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Enhancing E-commerce Insights: Sentiment Analysis Using Machine Learning and Ensemble Techniques

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***Abstract*- This research aims to explore the impact of customer reviews on consumer decisions in the e-commerce era. Machine learning techniques, including Naive Bayes, Random Forest, Decision Tree, Extra Trees, and Logistic Regression, are utilized for sentiment analysis of customer reviews. A comprehensive dataset is collected through web scraping and subjected to exploratory data analysis (EDA) to gain a deeper understanding of its characteristics. Feature extraction techniques are applied to convert raw text data into meaningful numerical representations. The ensemble learning approach, specifically the voting ensemble method, is employed to combine individual model predictions, enhancing overall performance and robustness. The findings contribute valuable insights into customer sentiment, empowering businesses to understand preferences and enhance their offerings.**

Keywords - Machine Learning; TF-IDF; SVM; Naïve Bayes; Decision Tree; Logistic Regression; Ensemble Models; Sentiment Analysis; Natural Language Processing

I. INTRODUCTION

E-commerce, also recognized as electronic commerce, pertains to the online transactional exchange of goods and services.[1] It has brought about a transformative shift in the operational landscape of businesses and consumer shops by providing a convenient and accessible platform for transactions. Online shopping, a major component of e-commerce, allows customers to browse and purchase products or services through websites or mobile applications. One of the significant advantages of e-commerce and online shopping is the convenience it offers.[2] Customers can shop anytime, anywhere, without being limited by physical store hours or location. Consumers can conveniently compare prices, access product reviews, and make well-informed purchasing choices without leaving the comfort of their own homes or while on the go[2]. In the era of e-commerce, online reviews have become an essential part of the decision-making process for customers. Nowadays, customers rely heavily on reviews posted by other customers to make their purchase decisions.[3][1] Therefore, e-commerce businesses must monitor and analyze customer feedback to improve their products or services and build brand loyalty. One of the best ways to analyze customer feedback is through sentiment analysis.[3] Sentiment analysis employs a combination of natural language processing (NLP) and machine learning techniques to evaluate the sentiment expressed in customer reviews shared on e-commerce platforms.[4] This analysis aims to extract insights from customer feedback, identify customer sentiment toward products or services, and identify areas for improvement [5]. This article will discuss the benefits of sentiment analysis of customer reviews of e-commerce and the steps involved in performing this analysis. Sentiment analysis allows e-commerce businesses to understand customer sentiment toward their products or services. By analyzing customer reviews, businesses can identify positive and negative feedback and take action to address areas of concern. By analyzing customer feedback, e-commerce businesses can identify areas for improvement in their products or services.[5] This feedback can be used to enhance product features, improve customer service, and provide a better overall customer experience. By addressing areas of concern highlighted in customer reviews, e-commerce businesses can enhance customer satisfaction. Satisfied customers are inclined to share positive reviews, which in turn have the potential to draw in new customers and increase sales.[6] By monitoring and responding to customer feedback, e-commerce businesses can build a positive brand reputation. Positive reviews have the potential to attract fresh custo*mers while addressing negative reviews showcases a dedication to customer service and fosters customer loyalty.[5] The rapid growth of e-commerce has presented businesses with the challenge of effectively utilizing customer feedback to improve their products or services and build customer loyalty.[6] In the context of online reviews, businesses struggle to analyze and extract meaningful insights from the vast amount of unstructured data available. The problem at hand is how to leverage sentiment analysis techniques to understand customer sentiment toward products or services in the e-commerce industry. By addressing this problem, businesses can identify areas for improvement, enhance the overall customer experience, and ultimately drive sales.[5] Additionally, it is crucial to explore the challenges specific to sentiment analysis in the e-commerce domain, such as dealing with the unique language and nuances found in customer reviews. Finding effective strategies to overcome these challenges is paramount to gaining accurate and actionable insights from customer feedback.[7] By delving into these problem areas, businesses can leverage sentiment analysis to its fullest potential, leading to improved customer satisfaction and a competitive advantage in the e-commerce market[8]. The main contribution of this paper is to do a sentiment analysis of real customer reviews available on e-commerce sites. Classify the polarity of the sentiment in reviews, use machine learning models to classify the reviews, and compare the results of machine learning algorithms.

II. LITERATURE REVIEW

To accurately perform the sentiment analysis of the raw reviews this paper uses the feature extraction methods. Results show that a good approach greatly improves sentiment analysis performance. finding the performance of the models using datasets and learning more NLP techniques [1]. The experimental findings demonstrate that the proposed algorithm outperforms existing methods in terms of performance. Moving forward, the researchers aim to develop innovative approaches utilizing tags and knowledge graphs as supplementary information to further enhance recommendation accuracy. Additionally, they plan to introduce a tag recommendation model that leverages dynamic user preferences, offering personalized recommendations based on evolving user interests and preferences. These future advancements hold promise for improving the overall effectiveness of the RS. [2] Understanding the limitation of the study is most important, which primarily focused on attractions and relied solely on data from TripAdvisor, potentially introducing platform bias. To validate the findings, future research should explore information and services. [3] The study encompassed a comprehensive literature review aimed at identifying and classifying existing studies that employed sentiment analysis on COVID-19 Twitter data, particularly focusing on machine learning (ML) techniques. Through a multistage screening process, 40 papers were selected out of an initial pool of 425 publications from reputable journals. The findings indicated that sentiment analysis in the context of COVID-19 is predominantly tailored to specific domains and applications. Ensemble models and deep learning (DL) classifiers demonstrated superior performance compared to single classifier models. Notably, pre-training BERT or RoBERTa models on Twitter data yielded promising outcomes[4]. This paper discusses the use of Chinese social e-commerce for hotel bookings and the importance of customer reviews. The study uses hotel review data from Ctrip and applies emotion analysis using a BERT model.[5] The paper introduces a novel approach that combines feature extraction techniques to achieve precise sentiment analysis of unprocessed online reviews. By leveraging temporal sentiment analysis, researchers can gain insights into the fluctuating emotional states and their interconnectedness with various contextual factors, thereby facilitating a more comprehensive understanding of the subject matter.[6] The study suggests that developers should focus on improving usability and affection levels in non-gamified applications and consider users' emotional values to enhance their satisfaction. However, the study has some limitations, such as the lack of user demographic information and the generalizability of results to other app stores, and future research can address these limitations using more advanced natural language processing techniques. [7] The study also finds that consumers are more strict when assigning positive sentiment toward star ratings when viewing them as consumers.[8] This paper proposes a method for sentiment analysis of Twitter tweets using a stochastic gate neural network (SGNN) and a pre-trained word embedding feature based on the polarity of the lexicon and n-grams. The approach applies to diverse social media platforms and serves as a valuable tool for researchers operating within the specified domain.[9] The research explores the connections between physician characteristics and sentiment analysis scores obtained from reviews and ratings. Additionally, it explores the influence of frequently used words on the overall positivity of reviews. The results indicate to receive higher ratings, and the inclusion of pleasant personality descriptors in reviews has a positive effect on their sentiment.[10]

A. Data Collection: -

The data collection process involved gathering data on 13 different smart TVs. The dataset consists of 24,000 rows and was obtained through web scraping techniques.[10] To begin the data collection process, a set of 13 specific smart TVs was selected for analysis. These TVs were chosen based on various criteria such as their popularity, customer ratings, or specific brands and models of interest. Web scraping, a method of automatically extracting data from websites, was employed to collect the necessary information.[10]

III. METHODOLOGY

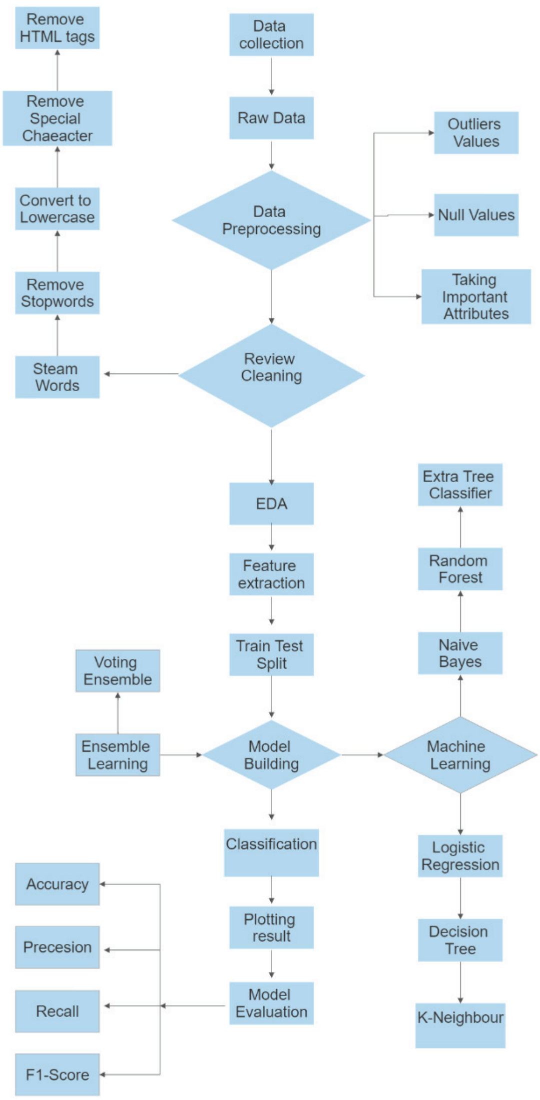

Fig. 1. Methodology

The web scraping script or tool accessed relevant e-commerce websites that sell smart TVs. It navigated to the product pages of the selected 13 models and extracted specific details required for sentiment analysis, with a particular focus on customer reviews.[10] The extracted information encompassed various elements such as product names, descriptions, prices, customer ratings, reviews, and any other pertinent data that could contribute to sentiment analysis. During the web scraping process, the script or tool systematically accessed each smart TV's web page. It located the customer review section on the page and retrieved relevant content, including the review text, reviewer's name, rating, and any other associated information. To ensure comprehensive data coverage, the web scraping script or tool likely iterated through multiple pages of reviews for each smart TV. This involved navigating to subsequent pages and systematically extracting the reviews until all available data was collected. The resulting dataset comprises 24,000 rows, indicating a substantial volume of customer reviews for the 13 selected smart TVs. This large dataset can provide a robust foundation for sentiment analysis, allowing for in-depth insights into customer sentiments toward the different smart TV models. Throughout the web scraping process, it is essential to consider ethical considerations and adhere to legal requirements. Compliance with the terms and conditions of the websites being scraped is crucial.[10] Additionally, it is important to be mindful of any rate limits or restrictions imposed by the websites to avoid overloading their servers or violating their policies. In summary, the data collection phase of the paper involved systematically scraping customer reviews for 13 smart TVs from e-commerce websites. The process automated the extraction of relevant information from multiple pages, resulting in a substantial dataset of 24,000 rows suitable for sentiment analysis.

A. *Data Preprocessing: -*

After collecting the data preprocessing is an important part of data analysis in preparing data for further analysis.

1) *Removing duplicates:*

It's important to check for and eliminate any duplicate rows or reviews within the dataset. Duplicates can skew the analysis and introduce bias. By comparing the content of each review, you can identify and remove duplicate entries.

2) *Handling missing values:*

Missing data occurs when fields are not filled out or captured during web scraping. Proper handling involves removing rows, imputing values using statistical measures, or using advanced imputation techniques to avoid bias or impact on analysis.

B. *Review text cleaning: -*

1) *Removing HTML tags:*

When scraping data from websites, the collected text data often contains HTML tags used for formatting and styling. Removing these tags is essential to focus solely on the textual content of the reviews.[9] This can be done using regular expressions or HTML parsing libraries.

2) *Removing special characters:*

Special characters such as punctuation marks, symbols, or non-alphanumeric characters can add noise to the text data and may not contribute significantly to sentiment analysis.[1] Removing these special characters helps in reducing noise and improving the accuracy of subsequent analyses[1].

3) *Lowercasing the words:*

Text data often contains words in various cases (uppercase, lowercase, or mixed). Converting all the words to lowercase standardizes the text, ensuring that the same word in different cases is treated as the same word. This process helps in avoiding duplication and improves the efficiency of subsequent analysis.

4) *Remove Stop words:*

Stop words are common words with no significant meaning or contribution to sentiment analysis.[6] To reduce the dimensionality of the data we can remove the stop words that are in our dataset so that the model can move precisely to make prediction. Some stop words are ‘is’, ‘and’, ‘the’ like this stop words we can remove. [6][10].

5) *Stemming words:*

In the steaming words process convert the words to their base forms. For example, stemming the word "running," "runs," and "ran" would result in the base form "run." Stemming helps in consolidating words with similar meanings, reducing vocabulary size, and improving the accuracy of sentiment analysis [6].

C. *Sentiment Analysis-*

Sentiment analysis, a natural language processing technique, detects emotions expressed in text, also known as opinion mining. It helps organizations analyze and categorize sentiments related to products, services, or concepts. Sentiment analysis classifies opinions to determine a writer's attitude towards a subject, product, or entity, determining whether it is positive, negative, or neutral. Tools for sentiment analysis are crucial for identifying and comprehending emotions. These tools can help businesses and organizations better understand how people feel and boost productivity. Utilizing sentiment analysis techniques, businesses can learn how to increase customer satisfaction and experience.

1) *Tokenisation:*

Tokenization in sentiment analysis is the process of breaking down a piece of text, such as a customer review, into individual units called tokens. These tokens can be words, phrases, or even individual characters.[6] The first and important step in Natural language processing is Tokenization, as Tokenisation makes the data into small small tokens so that the machine learning model can understand it easily.

2) *Lemmatization:*

The lemmatization technique is used. It is a text processing technique that reduces words to their base or dictionary form, known as the lemma. It aims to normalize words by considering their morphological variants. Unlike stemming, which simply chops off word endings, lemmatization takes into account the word's context and grammar to produce meaningful lemmas.[6] For example, lemmatizing the word "running" would result in "run," and "better" would be reduced to "good." By performing lemmatization, we can improve the accuracy and effectiveness of various natural language processing tasks such as text classification, sentiment analysis, and information retrieval

3) *Polarity:*

The emotional tone or mood communicated in a text is referred to as its polarity, indicating whether it is positive, negative, or neutral [2]. Polarity is often represented on a numerical scale, such as -1 to +1, to indicate the emotional sentiment associated with a text or data. In this scale, a value of -1 signifies a highly negative emotion, +1 represents a strongly positive emotion, and 0 indicates a neutral emotion. [10] By examining the words and phrases used and taking into consideration the sentiment they are linked within a predetermined sentiment lexicon, or by using machine learning algorithms trained on labeled data, it is possible to compute the polarity score of a text. [4] [10]

After calculating the Polarity, we classify the reviews as positive negative, and neutral. Based on that we can understand the actual feeling in the review text.

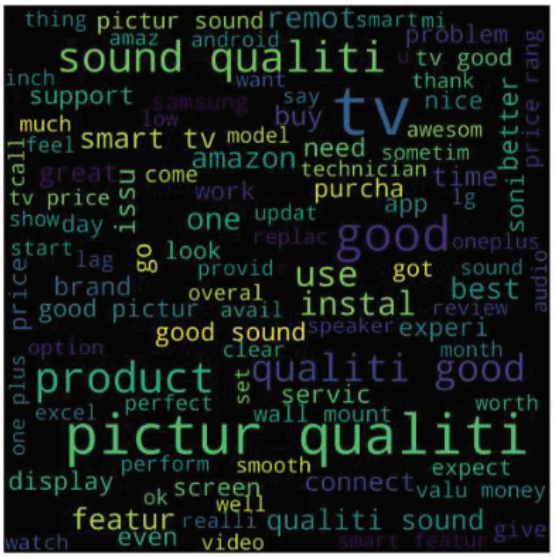

Fig. 2. Word cloud of positive reviews

The above diagram Is of word cloud of the positive reviews posted on the e-commerce platform. From this word cloud, we can observe that the peoples' are satisfied with the TV's picture quality and the sound quality of the TVs. By this word cloud, we understand that people are happy about the prices of TVs also people are happy about the speaker, smooth performance, display, and so on.

Fig. 3. Word cloud of negative reviews

The above word cloud diagram is of the negative reviews posted on the e-commerce platform. By this word cloud, we can understand that the users are also not satisfied with the products. Some of the consumers have problems related to customer service some of the users have problems related to the price. Does not satisfied with the customer care service, delivery, screen display, picture quality, and so on.

Fig. 4. Word cloud of neutral reviews

The above word cloud is of the neutral review posted on the e-commerce platform. By this word cloud, we can understand that the reviews have words like product, quality, money, TV, amazon, service, install replace, and many more. By this word cloud, we can understand that people are happy about the product, product quality, and customer care.

D. Models Used: -

1) Multinomial Naïve Bayes (MNB):-

Multinomial Naive Bayes is one of the most well-liked supervised learning classifiers used to analyze categorical text data. The method predicts the tag or category of a text by applying the principles of Bayes theorem [2]. It calculates the probabilities of each class for a given sample and assigns the class with the highest probability as the output prediction.

2) Logistic regression(LR): -

LR is a statistical method that is widely used to solve the classification problem by predicting the probability of an outcome falling into one of two categories [2][3]. The output is derived by applying a logistic function to a linear combination of input variables, enabling the transformation of the inputs into a probability-based outcome.[3] This model is trained using maximum likelihood and based on that tries to find the best-fit line.

3) K-nearest neighbors (KNN)

Classifier is a versatile machine learning algorithm capable of handling both classification and regression tasks.[11] It operates as a non-parametric approach, relying on the similarity between input data points and their neighboring data points to make accurate predictions. The KNN is identified based on the minimum distances and assigned the class label that is most prevalent among its K nearest neighbors.[12] The choice of K is an important parameter in the algorithm. It is suitable for online learning scenarios and can capture complex decision boundaries.

4) Decision Tree (DT):

The machine learning algorithm called Decision Tree is generally used for classification tasks basically Decision Tree from a tree-like structure it makes nodes and sub nodes.[11] Decision trees are known for their interpretability Also decision Tree can be able to hand both numerical data and also categorical data.[12] However, a potential drawback of decision trees is their tendency to overfit the training data. To mitigate this issue, methods like pruning, ensemble learning, and regularization can be employed to enhance the generalization and performance of decision tree models [12].

5) Extra tree (ET): -

The Extra Trees Classifier is an ensemble machine learning algorithm that works by constructing multiple decision trees and selecting random subsets of features for each split. This randomization reduces the variance of the model, making it less prone to overfitting.[12] During the prediction phase, the class label with the majority vote from the decision trees is selected as the predicted class. The key advantages of the Extra Trees Classifier include its ability to handle high-dimensional datasets, its resistance to overfitting, and its efficiency in terms of training time.[12] However, the randomization may lead to a slight decrease in predictive accuracy and reduced interpretability.

6) Random Forest (RF):

Random Forest is a combination of different decision trees.[11] It can be used for classification as well as for regression. Random Forest is most suitable for high-dimension noisy data. Random Forest Algorithm works with the majority votes in classifying classes using different decision trees.[12]

E. Ensemble model (Voting Ensemble)

To get the accurate result of the models we have used ensemble learning methods. Ensemble learning methods are used to get more accurate results than the traditional models.[11] The voting ensemble is a popular ensemble learning method it gives the output by combining the results of all models used it aggregates the results to make the predictions. The aim behind the voting ensemble is to combine models' predictions and aggregate them to get more accurate results and predictions. This method has three types majority voting, weighted voting, and soft voting. In this study, we have used the soft voting technique. Soft voting sums up the probabilities of each class predicted by models and selects the highest summed probability.

F. Evaluation parameter: -

1) Accuracy:

The accuracy is used to understand the overall correctness of the machine learning model. The calculation entails evaluating the precision of sentiment predictions (positive, negative, neutral) by contrasting the count of accurately predicted sentiments with the total number of reviews present in the dataset.[9] Accuracy provides a general overview of the model's performance, indicating how well it predicts sentiment across all classes.[2] However, accuracy may not be the best metric when dealing with imbalanced datasets, where one sentiment class dominates. Accuracy generally defines the ratio of the correct perfection of models to the total number of predictions.

$$\text{Accuracy} = (TP+TN)/(TP+TN+FP+FN) \quad [5]$$

2) Precision:

Precision is a metric that focuses on the positive outcomes made by the model. The precision is calculated by taking the ratio of the instances that are positively predicted to the instances of all positives means True positive and false positive.[9] It is generally used to measure the working of the model to ignore the false positive. [2]i.e., correctly identifying positive sentiments without misclassifying negative or neutral sentiments as positive. A low rate of false positives means it will give a high value.

$$\text{Precision} = TP/(TP+FP)$$

3) Recall:

Recall refers to the true positive and sensitivity, and also evaluates the model capacity to correctly capture all positive instances. This method identifies the relation between the actual positive data present in the dataset with the correctly predicted positive dataset.[9] By measuring recall, the model's performance in accurately identifying all positive sentiments, without overlooking any, is assessed.[2] A high recall value signifies that the model effectively minimizes the occurrence of false negative predictions by accurately identifying positive sentiments and avoiding misclassifications as negative or neutral.

$$\text{Recall} = TP/(TP+FN) \quad [5]$$

4) F1 Score:

The harmonic mean of recall and precision, and also provides the balance of model performance. F1 score consists of precision as well as recall to make the predictions. The F1 score considers the trade-off between precision and recall and provides a single value that represents the model's overall performance. [2] The F1 score proves valuable in scenarios where there is an imbalanced class distribution or when the significance of false positives and false negatives is equal[9].

$$\text{F1score}=(2\times\text{Precision}\times\text{Recall})/(\text{Precision} + \text{Recall}) \quad [5]$$

IV. Results And Discussion

A. Data Balancing:

As we can see our data is imbalanced. Imbalanced data can cause lower accuracy of the machine learning models or can be performed overfit to the data. so firstly we will balance our data. for the balancing, we have used resample techniques. There are different types of resampling techniques present we have used random over-sampling technique. in this technique we have the minority class distribution and majority class distribution so on that minority class we have randomly increased the minority class by replacing them randomly and getting enough classes the same as the majority class.

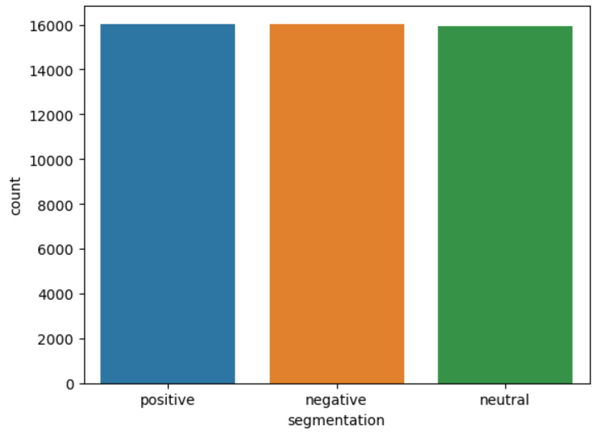

Fig. 5. Classification of Balanced Classes

B. Model result

The ML models were built to classify the sentiment recorded. The models used were (MNB), (RF), (ETC), (LR), (DTC) and (KNC). The performance matrices like precision, recall, F1 score, and accuracy were used. Out of the all algorithms used for sentiment analysis, we can understand that the random forest algorithm performs best. We can see that the multinomial Naïve Bayes and k neighbor classifier before was not good because the shows less accuracy than other algorithms. Other algorithms like (ETC), (LR), (and DTC) classifiers perform well and have the accuracy same as the random forest but as we can compare the confusion matrix of each model we can say that these models can be overfitted or can have less ability to predict true positive elements[13-16].

TABLE I. EVALUATION PARAMETERS FOR MODEL COMPARISON

Model	MNB	RF	ET	LR	DT	KNN
Accuracy	0.86	0.98	0.99	0.97	0.99	0.78
Precision	0.87	0.98	0.99	0.97	0.99	0.85
Recall	0.86	0.98	0.99	0.97	0.99	0.78
F1 Score	0.86	0.98	0.99	0.97	0.99	0.78

The below figure shows the evaluation parameter of each model which is used for the sentiment analysis. Here we can see that as compared to other models K neighbours have less value in the evaluation matrix. The random forest has good values as compared to other machine learning algorithms. Therefore, we can say that random forest performs better as compared to other algorithms. Table III shows the classification report of the voting ensemble technique. Here we can see that the accuracy of this model is 99% and the good score of precision-recall and f1 score. Here the precision value for class 0,1,2 is 1, 0.98, 0.98 respectively.

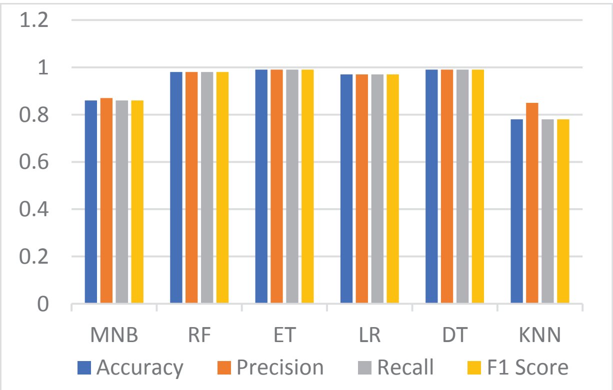

Fig. 6 Model Evaluation Parameters

TABLE II. ENSEMBLE MODEL EVALUATION PARAMETER

Model	Precision			Recall			F1-Score			Accuracy
	0	1	2	0	1	2	0	1	2	
Voting Ensemble	1	0.98	0.98	0.96	1	1	0.98	0.99	0.99	0.99

V. CONCLUSION

The research concludes that customer reviews play a crucial role in determining customer satisfaction and sentiment toward products. The study specifically focused on analyzing the sentiment polarity of Smart TV purchases using reviews from e-commerce platforms. Machine learning classification algorithms, including Extra Tree Classifier (ETC), Multinomial Naïve Bayes (MNB), Decision Tree Classifier (DTC), Random Forest (RF), Logistic Regression (LR), and K-Nearest Neighbor Classifier (KNC), were employed, along with ensemble learning using the voting ensemble method. Feature extraction was performed using TFIDF Vectorizer. Among the models evaluated using various metrics such as accuracy, precision, recall, and F1 score, the Random Forest classifier demonstrated the highest performance with an accuracy of 99% and an F1 score of 0.99. Other models, such as Logistic Regression (LR), Multinomial Naïve Bayes (MNB), Decision Tree Classifier (DTC), Extra Tree Classifier (ETC), and K-Nearest Neighbor Classifier (KNC), achieved accuracies of 87%, 99%, 98%, 99%, and 79%, respectively. Furthermore, the research implemented an ensemble method using the voting ensemble technique, which performed well with an accuracy of 99%. The ensemble method also achieved the highest precision and recall and F1-scores of 0.98, 0.98, and 0.98 respectively. The future of sentiment analysis in e-commerce holds exciting possibilities, with advancements in technology leading to more sophisticated algorithms that better understand and classify customer reviews. These advancements will enable businesses to gain clearer insights into customer sentiment across different languages and platforms, fostering increased customer loyalty and success in the online marketplace.

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