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Machine Learning Approach for Prediction of the Online User Intention for a Product Purchase

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Abstract-- The deployment of self-learning computer algorithms that can automatically enhance their performance via experience is referred to as machine learning in ecommerce and is a crucial trend of the retail digital transformation. Machine learning algorithms can be unambiguously trained by analysing big datasets, identifying repeating patterns, relationships, and anomalies among all of this data, and creating mathematical models resembling such associations. These models are improved when the algorithms analyse ever-increasing amounts of data, providing us with useful insights into specific ecommerce-related events and the links between all the variables that underlie them. A tool that has been quite effective in studying current affairs, predicting future trends, and making data-driven decisions. The present work investigates the implementation of machine learning algorithms to predict the user intention for purchasing a product on a specific store's website. An Online Shoppers Purchasing Intention data set from the UC Irvine Machine Learning Repository was used for this investigation. In this study, two classification-based machine learning algorithms i.e. Stochastic Gradient Descent (SGD) algorithm and Random Forest algorithm were used. SGD algorithm was used for first time in prediction of the online user intention. The results showed that the Random Forest resulted in the highest F1-Score of 0.90 in contrast to the Stochastic Gradient Descent algorithm.

Keywords- machine learning, SGD algorithm, random forest, user intention

I. INTRODUCTION

All of the client data can be used by computers thanks to machine learning. It adheres to the pre-programmed instructions while also changing or adapting in response to new situations. Data causes algorithms to adapt and display previously unprogrammed characteristics [1-3]. If a digital assistant could read and understand context, it might be able to scan emails and extract the important content. This learning comes with the ability to predict future client behaviour as a built-in capability. As a result, you may be more proactive and responsive to the needs of your clients. Deep learning is a part of machine learning. A three-layer artificial neural network is essentially what it is. Uncertain predictions can be made by one-layer neural networks. Accuracy and optimization can be enhanced by incorporating additional layers [4–10]. Machine learning is helpful in a variety of fields and has the ability to develop throughout time. [11-15].

It is difficult to create prosthetic controllers that are clever enough to understand user intent across users. Methods for anticipating a user's locomotor mode can be developed using machine learning techniques. In the most recent state-of-the-art for subject dependent models, linear discriminant analysis (LDA) provides the standard answer and has been utilized in the creation of topic independent applications. Though, subject independent model presentation is significantly different from that of their dependent counterpart. Additionally, the majority of research restrict evaluation to a fixed terrain with unique stair height and ramp inclination. Your customer experience will improve and your

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conversion, revenue, and profit will all increase dramatically with a good AI solution that uses machine learning. With the aid of artificial intelligence (AI), online shops may automate their task and do away with a lot of the labour-intensive physical labor. Today, all of the main e-commerce platforms and online retailers use recommendation systems based on machine learning as a marketing cornerstone. These tools can analyze historical sales data, identify recurring purchase patterns among typical buyer archetypes, and forecast the products that may catch the attention of particular users to offer them personalized suggestions. Predictive analytics in marketing is typically used on a larger scale. But not all recommendation systems are created equal. In fact, they might use collaborative filtering and content-based filtering separately or together in some kind of hybrid system. It could be required to direct visitors of an ecommerce platform to the aforementioned portal before providing them products. Potential clients can be segmented—that is, divided into subgroups based on shared traits—and then targeted with customised adverts depending on a range of criteria in order to carry out this routing procedure. These comprise their interactions on social media, earlier online transactions (including those made in virtual storefronts), Google search history, and other big data types applied to e-commerce. AI can detect both micro- and macro-trends faster than any human. Fancy advertisements won't work if the goods you sell are considerably more expensive than what potential customers are willing to pay. Because of this, a number of e-commerce platforms and online retailers use machine learning to boost personalisation through personalized discounts and other promotions while also optimizing their pricing tactics. This strategy, which is also known as dynamic pricing, entails routine and specific price adjustments (even every few minutes, as is the case with Amazon), which are based on the individual user's data, pricing history of comparable products, sales trends, competitors' offers, demand versus supply, and other factors. As you may anticipate, the goal is to increase revenue while lowering client attrition. In the next sections, Literature Review, Experimental Procedure, Results and Discussion will be discussed thoroughly.

II. LITERATURE REVIEW

Many of the best technologies for web search, image identification, self-driving cars, and natural language processing are made possible by machine learning. It now allows businesses to more accurately and quickly anticipate the requirements and wants of their customers, transforming the way they conduct business. Bhakta et al. [16] explored the application of the XGBoost algorithm for creating a model that is independent of the subjects among 8 people who had transfemoral amputations. The social media revolution has given the online community the chance and means to express their thoughts, intents, and ideas on things like policies, services, and goods. The intent identification process seeks to identify user reviews' intentions, or whether they have any at all. Business companies can identify user purchasing intents with the use of the intent identification, also known as intent mining. The earlier research concentrated on feature extraction without keeping the sequence correlation using only the CNN model. Furthermore, a machine learning classifier is deployed after numerous recent investigations have used traditional feature representation techniques. Using a deep learning model, Khattak et al. [17] looked at the intention review detection problem with a focus on keeping the sequence correlation and long-term memory. The convolutional neural network and long short-term memory used in the suggested method are used to effectively determine if a given review has an intent or not. The experimental results show that, with accuracy of 92% for Dataset1 and 94% for Dataset2, the suggested system performs better than the baseline techniques. Additionally, statistical analysis shows how well the proposed strategy performs in comparison to other methods[17]. The goal of the research was to investigate data-driven machine learning and neural network techniques in the selling environment based on a thorough literature review. By pointing out that user decision-making algorithms across the internet environment can be crucial in artificial intelligence technologies to better comprehend the customer experience, Kliestik et al. [18] contribute to the body of literature. This study [18] combined earlier findings demonstrating that big data and machine learning algorithms can be used to determine client brand impression and happiness. The general populace is gradually using conversational aides. However, they are unable to manage complex information-seeking activities that call for several information exchange iterations. Conversational assistants must accurately recognize and forecast user intent in information-seeking deliberations due to the constrained transmission bandwidth in informal search. In their paper, Qu et al. [19] looked into two facets of predicting user intent in an environment where people are looking for information. In order to do user intent prediction, they first extracted topographies based on the content, structural, and sentiment aspects of a given speech. They then used traditional machine learning techniques. Then, in order to discover crucial features for this prediction task, performed an extensive feature importance analysis. They discovered that structural factors have the greatest impact on prediction accuracy. The research community has begun to pay consideration to mechanically determining the human determined behind web inquiries meanwhile it enables search engines to improve user experience by customizing results to that objective. The three fundamental motivations behind search queries—navigational, resource/transactional, and informational—are generally acknowledged. This task has been regarded as a multi-class classification issue as a natural result. The majority of current research has compared several machine learning techniques that employ words as features. The impact of different features on three categorization systems was studied by Figueora et al. [20]. It concentrates in particular on the role played by linguistic-based qualities. The majority of natural language processing technologies, however, are made for documents rather than web searches. We thus benefited from caseless models, which are trained on normally labeled data, but all terms are changed to lowercase before their production, to bridge this language divide. The main research challenge for delivering tailored experiences and services in machine-human interaction has been the issue of determining a user's intents. On modeling and inferring user activities in a computer, Chen et al. [21] offered novel ways. Intention modeling uses two linguistic aspects that are taken from the semantic context: keyword and concept features. The conceptualization of keywords are concept features. Finding the appropriate notion for a related term is done through association rule mining. Their purpose modelling employs a modified Naive Bayes classifier. According to experimental data, our suggested approach was able to predict user intentions with an average accuracy of 84%, which is comparable to the human prediction precision of 92%.

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III. MACHINE LEARNING ALGORITHMS

Similar to how the human brain gathers knowledge and makes sense of the world, machine learning relies on input, such as training data or domain knowledge, to grasp things, domains, and the relationships between them. Before beginning deep learning, entities must be defined. Machine learning starts with observation or data, including examples, firsthand experience, or instructions. In order to later derive conclusions from the supplied instances, it looks for patterns in the data. The primary objective of ML is to enable computers to learn independently, without assistance from humans, and to modify their behaviour accordingly. Machine learning has been a concept for some time. The term "machine learning" is credited to Arthur Samuel, an IBM computer scientist and pioneer in artificial intelligence and computer gaming. Samuel built a computer software that can play checkers. The application used algorithms to predict outcomes and gained knowledge from experience as it was used more frequently. The study of developing algorithms that can learn from and predict data is known as machine learning. The three primary categories of machine learning algorithms are supervised, unsupervised, and reinforcement learning. Supervised machine learning algorithms employ labelled examples to apply what they have learnt in the past to new data in order to predict future events. By analysing a known training dataset, the learning approach develops an inferred function to forecast output values. The system may provide targets for any new input after sufficient training. It can also compare its output with what is appropriate and planned in order to find weaknesses and adjust the model as needed. Unsupervised machine learning strategies are used when training data is neither categorised nor labelled. Unsupervised learning looks into the possibility that systems could infer a function from unlabeled data to explain a hidden structure. The output of the system can never be guaranteed to be accurate. Instead, it extrapolates the expected outcome from datasets. Reinforcement learning algorithms engage with their environment by acting and evaluating their outcomes. Two of the most crucial aspects of reinforcement learning are trial-and-error learning and delayed rewards. This method makes it possible for machines and software agents to automatically decide which course of action is optimal in a particular circumstance in order to improve efficiency. To determine which behaviour is preferable, the agent needs the reinforcement signal, which is a simple reward feedback.

IV. EXPERIMENTAL PROCEDURE

The output of the system can never be guaranteed to be accurate. Instead, it extrapolates the expected outcome from datasets. For this experiment, a data set on online shoppers' purchasing intentions was used from the UC Irvine Machine Learning Repository. The data collection was designed so that each session over the course of a year would be connected to a separate person, preventing any tendency to a specific campaign, noteworthy day, user profile, or timeframe. The data set's main goal is to foretell a website visitor to this specific store's likely purchasing behavior. There are extremely few missing values in this dataset, and all of its attributes are pertinent to the inferred purchasing intention. The information regarding the columns present in the dataset is shown below:

Administrative Duration: This shows how long a page in this category was active.

This provides information about how many pages of this type the user visited.

Informational Duration: This shows how long visitors spend reading pages under this heading.

ProductRelated: This indicates how many pages in this category the user visited overall (product-related).

ProductRelated Duration: This displays the amount of time spent on pages that fall within this category.

BounceRates: The percentage of website visitors who arrive on a page before leaving without taking any further action.

ExitRates: The percentage of website visitors who leave after seeing a certain page.

PageValues: The average value of the page when compared to the value of the target page or when an eCommerce transaction has been successfully completed.

Figure 1 shows the methodology flowchart used in the present work. The initial step is to import the given dataset into the Python working environment. The later step is to perform the statistical analysis after it is subjected to various machine learning classification-based algorithms. The last step is to measure the F1 score of used classification-based algorithms in order to find which algorithm is better.

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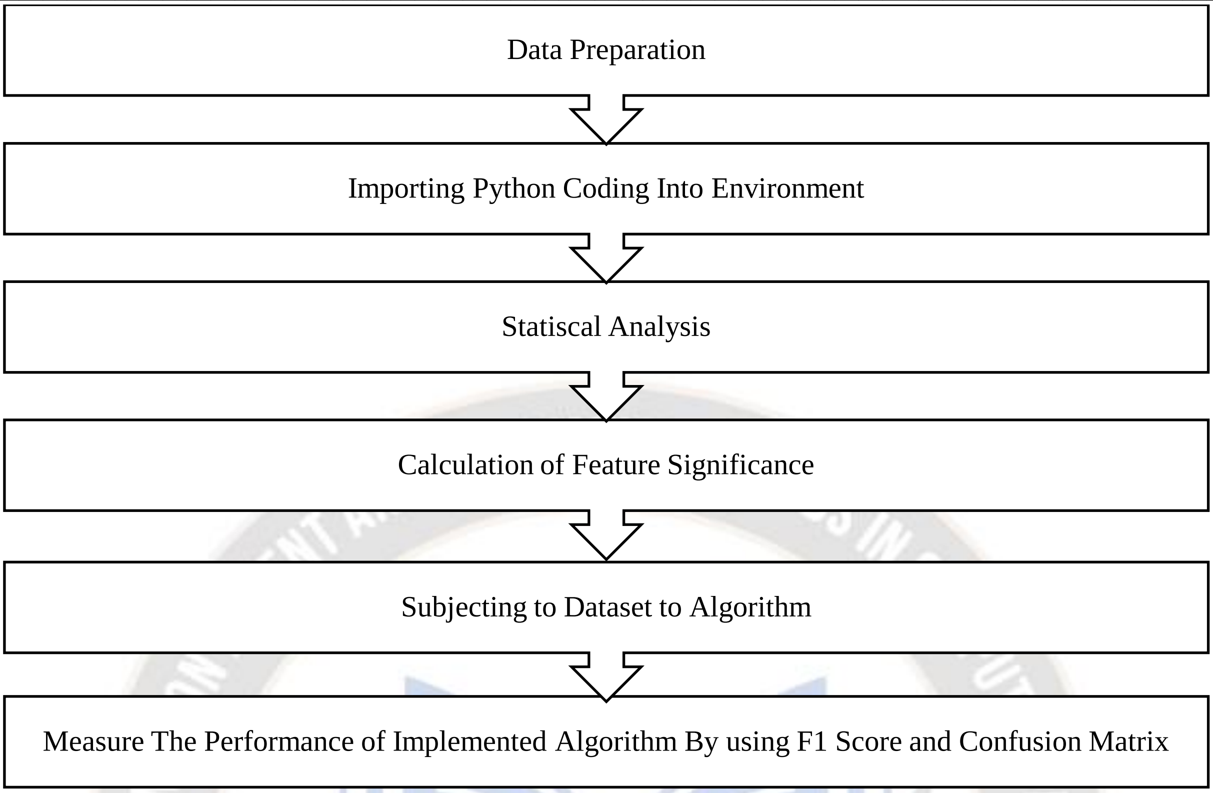

Figure 1. Methodology Used In The Present Work

The dataset has 10 numerical and 8 category attributes. The value of the 'Revenue' attribute may represent the class label. The dataset had a total of 12,440 sessions, of which 11,411 were samples from the negative classes and the remaining 1908 were samples from the positive classes that included shopping.

The phrases "Administrative," "Administrative Duration," "Informational," "Informational Duration," "Product Related," and "Product Related Duration" denote how many different page types the visitor visited during that session and the total amount of time spent on each of these page types. The values of these features are changed in real time in response to user actions, such as page switching, based on the URL information of the user's previously viewed pages. The "Bounce Rate," "Exit Rate," and "Page Value" features are some of the metrics that "Google Analytics" tracks for each page of the e-commerce website. The "Bounce Rate" for a certain page is the proportion of users who land on that page of the website, see it for a little period, and then exit without sending any more requests to the analytics server. For a certain web page, the "Exit Rate" metric is calculated using the percentage of pageviews that were the last in the session. The "Page Value" feature displays the typical value of each web page a consumer saw at prior to completing an e-commerce transaction. A site visit's proximity to a certain holiday, such as Mother's Day or Valentine's Day, when transactions are more likely to be completed, is shown by the "Special Day" feature.

By taking into account e-commerce phenomena like the interval between the order date and the delivery date, the significance of this property is determined. For example, this number has a nonzero value for Valentine's Day from February 2 to February 12, zero before and after this day unless it is close to another special day, and reaches its maximum value of 1 on February 8. Additionally included in the collection are the operating system, browser, region, traffic type, visitor type (returning or new), a Boolean value indicating whether the visit date is on the weekend, and the month of the year. In the current work, the "Revenue" attribute served as a class label.

Two machine learning techniques, Random Forest and SGD, were applied to the dataset.

Random forests (RF) construct a variety of unique decision trees during training. Predictions from all trees are integrated to provide the final prediction, which is either the mean prediction for regression or the mode of the classes for classification. Because they integrate results to make decisions, they are referred to as ensemble approaches. The importance of a characteristic is determined by the weighted decrease in node impurity divided by the probability of reaching that node. By dividing the total number of samples by the number of samples that reach the node, the node probability may be calculated. The more valuable the trait, the more important it is. The relevance of each feature on a decision tree is then established using equation 1.

$$fi_i = \frac{\sum_{j:node\ j\ splits\ on\ feature\ i} ni_j}{\sum_{k \in all\ nodes} ni_k} \quad (1)$$

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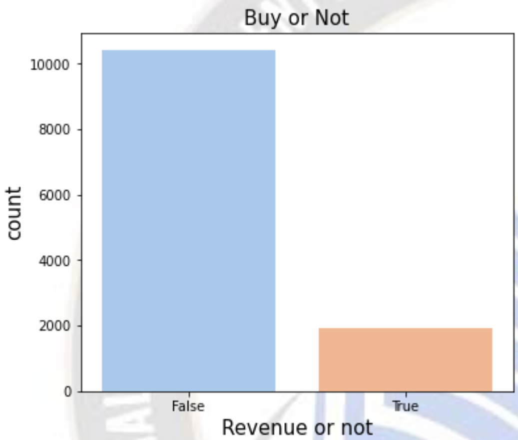
Gradient descent is by far the most well-liked technique for optimising neural networks and one of the most regularly utilised optimization algorithms. At the same time, the documentation for Lasagne, Caffe, and Keras, for example, show implementations of different techniques to optimize gradient descent. However, because it is difficult to find useful justifications for these algorithms' advantages and disadvantages, they are frequently employed as "black-box" optimizers. Gradient descent is a way to minimize an objective function $J(\theta)$ parameterized by a model's parameters $\theta \in R^d$ by informing the parameters in the opposite path of the gradient of the objective function $\nabla J(\theta)$ with reverence to the parameters. The learning rate determines the magnitude of the steps we take to reach a (local) minimum. To put it another way, we go along the objective function-produced surface's slope until we reach a valley.

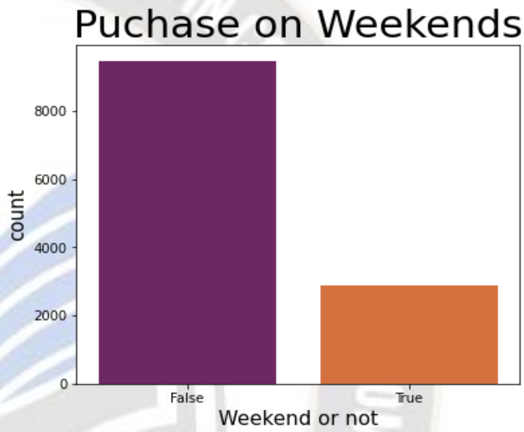
V. Results and Discussion

Figure 2 shows the visualization result of the univariate analysis for Revenue, Weekend, Operating System, Browser, Month, VistorType, TrafficType, and Region. From Figure 2 a) and 2 b) it is observed that there is an imbalance in data. From Figure 2 c) it is observed that 95% of this dataset is covered by the top 3 operating systems. In order to grow our business, we ought to concentrate on them. It's remarkable that more than 85% of visitors come back again and again as observed in Figure 2 f). This knowledge could be useful for marketing. From Figure 2 g) it is observed that different types of traffic are not distributed in a regular (Gaussian) way. This data is dispersed exponentially. Therefore, we must pay attention to this type distribution.

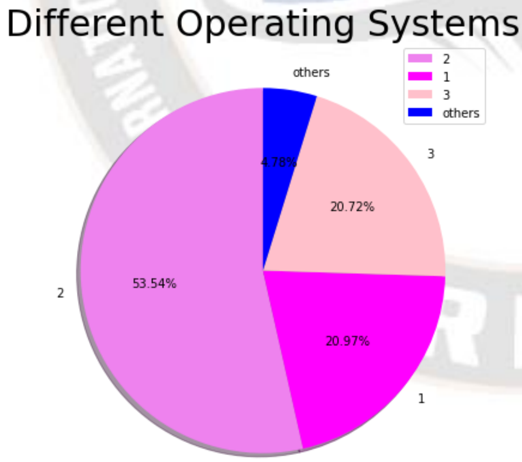
Figure 3 shows the result obtained by the multivariate analysis of the features.



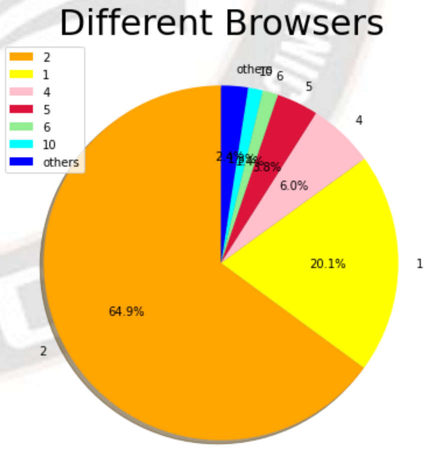
a)



b)



c)



d)

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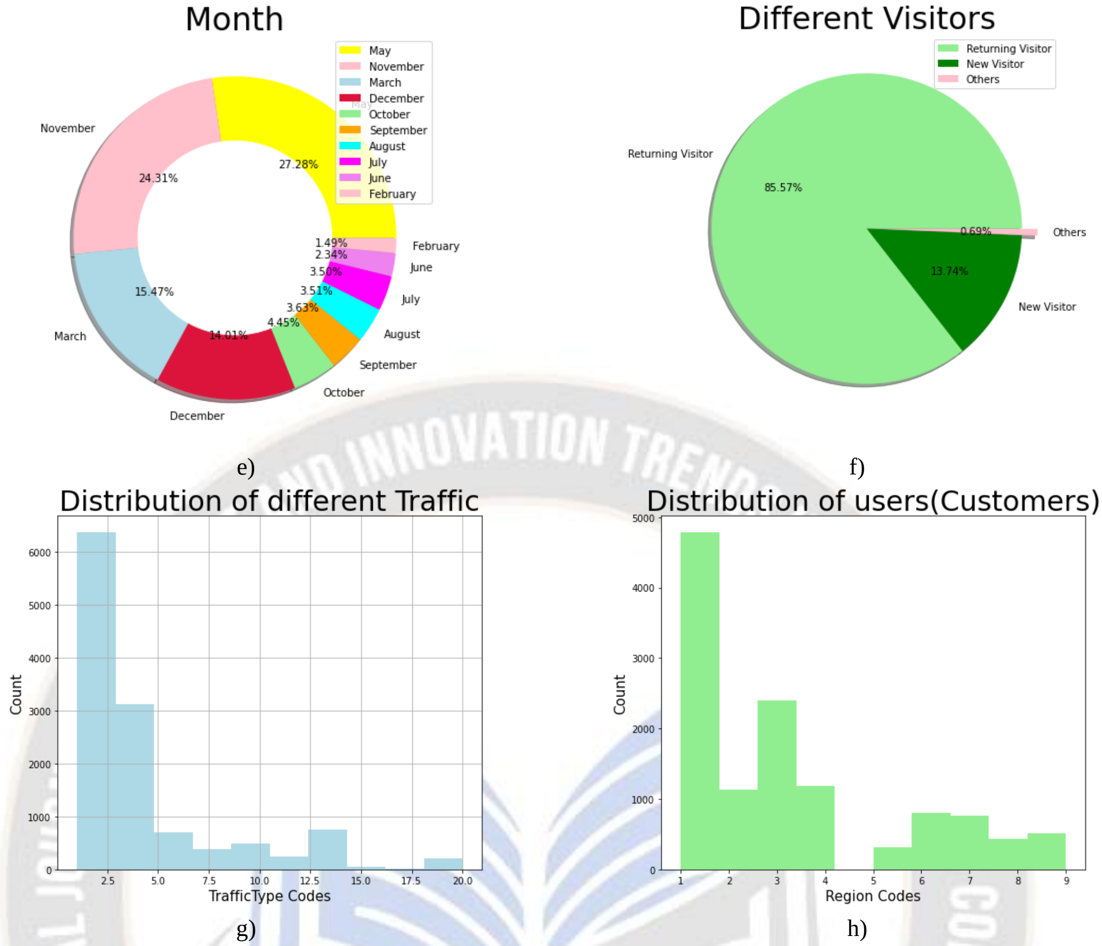

Figure 2. Visualization results of Univariate Analysis

	Multivariate_features	W.R.T	Distribution	Revenue_True	Revenue_False	Outliers	Importance
0	month vs pagevalues	Revenue	Gaussian	High	Low	Low	High
1	month vs exitrates	Revenue	Gaussian	Low	High	Medium	Medium
2	month vs bounceRates	Revenue	Gaussian	Low	High	Medium	High
3	visitor type vs BounceRates	Revenue	Exponential	Low	High	Low	High
4	visitor type vs exit rates	Revenue	Exponential	Low	High	High	Medium
5	visitor type vs exit rates	Revenue	Exponential	High	Low	High	Medium
6	region vs pagevalues	Revenue	Exponential	Low	High	High	High
7	rigion vs exit rates	Revenue	Gaussian	High	High	High	Medium

Figure 3. Multivariate analysis of the features

A3 w`s3wa es3w1

Outlier analysis is a method for locating outliers, or unusual occurrences, in a dataset. Cleansing is an important step in the data analysis process because it gets rid of inaccurate or erroneous observations that may otherwise skew the results. This process is also known as outlier detection as shown in Figure 4.

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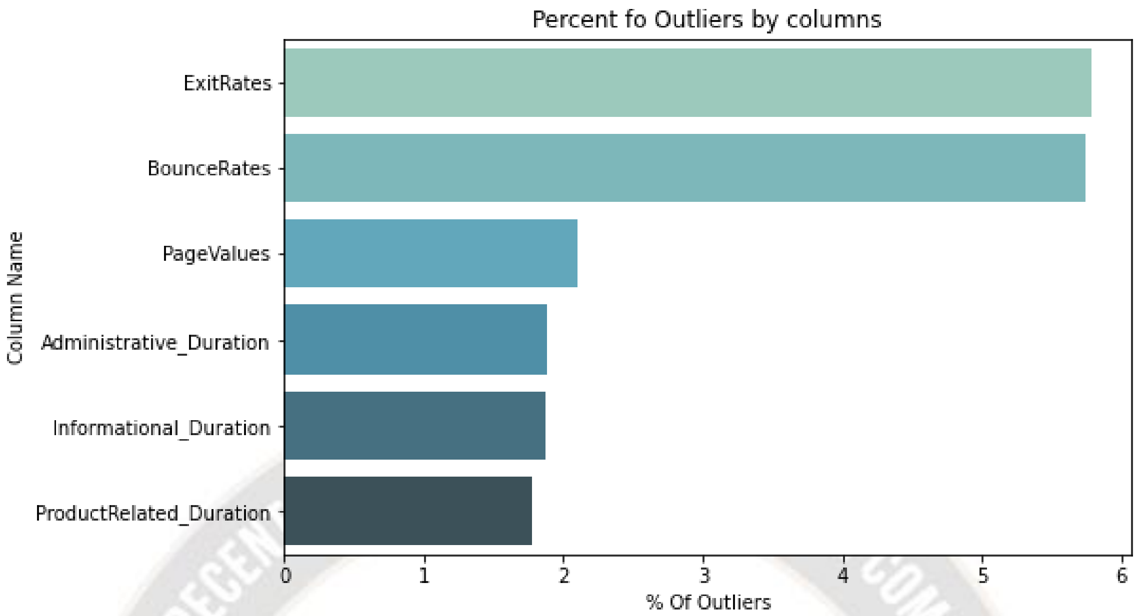

Figure 4. Outlier Analysis

Let's now talk about the outcomes of the classification-based machine learning algorithms. The Stochastic Gradient Descent algorithm and the Random Forest algorithm are two forms of classification-based machine learning algorithms that are used in the current study. The F1-score results are displayed in Table 1 below. Accuracy is a metric for classification models that measures the percentage of predictions that are correct out of all the predictions produced. For instance, if 90% of your projections come true, your accuracy is 90%. Accuracy is only a relevant metric when the distribution of classes in your categorization is equal. Therefore, if your use case includes observing more data points of one class than another, precision is no longer a useful statistic. Precision and recall are the two most used metrics that take class imbalance into account. They also form the foundation of the F1 score. Precision is the first element of the F1 Score. It can be used independently as a machine learning metric. A less accurate model might find a lot of positives, but because of its noisy selection process, it might also mistakenly find a lot of false positives. Even if a precise model misses some positives, the ones it does categorise as positive are virtually surely true. This makes precise models relatively "pure." The precision is calculated using Equation 2. Recall is the second element that goes into calculating the F1 Score, while recall can also be used as a separate machine learning metric. A model with high recall does a good job of finding all the positive cases in the data, even though they might occasionally mistake some negative examples for positive ones. A model with limited recall cannot find any positive examples in the data (or a large part of any positive cases). The recall value is calculated using Equation 3. Precision and recall are the two factors that make up the F1 score. The F1 score should be used to aggregate the precision and recall metrics into a single number. Additionally designed to work effectively with uneven data, the F1 score. The F1-Score value is calculated using Equation 4.

$$Precision = \frac{Number\ of\ True\ Positives}{Number\ of\ True\ Positives + Number\ of\ False\ Postives} \quad (2)$$

$$Recall = \frac{Number\ of\ True\ Positives}{Number\ of\ True\ Positives + Number\ of\ False\ Negatives} \quad (3)$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

Table1. Results obtained for Classification-based algorithms

Algorithms	Precision of 0	Precision of 1	Recall of 0	Recall of 1	F1-Score
SGD Algorithm	0.91	0.42	0.83	0.61	0.79
Random Forest	0.91	0.77	0.97	0.56	0.90

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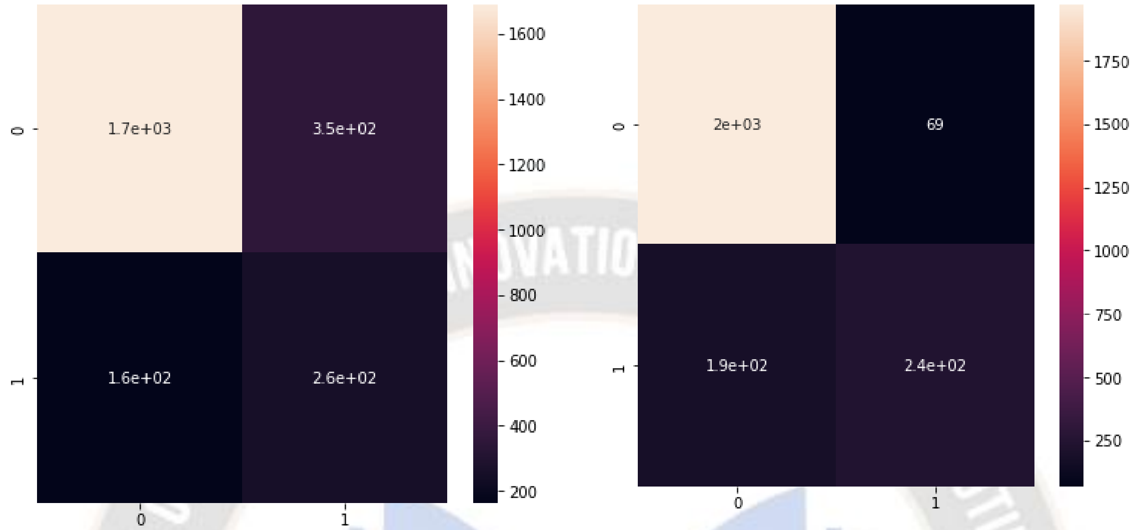
Figure 5 shows the confusion matrix plot obtained for the implemented algorithms. The summary of the results of the predictions is a confusion matrix. In a number count, a confusion matrix produces both the right and wrong values. It facilitates effective data visualization for us. More importantly than just the faults a classifier is making, it informs us about the many kinds of errors that are being made.



a) SGD Algorithm

b) Random Forest Algorithm

Figure 5. Confusion Matrix plot

From Table 1 it is observed that the Random Forest has highest F1-Score when measured against the SGD Algorithm. Random forests are used to offer estimates of varying relevance, also known as neural nets. They also offer a more effective method of handling missing data. The gaps created by missing values are filled in by the variable that appears the most frequently in a specific node. Of all the categorising methods now in use, random forests have the highest accuracy. The random forest method is also capable of handling huge data sets with a huge variety of factors. It can automatically balance data sets when one class in the data is less frequent than other classes. The method is suitable for difficult assignments because it handles variables rapidly.

VI. CONCLUSIONS

Machine learning has several business advantages, along with other technologies like augmented reality. particularly to online merchants. It is crucial that algorithms can make sense of enormous amounts of data. Almost all facets of ecommerce operations now have machine learning applications. Ecommerce machine learning really delivers, from customer experience to inventory management. For any ecommerce website, converting browsers into online buyers is essential. Because of this, you'll undoubtedly be a touch fixated on the conversion rate of your website. Machine learning may in many ways help increase that rate, which is one reason why it is so beneficial to e-commerce. From the present study it is observed that Random Forest algorithm resulted in highest F1-Score of 0.90. Surprisingly, SGD frequently favors low generalization error solutions above low optimisation error ones. This indicates that it operates as a regularizer and will favor solutions with better test accuracy over those with lower training loss. It might be said that machine learning enables a quicker and more accurate analysis. Computer programmes can be used to compute e-commerce sales, storage costs, tax effects, and other variables. It can help with demand predictions as well. You now possess all the information required to put the best practises into practise.

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