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Optimizing Classification Methods for Online Buyers' Purchase Intentions in Bangladesh

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Abstract: The classification of online buyers' purchasing intentions is of paramount importance, especially in the context of the period of the COVID-19/post-COVID-19 pandemic, as it carries significant implications for the business industry. However, effectively managing the diverse, ever-changing intentions of individual Internet customers remains a challenging task. This study aims to enhance the classification techniques used to categorise various types of online buyers' purchasing intents in Bangladesh. A comprehensive analysis of different classification algorithms reveals that the Random Forest algorithm outperformed other methods, achieving exceptional accuracy rates of 99.9% in training and 89.7% in testing. Conversely, the Gaussian Naive Bayes algorithm demonstrated comparatively lower accuracy, with training and testing accuracies of 80% and 79%, respectively. This study contributes not only to a better understanding of online buyers' purchase intentions in Bangladesh but also provides valuable insights into the business industry. Moreover, our work highlights the potential for future investigations in recognising Bangla numerals through gestures to enhance the accuracy of categorising online buyers' intended purchases. This research serves as a stepping stone for further advancements in classifying and understanding online buyers' purchase intentions, ultimately fostering more accurate decision-making in the realm of E-commerce in Bangladesh.

Keywords: Machine Learning, Online Purchase Intention, Random Forest, MLP Classifier, Decision Tree Classifier.

I. INTRODUCTION

Online shopping has become a popular way to meet the demands of our busy lives in today's fast-paced society [1].

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Online shopping refers to the practice of conducting electronic commerce, where customers can directly purchase goods or services from sellers via the Internet [2]. A crucial aspect of online shopping is understanding customers' purchase intention, which reflects the strength of their inclination to engage in a specific behaviour or make a purchasing decision [3]. Customer online buying intention is the idea that determines how strongly a customer intends to make an online purchase. Online or Click-and-Order business methods have replaced the traditional Brick-and-Mortar business model. More people than ever are buying almost everything from houses to vehicles, clothes to stationery, food to medicine, and train to airline tickets online. Customers today have numerous options for the products and services they want while purchasing online. Customers' shopping habits have changed drastically in the past decade. While some still shop at physical stores, many find online shopping more convenient. Today's consumers rely on online purchases due to time constraints or busy schedules. Online shopping has experienced rapid growth both globally and in Bangladesh; its potential for further expansion in the coming years is significant, driven by the widespread availability of internet connectivity in rural areas [1]. Finally, because online purchasing has advantages and disadvantages, customers' purchasing intentions change over time. Additionally, it is crucial to anticipate their intentions because they have a direct impact on other aspects of online business policy. In this study, we propose categorising online shoppers' intent to purchase using several classification algorithms and comparative analysis. Ten classification methods in total were used to accomplish the intended aims. A significant number of datasets, focusing on online buyers' purchase intentions, were gathered after considerable effort. The online shoppers' purchasing intention dataset from the UCI machine learning repository was one of the datasets heavily utilised in this study. This dataset was carefully selected because it is directly relevant to the project's objectives. The study aimed to generate informed predictions by utilising this vast dataset and a range of classification algorithms to gain valuable insights into the factors influencing online buyers' purchasing decisions.

II. RELATED WORK

Online shopping, particularly grocery shopping, has increased significantly due to the COVID-19 pandemic, as customers sought alternative means of making purchases while adhering to social distancing rules.

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To understand the effects of this tendency, numerous studies have been conducted, including both descriptive and statistical analyses. Additionally, as seen by the availability of published literature, machine learning techniques have been widely used in the online retail sector. These studies investigate various aspects of online shopping-related activities, examine factors influencing online purchasing behaviour, and solicit feedback and input from customers [1, 4-11]. Some analyses attempt to categorise visits based on information about user behaviour and the specifics of the user's session [12].

In one of these experiments, Moe [13] tried to identify visits using information from a particular online store in the hopes of creating a system that takes specific actions based on the visitors. To achieve this, a collection of traits was extracted from the visitors' page-to-page control input and used in the k-Means clustering method to categorise visits according to their likelihood of making a purchase. The resulting clusters, dubbed "Directed Buying," "Search/Deliberation," "Knowledge Building," "Hedonic Browsing," and "Shallow," were revealed to have different purchasing intentions when the user behaviors in each group were assessed. The "Directed Buying" cluster represents people who visited the website intending to make a direct purchase, whereas the "Shallow" cluster represents users who abandoned the site after just two page views. In another research, Mobasher et al. [14] employed two different clustering methods depending on user purchases page views to provide valuable aggregate use profiles those recommender systems may use to perform specific responses in real-time. The results demonstrated that profiles generated from customer devices could aid in efficient personalization during the initial stages of a user's stay in a virtual retail context. The extracted attributes, which were used to categorise the visits based on the visitor's purpose, are utilised to build a training data problem in the first module of their system as a means of assessing the visitor's propensity to complete the transaction. As a result, they identify people who visit the site with a direct purchase purpose and only provide material to those visitors, regardless of whether they will depart the site without completing the transaction. They also use filter feature selection approaches to discover the most discriminative characteristics in forecasting purchase intent. Suchacka Chodak [15] sought to define e-customer behavior using Web application system logs in a recent survey. The data came from an online bookshop developed on the Commerce platform. On this dataset, they employed a mining technique to evaluate the customer purchase probability of visitors, retrieving valuable knowledge about the responses of various customer profiles. The forecast of purchase intention issue was developed as a set of training data in [16], identical to the first module of their approach. Existing data from an online bookshop was utilised to categorise user activities as either exploring or buying experiences. One of the classifiers used in their comparative study was SVMs with different kernel choices for classification. SVMs have achieved success in a variety of machine-learning techniques [17]. In another work, a relatively similar dataset was employed with a k-NN classifier to achieve an identical aim [18]. Many studies have been conducted to predict user behaviour in real-time, allowing for customised actions to be taken and utilising sequential data. Budnikas [19] stressed the importance of eyeing behavior in real time taking the proper action in a virtual purchasing environment. To determine the website feature that has the most significant impact on the accomplishment of business objectives, the author has [19] advised categorizing visitor behavior patterns. The data collection process involved the implementation of the Google Analytics tracking code [20]. This enabled the monitoring and analysis of website visitor activities. To assess a website visitor's readiness to complete a transaction, a comprehensive model of on-site consumer behaviour was developed. This model utilized Naive Bayes multilayer perceptron classifiers, which are machine learning algorithms known for their effectiveness in classification tasks. By leveraging these classifiers, the project aimed to accurately determine the likelihood of a visitor converting into a customer based on their online behaviour. Yeung [21] has shown that it is possible to predict visitors' behavior by using their e-commerce site navigation habits. HMM is used in several types of research [22–24] to calculate the frequency of the pathways that are repeatedly studied during a session. The most common navigation paths are used to choose the Websites the visitor is eager to see in the following stages, extending their time on the site. User suggestions are then made for these pages. To prioritize sessions based on the money that will be generated utilizing early clickstream data session information, Poggi et al. [25] devised a system in response to the reduction in Web server speed brought on by overcrowding. To correct the misclassification, a training dataset was created using 7,000 transactions, with 50% of those transactions belonging to the "buying" class. To calculate the likelihood that consumers will make a purchase, they combined Markov chains, linear logistic regression, decision trees, and Naive Bayes. By using HMM to simulate visitor clickstream data, Ding et al. [26] showed that predicting the user's intent in real-time and applying personalized actions can increase conversion rates and lower the rate of shopping cart abonnement. Instead of using HMM to process the clickstream data in their study, they use LSTM, RNN, and LSTM-RNN. This is based on the finding that RNN creates models with better learning capabilities and generalization performance than HMM as the sample size in the sequence rises [27]. Even though a few studies have recently used RNN to evaluate data from the e-commerce industry, these studies concentrate on session-based recommendation systems, which offer suggestions in response to the user's subsequent clicks [28]. In contrast to earlier studies, we utilise sequential clickstream data to train an LSTM-RNN model to predict the probability that a user will leave the website within a specific time frame.

However, predicting purchase intention in the realm of online shopping holds significant importance for businesses, as it enables them to comprehend better and fulfil their customers' needs. This understanding empowers companies to tailor their strategy offerings to cater to customer preferences and maximize customer satisfaction effectively.

In this study, we have undertaken an analysis focused on predicting online shoppers' purchase intentions through the application of classification algorithms and comparative analysis.

We have employed various classification algorithms, including Random Forest, Gradient Boosting, AdaBoost, MLP, Decision Tree, and Gaussian Naïve Bayes, to develop models capable of accurately forecasting online shoppers' purchase intentions. We draw on a dataset of numerical and categorical variables pertinent to online buying, obtained from the UCI machine learning repository, to conduct the study. Through the analysis and evaluation of these algorithms, we aim to enhance our understanding of the factors that influence purchase intention, thereby contributing to the advancement of effective strategies in the online shopping domain.

III. METHODOLOGY

Here, we describe the entire methodology of this study in detail, including our novel approach to the application of all classification algorithms that we have used for this study. A thorough description of how to use the model has also been provided, along with a quick summary of each element of the methodology. This section begins with a description of the data gathered and then proceeds to outline the entire experiment process. The data were pre-processed as needed, including the conversion of categorical data into numerical data, where the working methods of the suggested classification algorithms are described. The proposed model is primarily divided into two parts. The first part involves pre-processing data from the dataset of online shoppers' purchases, and the second part consists of setting up models for various classification techniques. We employed pre-processing techniques to enhance the output, including outlier detection and normalisation. Figure 1 presents a framework of the proposed model workflow.

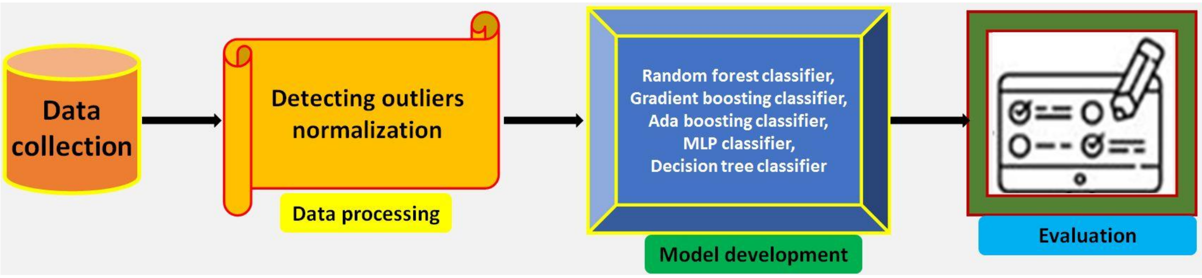

Figure 1. Schematic Diagram of the Function Flow of the Proposed Model

A. Data Collection

In this work, we use a binary classification problem to assess a shopper's propensity to make a purchase. We aim to serve only those interested in purchasing our content rather than casual browsers. The categorical quantitative features used in the model to predict future purchases are displayed in Tables 1 and 2, respectively.

Table 1: Classification Models' Numerical Features

Parameters	Description	Min. Value	Max. Value
Administrative	Count of account management pages that the visitor saw	0	27
Administrative hours	The total time the visitor spent (in seconds) on pages related to account management	0	3398
Informational	Information on the visitor's website visits, communication, and location of the shopping site	0	24
Informational period	The duration (in seconds) of time the visitor spent on each informational page overall	0	2549
Product related	How many product-related pages were visited by visitors	0	705
Product-related time	Total time spent by visitors on pages connected to products (in seconds)	0	63973
Bounce frequency	An average bounce rate of the visitor's pages	0	0.2
Exit rate	Average exit rate of the visitor's pages	0	0.2
Page rate	Value of an average page that a visitor has viewed	0	361
Exceptional day	The proximity of the visitation period to a special day	0	1

Table 2. Categorical Features Used in the Classification Models

Parameters	Features description	Number of Categorical Values
Functional Systems	The user's computer's operating system	8
Browser	One of the visitor's browsers	13
Section	The location of the visit from which we first arrived to begin the session	9
Traffic Type	Source of traffic (such as a banner, SMS, or direct) through which the visitor entered the website	20
Visitor Type	"New Visitor," "Returning Visitor," and "Other" visitor types are available	3
Weekend	Whether a Boolean value indicates a weekend visit date	2
Month	Value of the visit date for each month	12
Profits	Whether the visit has resulted in a transaction will be indicated by a class label	2

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Feature vectors represent approximately 12,330 sessions in this data collection. The dataset was constructed to ensure that each session belonged to a different person throughout the year, thereby eliminating any bias toward a specific event, special day, user profile, or time frame.

A total of 12,330 sessions were included in the dataset, with 84.5% of these being samples from the negative category that did not involve shopping; the remaining samples were from the positive class, which did end with shopping. The numerical statistical factors are presented in Ref [29].

These metrics reveal the variety of page types viewed by the user and the overall time spent on each type of page during the session. When the user takes action, such as moving from one screen to another, the resulting values of these characteristics are created based on the URLs of the sites visited by the user. The "Exit Rate" property for a given webpage is calculated as the percentage of users whose visits to that page were their last of the session, divided by the total number of page views for that webpage. When a customer considers an online purchase, they will feel the page's total value, which is reflected in the "Page Value" attribute. In the "Special Day" section, you'll see how close the current time is to a particular special day, on which sessions are much more likely to end with a purchase. Considerations unique to online shopping, like the length of time between making a purchase and receiving it, are used to calculate the occurrence of this feature.

B. Data Pre-Processing

This dataset includes both numerical and categorical features related to online shoppers' purchasing intentions. As we build six classification models based on six classification algorithms, such as the Random Forest classifier, the Gradient Boosting classifier, the AdaBoost classifier, the MLP classifier, the Decision Tree classifier, and the Gaussian Naïve Bayes classifier, we evaluate their results to determine the best model. We must also detect outliers as a first pre-processing step. We must detect these to avoid any uncertain errors. Additionally, we must perform normalisation as a second pre-processing step to convert categorical variables into numerical variables. Figure 2 shows the positive or negative correlation between attributes.

Figure 2. The Positive or Negative Correlation Between Attributes

C. Model Development

We have employed six classification algorithms, including the Random Forest classifier, the Gradient Boosting classifier, the AdaBoost Classifier, the MLP classifier, the Decision Tree classifier, and the Gaussian Naïve Bayes classifier, for our research purposes. We trained our dataset and also created models for these algorithms. The working principles and properties of each classifier are described briefly.

a. Random Forest Classifier

Random Forest is a practical machine learning approach that enhances prediction accuracy across a dataset by utilising a collection of decision trees. This technique involves training individual decision trees on different sections of the training sample and then averaging their results. A notable advantage of Random Forest is its ability to handle both continuous data, as seen in regression tasks, and categorical data, as encountered in classification tasks. Particularly, it has been observed to outperform other algorithms in classification tasks. To achieve the desired objectives using Random Forest, four distinct stages need to be followed:

– Selection of Random samples from the specified dataset.

– Construction of a decision tree for every sample, forecasting the outcome of each decision tree.

– Casting a vote for each expected outcome.

– Selection of expected outcome, choosing the most votes as the final forecast [30].

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b. Gradient Boosting Classifier

When many fragile learning methods are combined, a robust prediction model is produced; this is what gradient boosting does in machine learning. Most frequently, decision trees are used in gradient boosting. It's a common technique for improving performance.

If a prior forecast were incorrect, it would be corrected by the next one. Unlike Adaboost, the training examples' weights are not altered; instead, the residual error terms from the previous predictor are used to label the new predictors. The theory suggests that combining the best possible future model with historical models yields more accurate predictions. If changing a case's forecast by a small amount does not affect the error, the case's following expected result is zero [31].

c. AdaBoost Classifier

AdaBoost is a boosting technique used in ensembles for machine learning. It is a meta-estimator that operates by first fitting a classifier to a dataset, then fitting numerous instances of that classifier to the same dataset while adjusting the weights of instances that are incorrectly classified, so that subsequent classifiers pay greater attention to challenging situations. As a result of this process, cases that were incorrectly classified receive bigger weights than those that were correctly classified. Adaptive boosting is the term for this method. When applied to a machine learning model, AdaBoost can significantly improve its efficiency. These are algorithms with classification accuracy just slightly higher than chance. The most popular effective algorithm used with AdaBoost is a decision tree with only one level [32].

d. MLP Classifier

A feedforward artificial neural network model with several nodes connected in a directed graph is called a multilayer perceptron (MLP). Neurons make up both the hidden layer and the output layer. A neuron can be compared to a tiny computer. Our MLP model consists of inputs, outputs, and a single hidden layer. MLP may represent complicated nonlinear events by using a nonlinear activation function in its hidden layer [33, 34]. Backpropagation, a standard learning method, is typically used to increase a neural network's weight [35]. When it comes to training neural networks, resilient back-propagation is one of the most efficient methods [36-38]. The MLP's second stage is a perceptron with hidden unit inputs [39].

e. Decision Tree Classifier

Supervised learning algorithms like decision trees constantly divide information based on some guiding criterion [40]. The benefits of the decision tree, in contrast to a random forest, are as follows:

• Random forest is easy to calculate, and can be used as an example to show why one variable is more crucial.
• By displaying the tree, it is easier to explain the model implementation to non-technical persons.
• Less parametric data.

f. Gaussian Naive Bayes

One variant of Naive Bayes, called Gaussian Naive Bayes, can handle continuous data using the Gaussian normal distribution. The Bayes theorem serves as the foundation for the class of supervised machine learning classification algorithms known as naive Bayes. It's a straightforward method of classification, yet it has considerable utility. This form of naive Bayes generalization is known as Gaussian Naive Bayes. While other functions may be used to determine data distribution, our training data calculates the mean and standard deviation relatively simply [41].

IV. RESULT ANALYSIS, PERFORMANCE EVALUATION, DISCUSSION

Implementation in computer science is the process of transforming a technical specification into a usable computer system, programme, or piece of software, including the creation, installation, and operationalisation of the new system. The theoretical design is translated into a workable, practical solution during the execution stage. The most crucial aspect in establishing a new, successful system is ensuring it operates efficiently and effectively. This new system results from the implementation, for which we can measure the accuracy. Based on the performance, we can take the necessary steps for further research. In the experiment, the dataset was split into training and testing sets using a 70%:30 % split ratio. Our experiments were completed with a training accuracy of 99.9% and a testing accuracy of 89.7% for the Random Forest algorithm. In comparison, the Gaussian Naïve Bayes algorithm exhibited the lowest training accuracy (around 80%) and testing accuracy (about 79%), as shown in Table 3. The precision, recall, and F1-score for each classification algorithm are summarised in Table 4. The confusion matrices for these algorithms are shown in Figure 3.

Table 3. Summary of Training and Testing Accuracy for Each Classified Algorithm.

Algorithms	Training Accuracy	Testing Accuracy
Random forest classifier	0.999884	0.897269
Gradient boosting classifier	0.922141	0.890240
Ada Boost Classifier	0.899779	0.876723
MLP classifier	0.887266	0.871046
Decision tree classifier	1.0	0.862124
Gaussian Naïve Bayes	0.801065	0.790213

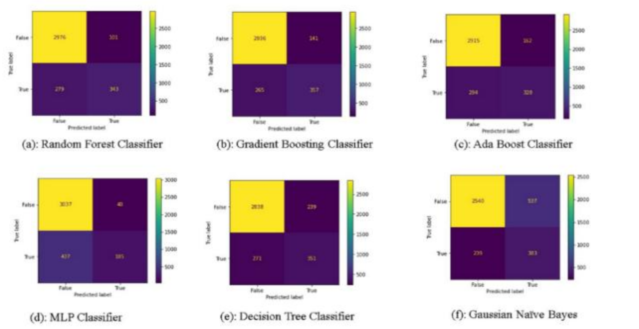

Figure 3. Confusion Matrix for all Classification Algorithms

Table 4. Summary of the Precision, Recall, and F1-score for Each Classification Algorithm

Algorithms		Precision	Recall	F1-score
Random forest classifier	False/True	0.91/0.77	0.97/0.55	0.94/0.64

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Gradient boosting classifier	False/True	0.92/0.72	0.95/0.57	0.94/0.64
Ada Boost Classifier	False/True	0.91/0.67	0.95/0.53	0.93/0.59
MLP classifier	False/True	0.87/0.82	0.99/0.30	0.93/0.44
Decision tree classifier	False/True	0.91/0.59	0.92/0.56	0.92/0.58
Gaussian Naïve Bayes	False/True	0.91/0.42	0.83/0.62	0.87/0.50

V. CONCLUSION

Online shopping is becoming increasingly popular day by day. But intentions vary from shopper to shopper every day, in every situation. Sometimes, they become choosy and can be confused about trusting online pages for various reasons. This research work proposes classifying online shoppers' purchasing intentions and identifying the best model through a comparative analysis of the models. This task is tricky enough, as online shoppers' intentions are not fixed. But some predictions are possible instead of these complications. The results indicate that the Random Forest Classifier algorithm is the best for this task among the 6-classification used in this paper. We attempted to develop a more effective model for classifying online shoppers' purchasing intentions. We believe the outcomes may influence shoppers to design their online shops for best-selling practices. Overall, this study can contribute to the emerging field of online shopping research and significantly emphasise the potential of machine learning techniques in analysing and predicting consumer behaviour in the E-commerce industry. The findings can help businesses make informed decisions and implement effective strategies to enhance customer satisfaction and drive online sales.

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Availability of Data and Material/ Data Access Statement	Not relevant
Authors Contributions	All authors have equal participation in this article.

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