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FAKE REVIEW DETECTION SYSTEM USING CLASSIFICATION ALGORITHMES ON AMAZON DATASET

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Abstract: Fake reviews are a significant problem in e-commerce, online businesses, and other online platforms that rely on customer reviews to drive sales and build reputations. These reviews can be written by dishonest individuals, competitors, or even bots, and can severely mislead potential customers. To combat this issue, various methods have been developed for detecting and removing fake reviews. One approach is to use machine learning algorithms that analyze text data to identify patterns and features that are characteristic of fake reviews. These algorithms can be trained on large datasets of both genuine and fake reviews, allowing them to learn to distinguish between the two types. Some of the key features that these algorithms look for include the use of overly positive language, the inclusion of irrelevant information, and the presence of suspicious patterns in the review data. Another method for detecting fake reviews involves using data mining techniques to identify patterns in the data. This can involve analyzing user behavior, such as the frequency and timing of reviews, or looking at the metadata associated with the reviews, such as the IP address or location of the reviewer. Overall, the development of fake review detection systems is an ongoing area of research, as new techniques and approaches are constantly being developed to combat this problem. As e-commerce and other online businesses continue to grow in popularity, the need for effective fake review detection systems will only become more important in ensuring the integrity of online platforms. In addition to the review feature extraction approach, the method we propose is employed to detect fake online reviews on the Amazon Fashion and Amazon Electronics datasets. On the Amazon Fashion dataset and the Amazon Electronics dataset, the suggested algorithm is 94% and 97% accurate, respectively.

Keywords—Fake reviews detection, data cleaning, SVM, feature engineering, NLP

I. INTRODUCTION

Reviews are expressions of someone's ideas, beliefs, or personal encounters with a given item on the market. On online e-commerce sites, people write product reviews to share their opinions and experiences with the manufacturers, suppliers, and other buyers of the products. The provided user experience can help any organization expand for better by looking at the ideas. Any product provider will make money or lose money depending on the polarity of the reviews. [8]. The use of the Internet and online marketing has grown in popularity in recent years. Millions of items and services are offered inonline marketing, generating a massive amount of data. As a result, finding the most relevant services or goods compatible with the criteriais challenging. Customers make direct decisions based on evaluations or comments expressed by others based on their own experiences. According to American studies, product feedback influences 80% of purchasing decisions. The issue is determining if the feedback providedis legitimate or fake.

Untrusted (false) reviews, reviews based entirely on the product name,and non-reviews are the 3 types of fictitious reviews. To purposefully mislead and cheat buyers and consumers, fake reviews are posted online. These reviews may give specific preferred products unjustly high ratings in order to promote them or low ratings in order todisparage worthy products. [4]. Hyperactive fake reviews are associated to this kind of review. The second form of false review thatcan be created to influence product brands specifically focuses on reviews on specific product brands. There are two categories of nonreviews: advertisements and unrelated reviews [4] are twoexamples. Negative reviews may lead customers to explore for alternatives, which could result in loss of revenue, whilst positive ratings encourage shoppers and customers to acquire products, enhancing companies' financial benefits. Various businesses hire people to post false good evaluations about their services or products, as well as false negative reviews about their competitor's services or products [5]. In order to determine how the general public feels abouta specific good, service, or concept, natural language processing (NLP)is employed. Untrue opinions are those that are expressed negatively with the intent to harm a company's reputation or to unjustly advance abusiness. Similarly, good comments are supplied in order for an organisation to develop fame in an unethical manner. This approach provides inaccurate information to potential customers who want to buy such items; therefore, we need a mechanism to detect and eradicatesuch fake reviews. The following features summarise the research's novelty: First, a multi-level feature extraction approach is used to pickfeatures. This work included several feature engineering methodologies to extract distinctive behaviours of the reviewer and reviews Not only was Natural Language Processing used on the corpusto extract features for classifiers, but the process of feature engineeringalso involved extracting behavioral features. The behavioural elementsof a user's review are a representation of its statistical significance. They are related to the reviewer even though they might not directly increase classification accuracy. Examples include the length of the review, the writing style, the punctuation, the ratio of verbs to nouns, and the associated

terminology. All of these factors had an impact on how the results were generally classified, both accurately as well as with integrity. We also attempted to obtain samples from the training and testing datasets that fit together the best in order to acquire the best classifier results.

II. LITERATURE REVIEW:

Machine Learning Methods for Detecting Fake Reviews. Jindal et al. [1] published the first study in detecting fake reviews. Duplicate or almost identical Amazon product reviews that included information about the reviewer and review text. The logistic regression technique was used to identify reviews as true or false, with an accuracy of 78%.

Tufail, H. et al. [2] employed the SKL method for false review detection, emphasising the relevance of the data set's robustness in spam detection. The proposed model has a 95% accuracy rate.

S.N. Alsubari et al. [3] proposes a hyper neural network model based on CNN-LSTM approaches for detecting and classifying review content as fraudulent or true. The CNN technique's convolutional and max-pooling layers extract and select features. For the last layer of contextual information processing of input sequences, the LSTM approach is paired with CNN. The proposed model has an accuracy of 89%.

Crawford, M. et al. [4] discussed different machine learning algorithms that can be used to detect bogus reviews. It also emphasizes the significance of a high-quality data set. It also compares various machine learning methods that can be used to detect bogus reviews. For instance, NB classifier, SVM, and Logistic regression.

Fang, X., and Zhan, J. [5] investigated different classification models such as Naive Bayesian, Random Forest, and Support Vector Machine, and found that the averaged sentiment score is a strong feature in and of itself, achieving an F1 score greater than 0.8 for sentence-level categorization with the entire set. The feature is capable of producing an F1 score greater than 0.73 for review-level classification with the entire set.

Barbado et al. [6] provided a framework of significant features for detecting fake reviews. They conducted trials utilizing several supervised machine-learning approaches based on online Yelp product reviews. Review features (sentiment score) and reviewers (personal, social, review activity, and trust) were used as features. According to their experimental findings, the AdaBoost algorithm performed best, with an accuracy rate of 82%.

Elmogy, A.M. et al [7] A new method has been created to analyze both the characteristics of reviews and the behavior of reviewers, and it was tested using data from Yelp. The technique uses several different classifiers and compares the results obtained from using bi-gram and tri-gram language models. The results indicate that the KNN classifier, with a K value of 7, is the most effective at identifying fraudulent reviews. Furthermore, the study shows that incorporating information about reviewer behavior improves the accuracy of the method by 3.80% in terms of f-score.

Alsubari et al. [8] different supervised machine learning models, including Random Forest, AdaBoost, and Decision Tree, are provided. The standard Yelp product review dataset was used. The information gain method was employed as a feature selection technique. The AdaBoost algorithm produced the best performance, with 97% accuracy, according to their experimental findings.

S. P. Rajamohana et al. [9] developed an excellent feature selection technique. It is known as a cuckoo search when combined with a harmony search. On the other hand, Nave Bayes is use to categorising ham or spam. Evolutionary algorithms are used for feature selection because they can handle the high spatiality of the feature by removing unnecessary, distracting features and taking into consideration the excellent feature selection to speed up processing and improve prediction accuracy.

Zeng et al. [10] suggested a bidirectional long-short technique based on recurrent neural networks for spotting fake reviews. The first sentence, the middle context, and the last sentence were used to divide the review text into three parts. Their technique yielded the best outcomes in terms of accuracy, coming in at 85%.

III. BACKGROUND:

Machine learning is a significant technological advancement that is used in many critical applications. Its primary benefit is that it enables computers to learn and improve automatically from their previous experiences [17]. Three categories of machine learning algorithms exist: supervised, semi-supervised, and unsupervised methods. The data required for training must be identified and categorised, and the surprised approach supplies both input and output data. [18]. Unsupervised learning approaches aim to find and understand the underlying patterns in the data by using only the data; no categorization or labels are needed. During unsupervised learning, the strategy's objective is to find every piece of unlabelled data.[8]. The semi-supervised learning technique has partially labelled the data that is being displayed. The supervised and unsupervised learning methods are combined in semi- supervised learning. It allows for the training of a model on a small sample of labelled data before repeatedly applying it to a larger sample of unlabelled data. Our research focuses mostly on supervised machine learning techniques. Several classification techniques are utilised for supervised machine learning. These algorithms' main goal is to develop a model that will effectively distribute the training data [8]. The objective of a Support Vector Machine is to identify the hyperplane that best classifies the data points. A hyperplane is a two-dimensional higher dimensional line or plane that splits data into halves. Finding the hyperplane that maximises the margin i.e., the separation between the hyperplane and the closest data points for each class is the objective. A supervised learning technique used for classification issues where the output variable is categorical is logistic regression. A logistic function (sigmoid function) is used in this statistical analysis technique to forecast the likelihood of a binary response variable based on one or more predictor variables (features). Another popular algorithm is the Naive Bayes one. It is founded on the Bayes theorem, which determines the likelihood of an occurrence using information about potential confounding factors. The characteristics are assumed

to be independent of one another under the "naive" assumption, which is used to streamline Naive Bayes. Naive Bayes determines the likelihood of each class based on the values of the characteristics and chooses the class with the highest probability as the predicted class. Another powerful algorithm often used now-a-days is XG boost algorithm. The supervised learning algorithm XGBoost (Extreme Gradient Boosting) is utilized for regression, classification, and ranking applications. It is an application of the gradient boosting algorithm that combines a number of decision trees, which are weak models, to produce a strong model. Large dataset handling performance and speed are strengths of XGBoost. By using cache-aware access patterns and parallelizing tree construction, it is intended to maximize performance and reduce computing resources. The two basic parts of the procedure are a regularised model and a loss function. By including penalty terms in the loss function, which compares predicted and actual values, the regularised model lowers overfitting. Aside from this, numerous other algorithms are used in the supervised machine learning technique. The approach chosen is determined by the situation, the volume and complexity of the data, and the desired performance criteria. Each algorithm has advantages and drawbacks.

IV. PROPOSED APPROACH:

For the analysis we used the Amazon fashion dataset used by Jianmo Ni, Jiacheng Li, Julian McAuley for their research [12]. The main motive behind using this dataset is, it is already labelled into the categories of True and False where False refers to the review generated by some Fake reviewer. The dataset consists of 883635 reviews out of which we have used 5079 reviews for our analysis. The dataset consists of the following:

- ReviewerID
- reviewerName
- reviewText
- overall (review rating out of 5)
- reviewTime
- summary
- unixReviewTime
- asins
- image
- style
- vote
- verified (T/F)

1.1. Pre-processing of Data

The first step in machine learning methods is data pre-processing, which is crucial. Data preparation is necessary because using all the available data without any filtering is not feasible. In this study, different techniques were employed to prepare the raw data from the Amazon fashion dataset for computational purposes.

Tokenization:

Tokenization is an important technique for natural language processing. Before moving on to any additional preprocessing steps, it is a need. The text is made up of discrete words called tokens. Let's say we have a sentence, (“An eye for eye will make the whole world blind”) in this sentence the tokens formed will be as follows:

(“An”, “eye”, “for”, “eye”, “will”, “make”, “the”, “whole”, “world”, “blind”, “.”)

1) Stop Words Removal: The technique of removing stop words is includes eliminating words from a text or document that are frequently used but lack substantial significance or worth. Usually, these are simple, everyday terms like "the," "and," "is," "in," and "of "[13]. Stop words are frequently eliminated when doing text analysis or processing tasks.

2) Lemmatization: This technique is used to change plural formats into single ones. Only inflectional endings will be removed in order to restore the word's dictionary-base form. Changing the word "plays" to "play," for instance [14].

3) POS Tagging: In POS tagging the text corpus is tagged by associating each word with a suitable part of speech, such as a noun, verb, adjective, adverb, preposition, conjunction, interjection, and so on. POS tagging is an important preprocessing step in natural language processing (NLP) applications such as text classification, named entity recognition, sentiment analysis, and machine translation., POS tagging is a crucial pre-processing step. The POS tagger used in our research is the Averaged Perceptron Tagger. It utilizes average perceptron for the training.

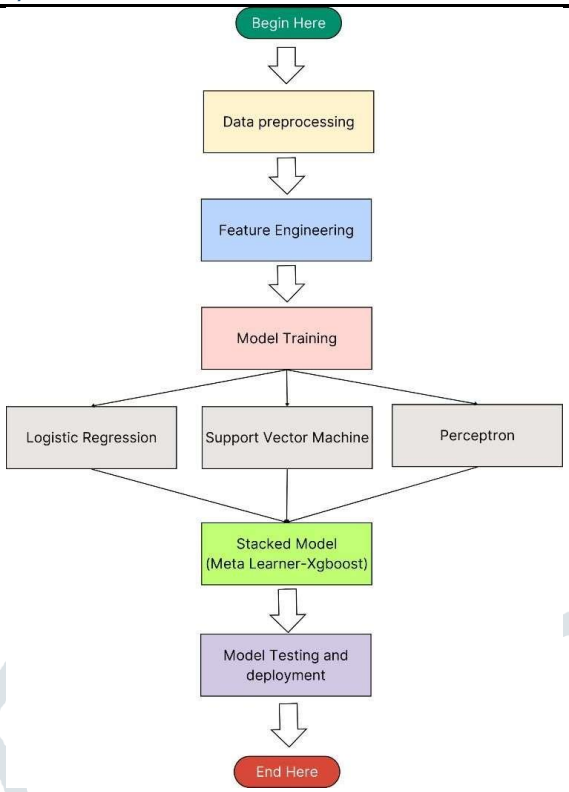

Figure 1: Proposed framework

1.2. Feature Extraction:

Enhancing a pattern recognition or machine learning system's performance is the goal of feature extraction. A reduction technique that produces more useful data for machine learning models is feature extraction. It primarily involves removing unwanted and useless features from data, which could actually make the model less accurate [15]. For the analysis certain features such as asins, image, style was dropped as the proposed system utilizes the review related features for the learning.

1.3. Feature Engineering:

The procedure in which current data points are used to generate new variables that are not part of the training set is referred to as feature engineering. It can be used to produce new features for both supervised and unsupervised learning, with the goal of streamlining and accelerating data transformations while also boosting model correctness. Review length, sentiment score, an reviewer behaviour are features produced by the feature engineering approach in this study. The group by function is used to estimate the number of reviews per user. [7]

Table I. Summary of Amazon Fashion Dataset

Total no of reviews	5079
Total no of Real reviews	4604
Total no of Fake reviews	475
Minimum review length	4
Maximum review length	6059
Average review length	35
Minimum sentiment score	-0.85
Maximum sentiment score	1
Minimum no of review per user	1
Maximum no of review per user	16
Total no of tokens	41187
Minimum review rating	1
Maximum review rating	5

Table II. Summary Of Amazon Electronic Dataset

Total no of reviews	5000
Total no of Real reviews	4765
Total no of Fake reviews	235
Minimum review length	45
Maximum review length	8351
Minimum sentiment score	-0.80
Maximum sentiment score	1
Total no of tokens	174246
Minimum review rating	1
Maximum review rating	5

There are various methods to perform fake review detection such as review centric, reviewer centric, product centric etc.

a) *Review-centric approach*: This method focuses on the textual characteristics of the review text, such as length, the total number of capital letters in the text, the total number of punctuation marks, the user's use of emojis, the various parts of speech conveyed in the text, and the rating given by the user.
b) Reviewer-centric approach: It is based on the reviewer's behaviour, such as how often a given user posts reviews, how frequently they do so over the course of a set period of time.
c) Product centric review*:* It involves identifying the category and ranges, as well as the manufacturers, of the product that obtains the most positive or negative reviews.

Fake reviews are highly challenging to spot using textual features because they heavily depend on identifying the user's thought process, writing style, and the word choice. The proposed Framework tries to solve this problem using the review centric approach along with considering the reviewer's behaviour by identifying the number of reviews per person. Since it is the task of classifying reviews into two categories of Real and Fake various machine learning classification algorithms were employed earlier by many researchers. Classification is the division of data into two or more categories or labels. Numerous classification techniques are available through machine learning. [2]. Based on our experiments, we identified the most commonly used algorithms for dealing with this problem, such as **LR, SVM, KNN, Decision Tree, Random Forest, ANN, CNN,** and many deep learning models, among others. We began with the Logistic Regression algorithm as it is a powerful algorithm used for both Regression and Classification. It utilizes the sigmoid activation function, Logistic loss function along with the gradient decent algorithm. To categorize reviews into the Real and Fake categories, we used the SVM with both the Linear kernel and the Radial Basis Function (RBF) kernel. We found that the RBF kernel works well for doing this. After detecting the extreme points within the dataset, it generates a decision boundary, commonly known as the hyperplane [2]. The Perceptron method is also used to classify the reviews. In machine learning, a perceptron model is a method for supervised learning that employs binary classifiers. The perceptron model, which is made up of a single neuron, determines if a function is an input or not and classifies it into one of two categories. All of the algorithms listed above were used to complete the problem of fake review detection

For classification problems where the objective is to predict a category outcome based on a collection of input features, stacked models that include LR (Logistic Regression), SVM (Support Vector Machine), Perceptron, and XGBoost can be employed.

A stacked model works by training many models on the same dataset and combining their predictions to produce a more accurate forecast. In this situation, we can independently train the LR, SVM, and Perceptron models and then use their predicted probabilities or class labels as XGBoost features. Afterwards, XGBoost can figure out how to integrate these attributes to arrive at the final prediction.

We used features such as the length of the review, review text, review rating, sentiment score of each review, and the number of reviews per user to train our model. After training, the models will be evaluated against the dataset to predict the outcome. The tables below illustrate the performance as well as a comparison of the various methods utilized in the analysis.

V.EXPERIMENTAL RESULT:

Table III. Performance Metrics of Classification Algorithms on Amazon Fashion Dataset

Algorithm	Accuracy	Precision	Recall For	F1-score	AUC
		70-30 Split			
LR	0.92	0.92	0.99	0.96	0.82
SVM	0.91	0.91	1.0	0.96	0.81
Perceptron	0.91	0.95	0.95	0.95	0.82
Decision Tree	0.90	0.95	0.95	0.95	0.72
Proposed system	0.94	0.95	0.99	0.97	0.77
		For 85-1 5 Split			
LR	0.92	0.92	0.99	0.96	0.80
SVM	0.95	0.95	0.99	0.97	0.79
Perceptron	0.75	0.95	0.77	0.85	0.76
Decision Tree	0.90	0.94	0.95	0.94	0.69
Proposed system	0.95	0.95	0.99	0.97	0.77
		For 90-10 Split			
LR	0.92	0.92	1.0	0.96	0.77
SVM	0.94	0.94	0.99	0.97	0.76
Perceptron	0.93	0.95	0.98	0.96	0.77
Decision Tree	0.91	0.95	0.95	0.95	0.71
Proposed system	0.94	0.95	0.99	0.96	0.80

Table III sums up the performance metrics of the Classification algorithms used in the analysis. The pre-processed text was vectorized using the TDIDF vectorizer, and then it was combined with the sentiment score of the text, the review rating, and the number of reviews per user into a single feature vector using the concatenate function. In all three data split scenarios, Logistic Regression achieves an average accuracy of 92%, while SVM achieves an average accuracy of 94% whereas Decision tree provides an accuracy of 95%. The perceptron approach has the lowest average accuracy of all of them, at 86.33%.

On the other hand, Table VI summaries, the performance metrics on different data split scenarios on Amazon Electronic dataset. However, the feature matrix was developed utilizing the sentiment score, review length, and review rating rather than taking into account the number of reviews per user. Results show that the average accuracy scores for LR and SVM are pretty similar, at roughly 97% and 98%, respectively.

Fig.2 illustrates the distribution of average accuracy and F1-score for the Logistic Regression, Support Vector Machine, Perceptron, Decision Tree and Hybrid Meta Classifier used in the Amazon Fashion dataset analysis. With an average F1-score of 97%, the suggested approach exceeds all other algorithms.

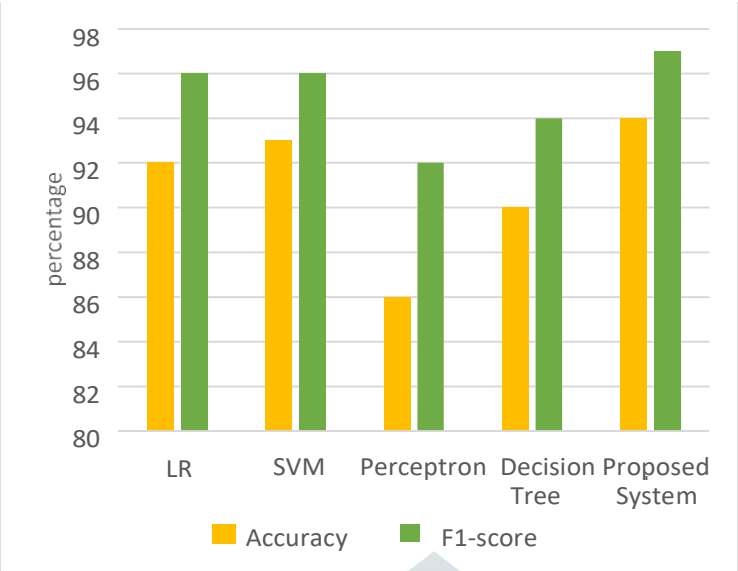

Figure 2: Average Accuracy and F1-score of classification algorithms on Amazon Fashion dataset

Table IV. Performance Metrics For Classification Algorithms On Amazon Electronic Dataset

Algorithm	Accuracy	Precision	Recall For	F1-score	AUC
			70-30 Split		
LR	0.97	0.97	0.99	0.98	0.97
SVM	0.98	0.98	0.99	0.99	0.97
Perceptron	0.96	0.96	0.99	0.98	0.63
Decision Tree	0.97	0.98	0.99	0.99	0.83
Proposed system	0.97	0.99	0.99	0.99	0.94
			For 85-15 Split		
LR	0.98	0.98	0.99	0.99	0.99
SVM	0.95	0.95	0.99	0.97	0.79
Perceptron	0.95	0.95	1.0	0.98	0.53
Decision Tree	0.98	0.99	0.99	0.99	0.87
Proposed system	0.97	0.98	1.0	0.99	0.94
			For 90-10 Split		
LR	0.98	0.99	0.99	0.96	0.98
SVM	0.97	0.91	1.0	0.95	0.99
Perceptron	0.96	0.96	0.95	0.98	0.54
Decision Tree	0.98	0.98	0.99	0.99	0.85
Proposed system	0.98	0.99	0.99	0.99	0.97

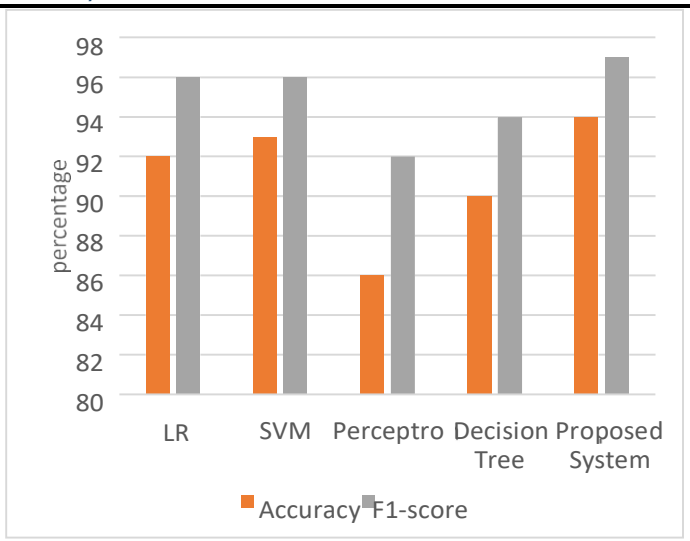

Figure 3: Average F1-score and AUC of classification algorithms on Amazon Electronic Dataset.

Similarly, Fig.3 depicts the average accuracy and F1 -score of the classification algorithms, along with the Hybrid Meta Classifier, for the Amazon Electronic Dataset research, where the proposed approach yields a F1-score of 99%.

As we go through our research and analysis, we found that Decision Tree performs well as Decision trees can capture non-linear relationships between the input features and the output variable. This is especially important in fake review detection since the relationships between the features and fake reviews can be complex and non-linear. In order to increase the precision of predictions, we tried to integrate the predictions of LR, SVM and Perceptron algorithm with Decision Tree hence, a machine learning algorithm called stacked model combining Xgboost with LR, SVM, and Perceptron integrates various algorithms. The model is composed of three separate base learners: perceptron, logistic regression, and support vector machines. These base learners are trained independently using the same dataset, and they combine their predictions to create a meta-learner. The metalearner is then taughtusing the base learners' outputs to provide the final prediction.

As the meta-learner, the XGBoost algorithm, a strong and effective gradient boosting method that can handle big datasets and gives high accuracy, is utilized. To enhance the model's generalization capabilities and prediction accuracy, multiple decision trees are combined. There are training and validation sets created from the dataset. With the help of the LR, SVM, and Perceptron algorithms, three base learners were trained independently on the training set. For each occurrence in the validation set, a meta-feature vector is created by combining the predictions of the three base learners. The first algorithm used to make predictions is Logistic Regression, followed by Support vector Machine and last the Perceptron model and this same order is retained while stacking the algorithms with Xgboost. The XGBoost meta-learner is trained on the validation set using the meta-feature vectors. It uses the trained metalearner to predict outcomes on the test set. Compared to conventional machine learning models, the hybrid stacking model employing Xgboost with LR, SVM, and Perceptron has a number of benefits. It can handle relationships that aren't linear between the input features and the goal variable, increase prediction accuracy, and decrease overfitting. However, it is more sophisticated and calls for more processing resources than conventional methods.

VI.CONCLUSION:

According to proposed methodology, no algorithm can entirely tackle this problem because it is difficult to discern between genuine and fake reviews, which is dependent on the variety of the dataset used to train the model. Our suggested system obtains an accuracy of 94% on a 70- 30 data split with an F1-score of 97.4% on the Amazon Fashion dataset, and an accuracy of 97.40% with an F1-score of 97.4% on the Amazon Electronics dataset. However, the dataset's resilience is quite important. Supervised learning is the method utilized for the detecting procedure. We plan to investigate the supervised and unsupervised methods that can be used to address the problem statement in the future. The effectiveness of systems for detecting fraudulent reviews could be increased by combining collaborative filtering, sentiment analysis, and other techniques. As each review would be stored on an immutable ledger, integration with blockchain technology could help prevent the creation and dissemination of fraudulent reviews.

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