**PROJECT PROPOSAL**

# Deep Learning for Demand Forecasting in Retail Using Hybrid CNN-RNN and Transformer Models

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## SUMMARY:

Within the evolving retail context, forecasting demand is essential to maximize stock, minimize waste, and ensure product continuity. Traditional approaches have not been able to realize the complex, nonlinear patterns of consumer action and environmental factors such as seasonality. The objective of this project is to apply deep learning models to accurately forecast demand using historic retail sales data. The motivation behind this research is to increase supply chain efficiency and decision making through the development of models that not only predict future sales but are also robust with respect to data anomalies as well as noise. The research assumes even greater significance in the context of overstocking and understocking problems that retail firms face on a regular basis.

## OBJECTIVES:

• To develop and compare different deep learning architectures for time series forecasting, including CNN-RNN, GRU, LSTM, and transformer models.

• To improve model robustness by incorporating synthetic noise and using autoencoders for denoising input data.

• To compare the impact of noise on model performance and output with and without denoising.

• To enhance the accuracy of forecasting and compare the performance of every model with statistical and graphical approaches.

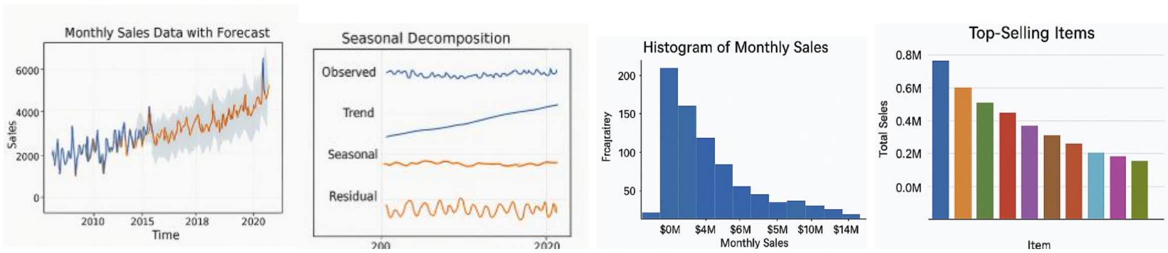
• To understand how retail demand is affected by seasonality and externalities.

### METHODOLOGY:

The workflow will begin with grand data preprocessing like missing values handling, date-time conversion, normalization, and creation of lag features. We will execute categorical encoding and scale the numeric values using MinMaxScaler. The backbone model architecture will be CNN-RNN hybrid, which is capable of extracting local time features as well as long-range dependencies. More models like GRU, LSTM, and Transformer will be included for comparison of performance. For adding complexity, we will add Gaussian noise to the data and train denoising autoencoders to learn to reconstruct clean data. We will use clean and noisy data thus obtained for tracking the robustness of each model. Training will involve time-based train-test splits, early stopping, and hyperparameter tuning. Seasonal decomposition and data augmentation will be employed for handling seasonality. Both the models will be trained on noisy as well as clean data to determine whether there is any variation in performance.

**EVALUATION:**

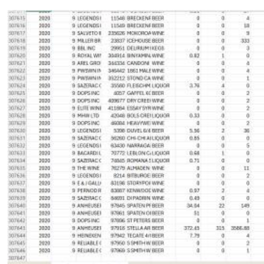
All the performance in the project will be evaluated using MAE , RMSE, MAPE and R squared metric. Visualizations such as line plots comparing predicted vs actual demand and error distribution plots will be used to understand the behavior of the model. Analyzation of the impact of denoising by comparing error metrics before and after autoencoder processing. Additionally in this project inclusion of a statistical test like paired t tests are planned to include to determine the significance of performance improvements.




**SAMPLE PLOTS**

**DATASET:**

The dataset used in the project is "Warehouse and Retail Sales" dataset from Data. gov (https://catalog.data.gov/dataset/warehouse-and-retail-sales). The data set has 307,000 rows and monthly sales data for each item by supplier. Its dataset size and volume are just perfect for deep learning based time series forecasting, one that involves understanding demand trends across category.



**DATASET SAMPLE**

**REFERENCES:**

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