JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

FAKE NEWS DETECTION USING MACHINE LEARNING

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***Abstract*:** The development of the World Wide Web and the quick adoption of social media platforms (such as Facebook and Twitter) prepared the door for the most rapid transmission of knowledge in recorded human history. Consumers are producing and spreading more information than ever before, some of it erroneous and unconnected to reality, thanks to social media platforms. Using an algorithm to identify text that contains erroneous or misleading information is difficult. Even a subject area expert must consider a variety of factors when deciding whether something is genuine or false. For the automated categorization of news stories, we suggest an ensemble machine learning approach in this study. Our research looks at a variety of linguistic traits that can be utilized to tell false information from true. We train a range of distinctive machine learning algorithms utilizing those characteristics in a variety of ensemble approaches, and then we evaluate their performance on four real-world datasets. Experimental testing shows that our suggested ensemble learner technique works better than individual learner approaches.

Keywords: Fake News, social platforms, deep learning

I. INTRODUCTION

Because they allow users to discuss, exchange, and debate topics like democracy, education, and health, these social media platforms are incredibly powerful and advantageous in their current condition. Similar platforms are, however, also used adversely by some organizations, such as to spread satire or nonsense, encourage discrimination, and change attitudes [3, 4]. False news is the term used to describe this situation. Over the past 10 years, false news has spread much more, most notably during the 2016 US elections [5]. The proliferation of false information on the internet has caused numerous issues, not just in politics but also in sports, health, and education [3]. Financial markets are one field where false news is common [6], where a rumor might have negative effects or even stop the market completely. Our ability to make decisions and our perspective are both significantly impacted by the information we ingest.) Consumers may have responded irrationally to news that later proved out to be false, according to mounting evidence [7, 8]. One recent example is the advent of the new corona virus, which led to the internet dissemination of erroneous information regarding the virus's biology, origin, and behavior [9].) The problem grew worse as more individuals became aware of the false online information. Finding such news on the internet is difficult...

There are several computational algorithms that can be used to identify bogus articles based on their linguistic content, which is excellent news [10]. Fact-checking websites like "PolitiFact" and "Snopes," among others, are heavily cited in these tactics. There are several archives available to researchers that list websites that have been flagged as being dubious or fraudulent [11]. The issue with these services is that authentic individuals are required to recognize phony content and websites. More significantly, fact-checking websites only include content from specific disciplines, like politics, and lack the ability to distinguish between fake news originating from a variety of sources, including entertainment, sports, or technology. . The World Wide Web is home to many various types of material, including documents, movies, and audio files. Since it involves human involvement, unstructured material delivered online (such as news, articles, videos, and audios) is difficult to recognize and categorize. But it is feasible to use computer techniques like natural language processing (NLP) to spot characteristics that distinguish false information from factual content [12].

Ahmed et al. [17] extracted linguistic features like n-grams from textual articles using a variety of machine learning models, including K-nearest neighbor (KNN), support vector machine (SVM), logistic regression (LR), linear support vector machine (LSVM), decision tree (DT), and stochastic gradient descent (SGD). SVM and support vector generated more accurate results (92 percent). A study found that as the number of n-grams produced for a single article increased, learning models' overall classification accuracy fell.) Various phenomena have been seen with categorization learning models. Shu et al. [12] coupled textual characteristics with auxiliary data, such as user social behaviors on social media, in order to improve accuracy using multiple models.) Additionally, the writers covered social and psychological concepts as well as methods for identifying false information on the internet utilizing these theories. The authors also covered a number of data mining feature extraction and model building strategies. Articles with a title, body, and label were included in the dataset. On test cases, the system performed well for the "agree" label but badly for the "disagree" label.) The authors were able to achieve an overall accuracy of 88.46 percent by combining a straightforward MLP with little changed hyperparameters.

Several examples of classification and regression problems were used to classify the text in the current corpus of false news [20, 21]. Instead, a significant amount of research focuses on certain datasets or genres, with politics being the most prevalent [10, 19, 21].

. The algorithm does not provide the best results when applied to articles from other domains since it has been taught to perform best on the domain of a certain type of article. It is challenging to train an universal algorithm that performs well across all news categories since news items from different disciplines have distinct textual patterns. In this paper, we use a machine learning ensemble technique to offer a solution to the false news identification challenge. Our study looks at a variety of linguistic traits that can be utilized to tell phony information from true information. . We train a combination of various machine learning algorithms using various svm classifiers that are not fully explored in the current research, using those properties.e ensemble learners have clearly established to be useful in a number of uses, as the simulations tend to reduce error rate by using tools like bagging and boosting [22]. These methods make it easier to more effectively and efficiently train various machine learning algorithms. We also conducted extensive testing on four openly available real-world datasets.) The four often utilized quality objectives—accuracy, precision, recall, and F-1 score—verify the increased effectiveness of our suggested technique.

II. LITERATURE REVIEW

"Fake News Detection Using Naive Bayes Classifier," Volodymyr Mesyura and Mykhailo Granik. In 2017, Vinnytsia from the Ukraine published a book. The paper illustrates a basic method for detecting fake news using a naive Bayes classifier. Data from a sample of recently posted Facebook posts was used to evaluate a software system based on this methodology. Given the model's relative simplicity, it is impressive that we were able to generalize roughly 74% of the time on the test set. The findings might be improved in a number of ways, all of which are covered in the article. The findings show that the issue of recognizing fake news may be overcome by using artificial intelligence approaches. ..

Identifying Fake News with Amey Kasbe and Akshay Jain In 2018, a series was written in Bhopal, India. The veracity of information on the internet, particularly social media, is becoming increasingly crucial, yet owing to web-scale data, it is difficult to locate, assess, and rectify such content, or so-called "fake news," which is pervasive on these platforms. In this essay, we provide a technique for spotting "fake news" and strategies for using it on Facebook, one of the most popular social media platforms online. Using the Naive Bayes classification model, this technique predicts whether a Facebook post will be classified as REAL or FAKE. Some of the tactics mentioned in the study might be used to improve the conclusions. The results suggest

III. METHODOLOGY

A. Logistic Regression

Logistic regression, which has two alternative outputs, is used to describe the likelihood of classification challenges. Regression models are a more complex form of binary categorization...

1. LCR limitations

The linear regression model performs well for regression but poorly for classification. What is the specific justification for this? What is happening? What precisely is happening? One class employs linear regression for one class, one class employs 0 for two classes, and one class employs 1 for one class. Weighting is used in the majority of linear models, and it is theoretically effective. There are a couple issues with this approach, though:

Instead of treating them as classes, a linear model will consider them as scores in the ideal support vectors, which will shorten the distance between any two and establish the exact. It doesn't constitute a guarantee; it only links several things.

A linear model extrapolates to provide outcomes that are both below and above zero.

Since the result is a linear mixture of bits rather than a certainty, there is no meaningful threshold for class differentiation. Stack overflow is a good illustration of this issue.

Multi-class classification issues can't be solved by linear models.

It's important to focus on classes 2 and 3, as well as other subjects. The linear model would create an unexpected link between the traits and your predicted class even if the classes were not in any logical order. Even if classes that are equivalent to other classes are not close, the prognosis is better the greater the positive quality...Figure 1 shows how the rumour spreads

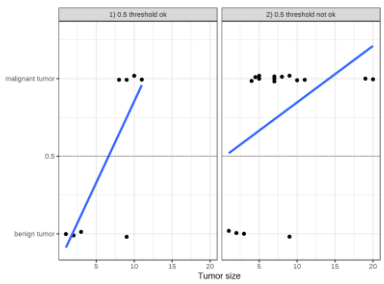

Figure 1 rumor

B. Decision Tree

When features and outcomes are non-linear or interact with one another, logistic regression and linear regression both fail. Your opportunity to stand out in the decision tree is now! The size of the data in tree-based models is determined by certain feature cut-offs. Various sub-sets are created by using a sub-set for each instance. The final subsets are denoted by end nodes or feature nodes, whereas the further subsets are described by internal nodes or splits. The average training results for each node are used to calculate the likelihood. Trees can be used for detection and inhibition..

A tree can be created by combining many algorithms. The division criterion, the method for assessing the fundamental models at the leaf nodes, and the tree structure (such as the number of splits per node) may all be modified. The classification and regression tree is one of the methods for tree induction that is most often employed (CART). Although we concentrate on CART, the approach may be used to a broad variety of trees. Friedman's book "Essential numerical learning components"17 is a fantastic reference for a more thorough analysis of CART..Feature extraction is shown in figure 2

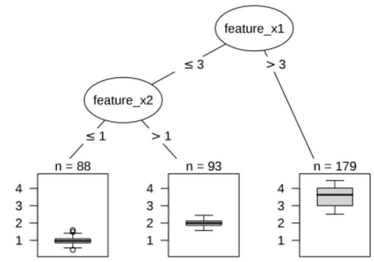

Figure 2 Feature Extraction

1. Decision Rules

A rule of decision is an IF-THEN fundamental general statement that includes a prediction and a skin condition. For instance, if it rains today AND tomorrow is April, the weather will change (prediction). One decision rule or a set of rules can be used to make forecasts.

When the elements are really in harmony, all of the governing principles follow the same structure: a distinct prediction is created. Decision The most basic and direct prediction models are rules. In our opinion, the IF-THEN form functions as a regular language, and the condition is succinct and has few rules.

The IF-THEN condition has a straightforward justification. In the field of automation, using an algorithm to learn judgements is a new idea....

Think about a method for deciding how much a house is worth (low, medium or high). According to one guideline this model established, a home with a garden larger than 100 m2 is worth a lot of money. Additionally, the size equals high if it is greater than 100 and the garden is one.

To construct a new condition, the criteria are joined by an AND. Both must be true for the rule to be applicable.

The result is anticipated to be good (THEN part)...

There is no limit on how many more "AND" statements may be used for a decision rule in a condition, but at least one function = value declaration must be utilized. The predetermined rule that takes effect in the absence of any other rules; however, more on that later. The variables accuracy and support serve as a summary of a decision rule's validity.

The proportion of time that a rule demand is in force

.. A group of viewpoints is comparable to a society with fixed norms. The rules in a set are now either self exclusive to the or there is a method for settling disputes, such a majority vote, which may be examined in relation to specific rules or other quality indicators.

Listings and sets of decisions may be impacted by the absence of a rule in the case. This issue may be resolved using a standard rule. If no alternative choice is given, the default rule is used. The most frequent type of data points that are not sensitive to additional rules are those that can be predicted using the default rule. If a set of rules or a list encompasses the whole feature space, it is said to as expansive.

There are several approaches to data rules, and this book does not cover them all. Each approach was chosen to address a different set of topics. OneR is capable of learning rules using just one element. OneR is considered as a standard because of its ease of use, perception, and usefulness.

Continually learning new rules and eliminating data items that are no longer covered by the present rule are necessary for the general concept of sequential coverage. Many rule algorithms use this technique.

A list of judgments is created using Bayesian data and placed before my typical patterns in the Bayesian Rule list. Pre-mining patterns is a method used by several rule learning systems...

C. Bayesian Rule Lists for Learning

The objective of the BRL algorithm is to provide a precise list of decisions with a minimal number of rules and short phrases. By providing early dispersion choice lists for the set of regulations and the breadth of the criteria, BRL was successful (preferably a shorter list).

After examining the list confidence interval, we may assess a list's probability and its ability to accurately represent the facts. Our goal is to develop a list that fully utilizes its capabilities. Since the precise optimum list cannot be determined only from the list distributions, BRL provides the following formula.:

1) Create a randomly chosen list of first choices based on the distribution of priorities.

(2) Update the list, essentially, by adding, changing, and removing criteria to ensure that the created lists are disseminated later.

3) Choose the power brokers list with the highest probability following distribution from the sampled lists.

Permit the algorithm to reduce the distance further: Pre-mining value patterns is started using the FP-Growth techniques...

BRL presupposes both the desired spread and the target population parameter's distribution. The Bayesian representation is as follows. Don't get too enthusiastic about this logic if you're not familiar with Bayesian statistics. It is critical to comprehend that Bayes' method combines facts with prior knowledge or requirements (referred to as prior distributions). This is a strategy. Due to the fact that prior assumptions restrict the number of possibilities and keep the underlying concepts simple, Bayesian technology allows for the listing of alternatives...

D. Random Forest Classifier

It uses a tree-based approach to learning. A group of randomly produced decision-making bodies makes up the Random Forest Classification. Votes from various life choice trees support the test item's ultimate class...

1. Ensemble Algorithm :

A number of classification techniques are included in composite algorithms, some of which are related and others which are unrelated. The test item for the class is decided upon following the predictions for the Naive Bayes, SVM, and Decision Tree runs...

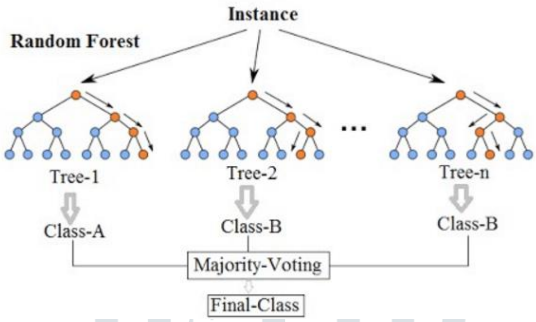

Figure 3. Structure of Random Forest Classification

2. Types of Random Forest models:

1. The majority of all prediction classes over b-trees, according to random forestry prediction F(x). Figure 3 shows the structure of the random forest

2. Random prediction for the forest problem: f(x) = sum of all substrate forecasts distributed among B trees.

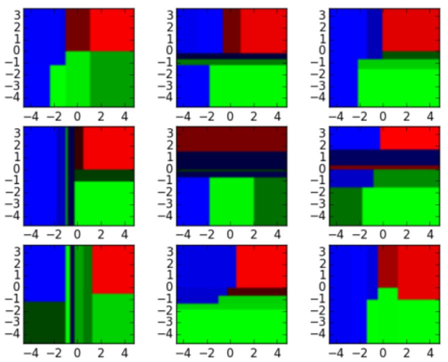

Figure 1 There are nine different types of decision tree classifiers.

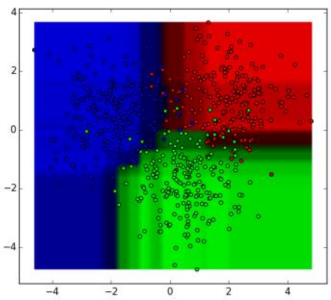

Figure 5 The output of the 9 Decision Tree Classifiers combined

In a random forest, the nine decision-making tree types mentioned above in figure 4 can be mixed (on the right). The x1 and x2 can be thought of as attributes of the x and y direction axes in the decision tree output shown above in figure 5 . The classification of the values "blue," "green," "red," and so on is done using a decision tree.

Each decision tree is completed by the output of a single input parameter that combines these results into averages or model votes....

3. Features and Advantages of Random Forest :

One of the most accurate algorithms is this one. Different data sets are accurately categorized.

With enormous datasets, it works fantastically.

It is capable of processing hundreds of inputs without removing any of them.

It identifies the determining elements in categorization.

Internal, objective evaluations are produced when the forest structure changes.

When a significant amount of data is absent, the forecasting method is quick and accurate

IV. SIMULATION AND RESULTS

Thus, altering random forest values for this type of data is incorrect.

incorporation of actual data Classification with Random Forests:

1. Collect information and enter it into a dataset.

```
# Importing the libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

```
# Importing the dataset
from sklearn.datasets import load_iris
dataset = load_iris()
```

2. Using the dataset to create a training and test set

```
# Fitting the classifier to the Training set
from sklearn.tree import DecisionTreeClassifier
model = DecisionTreeClassifier(criterion = 'entropy', splitter = 'best', random_state = 0)
model.fit(X_train, y_train)
```

```
DecisionTreeClassifier(class_weight=None, criterion='entropy', max_depth=None,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_state=0,
            splitter='best')
```

```
# Fitting the classifier to the Training set
from sklearn.ensemble import RandomForestClassifier
model = RandomForestClassifier(n_estimators=100, criterion='entropy', random_state = 0)
model.fit(X_train, y_train)
```

```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='entropy',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=100, n_jobs=None,
            oob_score=False, random_state=0, verbose=0, warm_start=False)
```

3. Developing and implementing an RFC model.

4. Analyse the test outcomes to develop the Confusion matrix.

```
# Predicting the test set result
y_pred = model.predict(X_test)
```

```
# Making the confusion matrix
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
cm
```

```
array([[16,  0,  0],
       [ 0, 17,  1],
       [ 0,  0, 11]])
```

```
# Getting the score for our model
model.score(X_test, y_test)
```

```
0.9777777777777777
```

A. Classification using a Gradient Boost

1. Ensemble Methods

In most cases, it is better to utilize many excellent predictors than one, as this increases the 0.0001 accuracy. The parts of the puzzle are starting to fit together. A higher grade than a single predictor model is provided by ensemble learning, which makes use of a variety of predictors and data training. For instance, the Random Forest is nothing more than a collection of decision trees that have been compressed or combined..

Ensemble methods could make use of orchestral techniques. A big number of individuals play a variety of instruments and combine all the musical groupings to produce a more expansive sound than just one person playing an instrument. Although gradient boosting is a technique for ensemble learning, it is especially helpful for improving performance...

A. In the majority of cases, using many excellent predictors rather than one enhances the 0.0001 accuracy. The parts of the puzzle are starting to fit together. When compared to a single predictor model, ensemble learning achieves a superior grade thanks to a variety of variables and data training. For instance, the Random Forest is nothing more than a collection of decision trees that have been compressed or combined..

Similar structures can be employed with orchestral methods. A big number of individuals play a variety of instruments instead of just one, mixing all the musical ensembles to produce a more expansive sound. Although gradient ramping is a technique for ensemble learning, it is especially helpful for improving performance..:

B Adaptability boost: The gradient is improved.

C. However strong many complicated learning algorithms may be in Kaggle competitions, the Gradient Boosting Models are a model that frequently shows up in such category. The GBM methodology's XGBOOST variant is credited with Alexey Noskov's accomplishments.

D.. Many specialists still consider this approach to be a "black box" despite its widespread use. Therefore, the objective of this project is to create a user-friendly infrastructure based on a good machine learning methodology...

E Boosting is a method for raising the performance of pupils who are struggling. The most recent iteration of the initial data set was used to construct each new tree. The AdaBoost method is the simplest approach to describe gradient boosting (gbm). The first step in the AdaBoost method is to create an equally weighted decision tree for each witness. After examining the first tree, we give these conclusions more weight and less weight to those that are obvious.

F. The second tree is built using this weighted values. This is a suggestion to improve the predictions of the first tree. Our new model is Tree 1 Plus Tree 2, as a consequence. After that, a third tree is made to look at residues and the categorization error is computed. A predetermined number of times are used to repeat this process. These trees help us categorize observations that the earlier trees were unable to do correctly. As a result, the projections from the final ensemble model are the score that reflects the prior tree that resulted in large-scale..

G .. Gradient is advantageous for many models, including progressive, additive, and sequential models. The key contrast between AdaBoost and Gradient Improvement Algorithm is how they identify weak learner inadequacies (eg. decision trees). The AdaBoost model uses high-weight sample points to identify issues, while the valley boost program uses loss grades to achieve the same results. The model coefficients' response to changing the baseline data is shown via the knn algorithm. Gaining the most complete knowledge of the loss function is our main goal.

H .. The equation is assessed by the difference between actual and predicted housing prices, for instance, if we use a predictor to estimate the purchase price. The loss function will be used to investigate credit failures and assess how well our prediction model's classification of subprime loans worked. Gradients offer the advantage of enabling you to maximize a set of user-defined parameters as opposed to a fuzzy system, which is less effective and does not satisfy specified purposes.

2. Training a GBM Model in R

The R gbm model cannot be trained until the gbm library has been installed and run. To use the gbm function, you need to supply the required arguments. The moment has come to start formatting. These are the components that make up your reaction and forecast. Finding out how your variables are distributed is the next step. In the absence of information, GBM will hazard a guess. Some of the most well-liked designs include "Bernoulli," "tdist," and "poisson" (count outcomes). The variables data and n.trees are also supplied at the conclusion. The gbm model measures the performance of our gbm using a standard of 100 arbours, and it can do so well..

Training the Titanic Dataset gbm model on Kaggle: I used the well-known Titanic data set from Kaggle to demonstrate how a gbm model may be constructed. I import the Titanic data into my R terminal using the read.csv() function. The initial data collection was divided using Create Data Partition into discrete train and test sets (). This distinction is particularly important if the accuracy can be assessed on a single holdout dataset (test data) and the AUC value may be used in subsequent stages. The R code is displayed on the displays below...

```
install.packages("gbm")

library(gbm)

GradientBoostingModel<-gbm(formula = response ~.,
                           distribution ='bernoulli',
                           data=train,
                           n.trees = 1000)
```

Please take note that, in respect to the size of the data collection, I have only included 750 train inspections and 141 holdout occurrences. I've also made sure to use the same integer each time a seed value is created. As a result, there is less variation in the model's results, which makes it simple to evaluate the model's quality...

```
Train<-read.csv("train.csv")

set.seed(77850)
inTrain <- createDataPartition(y = Train$Survived,
                               p = 750/891, list = FALSE)
Train <- Train[ inTrain,]
Test <- Train[ -inTrain,]
```

Train a GBM model using our holdover. There are two more factors, interaction, depth, and broadening, which are similar to the assertions made in the preceding section. The degree of contact affects each tree's depth and breadth. The capacity for learning is declining among people. The impact of each important student is reduced or removed (tree). By making consecutive steps smaller, it gradually reduces the importance of each repetition.....

```
SimpleGBMModel<-gbm(Survived~.-PassengerId-Name-Ticket,
                    distribution="bernoulli",
                    data=Train,
                    n.trees=1000,
                    interaction.depth = 4,
                    shrinkage = 0.01)

print(SimpleGBMModel)

summary(SimpleGBMModel)
```

Although we previously trained the classifier with 1,000 trees, we may use out-of-back or pass techniques to reduce the number of trees in order to change the parameters. We'll see how to include this into our gbm model later....

B. Results

Examine the Logistic Regression findings.

1. Logistic Regression

```
In [28]: from sklearn.linear_model import LogisticRegression

In [29]: LR = LogisticRegression()
         LR.fit(xv_train,y_train)

Out[29]: LogisticRegression()

In [30]: pred_lr=LR.predict(xv_test)

In [31]: LR.score(xv_test, y_test)

Out[31]: 0.9885026737967915

In [32]: print(classification_report(y_test, pred_lr))
              precision    recall  f1-score   support

           0       0.99      0.99      0.99      5883
           1       0.99      0.99      0.99      5337

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

Apply Decision Tree and check the results.

2. Decision Tree Classification

```
In [33]: from sklearn.tree import DecisionTreeClassifier

In [34]: DT = DecisionTreeClassifier()
         DT.fit(xv_train, y_train)

Out[34]: DecisionTreeClassifier()

In [35]: pred_dt = DT.predict(xv_test)

In [36]: DT.score(xv_test, y_test)

Out[36]: 0.9945632798573975

In [37]: print(classification_report(y_test, pred_dt))
              precision    recall  f1-score   support

           0       1.00      0.99      0.99      5883
           1       0.99      0.99      0.99      5337

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

Gradient Boosting should be used and the outcomes should be checked..

3. Gradient Boosting Classifier

```
In [38]: from sklearn.ensemble import GradientBoostingClassifier

In [39]: GBC = GradientBoostingClassifier(random_state=0)
         GBC.fit(xv_train, y_train)

Out[39]: GradientBoostingClassifier(random_state=0)

In [40]: pred_gbc = GBC.predict(xv_test)

In [41]: GBC.score(xv_test, y_test)

Out[41]: 0.9955436720142602

In [42]: print(classification_report(y_test, pred_gbc))
              precision    recall  f1-score   support

           0       1.00      0.99      1.00      5883
           1       0.99      1.00      1.00      5337

    accuracy                           1.00     11220
   macro avg       1.00      1.00      1.00     11220
weighted avg       1.00      1.00      1.00     11220
```

4. Random Forest Classifier

```
In [43]: from sklearn.ensemble import RandomForestClassifier

In [44]: RFC = RandomForestClassifier(random_state=0)
         RFC.fit(xv_train, y_train)

Out[44]: RandomForestClassifier(random_state=0)

In [45]: pred_rfc = RFC.predict(xv_test)

In [46]: RFC.score(xv_test, y_test)

Out[46]: 0.9915329768270945

In [47]: print(classification_report(y_test, pred_rfc))
              precision    recall  f1-score   support

           0       0.99      0.99      0.99      5883
           1       0.99      0.99      0.99      5337

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

Check the outcomes of Random Forest..

V. CONCLUSION

. As more individuals use the internet, spreading false information is easier. Many people use the Internet and social media often. Nothing is prohibited from being uploaded on these websites. As a result, some people use these networks to start disseminating erroneous information about specific people or groups. This might damage someone's reputation or have a bad effect on a business. Untrue rumors about a political party can also affect the general public's opinion. Exposing this erroneous information is necessary....

This research has covered the topic, the manufacturer's challenges, and the dishonest newsagent. News items, providers, and concerns, according to diverse social networks, contain a range of overt and covert components. In a variety of applications, classificatory for machine learning is also used to identify fake news. The classifiers are trained using a training data set, which is a collection of data. After that, these classifiers can recognize false information on their own.

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