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NNPIGAE24: Artificial Neural Network-Based Propaganda Identification on Social Media During Indian Election-2024

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Abstract

Many modern computational social science academics are concerned about the recent trend of information sharing. Platforms for online social networks are being exploited to spread propaganda. These days, this is a lethal tool used to undermine democracies and other religious or political gatherings. Virtually every region of the planet was impacted by the political campaign. During the height of the 2024 Indian General Assembly election, A large volume of tweets has been shared that advocate various kinds of propaganda. The research proposes a cutting-edge strategy based on artificial neural networks that categorizes tweets into Propagandistic and Non-Propagandistic categories. Data is severed out with multiple ambiguous hashtags, and after the extraction, the approach is manually annotated into binary classes. Hybrid feature engineering has been used to merge the features of "Term Frequency (TF)/Inverse- Document Frequency (IDF), Tweet Length, and "Bag of Words,". The planned approach is compared with logistic regression, SVMs, and multinomial naïve Bayes. The results showed that the Artificial-Neural-Network performed with a recall of 77% along with an accuracy of 77.15% and a precision of 79% in comparison with a number of other machine learning algorithms. A step forward could see deep learning techniques such as LSTM used for such classification assignments.

Keywords: Indian General Assembly Election, Machine Learning, Neural Networks, Online Social Network, Propaganda.

Introduction

There are many researchers working to detect fake news. Machine learning is useful in this space. Research on fake news detection uses many algorithms. Fake news is hard to identify. They used machine learning to help identify fake news. It is given that there is a rise of fake news with time. For this reason, we require fake news, and machine-learning classifiers have been developed to notice phony publications. The machine learning algorithms are capable of automatically identifying bogus news once they have been trained (1). It makes sense to believe that some types of fake news will be more prevalent in a given culture. For example, the story of a well-known individual breaking social standards would probably spread more quickly in a culture that learns more collectively than in one that values individualism. If so, the first question is: do authors target this type of fake news with communities scrambled up in specific pseudo-insets that think this is the best flavor of personal fake news for their culture (2). One of the main causes of fake news is the use of heuristics when making decisions. Excellent examples of research have been compiled regarding the secret ones, giving rise to the credence of information presented in the leaks format or than speech that at the least has a kernel of reality. Although there aren't many studies in this sector, there is a connection between study and culture. For instance, inferential secrecy may be more common in societies with a large power differential since individuals are not used to being aware of the specifics of those in positions of authority (3). Conclusion: Before we can trust or act upon something, we need to investigate it, whether it is true or not.

As communication platforms and related networks, online social media sites are crucial in today's world. Social media accessibility People can now connect with others wherever they are in the world and communicate easily. These platforms are capable of disseminating broadcasts across the world in a timely manner. Although these platforms have multiple advantages, they also come with limitations. While these platforms

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are driven by the algorithms that promote hate and disinformation, hateful and malicious users will populate them anyway. This wide array of information/media is divided into two: disinformation and misinformation. Misinformation is information that someone passes along without knowing (4). This data class is applied to many things, elections, trends, religion, and so on. False information is information that is posted/shared on purpose. In this message, the user is very likely sharing misinformation. That kind of message could potentially cause havoc on society/nation at large. These are not isolated incidents – even if they are, their implications have been much wider than their scope of coverage on a national level, where more recently, misinformation has run rife during the 2024 Indian general election on social media. Diversity in India as well as ambiguity can significantly have an effect on people a bigger way misunderstanding can produce a place and disrespect the election process. In some countries like India, the tension has already escalated, it is far more dreadful, and moreover, this is very sensitive in context to myriad mismatches (5).

Social media provides an excellent platform for being transparent. The Army Emotional Restructuring Through Person-Setting. The goal of character propaganda is to confuse the general public. Thus, those posts may include text, multimedia, and images (6). Marketing details are classified into political events, religious events, discussions of cults, and events with a widely popular personality. These messages are crafted in a way that the user does not know that the message they are receiving is propaganda. The political parties sponsor a few news channels in some democratic countries. This media serves the sole purpose of spreading hatred news and propaganda about world affairs (7). Humans have transformed from a historical stage to a century-old high stage called education. But, these mothers of news have a lot of business news from higher media. Whether it is merely propaganda or not, we know that the system is working minute by minute to create the official list. Yar The new element of the year of the arts (including artists who demonstrate superior excellence in robotics, education, medicine, and all other professions) (8, 9). Now it analyzes the data using machine learning." Now it is highly performed on text, image classification, etc., through machine learning algorithms it also be applied to detect spammer and rumors, on social networking sites (10). The learning process can be carried out through both supervised and unsupervised learning. To determine the output class in supervised training, we trained the machine-learning algorithm (11). We show data from machine learning algorithms without production type in the case of unsupervised learning (12, 13). Classification tasks can be completed using a variety of supervised machine-learning tactics. Naïve-Bayes, decision-trees, and LR are a few of the operational techniques. In this paper, we have focused on using Support vector machines for the classification of tweets. The original contributions associated with this article include:

- A framework, specifically pointing toward the identification of propaganda that has emerged on online social networks by using machine learning algorithms, is proposed here.
- Annotation of the received tweets through various keywords including #IndianElection, #Election2024, #AssemblyElection2024, #BJPElection2024, #INCElection2024 #GeneralElection2024.
- Data annotation is attained through various techniques, these techniques include Bandwagon, Name calling and Testimonial.
- Combining various features, such as "TF/IDF," "Tweet Length," and "Bag of words," to train machine learning algorithms enhances feature engineering.
- The features chosen using the suggested hybrid feature selection method are used to fine-tune and train the artificial neural network.

This paper is separated into six pieces. The initial one provides a brief overview of the Indian General Election of 2024 and the effects of propaganda and disinformation at that time. A thorough history of disinformation and manipulation on social media is given in Section 2. We shall talk about the history of machine learning algorithms in Section 3. Section 4 will describe the suggested approach. Section 5 will address the findings, and Section 6 will wrap up the work. The growing attraction and the charm of using social platforms also make an impression in our lives, either by persuading it straight or obliquely deciding after reading the comments, and suggestions from others whether while buying goods or merchandise and taking part while giving votes on social media or during the voting while forming new governmental setup online, not shockingly, therefore has become one instrument for manipulating one's emotions through diffusive misinformation. The causes behind the widespread acceptance of propaganda and fake news on social media must be acknowledged and combated). The authors looked into the traits of dishonest User IDs, focusing on textual URL messages in particular (14). As more people use social media and political events and government efforts become more widely discussed, social media misuse has become more widespread. The identification and tracking of electoral errors in social media platforms (15). The structure of the network was a little unusual during the election and was seen as a social networking structure during the election period (16). They have designed a dynamic thinking model to reflect how broad-field parties survived collecting only a minimal number of votes in the period of the elections. Information was gathered and the political uncertainty surrounding social networks was taken into account (17). He pinpointed relevant elements, collected information from the event itself, and monitored the development of the phenomena. As the chosen political institution evolved, they tracked the educations and careers of individual political officials and registered inner circles of influence political officials who operate within the government structure but are concealed behind their official employment networks (18). To do so they employed three methods: networking, community discovery, and community evolution. Online social network sites were investigated and a new detection method for stealthy accounts was developed in a past research (19). The techniques include the following tasks: defining characteristics, classifying, locating stealthy Sybils, and community detection at node levels. The implementation of coronavirus detection using clinical textual reports was carried out (20). Political leanings were computed using tweets, retweets, and re-tweeters. The activity of the procedure among Twitter users was established social networking allows for the simultaneous occurrence of numerous events. The detection of social network events (21, 22). They clustered features using wavelet analysis, clustered documents using TF/IDF, and clustered topics using LDA in order to identify unknown events on the social networks. It looked into how social media bots are used in politics, namely in political propaganda. It is claimed that social bots only hurt politics (23). They found that Twitter botnets are essential to the dissemination of phony messages, and that accounts that frequently post misleading information are far more likely to be bots. The only people spreading hate and terror on social media are extremists. Semantic graphs are employed to: detect radicalization on social media (24). Whereas those who oppose ISIS typically discuss politics, geography, and anti-ISIS campaigns, ISIS supporters mostly discuss religion, history, and ethnic origin. They also spread false posts on social media sites. Using cognitive psychology (25), researchers found harmful information on social media websites. The mental process consists of the following elements: broad acceptance, source credibility, message coherence, and consistency. The Twitter API was used to scrape the data sets, and the following tags were used to retrieve them: #Syria, #Egypt, etc. A popular communication method that is socially mediated and heavily impacted by social networking is covered (26). They attempted to assess the extent of populist communicative ideology through concepts like "Appeal to the individuals," "targeting the Elite," and "ostracizing the others." During the COVID-19 outbreak, numerous propagandistic posts were shared on Twitter, utilizing various hashtags. The majority of the tweets that were shared during the COVID-19 timeframe were on online education, according to Mujahid *et al.* analyze sentiments on numerous themes (27). Taking into account variables such as age, gender, illness outcomes, prediction techniques, and the influence of pre-existing medical disorders (28), researchers divide the results into nine groups. Table 1 summarizes the latest research on this topic. In this context, P represents precision, R denotes recall, and F1 refers to the F measure. From the previous literature reviews, the following conclusion can be deduced. Clustering algorithms can be used to detect propaganda, classification algorithms can then be used to derive greater accuracy, and more study needs to be done. Most of the task is being performed on news-let databases, although online social networking platforms can also be used. Because of their semantic nature, the propaganda posts are hard to spot, necessitating manual annotation. Another area is feature engineering that could be done using multiple features like semantic and emphatic.

Table 1: Overview of Recent Works

Author	Year	Contribution	Results	Research Gap
Morio *et al.* (29)		Researcher employed P-o-S alongside Conventional NN.	P-56.54, R-.47.37 and F1-51.55	Performance can be enhanced with more feature engineering.
Jurkiewicz *et al.* (30)		The writers made use of CRF	P-59.95, F1-49.15 and R-41.65	Performance might be enhanced by more data.
Chernyavskiy *et al.* (31)		CRF embeddings were used by the authors.	R-45.56, F1-49.10 and P-53.23	You can use a language other than English
Khosla *et al.* (32)		LSTM Bag of Words was used by the authors.	P-50.97, F1-47.66, and R-44.76	The LSTM can be utilized with TF/IDF.
Paraschiv and Cercel (33)	2020	LSTM embeddings were used by the authors.	P-58.61, F1-46.6, and R:-37.94	Performance can be enhanced with more data.
Dimov *et al.* (34)		The researcher employed N-Grams and LSTM.	F1-,44.68, R-37.34 and P:-55.62	Other aspects might be taken into consideration in the future, but the writers have only employed the n-Gram feature.
Blaschke and others (35)		Researcher utilized .PoS. with support vector..	P-42.16, F1-43.86, and R-45.7	To increase accuracy, one can experiment with different SVM kernels.
Verma *et al.* (36)		The authors made use of CNN and ELMo.	P-49.86 F1-43.60, and R:-38.74	There is potential for more feature engineering.
Singh *et al.* (37)		PoS with BERT was used by the authors.	P-46.52, F1-42.21, and R-38.63	Only 536 publications were used by the authors, and BERT requires further details.
Ermurachi and Gifu (38)		LR and MNB were merged by the authors in their Bag of Words.	P-24.49, F1-33.21, and R-51.57	Additional characteristics like sentimentality and fervor could enhance the performance.
Dewantara *et al.* (39)		Authors employed CNN with embedding.	F1: 23.47, P: 22.63, and R: 24.38	More embeddings can be used in order to achieve better results.
Daval-Frerot and Yannick (40)		RF embeddings were used by the authors	R-12.39, F1-18.18 and P-34.14,	RF can be used with Bag of Words and Tf/IDF.

Background Knowledge

The rapid development of data mining procedures and techniques led to the emergence of machine learning as a distinct field within computer science. The fundamental principle is that a system, such as an algorithm or computer program, may learn from its own behavior. One could consider it a subset of artificial intelligence. It was described as “a field of study that concentrates on the capacity of computers to acquire knowledge without being explicitly programmed" by Arthur Samuel in 1959. Experience E can teach a computer program about a class of tasks T and a performance metrics P if it results in a gain in performance, measured by P, on tasks in T (41). The general objective of the learning algorithm of the machine is to solve a specific task according to its training. This model relies on the input dataset to serve as a basis for training, then uses it to make predictions Machine learning finds applications across various domains within computer science, including the Internet of Things (IoT), image processing, and natural language processing (NLP). It is increasingly utilized in numerous daily human activities for the purpose of discovery (42). During the COVID-19 pandemic, machine learning has been instrumental in identifying the virus through analysis of X-ray chest images (43). In the realm of text mining, machine learning algorithms are utilized to assess the sentiment expressed in diverse texts, which may include documents, product reviews, news articles, or tweets (44). The identification of propaganda can be regarded as a classification or clustering challenge within machine learning; specifically, the unidentified propaganda text should be categorized into distinct clusters according to the features identified by the algorithm. Conversely, we can reframe this issue as a classification task by training the model on a larger dataset comprising both propaganda and non-propaganda files. This challenge can be streamlined to a classification problem focused solely on recognized propaganda, utilizing a limited number of classes—specifically, one for propaganda and another for non-propaganda. In classification tasks, determining the correct class is generally more straightforward, leading to results that are more precise compared to clustering techniques. Below, several machine learning algorithms are outlined.

Logistic Regression: It predicts the class of the numeric variable based on the correlation between the label and the numeric variable (45). A table is supplied as an input containing the features selected by feature engineering values. Generally speaking, the procedure forecasts the likelihood of belonging to a specific class. Here, we have two classes. y is between 0 and 1. To determine the posterior probability, consult equation no. [2].

$$P(x) = \frac{exp\varphi^{T\theta_k}}{1 + \sum_{k=1}^{3} exp^{\varphi^{T\theta_k}} \forall k = 1} \qquad [1]$$

$$P(y = 0 \mid x) = \frac{exp\varphi^{T\theta_k}}{1 + \sum_{k=1}^{3} exp^{\varphi T\theta_k}} \qquad [2]$$

Multinomial Naıve (MNB). It stands for multinomial Nañve Bayes. In the past research (46), it applies the Bayes rule to determine a text's class probability. For both binary and multiple classes categorization problems, it is helpful. The basic idea is that characteristics ought to be evaluated independently. The conditional probability of a feature having a relationship is calculated by the naïve-bayes classifer using the Bayes-theorem. That reason this method is called "naive" is also because qualities in real-world activities are typically slightly connected. In our scenario, let A represent a collection of classes. A = 0 and A = 1 are the two varieties. Furthermore, the number of characteristics is N. The class having greatest P(a | ti), wherein ti is test, is then chosen by MNB in accordance with bayes rule we applied in equation no. [3].

$$P(a \mid t_1\, i) = \frac{((P(a)P(t_i|a))}{P(t_i\,)}, \qquad a \,\epsilon\, A. \qquad [3]$$

P(a) = is the ratio of total no of text records versus of records tagged to be a class a. P (ti\a) = The likelihood of receiving text data in class A that is comparable to ti can be computed as follows:

$$P(\,t_i|\,a) = \frac{(\sum_n\, f_{ni})!\, \Pi_n P(\omega_n|a\}^{f_{n^i}}}{f_{ni^!}} \qquad [4]$$

In our corpus, f in is the total count of times term "n" occur. The chance that word "n" will be used in class an is Ti P (wn|c). Using the training data, Equation [5] calculates the final probability:

$$P(a) = \left(\frac{1 + F_{na}}{N + \sum_{x=1}^{N} F_{xa}}\right), \qquad [5]$$

where the frequency of word is "x" in each piece of training-dataset belonging to the class an is denoted by Fxc. The Laplace estimator, which allocates one to the count of each word, is used to prevent the zero-frequency issue. Simplicity and easy of comprehension are two of this strategy's key characteristics. Additionally, this method is effective for datasets that contain irrelevant attributes, as the likelihood of these attributes influencing the outcome is minimal. Since this method merely computes the probability of features and classes—rather than identifying coefficients as other methods require—it usually uses fewer resources. As mentioned before, its biggest weakness is that every task is dealt with differently, which isn't practical in vast cases.

Support-Vector-Machine (SVM)

One well-liked technique for text classification using supervised-ML is the support-vector-machine (SVM) classifier (47). Finding a hyperplane efficiently parts the various classes is the main objective. The information points that are closest to the hyperplane known as support vectors, should be highlighted; if these points were to be removed, the location of the hyperplane would change. The margin is the space between the support vectors and the hyperplane. For the given text connected to a certain label, it needs a certain amount of features. (yk, xk) n1 is the representation of the training set points, here "n" is the no. of gathered features. The input source is a table containing the feature values chosen throughout the feature engineering process. The goal of Support Vector Machines (SVMs) is to develop a classifier by applying the following formula:

$$y(x) = sign\left[\sum_{(k=1)^n} \alpha_k y_k \psi(x, x_k) + b\right], \quad [6]$$

Wherein, αk represents a +ve real constant, while b denotes a real-constant.

$$\psi(x, x_k) = \{x_k^T, x{:}\, Linear\ SVM, (x_k^T x + 1)d, Polynomial\ SVM\ with\ degreed, \quad [7]$$

where α and k are constants.

Based on the following presumptions, the classifier is built:

$$\omega^T \varphi(x_k) + \geq 1, if\ y_k = +1,$$
$$\omega^T \varphi(x_k) \leq -1, if\ y_k = -1 \quad [8]$$

This-can-be-understood-as

$$y_k \omega^T \varphi(x_k) + b \leq -1, if y_k = -1, k = 1, \dots, n, \quad [9]$$

Here, φ • refers to the nonlinear function that takes the input spaces and maps them to a higher-dimensional space. We use a hyperplane for classification, and it acts as a separator between the two classes. Therefore, it will be needed to propose a new variable xik. The equation for the hyper-plane is-

$$y_k[\omega^T \varphi(x_k) + b] \geq 1 - \xi_k, k = 1, \dots \dots, n \quad [10]$$
$$\xi_k \geq 0, k = 1, \dots \dots, n \quad [11]$$

SVMs are known for achieving top-notch accuracy, particularly when working with "cleaned" datasets. When there are more dimensions than samples, they perform well in high-dimensional situations. However, they typically shine even more with large datasets that have a lot of noise or overlapping classes. Keep in mind, though, that training can take longer while dealt with these huge datasets.

Methodology

The methodology used in this paper is divided into four stages. The process includes gathering data and adding annotations, going through preprocessing, performing feature engineering, and finally, classification. Figure 1 provides a graphic depiction of the suggested process.

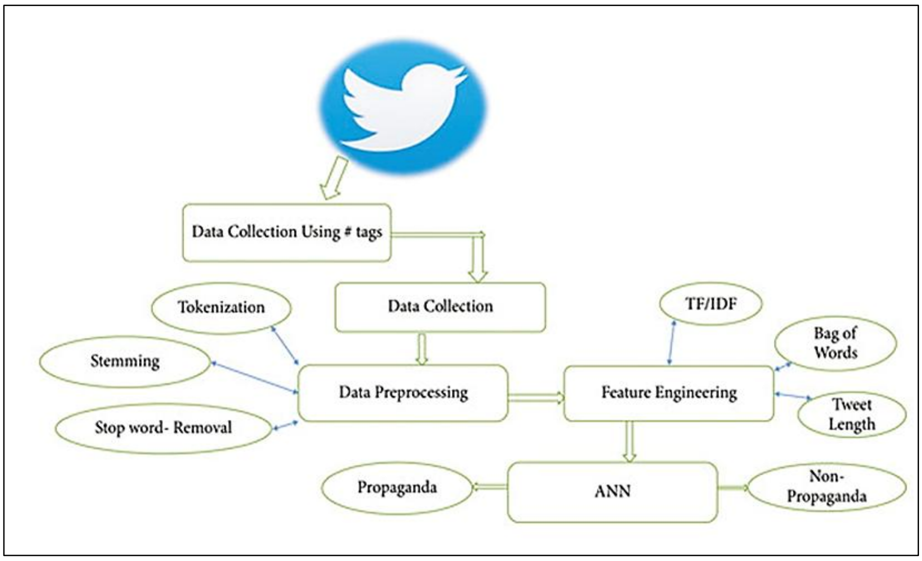


Figure 1: The Proposed Methodology

Data Extraction and Annotation

Data form the backbone of any research. We collected data for our study from social media platforms using a variety of methods, including web crawlers and APIs. In particular, we used Twitter's REST API to extract data from the well-known social networking site. We used a variety of hashtags to track events that were linked to the data we gathered.

Data Extraction: The foundation of any research project is data. The first step is keyword-based extraction because propagandistic content is semantic. Figure 2. shows the how we extracted tweets from Twitter using the Twitter API, which stands for Application Programming Interface (48). Five unclear terms that were commonly used during the Jammu and Kashmir Assembly elections were identified by us. We used the following keywords: #IndianElection,#Election2024,#AssemblyElection2024,#Indianassemblyelection2024,#BJPElection2024,#INCElection2024 for data extraction.

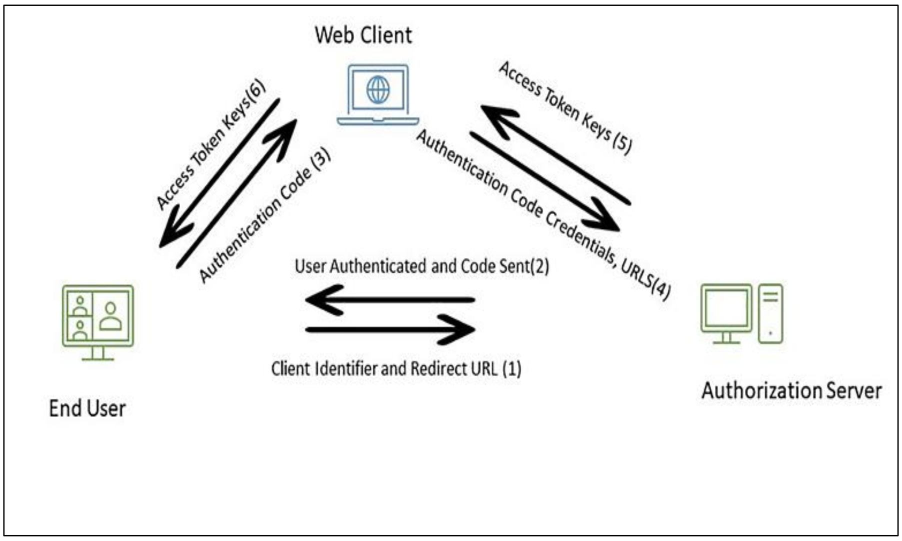


Figure 2: Data Extraction using Twitter API

Annotation: Instead of using crowd-sourcing like Monkey Learn, we decided to manually annotate the propagandistic tweets because of their semantic character. Using the aforementioned propaganda strategies, the tweets were divided into two classes: Glittering Generality, bandwagons, testimonials and name-calling. Three journalists labeled roughly 5K tweets. The overall span of annotated tweet in the propaganda class and non-propaganda is shown in Figure 3.

Data Preprocessing: Preprocessing is crucial in text categorization problems. We must clear the data because there are too many extraneous spaces, connections, etc. Several preparation tasks are used for this task. The following preprocessing methods are employed to improve the text (49).

Tokenization: The tweets are separated into various token so that we quickly edit the tweet by eliminating extraneous word and numbers.

Punctuation-removal: Punctuation like commas, full stops, and semicolons are eliminated at this stage. Humans primarily utilize punctuation as a means of communication among one another.

Number-removal: A range of number without any sentiment are included in the tweet. At this stage, numbers are removed because they are the least desired in text analysis (50).

Stop Words: Since stop words play a very minor part in a classification problem, this task eliminates them completely. Since we have only worked with English-language tweets, we eliminated the stop words using the English stop terms dictionary.

Spell Checking. When writing a post or tweet, humans are prone to committing grammatical or spelling errors. During this stage, a Python package called "pyspellchecker" is used to fix a variety of misspelled words.

Stemming: In order to generate the word's true meaning, every phrase stems back to its root word. The process frequently involves the elimination of derivational affixes and the shortening of word endings, with the expectation that this objective will be successfully accomplished in the majority of instances.

Feature Engineering: We must select features on which to train algorithms for each machine learning method. To choose the most pertinent features, we employed a variety of feature engineering methodologies. To obtain the most pertinent traits, we combined a number of approaches in our work. The following techniques are employed in this work:

The variable D represents the overall count of tweets contained within the dataset (document space). W represents each tweet in the corpus, and t represents the word as a component.

Bag-of-words: The process of extracting knowledge from text and incorporating it into machine learning algorithms is known as text mining. A text representation known as "Bag of Words" explains the existence of words within the textual content of a document. In this work, we employed tri-gram and bi-gram terms to extract additional information from the text.

Length: The total length of the tweet is another factor that increased accuracy. It is too difficult to identify the propaganda in this little remark because a message on Twitter is limited to 280 characters. This is a feature that we employ to enhance our classifier's performance. After combining all of the previously chosen features, we used the Gini coefficient to choose the 40 most pertinent features.

TF/IDF: The freq. of terms/Inverse document-frequency provides quantitative insights that indicate the significance of words within tweets or across an entire corpus. The associated condition is utilized to ascertain this significance.

$$TFIDF(t,w,D) = TF(t,w) * IDF(t,D), \quad [12]\ IDF(t,D) = log \frac{|D|}{1+|(w \in D: t \in w)|},$$

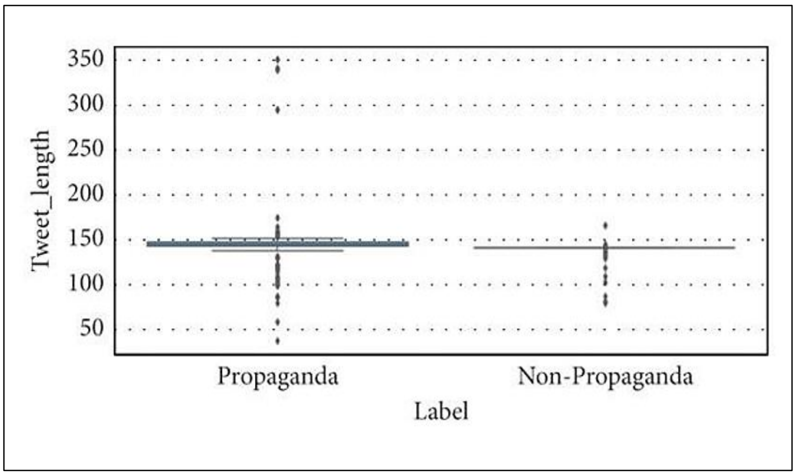


Figure 3: The Class on Propaganda and Non-Propaganda, along their Respective Durations

Classification: The purpose of the categorization procedure is to divide the given material into two different categories. Propaganda (a propagandistic tweet) and non-propaganda (a regular tweet) are the two categories. To mastermind the material into various classes, an artificial neural network technique is employed.

One of the classification techniques, the multilayer perceptron classifier (MLPC), is the main one that is dependent on the framework. Backpropagation becomes the method of learning in MLPC (51). The number of classes in relation to the yield layer forms the number of hubs. MLPC is made up of the data layer, which represents the hidden layers (the center layers), yield layers, and other hubs. With the data layer, cover layer, and yield layer in the framework, we can generate a link between every layer and the connecting layer.

The way we perceive information is primarily handled by the neurons in the data or input layer. These neurons work similarly to data pointers in that they produce comparable output. Information is represented by hubs within this data layer. Each hub commits to providing output by combining a blend of activation functions with weights (w) and biases (b). The multi-layer perceptron classifier (MLPC) is structured with K+1 layers in total.

Require: filtered tweets $\left(T_{input}\right)$

Ensure: propaganda tweet (T_{Pr}) and non-propaganda tweet $\left(T_{Np}\right)$

Filtered tweets→ T_{input}

Propagnanda tweets→ T_{pr}

Nonpropagnanda tweets→ T_{Np}

Tokenization→ T

Stop word removal→ SW

Semming → S

Total Number of Tweets→ n

Term frequency/ inverse document frequency ⟶ TF/IDF.

Bag of Words →B

Initiate

for *I* from 1 to ***n*** **do**

$$C[I] = T_{input}[I] + Label \ //manual\ annotation\ \ T[I] = Tweetlength(C[I])$$

$$End - for$$

for I from 1 to n **do**

Pro$[i] = T(C[I])$

Pro$[I] = SW($Pro$[I])$

Pro$[I] = S($Pro$[I])$

end for

for I from 1 to **n do**

$F[I] = B($TF/IDF(Pr$[I]))$

$$F[I] = F[I] + T[I]$$

$$End\ for$$

ANN($F[I]$) (-Classifier)

$$Exit$$

Algorithm1*:* Hybrid Feature Engineering Artificial Neural Network for Twitter Classification(HFENNBPI).

The information and output layers are separated by hidden or middle layers. The number of hidden layers often varies between one and a sizable number. The capabilities of the focused computing layer play a key role in determining how much each node contributes to the final output. In the intermediate layers, the nodes employ a sigmoid function for strategic operations. The last layer of a neural network, known as the output layer, is tasked with converting the results back to their original form. Additionally, the structure of a neural network organizes the earlier layers based on how effectively they learned from the input and improved their performance. The output layer nodes apply the SoftMax function. The number of classes is equal to the node count N in the output layer (see Algorithm 1.)

Table 2: Classification Report of Algorithms

Algorithms	Recall value(%)	F1-score value(%)	Precision value(%)	Accuracy value(%)
LR-	67	59	64	67.2
MNB	67	58	67	68.2
SVM	75	72	76	74.8
DT	69	62	67	68.65
ANNBPI	76	75	78	76.15

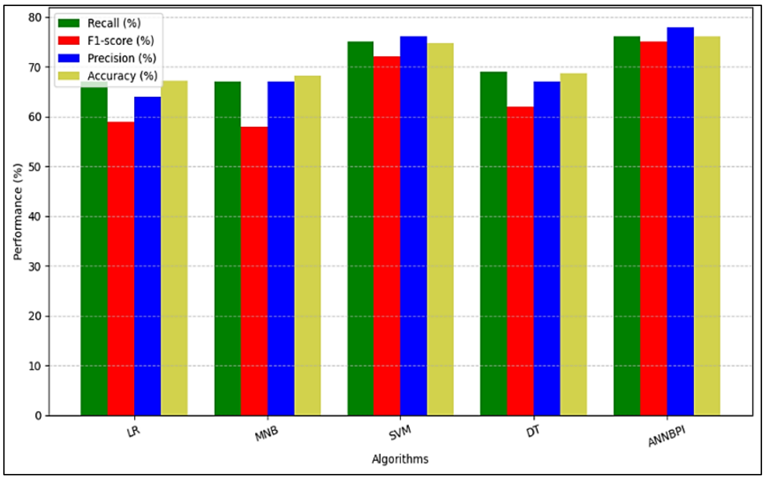
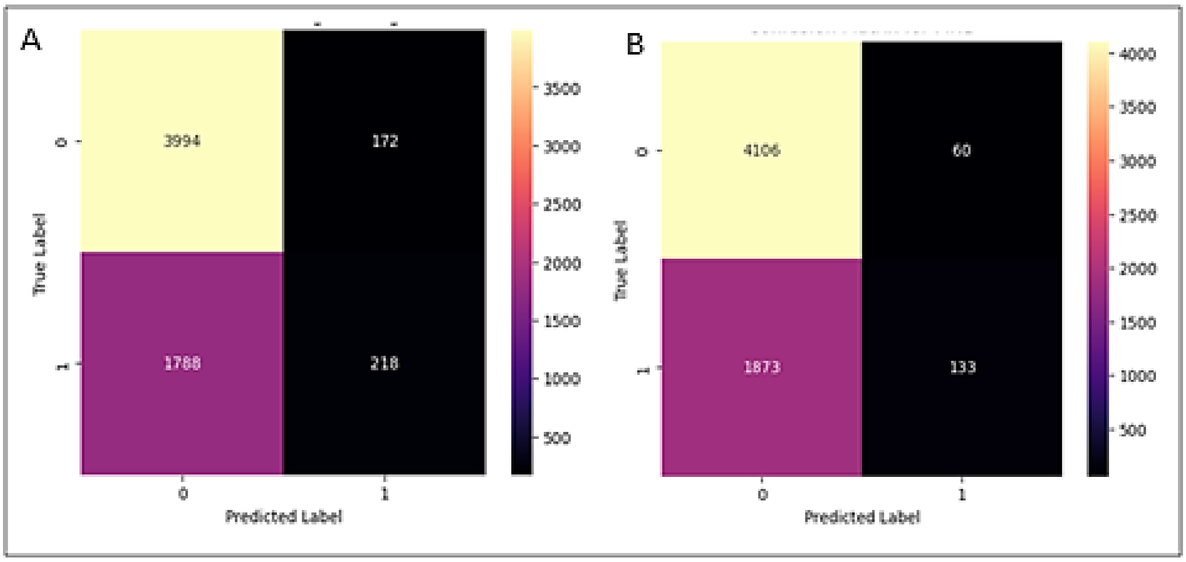


Figure 4: Classification Report of Various Algorithm

Results and Discussion

The workstation used for the experiment has a GPU and 16 GB of RAM configured. The dataset is divided into many ratios. Initially, the data was divided 50:50, meaning that half was utilized for testing and the other half for training. It was discovered that the accuracy was lower than when the data were divided into 60:40. The dataset was determined to be the result of classification. The highest accuracy is achieved when the data is fragmented into 80:20 ratio, which means 80% of the data is set aside for training while the remaining 20% is used for testing. To evaluate the models and measure precision, recall, F-measure, and accuracy, we applied Equations [13], [14], [15], and [16]:



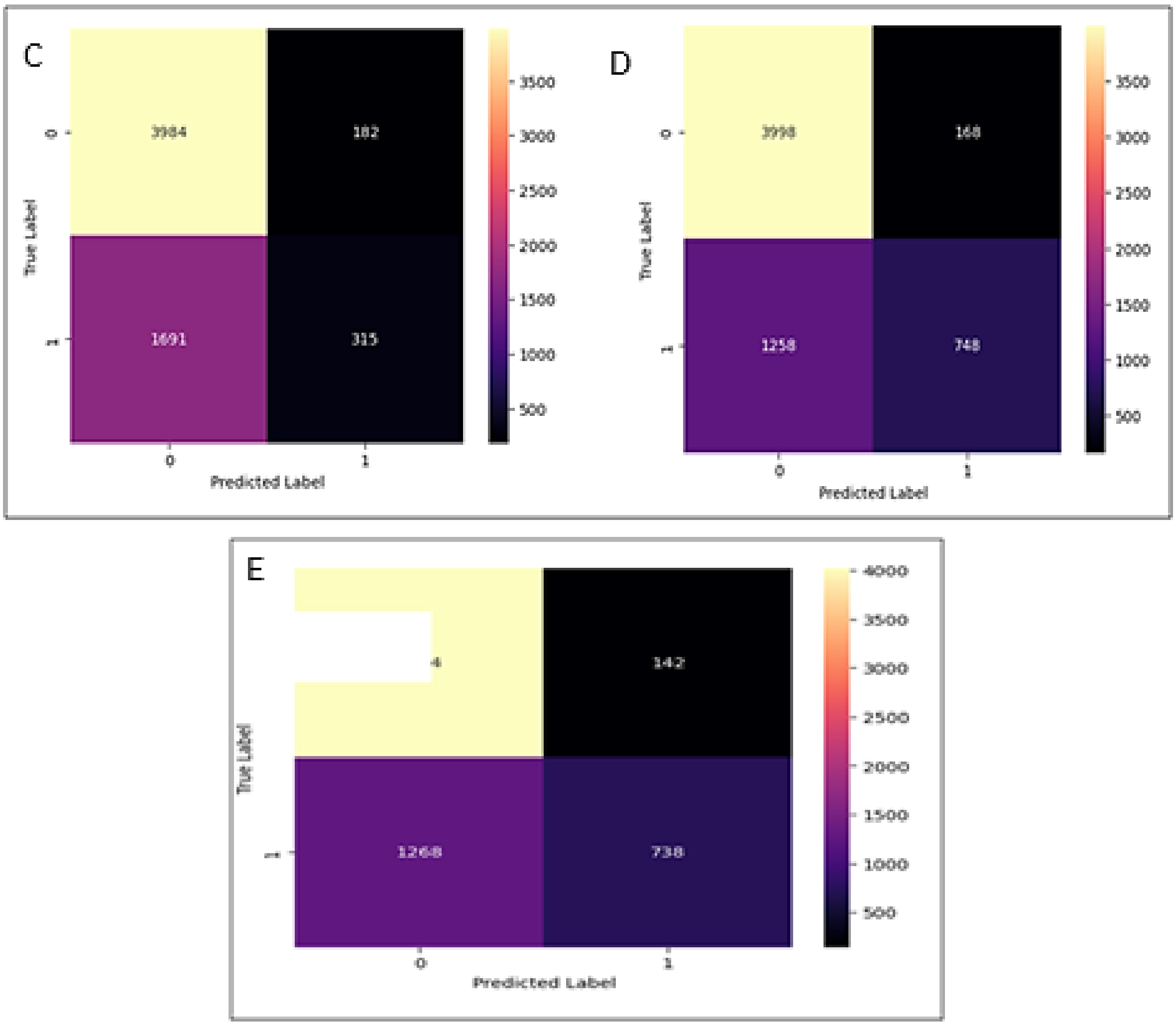


Figure 5: (A) Confusion Matrix for Logistic Regression, (B) Confusion Matrix for MNB, (C) Confusion Matrix for SVM, (D) Confusion Matrix of DT, (E) Confusion Matrix of ANN

$$P = \frac{Tp}{(Tp + Fp)}, ---[13]$$

Where Tp is the true positive, and Fp is the false positive.

$$P = \frac{Tp}{(Tp + Fp)}, ---[14]$$

Where Tp is the true positive, and Fp is the false positive.

$$R = \frac{Tp}{(Tp + Fn)}, ---[15]$$

Where Tp is the true positive, and Fp is the false negative.

$$F = \frac{(2 * P * R}{(P + R)}. ---[16]$$

With an accuracy of 76.15% throughout model testing and training, the ANN outperformed competing techniques as shown in Figure 4. The classification report of various machine learning algorithms were showed in Table 2. The purpose of the factual examination is to gather as much information as possible about the facts that will be used for the classification task. For the previous work, we utilized the Spyder IDE along with the Python programming language. The data is presented in a table format featuring 40 selected attributes. To accomplish the task at hand, several libraries were employed. Some of the libraries used include NLTK, scikit-learn, and pandas, among others. Table 3 presents a comparison of various approaches to binary categorization. While Figure 5-E displays the confusion matrix of EANNBPI, Figure 5-A, 5-B, 5-C, 5-D shows the confusion matrix associated with traditional machine learning methods.

Table 3: Classification Report of Algo's. With Existing Work

Algorithm	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)
LR	64	67	59	67.2
MNB	67	67	58	68.2
SVM	76	75	72	74.8
DT	67	69	62	68.65
ANNBPI	78	76	75	76.15
Morio{29}	56.45	47.37	51.55	NA
Jurkiewicz [30]	59.95	41.65	49.15	NA
Chernyavskiy [31]	53.23	45.56	49.10	NA

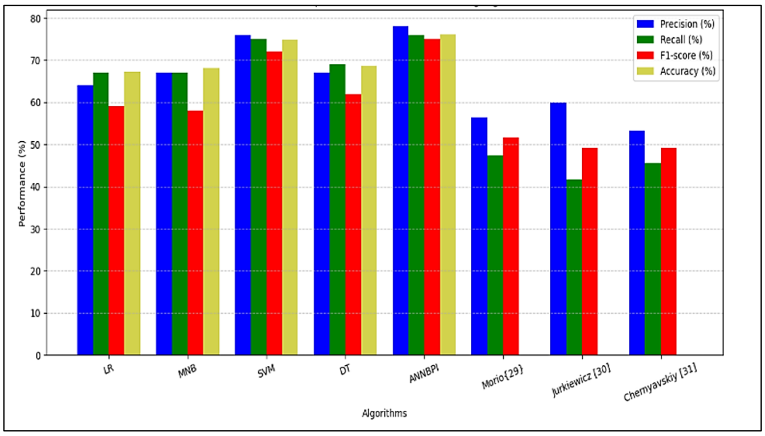


Figure 6: Comparison of Proposed and Existing Work

Comparative Study

The results obtained with the proposed method were verified against the existing work as shown in Figure 6. The proposed methodology was applied to experiment with a similar dataset that was used by other researchers. After fine-tuning the earlier methods like Logistic-regression, DT, Multinomial-Naïve-Baies, SVM and Artificial Neural Network, it was found that these algorithms were more efficient than those that were studied earlier. The evaluation metrics showed that EANNBPI excelled on the dataset, with impressive results: 78% precision, 76% recall, 75% F1-score, and 76.15% accuracy. The comparison between the suggested work and current methods in this field is displayed in Table 3.

Conclusion

On online social networks, propaganda is a deadly weapon. Data was collected from the social media platform -Twitter, utilizing its Application Program Interface. The information was carefully labeled using a variety of propaganda identification methods. This process combines different feature engineering techniques, including Tweet length, TF/IDF, and Bag of Words. By applying these methods, we narrow down to the top 40 features. The labeled dataset is split into a 80:20 ratio for training and testing machine learning classifiers. The results showed that artificial neural networks (ANN) excelled compared to other algorithms. Specifically, ANN achieved 78% precision, 76% recall, 75% F-measure, and an accuracy of 76.15%. These algorithms might get additional data down the line, and Future developments in deep learning are also planned.

Abbreviations

ANN: Artificial Neural Network, ANNBPI: Artificial Neural Network Based Propaganda Identification, API: Application Programming Interface, BERT: Bidirectional Encoder Representations from Transformers, BJP: Bhartiya Janta Party, CNN: Convolutional Neural Network, CRF: Conditional Random Fields, DT: Decision Tree, IDF: Inverse Document Frequency, INC: Indian National Congress, IoT- Internet of Things, LR: Logistic Regression, LSTM: Long Short Term Memory, MLPC: Multi Layer Percepteron, MNB: Multinom-ial Naïve Bayes, NLP: Natural Language Processing, NNPIGAE24: Neural Network based Propaganda Identification on Indian General

Assembly Election 2024, Pos: Part of Speech, SVM: Support Vector Machine, TF: Term Frequency.

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Pankaj Verma: Performed experimental work, Sunita Mahajan: Worked on grammatical, formatting part.

Conflict of Interest

The authors declare no conflicts of interest related to this work.

Ethics Approval

Not Applicable.

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