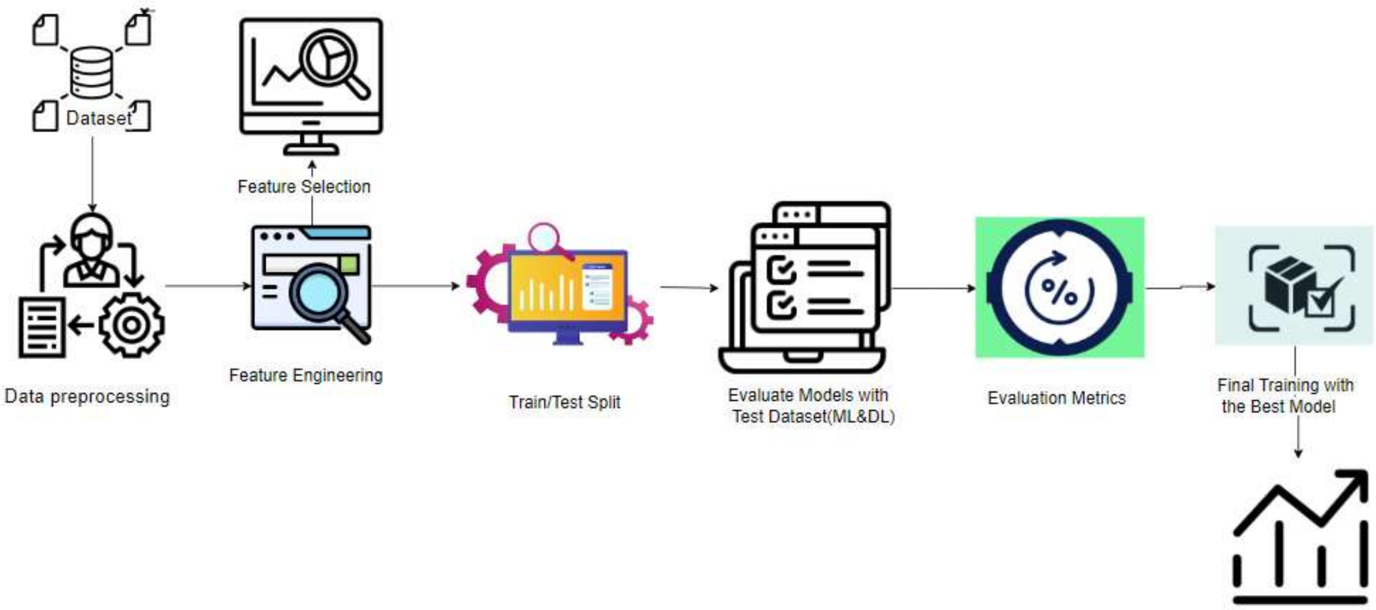
3. PURPOSE OF THE STUDY

The purpose of the study is to minimize both overstocking and understocking issues to improve the sales. This efficiency leads to cost savings, streamlined processes, and better resource utilization

4. PROPOSED MODEL

The proposed system involves working with a dataset, which includes 5 years of sales data for 50 different items across 10 different stores. Our goal is to predict the sales for these items at these stores over a period of 3 months. To achieve the sales prediction goals, we are employing a variety of machine learning and deep learning techniques to forecast future sales trends. Specifically, the machine learning techniques we plan to utilize include Linear Regression and XGBoost. In terms of deep learning, we are exploring the use of LSTM, CNN, LSTM+CNN, and GRU models. The main aim is to compare these models and identify the best-performing one for sales prediction. To compare different models, and evaluate the accuracy of predictions, RMSE(Root Mean Squared Error), R2(R-squared), MAE(Mean Absolute Error), MAPE(Mean Absolute Percentage Error) & MSE(Mean Squared Error) metrics are used for forecasting. By applying various accuracy metrics, it will give a better forecasting and decreases the error. Additionally, we have developed a user interface that allows forecasting of sales on a weekly, monthly, daily, and yearly basis. This feature is designed to assist retailers in optimizing their inventory and increasing overall revenue. The visualizations will help the retailers for better understanding and management.



5. METHODOLOGY

5.1 DATASET

Datasets play a vital role in research, analysis, model development, and decision-making across diverse fields. They serve as foundational building blocks for extracting data-driven insights and fostering innovation. The dataset under consideration comprises a train and test dataset. The train dataset consists of 913,000 records with attributes including date, store, item, and sales, while the test dataset consists of 45,000 records with attributes such as id, item, store, and date. This dataset was sourced from Kaggle and provides valuable information on sales from the years 2013 to 2017.

5.2 DATA PREPROCESSING

The initial dataset comprised 4 attributes. Data preprocessing, the foundational step in data preparation, encompasses actions like data cleaning, transformation, and organization to make the data suitable for analysis. This includes tasks such as handling missing values, encoding categorical data, scaling numerical features, and eliminating outliers to enhance data quality and model performance. In our data preprocessing efforts, we placed a strong emphasis on addressing issues related to missing and null values to ensure the overall data quality. We also executed tasks like renaming columns and removing redundant attributes to streamline the dataset. Additionally, we converted categorical variables into binary numeric values to ensure compatibility with analytical models.

5.3 FEATURE ENGINEERING

In this study, extensive feature engineering techniques were applied to enhance the predictive capabilities of the models for sales forecasting. Date-related features were systematically extracted from the 'date' column, which was converted to datetime format to facilitate manipulation. These features included 'weekday', 'dayofyear', 'year', 'month', 'day', 'week', and 'quarter', providing insights into the temporal patterns and seasonal trends within the dataset. Additionally, features such as 'daily_avg', 'monthly_avg', and 'mean_store_item_month' were computed to capture the average sales behavior at different granularities, including daily, monthly, and monthly averages per store and item. These engineered features aim to encapsulate the underlying patterns and relationships present in the data, empowering the models to better capture and predict sales fluctuations over time. sssBy incorporating these meticulously crafted features into the model training process, we aimed to improve the models' accuracy and robustness in forecasting sales, thereby contributing to more effective decision-making processes for inventory management and business operations.

5.4 ALGORITHMS USED

5.4.1 LINEAR REGRESSION

Linear Regression is a statistical technique that models the relationship between a dependent variable (demand) and one or more independent variables (predictors), such as historical sales data, market trends, and promotional activities. The model is trained using historical sales data to learn the underlying patterns and relationships, and then used to predict future demand based on new input data.

```
[ ] #Linear Regression Model
    model_lr = LinearRegression()

[ ] #prediction on test data
    model_lr_preds_test = model_lr.predict(x_test)
```

5.4.2 XGBOOST

The XGBoost (Extreme Gradient Boosting) algorithm has emerged as a powerful tool for demand-driven supply chain forecasting due to its exceptional predictive performance and flexibility. In our research, we implemented the XGBoost model to forecast future demand for products in the supply chain management context. The XGBoost algorithm operates by constructing an ensemble of weak prediction models, typically decision trees, in a sequential manner. Each subsequent model corrects the errors made by the previous models, resulting in a strong predictive model. Through extensive experimentation, we observed that the XGBoost model consistently delivered superior results in terms of accuracy and reliability compared to traditional machine learning algorithms.

```
[ ] model_xgb=XGBmodel(x_train_v2, x_val_v2,y_train_v2,y_val_v2)

[ ] #Prediction on test data
    model_xgb_preds_test = model_xgb.predict(xgb.DMatrix(x_test_v2))
```

5.4.3 CNN (CONVOLUTIONAL NEURAL NETWORK)

In our research, we employed a CNN architecture specifically designed for time-series forecasting to predict future product demand in the supply chain management domain. The CNN model's capability to automatically learn hierarchical representations of sequential data renders it highly suitable for demand forecasting tasks, empowering supply chain professionals to make data-driven decisions in inventory management and production planning.

```
[ ] #predicting on test data
    y_pred_cnn = model_cnn.predict(x_test_v2)
```

5.4.4 LSTM

The LSTM model's unique architecture includes memory cells and gates that enable it to retain information over extended time periods, making it particularly well-suited for modeling time-series data with complex temporal dynamics. The LSTM model's capability to learn from historical sales data and adapt to changing market conditions empowers supply chain professionals. Through experimental evaluation, we observed that the LSTM model consistently delivered accurate predictions of future demand.

```
[ ] #predicting on test data
    y_pred_lstm = model_lstm.predict(x_test_v2)
```

5.4.5 GRU

The GRU model is a type of recurrent neural network (RNN) architecture designed to capture temporal dependencies in sequential data while addressing some of the limitations of traditional RNNs, such as vanishing gradients. The GRU model's architecture includes gated mechanisms that regulate the flow of information within the network, allowing it to selectively retain and update information over time. We configured the GRU model with reduced units to optimize computational efficiency while maintaining predictive performance.

```
[ ]  #predicting on test data
     y_pred_gru = model_gru.predict(x_test_v2)
```

5.4.6 CNN+LSTM

In our research, we proposed a hybrid CNN+LSTM model tailored for demand-driven supply chain forecasting, which combines the strengths of both Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. By integrating both CNN and LSTM layers, the hybrid model can effectively capture both local and global patterns in the time-series data, leading to more accurate demand forecasts.

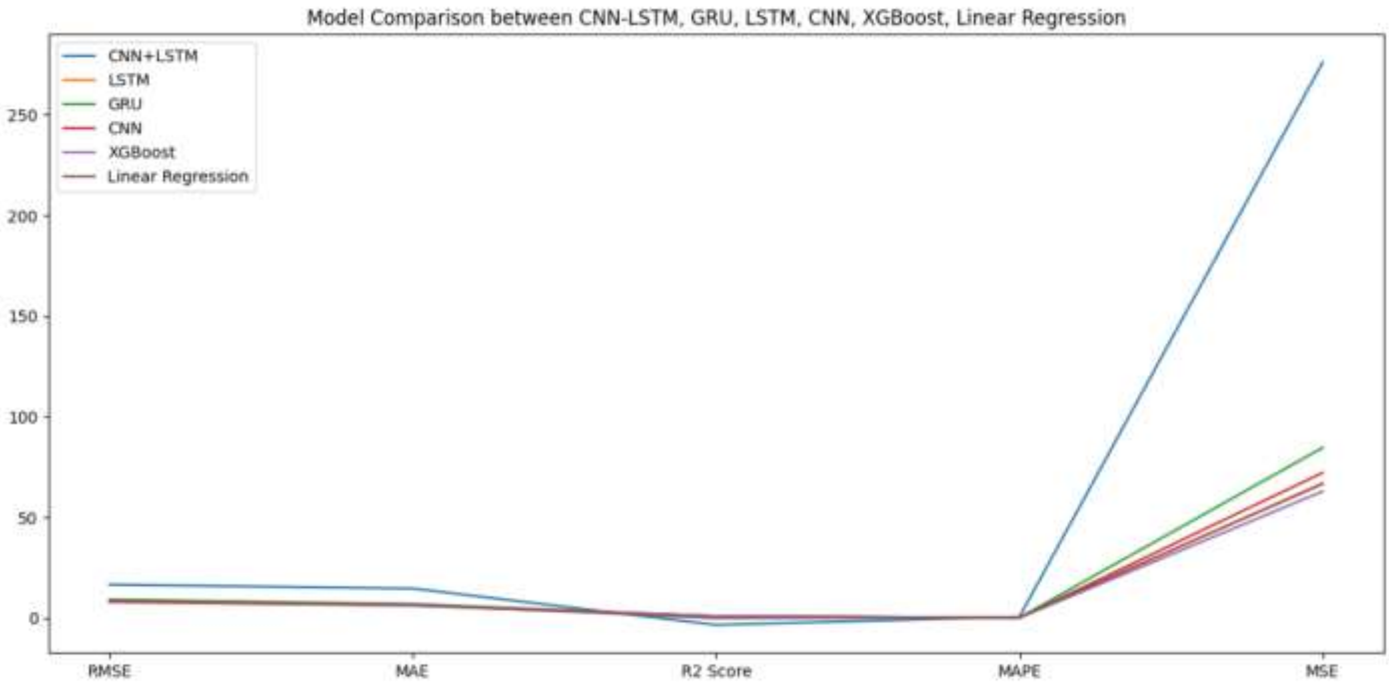
```
[ ]  y_pred_cnn_lstm = model_cnn_lstm.predict(x_test_v2_series_sub)
```

6. COMPARITIVE ANALYSIS

We thoroughly explored a range of machine learning and deep learning techniques to identify the most effective model for predicting sales. Among the models considered, including Linear Regression, XGBoost, CNN, LSTM, LSTM+CNN, and GRU, LSTM emerged as the top performer. The decision to prioritize LSTM was based on its ability to effectively capture long-term dependencies in sequential data, crucial for forecasting future sales in supply chain management.

7. RESULTS AND ANALYSIS

7.1 MODELS COMPARISON



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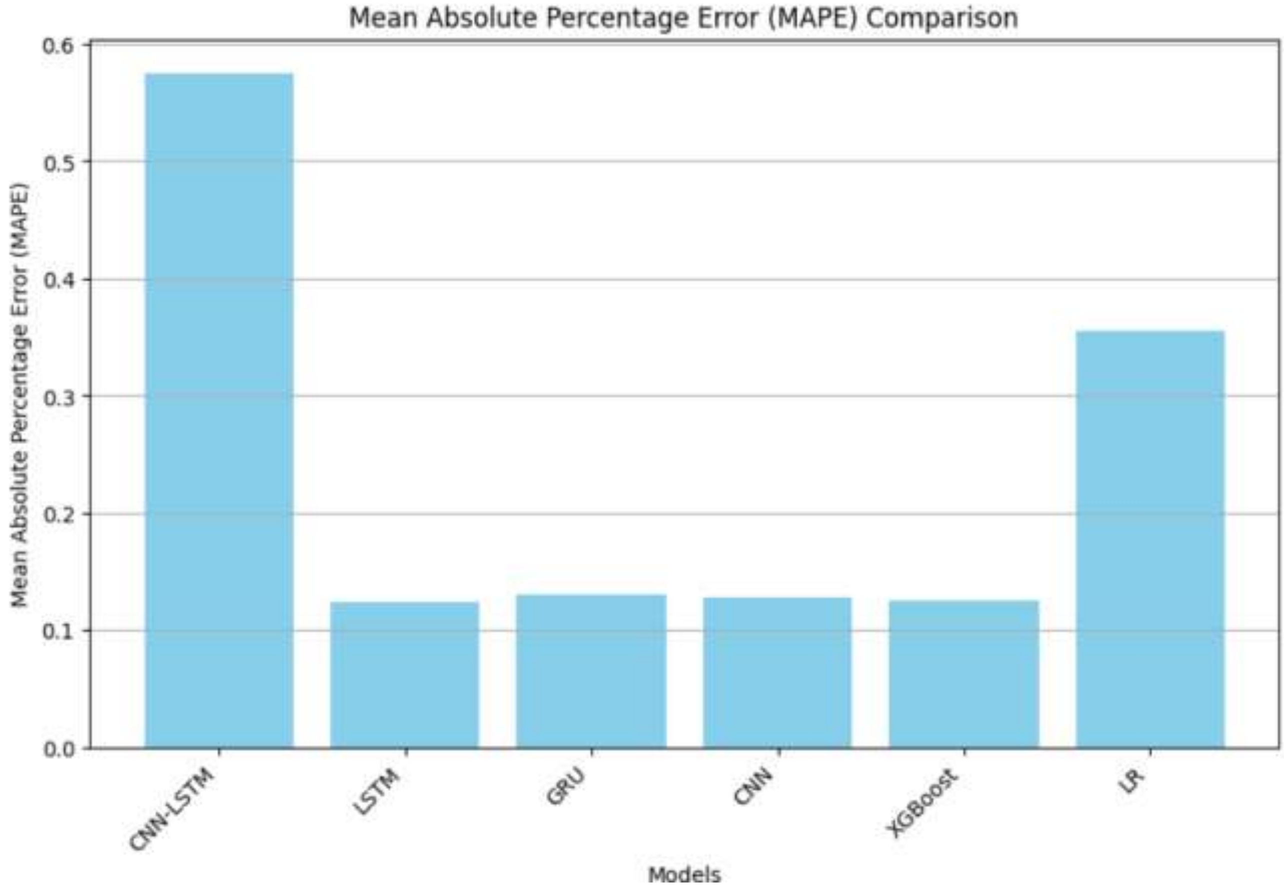
7.2 BAR CHART ACCORDING TO MEAN ABSOLUTE PERCENTAGE ERROR (MAPE)



7.3 USER INTERFACE

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7.4 FORECASTS OF 3 MONTHS

Figure1. Time Series Line Chart

Figure2. Pie Chart

Figure3. Bar Graph

8.CONCLUSION

In conclusion, demand-driven supply chain forecasting in supply chain management has yielded highly impressive outcomes. The six models we employed, both from deep learning and machine learning - namely XGBoost, Linear Regression, CNN, LSTM, CNN+LSTM, and GRU - have displayed robust performance, boasting notably low error rates. XGBoost stood out with an outstanding MAPE score of 0.1248 among machine learning models, while LSTM stood out with an exceptional MAPE score of 0.1243 among deep learning models. We consider LSTM as the best model. By using a user interface with the help of the best model, we predicted the sales of the upcoming 3 months. The forecasts are visualized on a daily, weekly, monthly, and yearly basis. These visualizations will assist the supply chain in eliminating overstocking and understocking issues.

9. FUTURE WORK

Future enhancements to this project could involve leveraging sentiment analysis of customer feedback and social media data to

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refine sales forecasts for highly engaging products. Additionally, integrating sustainability metrics such as carbon emissions and waste generation into supply chain forecasting could help mitigate environmental impact. Furthermore, employing demand-driven forecasting to offer personalized product recommendations to customers based on their past purchases, preferences, and online behavior using machine learning algorithms could enhance the overall customer experience.

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