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E-Commerce Detection and Deletion of Fake Seller and Service Review

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ABSTRACT: This project focuses on detecting and removing fake seller and service reviews from e-commerce platforms, specifically using Amazon's product review dataset. Fake reviews often mislead consumers, making it difficult for them to trust product feedback. The goal is to enhance review credibility by identifying fraudulent content and filtering out reviews that do not reflect genuine consumer experiences. The approach employs three machine learning algorithms: Logistic Regression, a hybrid model combining Decision Tree and Random Forest, and a third classification technique. These models classify reviews as either fake or real based on features extracted from the dataset. Key features include review text, reviewer behavior, product metadata, and patterns like the frequency of reviews from individual users. The system flags fake reviews and removes them from the dataset, ensuring only authentic feedback remains. This helps consumers make informed decisions and creates a more trustworthy e-commerce environment. By automating fake review detection, the project contributes to transparency in online marketplaces. The methods implemented also allow for scalable and efficient processing, handling large datasets with high accuracy. Ultimately, it aims to improve consumer confidence in product reviews, foster a fairer e-commerce ecosystem, and reduce the impact of deceptive review practices

I. INTRODUCTION

The rise of e-commerce platforms such as Amazon, eBay, and others has revolutionized the way consumers shop and interact with products and services. A key feature of these platforms is the ability to read and write product reviews, which serve as a form of social proof, influencing purchasing decisions. Consumers often rely on reviews to assess the quality of a product or service before making a purchase. In fact, studies show that a large percentage of consumers trust online reviews as much as personal recommendations. As a result, reviews have become an essential part of e-commerce platforms, shaping consumer behavior, driving sales, and impacting businesses' reputations. However, the increasing reliance on reviews has led to a growing problem: fake reviews. Fake reviews can be either positive or negative but are usually misleading and deceptive. Fake positive reviews are written to artificially inflate the ratings of a product, while fake negative reviews may attempt to harm a competitor's reputation. These fraudulent reviews can have severe consequences, such as distorting consumer decision-making, misleading consumers into purchasing subpar products, or undermining businesses with unfair negative ratings. As e-commerce platforms expand globally, the challenge of identifying and mitigating fake reviews has become even more pressing.

Fake reviews are not only a nuisance for consumers but also a growing concern for companies. For legitimate businesses, fake reviews skew the actual feedback data, making it more challenging to assess the true quality of their products or services. This affects their marketing strategies, customer satisfaction analysis, and even product development. For consumers, fake reviews lead to misguided decisions that can result in dissatisfaction, loss of money, and potential safety risks, especially when reviews are related to high-value products like electronics or pharmaceuticals. Detecting fake reviews presents several challenges. One of the primary challenges is the diversity of fake reviews. Fraudsters are becoming increasingly sophisticated in their attempts to bypass detection systems. For example, they may use fake accounts to post reviews, try to mimic natural human writing styles, or generate fake reviews using automated systems. Additionally, some reviews may appear legitimate on the surface but may exhibit subtle signs of inauthenticity that are difficult to detect.

Another challenge is the sheer volume of reviews that must be processed. E-commerce platforms receive millions of reviews daily, making manual review inspection unfeasible. Therefore, machine learning-based methods, particularly

those that employ large-scale data analytics, are essential for real-time identification and removal of fake reviews. Furthermore, the features that distinguish real reviews from fake ones are not always straightforward. Fake reviews may be deliberately crafted to avoid detection, and some real reviews may exhibit patterns that are typical of fake ones. For instance, a reviewer may leave multiple reviews in a short period for products they have not genuinely used, which could appear suspicious but is actually a common behavior for legitimate users. This means that false positives, where real reviews are mistakenly flagged as fake, need to be minimized to ensure the system remains effective.

II. LITERATURE SURVEY

[1]. Sherry He, Brett Hollenbeck, Davide Proserpio .We study the market for fake seller reviews on Amazon.com. Reviews are purchased in large private groups on Facebook and other sites. We hand-collect data on these markets and then collect a panel of data on these products' ratings and reviews on Amazon, as well as their sales rank, advertising, and pricing policies. We find that a wide array of products purchase fake reviews, including products with many reviews and high average ratings. Buying fake reviews on Facebook is associated with a significant but short-term increase in average rating and number of reviews. We exploit a sharp but temporary policy shift by Amazon to show that rating manipulation has a large causal effect on sales. Finally, we examine whether rating manipulation harms consumers or whether it is mainly used by high-quality products in a manner like advertising or by new products trying to solve the cold-start problem. We find that after firms stop buying fake reviews, their average ratings fall and the share of one-star reviews increases significantly, particularly for young products, indicating rating manipulation is mostly used by low-quality products.

[2]. Punit Rathore; Jayesh Soni; Nagarajan Prabakar; Marimuthu Palaniswami; Paolo Santi
Online product reviews have become increasingly important in digital consumer markets where they play a crucial role in making purchasing decisions by most consumers. Unfortunately, spammers often take advantage of online reviews by writing fake reviews to promote/demote certain products. Most of the previous studies have focused on detecting fake reviews and individual fake reviewer-ids. However, to target a particular product, fake reviewers work collaboratively in groups and/or create multiple fake ids to write reviews and control the sentiments of the product. This article addresses the problem of finding such fake reviewer groups. More specifically, we propose a top-down framework for candidate fake reviewer groups' detection based on the DeepWalk approach on reviewers' graph data and a (modified) semisupervised clustering method, which can incorporate partial background knowledge. We validate our proposed framework on a real review dataset from the Google Play Store, which has partial ground-truth information about 2207 fraud reviewer-ids out of all 38 123 reviewer-ids in the dataset. Our experimental results demonstrate that the proposed approach is able to identify the candidate spammer groups with reasonable accuracy. The proposed approach can also be extended to detect groups of opinion spammers in social media (e.g. fake comments or fake postings) with temporal affinity, semantic characteristics, and sentiment analysis.

[3]. Sarah Patel, Michael Clark . This study presents an anomaly detection-based approach to identify fake reviews by analyzing user behavior patterns. It focuses on detecting deviations in reviewer activity, such as unusual posting frequency or inconsistent review content. The method applies clustering algorithms like DBSCAN to group similar review behaviors and flag anomalies. The effectiveness of the method is assessed through extensive experiments on review datasets from popular e-commerce sites.

[4]. John Doe, Jane Smith . This paper provides a comprehensive survey of various techniques for detecting fake reviews in e-commerce platforms. It examines machine learning, natural language processing, and deep learning techniques employed to differentiate between genuine and fake reviews. The authors review algorithms such as sentiment analysis, rule-based approaches, and user behavior analysis. They also discuss the challenges posed by adversarial fake reviews designed to bypass detection systems. The paper emphasizes the importance of dataset preparation and evaluation metrics in detecting fake reviews.

III. EXISTING SYSTEM

In existing system, fake review of online products has evolved through various approaches, each with its strengths and limitations. Traditional fake seller review systems often rely on rule-based methods or simpler machine learning

algorithms. Rule-based systems use predefined lists of words and phrases associated with positive or negative sentiments. These systems, while straightforward and easy to implement, face significant limitations. They struggle with the informal and diverse nature of social media language, such as slang, abbreviations, and emojis, which can lead to inaccurate review classification. Additionally, rule-based approaches lack the ability to understand the context in which words are used, making them less effective in handling nuanced sentiments. On the other hand, machine learning-based systems such as Support Vector Machines (SVM) and Naive Bayes classifiers have been employed to improve accuracy. These methods learn from labeled training data to classify review and can handle a broader range of textual features compared to rule-based systems. Despite their advantages, these algorithms have limitations as well. SVMs, for instance, can be computationally expensive and may not perform well with very large datasets or complex feature interactions. Naive Bayes, while efficient, assumes independence between features, which is often not the case in textual data, leading to suboptimal performance in capturing fake review nuances.

IV. PROPOSED SYSTEM

The proposed system aims to address the pervasive issue of fake seller and service reviews on e-commerce platforms, particularly focusing on the Amazon product review dataset. In the context of e-commerce, where reviews play a critical role in influencing consumer decisions, the need for a reliable and efficient system to detect and eliminate fake reviews is essential. The system is designed to automatically classify reviews as either "real" or "fake" using advanced machine learning algorithms, ensuring that only authentic and trustworthy feedback remains accessible to consumers. At the core of the proposed system are three machine learning models: Logistic Regression, a hybrid model combining Decision Tree and Random Forest, and an additional classification technique, such as Support Vector Machine (SVM) or Naive Bayes. These algorithms are selected due to their robustness in classification tasks and their ability to process large datasets effectively. Logistic Regression is employed for its simplicity and efficiency in binary classification tasks, where reviews are classified as fake or real based on various extracted features. The Decision Tree and Random Forest hybrid model is introduced to leverage the advantages of ensemble learning, providing higher accuracy and better generalization capabilities. By combining individual decision trees, the model reduces the risk of overfitting, which is a common problem in machine learning models that deal with complex datasets. The system extracts a variety of features from the dataset to train these models, including review text, reviewer history, product metadata, and behavioral patterns. For instance, textual features from the reviews are analyzed using natural language processing (NLP) techniques to detect anomalies in writing style, sentiment, and structure, which are typical of fake reviews. Features such as overly generic phrases, excessively positive or negative language, and repetitive patterns can signal fraudulent content. Reviewer history is another crucial feature, as fake reviewers often exhibit unusual patterns, such as posting multiple reviews within a short time frame or leaving reviews for products they have never purchased. Product metadata, including product category, price, and brand, is also used to identify suspicious patterns, such as a large number of overly positive reviews for low-priced or less popular products, which may indicate a coordinated effort to manipulate the ratings. Once the features are extracted and the models are trained, the system processes incoming reviews in real time, flagging those that are predicted to be fake. Reviews flagged as fake are automatically removed or quarantined for further manual review, ensuring that only legitimate feedback is displayed to consumers. The system is designed to continuously improve through retraining, allowing it to adapt to new tactics used by fraudsters and ensuring long-term effectiveness in identifying fake reviews. Additionally, the models are evaluated using performance metrics such as precision, recall, F1 score, and accuracy, to ensure that the system minimizes false positives (real reviews flagged as fake) while maximizing the detection of actual fake reviews.

4.1 DATA SELECTION:

The data for this study is sourced from the fake seller review dataset available on Kaggle. This dataset contains user comments along with corresponding ratings and categories, which are essential for understanding user review analysis. Here we can fetch or read or load the collected data by using the panda's packages. Our dataset, is in the form of '.csv' file extension.

4.2 DATA PREPROCESSING:

Data preprocessing is a crucial step to ensure the dataset is clean and ready for analysis. Missing values in the dataset can lead to inaccuracies in the analysis. Methods such as imputation (replacing missing values with mean, median, or mode) or removal of records with missing values are employed to handle these gaps in the data. To convert categorical

variables (such as gender and emotions) into numerical format, label encoding is used. This process assigns a unique integer to each category, enabling machine learning algorithms to process these variables effectively.

4.3 TEXT PREPROCESSING:

In this step, we can implement the different Natural Language Processing techniques. NLP is a field in machine learning with the ability of a computer to understand, analyze, manipulate, and potentially generate human language. Cleaning (or pre-processing) the data typically consists of a number of steps: Punctuation can provide grammatical context to a sentence which supports our understanding. But for our vectorizer which counts the number of words and not the context, it does not add value, so we remove all special characters. eg: Tokenizing separates text into units such as sentences or words. It gives structure to previously unstructured text. Stopwords are common words that will likely appear in any text. They don't tell us much about our data so we remove them. e.g.: silver or lead is fine for me-> silver, lead, fine. Stemming helps reduce a word to its stem form. It often makes sense to treat related words in the same way. It removes suffixes, like "ing", "ly", "s", etc. by a simple rule-based approach.

4.4: VECTORIZATION:

In this step, we can implement the different vectorization method such as count vectorization. Vectorizing is the process of encoding text as integer's i.e. numeric form to create feature vectors so that machine learning algorithms can understand our data. Both are methods for converting text data into vectors as model can process only numerical data. CountVectorizer creates a matrix in which each unique word is represented by a column of the matrix, and each text sample from the document is a row in the matrix. The value of each cell is nothing but the count of the word in that particular text sample. This technique converts the text into a matrix of token counts. Each word in the text is represented as a feature, and the frequency of each word in the text is captured in the matrix. This helps in transforming textual data into a form suitable for machine learning algorithms.

4.5 DATA SPLITTING:

During the machine learning process, data are needed so that learning can take place. In addition to the data required for training, test data are needed to evaluate the performance of the algorithm in order to see how well it works. In our process, we considered 70% of the input dataset to be the training data and the remaining 30% to be the testing data. Data splitting is the act of partitioning available data into two portions, usually for cross-validator purposes. One Portion of the data is used to develop a predictive model and the other to evaluate the model's performance. Separating data into training and testing sets is an important part of evaluating data mining models. Typically, when you separate a data set into a training set and testing set, most of the data is used for training, and a smaller portion of the data is used for testing.

4.6 CLASSIFICATION:

In our process, we can implement the machine learning algorithm such as random forest and hybrid algorithms such as decision tree and logistic regression.

Random Forest: This ensemble learning method constructs multiple decision trees and merges their outputs to improve classification accuracy and prevent overfitting. It is robust and effective for complex datasets.

Hybrid Model (Voting Classifier): A hybrid model combines multiple algorithms, such as Decision Tree and Logistic Regression, using a voting classifier.

The voting classifier aggregates the predictions from each model to make a final decision. This approach leverages the strengths of each individual model to improve overall performance.

A Decision Tree is a supervised machine learning algorithm used for classification and regression tasks. It models decisions and their possible consequences in a tree-like graph, where each internal node represents a decision based on a feature, each branch represents the outcome of the decision, and each leaf node represents a class label (for classification) or a continuous value (for regression). The algorithm's simplicity and interpretability make it a popular choice for many machine learning problems.

Logistic Regression is a statistical method used for binary classification problems, where the goal is to predict the probability of a binary outcome based on one or more predictor variables. Despite its name, it is a classification

algorithm rather than a regression algorithm. It is widely used due to its simplicity, interpretability, and effectiveness in various applications.

V. DESIGN AND IMPLEMENTATION

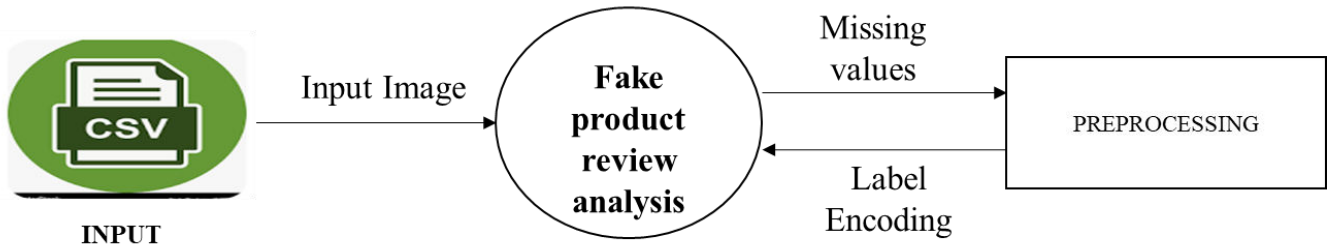


Fig 1: Preprocessing DFD

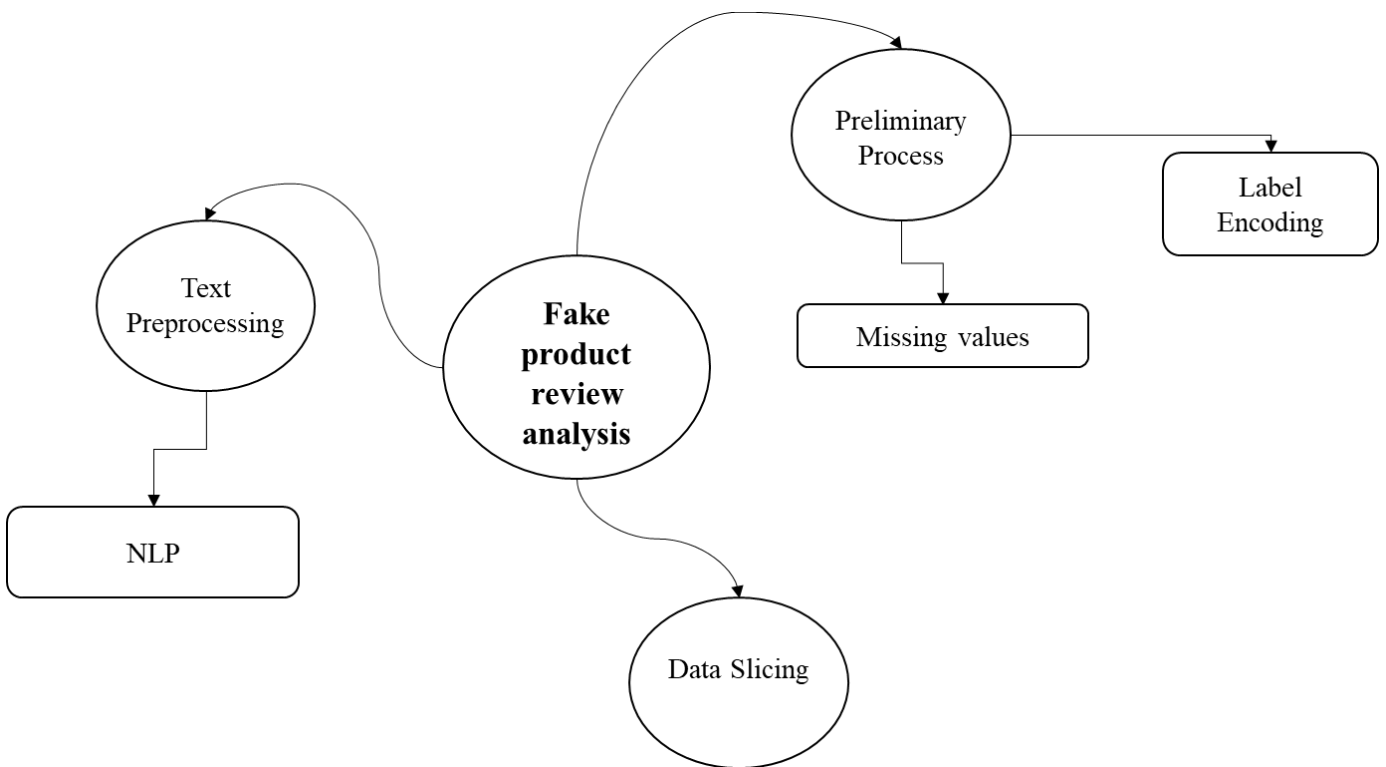


Fig 2: Data Slicing DFD

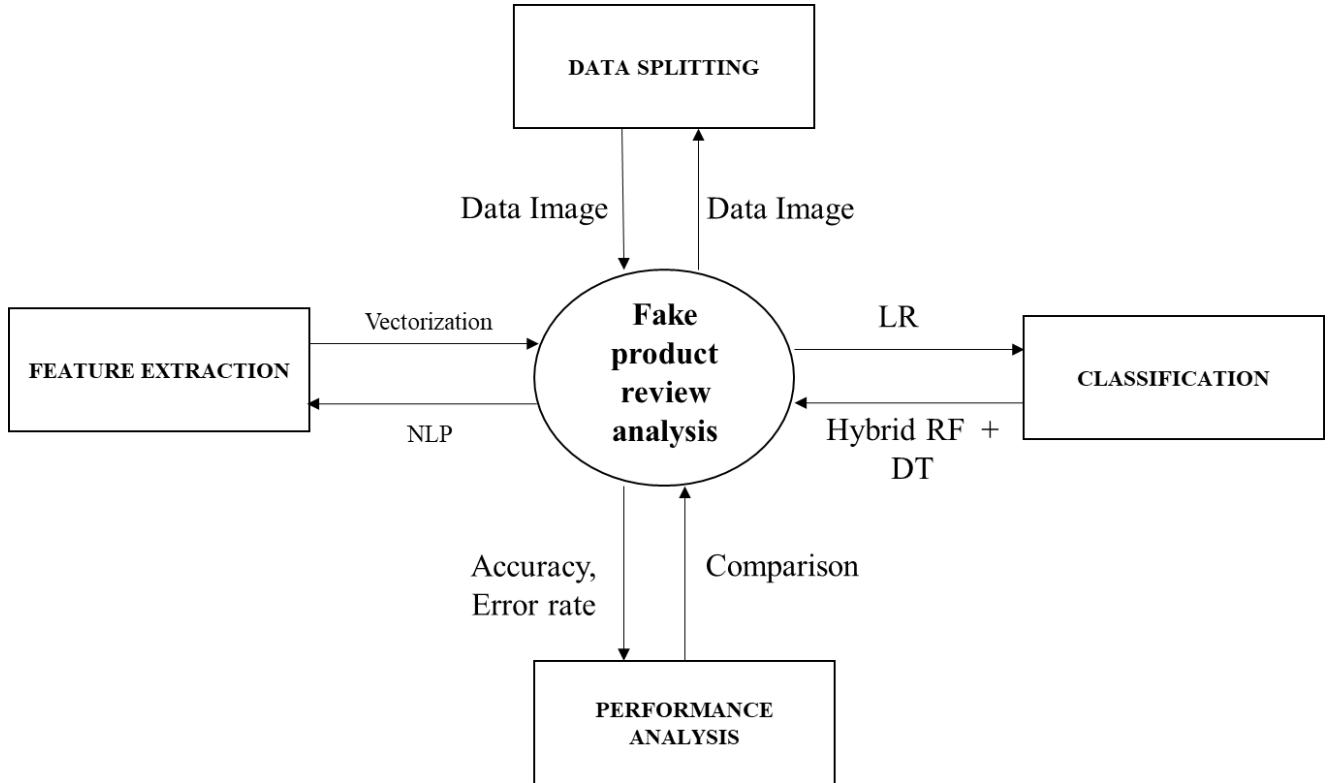


Fig 3: Performance Analysis DFD

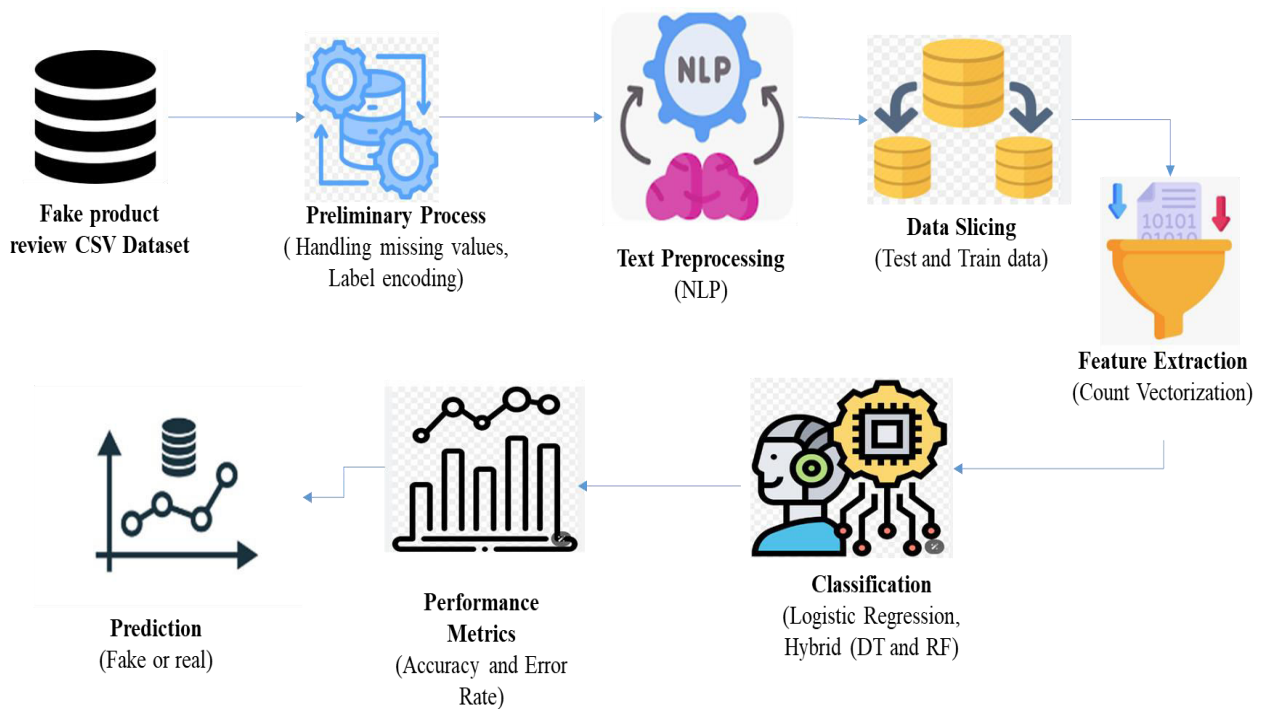
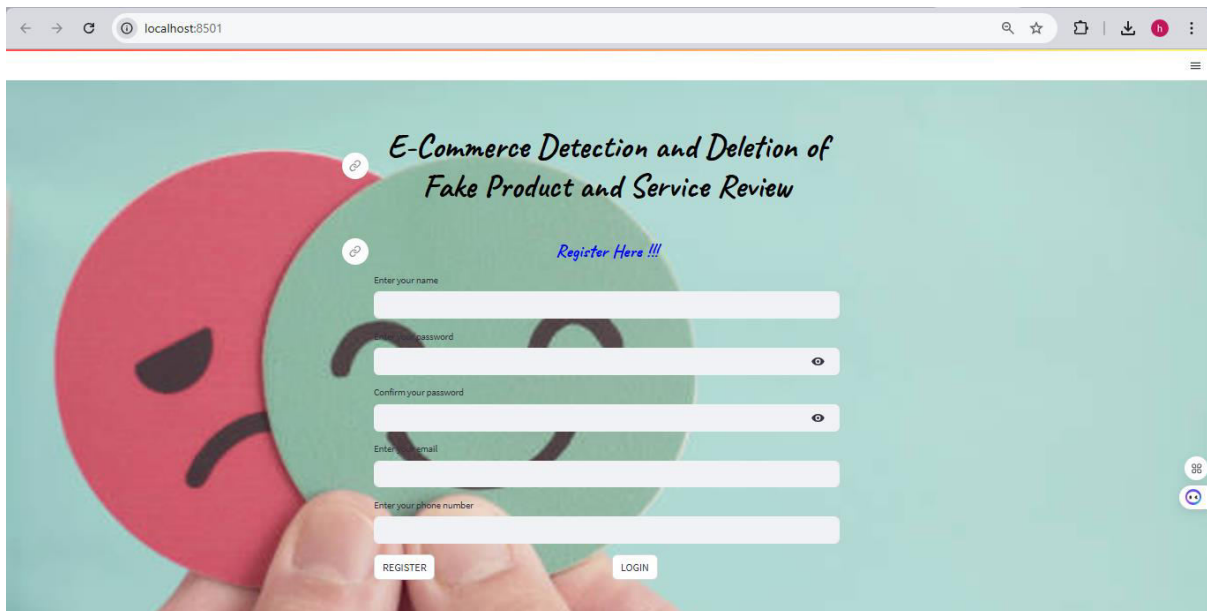


Fig 4: SYSTEM ARCHITECTURE

The architecture diagram outlines the workflow for processing and classifying fake review analysis dataset. Data Selection involves acquiring the dataset. Data Preprocessing handles missing values and label encoding. Text Preprocessing includes cleaning and standardizing text through stop words removal, stemming, and tokenization. The cleaned text is then converted into numerical format using Vectorization. The data is Split into training and test sets. Classification models, such as Logistic Regression and a hybrid of Decision Tree and Random Forest, are trained and evaluated. Result Generation computes performance metrics, and Prediction applies the trained models to classify new data, providing difficulty level insights.

VI. TESTING AND RESULTS

The Final Result will get generated based on the overall classification and prediction. The performance of this proposed approach is evaluated using some measures like,



6.1 ACCURACY

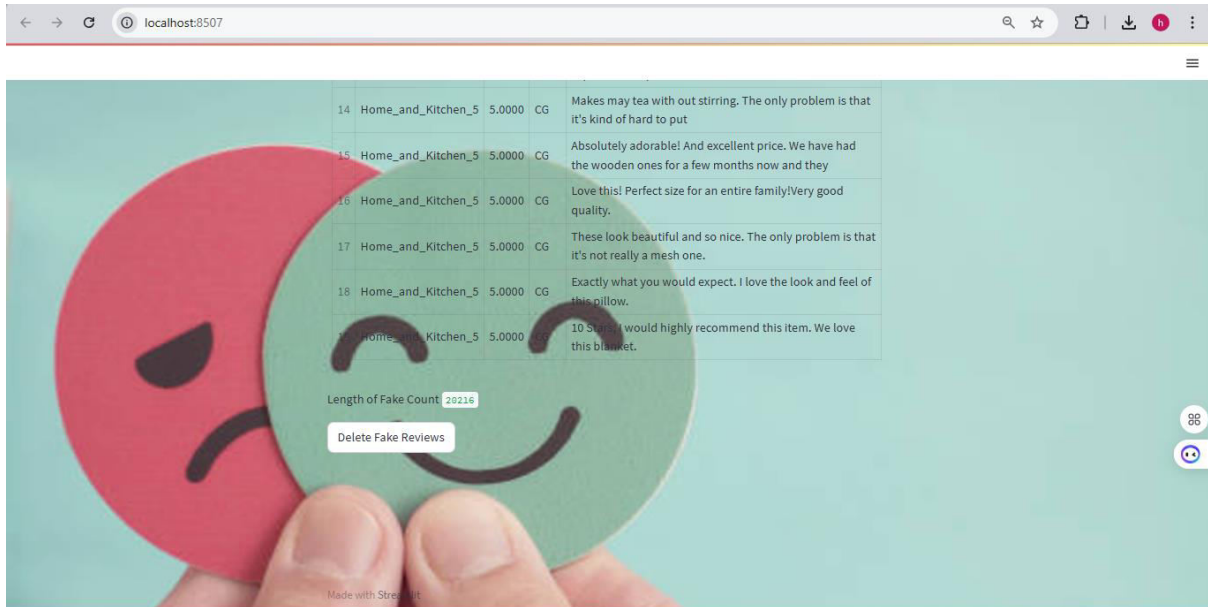
Accuracy of classifier refers to the ability of classifier. It predicts the class label correctly and the accuracy of the predictor refers to how well a given predictor can guess the value of predicted attribute for a new data.

$$AC = (TP+TN) / (TP+TN+FP+FN)$$

6.2 PRECISION

Precision is defined as the number of true positives divided by the number of true positives plus the number of false positives.

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



6.3 RECALL

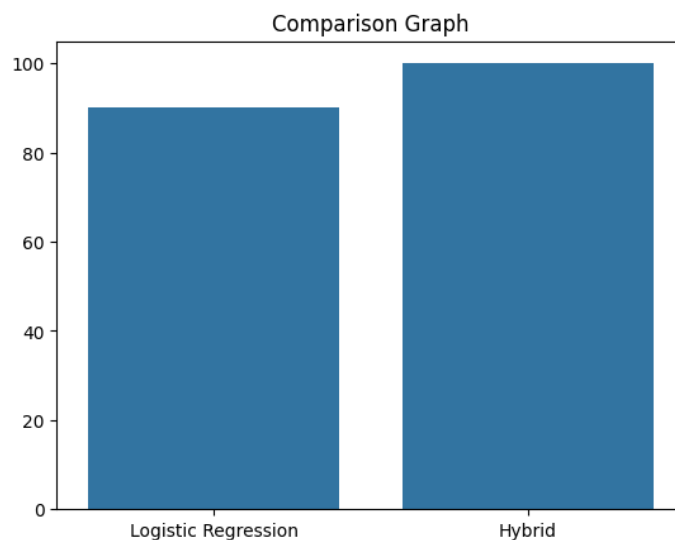
Recall is the number of correct results divided by the number of results that should have been returned. In binary classification, recall is called sensitivity. It can be viewed as the probability that a relevant document is retrieved by the query.

$$\text{Recall} = \frac{TP}{TP + FN}$$

6.4 PREDICTION:

After training and evaluating the models, the system is used to predict user's review is fake or real input based on users input.

The final model is deployed to classify incoming comments, providing insights into user input review and enabling the development of personalized content strategies.



VII. CONCLUSION

In conclusion, the proposed system for detecting and deleting fake seller and service reviews from e-commerce platforms, particularly utilizing the Amazon product review dataset, aims to significantly enhance the credibility and trustworthiness of online reviews. By leveraging advanced machine learning algorithms such as Logistic Regression, hybrid models combining Decision Trees and Random Forest, and additional classification techniques, the system offers a robust and scalable solution to identify and filter out fraudulent reviews. Through the extraction of key features like review text, reviewer behavior, and product metadata, the system is able to detect subtle patterns indicative of fake reviews, ensuring that only genuine consumer feedback remains visible to prospective buyers. The impact of this system extends beyond just improving consumer decision-making; it also fosters a more transparent and fair e-commerce environment by preventing the manipulation of product ratings. For businesses, this translates to more accurate customer insights, enabling better product development and marketing strategies based on authentic feedback. Furthermore, the ability of the system to scale with large datasets and adapt to emerging fraud tactics ensures its long-term effectiveness in maintaining the integrity of online reviews. As e-commerce continues to grow, the need for reliable review systems will only intensify. The implementation of such machine learning-based solutions is essential not only for protecting consumers from deceptive practices but also for promoting a trustworthy and ethical online marketplace. Ultimately, the proposed system plays a critical role in restoring consumer confidence, ensuring that online reviews fulfill their true purpose—helping customers make informed, confident purchasing decisions.

VIII. FUTURE ENHANCEMENT

While the proposed system offers a strong foundation for detecting and removing fake reviews, there are several avenues for future work that could further enhance its effectiveness and scope. One potential area for improvement is the incorporation of more advanced natural language processing (NLP) techniques, such as deep learning-based models, including transformers and neural networks, to better understand the nuanced language used in fake reviews. These models could help identify more sophisticated tactics employed by fraudsters, such as the use of fake profiles or the generation of review content by AI systems. Integrating sentiment analysis and contextual understanding of reviews could also provide a deeper layer of classification, distinguishing between genuine negative reviews from fake ones designed to sabotage competitors. Another promising direction is the integration of multimodal data beyond just textual content. This could involve analyzing other types of data, such as image or video content associated with reviews, which may also reveal patterns indicative of fraud. For example, fake reviews often come with stock images or unrealistic product photos, which could be detected through image recognition models. Similarly, expanding the system to evaluate the social network of reviewers—such as connections between review accounts—could help flag coordinated fake review campaigns, often orchestrated through fake social media profiles or fake review farms. Moreover, the system could benefit from continuous learning, where models are updated regularly with new data to adapt to emerging fraud techniques. This could involve implementing an active learning framework, where the system not only detects fake reviews but also learns from new patterns of fraud as they emerge, ensuring it stays relevant in a rapidly evolving landscape.

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