ProblemSet

In order to promote their products, people write unworthy positive reviews. In some instances, maliciously negative reviews of other (competitive) products are written to hurt their reputations. The main test is that a word can be both positive and negative in various settings. For instance, a positive opinion is expressed when the battery life of a product is described as "long," while a negative opinion is expressed when the start time is described as "long." Another challenge is that people don't always express opinions the same way.

Lastly, there are occasions when individuals make statements that are in opposition to one another, making it hard to understand the nature of opinion. A negative review may conceal a positive impression. Additionally, there may be mixed reviews of the product at times. A person's words and actions can be significantly influenced by their emotions. combining a positive and negative comment with the same emoji. Finding reviews that are not genuine or that are used to influence consumers' opinions becomes even more difficult after these difficulties.

Proposed Solution

The proposed method for solving the problem of detecting fake reviews involves using a combination of machine learning algorithms and natural language processing techniques. We will be using CNN and ANN to get a precise cumulative model.

First , we will extract additional features that can provide insights into the authenticity of the reviews. These features may include the review's sentiment, verified purchases, ratings, product category, and overall score. By comparing these features between genuine and fake reviews, we can identify patterns that can be used to distinguish between the two types of reviews.

To perform the classification, we will use several classification algorithms, including Naive Bayes, SVM, Random Forest, Decision Trees, and Logistic Regression. These classifiers will be trained on the preprocessed data and the additional features extracted earlier. We will also use techniques like cross-validation and hyperparameter tuning to improve the accuracy of the models.

In addition to the above techniques, we will also use advanced natural language processing techniques like LSTMs, transformers, and recurrent neural networks to further improve the accuracy of the models. These techniques can help capture the context and semantics of the text data and can provide more accurate predictions.

Finally, we will evaluate the performance of the models using various metrics such as accuracy, precision, recall, and F1 score. We will also perform a comparative analysis of the different models to identify the best-performing model for detecting fake reviews.

Overall, the proposed method combines several machine learning and natural language processing techniques to detect fake reviews accurately. By using a combination of features and classifiers, we aim to achieve high accuracy in detecting fake reviews and provide a reliable solution for addressing the problem of opinion spamming in online websites.

Literature Review

Since 2007, the study of fake review detection has been conducted through review spamming analysis . The case of Amazon was looked at in this study, and the authors came to the conclusion that manually labeling fake reviews can be difficult because fake reviewers may carefully craft their reviews to make them more trustworthy for other users. As a result, they suggested using duplicates or nearly duplicates as spam to create a model that could identify fake reviews . Additionally, research on distributional footprints has demonstrated a link between distribution anomalies and deceptive hotel and Amazon product reviews. Some of the links we have referred from are :

https://ieeexplore.ieee.org/document/8335018 →This paper proposes a CNN-based approach for fake review detection and compares its performance with traditional machine learning methods.

Fake Review Detection: Classification and Analysis of Real and Pseudo Reviews →This paper describes features used in the model including sentiment analysis, part - of - speech tagging. And user behaviour analysis. The author concludes with the approach that it can automatically detect and remove fake reviews, improving the overall quality.

Detection of fake reviews using NLP &Sentiment Analysis | IEEE Conference Publication→This paper uses CNN and DT. This system extracts features from the text of reviews using CNN and DT to classify whether they are genuine or fake.

Detecting Fake Reviews Utilizing Semantic and Emotion Model | IEEE Conference Publication → This paper proposes a heuristic-based approach for detecting opinion spam. The approach uses the sentiment of the review and the frequency of specific words to identify spam.

A Study on Identification of Important Features for Efficient Detection of Fake Reviews | IEEE Conference Publication → This paper discusses the impact of the fake review on business, and the different techniques. Used to detect them, including ML, NLP, DL and data mining.

A Deep Learning Approach for Fake Review Detection →This paper proposes a deep learning framework that combines CNN and ANN for fake review detection and achieves high accuracy on a large dataset.

Detecting Fake Reviews Using Convolutional Neural Networks" → by H. F. El-Sofany et al. This paper presents a CNN-based approach for fake review detection and compares its performance with traditional machine learning methods on a dataset of Amazon product reviews.

Dataset Description

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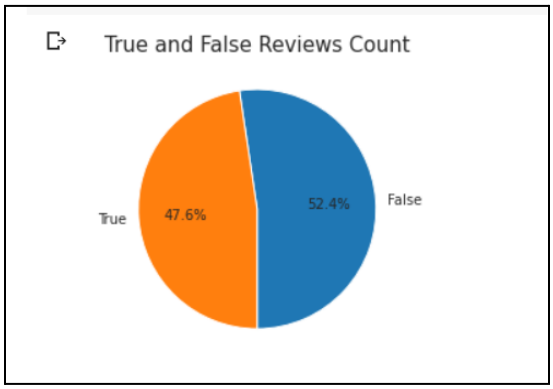
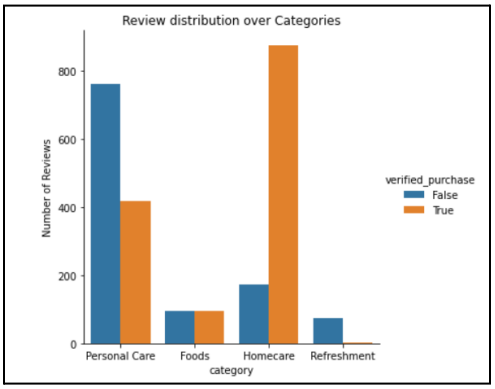
Data columns (total 32 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   report_date             2501 non-null   object
 1   online_store            2501 non-null   object
 2   upc                     2501 non-null   float64
 3   retailer_product_code   2501 non-null   object
 4   brand                   2501 non-null   object
 5   category                2501 non-null   object
 6   sub_category            2501 non-null   object
 7   product_description     2501 non-null   object
 8   review_date             2501 non-null   object
 9   review_rating           2501 non-null   int64
 10  review_title            2403 non-null   object
 11  review_text             2501 non-null   object
 12  is_competitor           2501 non-null   int64
 13  manufacturer            2501 non-null   object
 14  market                  2501 non-null   object
 15  matched_keywords        0 non-null      float64
 16  time_of_publication     0 non-null      float64
 17  url                     1654 non-null   object
 18  review_type             2501 non-null   object
 19  parent_review           2501 non-null   object
 20  manufacturers_response  0 non-null      float64
 21  dimension1              2501 non-null   object
 22  dimension2              2501 non-null   object
 23  dimension3              2310 non-null   object
 24  dimension4              0 non-null      float64
 25  dimension5              0 non-null      float64
 26  dimension6              0 non-null      float64
 27  dimension7              2499 non-null   object
 28  dimension8              2501 non-null   object
 29  verified_purchase       2501 non-null   bool
 30  helpful_review_count    2501 non-null   int64
 31  review_hash_id          2501 non-null   object
```

The dataset taken for our model is the Amazon Reviews dataset. It is focused on the products sold on Amazon website and the reviews that are added by the customers about the products. The dataset contains 2500 rows and 32 columns.

Exploratory Data Analysis



Percentage of True and False Reviews in the dataset



No of True and False Reviews per category

WordCloud showing common words in the reviews

Data Preprocessing

> Few columns contain many null values, so replacing these values with the mean values of the columns.
> Duplicate values were also removed.
> Feature Transformation: The data present is categorical, so the string values have been scaled to Integer for model prediction.
> Feature selection: On the basis of Information Gain, some of the attributes like dimensions, time-of-publication, category and few more columns which are product descriptive and which provide low information gain for review (dependent variable) are dropped.

After these steps, text processing was done like spelling correction: using TextBlob()
removing punctuations: using regex,
removing stopwords: from NLTK SW library ,
lemmatisation and tokenisation.

Baseline Models

After preprocessing the data, we have used several Machine Learning models to classify reviews based on the features in the sample.
We have used the following classifiers:

1. Logistic Regression: It is a type of regression used in case of classification problems. It learns a linear relationship from the given dataset and then introduces a non-linearity in the form of the Sigmoid function.

2. Gaussian Naive Bayes: It is a type of classification model which uses Bayes algorithm. It is easy and fast in multiclass classification as it needs less training data. It is used to determine the benchmark performance of the models.

3. Random Forests Classifier: It is ensemble learning of Decision Trees(which provides interpretability and is non-parametric in nature) where some weak classifiers are combined and the prediction is done by majority voting for classification problems.

4. Decision Tree Classifier: A decision tree is a non-parametric supervised learning algorithm which provides interpretability while doing classification. At each level, a feature is chosen as per its information gain or entropy for classifying data and final classification is obtained at the leaf level.

5. SVM : A support vector machine (SVM) is a supervised learning algorithm to classify or predict data groups. The goal of the SVM is to determine the unique decision boundary known as Optimum Separating Hyperplane (OSH) that can segregate n-dimensional space into the required number of regions for classification.

6. Additional Models used -
CNN - Convolutional Neural Networks are deep learning models used to reduce multidimensional data to scalar data so that it can be used in a neural network for classification.

ANN- Artificial Neural Networks are based on the working of a human brain neuron. Each node in the network is assigned a weight to it which is updated during backpropagation of the error between predicted and actual labels. Finally we get the set of optimal weights.

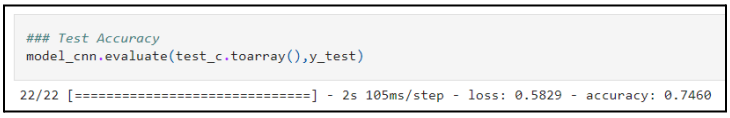
Results and Analysis

We have implemented two additional models CNN and ANN . We have used word Vectorization method of converting words or phrases from a vocabulary into a corresponding vector of real numbers, which can be used to analyze word predictions and semantics. This vectorizer matrix is passed into the models as training data . Some of the results of our models are shown below.

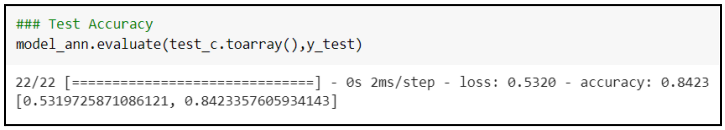
Accuracies of baseline models

	MNB	SVM	LR	DT	RN
Count Vectorizer	80	80	82	76	78
Tfidf Vectorizer	79	82	82	76	76

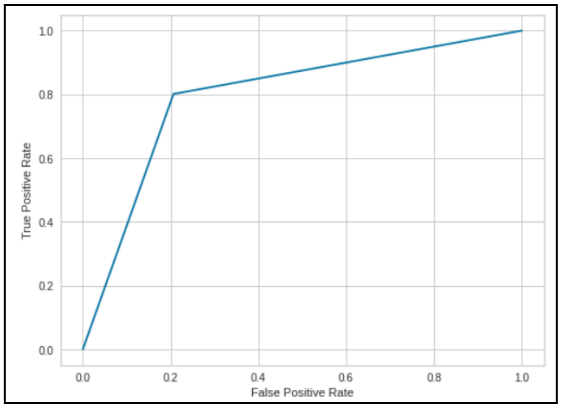
Accuracy of CNN



Accuracy of ANN



ROC- Curve of CNN



The CNN model was trained on a dataset using binary cross entropy loss. Adam optimizer. The model achieved 74.6% accuracy on the test data. The confusion matrix plotted shows the true positives , true negatives , false positives and false negatives. The area under ROC came out as 0.797,which is an indication of the model's ability to distinguish between positive and negative classes.

In ANN the model has achieved the accuracy of 84.23% on the test set, and the area under the CURVE (ROC) is 0.82. The ROC curve is a graphical representation of the performance of a binary classification model at different

thresholds. The Higher the AUC, the better the model's performance.

Precisions of various models

	MNB	SVM	LR	DT	RN
Count Vectorizer	79	74	75	69	71
Tfidf Vectorizer	81	77	81	69	69

Recalls of various models

	MNB	SVM	LR	DT	RN
Count Vectorizer	77	89	91	85	87
Tfidf Vectorizer	72	86	81	85	85

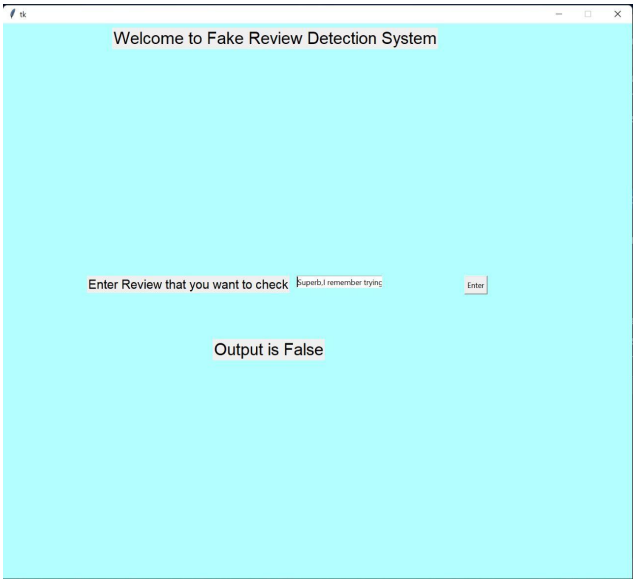
F1-scores of various models

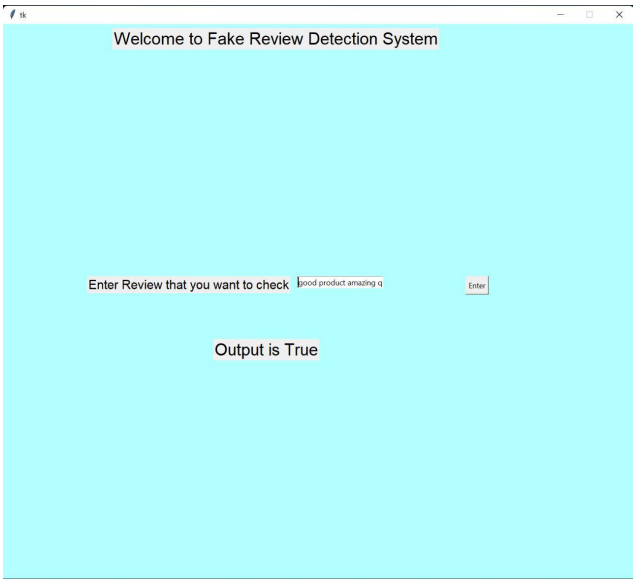
	MNB	SVM	LR	DT	RN
Count Vectorizer	78	81	83	85	87
Tfidf Vectorizer	76	81	81	85	85

From the above results , the overall accuracy were close to 80% for all the models. Also the precision is higher for some models while recall

Front End Design

Our model takes user reviews and the classify the input into true or false review using ANN classifier. Some screenshots of our model are:





> To apply and compare NLP-based models like Lstms and Transformers in order to broaden the scope of the study to deep learning methods.

> To create a method that is comparable for unsupervised learning of unlabeled data in order to identify fake reviews

Conclusion

The purpose of the fake review detection is to filter out fake reviews. Random Forests outperformed other classifiers when it came to classifying our dataset in this study. It shows that absolute classifiers are better for this errand. Exploring the dataset was made easier by the data visualization, and the features that were found improved the classification's accuracy. The accuracy of the various algorithms used demonstrates how well they have performed in relation to their accuracy factors.
In addition, the method gives the user the ability to recommend the most honest reviews so that the customer can make decisions about the product.

Future Work

> To make use of real-time or time-based datasets, which will enable us to compare the timestamps of the user's reviews in order to determine whether a particular user is posting an excessive number of reviews in a short amount of time.