Time Series Forecasting of Daily Sales using Deep Learning and Ensemble Models

Objective

The primary goal of this project was to accurately forecast daily item sales using historical transaction data. The predictions would support better inventory management and business decision-making in a retail setting.

Dataset

The dataset contained transaction-level sales data with the following key features:

- **Date**: Transaction date
- **Item Details**: item_name, price, kcal
- **Store Details**: store_name
- **Sales Target**: item_count (number of items sold)

Time-based features such as day of week, month, quarter, and year were engineered to enrich the dataset.

Modelling Approaches

1. Traditional Machine Learning Models

We trained and evaluated:

- **Linear Regression**
- **Random Forest Regressor**
- **XGBoost Regressor**

Hyperparameter tuning was performed using GridSearchCV with TimeSeriesSplit cross-validation. Feature preprocessing included:

- Standard scaling for numeric features
- One-hot encoding for categorical features

Best Test RMSEs:

- Linear Regression: **18.61**
- Random Forest: **6.49**
- XGBoost: **10.52**

2. Ensemble Learning

We built an ensemble by averaging the predictions of the top-performing models (Random Forest, XGBoost, Linear Regression).

Random Forest Test RMSE: **6.49**

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3. Deep Learning with LSTM

To capture temporal dependencies, we developed LSTM-based models using Keras:

- Sequential LSTM and Bidirectional LSTM layers
- Window sizes from 10 to 30 days
- Units varied from [16, 32] to [128, 64]
- MinMaxScaler used for normalization

Best Deep Learning Model Results:

- **Window Size**: 10
- **LSTM Units**: [128, 64]
- **Bidirectional**: Yes
- **RMSE**: **1547.96**
- **MAPE**: **24%**
- **Average Sales**: 5842.83

These results showed that deep learning significantly outperformed traditional ML models in terms of **absolute** and **relative** error.

Evaluation Metrics

- **RMSE** (Root Mean Squared Error): Measures absolute prediction accuracy
- **MAPE** (Mean Absolute Percentage Error): Measures relative prediction accuracy

Goal: Minimize both RMSE and MAPE for robust performance
Conclusion: A good model should have **low RMSE and low MAPE**

Conclusion

- **Random Forest** performed best among ML models.

- **Bidirectional LSTM** with optimal window and unit configuration gave the best overall performance.
- Deep learning is more suitable when long-term temporal dependencies are critical.
