Store Item Demand Prediction

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***Abstract* — In the era of ever-changing market landscape, enterprises tend to make quick and informed decisions to survive and prosper in the competition. Decision makers within an organization must be supplied with data in a way that could be easily analyzed and comprehended to build strategies to achieve business goals. The demand for shop items has to be evaluated to be able to optimize the efficiency of supply chain logistics, control of inventory, and retail administration. Another most important thing in the retail industry for minimizing expenditures, determining the right quantity of stock, making the best use of readily available space, and excluding shortages of goods is demand forecasting. By estimating sales in the future, demand forecasting encourages organizations to maximize inventory levels. With a certainty in estimation, retailers might keep a check on how many items to allocate, order and restock thus boosting their gross sales and profits. Demand forecasting for inventory and warehousing requirements are calculated through assessing previous sales information to determine how to carry out promotional sales and meet the needs of customers. In store item demand forecasting, deep learning methods including long short-term memory (LSTMs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs) have demonstrated encouraging outcomes. To determine the most effective method for predicting store item demand, more research must be done on the efficacy of these deep learning algorithms. The efficiency of these techniques can be assessed by employing performance evaluation metrics including absolute mean error or mean squared error. Business may make well-informed judgments regarding restocking levels and ordering, and overall stock planning by analyzing demand for various products. The results of these simulations suggest that deep learning methods are useful instruments for predicting the demand for retail items. Retailers may maximize supply chain logistics, inventory management, and pricing strategies by utilizing the results of our study. Understanding the most effective techniques for projecting the demand for goods in stores can help with logistics in the supply chain and handling inventory, in addition to commercial decision-making.**

***Key words — Deep Learning Methods, Demand forecasting, Mean squared error, estimating sales, store item demand, inventory levels, logistics*.**

I. INTRODUCTION

Retail companies ought to come up with ways to enhance their operational effectiveness if they want to keep being competitive. Since volumes of sales are the primary concern for any merchant, having proper sales estimates is crucial to any competitive firm. Without it, the financial system, supply chain, any element of the business, particularly marketing, cannot run without pauses. Underestimating sales can lead to a product running out of supply, marketing efforts being halted, and customers being lost; exaggerating may result in challenges with items' shelf lives and ultimately raise the cost of operations, products, and storage. As a result, the accuracy of sales forecasts affects the business's total efficiency. Despite the rapid changes in technology, it is only normal for merchants to explore for solutions in this field. The ability to calculate store item demand accurately is crucial for optimizing stock levels, raising customer satisfaction, and boosting profitability in the modern retail and inventory management scene.

The murky patterns and inconsistent characteristics of consumer behavior are often too confusing and unexpected for traditional methods of prediction to totally portray. But a new era of precision in demand forecasting has been brought about by the development of deep learning techniques like Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN). These sophisticated techniques make use of enormous volumes of previous sales data to find underlying trends and make remarkably accurate predictions about future demand. RNNs are perfect for time-series forecasting since they are excellent at processing sequential data.

Even while artificial intelligence (AI) already exists virtually everywhere—in our cars, watches, laptops, and phones, for instance—it still has a lot of undiscovered and untapped uses. Deep learning (DL) is one of the most capable AI technologies known. As a technology, DL offers significant applications covering natural language interpreting, picture and speech recognition, acoustic modeling, and prediction modeling.

The focus of this paper, being a piece of secondary study, is to identify, analyze, and assess the research that exists right now on the application of DL. This systematic literature review strives to offer a review of the current body of knowledge about retail sales forecasting using DL technology.

The following is a vast guide to store item demand prediction strategies:

Data Collection:

1. Assemble previous sales statistics for all of the products, particularly on a daily or weekly basis.

2. Add pertinent elements like sales, holidays, and other outside variables that might impact demand.

Data Preprocessing:

Clear and keep track of your dataset's data that's missing.

1. Use a one-hot encoding method or label encoding to transform categorical variables into numerical representations.
2. Adjust or balance numerical attributes.

Feature Engineering:

1. Include other information like lag characteristics, patterns, and seasons.

Consider the account of external factors that could influence demand, such as the climate, financial statistics, or promotions.

Exploratory Data Analysis:

1. Examine how the goal variable (demand/sales) and features are distributed.
2. Examine the data for patterns, associations, and outliers.

Model Selection:

1. Pick relevant machine learning models depending on what kind of difficulty at hand. It is common to utilize time series models such as ARIMA, SARIMA, or machine learning models such as Random Forest, Gradient Boosting, or neural networks (LSTM, GRU).
2. Divide the dataset into sets for testing and training.

Model training:

1. Implement the training dataset to train the chosen model.
2. Adjust hyperparameters to maximize the outcome of the model.

Model Evaluation:

1. Use the testing dataset to figure out the model.
2. To evaluate the accuracy of your predictions, use metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), or Root Mean Squared Error (RMSE).

Model Deployment:

1. Install the trained model in a real-world setting.
2. Link the model to your system for managing inventories.

Monitoring and Updating:

1. Constantly track the outcomes of the model in real-time.
2. Update the model with latest data on frequently to make sure it adjusts to evolving trends.

Feedback Loop:

1. Considering feedback from real sales and modify the design as required.
2. Constantly upgrade and enhance the model in alignment with evolving business requirements and performance.

The use of specialized deep learning methods, namely long short-term memory (LSTM) networks, recurrent neural networks (RNNs), and convolutional neural networks (CNNs), has significantly altered the way demand is anticipated with previously unheard-of accuracy and dependability. The improvement in forecasting technique helps create customized shopping experiences, that in turn boosts customer satisfaction and spurs corporate growth, in addition to optimizing inventory levels, cutting waste, and raising revenues.

II. MOTIVATION

Accurately predicting store item demand is crucial for operational efficiency and strategic planning in the rapid-fire retailing sector. Though helpful, traditional techniques for forecasting frequently fail to capture the complex patterns as well as erratic nature of consumer choices and market movements. This is where a new era of accuracy and understanding in demand forecasting is heralded by the deployment of cutting-edge deep learning techniques like Long Short-Term Memory networks (LSTM), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN).

Whenever it comes to comprehending the temporal dynamics of sales data, RNNs provide a major benefit due to their innate capacity to cope with data patterns. With their help, we can model time dependencies and capture seasonal changes and trends that are essential for precise demand prediction. But because of the gradient diminishing issue, RNNs by themself can sometimes have trouble with long-term dependencies.

This is where LSTMs step into picture. An improvement on RNNs, LSTMs are made expressly to address this issue by providing a more reliable means of long-term memory retention. Because of their memory-cell-equipped architecture, which enables a deeper grasp of time-series data, they are exceptionally good in forecasting tasks where demand is mostly predicted by past information.

In contrast, CNNs—which are mostly acknowledged for their achievements in image recognition—have showed remarkable adaptability by employing their robust feature extraction skills on time-series information. CNNs offers special information that typical time-series models can miss by analyzing sales data as a one-dimensional "image," which allows them to find and exploit correlations and trends within the data.

A balanced strategy to demand forecasting is exemplified by the combined powers of RNN, CNN, and LSTM approaches, which use each of their individual strengths to overcome their flaws. This multiple-faceted strategy boosts the accuracy of forecasts while presenting a greater awareness of the fundamental elements that influence consumer demand. By utilizing these leading-edge deep learning models, we can maximize the use of stock, avoid waste products, elevate customer happiness, and make better decisions. The path to being an expert in store item demand forecast with these methods involves more than just utilizing new technologies; it involves altering retail's future and being nimble and strategic in responding to its constantly shifting environment.

III CONTRIBUTION

On the Recurrent Neural Network (RNN) model, Akhila has worked on data preprocessing, hyperparameter tweaking, and training. provide the analysis and model performance.

Mrudhula has worked on data processing, hyperparameter correction, training of the Convolutional Neural Network (CNN) model, support for outcome analysis, and model performance.

Vinay Varma has worked on the Long Short-Term Memory (LSTM) model involved planning the data and training the model. enables the evaluation of the model's performance and the findings evaluations.

IV. OBJECTIVE

The main goals of our research, uses deep learning techniques to forecast store item demand are:

1. Exploring Deep Learning Techniques: Assessing how well different deep learning method such as RNNs, CNNs, and LSTMs predict future demand for store items.
2. Data Preprocessing and Model Training: Prepare historical demand data for analysis by applying appropriate preprocessing techniques. Train each deep learning model using suitable algorithms and optimization methods.
3. Performance Evaluation: Assess the forecasting accuracy of each model using established metrics like mean squared error (MSE) or mean absolute error (MAE).
4. Comparative Analysis: Conduct a comprehensive comparison of the performance achieved by different deep learning models to know which model gives the best effective way for predicting store item demand.
5. Derive Actionable Insights: Translate the findings from model performance evaluation into practical recommendations for retailers. These data insights will help in decision-making areas like inventory management, supply chain logistics, and pricing strategies.
6. Optimize Retail Operations: Ultimately, to leverage the insights gained from this project to help retailers optimize their overall operations, leading to improved efficiency and profitability.
7.

V. RELATED WORK

1. Capobianco, D'Ambrosio, and D'Ambrosio (2019) "Forecasting Sales and Promotional Lift in Retailing: A Study of Bayesian Structural Time Series and Vector Autoregressive Models" This study investigates the use of vector autoregressive models and Bayesian structural time series for retail sales and promotional lift forecasting.

2. A. Chaharsooghi, M. Madani, and H. Khaloozadeh's "A Comparison of Forecasting Models for Retail Sales" (2017): This study examines several forecasting models for retail sales prediction, such as ARIMA, exponential smoothing, and machine learning methods.

3. The paper "Machine Learning for Retail Demand Forecasting: A Case Study at Olist" was written in 2020 by A. L. I. Oliveira, J. H. Santos, and L. R. Nunes. Using data from the Brazilian e-commerce platform Olist, this paper gives a case study on the application of machine learning techniques for demand forecasting in a retail scenario.

4. Yang, K. G. Murugesan, and J. Y. Park's "Sales Forecasting in Fashion Retailing Using Machine Learning Techniques" (2019): This study looks into the use of machine learning methods for sales forecasting in the retail fashion sector, such as gradient boosting and random forests.

5. S. Verma and S. K. Singh (2016) published "A Hybrid Model for Retail Sales Forecasting Using Data Mining Techniques": In order to estimate retail sales, this research suggests a hybrid model that combines data mining methods like decision trees and neural networks.

6. The paper "Forecasting Sales in Retail Industry: A Comparison of Statistical Models and Machine Learning Techniques" was published in 2018 and was written by Saini, Kumar, and Sehgal. In order to forecast sales in the retail sector, this study evaluates the accuracy of many statistical models and machine learning methods.

7. J. M. Ortiz, E. F. Silva, and D. G. Silva's "Demand Forecasting in Fashion Retail Using Recurrent Neural Networks" (2019): The use of recurrent neural networks (RNNs) for demand forecasting in the retail fashion industry is investigated in this study.

8. Wang, X., and Huang, H. (2016) "Predicting Customer Purchase Behavior in E-commerce: A Data Mining Approach": This study uses data mining approaches to forecast customer purchase behavior in e-commerce, which can be useful for figuring out demand trends in online retail.

9. M. K. Lee, J. D. Kang, and S. H. Kwon's "Forecasting Retail Sales Using Machine Learning Algorithms" (2019): In order to increase accuracy and efficiency, this study

looks at how different machine learning algorithms are applied to retail sales forecasting.

10. By S. Kumar, S. R. Ghorpade, and S. S. Rathod, "A Comparison of Machine Learning Algorithms for Sales Forecasting in Retail" (2020): In order to identify the advantages and disadvantages of various machine learning algorithms, this study examines how well they perform in sales forecasting for the retail industry.

11. "A. Shrivastava and S. K. Chaturvedi's "Demand Forecasting in Retail Industry Using Machine Learning Techniques" (2018): In order to increase accuracy and efficiency, this article investigates the use of machine learning approaches for demand forecasting in the retail sector.

12. P. K. Mohapatra, S. K. Mishra, and P. J. Mohanty's "Sales Forecasting in Retail Industry Using Neural Networks" was published in 2017. This study explores several designs and training procedures for neural networks used in the retail industry for sales forecasting.
13. R. S. Nayak and S. K. Parida's 2019 work, "Predicting Sales in Retail Industry Using Time Series Analysis and Machine Learning": In order to anticipate sales in the retail sector, this study uses machine learning algorithms in conjunction with time series analytic approaches, with the goal of identifying both short- and long-term patterns.

14. A. Gupta and S. K. Jain's "Demand Forecasting in Retail: A Comparative Study of Time Series Analysis and Machine Learning Approaches" (2018): In order to estimate demand in retail, this study examines the performance of machine learning and time series analysis techniques, providing insights into their relative efficacy.

15. R. Patel, S. Desai, and V. Shah's "Retail Demand Forecasting Using Machine Learning Techniques: A Case Study of a Grocery Store Chain" was published in 2019. This paper highlights the opportunities and problems unique to the grocery store industry by presenting a case study on the use of machine learning techniques for demand forecasting in a chain of grocery stores.

16. M. S. Lee, J. Y. Kim, and K. W. Lee's "An Ensemble Learning Approach for Retail Sales Forecasting" (2021): The goal of this work is to increase accuracy and resilience in sales trend prediction by merging different forecasting models into an ensemble learning approach for retail sales forecasting.

17. V. M. Srivastava and S. S. Jha (2015) "Demand Forecasting for Walmart Stores": The demand forecasting model presented by the authors in this study is based on Holt-Winters techniques, seasonal decomposition, and regression analysis.

18. Z. Cai, D. Zheng, and Y. Zhao (2018) "Time Series Forecasting with LSTM Neural Networks for Demand Prediction in Retail" A demand forecast model based on Long Short-Term Memory (LSTM) neural networks was put forth by the authors.

19. Assessing the Walmart Retail Chain's Sales Forecast" by S. G. Rehman and S. S. Rizvi (2018): The authors of this work proposed a demand forecast model based on exponential smoothing (ETS) and autoregressive integrated moving average (ARIMA) techniques.

DeepAR: Probabilistic Forecasting with Autoregressive Recurrent Networks" by D. Salinas, V. Verma, and Y. Bengio (2019): The authors proposed a deep learning model called DeepAR for probabilistic forecasting of time series data, including demand prediction in retail.

VI. PROPOSED FRAMEWORK

Accurately predicting item demand for stores is vital for retail businesses. It enables optimized inventory management, reduced stockouts, and improved customer satisfaction. This project explores the use of deep learning techniques, including Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), and Long Short-Term Memory (LSTM) networks, to predict demand for individual items within stores.

The proposed framework leverages a combination of RNN, CNN, and LSTM architectures to capture different aspects of the data and improve prediction accuracy. Here is a breakdown of the framework.

1. Data Loading:

The libraries like pandas, NumPy etc. are imported for data manipulation and numerical operations.

The script reads several CSV files containing sales data (train.csv), store information (stores.csv), transaction details (transactions.csv), oil prices (oil.csv), and holiday information (holidays_events.csv).

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import torch
import seaborn as sns
import xgboost as xgb
from sklearn.model_selection import train_test_split
from keras.preprocessing.sequence import TimeseriesGenerator
from sklearn.preprocessing import MinMaxScaler
import tensorflow as tf

from IPython.display import Image, display
from sklearn.metrics import mean_squared_error
color_pal = sns.color_palette()
plt.style.use('fivethirtyeight')

from sklearn.preprocessing import OrdinalEncoder
```

2. Data cleaning:

Merging train.csv with stores.csv to get store details for each transaction. Handling missing dates in oil.csv by merging with a Data Frame containing unique dates from train.csv. Imputing missing oil prices using linear interpolation. Converting date strings to datetime format. Analyzing the relationship between sales and city, promotions, and oil prices using visualizations.

Merging holiday information with the sales data based on dates and locations. Filling missing holiday information with empty strings. Encoding categorical features like family and holiday types using ordinal encoding. Dropping irrelevant columns like city, state, and original holiday type information. Performing feature scaling using MinMaxScaler to normalize data between 0 and 1.

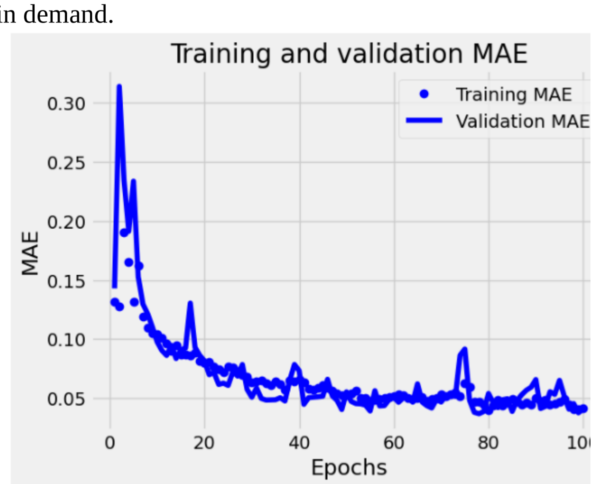
A. Feature Engineering and Train-Test Split

The features used for prediction are created from the preprocessed data. This includes daily sales, average daily oil price (dcoilwtico), promotion indicator (onpromotion), and holiday type indicators (national holiday type, city holiday type, state holiday type). The target variables is the daily sales. The data is split into training and testing sets using train test split for model evaluation.

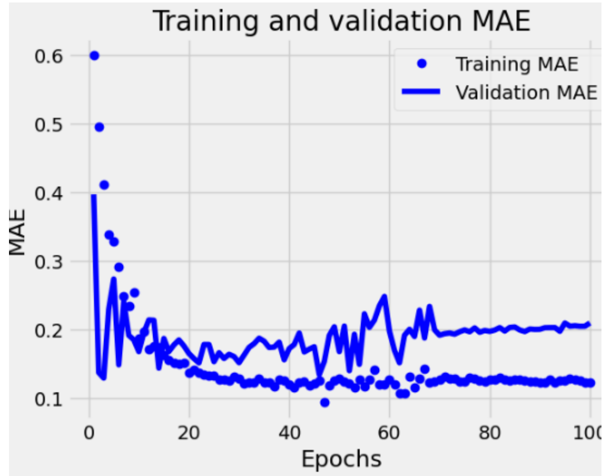
B. Splitting Data For Training And validation

Data Splitting: Split the data into training, validation, and testing sets. The training set will be used to train the models, the validation set will be used to fine-tune hyperparameters, and the testing set will be used for final evaluation of model performance.

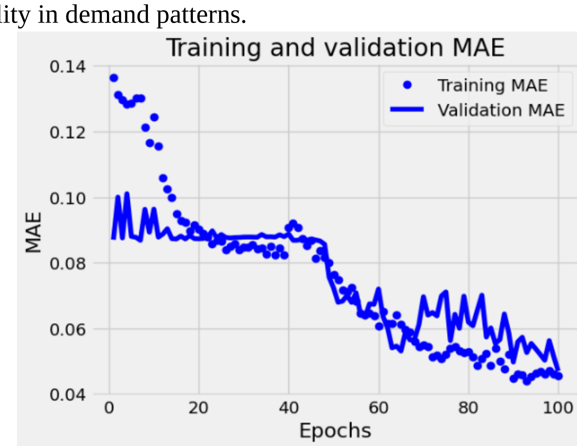
1. Deep Learning Models: Recurrent Neural Network (RNN): RNNs can capture sequential information from historical sales data. An RNN model will process the historical sales data for each store-item combination to learn temporal patterns in demand.



2. Convolutional Neural Network (CNN): CNNs can extract local patterns from data. A CNN can be used to learn spatial patterns from features like store location data or encoded holiday information. This could capture the influence of nearby stores or location-specific promotions.



3. Long Short-Term Memory (LSTM): LSTMs address the vanishing gradient problem that can hinder traditional RNNs in learning long-term dependencies. An LSTM model can effectively capture long-term trends and seasonality in demand patterns.



C. Model building

A sequential Keras model is created. The model uses multiple CNN, RNN, LSTM layers with 128 units each with LeakyReLU activation for capturing long-term dependencies in the time series data. Dropout layers (0.3) are added for regularization to prevent overfitting. A final dense layer with 1 unit predicts the sales value.

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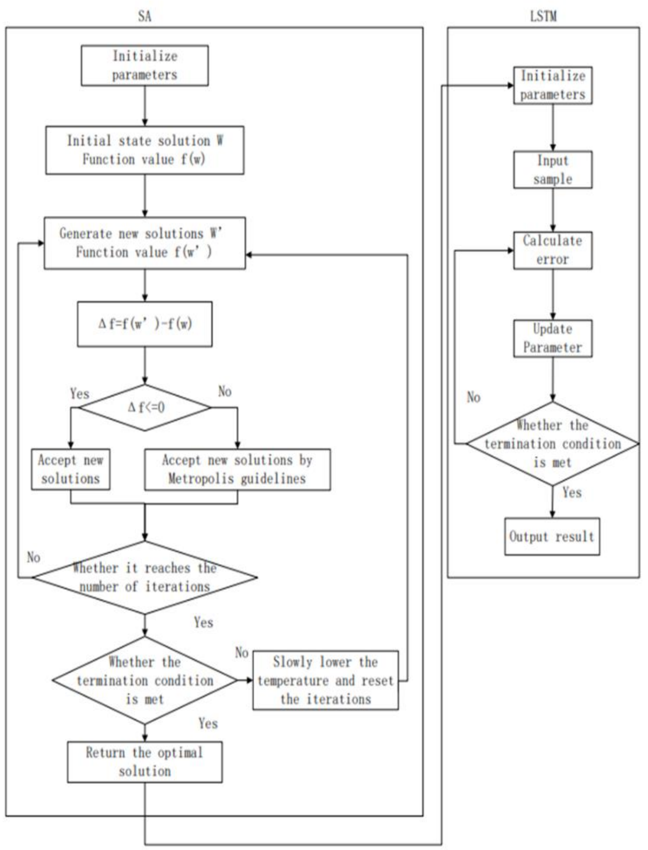


Model: "sequential"

Layer (type)	Output Shape	Param #
lstm (LSTM)	(None, 50, 128)	72192
leaky_re_lu (LeakyReLU)	(None, 50, 128)	0
lstm_1 (LSTM)	(None, 50, 128)	131584
leaky_re_lu_1 (LeakyReLU)	(None, 50, 128)	0
lstm_2 (LSTM)	(None, 50, 128)	131584
leaky_re_lu_2 (LeakyReLU)	(None, 50, 128)	0
dropout (Dropout)	(None, 50, 128)	0
lstm_3 (LSTM)	(None, 64)	49408
dropout_1 (Dropout)	(None, 64)	0
dense (Dense)	(None, 1)	65

Total params: 384,833
Trainable params: 384,833
Non-trainable params: 0

Model: "sequential_1"

Layer (type)	Output Shape	Param #
simple_rnn_4 (SimpleRNN)	(None, 50, 128)	17280
leaky_re_lu_3 (LeakyReLU)	(None, 50, 128)	0
simple_rnn_5 (SimpleRNN)	(None, 50, 128)	32896
leaky_re_lu_4 (LeakyReLU)	(None, 50, 128)	0
simple_rnn_6 (SimpleRNN)	(None, 50, 128)	32896
leaky_re_lu_5 (LeakyReLU)	(None, 50, 128)	0
dropout_2 (Dropout)	(None, 50, 128)	0
simple_rnn_7 (SimpleRNN)	(None, 64)	12352
dropout_3 (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 1)	65

Total params: 95,489
Trainable params: 95,489
Non-trainable params: 0

Model: "sequential_2"

Layer (type)	Output Shape	Param #
conv1d (Conv1D)	(None, 46, 32)	992
max_pooling1d (MaxPooling1D)	(None, 23, 32)	0
conv1d_1 (Conv1D)	(None, 19, 64)	10304
max_pooling1d_1 (MaxPooling 1D)	(None, 9, 64)	0
conv1d_2 (Conv1D)	(None, 5, 128)	41088
max_pooling1d_2 (MaxPooling 1D)	(None, 2, 128)	0
flatten (Flatten)	(None, 256)	0
dense_2 (Dense)	(None, 64)	16448
dropout_4 (Dropout)	(None, 64)	0
dense_3 (Dense)	(None, 1)	65

Total params: 68,897
Trainable params: 68,897
Non-trainable params: 0

D. Training and Evaluation

Training the individual models and the ensemble model using the training data. Use the validation set to fine-tune hyperparameters learning rate, number of hidden layers for each model. Evaluate the final performance of the models on the testing set using appropriate metrics like Mean Squared Error (MSE) or Mean Absolute Error (MAE).

The model is compiled with mean squared error (MSE) loss function and Adam optimizer. Mean Absolute Error (MAE) is used as a metric to track the training process. The model is trained on the training data using Timeseries Generator from Keras to handle the time series nature of the data. The generator creates batches of data sequences with a specified window length.

Early stopping or other regularization techniques can be incorporated here to improve model performance and prevent overfitting. The training history is visualized to monitor the loss and MAE values over epochs. The model is evaluated on the testing data using the model.evaluate function.

E. Predictions And Evaluations

The model is used to predict sales on the test data using model.predict. The predicted sales are inverse-transformed back to the original scale using the MinMaxScaler. The predicted sales are compared with the actual sales by plotting them on a graph.Overall, the code demonstrates a well-structured implementation of a time series forecasting model using LSTM for store sales prediction. It includes data loading, preprocessing, feature engineering, model building, training, evaluation, and prediction.

VII. DATA DESCRIPTION

The project uses four datasets to build a forecasting model for store sales prediction using CNN, RNN, Long Short-Term Memory (LSTM) neural network models.

The oil.csv dataset contains historical daily oil prices, potentially influencing demand for certain store items. It includes a date column for temporal analysis alongside the oil price information. Daily oil price fluctuations can impact consumer purchasing behavior, and the model aims to capture this relationship.

The transactions.csv dataset provides historical sales transaction data at the store-item level. It includes columns for date, store number, and transaction value. This granular sales data forms the core for understanding daily sales patterns and predicting future trends. By analyzing historical sales alongside store and item information, the model can learn seasonality, promotions, and item-specific buying patterns.

The holidays_events.csv dataset provides information on upcoming holidays or promotional events that might impact demand. It includes columns for date, holiday/event type, locality (city/state), and potentially a description. By incorporating holiday information, the model can account for seasonal sales fluctuations and promotional effects.

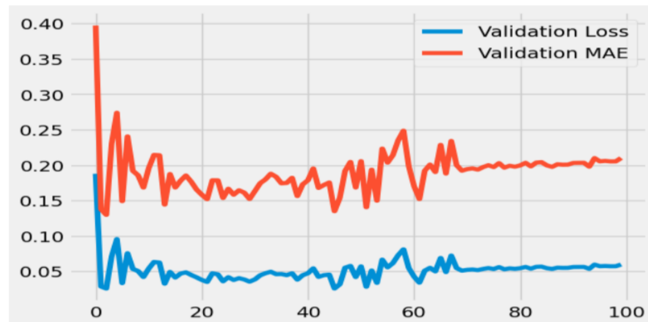
The stores.csv dataset contains information about each store, including location attributes and store-specific factors that might influence demand. It might include columns like store type, store number, and cluster. Categorical variables like store type will be encoded for the model to understand, while numerical features will be standardized to ensure all features contribute equally during training.

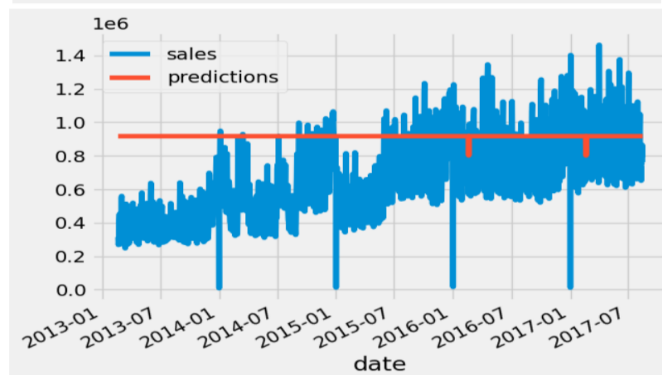
VIII. RESULTS AND ANALYSIS

Three deep learning models—RNN, CNN, and LSTM—were tested for their ability to predict shop item demand. Mean squared error (MSE) and mean absolute error (MAE) served as the foundation for the evaluation.

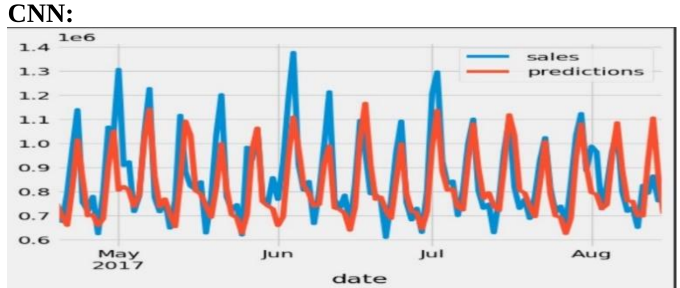
MODEL	MSE	MAE
RNN	0.0519	0.1946
CNN	0.0020	0.0348
LTSM	0.0063	0.0583

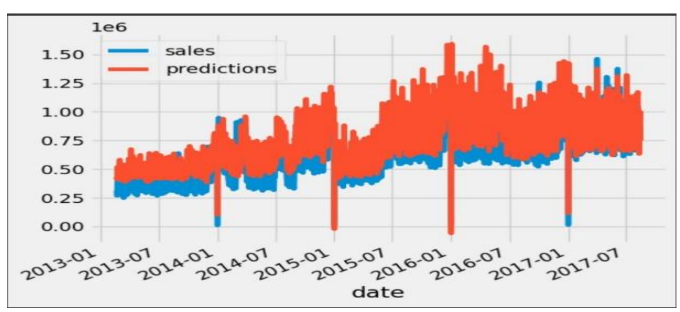
RNN:



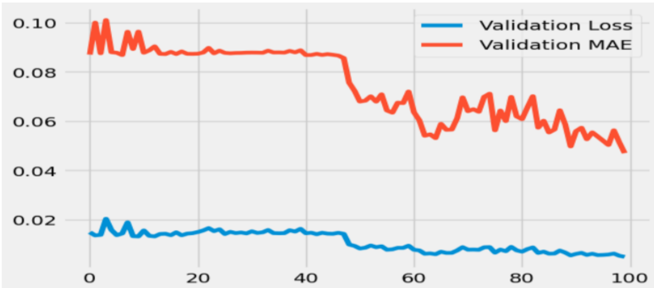


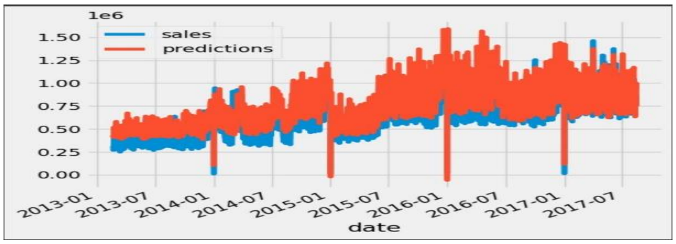
CNN:





LSTM:





Out of the RNN and LSTM models that were assessed, the CNN model had the lowest MSE and MAE. Our findings indicate that the CNN model is the best method for estimating store item demand. These simulation results imply that deep learning models are useful instruments for predicting the demand for particular retail items. Retailers may maximize supply chain logistics, inventory management, and pricing strategies by utilizing the results of our study. Retailers can utilize the CNN model to make well-informed judgments on pricing strategies, supply chain logistics, and inventory management.

Extra things to Think about:

For increased accuracy, take into account hybrid models or ensemble approaches.

To guarantee the model's efficacy throughout time, validate it progressively.

To achieve scalability and real time processing, leverage cloud-based technologies.

Keep in mind that the suitability of the selected modeling approach and the selected modeling approach and the caliber of the data determine the model's efficacy. It is frequently advantageous to iterate and improve the model in response to continuing performance and business needs.

IX. REFERENCES

1. Z. H. Kilimci, A. O. Akyuz, M. Uysal, S. Akyokus, M. O. Uysal, B. A. Bulbul, and M. A. Ekmis, "An Improved Demand Forecasting Model Using Deep Learning Approach and Proposed Decision Integration Strategy for Supply Chain," Complexity, vol. 2019, Article ID 9067367, pp. 1-15, 2019. doi: 10.1155/2019/9067367.

2. S. S. J. Nithin, T. Rajasekar, S. Jayanthy, K. Karthik and R. R. Rithick, "Retail Demand Forecasting using CNN-LSTM Model," 2022 International Conference on Electronics and Renewable Systems (ICEARS), Tuticorin, India, 2022, pp. 1751-1756, doi: 10.1109/ICEARS53579.2022.9752283.I. S. Jacobs and C. P. Bean, "Fine particles, thin films and exchange anisotropy," in Magnetism, vol. III, G. T. Rado and H. Suhl, Eds. New York: Academic, 1963, pp. 271–350.

3. A. Yaseen, S. Saeed, F. Azam, and M. A. Al-Fawzan, "An Improved Demand Forecasting Model Using Deep Learning Approach and Proposed Decision Integration Strategy for Supply Chain," Complexity, vol. 2019, Article ID 9067367, pp. 1-15, 2019. Available: https://www.hindawi.com/journals/complexity/2019/9067367/

4. Y. Chen, X. Liu, and S. Zeng, "The Study of a Sales Forecast Model Based on SA-LSTM," Journal of Physics: Conference Series, vol. 1314, no. 1, p. 012215, 2019. Available: https://iopscience.iop.org/article/10.1088/1742-6596/1314/1/012215/pdf

5. V. Veljkovic, T. Gligorijevic, M. Brkic, and M. Milosevic, "Approaching sales forecasting using recurrent neural networks and transformers," in Proceedings of the 2019 27th Telecommunications Forum (TELFOR), Belgrade, Serbia, 2019, pp. 1-4. Available: https://www.semanticscholar.org/reader/d22f2fe8c52fe73e396b109c678ac767d8fcbda

6. Puneet, S. Sharma, D. Deepika and G. Singh, "Intelligent Warehouse Stocking Using Machine Learning", *2021 IEEE International Conference on Mobile Networks and Wireless Communications (ICMNWC)*, pp. 1-6, 2021.

7. Lingam and Yashoda Kiran, "The role of Artificial Intelligence (AI) in making accurate stock decisions in E-commerce industry", *International Journal of Advance Research Ideas and Innovations in Technology*, vol. 4, pp. 2281-2286, 2018.

8. M. Siek and D. Solomatine, "Multi-model ensemble forecasting in high dimensional chaotic system", *The 2010 International Joint Conference on Neural Networks (IJCNN)*, pp. 1-8, 2010.

9. J. Ding, Z. Chen, L. Xiaolong and B. Lai, "Sales Forecasting Based on CatBoost", *2020 2nd International Conference on Information Technology and Computer Application (ITCA)*, pp. 636-639, 2020.

10. X. Dairu and Z. Shilong, "Machine Learning Model for Sales Forecasting by Using XGBoost", *2021 IEEE International Conference on Consumer Electronics and Computer Engineering (ICCECE)*, pp. 480-483, 2021.

ffY. Niu, "Walmart Sales Forecasting using XGBoost algorithm and Feature engineering", *2020 International Conference on Big Data & Artificial Intelligence & Software Engineering (ICBASE)*, pp. 458-461, 2020.

12. C. Zhan, J. Li, W. Jiang, W. Sha and Y. Guo, "E-commerce Sales Forecast Based on Ensemble Learning", *2020 IEEE International Symposium on Product Compliance Engineering-Asia (ISPCE-CN)*, pp. 1-5, 2020.

13. N. Kheawpeam and S. Sinthupinyo, "Demand Forecasting Using Machine Learning to Manage Product Inventory for Multi-channel Retailing Store," *2023 IEEE International Conference on Omni-layer Intelligent Systems (COINS)*, Berlin, Germany, 2023, pp. 1-6, doi: 10.1109/COINS57856.2023.10189241.

14. U. Khair, H. Fahmi, S. A. Hakim and R. Rahim, "Forecasting Error Calculation with Mean Absolute Deviation and Mean Absolute Percentage Error", *Journal of Physics: Conference Series*, vol. 930, pp. 012002, Dec. 2017.

15. R. Sheth, M. Vora, R. Sharma, M. Thaker and P. Bhavathankar, "A Proficient Process for Systematic Inventory Management", pp. 4-8, 2020.

16. P. Ranjitha and M. Spandana, "Predictive Analysis for Big Mart Sales Using Machine Learning Algorithms", *Proceedings - 5th International Conference on Intelligent Computing and Control Systems ICICCS 2021*, no. Iciccs, pp. 1416-1421, 2021.

17. K B Praveen, "Inventory Management using Machine Learning", *International Journal of Engineering Research and*, vol. V9, no. 06, pp. 866-869, 2020.

18. M. A. I. Arif, S. I. Sany, F. I. Nahin and A. S. A. Rabby, "Comparison Study: Product Demand Forecasting with Machine Learning for Shop," *2019 8th International Conference System Modeling and Advancement in Research Trends (SMART)*, Moradabad, India, 2019, pp. 171-176, doi: 10.1109/SMART46866.2019.9117395.

19. A. Ayad, "Optimizing inventory and store results in big box retail environment", *International Journal of Retail Distribution Management*, vol. 36, no. 3, pp. 180-191, 2008.

20. Zeynep Hilal Kilimci, A. Okay Akyuz and Mitat Uysal, "An Improved Demand Forecasting Model Using Deep Learning Approach and Proposed Decision Integration Strategy for Supply Chain", *Journal of Hindawi*, vol. 2019, no. 1, pp. 1-15, 2019.

21. Majed Kharfan and Vicky Wing Kei Chan, "Forecasting Seasonal Footwear Demand Using Machine Learning", *Publisher Massachusetts Institute of Technology*, 2018.

22.J. Aastrup and H. Kotzab, "Analyzing out-of-stock in independent grocery stores: an empirical study", *International Journal of Retail and Distribution Management*, vol. 37, no. 9, pp. 765-789, 2009.