International Journal of Gender, Science and Technology
ISSN: 2040-0748
UGC Care Group I Journal.
Vol-13 Issue-02 July 2024

FOOD DEMAND SUPPLY CHAIN FORECASTING AND MODELING USING TIME SERIES AND REGRESSOR ANALYSIS

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ABSTRACT: Precise demand forecasting has become crucial, particularly in the food sector where a lot of products have limited shelf lives and mishandling inventories can cost the company a lot of money. The following regression models were used in this project: CNN-2D, Long-short Term Memory (LSTM), Bidirectional LSTM (Bi LSTM), Random Forest Regressor, Gradient Boosting Regressor (GBR), Light Gradient Boosting Machine Regressor (Light GBM), and Extreme Gradient Boosting Regressor (XG Boost).

1.INTRODUCTION

Because of the shopper's changing requirements and expanding levels of seriousness among organizations, most organizations in the present market are moving their concentration to request guaging for the compelling interest store network the executives. Request gauges are past the extent of any arranging choices, as they straightforwardly influence an organization's productivity. Off base estimate of interest can either cause an excess of stock, which in the end brings about a high gamble of wastage and significant expenses to pay or too little stock, prompting out of stocks which eventually pushes the organization's clients to look for administrations from its rivals. For these very reasons, the utilization of interest determining techniques is quite possibly of the most. basic parts of the essential preparation and organization of an organization's coordinated factors. Its significance becomes clear as its result is involved by numerous regions in the organization: the monetary office utilizes it to appraise costs, benefit levels, and the necessary capital; the showcasing division utilizes it to design its game-plan and examine the effect of different advertising systems on the volume of deals; the buying division might devise their arrangements of short-and long haul ventures; lastly, the tasks division can deal with their arrangement of buying the fundamental unrefined components, hardware, and work well ahead of time. It is, subsequently, concordant that gauges are helpful, and their high exactness can possibly demonstrate rewarding, further develop request store network the executives, and lessen. Its wastage significance becomes apparent as its result is involved by numerous regions in the organization: the monetary department `12uses it to assess costs, benefit levels, and the expected capital; the advertising division utilizes it to design their game-plan and break down the effect of assorted promoting systems on the volume of deals; the buying division might devise their arrangements of short-and long haul speculations; lastly, the tasks division can deal with their arrangement of buying the important unrefined substances, apparatus, and work well ahead of time. It is, thusly, concordant that gauges are exceptionally helpful, and their high exactness can possibly demonstrate rewarding, further develop request production network the board, and lessen wastage.

2.LITERATURE SURVEY

Machine Learning Applications in the Supply Chain: A Comprehensive review:

Authors: Kouhizadeh, & Makui,Published in: Computers & Industrial Engineering, 2018. Summary: This review explores various applications of machine learning in supply chain management, providing insights into demand forecasting and optimization.

"A Comprehensive Review on Food Demand Forecasting"

Authors: Chen, Y., Jiang, W., & Li, X. Published in: Journal of Food Engineering, 2020. Summary: Focusing specifically on food demand forecasting, this review offers insights into traditional methods and challenges, setting the foundation for advanced techniques.

"Time Series Forecasting with Deep Learning: A Survey"

Authors: Lipton, Z. C., Berkowitz, J., & Elkan, C. Published in: Journal of Machine Learning Research, 2015. Summary: This survey provides a comprehensive overview of deep learning techniques for time series forecasting, offering principles applicable to your study.

"CatBoost: unbiased boosting with categorical features"

Authors: Prokhorenkova, L., Gusev, G., & Vorobev, A.Published in: NeurIPS, 2018.

Summary: Introducing CatBoost, this paper discusses a gradient boosting algorithm designed for efficient handling of categorical features, relevant to your use of Cat Boost.

3. PROPOSED SYSTEM

In this project, to predict the number of meals for the next weeks using machine learning and the deep learning regressors mentioned above. Significant contributions of the work manifested in this paper include: 1) Traditional Random Forest Regressor is optimized and implemented as the baseline model.

2)Boosting algorithms like GBR, LightGBM, XGBoost and Cat Boost Regressor are applied since they are more adaptable to categorical and numerical features.

3) Only the lag and EWMA features are used with LSTMs and Bidirectional LSTMs because they are more reliable in analyzing historical data and forecasting using the same.

4) The Root Mean Squared Log Error (RMSLE), Root Mean Square Error (RMSE), Mean Average Percentage Error (MAPE) and Mean-Average Error (MAE) reach values 28.18, 18.83, 6.56%, and 14.18 respectively.

As extension we have used CNN2D (convolution neural networks2 Dimension) algorithm which will optimized dataset features with multiple neurons and can able to extract more accurate features from dataset which help in more accurate forecasting and this algorithm is giving better results compare to other algorithms.

Advantages: These deep learning models are capable of identifying the time-variant characteristics and significant trends of historical data as well as predicting the future tendency. Accuracy is high so there risk of food wastage.

3.1 IMPLEMENTATION

As extension we have used CNN2D (convolution neural networks2 Dimension) algorithm which will optimized dataset features with multiple neurons and can able to extract more accurate features from dataset which help in more accurate forecasting and this algorithm is giving better results compare to other algorithms.

3.2 ALGORITHMS

Deep Learning is turning into a very famous subset of laptop studying due to its excessive degree of overall performance throughout many sorts of data. A amazing way to use deep gaining knowledge of to classify pix is to construct a Convolutional

Neural Network (CNN). The Keras library in Python makes it extraordinarily easy to construct a CNN. Computers see pictures the usage of pixels. Pixels in pix are typically related. For example, a sure team of pixels may additionally signify an part

in an photograph or some different pattern. Convolutions use this to assist become aware of images. A Convolution multiplies a matrix of pixels with a filter matrix or kernel and sums up the multiplication values. Then the convolution slides over to the subsequent pixel and repeats the identical technique till all the photograph pixels have been covered.

Convolutional Neural Networks are very comparable to everyday Neural Networks; they are made up of neurons that have learnable weights and biases. Each neuron receives some inputs, performs a dot product and optionally follows it with a non-linearity.

Regular Neural Nets don't scale nicely to full images. Consider a picture of measurement 32x32x3(32 wide, 32 high, three colour channels), so a single utterly related neuron in a first hidden layer of a everyday Neural Network would have 32*32*3 = 3072 weights. This quantity nevertheless appears manageable, however simply this completely linked shape does no longer scale to large images. For example, an photo of extra first rate size, e.g.200x200x3, would lead to neurons that have200*200*3 = 120,000 weights. Moreover, all of us desire to have numerous such neurons, so the parameters would add up quickly! Clearly, this full connectivity is wasteful and the massive variety of parameters would rapidly lead to overfitting.

Convolutional Neural Networks take gain of the truth that the enter consists of snap shots and they constraint the structure in a greater good way. In particular, not like a ordinary Neural Network, the layers of a ConvNet have neurons organized in three dimensions: width, height, depth. For example, the enter photograph with dimensions XxYxZ (width, height, depth respectively), the neurons in a layer will solely be linked to a small vicinity of the layer earlier than it, rather of all of the neurons in a fully-connected manner, the remaining output layer would have dimensions(1,1,C), because with the aid of the quit of the ConvNet architecture, it will limit the full photo into a single vector of category scores, organized alongside the depth dimension.

3.2.1 Layers in Convolutional Neural Network•

The convolutional layer will compute the output of neurons that are linked to local regions in the input, with each neuron computing a dot product between their weights and a small region in the input volume to which they are reconnected.

• At zero, the RELU layer will use an element-wise activation function, such as the max(0,x) thresholding. .The POOL layer will undertake down sampling along the spatial dimensions (width, height).The FULLY linked layer will compute the class scores, producing in a volume of size [1x1xX], where X integers correspond to class scores.

3.2.2 Convolution layer

When dealing with excessive dimensional inputs such as images, as considered above it is impractical to join neurons to all neurons in the preceding volume. Instead, it will join every neuron to solely a nearby location of the enter volume.

The spatial extent of this connectivity is a hyperparameter referred to as the receptive discipline of the neuron (equivalently this is the filter size).The extent of the connectivity alongside the depth axis is usually equal to the depth of the enter volume. It is vital to emphasize once more this asymmetry in how to deal with the spatial dimensions (width and height) and the depth dimension: The connections are nearby in house (along width and height), however constantly full alongside the complete depth of the enter volume. Example1: For example, believe that the enter extent has dimension [32x32x3], (e.g. an RGBCIFAR-10image). If the receptive field (or the filter size) is5x5, then every neuron in the Convolution Layer will have weights to a [5x5x3] vicinity in the enter volume, for a whole of 5*5*3=75 weights(and +1 bias parameter). Notice that the extent of the connectivity alongside the depth axis ought to be 3, due to the fact that this is the depth of the enter volume.

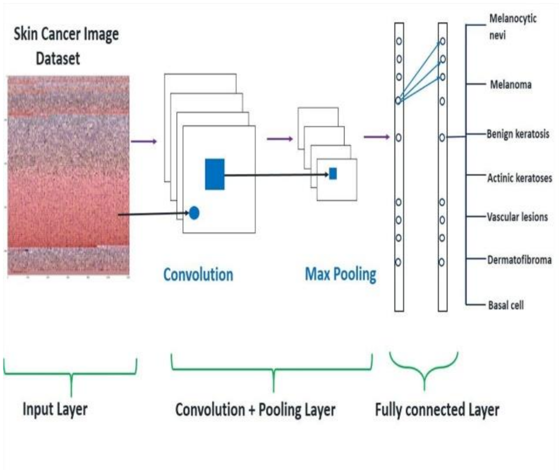


Fig 1: Convolutional- layer representation

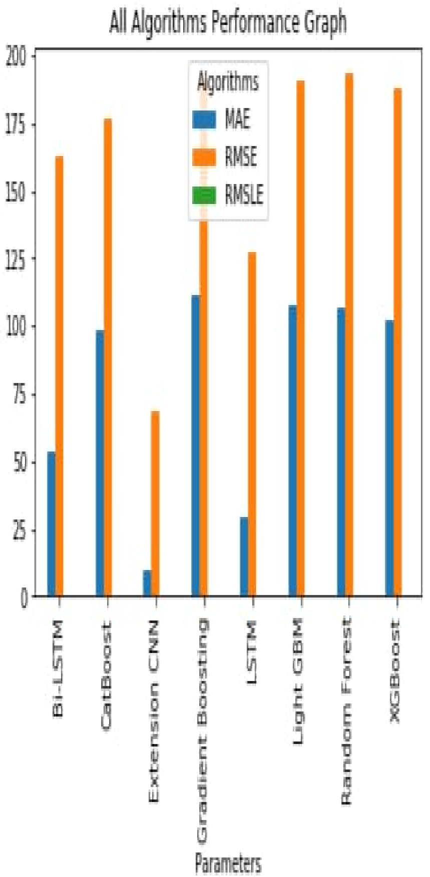
An example red input volume (e.g., a 32x32x3 CIFAR-10 image) and an example volume of neurons in the first Convolutional layer are shown on the left. Each neuron in the Convolutional layer is spatially related only to a tiny region in the input volume, but to the entire depth (i.e., all colour channels). It should be noted that there are several neurons (5 in this case) along the depth, all of which are staring at the same place in the input.

Right: The neurons from the Neural Network chapter are unaltered: They still calculate a dot product of their weights with the input, followed by a nonlinearity, but their connectedness is now spatially limited to be local. 1) Convolutional Layer: In a typical neural network each input neuron is connected to the next hidden layer. In CNN, only a small region of the input layer neurons connect to the neuron hidden layer. 2)Relu Layer:- In this layer we apply activation function.

3) Pooling Layer: The pooling layer is used to reduce the dimensionality of the feature map. There will be multiple activation & pooling layers inside the hidden layer of the CNN.

4) Fully-Connected layer: Fully Connected Layers form the last few layers in the network. The input to the fully connected layer is the output from the final Pooling or Convolutional Layer, which is flattened and then fed into the fully connected layer.

4.RESULTS AND DISCUSSION



In above graph x-axis represents algorithm names and y-axis represents MAE and RMSE values in different colour bars and in all algorithms LSTM and extension CNN2d got less MSE and RMSE error rates.

	Algorithm Name	MSE	RMSE	RMSLE
0	Random Forest	106.847025	193.153677	0.704723
1	Gradient Boosting	111.228799	191.948277	0.759446
2	Light GBM	107.335889	190.582220	0.697293
3	CatBoost	98.277249	176.999181	0.656369
4	XGBoost	101.924355	187.536650	0.691871
5	LSTM	29.706652	127.531458	0.435268
6	BI-LSTM	53.219438	162.826366	0.573238
7	Extension CNN	9.761380	68.732609	0.188711

In above screen displaying all algorithm performance in tabular format

```
Test Data : [1151666 1 89 2640 281.33 280.33 0 0 703 56 'TYPE_A' 4.8] Predicted Sales ===> 205.91173
Test Data : [1048572 1 89 1878 282.33 280.33 0 0 703 56 'TYPE_A' 4.8] Predicted Sales ===> 289.71167
Test Data : [1379525 1 89 2306 243.5 242.5 0 1 703 56 'TYPE_A' 4.8] Predicted Sales ===> 556.96893
Test Data : [1152138 1 89 1216 456.93 454.93 0 1 703 56 'TYPE_A' 4.8] Predicted Sales ===> 412.3625
Test Data : [1478586 1 89 2126 487.0 485.0 0 0 703 56 'TYPE_A' 4.8] Predicted Sales ===> 68.18612
Test Data : [1092935 1 89 2826 341.44 342.44 0 0 703 56 'TYPE_A' 4.8] Predicted Sales ===> 129.0887
Test Data : [1090744 1 89 1754 284.27 283.27 0 0 703 56 'TYPE_A' 4.8] Predicted Sales ===> 300.8519
```

In above screen reading test data and then normalizing and then predicting test data with extension CNN model and then in output before arrow symbol =➔ we can see TEST data and after =➔ symbol we can see predicted sales for that week.

5.CONCLUSION

Accurate forecasting is essential in the food industry to optimize supply chain management, especially for products with a short shelf life.

The results of the project demonstrated the potential of deep learning models, particularly LSTM, in accurately forecasting the number of orders. LSTM outperformed other algorithms in terms of forecasting accuracy.

Evaluation metrics such as RMSLE, RMSE, MAPE, and MAE were employed to assess the forecasting models' performance.

The ensemble model "Voting Regressor" and deep learning model "CNN" which is an extension excels with least mean absolute error , demonstrating superior performance , making it an effective solution for food demand supply chain management .

Integrating a user-friendly Flask interface with secure authentication improved the overall user experience during system testing, where we input data to evaluate its performance.

6.REFERENCES

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