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*RESEARCH ARTICLE - MANAGEMENT*

# Food Sales Prediction Using MLP, RANSAC, and Bagging

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**Abstract**

Many datasets about food sales, these datasets contain different features depending on the data present. Also, the way these features are correlated differs from one dataset to another. The researchers used several artificial intelligence algorithms and applied them to food sales datasets. Despite the necessary pre-processing and cleaning of the datasets, some of the algorithms used in these studies did not give the desired results. Therefore, this study proposes a model based on two objectives, the first objective is to make a comparison between three different food sales datasets. the second objective is to apply three various Artificial Intelligence algorithms to obtain the best algorithm that gives the highest prediction accuracy with the specified dataset. Some studies used classical machine learning algorithms, some used deep learning algorithms, and others used ensemble techniques. To achieve a comprehensive comparison, one algorithm was chosen from each of the above. To measure the correlation between features used a tool available from the Seaborn library in Python. This tool is called a "Heatmap". For comparison, used three datasets on which we performed the necessary preprocessing operations, after applying three algorithms, these algorithms are Multilayer perceptron, RANSAC, and Bagging regression. Then used several metrics to measure the accuracy of the algorithm applied to the specified dataset. Finally, identified the best dataset that gives excellent prediction results with these algorithms. The results showed that the first dataset gave ideal accuracy by using the Bagging regression algorithm, unlike the second dataset with medium correlation and the third dataset with weak correlation. This study lays the foundation for subsequent studies and saves them time in terms of choosing the datasets.

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**Keywords**: Machine Learning Algorithms; Seaborn Library; Multilayer Perceptron; RANSAC; Bagging Regression.

## 1. Introduction

Many companies that work in the field of food sales seek to achieve large profits without losing products as a result of their spoilage due to exceeding their expiration date [1]. Here it is the responsibility of the researchers to provide the best forecasting methods to provide these companies with a plan that shows them their actual need for the products that they will sell. Forecasting is important for several processes and decisions that increase the profit of companies [2]. The way the attributes are correlated in the datasets is one of the important things that reflect tremendously on the results of the applied artificial intelligence algorithms. Artificial intelligence algorithms will be used to obtain the necessary predictions. Machine learning is a branch of artificial intelligence that relies on experience to learn and perform the necessary tasks without human intervention [3]. To provide a comprehensive understanding for subsequent researchers and target companies; three different datasets with varying correlations between their features are studied and conduct the necessary processing operations on them. Then applied three important algorithms to it, these algorithms are Multilayer perceptron, RANSAC, and Bagging regression. Finally, using the results obtained from these algorithms, we will get the dataset that achieved the best result with these algorithms. Since most of the forecasting methods used aim to improve sales, they may fall into problems of not selecting the correct variables that affect sales as well as global change factors. Thus, this study will provide an important foundation for many researchers and many future works to adopt them when choosing the datasets used, as well as the required artificial intelligence techniques. Food sales researchers used many datasets. After they did a lot of processing operations on those datasets, they did not get the perfect results because of the mechanism of correlation between features. According to the study [4], researchers put a comparison for sales predictions with nine Machine Learning algorithms and three classical methods. They used typical horticultural retail data with important features, regarding size and seasonality. They adopted a predictive model affected by the influencing factors to simulate a realistic system that takes into account the constantly changing factors to deal with them appropriately. They found that machine learning approaches especially of the ensemble learner are best. This was evident in the large multi-feature datasets. In addition, they found that the subject is getting wider after adding weather factors or holidays. Finally, they found that Extreme Gradient Boosting (XGBoost) is computationally efficient. In the study of [5], the goal was to use real-world data to find an appropriate model that can predict horizons of at least one week. They used three datasets with over 20 models. They found that "recurrent neural network" (RNN) models are better than other models.

Also, static context injection and using the "Temporal Fusion Transformer" (TFT) model gave good results. When used TFT in one-day forecasting, it gave bad performance compared with the "ridge regression" method using the daily differenced dataset, but when used the ridge

| Nomenclature & Symbols | | | |
|---|---|---|---|
| RMSE | Root Mean Square Error | LGBM | Light Gradient Boosting Machine Learning |
| MSE | Mean Square Error | RANSAC | The Random Sample Consensus |
| ML | Machine Learning | MLP | Multilayer Perceptron |
| MAE | Mean Absolute Error | XGBoost | Extreme Gradient Boosting |
| RRN | Recurrent Neural Network | TFT | Temporal Fusion Transformer |
| SVM | Support Vector Machines | | |

model with current models could not scale to a one-week prediction. While the RNN models do well to provide perfect results in either one-day or one-week forecasting. In the article [6], they studied machine learning algorithms to perform appropriate predictions of products in a grocery retailer. The goal of this is to provide tools necessary to achieve good accuracy prediction results for the grocery sector that allow cutting waste and increasing profits. Performance measures denote that the "Gradient Boosting" algorithm is the best method to be applied when required time to create the prediction models. The results by using "Root Mean Square Error" (RMSE) show that when using the "Linear Regression method" the result was 11.97 and when using the “Gradient Boosting method”, the RMSE was 9.5, also when using the Neural Network method, the RMSE was 9.82, and “Support Vector Machine” didn’t give result although it Still running for 5 hours. From these results, it becomes clear that Gradient Boosting is the best method with the lowest RMSE. Also, we can see in [7], that the researchers suggested a new method that predicts the sales of items in restaurants. They presented two Bayesian additive methods. The first model depends on normal distribution for future sales, while the other one uses negative binomial distribution. "shrinkage priors" are used by Both approaches for learning important multiple seasonal effects. The direct human interpretation of the features learned by the models can help users develop trust and confidence in the methodology. They compared the performance of their approach with other well-established forecasting methods. They used two datasets from POS systems in a restaurant and a staff canteen. The results proved that their approach provided the most perfect point predictions overall. The prediction by using their model with the negative binomial distribution was more accurate than the others obtained by the other models.

According to [8], This paper aimed to create a model that can predict the sales of groceries. The researchers used the LGBM algorithm, and they divided the data into multiple periods by using time series. By using the MSE measurement method, their model gave accuracy (0.350). However, the problem of using this model requires a very large data set for training. So, in the case of using fewer data, the author hypothesized that two problems occur: the first one is, that the training error is smaller than the test error and the second one is, that the training error and the test error are similar, but the test error is very large. The occurrence of the first problem makes the model over-fitted, which means not enough samples. To solve such problems, dimensionality reduction can be used. The occurrence of the second problem means that the model does not have enough complexity (simple model). To solve this problem must use more complex models, such as Neural Networks or models with hidden variables or ensemble-like methods, using Random Forest, or other models.

Above, some studies related to this study are listed and show that most researchers used one dataset and a few algorithms. This study will discuss the three datasets and how to use them in the proposed model. It will also explain why the three algorithms are used and give a theoretical overview of them. After that, the obtained results are presented using appropriate accuracy metrics.

## 2. Materials and Method

This study applied three different datasets in the degree of correlation between their features under three different algorithms. This step aims to prove that the correlation between the features of food sales datasets has a significant impact on the prediction results extracted from artificial intelligence algorithms. To make the comparison between the used datasets efficient, three datasets with clear differences were selected in terms of the data used for food sales. These datasets were presented to the available algorithms to show the significant difference in the accuracy obtained from these algorithms in forecasting food sales. By quickly explaining the most important steps on which this study will be based. In the beginning, Pre-processing of the used data sets was performed. After this step, clean and suitable datasets were obtained for use. To find out the way the features are correlated, the Correlation Matrix was relied upon, which in turn gave the degree of Correlation. Later, the three algorithms are applied (Multilayer perceptron, RANSAC, and Bagging regression). Finally, used different metrics such as Root Mean Square Error (RMSE) and Mean Square Error (MSE) to know the accuracy of each algorithm applied to each dataset separately. To get the perfect results, which will give us full knowledge regarding the impact of the correlation between food sales datasets on the prediction results. As we noted previously. Three datasets were used in this study. These datasets differ in the degree of correlation between their attributes. Pre-processing and cleaning were done on these datasets, and it was well prepared for applying the specified algorithms to them.

### 2.1. Datasets

The first dataset contains 15 attributes and 1000 objects sourced from “publicly available Alibaba's Tianchi platform data”, as shown in Table 1.

Table 1. The first dataset

| Invoice ID | Branch | City | Customer type | Gender | Product line | Unit price | Quantity | Tax 5% | Date | Time | Cost | gross income | Rating | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 765-26-6951 | A | Yangon | Normal | Male | Candy | 72.61 | 6 | 21.783 | 1/1/2019 | 10:39 | 435.66 | 21.783 | 6.9 | 457.443 |
| 530-90-9855 | A | Yangon | Member | Male | Drinks | 47.59 | 8 | 19.036 | 1/1/2019 | 14:47 | 380.72 | 19.036 | 5.7 | 399.756 |
| 891-01-7034 | B | Mandalay | Normal | Female | Fruits | 74.71 | 6 | 22.413 | 1/1/2019 | 19:07 | 448.26 | 22.413 | 6.7 | 470.673 |
| 493-65-6248 | C | Naypyitaw | Member | Female | Candy | 36.98 | 10 | 18.49 | 1/1/2019 | 19:48 | 369.8 | 18.49 | 7 | 388.29 |

| | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 556-97-7101 | C | Naypyitaw | Normal | Female | Fruits | 63.22 | 2 | 6.322 | 1/1/2019 | 15:51 | 126.44 | 6.322 | 8.5 | 132.762 |
| 133-14-7229 | C | Naypyitaw | Normal | Male | Dairy products | 62.87 | 2 | 6.287 | 1/1/2019 | 11:43 | 125.74 | 6.287 | 5 | 132.027 |
| 651-88-7328 | A | Yangon | Normal | Female | Biscuit | 65.74 | 9 | 29.583 | 1/1/2019 | 13:55 | 591.66 | 29.583 | 7.7 | 621.243 |
| 182-52-7000 | A | Yangon | Member | Female | Candy | 27.04 | 4 | 5.408 | 1/1/2019 | 20:26 | 108.16 | 5.408 | 6.9 | 113.568 |
| 416-17-9926 | A | Yangon | Member | Female | Fruits | 74.22 | 10 | 37.11 | 1/1/2019 | 14:42 | 742.2 | 37.11 | 4.3 | 779.31 |

To know the degree of correlation between features in this dataset. Heat map tool had been used; this tool is available from the Seaborn library in the Python language. A heatmap is a correlation matrix that gives us the correlation between the dataset's features and determines if that correlation is positive or negative. As shown in Fig. 1, the white color in this matrix indicates the weakness of the correlation of the element with the corresponding element, and on the contrary, whenever the color is tilted to dark, this indicates a strong correlation. From this matrix, we conclude that this dataset has a good correlation between its features.

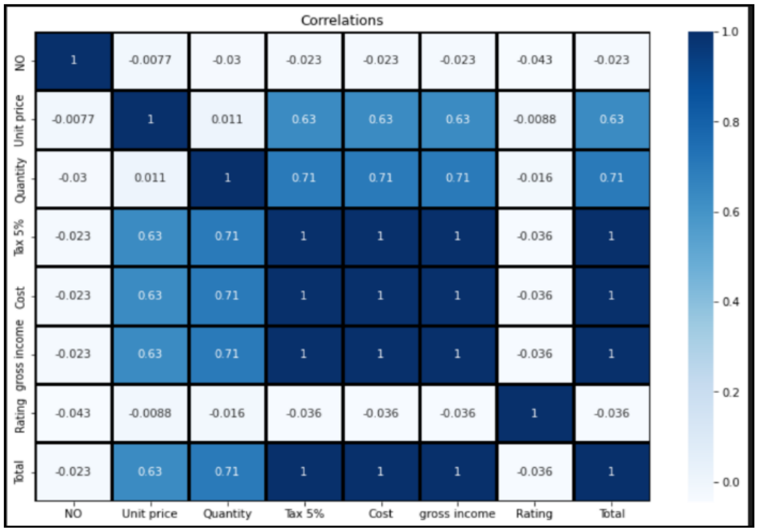


Fig. 1. The correlation between features of the first dataset

The second dataset consists of 12 attributes and 8523 objects including sales data from ten stores in different cities, this dataset is sourced from Kaggle, Table 2.

Table 2. The second dataset

| Item Id | Item Weight | Fat Content | Item Visibility | Item Type | Retail Price | Store Id | Store Establishment Year | Store Size | Store Location | Store Type | Total Sales |
|---|---|---|---|---|---|---|---|---|---|---|---|
| FDA15 | 9.3 | Low Fat | 0.016047 | Dairy | 249.8092 | OUT049 | 1999 | Medium | Tier 1 | Supermarket Type1 | 3735.138 |
| DRC01 | 5.92 | Regular | 0.019278 | Soft Drinks | 48.2692 | OUT018 | 2009 | Medium | Tier 3 | Supermarket Type2 | 443.4228 |
| FDN15 | 17.5 | Low Fat | 0.01676 | Meat | 141.618 | OUT049 | 1999 | Medium | Tier 1 | Supermarket Type1 | 2097.27 |
| FDX07 | 19.2 | Regular | 0 | Fruits and Vegetables | 182.095 | OUT010 | 1998 | | Tier 3 | Grocery Store | 732.38 |
| NCD19 | 8.93 | Low Fat | 0 | Household | 53.8614 | OUT013 | 1987 | High | Tier 3 | Supermarket Type1 | 994.7052 |
| FDP36 | 10.395 | Regular | 0 | Baking Goods | 51.4008 | OUT018 | 2009 | Medium | Tier 3 | Supermarket Type2 | 556.6088 |
| FDO10 | 13.65 | Regular | 0.012741 | Snack Foods | 57.6588 | OUT013 | 1987 | High | Tier 3 | Supermarket Type1 | 343.5528 |
| FDP10 | | Low Fat | 0.12747 | Snack Foods | 107.7622 | OUT027 | 1985 | Medium | Tier 3 | Supermarket Type3 | 4022.764 |
| FDH17 | 16.2 | Regular | 0.016687 | Frozen Foods | 96.9726 | OUT045 | 2002 | | Tier 2 | Supermarket Type1 | 1076.599 |

By using the Heatmap tool, the degree of correlation between features in this dataset was determined. As can be seen in Fig. 2, the common color is close to white (the degree of correlation tends to be zero or negative), which indicates a weak correlation between features in the second dataset, or it may be a medium correlation in some cases.

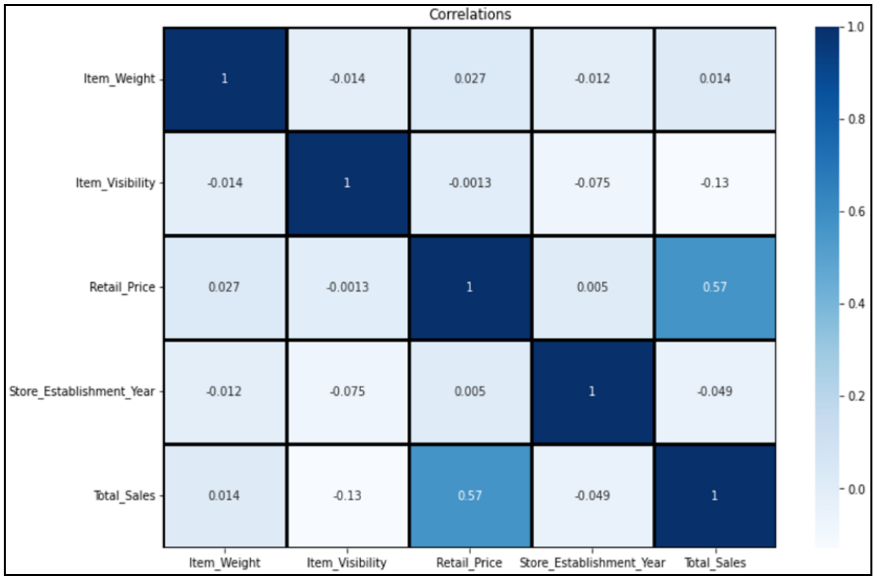


Fig. 2. The correlation between features of the second dataset

The third dataset consists of 10 attributes and 9995 objects including sales data from different stores in several cities, and each store has different categories and multiple subcategories, this dataset is sourced from Kaggle, Table 3.

Table 3. The third dataset

| Order ID | Customer Name | Category | Sub Category | City | Order Date | Region | Quantity | Discount | Profit |
|---|---|---|---|---|---|---|---|---|---|
| OD1 | Harish | Oil & Masala | Masalas | Vellore | 11/8/2017 | North | 1254 | 0.12 | 401.28 |
| OD2 | Sudha | Beverages | Health Drinks | Krishnagiri | 11/8/2017 | South | 749 | 0.18 | 149.8 |
| OD3 | Hussain | Food Grains | Atta & Flour | Perambalur | 6/12/2017 | West | 2360 | 0.21 | 165.2 |
| OD4 | Jackson | Fruits & Veggies | Fresh Vegetables | Dharmapuri | 10/11/2016 | South | 896 | 0.25 | 89.6 |
| OD5 | Ridhesh | Food Grains | Organic Staples | Ooty | 10/11/2016 | South | 2355 | 0.26 | 918.45 |
| OD6 | Adavan | Food Grains | Organic Staples | Dharmapuri | 6/9/2015 | West | 2305 | 0.26 | 322.7 |
| OD7 | Jonas | Fruits & Veggies | Fresh Vegetables | Trichy | 6/9/2015 | West | 826 | 0.33 | 346.92 |
| OD8 | Hafiz | Fruits & Veggies | Fresh Fruits | Ramanadhapuram | 6/9/2015 | West | 1847 | 0.32 | 147.76 |
| OD9 | Hafiz | Bakery | Biscuits | Tirunelveli | 6/9/2015 | West | 791 | 0.23 | 181.93 |

Also, Using the Heatmap tool, the degree of correlation between features in the third dataset was determined. As note in Fig. 3, the common color is close to white (the degree of correlation tends to be zero or negative), which indicates a very weak correlation between features in the third dataset.

### 2.2. Pre-processing

In this study Perform the appropriate processing operations on each dataset according to its data. The datasets were inspected and the missing values were known and they were compensated in several ways, as well as the repeated values were calculated and their subject was taken into consideration, and the errors that occurred as a result of the entry were searched and corrected. After these stressful operations, an inspection was conducted on each dataset separately to see the extent of its readiness for later use with the specified algorithms.

### 2.3. Algorithms used

In this study used three algorithms are used (Multilayer Perceptron, Bagging Regressor, and RANSAC Regression). These algorithms were chosen precisely because each of them belongs to a specific technology, as the RANSAC algorithm is one of the machine learning algorithms, the Multilayer Perceptron algorithm is one of the deep learning algorithms, and the Bagging Regressor algorithm belongs to the machine learning algorithms that depend on the ensemble learning technique.

#### 2.3.1. Multilayer perceptron (MLP)

Multilayer Perceptron is a popular type of neural network that is fully connected between inputs and output [9]. A Multilayer Perceptron consists of input and output layers, with one or multiple layers called hidden layers [10]. The layer is a row of neurons [11]. MLP algorithm works with a function called an activation function as shown in Fig. 4. This activation function works to determine whether the neuron should be activated or not, and thus it decides whether the input of the neuron is important or not, using certain mathematical operations [12]. Multilayer Perceptron is a type of feedforward algorithm because it used initial weights combined with input in a weighted sum and inserted into the activation function

[13]. Each layer makes a computation and then feeds the result to the next one. This operation continues through the all hidden layers to reach the output layer. MLP couldn't learn the weights that give the best cost function If it made sums to the weighted in every neuron, and gave the final result to the output layer only. Doing just one iteration is useless for actual learning. To solve this problem a Backpropagation was used [14]. Multilayer Perceptron uses Backpropagation as a learning mechanism for adjusting the weights in the network iteratively, this is based on the goal of giving a minimum-cost function [15]. Data prepared for training. All data were converted into numerical data before being entered into the neural network. Predictions are performed on test data to know the skill of the algorithm on unseen data.

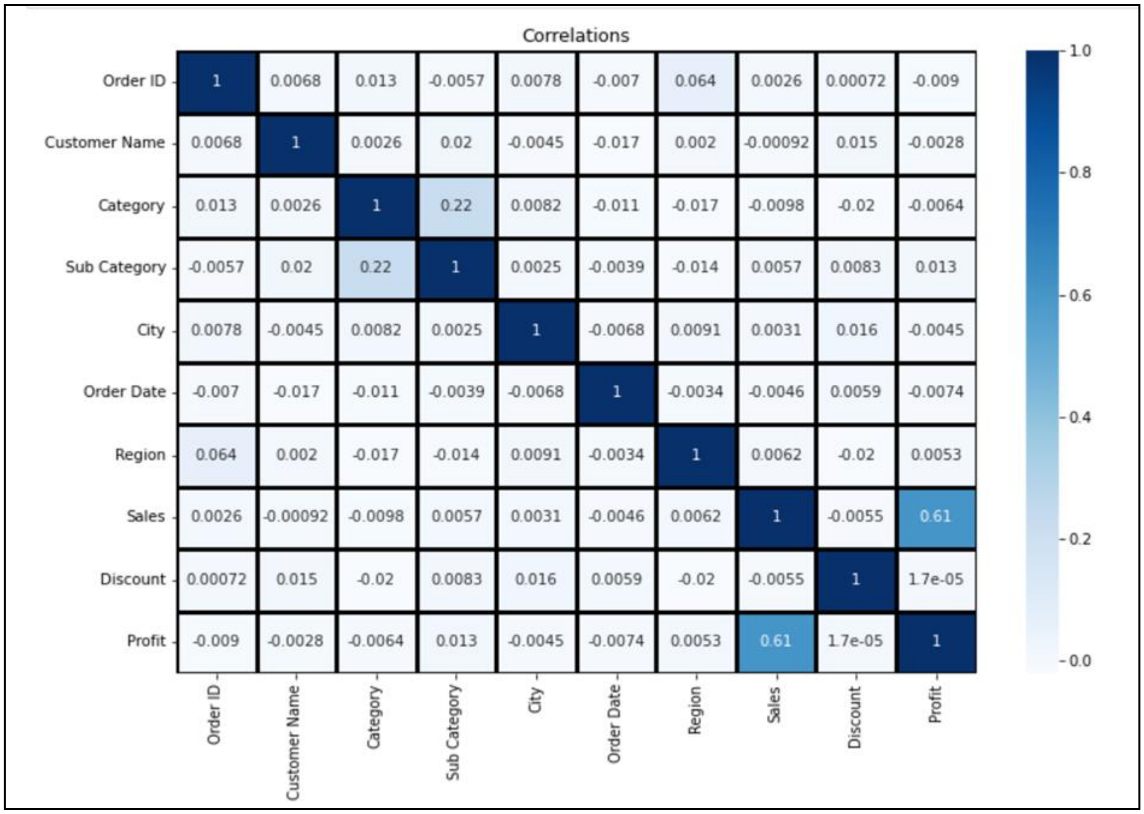


Fig. 3. The correlation between features of the third dataset

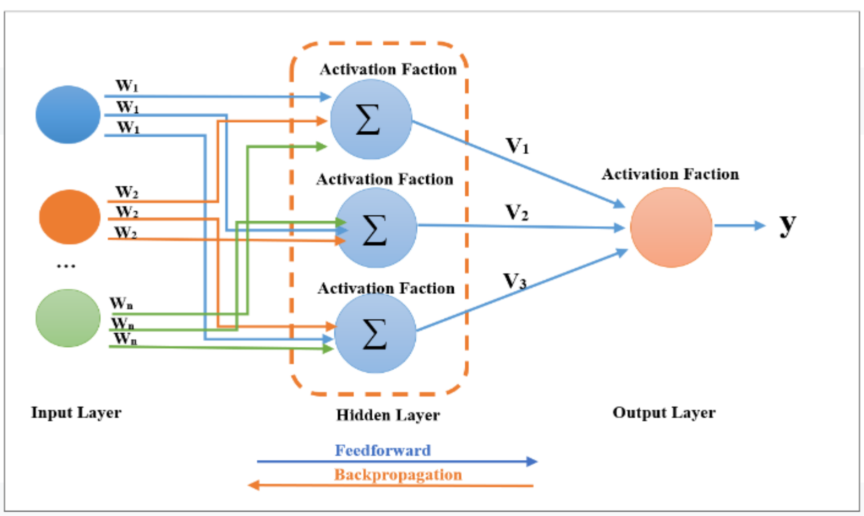


Fig. 4. Multilayer perceptron

2.3.2. Bagging regressor

Bagging is a technique that depends on ensemble learning, also called bootstrap aggregation, which improves the efficiency and performance of machine learning algorithms [16]. The bagging algorithm is suggested by Leo Breiman in1996 [17] with three basic steps:

- Bootstrapping: Bagging worked by taking different subsets randomly from the training dataset with replacement. and fits the regressor to each subset [18].
- Parallel training: The samples created by bootstrapping trained independently and parallelly with each other by using base learners or weak learners [19].

- Aggregation: Depending on the study task (regression) compute an accurate estimate by using an average of all the outputs generated by the prediction of the individual classifiers.

From the above, we conclude that Bagging reduces the variance of a prediction model and is used to deal with bias-variance trade-offs [20]. It is used with regression and classification to avoid overfitting data [21]. Bagging gives a better prediction by combining multiple predictions by using a majority vote or by making aggregation to the predictions [22]. Many ensemble techniques depend on the bagging technique [23].

2.3.3. RANSAC regression

Random sample consensus, or as called RANSAC, is an iterative supervised machine learning algorithm that estimates a mathematical model by cleaning outliers from the data set [24]. This algorithm identifies the outliers and estimates the perfect model [25]. RANSAC was suggested by Fischler and Bolles [26]. In this study, Random sample consensus had been used for regression because It handles outliers well. A subset of data samples is selected randomly and then used for estimating the parameters of the model [27]. In the next step, RANSAC worked by finding samples that fell within the error tolerance range of the model [28]. These samples are a consensus set. So, inliers data are called for the data samples in the consensus, and the rest data are called outliers data [29]. This algorithm trained the model by using inliers if it has a high count. By repeating these steps for multiple iterations, RANSAC gave the model that had the smallest error [30].

## 3. Results and Discussion

The proposed model in this study dealt with three important algorithms (RANSAC, Multilayer Perceptron, and Bagging Regressor), where the first belongs to the classical machine learning algorithms, the second belongs to the deep learning algorithms, and the last one uses ensemble learning technique. Also, this study establishes a clear comparison between three different datasets in terms of the correlation between features. Where used Root Mean Square Error (RMSE) and Mean Square Error (MSE) to measure the results of the applied algorithms. According to Tables 4, 5, and 6, the results clearly showed that the Bagging Regressor Algorithm is the best when applied to Dataset (1) and Dataset (2). And the best algorithm applied to dataset (3) is MLP. Also, the first dataset gave ideal and close-to-real results, unlike the second algorithm with medium correlation and the third algorithm with weak correlation. It was evident that the correlation between features does not affect in a small and superficial way, but rather affects very much the results of forecasting in food sales.

Table 4. Results of the three algorithms using the first dataset

| Algorithm | RMSE | MSE | Accuracy |
|---|---|---|---|
| Multilayer perceptron | 1.6656 | 2.7744 | 65.19 |
| Bagging Regressor | 0.1291 | 0.1558 | 98.38 |
| RANSAC | 1.1622 | 1.3509 | 83.05 |

Table 5. Results of the three algorithms using the second dataset

| Algorithm | RMSE | MSE | Accuracy |
|---|---|---|---|
| Multilayer perceptron | 1248.7753 | 1559439.8841 | 46.72 |
| Bagging Regressor | 1199.2203 | 1438129.3822 | 50.86 |
| RANSAC | 1498.8840 | 2246653.2482 | 23.24 |

Table 6. Results of the three algorithms using the third dataset

| Algorithm | RMSE | MSE | Accuracy |
|---|---|---|---|
| Multilayer perceptron | 469.1397 | 220092.1169 | 33.91 |
| Bagging Regressor | 477.2453 | 42186.1391 | 31.61 |
| RANSAC | 549.0156 | 301418.1745 | 9.49 |

## 4. Conclusions

This study focused on using three different and important algorithms and discusses the degree of correlation between the features of the dataset used in the model because the researcher noticed a significant reflection on the results of prediction in food sales when the degree of correlation decreases. Where the used algorithms gave matching results sometimes with 98% between the real values and the values resulting from the model prediction test when the study used the perfect correlation dataset, and quite the opposite when the algorithms dealt with a dataset with a weak correlation between its features, these algorithms gave very poor results. This study lays the foundation for subsequent studies and saves them time in terms of choosing the dataset. It stresses the hands of researchers in the field of food sales by choosing datasets with high correlations between their features because it reflects on the results achieved largely.

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