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Enhancing Raw Material Demand Planning In Restaurants Through Time Series Analysis

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Abstract
According to the Food and Agriculture Organization (FAO) of the United Nations, an estimated 1.3 billion tons of food are wasted globally each year, which is equivalent to one-third of all food produced for human consumption. The economic value of this wasted food is estimated at around $1 trillion. There have been some studies and projects aimed at developing techniques for the Supply chain for Raw materials using various machine learning and deep learning techniques. However, there is still room for improvement in the accuracy and efficiency of these techniques.
In this approach is to develop a system to recommend the quantity of raw materials to be purchased to reduce the stockouts and overstocking by using various machine learning techniques that involves analyzing data on food consumption and waste, identifying patterns and trends in the data, and using machine learning algorithms to develop predictive models that can help reduce food waste. The optimization will be done to the model using techniques such as cross-validation and hyper parameter tuning. The accuracy of the models is evaluated using metrics such as MAE, MSE, RMSE and R2 SCORE. This system will improve overall customer satisfaction, and restaurant profit and reduces the wastage of raw materials.
Keywords: *Food and Agriculture Organization (FAO), Histogram Gradient Boosting, Machine Learning, sales forecasting, Historical sales data, Gradient Boosting With Stl*

I. INTRODUCTION

All living things, including humans, must have food to survive. It is an essential need for surviving, growing, and developing because it gives the body the nutrients and energy it needs to function properly. Despite this, the restaurant industry is no exception and requires effective demand planning in order to operate smoothly and profitably. It becomes challenging to accurately forecast the demand for raw materials in a market where seasonality, customer preferences, and market conditions are ever-changing [1]. The ability of a restaurant to precisely predict and plan for future demand can have a significant impact on its ability to optimise inventory levels, reduce waste, and ensure the timely availability of products.

A general overview of the study's topic, focusing on the predictive analysis techniques used to forecast raw material demand in the context of restaurants. It tries to highlight the importance and value of sound demand planning in this particular industry, where inventory management and cost control are crucial for success. It will include an overview of the approach used, which may include gathering and analysing historical sales data, market trends, consumer preferences, and external variables driving demand patterns. It will also discuss the use of statistical algorithms, machine learning methods, or other predictive modelling strategies to provide precise projections. This will make it possible for interested parties, such as restaurant owners, managers, and researchers, to assess the research's relevance and 2 potential applications in their particular contexts, ultimately promoting better decision-making and advancing demand planning techniques [2].

1.1 PROBLEM STATEMENT

The purpose of this work is to develop an Raw Material Demand forecasting system for Restaurants. The system should be able to predict the number of orders and suggest the Raw materials requirement for the given input. The Prediction is done by various machine learning techniques.

1.2 PROPOSED SOLUTION

The first step in the raw material demand planning process is gathering the data sets. The first data sets come from Kaggle and include historical sales reports, which consist of 456549 records. Users can publish datasets, collaborate with other data scientists and machine learning engineers, search for datasets to use in AI and ML models, and enter competitions on the Kaggle platform. The second data set is made up of

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records for recipe ingredients and raw materials that were taken from the Recipe DB website using web scraping. The final set of data is a volume conversion of raw materials that was collected from the websites aqua-calc and the calculator site website. The next step is to clean and pre-process the data that we have gathered. After pre-processing the historical sales report data is fit into various machine learning algorithm to train the model on these inputs and to predict the number of orders. After training the model, the model is tested on test data to find the accuracy of the model. The final step is to optimize the solution using Hyper Parameter Tuning. The Grid Search Cv algorithm is used to fit the best fit model for the 3-demand forecasting of raw materials which in turn it will increase the accuracy of the system.

1.3 OBJECTIVE OF THE STUDY

The objective is to develop accurate predictive models using machine learning algorithms to estimate the demand for raw materials in restaurants, aiding in effective inventory management and supply chain optimization. Optimize prediction accuracy by fine-tuning model hyperparameters to improve prediction rates and enhance overall performance. To predict the number of orders and calculate raw material quantity, use STL algorithm for seasonal, trend, and residual analysis. Apply predictions to ingredient quantities based on order estimates.

1.4 ORGANIZATION OF THE REPORT

The report is organized into the following chapters. Describing each part of the project with detailed illustration and system design diagram. Chapter 2: discussed the Literature survey detailed of the project alongside their methodologies, limitations of the existing project. Chapter 3: provides the detailed system design of the proposed work along with the proposed methodology and implementation. Chapter 4: explains the algorithm used for predicting the sales forecast system. Chapter 5: provides the experimental results and analysis obtained during the project. Chapter 6: concluding the report with the observation from the Time series sales foresting the system.

II. RELATED WORKS

This section discusses the various academic works gathered to gain insight into forecasting raw material demand using historical sales data. We will also look through the recipe database literature for information on the ingredient details. It also discusses the various models used in those literatures that give an idea about the model selection for the dataset.

a. RELATED WORK IN RAW MATERIAL DEMAND FORECASTING

Cameron McRae et.al [1] conducted research on sales forecasting in Quebec, Canada, to project demand for 13 newly launched yoghurt products for 17 months from 2015 to 2016, utilizing a unique loyalty programme dataset from a supermarket chain. This dataset of 330 attributes was designed to offer information on the product, marketing and promotions, shop, and neighborhood over time. Historical sales data, as well as external factors like weather and holidays. To analyze the data, they used Python 3, Google Collaboratory, and open-source frameworks. They discovered that their machine learning models, notably the random forest method, were highly accurate in anticipating market demand for yoghurt products with an accuracy of 84.0 % in the store level model and 57 % in the market level.

Dilkhush Mihirsen D et.al [2] the authors have contributed to the existing body of knowledge by implementing a machine learning system for sales forecasting in the restaurant industry and developing a restaurant-centric web application. By leveraging time series data and employing suitable machine 6 learning algorithms, the system aims to accurately forecast dish sales, optimise raw material procurement, reduce food waste, and improve overall restaurant performance. In order to create predictive models, the authors used time series data and the Holt Winter's and STL (Seasonal and Trend Decomposition using Loess) algorithms. Their study revealed that these machine learning models could predict sales cycles with accuracy and facilitate efficient procurement planning. The system reduced food waste and increased supply chain efficiency by preventing the over purchasing of raw materials. The machine learning-based sales forecasting system was easily accessible through the web application, which improved supply chain management and overall restaurant performance.

Dendy Rio et.al [3] they have implemented the Master Production Schedule (MPS) method in soku bakery production processes, which has been widely studied and recognised as an effective approach to optimising production planning, managing demand fluctuations, minimising waste, and improving cost control. The authors emphasised the need for precise demand forecasting as well as how the MPS can successfully schedule production operations to satisfy customer expectations while minimising inventory holding costs. According to their findings, the MPS technique enhanced production planning and lowered inventory levels, resulting in higher resource utilisation and cost reductions. To get the best results, the author employed the simple moving average approach in the Master Production Schedule (MPS) at Soku Bakery. Soku Bakery can predict future demand using simple moving average approaches. Because it is based on expected demand while taking on- hand inventory and net requirements into consideration, the organisation can better predict the production amount.

Culinary science, nutrition, and public health are just a few of the professions with an interest in the interaction of cuisine, culture, and health. This issue also includes an overview of relevant studies [4]. Devansh Batra et.al, they had made an effort to create a database that could have all the dish ingredient details with regard to the cooking process and the nutritional content in the dishes. Cooking has long been acknowledged as a cultural activity that turns uncooked ingredients into delectable dishes that reflect the knowledge and traditions of many nations. Cooking and the recipes that direct the process function as cultural time capsules that store information about social customs, sensory experiences, and nutrition in addition to food. Recipe databases offer organised collections of recipes from many cuisines and countries, together with information on ingredients, cooking methods, flavour profiles, and nutritional profiles. One such database is Recipe DB, which is referenced in the bibliography. Researchers can use these tools to look into the connections between recipes, flavour characteristics, and health effects.

Du Yanwei [5] focuses on using the exponential smoothing model to forecast raw material needs, specifically taking boiler manufacturers' characteristics into account. The study emphasises how crucial it is to choose appropriate weighted coefficients and initial values because these factors have a direct bearing on how accurate the forecasting results are. The mean square error (MSE) is computed to assess the prediction model's accuracy. The MSE is a metric used to assess the gap between expected outcomes and actual requirements. The effectiveness of the exponential smoothing model in accurately forecasting the raw material requirements for boiler manufacturers is shown through the verification process using an example, where it is shown that the error between the forecasting results and 8 the actual requirements is smaller. To determine whether the prediction was accurate.

K. Harshini etal.[6], they provide an overview of relevant studies that have explored the use of Ensemble Learning techniques for predicting sales, forecasting customer demand, and optimizing raw material procurement to address the challenges of food wastage in the restaurant sector. The authors utilised various machine learning techniques, including XG Boost, random forests, SVM, and ANN algorithms, to build a predictive model. Their results showed that the stacked ensemble approach improved the accuracy of sales predictions and enabled better inventory management, leading to reduced food waste. Utilisation ensemble models and regression models improve the accuracy of sales predictions and facilitate efficient resource allocation, ultimately minimising food waste and increasing operational efficiency in restaurants.

Kristian Sebastian et.al [7] addressed the increasing complexity and volume of network traffic, the study proposes an ensemble model that combines Seasonal and Trend Decomposition using Loess (STL) with a gated recurrent unit (GRU) neural network. The STL-GRU model individually forecasts decomposed components and then combines them to generate accurate traffic forecasts. By leveraging the decomposition process, the model mitigates the impact of noise and outliers in the time series data, resulting in improved forecasting performance compared to standalone statistical or machine learning approaches. The study demonstrates the effectiveness of the proposed hybrid scheme in achieving enhanced forecast accuracy.

Priyam Saha et.al[8] has observed the challenges faced by retailers in demand prediction or sales forecasting, particularly in the context of the Covid pandemic and increasing competition in the retail industry. This literature survey provides an overview of relevant studies that have explored 9 the application of advanced deep learning techniques, specifically LSTM and LGBM models, for sales forecasting and inventory management in the retail sector. The performance of LGBM and LSTM deep learning algorithms was compared by the authors, and it was discovered that LGBM had improved forecasting accuracy and quicker training times, making it a promising method for retail sales forecasting and inventory management. Their research showed how well LGBM models capture the influence of outside variables, such as lockdown measures and shifting consumer preferences, on the accuracy of sales forecasting.

A web service that was implemented as a novel method for an inventory management system that aids in managing and locating the food additives that are present in the global food additive database authorised by the Codex Alimentarius Commission is discussed in [9] by Pikulkaew Tangtisanon. Python is used to forecast the stock of food additives using four machine learning models: Naive Bayes, Decision Trees, Linear Regression, and Support Vector Regression.

Renfei He et.al [10] tried an approach that uses seasonal-trend decomposition to break down the rainfall time series into trend, seasonal, and remaining components. The STL-ML approach combines machine learning models like GRU, multi-time-scale GRU, and LightGBM to predict rainfall components and accurately estimate heavy rainfall events. It complements numerical rainfall prediction, making it valuable for flood prediction and hydrological disaster management.

The author [12] used different types of Machine Learning Algorithms to find out the gdp prediction of the country. From this paper we can easily analyze about the basic machine learning models which are used to do the prediction in some different scenario.

Xuhui Zheng et.al [12] the authors has proposed the idea to use a Self-Organizing Map (SOM) neural network clustering algorithm to study the 10 price trends of different food products over a period of more than a year in the same region. The aim is to forecast food prices and trends based on the analysis of price curves and three calculated indices. This literature survey provides an overview of relevant studies that have explored the application of SOM and similar clustering algorithms for price forecasting and trend analysis in the context of food products.

The price information for 42 different types of food consumed by urban residents over a given time period, as provided by the government's price department, served as the sample data for this article. The data spans a year, with time intervals of 10 days, 42 evaluation objects, and 39 evaluation indicator time points.

III. III. MATERIAL AND METHODS

a. Gradient Boosting

Gradient Boosting Regressor is an ensemble learning technique that combines multiple weak prediction models (typically decision trees) to create a strong predictive model. It sequentially trains the models to correct the mistakes made by the previous models, ultimately improving the overall prediction accuracy[13].

b. Histogram Gradient Boosting

Histogram Gradient Boosting Regressor is a variant of Gradient Boosting that utilizes histograms to speed up the training process. It discretizes the numerical features into bins, which reduces the computational complexity of finding the best splits during the tree building process.

c. Random Forest

Random Forest Regressor, on the other hand, is an ensemble learning technique that constructs a multitude of decision trees and averages their predictions to make the final prediction. It introduces randomness both in the selection of the features used for splitting and the data samples used for raining each tree, which helps to improve the model's generalization and reduce overfitting.

d. STL Algorithm

The Seasonal and Trend Decomposition using Loess (STL) algorithm is a method used for decomposing a time series into its constituent components: the seasonal component, the trend component, and the remainder component. The algorithm applies locally weighted regression to estimate the trend and seasonal components, and the remainder component is obtained by subtracting the estimated trend and seasonal components from the original time series. The components present in STL algorithm are.

Seasonal Component (S):

$S(t) = m(t) + R(t)$------ (3.1)

Trend Component (T)

$T(t) = d(t) + R(t)$------ (3.2)

Remainder Component (R):

$R(t) = y(t) - S(t) - T(t)$-----(3.3)

where:

- (t) represents the smoothed seasonal component at time t.
- T (t) represents the smoothed trend component at time t.
- R(t) represents the remainder component at time t.
- m(t) represents the seasonal subseries at time t.
- d(t) represents the detrended subseries at time t.
- y(t) represents the original value of the time series at time t.
- **Hyper Parameter Tuning**

Model performance, functionality, and structure are directly governed by hyperparameters. We can optimise model performance with hyperparameter tuning. The success of this process depends on selecting the right hyperparameter values, which is a crucial step in machine learning.

IV. IV.PROPOSED ARCHITECTURE

The system architecture discussed the various modules has been involved. The Raw material Demand forecasting system has various stages from data collection, cleaning, preprocessing, model. Training and testing and finally the system is optimized by the Hyper parameter tuning.

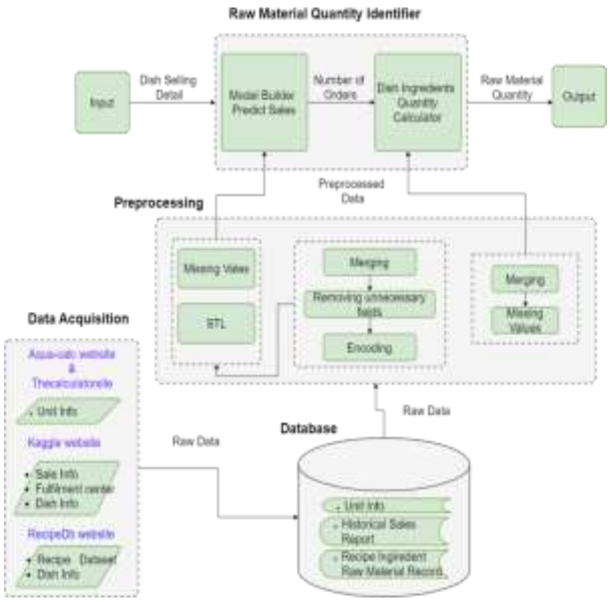


Figure 4.1: Architecture of Proposed System

a. Data Acquisition

To respond to the research question, historical sales data from Kaggle was collected. This dataset consists of various information related to sales, such as weekly sales data, details about the fulfillment centers, information about the dishes, and the recipes for different dishes. The dataset contains a total of 15 fields, which likely include attributes such as the week of the sale, base price checkout price etc., fulfillment center details (such as center ID, region ID and Output area), dish information (such as cuisine and category of dishes), and recipe details (possibly ingredients).

In terms of the dataset's size, it consists of 456,549 records. These records represent individual instances of sales transactions, each containing specific information about the sale. The dataset covers a period of 145 weeks of historical sales data. This timeframe indicates that the data spans a considerable duration and may allow for observing patterns, trends, or seasonality in the sales data. By utilizing this historical sales dataset, researchers can analyze and explore the data to gain insights, identify patterns, or build models to predict future sales or optimize business strategies in the food industry.

b. Preprocessing

The research project's preprocessing stage consists of three modules. The first processes historical sales data, the second handles recipe ingredient and raw material records, and the third utilizes the STL algorithm to calculate Seasonal, Trend, and Residual values for order numbers. Missing values in these columns are completed using the HistGradientBoosting model and IterativeImputer.

In the first module, the historical sales report is processed. This involves merging the dish dataset and fulfillment dataset with the sales report per week dataset. By merging these datasets, relevant information from each dataset is combined, allowing for a more comprehensive analysis of the sales data. Non-related fields that are not necessary for the research question are removed from the dataset to streamline the data and improve computational efficiency.

Additionally, categorical values in the dataset are encoded. Encoding categorical values involves converting them into numerical representations that can be used by machine learning algorithms. This step is important as many machine learning models require numerical inputs. Encoding categorical values enables the inclusion of categorical data in the analysis and model building processes.

In the second module, the recipe ingredient raw material record is preprocessed by merging the dish info dataset with the recipe ingredient dataset. This merging operation combines information about the dish and its corresponding recipe ingredients, creating a more comprehensive dataset for analysis. Additionally, missing fields in the recipe ingredient dataset are filled with suitable values. This step ensures that the dataset is complete and ready for further analysis, as missing data can impede the accuracy of subsequent analysis and modeling processes.

The third module in the workflow takes the input from the first module and applies the STL (Seasonal and Trend Decomposition using Loess) algorithm to determine the seasonal, trend, and residual values for the number of orders. These values are then added as new fields to the original data frame. Additionally, if there are any missing values in the seasonal, trend, and residual columns, the module utilizes the HistGradientBoosting model as the estimator within the IterativeImputer. This enables the module to fill in the missing values by iteratively fitting the data with the model. By incorporating these steps, the third module enhances the dataset by providing comprehensive seasonal, trend, and residual information while addressing any missing data issues. Overall, these preprocessing modules aim to prepare the datasets for subsequent analysis, model building, and answering the research question effectively.

4.4 Raw Material Quantity Identifier

This module consists of two sub-modules, each serving a specific purpose in the overall process. The first sub-module is designed to predict the number of sales that will occur in a given week. It takes as input various details related to the dish being sold, such as the base price, checkout price, and dish ID etc., . These input features are fed into a predictive model, which analyzes the data and generates an output representing the estimated number of orders to be sold in that particular week. The model employed in this sub-module is a regression model (Gradient boosting, Random Forest and Hist Gradient Boosting).

The second sub-module is responsible for calculating the quantity of ingredients required for that week. It takes into account the predicted number of sales from the first sub-module and the recipe ingredient dataset. By combining this information, the sub-module can determine the amount of each ingredient needed to fulfill the expected demand for the week. This calculation ensures that the required quantity of ingredients is available for preparing the dishes and meeting customer demand

Overall, these two sub-modules work together to optimize the sales and production processes. The first sub-module predicts the sales volume for the upcoming week, allowing for effective planning and resource allocation. The second sub-module calculates the ingredient quantities based on the predicted sales, ensuring that the necessary ingredients are available in the required quantities to meet customer demands efficiently.

V.OBTAINED RESULT

5.1 **Raw material quantity identifier Function**

- Read the recipe data from the "allRecipe.csv" file and sort it by ingredient name.
- Read the measurement data from the "vMeasurement.csv" file.
- Read the inventory data from the"inventory.csv" file.
- Set the variable ‘rb‘ as a reference to the measurement data.
- Perform preprocessing on the input data ‘dummy‘using the ‘preprocessModule1‘ function.
- Perform seasonal, trend, and residual decomposition on the pre-processed data using the ‘preprocessSTL’ function.
- Iterate over each index ‘i‘in the ‘dummy‘ data.
- Predict the number of orders using the ‘numOrderPredictor‘function for the data at index ‘i‘ and the given model.Calculate the quantity of raw materials required for the data at index ‘i‘ using the ‘quantityCalculator‘ function, considering the predicted number of orders and the inventory and recipe data.
- Convert the quantity of raw materials to the desired measurement units using the ‘quantityConverter‘function, considering the inventory, measurement, and reference measurement data.
- Return the raw material data where the quantity is not equal to zero.

Algorithm Pseudo code for raw Material Quantity Identifier Function

Require:

dum: Input data for raw material quantity identification

model: Model for prediction

Ensure:

rawMaterial: Identified raw material quantities

1. function RAW MATERIAL QUANTITY IDENTIFIER (*dum*, *model*)

2:*ar* ←Read CSV file "allRecipe.csv"

3. *ar* ←Sort *ar* by ”Ingredient Name”
4.*vm* ← Read CS file”vMeasurement.csv”←
5.*inventory* Read CSV file ”inventory.csv ”
6. *rb vm*
7.*dummy* ← *dum*
8.*dummy* ← Call preprocessModule1 function with *dummy* as input
9. *dummy* ← Call preprocessSTL function with *dummy* as input
10. **for** *i* in *dummy* index **do**
11.index numorder ← Call numOrderPredictor function with *dummy* atand model as inputs
12. Call quantityCalculator function with *dummy* at index *i*, *numOrder*, *inventory*, and ar as inputs
13. end for
14. *rawaterial* Call quantityConverter function with *inventory*, *vm*,*rb* as inputs
15. **return** *rawMaterial*[*rawMaterial*[”*Quantity*”] = 0]
16. **end function**

6. DISCUSSION

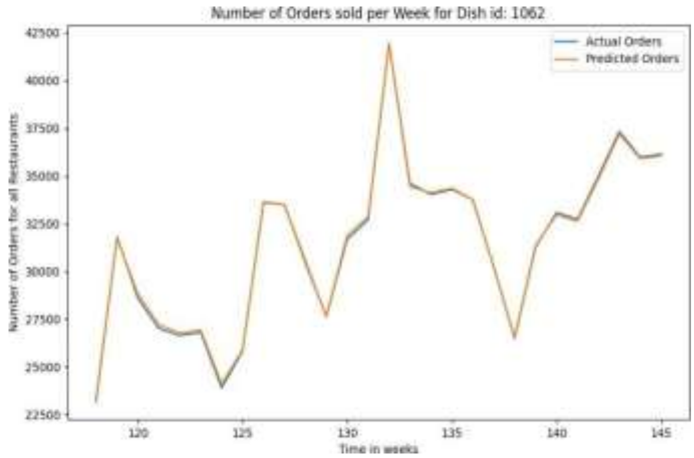
In Result 6.1.1, the Gradient Boosting Regressor model’s performance is assessed on historical sales data with Seasonal, Trend, and Residual components and fine-tuned hyperparameters. The evaluation shows an improved accuracy of 99.85%. Figure 6.12 presents a graphical representation of weekly orders for Dish Id 1062, highlighting the model’s ability to accurately capture sales trends.

Figure 6.1.1: The Evaluation Metric Values Using Gradient Boosting Regressor with STL

```
modelSummary(getModel('gradient_boosting'), X_test, Y_test)

Model :  GradientBoostingRegressor(max_depth=5, min_samples_leaf=5)
MAE :  8.420669381541527
MSE : 187.91212655805
RMSE : 13.708104411553409
r2 score : 0.9985973970846955
Accuaracy : 99.85973970846955 %
```

Figure 6.1.2: Graphical Representation of Actual and Predicted Values for Number of Orders per Week Using Gradient Boosting with STL



6.1 HIST GRADIENT BOOSTING WITH STL

In Result 6.2, the Hist Gradient Boosting Regressor model is evaluated on historical sales data with Seasonal, Trend, and Residual components and fine- tuned hyperparameters. The evaluation shows a significant improvement in accuracy (97.04%) and Figure 5.15 visualizes the weekly orders for Dish Id 1062, highlighting the model’s accurate sales predictions.

```
modelSummary(getModel('hist_gradient_boosting'), X_test, Y_test)
```

```
Model :  HistGradientBoostingRegressor(max_depth=5, min_samples_leaf=5)
MAE :  10.584536878165144
MSE : 3964.0180774139108
RMSE : 62.96044851661963
r2 score : 0.9704120036660719
Accuaracy : 97.0412003666072 %
```

Figure 6.2.1: The Evaluation Metric Values Using Hist Gradient Boosting Regressor

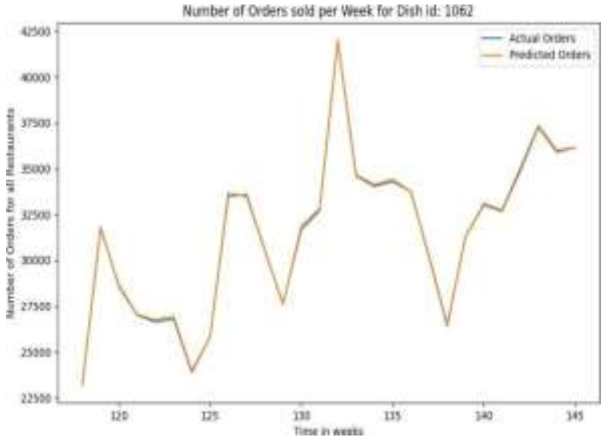


Figure 6.2.2: Graphical Representation of Actual and Predicted Values for Number of Orders per Week Using Hist Gradient Boosting

6.1 RANDOM FOREST WITH STL

In Result 6.31, the Random Forest Regressor model demonstrates an accuracy improvement of 96.48% on historical sales data with STL. The graphical visualization showcases its ability to predict sales dynamics accurately.

```
modelSummary(getModel('random_forest'), X_test, Y_test)
```

```
Model :  RandomForestRegressor(max_depth=5, min_samples_leaf=5)
MAE :  47.9952896204002
MSE : 4712.674016612653
RMSE : 68.64891853927965
r2 score : 0.9648239289520341
Accuaracy : 96.4823928952034 %
```

Figure 6.3.1 The Evaluation Metric Values Using STL and Random Forest Regressor

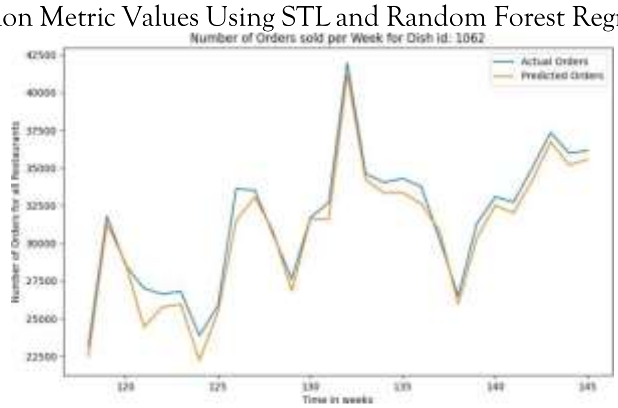


Figure 6.3.2: Graphical Representation of Actual and Predicted Values for Number of Orders per Week Using STL and Random Forest

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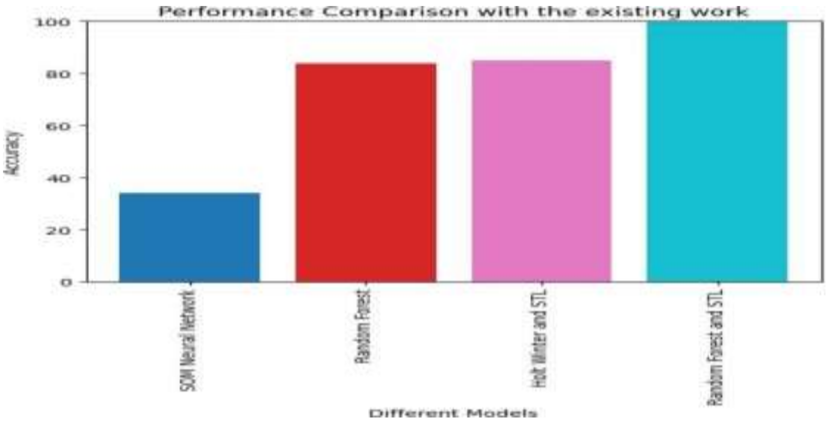
6.4. INSIGHTS FROM PREVIOUS STUDIES AND OUR APPROACH

Figure: 6.4.1 Comparison of Existing Work and Proposed Results From

TITLE	MODEL	MAE	MSE	RMSE	R2 SCORE	ACCURACY
Machine Learning-Based Food Price Analysis [11]	SOM Neural Network	-	-	-	0.34	34.0 %
Demand Forecasting of a Multinational Retail Company Using Deep learning Framework [8]	Light GBM	2125.28	-	4436	-	-
Heterogeneity in feature importance and prediction performance for sales at the market and store...	Random Forest	1.00E+05	4.90E+10	2.10E+05	0.84	84.0 %
Enhanced Demand Forecasting System For Food and Raw Materials Using Ensemble Learning [6]	Ensemble Technique	0.4 - 0.7	-	-	-	-
Time Series Analysis for Supply Chain Planning in Restaurants [2]	Holt Winter and STL	-	-	1989.9007	0.85	85 %
Predictive Analysis for Demand Planning of Raw materials in Restaurants [Proposed Work]	Gradient Boosting and STL	8.42	187.91	13.70	0.9985	99.85 %

The above figure 6.4.1, we can gather the following conclusions:
The “Machine Learning-Based Food Price Analysis ” study did not provide specific metrics (MAE, MSE, RMSE) but achieved an R2 score of 0.340 and an accuracy of 34.0%. The “Demand Forecasting of a Multinational Retail Company Using Deep Learning Framework ” utilized the Light GBM model and achieved an MAE of 2125.28, an RMSE of 4436, but did not provide values for MSE, R2 score, or accuracy.
The “Heterogeneity in feature importance and prediction performance for sales at the market and store levels: the case of branded yogurt products in Quebec ” study used the Random Forest model and obtained an MAE of 1.00E+05, an MSE of 4.90E+10, an RMSE of 2.10E+05, an R2 score of 0.840, and an accuracy of 84.0%. The “Enhanced Demand Forecasting System For Food and Raw Materials Using Ensemble Learning ” study employed an ensemble technique for demand forecasting and the MAE value lies between 04 to 07, and did not provide Other metrics for evaluation The “Time Series Analysis for Supply Chain Planning in Restaurants ”: The model used is Holt winter and STL algorithm and it achieved an RMSE of 1989.9007, an R2 SCORE of 0.85, and an accuracy of 85%. The “Predictive Analysis for Demand Planning of Raw materials in Restaurants [Proposed Work]” used the Gradient Boosting model with the STL algorithm and achieved an MAE of 8.42, an MSE of 187.91, an RMSE of 13.70, an R2 score of 0.9985, and an accuracy of 99.85%.



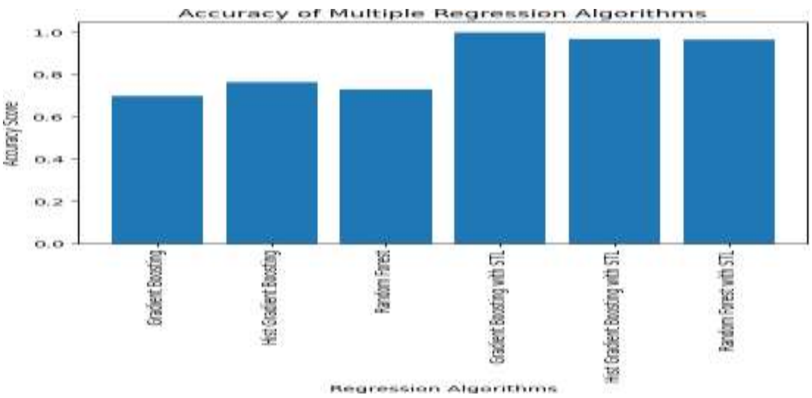


Figure 6.4.1: Comparative Analysis of Previous Work with Proposed Work

Through the implementation of the STL algorithm and Gradient Boosting Regressor, our sales forecasting system has significantly improved in accuracy. Compared to existing works, our model achieves the highest accuracy, showcasing the effectiveness of incorporating STL. This combination captures seasonality and trends, providing valuable insights. Figure 5.20 illustrates the accuracy of the top 3 fast-moving dishes, indicating their popularity.

Comparative Analysis of Multiple Regression Algorithms for Accuracy Classification:

From the figure 6.4.1 the accuracy scores of various Regression models with and without using the STL components can be seen. Based on the accuracy scores of the 6 different models, Gradient Boosting (70.45%), Gradient Boosting with STL (99.85%), Hist Gradient Boosting (76.40 %), Hist Gradient Boosting with STL (97.04%), Random Forest (73.06%) and Random.

Forest with STL (96.48%), it is evident that the Gradient Boosting with STL component archived the highest accuracy among them. With an accuracy of 99.85%, the Gradient Boosting Regressor outperformed the other models in accurately predicting the class of the crops. Overall, the Gradient Boosting Regressor with STL algorithm shows promising performance in the forecasting, with relatively low error and a good fit to the training data. The STL algorithm successfully captures the underlying Seasonal, Trend and the Residual obtained from it and these values are all used to train the model and predict the sales forecasting tasks.

CONCLUSION

In this implementation work is mainly focused on sales prediction is performed on historical sales data using three regression models, both with and without the use of the STL algorithm. The evaluation of model performance is based on various metrics. The conclusions obtained from the implemented work indicate that the Gradient

Boosting regressor with the STL algorithm achieves the highest accuracy of 99.85%.

Based on the results, the Gradient Boosting model demonstrates superior accuracy in predicting sales compared to the Gradient Boosting and Random Forest models using historical sales data. As a result, this model is being utilized in the development of a raw material quantity prediction system for restaurants. The aim of this system is to forecast the required raw materials for efficient restaurant operations.

In the future, further advancements can be made to enhance the efficiency of the sales prediction system. One potential approach is to reduce the computation time by implementing TensorFlow, a popular machine learning framework known for its computational efficiency. By incorporating TensorFlow into the Gradient Boosting model with the STL algorithm, the overall prediction process can be accelerated, allowing for faster and more real-time predictions. This improvement would greatly benefit the development of the raw material quantity prediction system for restaurants, enabling more efficient operations and better resource management.

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