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FAKE NEWS AND FAKE PROFILE DETECTION

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ABSTRACT

Traditionally we got our day-to-day news from newspapers and trusted mainstream media channels that are required to follow strict codes of practice. Nowadays, online news has become a great source of information for netizens. People's news consumption habits have been modified as a result of the rapid growth and popularity of social media. The internet has introduced a new way of publishing and consuming news articles having very few editorial standards. However, most of this news are specious and deceptive that includes clickbait, propaganda, satire, and misleading headlines. Many news articles surfacing on social media are hoaxes and lookalike actual news, making it difficult for the netizens to distinguish between the two. Fake profiles are the major sources for disseminating such rigged news on social media. Finding these profiles has grown to be a crucial study area that has lately received a lot of attention. Detecting these fake news and fake profiles fast and effectively, an automated tool has become an essential requirement. In our research work, we have used 5 distinct machine learning models on 3 distinct datasets to diversify the results and then selected the best model with the highest accuracy for detecting fake articles and profiles disseminating such rigged news. We have also used TF-IDF for the tokenization of news articles. Distinct ML algorithms specifically Naive Bayes, Decision tree, Passive-aggressive, Support Vector Machine, and Logistic Regression are trained multiple times to achieve maximum accuracy for all the utilized datasets. The accuracy of all machine learning models is compared to find out which one is the most accurate and suitable for an assigned task. Then we put forward a novel model to check the authenticity of news articles and profiles using the same platform. Achieving better accuracy, we recommend our proposed model for verifying the legitimacy of articles and social media handles.

Keywords: Classification, Fake News, Fake Profiles, Machine Learning.

I. INTRODUCTION

Over the past decade, there has been remarkable growth in the use of social media, like meta, by people and groups for the quick distribution of information. The importance of social media as a source of information about current events in India and throughout the world has grown.

This information is disseminated through a variety of news and discussions among users on various social media sites. As helpful as this information may be, it also raises concerns about the quick dissemination of false information. Fake news is a piece of purposefully manufactured misinformation or disinformation that is presented as genuine news. A big amount of bogus news on the internet has the potential to generate serious societal issues. People's views and responses to actual news are changed by fake news, and it may also influence them to believe false or biased information. Additionally, it often tends to harm people's reputations and cause stress and social discontent in numerous facets of society. Online false news is significantly harder for human fact-checkers to identify since it is real-time on social media.

The main channels for disseminating false information are fake profiles. Identifying such social media accounts that distribute false news has evolved to be a highly significant area of research that is now receiving a lot of attention.

Therefore, to ferret these manipulated news and fake profiles fast and effectively, automated fake news and fake profile detection tools have become an essential requirement.

A. Fake News Detection

Social media users use the social media platform to exchange information, join with people all across the globe and stay updated about various trends. Although such latest information emerging on the internet is doubtful and mostly planned to mislead. Such content is termed "Fake news". Serious problems can be generated in society due to the enormous spread of fake news. Society's way of interpreting and responding to real news changes due to fake news and it also persuades people into accepting false and biased beliefs. The way of accessing news has changed a lot due to rapid development and rising rage of various social platforms. Spammer profile are the vital source of false information on social media. Social networking services have attracted billions of users from all over the world. Famous social networking platforms like WhatsApp, Facebook, and Twitter discharge a large quantity of data. Fake news has a lot of exposure on social media. This results in the spread of erroneous information and the pollution of legitimate resources

Researchers have been working tirelessly to develop improved methods for effectively identifying fake news using machine learning and deep learning models. It is clear that the researchers employed a variety of ML and DL algorithms [1] to determine the nature of news. Some research works focused on limited amounts of data or information exclusive to one area, like politics. The expected and accurate outcomes for news items stationed in other fields will not be produced by this. Because of this, it is necessary to train the models on both a big dataset and a dataset that contains news items from other disciplines. The scientific community will gain from this work in order to develop effective and precise detection methods of determining news' nature appearing on social media platforms.

B. Fake Profile Detection

To tackle the problem of wide dissemination of fake news on microblogging sites, one must find out the origin of source for such fabricated information. On lucubration it becomes conspicuous that the sources are mostly the profiles which are intentionally created to spread negativity and propaganda for personal gains or to persuade the other users. Globally, social networking sites have attracted billions of users. Fake articles are mostly shared on social media sites like WhatsApp groups, Facebook pages, Twitter by such fake handles. Finding these fake accounts is essential for combating issues like cyberbullying and cyber stalking.

Researchers are always looking for improved ways to address issues that occur from anonymity, source detection, the dissemination of fake news, etc. We put forth a novel model for fake profile prediction by considering five main features of any social media account i.e., statuses count, followers count, friends count, listed count, favourites count(optional) and applying various machine learning models on it to get the best predictive performance.

The following is this paper's primary contribution:

1. Four ML algorithms have been trained on two different datasets comprising new articles from variety of fields to compare their performance difference and employ the best one.
2. Two datasets of variable lengths have been used to train the models to ensure the robustness.
3. Four different machine learning models have been trained on dataset comprising of various features of social media accounts to check the genuinity of users.
4. Finally, the news and profile detection tools are combined for tackling the problem of dissemination of fake news and fake profiles.

II. LITERATURE REVIEW

In this proposed paper **[1]**, two different datasets are used and on which the performances of various ML (Machine Learning) and DL (Deep Learning) models are evaluated. Embedding techniques like TF, TF-IDF are used to derive text representation. TF is used for machine learning algorithms to obtain text representation and TF-IDF is used for deep learning models, and then to evaluate performances of different models, evaluation metrics such as F1-score and accuracy as well as precision are used. Then, the novel stacking model is proposed to detect fake news that too with better accuracy. The proposed model uses stacking approach to ameliorate the performances of individual models. Stacking is the ensemble technique of combining multiple models using the concept of meta learner. Here, five ML algorithms namely Decision tree (DT), Random Forest (RF), k-nearest neighbors (KNN), Logistic regression (LR), and Support vector machine (SVM) along with three DL models namely Convolutional neural network (CNN), Long short-term memory (LSTM), Gated recurrent unit (GRU) are trained to increase diversity and to juxtapose the performance difference between discrete models. Here, the performances of 5 distinct Machine learning algorithms and 3 Deep learning techniques are compared on 2 different data sets. Then the model's performance is evaluated and the best one with highest accuracy is selected to detect fake news It also shows a novel stacking approach to find out the fake news precisely and efficiently. Also, this paper has three major contributions: -

1) Eight algorithms (Five ML and three DL) are trained to juxtapose the performances of individual models.
2) To examine the robustness, two discrete datasets which are of different sizes are used to train and test the models.
3) Overhauled version of McNemar's statistical test is employed to compare models' performances and choose the leading individual one.

The proposed stacking mechanism consists of four main steps, given here.

[2] The major goal of this research is to catalogue several strategies for Twitter spam detection and to propose a taxonomy by categorizing these strategies. The taxonomy for identifying spammers on Twitter is primarily divided into four classes: fake content stationed spam identification, recognizing spam in hot topics, detecting spam in URL-based spam, and identifying fake users. The suggested approach depends on user-level functions like URLs, Followers/Followees, Spam Words, Hashtags, and Replies. Naive Bayes and Decision tree are two ML models that are used. Aiming to improve spam detection, three metrics are calculated: Spammers Detection Accuracy, Non-Spammers Detection Accuracy, and Total Accuracy.

[3] The analysis proposes a novel perspective to detect rumors with the help of an entity identified on the post content alongside the features indicating reliability and consistency. This theory is described by 4 unique scores determined as, i) Famousness score, ii) Rareness score, iii) Reliability score, and iv) Consistency score. The rapid spread of rumors in networks makes it very difficult to distinguish between rumors and non-rumors. It is challenging to view the whole global stream of tweets in real-time due to the enormous volume and rapid arrival rate of real-time tweets. As a result, the rumors are divided into several categories. When such well-known entities or uncommon events are included in the tweet text, python-based natural language processing (NLP) packages like Spacy, NLTK, and Gensim are used to identify their existence. These entities might be a person, place, business, group, occasion, etc. Each object is given a score by calculating its Inverse Document Frequency (IDF) in relation to the Wikipedia dump in order to determine the likely targeted subjects. Similar to this, a score according to the event's topic of interest is given to unusual occurrences. These ratings are known as famous-ness ratings and rareness ratings. Every tweet's dependability and consistency are also considered in addition to these two factors. The proposed features' actual results show that they improve model performance and outperform the baseline perspective in many stages of the F1 score.

In this proposed paper **[4]** a tool which can perform (i) offline analysis and (ii) online analysis to predict the authenticity of specific user and news is proposed. (i)Offline analysis consists the use of deep learning techniques. This system performs double analysis i.e., prediction between news trustworthiness and user profile trustworthiness. A collection of both genuine and questionable social network profiles and news is built by taking a reference of popular fact checking website. Long-short term memory and a convolutional neural network are used to develop the deep learning model. (ii) The categorization of credible and unreliable user profiles using internet analysis involves actual users. To conduct the online analysis of the social context in which the news is placed, a survey was developed and distributed to actual users to gauge their trust in particular Twitter identities. The experimental findings that have been statistically validated show what data both machines and people can use to identify unreliable users.

III. MATERIALS AND METHODOLOGY

A. DATA-SET

On the internet, enormous amounts of data flows. Many datasets are available online and may be found on sites like Google Dataset Search, Kaggle, Data.World, GitHub, and others. For our study, we chose three separate datasets that contain news from a variety of disciplines, including politics, sports, and entertainment. They feature a decent mix of both real and fake news, as well as genuine and fake profiles. We obtained our datasets from kaggle.com, uvic.ca and GitHub. The first dataset i.e., Isot.csv consists of 44,898 records out of which 21417 are real news articles and 23481 are fake news articles. There are 5 features of this dataset namely, title, text, subject, date and label. Data set contains subjects like World-News, politics news, government news. The 2nd dataset i.e., news.csv is made up of 6335 records of these 3171 are genuine and 3164 are the fake. It features index, title, text, and label. It contains news articles related to US politics. Lastly, the third dataset which is users.csv and fusers.csv holds up to 2818 records of genuine and fake profiles. In order to train the model efficiently these two independent datasets are merged into one. It comprises of 35 different features. All the datasets used in this research work are of variable sizes. The biggest dataset is Isot.csv which comprises of 44,898 records while, news.csv consists of 6335 records. A little snippet from all the datasets is shown and delineated in following tables respectively.

Table 1: ISOT Dataset.

	title	text	subject	date	label
0	Trump FURIOUS After Federal Judge Stops His B...	Just hours before Donald Trump s new Muslim ba...	News	March 16, 2017	FAKE
1	Michael Flynn's Resignation Letter Omits One ...	Michael Flynn s sudden resignation in the wake...	News	February 14, 2017	FAKE
2	U.S. bombers, fighter jets in bombing drill ov...	SEOUL (Reuters) - The U.S. military on Monday ...	worldnews	September 18, 2017	REAL
3	Egypt's Muslim Brotherhood leader loses appeal...	CAIRO (Reuters) - The leader of Egypt s Muslim...	worldnews	November 15, 2017	REAL
4	Trump Jr. Throws Temper Tantrum While Comey T...	Donald Trump has been asked by Republicans to ...	News	June 8, 2017	FAKE
5	LOOK WHO "THE VIEW" HIRED To Replace Only "Con...	Jedediah Bila is at most, a lukewarm conservat...	politics	Sep 18, 2017	FAKE
6	KEITH SCOTT'S BROTHER Tells Charlotte Reporter...	The first Black (and half White) President has...	politics	Sep 23, 2016	FAKE
7	MEGYN KELLY IS DESTROYING NBC's Morning Show R...	The numbers are in, and Megyn Kelly Today is...	left-news	Oct 11, 2017	FAKE
8	UNDERCOVER JOURNALIST In Burka Is Offered Huma...		politics	Nov 7, 2016	FAKE
9	Russia hacked Republican state campaigns but n...	WASHINGTON (Reuters) - Russia hacked into Repu...	politicsNews	January 10, 2017	REAL

Table 2: KDnugget Dataset.

	Unnamed: 0	title	text	label
0	8476	You Can Smell Hillary's Fear	Daniel Greenfield, a Shillman Journalism Fello...	FAKE
1	10294	Watch The Exact Moment Paul Ryan Committed Pol...	Google Pinterest Digg Linkedin Reddit Stumbleu...	FAKE
2	3608	Kerry to go to Paris in gesture of sympathy	U.S. Secretary of State John F. Kerry said Mon...	REAL
3	10142	Bernie supporters on Twitter erupt in anger ag...	— Kaydee King (@KaydeeKing) November 9, 2016 T...	FAKE
4	875	The Battle of New York: Why This Primary Matters	It's primary day in New York and front-runners...	REAL
5	6903	Tehran, USA	\nI'm not an immigrant, but my grandparents ...	FAKE
6	7341	Girl Horrified At What She Watches Boyfriend D...	Share This Baylee Luciani (left), Screenshot o...	FAKE
7	95	'Britain's Schindler' Dies at 106	A Czech stockbroker who saved more than 650 Je...	REAL
8	4869	Fact check: Trump and Clinton at the 'commande...	Hillary Clinton and Donald Trump made some ina...	REAL
9	2909	Iran reportedly makes new push for uranium con...	Iranian negotiators reportedly have made a las...	REAL
10	1357	With all three Clintons in Iowa, a glimpse at ...	CEDAR RAPIDS, Iowa — "I had one of the most wo...	REAL
11	988	Donald Trump's Shockingly Weak Delegate Game S...	Donald Trump's organizational problems have go...	REAL
12	7041	Strong Solar Storm, Tech Risks Today | S0 News...	Click Here To Learn More About Alexandra's Per...	FAKE
13	7623	10 Ways America Is Preparing for World War 3	October 31, 2016 at 4:52 am \nPretty factual e...	FAKE
14	1571	Trump takes on Cruz, but lightly	Killing Obama administration rules, dismantlin...	REAL

Table 3: Users & fusers dataset.

statuses_count	followers_count	friends_count	favourites_count	listed_count	label
47	16	552	0	0	1
7902	281	599	13	6	0
61	19	494	0	0	1
106	45	167	0	0	0
62	16	561	0	0	1

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B. PRE-PROCESSING

Dataset from the internet cannot be utilized directly to train machine learning models since it comprises noise, empty cells, and improper formats. Data preparation is an essential process in cleaning a dataset and prepping it for machine learning models. Machine learning models benefit from data preprocessing since it improves efficiency and accuracy. The raw data is pre-processed using NLP (Natural Language Processing) methods such as stop-word removal, punctuation removal, and tokenization. By applying these actions on the dataset, it is possible to achieve consistency in format and structure.

The three datasets utilized in this experiment are all real-world news articles and profiles, therefore many of the characteristics include no information that is necessary for completion of this experiment. To obtain a consistent dataset, such features ought to be removed from the dataset. Therefore, we removed the title and subject from our initial dataset because they were not relevant to the experiment. Additionally, we eliminated the title field from the second dataset, KDnugget. Unnecessary characteristics are removed from the third dataset once it is created by merging two other datasets. Following the application of punctuation removal and stop word removal, the dataset is obtained with only the necessary fields.

1. DATA SPLITTING

Data splitting is a key component of machine learning, especially when building models that are driven by data. It entails segmenting the data into two or more groups. There is no such rule on how the dataset should be split, it mostly depends on the size of the datasets. Usually, the datasets are split into 8:2 ratios or 7:3 ratios, so that a high amount of data can be used for training. In our project, we have utilized the train test split function to obtain the train and test dataset by dividing the dataset into 8:2 ratio. It ensures there is sufficient data cases for training and testing the model. The dataset's subset used for training the machine learning model is known as the training set. By observing and optimizing any of its parameters, the model should learn from the training set. The testing set obtained after splitting contains 20 percent data that is used to test the performance and accuracy of the trained model.

2. TF-IDF

Once the dataset is splitted into train and test TF-IDF is applied to training and testing data. Term Frequency-Inverted Document Frequency transforms data into vectors. In order to better represent the text, we vectorize it. It assigns each word a score to reflect its significance to the corpus and the text. The score assigned shows the significance of each term in document. Here, the term's importance increases as the frequency of the term in the dataset increases. TFIDF is basically a product of TF and IDF. The term "term frequency" describes how frequently a word appears in an article relative to the total number of words in a phrase. The term "inverse document frequency" (IDF) refers to the ratio of the total number of sentences to the total number of sentences containing the word for which IDF is being computed. It is the inverse of the term "document frequency". It gives the relative weightage. Finally, the values for TF and IDF are multiplied to get the significance of the term.

$$TF = \frac{FrequencyOfWords}{TotalNumberOfWordsInSentence}$$

$$IDF = log(\frac{TotalNumberOfSentences}{NumOfSentencesContainingThatWord})$$

Figure 1: TF-IDF Equations

3. FEATURE EXTRACTION

Datasets acquired from the internet are frequently big, with a significant number of variables and characteristics that demand a lot of computing power to analyze. The technique of spatially reducing these massive datasets into manageable groupings is called feature extraction. It involves choosing or combining variables to create so-called features, which reduces the quantity of data that must be processed. The features are chosen in such a way that they do not compromise the dataset's accuracy or the original description.

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Feature extraction has the advantage of reducing the quantity of duplicate data in a particular study. This aids the machine learning process' speed and generalization processes.

C. MACHINE LEARNING MODELS

For this research work, five different machine learning models have been used to predict the authenticity of news and accounts considering several useful features from the mentioned datasets. The models used are:

1. Logistic Regression

A ML algorithm that hails from the category of supervised machine learning algorithms is logistic regression. It is adapted from statistics and built on the idea of probability. The categorical dependent variable is predicted using a specified set of independent variables. As the dependent variable is dichotomous in nature, there are only two viable classes. If put together in simple words, it means that the dependent variable is binary which means it can either be true or false, yes or no, 0 or 1. Instead of reporting an exact value from 0 to 1, it assigns probabilistic values that are in the range of 0 and 1. Logistic regression finds its best use for solving a classification problem. It has its significance as a machine learning model as it can assign probabilities as well as categorize all the new input data using continuous and discrete datasets.

In LR, by using a S-shaped logistic function we predict the outcome in only two classes i.e., 0 or 1, True or false as an alternative to using the regression line. The function depicts the probability of a variety of outcomes, including whether the news is true or not, etc.

2. PASSIVE-AGGRESSIVE

A family of machine learning algorithms known as passive-aggressive classifiers falls under the heading of "online-learning algorithms". Large-scale learning often uses passive-aggressive algorithms. Passive Aggressive Classifier as previously noted is an online learning technique that uses successively feeding it examples, either singly or in tiny groups termed mini-batches, to train a system gradually. The passive-aggressive model is built and put into use in online learning so that it can keep learning as new data sets are added. We may thus conclude that systems that receive input in a continuous stream benefit most from an algorithm like the passive aggressive classifier. The reason why passive-aggressive algorithms have that name is Passive: It keeps the model as it is and makes no changes if the prediction is true. Aggressive: It makes changes to the model and modifies it if the predictions turn out to be incorrect. In common words, modification of the model may make it work right.

3. NAÏVE BAYES

It is a deterministic technique for classifying data that makes use of the Bayes theorem. This particular method is used to categorize texts. In a naive Bayes classifier, the usage of tokens is connected with news that may be fraudulent or not fake, and the accuracy of the news is then determined using the Bayes theorem. This algorithm can quickly determine if a piece of news is legitimate or fraudulent by comparing it to the values of an earlier dataset. The following is the naive Bayes classification formula, which compares the probability of the current occurrence to that of the prior event.

$$P(A|B) = P(B|A) \cdot P(A) / P(B)$$

The data is divided into two categories in this instance: test data and train data. The train dataset is then divided into categories with similar entities After matching the test data, each group is assigned to the category to which it belongs. Next, the Naive Bayes classifier is used, and each word's probability is determined separately. A final calculation is made to determine the overall probability of the news as compared to the dataset after calculating each and every probability of the event. Inferring the approximate value from the total probability allows us to determine if the news is real or fake.

4. SUPPORT VECTOR MACHINE

The SVM is a supervised ML technique that is most widely applied on classification or regression problems. Although, the most common application is in classification problems. When employing the SVM algorithm, every data point can be represented as a point in an n-dimensional space, where n is a place holder for the number of features, and each feature's value corresponds to a certain position. Then, we carry out classification by locating the hyper-plane that successfully separates the two classes.

Hyperplane which is also called as the Decision boundary, decides that new data belongs to which class. We draw lines parallel to the hyperplane, which are just close to points that are nearest to the opponent class. Then the distance between these parallel lines is calculate which is termed as the 'Margin'. Margin is very helpful in determining the Hyperplane. The closest locations to the hyperplane are defined as the support vectors.

5. DECISION TREE

DT is a significant supervised algorithm in which, learning tasks are divided into smaller groups using a decision tree ML approach until each division is clear and pure, and data is then categorized according to its kind. Up till each division remains unchanged, the dataset is partitioned into smaller groups. A node in a decision tree can only be a leaf node, which is bound to a label class, or a decision node, which is in charge of making judgments.

Decision trees have a top-down structure and resemble trees. The pruning process is used for the tree's final construction once it has reached full growth in order to eliminate noise from the dataset. A decision tree is used because it is simple and easy to comprehend. Because it is a weak learner, it could do poorly on tiny datasets. Selecting the best attribute is the algorithm's key learning process. Metrics for various trees include information gain and gain ratio. Information Gain: Information gain quantifies the amount of uncertainty reduced by a particular feature and also serves as a criterion for choosing which attribute to use as a decision node or root node.

D. MODEL EVALUATION CRITERIA

Accuracy, precision, recall, f1-score are the evaluation metrics used to assess the performance of all the ML models. Among all this evaluation metrics, we considered accuracy as a cornerstone in selecting the best model for predictions. Formulas for finding such evaluation metrics are given below.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

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

$$\text{Precision} = \frac{TN}{TN + FP}$$

$$F1 - \text{Score} = 2\frac{(\text{Precision})(\text{Recall})}{\text{Precision} + \text{Recall}}$$

Figure 2: Evaluation Metrics

E. PROPOSED MODEL

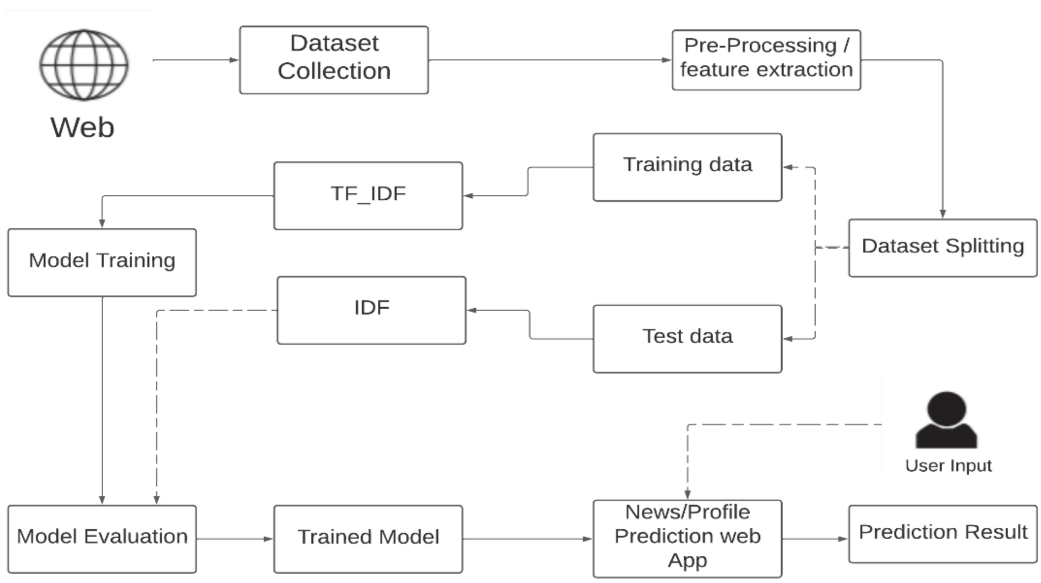

Figure 3: Proposed Model

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IV. RESULTS AND DISCUSSION

In this study, we did certain data cleaning and preparation procedures after gathering all the required datasets for this experiment. Stop words and punctuation are removed in this process. The frequency chart for the most often occurring terms was then shown after applying TF-IDF tokenization to produce the text representation. Furthermore, we trained all five machine learning models on these text representation features. All three datasets were divided in an 8:2 ratio for testing and training purposes. A total of eighty percent of the instances were utilized to train the models, with the remaining instances being used for testing. After training the individual models, the classification performances of all the models were summarized by using the confusion matrix. To determine which machine learning model is most appropriate for the goal of prediction, classification reports were also prepared. The experiment on all datasets was performed on the jupyter notebook by using latest version i.e., 3.9 of the python programming language. Different libraries of python like pandas and sklearn were used in performing this task. Finally, the model with highest accuracy was dumped into pickle file and utilized in the web app created using Flask framework.

Figure 4,5: Homepage of Web Application

Figure 6: Fake News Detection Tool

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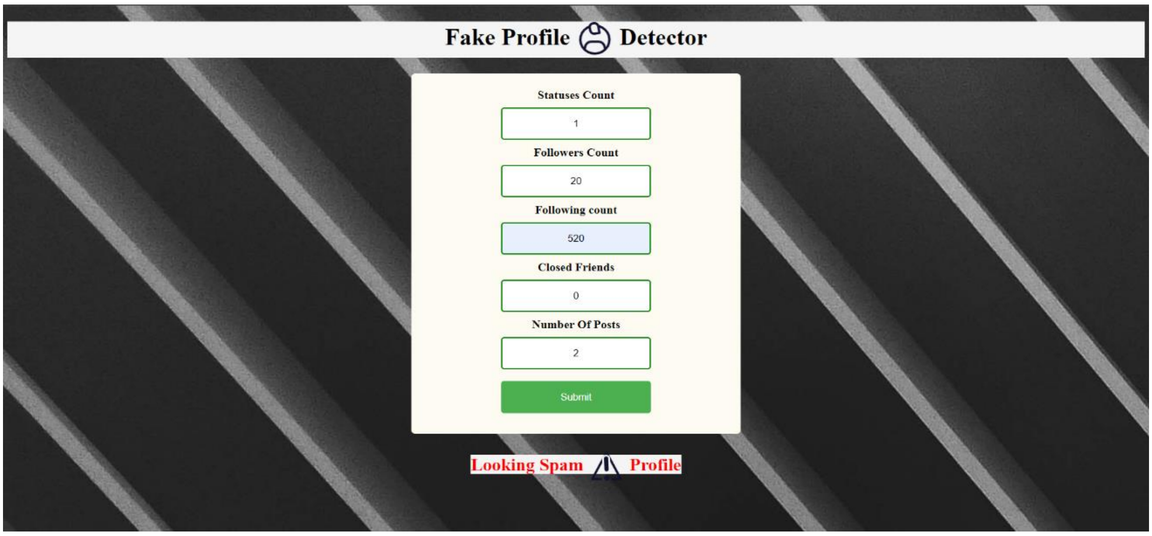

Figure 7: Fake Profile Detection Tool

1. MODEL CLASSIFICATION PERFORMANCE ON DATASETS

On a larger ISOT dataset, the effectiveness of machine learning models has been evaluated and also on comparatively smaller KDnugget dataset, both of these datasets are used for predicting the authenticity of news articles. According to the results obtained by training the models on ISOT dataset, decision tree with 99.68% outperformed rest of the models based upon the accuracy. The accuracy of the DT and passive aggressive algorithms varies quite slightly. Passive aggressive gives an accuracy of 99.44%, that of logistic regression has 98.31% whereas, the accuracy of naive bayes is the lowest of all, at 93.83%.

On the KDnugget dataset, the Passive Aggressive model which is an online learning algorithm fared better than the other three models, with an accuracy of 93.45%. DT provides the lowest accuracy of all, with an accuracy of 81.77%, while LR gives an accuracy of 91.48 and naive bayes at 83.19%. The best model for the prediction of fake news, according to an accuracy comparison of all the models, is DT, which has an accuracy rate of 99.68%, followed by the Passive aggressive algorithm.

Finally, on the datasets used for profile detection, DT outperformed all the remaining three models, i.e., SVM, passive aggressive and LR with an accuracy rate of 98.76. Accuracy of Passive aggressive and SVM differ very slightly. Logistic regression gives the lowest accuracy of 82.62% on the users and fusers dataset. Thus, the decision tree is declared as the most efficient model in predicting the nature of social media profiles in this experiment.

Table 4. Performance Comparison on different datasets

ISOT	DT>PaAgg>LR>NB
KDnugget	PaAgg>LR>NB>DT
Users & fusers	DT>PaAgg>SVM>LR

2. RESULTS OF THE PROPOSED SYSTEM

In order to combat propaganda, false narratives, and fake profiles on social media, a novel model for the detection of fake news and fake profiles has been proposed. Netizens may use the same tool to simultaneously check the veracity of news articles and profiles. Our model outperformed previous approaches with an accuracy of 99.68% on the ISOT dataset, 93.45% on KDnugget, and 98.76% on the users-fusers dataset. Because it may be readily employed in a real-time environment, the proposed model is highly advised for efficiently detecting fake news and fake profiles on social media.

V. CONCLUSION

In this paper, we have discussed building an efficient tool with better accuracy to predict fake news and fake profiles on social media. We have used five different machine learning models on three distinct datasets to diversify the results and then selected the best model with the highest accuracy to detect the fake news articles

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and the profiles disseminating such rigged news. After working on multiple datasets and machine learning algorithms, experimental results have demonstrated that the decision tree (DT) algorithm outperforms the rest of the algorithms with an accuracy of 99.68% for fake news detection and 98.76% for fake profile detection. We have also observed that the passive-aggressive algorithm, which is a member of the online learner family performs well on live, real-world news articles and gives a real-time prediction, making it more valuable than other algorithms. We have also compared the proposed model with already available models and deduced that this is a novel approach of combining two tools to provide the one-stop solution for tackling the problem of verifying the legitimacy of articles and social media handles. We intended to develop a web application for the same, and we strongly recommend it owing to its high performance and better accuracy compared to existing applications.

In the future, we will attempt to ameliorate the performance of our model by making use of deep learning and neural networks. Additionally, we want to make our model multilingual so that it may be utilized globally. Furthermore, we want to enhance the tool so that it automatically extracts required details from the micro-blogging applications with open APIs.

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