Open Journal of Business Entrepreneurship and Marketing
"Volume 1, Issue 2, Year 2025"
website: https://www.c5k.com

Research Article

Enhancing Digital Marketing Strategies in the Food Delivery Business through AI-Driven Ensemble Machine Learning Techniques

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ARTICLE INFO

Article history:
10 Sep 2025 (Received)
17 Oct 2025 (Accepted)
25 Oct 2025 (Published Online)

Keywords:
Digital marketing, Food delivery business, Machine learning, Artificial intelligence, Accuracy.

ABSTRACT

The digital marketing for food delivery business is the focus of this study, which investigates the use of ensemble machine learning (ML) approaches. The study's overarching goal is to pave the way for artificial intelligence (AI)-based recommendations by analyzing consumer data with the hope of discovering consumer preferences and predicting behavior. In order to improve the accuracy of predictions, the ensemble method combines the results of decision trees, naïve Bayes, and k-nearest neighbor algorithms. Both the decision tree and nearest neighbor algorithms were able to obtain perfect predictions with zero error and 100% accuracy, as seen in the accuracy matrix charts. On the other hand, the naïve Bayes method was able to accurately identify labels in all classes with a minimal error rate of 0.028 and a high accuracy of 97.175%. With a success rate of over 90%, the majority vote method allows models to be integrated using less than 50% of the randomized data, which minimizes customer dissatisfaction. When taken as a whole, these ML algorithms greatly improve the efficiency and efficacy of food delivery business digital marketing campaigns by cutting down on wasted time and money.

DOI: https://doi.org/10.63471/ojbem_25002

1. Introduction

New technology, more corporate consolidation, and fiercer price competition are the primary forces causing a sea change in the retail industry [1-3]. Retailers need to proactively address a number of critical trends and issues to stay competitive. Consumers today engage across several channels, including online marketplaces, mobile apps, and social media, necessitating seamless integration across all customer touchpoints. Consequently, an omnichannel approach is being prioritized [4]. Customization is also important; using data and analytics to provide personalized suggestions and special deals increases consumer happiness and devotion[5]. Also, by making things easy for customers and encouraging their participation, an outstanding customer experience can set you apart from the competition [6]. Further, when bigger companies

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Cite: Adib Hossain, Afia Fairooz Tasnim, Fariha Akhter, Mst Masuma Akter Semi, Rayhan Khan, Rukshanda Rahman, Sumaiya Yeasmin, Anseena Anees Sabeena (2025). Enhancing Digital Marketing Strategies in the Food Delivery Business through AI-Driven Ensemble Machine Learning Techniques. Open Journal of Business Entrepreneurship and Marketing, 1(2), pp 1-XY.

buy up smaller ones in the retail distribution industry, the competitive landscape is changing, therefore it's more important than ever for retailers to be flexible and quick to adjust [7].

The proliferation of digital technology and on-demand services has propelled the food delivery industry to unprecedented heights of expansion. According to Dey, et al. [8] , food delivery services see an increase in sales and retail enterprises use them to reach a wider audience. The business is clearly growing; according to Felix Martinez [9], worldwide sales of food ordered online will reach $466 billion in 2027, up from $296 billion in 2021, a growth of about 60%. In an effort to reduce the likelihood of contracting the COVID-19 virus, an increasing number of restaurants and customers have begun to place their orders online [10]. The rising popularity of food delivery websites is a result of the convergence of technical development and changing consumer habits around the world.

Staying competitive through efficient digital advertising methods is a challenge for food delivery firms, even while they are seeing fast development. The importance of digital advertising in reaching potential clients has been emphasized by Lee and Cho [11]. To stand out in a competitive market, focused campaigns are necessary [12]. Television, radio, and print ads are becoming less effective [13], thus companies are turning to digital platforms to reach their customers. Not only can digital advertising give immediate evidence of campaign success, but it also enables accurate targeting based on preferences and geography. According to Zhu and Gao [2], this change highlights how crucial digital marketing is for retail companies who want to engage and impress their consumers.

Many different strategies have been developed within the realm of traditional digital marketing in an effort to increase brand awareness and consumer engagement. This include tactics like SEO [14], PPC [15], and email marketing. Alves, et al. [16], Çiçek, et al. [17] and Rodrigues and Brandão [5] all agree that social media marketing, banner ads, and content marketing are crucial parts of this strategy. Manual processes for measuring and optimizing campaigns are often a part of these strategies, but they are helpful in creating consumer relationships and enhancing online visibility. Businesses may find it tough to attain ideal results due to the time and resources required for this.

An abundance of new opportunities have opened up for digital marketers with the rise of AI and ML. From creating targeted advertising to improving performance and tracking results, AI-driven online advertising automates many parts of campaign administration. Marketers may improve their tactics more efficiently with the help of AI, which uses algorithms to quickly analyze data and make smart judgments. Personalized content and tailored adverts not only increase the efficacy of marketing initiatives, but also save the time and money needed for conventional tactics [18-21].

There is a growing reliance on AI in the food delivery industry. With more and more people using smartphones and online meal ordering services, the food delivery app industry is booming [22]. Artificial intelligence (AI) is being used by businesses in this sector to improve customer service and streamline processes in order to stay competitive. Examples of AI in action include the following: assessing consumer behavior [23], spotting trends [24], and automating processes like content optimization (Cho et al., 2022) and consumer segmentation. Companies can better adapt their strategies and overall performance with the help of these technologies, especially in a market that is very competitive.

Although AI has great promise, it will necessitate a lot of time, money, and technical know-how to put into digital marketing. Software engineers and application developers with extensive knowledge of AI methodologies—including algorithms, data science, and analytics—are essential for businesses. Investment in suitable tools and technology, as well as the recruitment or retention of competent specialists, are additional requirements for the successful integration of AI solutions. Finding a happy medium between these needs and the demand for creative solutions to keep up with an ever-changing business is the real problem.

Combining artificial intelligence with random theory, this study presents a new method for making suggestions to customers in an effort to make the recommendation process more interesting and useful. The goal of this approach is to find patterns in consumer data that traditional algorithms miss in order to deliver more tailored recommendations by combining AI algorithms with random variables. By providing suggestions that pleasantly surprise and please consumers, we hope to increase user happiness and retention. By combining AI with random theory, this novel strategy has the ability to revolutionize digital marketing for food delivery by producing more engaging and interesting outcomes.

2. Methodology

Along with a simulation method called association rule learning, this study methodology employs a mathematical model to clarify input-output linkages in the context of a meal delivery service. The food delivery service's unique needs provide the basis for this framework's data, and the consumer is given with analytical results driven by AI. The system's learning capabilities are further enhanced by a method that allows customer decisions and comments to be integrated back into the association rule architecture. Figure 1 shows the study framework in detail, showing how it optimizes service delivery using advanced analytical tools.

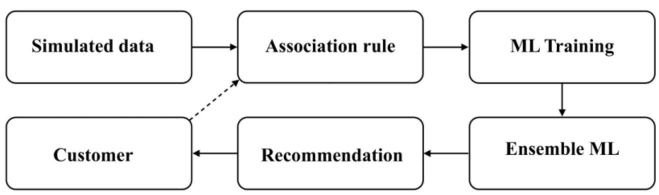

Fig. 1. Research model framework.

A crucial first stage in the AI process loop is creating simulated data. This allows for a controlled setting to build a ground truth for the correctness of the models. Researchers can guarantee that AI systems learn useful traits and produce accurate predictions by creating application-specific datasets. This methodical process allows for the creation of reliable models that can handle real-world situations with more precision. In order to test and validate models before deploying them in real-world applications, simulated data is used as a sandbox.

Establishing relationships between data values is the next critical step after building the simulated dataset. Association rule mining makes this possible by discovering previously unknown associations in massive datasets. Researchers can gain valuable insights and discover rules that control data interactions by examining hidden patterns and connections. In doing so, the interrelationships between data pieces are better understood, which lays the groundwork for developing reliable AI models.

After correlations have been identified, machine learning training is required to instruct AI models in pattern recognition and exploitation. It takes a lot of data and a solid understanding of data science and artificial intelligence concepts to train models for ML, so that they can learn from examples given to them. Artificial intelligence models enhance their accuracy and efficacy through this iterative learning process, which enhances their capacity to forecast results and make well-informed decisions.

Ensemble ML approaches can be used to improve and fine-tune model performance even more. The goal of this strategy is to improve upon the performance of each individual model by integrating their outputs. Ensemble approaches improve forecast accuracy and efficiency by combining a variety of algorithms to better handle complicated problems. Researchers can fine-tune the most successful models for certain applications by training multiple models concurrently and comparing their performance.

Recommendations can be made with more confidence after an ensemble of models has been built. Researchers can offer personalized recommendations for process optimization, product or service recommendations, or strategic guidance by utilizing the insights obtained via association rules and ensemble ML. In order to assist consumers in making decisions that are in line with their requirements and objectives, the recommendation engine converts data patterns into practical insights.

In the end, it's up to the buyer, not the recommendation engine, to decide. It is the responsibility of the consumer to assess the AI system's data-driven recommendations in light of their specific circumstances. Along with the AI system's output, other factors like efficacy, cost, and risk must be taken into account to ascertain the optimal course of action.

2.1. Programming language

When it comes to digital marketing, Mathematica is a sophisticated computer language that works well for developing AI. Mathematica is an AI-centric tool that improves ML algorithms through the use of symbolic computing, multi-threaded processes, and graphics processing unit (GPU) acceleration. With these features, we can optimize our marketing tactics, make real-time adjustments to our campaigns, and anticipate our customers' preferences with remarkable accuracy. By optimizing routing, predicting consumer demand, suggesting menu items, and creating tailored suggestions, Mathematica's advanced capabilities can improve customer happiness and cut costs in the food delivery industry. Focusing on ensemble methods within Mathematica and the Wolfram Language in its Trial Edition 13.0.1, this study investigates the use of AI in digital marketing for the food service industry. The research is carried out using a MacBook Pro equipped with an M1 processor and 8 GB of RAM, showcasing the functionality and advantages of Mathematica in realistic settings.

2.2. Ensemble ML

Using sophisticated AI techniques can greatly improve the efficacy of digital marketing campaigns for meal delivery services. Decision trees, naïve Bayes, and closest neighbors are three of the most well-known methods for assessing consumer data and making behavioral predictions; each of these approaches has its own distinct benefits. Ensemble methods, like as bagging, are extremely helpful for honing these strategies even more. In bagging, various algorithms are trained on separate data subsets and then their predictions are aggregated using a meta-learner. Not only does this method increase the precision of predictions, but it also gives a more complex picture of consumer tastes and habits. By integrating these techniques, companies may enhance the digital campaigns they run and better cater their marketing plans to the demands of their customers.

2.2.1. Decision tree

One effective approach for data classification is the decision tree, which sorts information into different sets according to its attributes [1]. It works by asking a series of binary questions that sequentially divide the data based on different criteria. A tree-like structure is produced, where each step's decisions are represented by internal nodes and the final consequences are represented by leaf nodes. For instance, a decision tree can be used to forecast consumer actions, like determining which consumers are likely to buy from you again or which food items they like. Its ability to identify the most powerful target segments and the platforms and content that resonate with them makes it a priceless asset for customizing marketing tactics. Establishing rules to classify data points according to the results of these binary decisions is the mathematical basis of a decision tree.

$$f(x)=T(x)+U(x)$$

Decision trees are fundamental for classification and regression tasks in programming, and the "Decision Tree" function is a useful tool for producing them. In order to build the tree, this function needs two basic parameters: a set of data and a target variable. Options for the tree's type (classification or regression), maximum depth, and splitting criterion allow users to personalize the tree's appearance and behavior. Objects with methods to analyze and alter the tree are returned by the function upon execution. This object's "visualize" function is one of its most useful features; it shows the user the tree's structure and the reasoning behind the decisions used to forecast the values of the target variables. You can also use the language's built-in performance evaluation features to see how well the decision tree you produced performed.

2.2.2. Naïve Bayes

A statistical classification algorithm called Naïve Bayes is based on Bayes' Theorem. It determines the probability of an occurrence using information about related conditions that is known in advance. If you need to estimate probabilities for data classification, this approach is your best bet. To simplify probability computation, it presumes that every characteristic in a dataset is present independently of all other features. Practical uses of Naïve Bayes include predicting consumer behavior based on the likelihood of different outcomes, including which products customers are likely to favor or which marketing campaigns they are likely to participate with. One use case is in helping businesses better target certain groups with marketing tactics and content by classifying consumer data to determine which sorts of food are most often ordered or which restaurants are most frequented. The algorithm is based on Bayes' Theorem, which states that given two events A and B, the likelihood of A occurring given B is equal to the likelihood of B given A, scaled by the previous likelihood of A, and then standardized by the previous probability of B.

$$P(A \mid B)=(P(B \mid A)P(A))/(P(B))$$

Where,

$P(A|B)$: probability of event A given event B,

$P(B|A)$: probability of event B given event A,

$P(A)$: probability of event A,

$P(B)$: probability of event.

Focusing on its implementation through function-based techniques, this work explores the use of naïve Bayes classifiers in programming languages. It takes a look at the standard method of using a function to categorize and forecast results from provided datasets. This method allows data to be classified into several classes by feeding the function a dataset and a group of classifiers that will decide the classification for each data point. This approach goes beyond only working with original datasets because it also makes it easier to anticipate classifications for fresh, unseen data points. The purpose of this research is to demonstrate how well naïve Bayes classifiers work in various programming environments and how versatile they are by delving into this topic.

2.2.3. Nearest neighbors

A variety of methods used in non-parametric regression and classification applications make up the nearest neighbors algorithm; it excels at predicting data with a lot of variation. To use this method, it is necessary to determine how close together data points are, sometimes called "neighbors," and then group them as a result. The idea of "neighborhood" is essential; it refers to the process of measuring the distance between data items in order to ascertain how similar they are. Discrete data can be compared using categorical methods, and numerical data can be compared using the standard distance measure, the Euclidean distance. After the distance has been determined, the algorithm clusters the data points according to the "nearest neighbor" principle, which essentially puts points that are geographically close together into one cluster. The method's flexibility makes it a potent instrument for a wide range of data analysis and prediction uses.

After locating the k-closest points to a certain data point, the nearest neighbors method sorts the data point according to the class labels or regression values of those points. Assume that there are n neighbors to take into account and that X is a data point in a feature space. X1, X2, …, Xn are the data points in the feature space that are k-nearest to X, as determined by the nearest neighbors technique. Finding the mean of the k-nearest neighbors' class labels or regression values is the next step in assigning X's class label or regression value. This formula provides a mathematical demonstration of the ideas of nearest neighbors:

$$Y=1/n(y_1+y_2+\cdots+y_n)$$

where yi is the class label or regression value of X1, X2, …, Xn. variables:

X: The given data point in a feature space.

n: The number of neighbors to be considered.

X1, X2, …, Xn: The k-nearest neighbors of X.

y1, y2, …, yn: The class labels or regression values of X1, X2, …, Xn.

Y: The class label or regression value of X.

As a comprehensive tutorial on how to use this technique in programming, this paper delves into the idea of nearest neighbors. They go over the essentials, such as normalizing and scaling the data, selecting a suitable distance measure, and applying the nearest neighbor method with working examples of code. The paper provides a thorough explanation of the steps involved in the process, which helps readers grasp the importance of these procedures and how to apply the closest neighbor algorithm successfully. The authors provide helpful ideas for programmers who want to incorporate this strategy into their practices through thorough explanations and research findings.

2.3. Programming procedure

Starting with problem identification and outcome definition, the machine learning (ML) workflow is an iterative and dynamic process. Gathering and preparing a training dataset that is properly prepared for the ML algorithm is the first step. The next step is to choose a model that can solve the problem effectively. Next, the selected model is trained using the dataset, which includes adjusting and optimizing hyperparameters to improve performance. To make sure the model is effective, it is evaluated and compared to other models after training. The next step is deployment, but that's not all. For ML models to be relevant and accurate, they need regular maintenance, data updates, and performance monitoring. The effectiveness of the model and its ability to react to new data depend on this iterative process of improvement (see Figure 2).

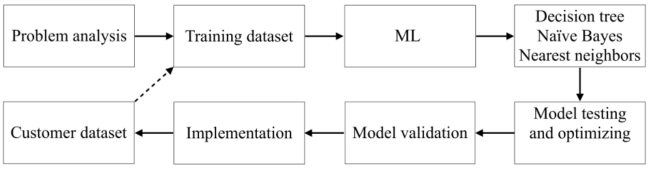

Fig. 2. ML model workflow.

2.2.1. Prepare the data

Data virtualization is crucial for successful machine learning (ML) uses for regions where real consumer data is banned. The complexity of real-world corporate data can be overcome by data simulation, which creates simplified versions that are representative and tailored to specific company needs. Businesses can more effectively group clients into subsets based on simulated data that represents characteristics like geography, spending habits, dietary habits, and delivery frequency in the setting of food delivery companies, for example. Researchers can use the Gaussian distribution to create realistic data groups by utilizing infer agreement and variable mathematical models. In the end, this method permits the creation of ML models capable of accurately classifying and predicting data by seeing patterns and correlations within it.

An essential initial step is to prepare the dataset for analysis by collecting, cleaning, and organizing the data. Consumer preferences and actions in relation to food categories and pricing were modelled using simulation data in this investigation. There were three price points in the dataset: general, high, and promotional, and four types of food: general, halal, vegetarians, and healthy. Using a mean vector and a covariance matrix, the food products and menu selections were represented by a multivariate standard (Gaussian) distribution. By offering a controlled yet variable data environment, this probabilistic framework helps the AI system learn, which is crucial for assessing and improving the AI model's performance through the recognition of patterns and correlations.

$$f(x_1, x_2, \ldots, x_n) = (2\pi)^{\left(-\frac{n}{2}\right)} exp^{-\frac{1}{2}\Sigma(x_i-\mu_i)^{\frac{2}{\mu_i}}}$$

The equation states that for each variable xi, μi represents its mean, σi its variance, and n its total number of variables. Figure 3 shows the probability density function plot of all four thousand menu items.

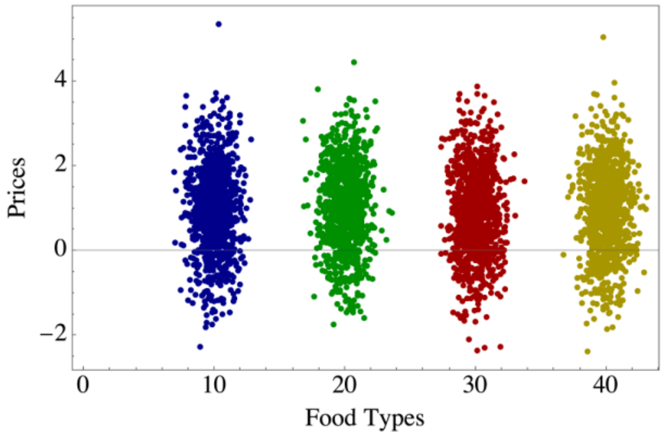

Fig. 3. The breakdown of prices and alternatives for four thousand different dishes is displayed. The x-axis shows the several categories of food: (1) general food (category 1), vegetarian food (category 2), halal food (category 3), and healthy food (category 4) (range 35–45). The prices are displayed on the y-axis, with the general price being zero, the high price being larger than zero, and the price advertised being less than zero.

Several Gaussian-distributed subsets of the set used for training can be generated by the simulation. See Figure 4 for the location of Code Snippet 1, which can be used to generate simulated data. The data set includes the food type and price.

```
sampledata[center_] := RandomVariate[
        MultinormalDistribution[center,
        IdentityMatrix[2]], 1000];

foodItems = sampledata /@
        {{10, 1}, {20, 1}, {30, 1}, {40, 1}};
```

Fig. 4. Code Snippet 1. Data from four sets of food items that follow a typical pattern in simulations.

2.3.2. Divide the data into training

Separating the data into a training set and a test set is a crucial next step after data preparation. The model is trained using the training dataset, and its performance is evaluated using the test dataset. The model is trained on the dataset using rule-based association learning, a supervised approach [1]. When used to market basket analysis, this method excels at finding the most popular combinations of products in huge databases in order to deduce hidden relationships between them. Definitions of association rules are provided by "support" and "confidence," which are measures that show how often products are bought together and how likely they are to be purchased together, respectively. Finding patterns and correlations in data is the goal of association rule learning. Associative rule learning aids in the development of models capable of outcome prediction based on subsets of variables by mining datasets for such patterns. By providing useful direction for future studies, these findings have the potential to improve decision-making and produce more precise predictive models (see Figure 5).

```
trainSet = <|Type1 → foodItems[[1]],
             Type2 → foodItems[[2]],
             Type3 → foodItems[[3]],
             Type4 → foodItems[[4]]|>;
```

Figure 5. Code Snippet 2. Here, "trainSet" refers to the data intended for training purposes. There is a relationship between the food kind and pricing that the association rule reveals.

Machine learning models rely heavily on customer history data, which provides invaluable insight into customer patterns and actions for businesses. Machine learning algorithms can analyze past consumer data to build precise segments according to attributes like ratings, purchasing habits, and other attributes. Businesses can improve their marketing efforts and the happiness of their customers by using this segmentation to target them with more specific offers, services, and goods. Particularly useful for online businesses, models that incorporate customer data can improve their churn prediction accuracy, spot outliers, and enhance customer service. Additionally, this information helps to improve customer segmentation procedures, which in turn enables the separation of different groups of customers according to demographic and behavioral characteristics. Customers get experiences that are uniquely tailored to their needs, which boosts value for the company and its customers.

```
customerBehavSet =
   If[Customers =!= {}, {},
     Table[Which[
         Customers[[i, 1]] === Type1,
         Type1 → Customers[[i]],
         Customers[[i, 1]] === Type2,
         Type2 → Customers[[i]],
         Customers[[i, 1]] === Type3,
         Type3 → Customers[[i]],
         Customers[[i, 1]] === Type4,
         Type4 → Customers[[i]]],
       {i, 1, Length[Customers]}]];
```

Fig. 6. Code Snippet 3. "customer Bahav Set" is a set of data that includes customer behavior for training purposes. Customer behavior is correlated with pricing type according to the association rule. This configuration, represented as the "If [condition, true, false]" function, will be empty if there is no past client information.

2.3.3. Choose and train the ML model

Selecting the appropriate machine learning (ML) model is crucial to the ML process, as it directly influences the effectiveness of the solution. The choice of model should align with the problem type, available data, and desired outcome, taking into account factors such as accuracy, scalability, and complexity. Various techniques, including decision trees, naïve Bayes, and nearest neighbors algorithms, are employed to fit and optimize the model through the loss function. Before training, data must be pre-processed and divided into training, validation, and test sets. The model is then trained on the training set with correct labels, allowing it to learn and predict labels for unseen data. This training involves tuning several parameters—such as learning rate, regularization, feature scaling, and optimization algorithms—to maximize predictive power while minimizing overfitting. It is important to recognize that achieving perfect accuracy from the outset is unrealistic; therefore, continuous testing and validation are essential throughout the iterative training process. Adjustments to features and hyperparameters, as well as experimenting with different algorithms, are necessary to enhance model performance. The training method utilized in this study is detailed in Code Snippet 4 (see Figure 7).

```
decisionTreeClassifier =
     Classify[Flatten[trainSet,
      customerBehavSet],
      Method → "DecisionTree"];
naiveBayesClassifier =
      Classify[Flatten[trainSet,
      customerBehavSet],
      Method → "NaiveBayes"];
nearestNeighborsClassifier =
      Classify[Flatten[trainSet,
      customerBehavSet],
      Method → "NearestNeighbors"];
```

Fig. 7. Code Snippet 4. Datasets "train Set" and "customer Behavior Set" are used to train the respective ML methods.

2.3.4. Test the model

To get an accurate picture of a machine learning model's predictive power, it's important to test it with a dataset that hasn't been seen before after training. There are a number of critical steps in this process. To get the data ready for testing, it needs to be pre-processed and cleaned up so it fits the model's parameters. The model is tested with different input values in multiple runs after receiving the prepared data. The accuracy of the model is evaluated by comparing its predictions with the predicted outcomes. It may be necessary to make changes to the model if inconsistencies are found. To ensure the model is performing as expected during testing, it must be carefully examined to see how well it matches the actual findings with its predictions. Additional optimization may be required if the model's performance does not meet expectations. Test data, as shown in Code Snippet 5, is generated at random and utilized for evaluation purposes. It contains food products with quantities ranging from 5 to 50 and prices from -3 to 4, as well as client history menus from 1 to 1000, which are used to measure performance.

```
type = Range[5, 50, {0.1}];
price = Range[−3, 4, {0.1}];
CustomerBehavMenu =
    RandomChoice[Range[1, 1000]];
customerMenu = Table[If[i > 0, {
        RandomChoice[
          Flatten[type, 1]],
        RandomChoice[
          Flatten[price, 1]]},
      Nothing], {i, 1,
      CustomerBehavMenu}];
```

Fig. 8. Code Snippet 5. A test dataset named "customer Menu" is created at random. In order to test the models, we randomly generate types, pricing, and menus for the consumer experience.

2.3.5. Ensemble ML

Ensemble methods enhance machine learning performance by combining multiple algorithms or techniques to create a more robust and accurate model. For instance, when integrating decision trees, naïve Bayes, and nearest neighbors, the ensemble approach leverages the strengths of each technique to yield superior results compared to any single model. This combined model excels in generalizing from data, which helps in reducing overfitting and improving overall accuracy. By amalgamating different predictions, ensemble methods address variance and bias, leading to more reliable and accurate predictions on unseen data. The effectiveness of ensemble methods is evident in their ability to provide a balanced and well-rounded approach to modeling, as demonstrated in various code implementations (see Figure 9).

```
EnsembleML = Flatten[ {
    decisionTreeClassifier[
      customerMenu,
      {"TopProbabilities", 1}],
    naiveBayesClassifier[
      customerMenu,
      {"TopProbabilities", 1}],
    nearestNeighborsClassifier[
      customerMenu,
      {"TopProbabilities", 1}]}]
```

Fig. 9. Code Snippet 6. A set of machine learning techniques that includes decision trees, naïve Bayes, and k-nearest neighbors.

A strong strategy for attaining high accuracy and generalizability is offered by ensemble ML algorithms. In order to provide extremely accurate and trustworthy forecasts, they integrate numerous data models. With ensemble approaches, more nuanced data may be captured than with individual models, leading to more accurate forecasts with 90%+ probability. When dealing with complicated datasets, ensemble approaches are useful because they can decrease data volatility and bias. In Code Snippet 7 (Figure 10), we can see that ensemble ML decisions are used in this investigation with a probability greater than 90%.

```
prob90Type = Table[
    If[Values[EnsembleML][[i]] > 0.90,
      EnsembleML[[i]], Nothing],
    {i, 1, Length[EnsembleML]}]
```

Fig. 10. Code Snippet 7. A machine learning ensemble approach to identifying foods.

Additionally, this research supports employing a combination of customer experience data and data created at random, but not more than 50%. You can utilize a random theory to use the results of these ensemble ML models for recommendations. Any company strategy can benefit from the random ratio advice, which helps to reduce customer aggravation and varies from 1% to 50%.

3. Results

3.1. Model learning

Metrics like loss scores and accuracy curves measure a model's generalizability to new, unseen data, which is a key component of machine learning (ML) model performance evaluation. As a measure of the model's performance during training, accuracy curves show the proportion of times the model got the prediction right. As the model starts to train, it is predicted to have poor accuracy and high loss scores initially. However, the model's performance dramatically improves throughout training, especially around the 700-data-point mark, as seen by a loss score decreasing below 0.01 and accuracy nearing 90%. With an accuracy of 99.23% ± 0.24% and a minimal loss score of 0.0476 ± 0.0069, the decision tree method stood out for its exceptional performance. An accuracy of 99.26% ± 0.32% and a low loss score of 0.0567 ± 0.0100 were achieved using the nearest neighbors approach, demonstrating its effectiveness in prediction tasks. On the other hand, the naïve Bayes technique demonstrated good performance with a loss score of 0.0948 ± 0.0110, highlighting the model's overall efficacy, even though its accuracy was slightly lower at 96.50% ± 0.70%.

The ML accuracy matrix graphic shows how different algorithms performed across different parts of the dataset visually. Finding out where the model excels and where it may use some work is made much easier using this matrix. The model's performance across multiple data segments can be easily discerned by using color-coding to indicate accuracy levels. Darker hues indicate more accuracy. In percentage form, accuracy indicates how close a model is to making perfect predictions, while error shows how far off the mark the model is. To quantify the model's performance, cross-entropy quantifies the difference between projected probability and actual labels. It is a fundamental loss function in ML. Better classification accuracy is shown by lower cross-entropy values, whereas higher values imply that there is potential for development. In order to evaluate the model's prediction power and check if it closely matches the actual distribution of data, this statistic is crucial.

The calibration curve, as depicted in Figure 12, illustrates the relationship between a model's predicted probability estimates and the actual class labels, serving as a measure of the model's overall accuracy. A perfectly calibrated model would produce a calibration curve that aligns with a diagonal line, reflecting optimal performance. In this instance, the calibration curve achieved a benchmark value exceeding 0.90, signifying robust accuracy. The accuracy matrix for the decision tree algorithm, shown in the accompanying plot, demonstrated a flawless performance with a 100.000% accuracy, zero error, and a mean cross-entropy of 0.0001010320. Similarly, the nearest neighbors algorithm also reached 100.000% accuracy, with no error and a mean cross-entropy of 0.0119720000, confirming its impeccable data prediction. The naïve Bayes algorithm, while slightly lower in performance, still exhibited high effectiveness with an accuracy of 97.175%, an error rate of 0.02825, and a mean cross-entropy of 0.0515655000. These results collectively underscore the models' exceptional ability to correctly classify data with high precision.

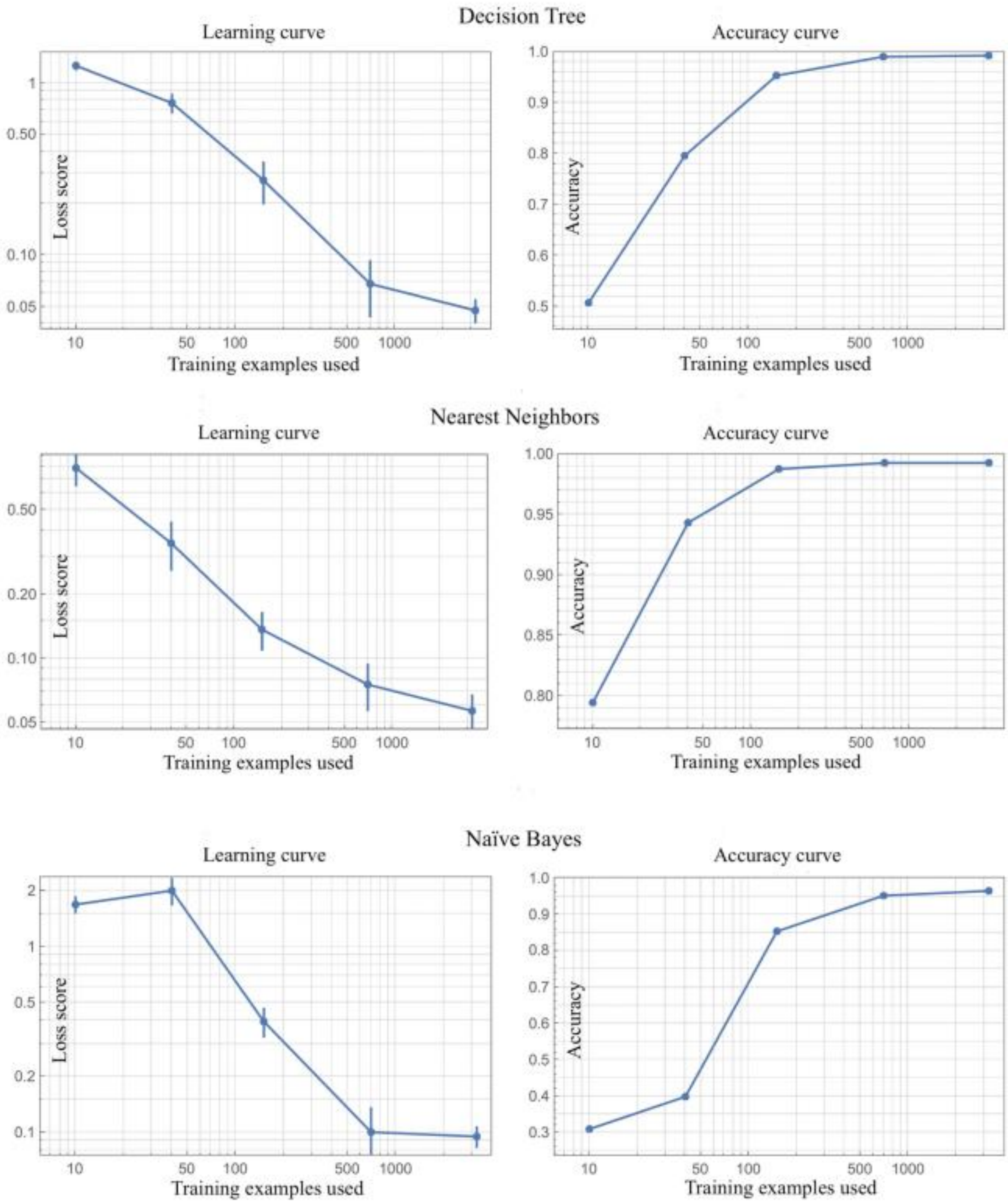

Fig. 11. All machine learning methods' learned and accuracy curves.

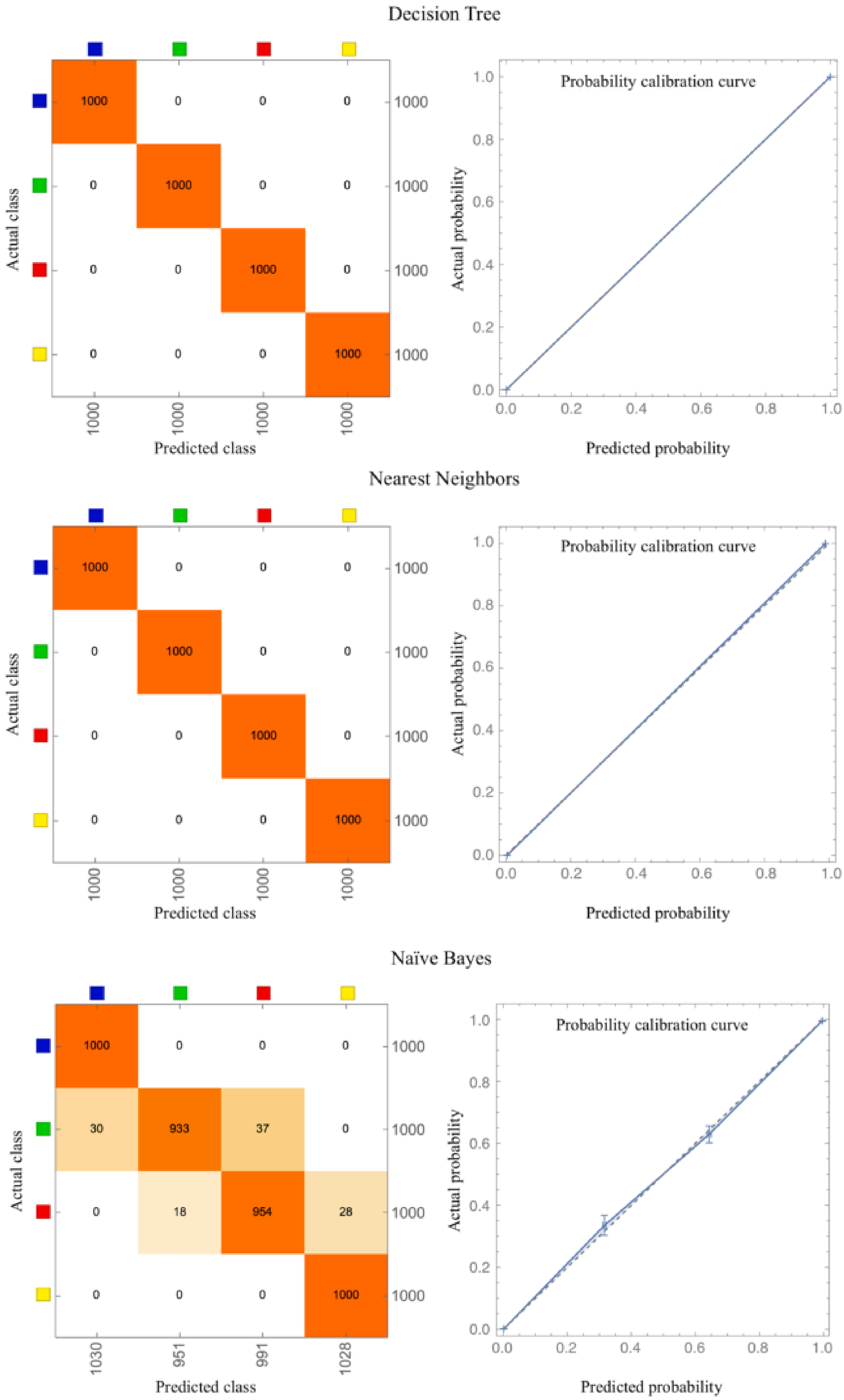

Fig. 12. Each ML method's probability calibration curve and ML accuracy matrix plotted.

3.2. Model validation

To evaluate and quantify a model's performance on data it hasn't encountered during training, model validation is an important part of developing machine learning algorithms. Testing the model's generalizability to previously unexplored data sets is the goal of this procedure. Developers can improve the model's accuracy and reliability by using statistical approaches to detect any potential biases or restrictions. There are usually two main steps to validate a model. In order to see how well the model does on untrained samples, it is first put through its paces on a validation dataset. Finding out how effectively the model's predictions spread is the goal of this initial assessment. To illustrate how the model's predictions could be tested on 100 menus, Code Snippet 8 shows a simulated dataset that was specifically constructed for this purpose (see Figure 13). This dataset reflects possible scenarios where repeating consumer actions or orders could mimic randomly.

```
type = Range[xMin, xMax, {0.1}];
price = Range[yMin, yMax, {0.1}];
nMenu = 100;
customerMenu = Table[If[i > 0, {
        RandomChoice[Flatten[type, 1]],
        RandomChoice[Flatten[price, 1]]
      }, Nothing], {i, 1, nMenu}]
```

Fig. 13. Code Snippet 8. The trained dataset and the unknown random dataset were both modeled using the identical parameters.

Additionally, a number of metrics, including as accuracy, precision, recall, F-score, and area under the curve (AUC), were used to thoroughly assess an AI model's performance on a test dataset. An accuracy value above 85% indicates excellent prediction accuracy, which is expressed as a percentage and measures the proportion of right predictions out of all guesses. A model was considered to have reliable performance if its recall was more than 85% and its precision was more than 85%, two metrics that measured its capacity to generate hopeful and true positive predictions, respectively. To show balanced prediction ability, the F-score—a harmonic mean of recall and precision—also strove for a threshold of 0.85 or higher. Furthermore, the area under the curve (AUC) evaluated the model's ability to accurately categorize various classes; AUC values greater than 0.85 often indicate strong classification performance. Achieving values above 85% throughout accuracy, precision, recall, F-score, and AUC gave a thorough evaluation of the model's performance in real-world scenarios, as these measures were taken together. See Table 1 for specific quantitative performance metrics.

Table 1. Validation of models benchmarks summarized from over a hundred independent tests.

ML Method	Accuracy (%)	Precision (%)	Recall (%)	F-score	AUC
Decision tree	81–91	75–100	62–100	0.73–0.96	0.74–1.00
Naïve Bayes	68–84	50–85	30–100	0.38–0.92	0.78–0.98
Nearest neighbors	93–100	76–100	85–100	0.86–1.00	0.98–1.00

In order to guarantee that machine learning models are suitable for real-world deployment and robust, validation of these models is essential. Careful testing and tweaking can help find and fix problems like overfitting, bias, and systematic mistakes before they happen. The test set is an important aspect of the validation process since it helps to fine-tune the model and gives insights into how well it can generalize to new data. We found that the nearest neighbor model was more efficient than naïve Bayes, which was often inadequate for classification tasks. We provide an ensemble strategy that outperforms all methods by more than 90% to deal with the performance variability of individual models. To help choose the best model for a given application, we compare various ML models in detail using metrics like accuracy, precision, recall, F-score, and area under the curve (AUC) (see Table 2). For informed decision-making in ML model selection, it is necessary to understand both the similarities and variations in model performance, as well as the associated computing costs.

Table 2. Data from over a hundred independent tests summarized for use in comparing models.

ML Method	Accuracy (%)	Precision (%)	Recall (%)	F-score	AUC
Class distribution	87–96	71–96	68–99	0.78–0.97	0.96–0.99
Logistic regression	88–98	71–100	60–100	0.75–0.98	0.99–1.00
Markov	22–40	10–33	12–52	0.16–0.41	0.57–0.71
Random forest	96–99	96–100	97–100	0.98–1.00	0.99–1.00

Support vector machine	98–99	95–100	92–100	0.96–1.00	0.99–1.00

3.3. Ensemble ML model and majority voting technique

The general success of a model for prediction was enhanced by combining numerous models using an ensemble ML approach. Excellent results were achieved by the ensemble ML model, which included three ML methods; the precision of all three techniques ranged from 68% to 100%. Instead of depending on just one ML result, this study found that majority voting was the most precise method to summarize all three ML outputs. This approach considered several points of view by picking the alternative with the highest chance of being the same in two or more ML results (with a probability greater than 0.9). A null statement need to have been utilized if the ML results did not share a choice with a probability higher than 0.9. Figure 6 displays the likelihood of the ML outcome. On the highest point of the surface, there was a probability value higher than 0.9. Anything with a surface probability of less than 0.9 was probably categorized as some other kind of food.

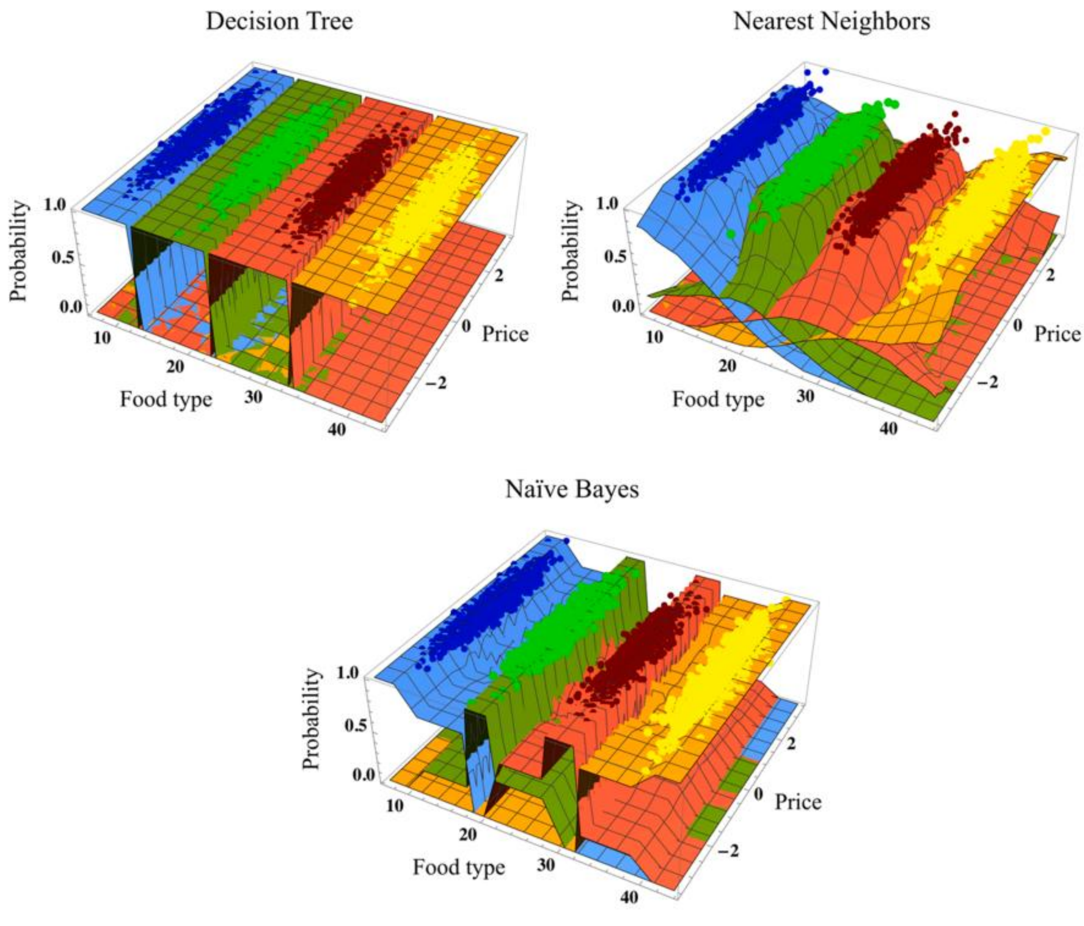

Fig. 14. These are the machine learning outcomes that display the ensemble ML method's probabilities. Blue is for general food, green is for vegetarian food, red is for halal food, and yellow is for healthy food; the x-axis shows these categories. You can see the likelihoods on the y-axis.

Table 3 displays a 90% chance of statistical significance, suggesting that the outcomes produced by ensemble ML methods are legitimate and dependable; hence, they can be relied upon to a certain degree when making selections. When making significant selections, having this level of confidence is valuable because it provides better assurance regarding choice. Statistical significance tests revealed a high degree of correlation between the two variables, indicating that the former significantly influences the latter. Also, if the result is substantial, then it's safe to assume that the dependent variable will be significantly affected by changes in the independent variable.

Table 3. Benchmarks for ensemble models summarized.

Food types	Accuracy (%)	Precision (%)	Recall (%)	F-score	AUC
General	90–100	90–100	90–100	0.90–1.00	0.90–1.00
Vegetarian	90–100	90–100	90–100	0.90–1.00	0.90–1.00
Halal	90–100	90–100	90–100	0.90–1.00	0.90–1.00
Healthy	90–100	90–100	90–100	0.90–1.00	0.90–1.00

4. Discussion

One kind of ML, known as the ensemble ML approach, uses a combination of algorithms to outperform each algorithm individually. A more solid forecast than any of each model would have made on their own would be the outcome of merging the predictions of numerous models. In order to better reflect the problem's complexity, ensemble approaches sometimes incorporate multiple algorithms into a single model, which is an improvement above conventional single-algorithm ML implementations. Predictive models may be made much more accurate and resilient with the help of ensemble ML models. Here, decision trees, naïve Bayes, and nearest neighbors were put to the test as three ensemble ML models. Bagging was the method that was selected. For high-performance prediction models, bagging ensemble models are a lifesaver, particularly when working with massive datasets and feature-rich, complicated problem spaces. Bagging reduces the likelihood of overfitting by training separate models on randomly selected data subsets. The combined forecasts of the multiple models allow the total model to outperform a single baseline model by a significant margin. Outperforming the single baseline model by a wide margin, the bagging ensemble models demonstrated remarkable performance in this study. Improving the precision of future projections is why this is crucial. Furthermore, the bagging ensemble demonstrated better cross-dataset generalization, indicating higher dependability when handling fresh data. Based on the results, it is clear that a combination of several ML models can improve predicted accuracy by more than 90%. To further improve predictions, future study might investigate other ensemble techniques like boosting or combinations of various ML models. The supervised learning approaches that have been effectively used as ensemble ML methods in this work are decision trees, naïve Bayes, and closest neighbors. To improve its ability to forecast future events from historical data, supervised learning, a subset of ML, use labeled training datasets. In this kind of learning, algorithms are used to convert inputs into outputs that are desired, with predictions being made along the way. Linear regression, logistic regression, support vector machine, and random forest are just a few of the many ML algorithms that can benefit from supervised learning techniques. Supervised learning techniques can increase the accuracy and reliability of all algorithms, even if they all use different approaches to finding patterns and making forecasts from the data. To build a good prediction model, ML's training dataset is crucial since it contains all the necessary data. Building a trustworthy ML algorithm is next to impossible without a well-labeled training dataset. Pattern recognition, difference detection, and prediction are all skills that the algorithms learn to use from the training dataset. To train algorithms to reliably foretell future events, we must supply them with pertinent and annotated contextual data. To further guarantee the system's efficiency and prevent bias and overfitting, accurately labeled datasets are essential.

When it comes to training, customer history data is king. Since ML models may learn from more contextual knowledge about an individual's past behavior, incorporating customer history data into the models can lead to more accurate predictions. When used in conjunction with other segmentation inputs, the customer history dataset can provide light on consumers' tastes and purchasing patterns, allowing for more precise segmentation and the delivery of tailored promotions to individual consumers. Marketers may increase engagement and sales by using customer data to create ads that are highly relevant to customers' requirements. In order to better meet the expectations of their consumers, businesses can learn more about their demands by examining the customer history record. By analyzing customer history data using ML, businesses may spot trends in customer behavior and react quickly to issues or changes in preferences, which helps to keep customers loyal and boost retention rates. In order to combine multiple ML models with a success probability above 90%, this study suggests a majority voting procedure. Digital marketers now have a more potent weapon to boost their value because to this technique, known as ensemble ML, which may inform and lead customer decisions. In addition, by decreasing the amount of false positives and false negatives, it has the ability to lower the cost of incorrect decisions. Even with the benefits that may be offered, less than half of the data that is randomized and mixed with customer experience data can be utilized to alleviate consumer irritation. Insights like this can help customer service teams improve their ability to understand and meet the needs of their most sophisticated clients by identifying which parts of the customer experience are in need of improvement. This research introduces a fresh approach to using AI-powered random suggestions. By taking into account different facets of consumer preferences and habits, random recommendations can deliver more precise recommendations to customers. To provide extremely tailored suggestions, for instance, patterns can be mined from consumers' reviews, purchases, and web browsing habits. With randomization, you may give customers suggestions in real time, which can increase their happiness. Furthermore, it is capable of swiftly identifying emerging trends and recommending items that clients might be interested in, as well as providing unique discounts. By randomly assigning customers to distinct groups, companies may better serve each group with personalized recommendations, thereby enhancing the customer experience. By catering to consumers' specific interests, this method has the potential to increase both sales and client loyalty. By accurately revealing consumer behavior and tailoring marketing messages based on these findings, randomization can also boost the efficiency of marketing initiatives. This has the potential to improve advertising efficiency while decreasing resource wastage. Last but not least, firms might acquire an advantage over their competitors by using randomization. In order to maintain a competitive edge and foster client loyalty, they will have access to sophisticated analytics that reveal consumer preferences and demands. With the use of AI, predictive analytics can help retailers win the price war. With the help of predictive analytics, which make use of past data to foretell future trends and consumer behavior, stores may better manage their inventory in response to anticipated demand. This can assist stores in improving their inventory management by providing a more precise picture of what is selling and what needs restocking. For shops, ML also means better product targeting, higher conversion rates, and greater revenues by revealing trends in consumer spending and suggesting complementary items. Another option is to use unsupervised learning, which is in addition to supervised ML. Considering the benefits and drawbacks of this method is crucial when choosing appropriate commercial applications for it. Supervised learning's main strength is in its predictive accuracy, which it achieves by utilizing labeled data. In addition, compared to unsupervised learning, the training procedure is less complicated and takes less time. Additionally, less data points are required to get accurate results. Nevertheless, acquiring tagged data comes at a price, and modeling intricate relationships without background knowledge is no picnic. Furthermore, without proper pre-processing, supervised models are likely to overfit. Unsupervised learning, in contrast, negates the need for labeled data and, by extension, the expense of label acquisition. It requires less data to be effective and can reveal hidden patterns in data that might not be obvious otherwise. Unfortunately, it requires significantly more computing power and, without labeling, cannot produce trustworthy findings. Finally, without the error or accuracy measurements needed for supervised learning, it is hard to evaluate the model's performance. Finally, it is important to weigh the benefits and drawbacks of supervised and unsupervised learning methods before deciding which one to utilize. An increasingly valuable tool for businesses in the future will be customer sentiment analysis powered by AI and ML. This will help with understanding customer behavior, tracking customer reactions to digital marketing campaigns, determining the success or failure of strategies, and swiftly addressing any issues that may arise. Another way sentiment research can be applied is to create targeted tactics for different client segments. This could lead to better campaign results and higher ROI. To better understand consumer sentiment, AI and ML algorithms can help sift through mountains of data, both organized and unstructured. Businesses may learn about their customers' habits and preferences across many different products with the use of AI and ML. By analyzing consumer comments on various online platforms, such as social media and web forums, organizations can gauge the overall customer opinion regarding a product or service. This data can then be used to make the appropriate adjustments. Another use is monitoring customer satisfaction over time; this can reveal shifts in attitude and inform choices for customer assistance and participation in the future. Thanks to advancements in AI and ML, firms can now have real-time insight into client sentiment, which has completely transformed their customer interaction strategies. Businesses may now handle client feedback and problems more efficiently with the help of AI and ML. With the further development of AI and ML, the role of these technologies in consumer sentiment monitoring is anticipated to grow in the future.

6. Conclusions

To produce and optimize both short-term and long-term sales, the food delivery company's digital marketing strategy can benefit from incorporating an AI-driven ensemble of three ML technologies. Companies in the food delivery industry have seen the light about the possibilities of using machine learning algorithms and data-driven insights to boost their productivity and efficiency. On top of that, there are a ton of practical advantages to incorporating AI-driven ML technology into food delivery companies' digital marketing campaigns. Businesses can save labor and free up resources for other operations by automating tasks like ad targeting, content customization, and campaign optimization. This helps the business expand. A key technique for improving the use of digital marketing in the food delivery company has been the implementation of supervised learning approaches employing algorithms such as decision trees, naïve Bayes, and closest neighbors. With these three algorithms working together, data-driven decisions like order frequency, promotional offers, and new product introductions are well-grounded. The trained models outperformed more conventional marketing approaches, proving that ML and AI are capable of making precise predictions about consumer tastes and habits. Businesses can swiftly gain valuable insight from the massive amounts of customer data gathered by integrating AI-driven MLsupervised learning technology. To lessen consumer discomfort, this process's majority voting mechanism has the ability to integrate models with a success rate of more than 90% using less than 50% of randomized data blended with customer experience data. Even though AI is still in its infancy in the food delivery industry, it has already led to considerable performance gains. With the help of this technology, businesses may gain a clear picture of their customers' habits and preferences, which is crucial for making data-driven decisions. Companies can get an advantage in their market competition by using ML algorithms correctly. The use of AI has helped the meal delivery company fine-tune its marketing campaigns to meet the specific demands of its clientele. With the use of AI and ML algorithms, businesses can personalize their content for customers and make more accurate predictions. Certainly, companies operating in the food service sector will reap enormous benefits from the ongoing advancements in this technology.

CRediT Authorship Statement

Declare the credit and contribution of each author in this research. For example:

First author: Conceptualization, writing original draft, methodology. **Second author:** data curation, writing original draft, validation, analysis.

Funding: Funding should mention according to the project

Acknowledgments: It is recommended to provide all acknowledgements

Conflicts of interest: Mention any financial or personal conflict of interest about the work and with the authors.

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