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Fake News Detection Using Machine Learning

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Abstract:

In today's world of social media and politics, detection of false news is a crucial area for research. There may be difficulties because there aren't as many resources, such as published literature and available datasets. In this work, we advise using machine learning techniques to spot fake news. Three different machine learning categorization methods are compared. Decision tree classifier, random forest classifier, and logistic regression were the three techniques we employed. We have obtained varying degrees of accuracy for each method. The obtained results are helpful in detecting the veracity of the specified news.

Keywords — **Machine learning, fake news, data pre- processing, deep learning**.

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I. INTRODUCTION

Any article, post, story, or publication that may be classified as false or truthful has gained significant attention from researchers all around the globe. Many analyses and investigations have been undertaken to ascertain the impact of any inaccurate or deceptive data on human beings when they have been exposed to it. Fake news or information can be used to sway someone's basic assumptions in favour of something that may not be real.

The worldwide pandemic scenario serves as the best illustration of bogus news. Many news stories have been fabricated in the past and are now being done so in order to confuse people, cause disruption, and lead them to believe incorrect information.

Fake news spread over social media platform in India convinced people to consume dung or cow wee in an effort to prevent infection, while in the country, artiodactyl wee- wee with lime was lauded as a coronavirus-preventing remedy. The researchers looked at a number of suggestions like consuming garlic, donning heat-generating socks for curing the potentially fatal conditions.

A. *Types of False News*

1) Pictorial-based:

Graphics, including altered photographs, videos, and mixtures of both, are frequently used as material in false news articles.

2) User-based:

This type of news is produced by fictional accounts. Generally, this kind of made-up news is targeted at certain audiences that may represent particular age groups, genders, cultures, and political allegiances.

3) Knowledge-based:

These articles offer scientific explanations for certain unsolved problems, giving users the impression that they are true. For instance, natural remedies for the body's excessive blood sugar levels.

4) Stance-based:

It serves as a true example of utterances that alter their meaning and aim in some way.

II. LITERARTURE REVIEW

Many authors have done preliminary research on "fake" news detection on twitter in the past. However, this topic became more well-known

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during the US Presidential election, and everyone tried their hardest to come up with some better answers for this classification. On "The Atlantic" news, a brief history was presented [1]. Some writers also used a machine learning strategy that was implemented as a software system [2]. Mykhailo Granik et al.'s study [3] demonstrates how simple it is to spot fake news using a Naive Bayes classifier. This strategy was examined using a sample of Facebook news posts, and it was then applied to a software solution. In addition to three significant mainstream political news websites (Politico, CNN, and ABC News), they come from three significant left- and right-leaning Facebook pages. They were successful in achieving a classification accuracy of around 74%. False news is classified with somewhat less precision. This skewness may be caused by the fact that false news makes up just 4.9% of the sample.

The authors of [4] recommended deception detection utilising the benchmark data set "LIAR" with clearly enhanced effectiveness in detecting false postings and news in their study. The authors argued in favour of using corpora for political NLP research, position categorization, opinion mining, and rumour identification.

In order to address a variety of issues, including as the lack of accuracy, BotMaker's temporal lag, and the lengthy processing time required to handle hundreds of tweets in only one second, Himank Gupta et al. [5] built a framework based on various machine learning approaches. Using the HSpam14 dataset, they first collected 400,000 tweets. The 250,000 non-spam tweets and the 150,000 spam tweets are then further explained. In addition to the Top-30 phrases from Bag-of-phrases model 4 that are producing the most information gain, they also deduced a number of lightweight features. They performed around 18% better than the previous response and had an accuracy of 91.65%. Need for hoax detection has been introduced by the authors of [6]. They combined social content and news content techniques while using ML. The writers assert that the performance is superior to what has been written about it. It was implemented by the authors using a Facebook Messenger chatbot. Facebook Italian news postings were pulled from three separate databases. Both content-based strategies leveraging Boolean crowd sourcing algorithms and social and content signals were used. Three classifiers were used in Mandical et al.'s proposed fake news classification system in order to accelerate the identification of false information. Eight datasets were implemented with this system [7].

Zhang *et al.* [8] observed the guidelines, procedures, and algorithms used for categorising fake and manufactured news articles, authors, and subjects from online social networks and assessing the reach and effectiveness of the accompanying efforts.

Bharadwaj and Shao [9] employed recurrent neural networks, a Naive Bayes classifier, and random forest classifiers with six feature extraction techniques on the kaggle.com false news dataset. Junaed *et al.* [10] provided a comprehensive performance study of several methodologies on three separate datasets.

This work ignored details like the source, author, or publication date that may have a significant influence on the outcome and instead concentrated on the language of the material and the mood it conveyed. Additionally, we included feelings while demonstrating our work in the detection process.

III. MEHODOLOGY

Three step methodology was employed in this investigation. In the first phase (pre-processing), the study used particular data filtering and cleaning techniques to extract semantic features from the raw data. The data was categorized using a stopword filter that eliminates prepositions. This study also employed non-English character removal technologies and HTML tags to filter the data and get rid of contaminants that weren't helpful for categorization. Semantic features were transformed into feature vectors during the second step (extracting numerical features), the final stage (classifiers) involved classifying the elements in the dataset using machine learning and deep learning classifiers. Separate applications of each of these techniques were made to the same dataset.

A. Used Dataset

The datasets we used for this analysis are available online as open source downloads. The information consists of both true and fraudulent news articles from various websites. The true news articles produced provide an accurate depiction of real occurrences, in contrast to fake news websites that make assertions that are not backed by the facts. Fact-checking websites like politifact.com and snopes.com may be used to manually verify many of the political assertions made in such

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publications. Two distinct datasets were used in this research.

TRUE.CSV and FAKE.CSV: These datasets were utilized. They have three columns: text/keyword, statement, and label (false/true).

B. *Pre-Processing*

Data cleaning, formatting, and transformation are essential steps in the pre-processing phase of machine learning, which prepares data for use in a machine learning algorithm. The accuracy and performance of a machine learning model are strongly influenced by the quality of the training data. Data must thus be pre-processed to ensure that it is accurate, trustworthy, and relevant to the current problem. Data cleaning, which entails deleting any blank or incorrect numbers and resolving discrepancies in the data, is the initial stage of data pre-processing.

C. *Algorithms used:*

i. *Logistic regression*

The objective of classification problems, where machine learning is applied, is to predict a discrete outcome or label based on one or more input factors. In logistic regression, the weighted sum of the input variables is calculated, and the result is then run through a logistic function to get a probability value between 0 and 1. The final categorization choice is made using this probability. To narrow the discrepancy between expected probability and actual label, the model is trained by increasing the weights of the input variables. With the use of methods like one-vs-all or SoftMax regression, logistic regression—a common solution for binary classification issues—can also be expanded to tackle multi-class classification issues.

ii. *Decision Tree*

The decision tree classifier has become an established artificial intelligence technique for classification tasks. The data is recursively partitioned based on the input attributes, a tree-like model is built, and a set of decision rules are created, leading to a final classification determination. The leaves of the tree represent the final classification decisions, while each node represents a decision rule based on a specific attribute. Decision trees are a well-liked option for applications where comprehending the model is crucial because they are simple to grasp and display. They are capable of handling categorical and continuous input data as well as binary and multiclass classification problems.

iii. *Random Forest Classifier*

A popular machine learning method for classifying tasks is Random Forest Classifier. It is an ensemble method that combines different decision trees to improve the model's overall accuracy and stability. During training, the random forest classifier creates a large number of decision trees and averages the forecasts of each tree to produce predictions. This method aids in improving the model's generalisation capabilities and decreasing overfitting. Additionally, random forests are capable of handling categorical and continuous input variables as well as binary and multiclass classification issues. Moreover, they can deal with missing data and outliers.

IV. WORKFLOW

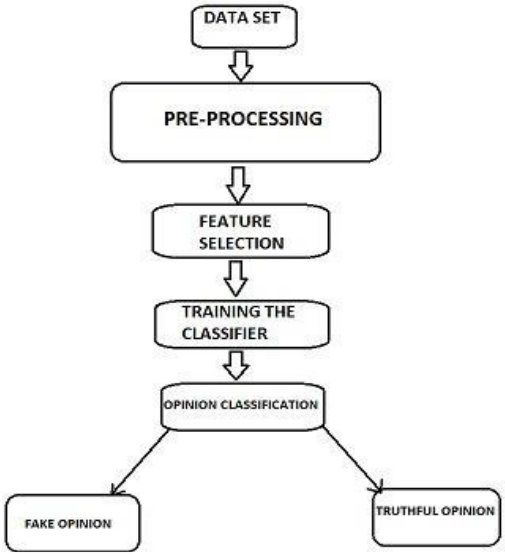

Fig. 1: Work Flow

The workflow in the Fig. 1 describes the standard process for identifying false news. The following steps make up the process:

Data gathering: The initial phase is gathering news items from numerous websites and social media platforms.

Text preprocessing: After the news items are gathered, any extraneous text, such as HTML elements, URLs, and stop words, is removed. This procedure is crucial since it aids in lowering the data's noise level and improving its suitability for analysis.

Feature extraction: The preprocessed news items are used to extract features in this stage. The characteristics of the news piece known as features

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can be utilized to differentiate between authentic and false news. The frequency of specific terms, the article's length, and the tone of the piece are a few prominent criteria used to identify false news.
Model selection: A machine learning model is selected to classify the news articles as real or fake once the attributes are extracted. Several models, including decision trees, logistic regression, and random forest classifier, can be used for this.

Model education: A collection of labelled data is used to train the chosen model once it has been chosen. Data that has been labelled as being either true or false news is referred to as labelled data. This stage is crucial because it teaches the model how to appropriately identify fresh news pieces.
Evaluation of the model: Using a set of test data, the model is assessed following training. The test data is used to gauge how effectively the model generalizes to new situations because it differs from the training data.

V. EXPERIMENT

We used Python as a programming language throughout the experiment. Steps are listed as follows:
1: Importing different libraries required for building a model, Fig. 2.
Pandas – Used to Read and write for SSV files.
NumPy – It helps in dealing with numerical tasks.
Matplotlib – It helps in displaying in graph format.
Seaborn – It is used for visualization.

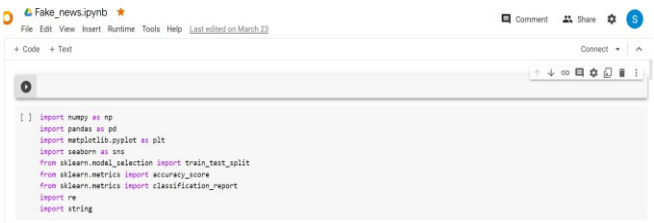

Fig. 2: Importing

Libraries 2: Data Pre-processing

In text mining, texts are regarded as unstructured data and may include a range of impurities, including HTML components, single letters, advertisements, non-English characters, numbers, and apostrophes. Data preparation is similar to text mining in this regard. Because of this, it is particularly challenging to express textual data in natural language. Unstructured data may be transformed using a variety of methods into structured data that computers can handle. The classification dataset was cleaned in this study using the stopword strategy. Stopword technology, which eliminates certain worthless words (such as the, in, a, an, with, etc.), is a typical approach applied for text classification, information retrieval, and data filtering. In other words, things that don't function as keywords yet impact classification are deleted. HTML tags were eliminated using the Python Standard Library's (remove_tags) function. The preprocess text feature then eliminated all non-English characters, Fig. 3.

Fig. 3: Data Preprocessing

3: MODEL BUILDING

Testing a machine learning model's performance on data that it has never seen before is essential. Due to this, the data was split into a training set and a test set.
The training set, which is frequently a larger portion of the data, is used to train the model. The model generates new predictions based on the values of the independent variables (attributes) and their corresponding dependent variables (labels) in the training set.
After model training, we evaluate the model's performance on an unfamiliar test set. To determine how effectively the model generalises to new data, we create predictions using the independent variables in the test set and then compare those predictions to the actual values of the dependent variables in the test set.
Scikit-learn's train_test_split function makes it simple to divide the data into training and test sets. The data is first divided into the desired proportions before being randomly shuffled using the programme. By default, training uses 80% of the data, while testing uses 20%.

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The independent variables (attributes) and dependent variables (labels) are sent in as different arrays when we run train_test_split. The four arrays that the function returns are X_train, X_test, y_train, and y_test. The independent and dependent variables for the training set are included in X_train and y_train, whereas the independent and dependent variables for the test set are contained in X_test and y_test.

In conclusion, separating the data into a training set and a test set enables us to train and test our model on several sets of data, preventing overfitting and enabling a more precise evaluation of the model's performance.

```
[ ] from sklearn.tree import DecisionTreeClassifier
    DT = DecisionTreeClassifier()
    DT.fit(xv_train,y_train)

    DecisionTreeClassifier()

[ ] pred_dt = DT.predict(xv_test)

[ ] DT.score(xv_test,y_test)

    0.9958110516934047

[ ] print(classification_report(y_test,pred_lr))

              precision    recall  f1-score   support

           0       0.99      0.98      0.99      5920
           1       0.98      0.99      0.99      5300

    accuracy                           0.99     11220
   macro avg       0.99      0.99      0.99     11220
weighted avg       0.99      0.99      0.99     11220
```

Fig. 4: Model Building using Decision tree classifier

```
[ ] from sklearn.linear_model import LogisticRegression
    LR = LogisticRegression()
    LR.fit(xv_train,y_train)

    LogisticRegression()

[ ] pred_lr = LR.predict(xv_test)

[ ] LR.score(xv_test,y_test)

    0.9865418094830066

[ ] print(classification_report(y_test,pred_lr))

              precision    recall  f1-score   support

           0       0.99      0.98      0.99      5920
           1       0.98      0.99      0.99      5300

    accuracy                           0.99     11220
   macro avg       0.99      0.99      0.99     11220
weighted avg       0.99      0.99      0.99     11220
```

Fig. 5: Model Building using Logistic Regression

```
[ ] from sklearn.ensemble import RandomForestClassifier
    RF = RandomForestClassifier(random_state = 0)
    RF.fit(xv_train,y_train)

    RandomForestClassifier(random_state=0)

[ ] pred_gb = RF.predict(xv_test)

[ ] RF.score(xv_test,y_test)

    0.9874331550802139

[ ] print(classification_report(y_test,pred_gb))

              precision    recall  f1-score   support

           0       0.99      0.99      0.99      5920
           1       0.99      0.99      0.99      5300

    accuracy                           0.99     11220
   macro avg       0.99      0.99      0.99     11220
weighted avg       0.99      0.99      0.99     11220
```

Fig. 6: Model Building using Random Forest

4: PREDICTING USING THE MODEL

Once we have separated our data into training and test sets, we may use the training set to train a variety of machine learning algorithms, including logistic regression, decision trees, and random forest classifier. The relationship between the independent (attributes) and dependent (label) variables, which these algorithms may learn from the training set, may then be utilised to predict results for newly discovered data.

When utilising a trained machine learning algorithm to forecast a new data point, we input the values of the independent variables, and the algorithm returns a predicted value for the dependent variable. The association that the algorithm discovered during the training phase provides the basis for this anticipated value.

The technique used for logistic regression describes the connection between the independent and dependent variables as a logistic function. This function produces a probability value, which is defined in order to classify the data point as belonging to one of two groups.

Depending on the independent variable values from the training set, the method for decision tree classifiers learns a decision tree. Following the decision tree's route according to the values of the independent variables, additional data points are then classified using this decision tree.

An ensemble of decision trees is created for random forest classifiers using the approach, with each tree being trained on an undetermined subset of the independent variables and an undetermined percentage of the training data. The algorithm combines the predictions from each tree when forecasting a new data point to produce a final forecast.

It's important to remember that the test set should first go through the same preprocessing steps as the training set before predictions can be made. This makes sure that the test set's input data are in the same format as the data used to train the algorithm.

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In conclusion, using the values of the independent variables for that data point, we may use logistic regression, decision tree, or random forest classifiers to make predictions on fresh data after training them on our training set. A projected value for the dependent variable will be produced by the algorithm based on the association it discovered during training.

Fig. 7: Predictions using the model

VI. RESULT

According to the three machine learning methods we employed for this research Fig. 8, Table I, accuracy rate of each algorithm when deployed to the dataset varies. The implementation of each algorithm's accuracy is as continues to follow:

A. *Random Forest*

With a 98% accuracy rating, Random Forest is the accurate classifier. This approach is well recognised for being able to handle large, complicated data sets and is notable for using a series of decision trees to increase prediction accuracy.

B. *Decision Tree*

The accuracy rating for the Decision Tree classifier is 99%. This algorithm models the data and generates predictions based on a set of rules using a hierarchical tree-like structure. Although decision trees are simple to understand and depict, they can be susceptible to noise and overfitting.

C. *Logistic Regression*

The classifier for logistic regression gets the accuracy rating 98%. A straightforward linear model is employed in this approach to solve binary classification issues. It operates by analysing the data and fitting a logistic function to it, which simulates the likelihood of an event. Although Logistic Regression is simple to use and comprehend, it might not work well with non-linear data sets.

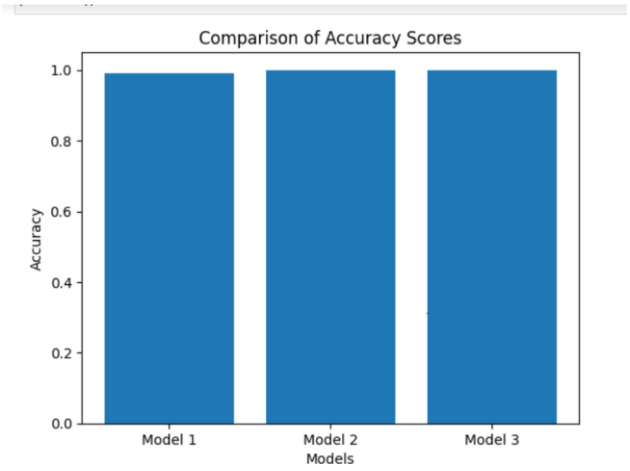

Fig. 8: Comparison of models

Table I: Accuracy of models

Classifier	Accuracy
Random Forest	98%
Logistic Regression	98%
Decision Tree	99%

VII.CONCLUSION

The effects of spreading erroneous information are always negative and harmful to society. The distinction between fake and true news continues to be widely misunderstood in society. Readers are frequently confused by false information, which causes them to get confused and behave improperly. This is why everyone's concern is unfounded. As a result, our paper can now utilise certainty to assess if the provided news is false or not. By considering the philosophy of the paper, people may at least confirm whether the news they are viewing is accurate. This paper discussed three approaches viz. random forest, decision tree and logistic regression. Their accuracies are shown in the Table I.

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