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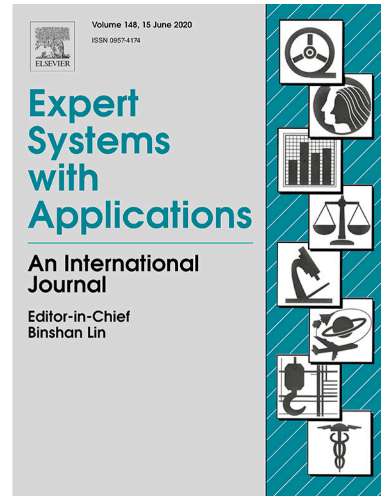

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Linguistic Feature Based Learning Model for Fake News Detection and Classification

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Abstract: Social media is used as a dominant source of news distribution among users. The world's preeminent decisions such as politics are acclaimed by social media to influence users for enclosing users' decisions in their favor. However, the adoption of social media is much needed for awareness but the authenticity of content is an unknown factor in the current scenario. Therefore, this research work finds it imperative to propose a solution to fake news detection and classification. In the case of fake news, content is the prime entity that captures the human mind toward trust for specific news. Therefore, a linguistic model is proposed to find out the properties of content that will generate language-driven features. This linguistic model extracts syntactic, grammatical, sentimental, and readability features of particular news. Language driven model requires an approach to handle time-consuming and handcrafted features problems in order to deal with the curse of dimensionality problem. Therefore, the neural-based sequential learning model is used to achieve superior results for fake news detection. The results are drawn to validate the importance of the linguistic model extracted features and finally combined linguistic feature-driven model is able to achieve the average accuracy of 86% for fake news detection and classification. The sequential neural model results are compared with machine learning based models and LSTM based word embedding based fake news detection model as well. Comparative results show that features based sequential model is able to achieve comparable evaluation performance in discernable less time.

Keywords: Fake news, Syntactic, Readability, Neural Network, Deep Learning, Machine Learning; LSTM.

1. INTRODUCTION

In today's scenario, the fast and extensive growth of social media has witnessed and a spike is created. News from social media is prevalent these days and people do rely on social media for the latest updates, trending stories, and mutual information. This demonstrates the lack of professional competence with traditional news platforms nowadays. Although distinguish the fake news and anomalous information from the online truthful signals is yet a challenging issue. It became an obstacle for the advanced computing technologies to deal with the variety of information and different meaning of the context. On the other end, much of the social media platforms are flooded with fake news that affects the news ecosystem, people's opinions, and stock markets. False/Fake news is basically rumoring, canard (hoaxes), dismembered news that hides or unravel the truthfulness of the news. Because of little knowledge of actual data young minds get attracted to satire/comedy sites and hence, get influenced by fake sources. Fake news put down your credibility. Throwing a shed light towards fake news is much more important for the sake of a peaceful society. Digital natives and Cybernauts are used to see viral posts, news, content, and images that can affect or change their mindset as well as community opinion. Their trust towards fake news became a disturbing manifestation to weaken the country's democratic process. Indeed, fake news can't help to make the world a better place but real news can benefit for growth. The prime purpose of click farm groups is to bump up the news in the popularity list. This has become a practice to use satire, shady means in content to commit fake/ fraudulent news.

In the literature, while there exists some related work to handle these categories of problems such as for identification of fake news (Girgis et al., 2018; Yang et al. 2018; Meel et al., 2019), satire news (Liu et al., 2019) detection, rumor detection (Alkhodair et al., 2020; Li et al., 2019), opinion leader (Jain et al., 2020), etc. Since many previous years, deep learning has been used to solve fake news detection problems efficiently and effectively. Fake news data contains high dimensionality and massive data size that is the reason for effective outcomes by deep learning models. Numerous earlier studies stated that deep learning models (Girgis et al., 2018; Wang 2017; Yang et al., 2018) are immensely successful but can be applied if data does not deal with heterogeneous nature and unknown factual facts. Existing work resolved this problem using statistical measure (Pérez-Rosas et al., 2017), user behavior analysis (Zhang & Ghorbani 2020; Bauskar, et al., 2019), social networking properties (Zhang et al., 2020 April; Shu et al., 2017 b) syntactic and semantic features (Bauskar, et al., 2019; Lillie et al., 2019). The most prominent are syntactic and semantic features of fake news content which reported promising results as news content is an important source to work on this problem. Thus, we characterized fake news evidence from linguistics features of used content. It is worth noting that in our work diverse content evidences are extracted in the form of enhanced language features to get a better result as compared to existing literature.

The various challenges faced to work in this direction are as follows:

- **Data challenge** (Zhou et al., 2019)**:** Limited high-quality data accessibility, high dimensionality data, heterogeneous nature, Factual Data unidentifiable, Massive data size.
- **Extensive and significant feature extraction:** Careful observation on news content features is needed this is still underexplored. Researchers either worked on syntactic or on semantic features of news content without even exploring the importance of features. Along this line, we have explored features to determine whether new features should be used or not.
- **Adequate Learning model:** Indeed, the adequacy of the learning model depends on the targeted dataset. For example, learning of data which is collected through real-time streaming for specific scenario news may require a memory-based learning model. On the other end, varying and diversified content can give better results for the semantic feature-based neural model. Henceforth, model competency is dependent on targeted dataset content and its features.

While the importance of detecting fake news has been widely recognized using deep learning models as well then also many ambits are untouched. Even, research work is validated on

various research directions of fake news such as creator/spreader identification (Conroy, Rubin, & Chen, 2015), target victim's recognition, fake/fraudulent news content, and social context (Kogan et. al.,2019). But the prime source is news content that influences the spread of fake information on social networks and plays a key role. There is limited knowledge to handle this issue with respect to linguistic feature-based driven learning fake news detection. To this end, this research paper presents a holistic view of linguistic feature-based selection to achieve competent fake news detection outcomes using a neural learning approach.
The goal is to enhance the fake news detection accuracy and to study the influential features in linguistic context. The research contribution (RC) of this work can be outlined as follows:

- **RC1.** To explore the importance of deep neural network model over machine learning models.
- **RC2.** To propose a linguistic feature-based driven deep learning model for effective fake news detection.
- **RC3.** To measure the impact of extracted linguistic features based on the comparative outcome with the deep learning model.

The overall skeleton of the paper is as follows: The first section (this section) gives an overview of significance, impact, and need of considered research problem. Section 2 provides the details of the studied literature and its integration with the targeted research problem. Section 3 presents the features set generation and some preliminary machine learning model experiments to showcase the importance of Neural network over machine learning based models for the specific problem. Further, Section 4 discusses the sequential neural network model and corresponding algorithms that are developed to train the system for fake news detection and classification. Section 5 reports the experimental setup and results of the applied neural network model which contains descriptive details about the dataset and its associated experimental outcome. Finally, section 6 concludes the paper and discusses future research directions.

2. Related Work

Fake news detection has become an emerging topic in the research field for highlighting the pace of the spread of false information/low-quality piece of information that is created intentionally. To proceed with the implementation work in this direction, we have read several high quality literatures that circumscribed for Fake news detection techniques. Precisely, detection of fake news relies on a number of features that exist in news content in form of text/images and a part of research work has been done on social network data (Alkhodair et al., 2020; Bauskar, et al., 2019) as well. Fake News detection research overviews the significance, challenges, detection approaches, important feature identification, and datasets (Zhang & Ghorbani 2020; Bondielli et al., 2019). This section discusses some of the recent and important contributions in this direction. The most recent work which we found in this direction is done by Jain et. al. in March 2020, their research work direction is towards opinion leader detection. They have used online social network data for empirical studies and used whale optimized algorithm for opinion leader detection (Jain et. al., 2020).
In 2019, Gravanis et al. performed a benchmark study on fake news and proposed a machine learning model based fake news detection approach (Gravanis et al., 2019). They worked on

an existing and extensive data source and introduced the “UnBiased”(UnB) Dataset also. Their experimental study concludes that enhanced linguistic feature set with advanced machine learning models are capable to classify fake news with effective accuracy. A number of research works have been done on similar ground and laid the foundation for many important and relevant fake news detection research challenges. Investigating the fake news on the basis of text has been explored by many researchers (Shu et al., 2017 a; Pérez-Rosas et al.2017; Zhou et al. 2019). Zhou et. al. proposed a theory-driven model for early detection of fake news using lexicon, syntax, and semantic level features. Various feature-driven machine learning algorithms based results are presented in this work and a number of machine learning techniques have been used. Out of all used techniques SVM, Random Forest, and XG Boost gave the best result. But, the best performance results of machine learning for readability features and syntactical features are 60% and 75% respectively in their work. The number of combinations of feature groups is validated by the author. Various future scopes are enlisted in their work out of which usage of deep learning techniques was one which we have experimented in the present work. Another one is that Zhou et.al. used a bag of words for fake news detection which is not required in case of a deep learning system. Henceforth, we noticed that usually machine learning based algorithms have been used on textual features such as syntax level (Zhou et al. 2019), semantic level based on POS tags (Zhou et al. 2019;), a bag of words (Zhou et al., 2019; Mohseni, et al., 2019), TF-IDF (Pérez-Rosas et al., 2017), and word2vec (Shu et al., 2017 c). Towards deep learning, the work mentioned in (Bauskar, et al., 2019) explored the content-based and social-based features and implement an NLP based hybrid model to detect fake news.
There exist a number of research tasks related to fake news such as rumor detection (Alkhodair et al., 2020), spam detection (Shen et al., 2017), satire news detection (Liu et al., 2019).
In 2020, a deep learning model has been implemented to automatically detect breaking news rumor (Alkhodair et al., 2020). Alkhodair and his team defined the term rumor to a post if its truthfulness has not been verified but this rumor could be turned to true/ false news at a later period (Alkhodair et al., 2020). Satiric news detection using the French satiric dataset was explored to detect spammers (Liu et al., 2019). Another unique challenge of fake news detection that to be handled by a neural network, author (Wang et al., 2018) proposed a framework termed as EANN-Event Adversarial Neural Network which can derive event-invariant features using multi-model extractor i.e used text feature and visual features to identify fake news in newly arrived events. To classify fake news based on Image is also validated explored by researchers primarily using a Convolutional neural network and its variant/ pre-trained models (Wang 2017; Yang et al., 2018).
Generally, fake news detection research work is very extensive. In some work, two or more category of data has been used for fake news detection i.e. both user-generated content and images, User-generated content and social network structure, etc. Shen et. al. discussed an impressive work in which they have provided a framework of multiple views to identify spammers (Shen, Ma, et al., 2017). One of the significant works regarding the propagation of messages in a social network was put forward (Wu & Liu 2018) in which a novel approach for classifying social media messages with diffusion network information was proposed. Further, the network-based analysis using news content/ article, creators and spreaders were

explored (Zhang et al., 2018). (Shu, Wang, Tang, Zafarani, & Liu 2017) provide a summarization of social network-based analysis.

An extension to user content based fake news detection work focuses on computing readability in fake news detection (Zhou et al., 2019; Pérez-Rosas et al., 2017). Fake news makes users targeted who get attracted by headings and does not make an effort to read the content and is aimed at claiming. Here, researchers used some quality features and calculate readability metrics (Horne & Adali (2017; Danielson, K. E. 1987; Feng et al., 2010; Flesch, R. 1951). But commonly used computing technique for readability metrics based detection is machine learning based models. The role of neural network needs genuine attention to validate the maturity level of content writing exploration for the targeted problem related to readability examination for fabricated content (Klare, G. R. 1976). Readability is considered as a highlighting process that is addressed by various authors and announced that the writer should pay attention to the reader as well as the writing phase likewise the shorter the sentences are the easier to read and understand (Chen et al., 2020). Therefore, in this work to deal with unfair, misleading news article efforts have been made with the help of some rarely used linguistic and readability metrics.

3. Feature Set Generation and Detailed Preliminary Experiments

Literature study and its significant integrations are foremost evidence and motivation behind the selection of the feature set. Syntax based features considered as the most commonly used feature set. Out of all used syntax-based features, word density has been used as a unique feature in our work. Undoubtedly, fake news comes in limelight to attract the audience and spread positivity/ negativity for a specific category of events. Therefore, another feature set in feature collection for fake news is sentiment-based features. POS tags have been extracted out of news which gives grammatical properties of news. Fake news content generators use the number of adjectives/ adverbs associated with Noun, hence it is used as a feature set. The last one which is uniquely used in our work is readability features. This feature is used for learning to validate readability based fake news detection performance. Readability is a rarely used feature and usually base machine learning models have been used by researchers with this feature. The researcher makes use of properties of the texts as readability metrics to analyze the difference between content generated by professional journals and not recognized webs (Reyes & Palafox 2019). Further, features' strength corresponding to all attributes is also computed using correlation which is detailed in the subsequent section.

The base definition in term of parameters is as follow: Given a set of *n* news articles which contain fake/real news content. Where $\mathcal{A}=A_i^n$ Fake news detection problem is to validate whether the news article in $\mathcal{A}$ are fake or not. According to the targeted dataset, this is a binary classification problem, where label set $\mathcal{Y}=[1,0]$, here 1 denotes real news and 0 represents fake news $A_i \in \mathcal{A}$. Fake news classification has been done based on four varying categories of features- Syntax-based features X_i^{sy}, Sentiment features X_i^{sen}, Grammatical evidence features X_i^{gr}, Readability features X_i^{R} which are introduced in detail in Section 3.1. These features are the prime parameters to train the sequential neural network model. Details about all parameters used in the study are enlisted in Table 6 which is shown at the end of the manuscript in Appendix A.

3.1 Linguistic feature-based evidences extraction

Due to the diverseness of content, identification of supreme features becomes extremely relevant in order to detect online fake information. Linguistic Analysis is well good stead to extract the structure from the text. This section studies the process to extract linguistic evidence for fake news detection.

3.1.1 Syntax-based evidences:

According to literature, syntax-based features are composed of several linguistic dimensions which satisfy a specific pattern to classify fake news. This phase consists of the extraction of fundamental evidence - count statistical evidence, sentence sentiment evidence, and grammatical property evidence. While the formation of fake news, the creator intentionally embeds title word, uppercase words, and even takes care of content length and their corresponding word density that is represented in Table 1. Digital natives get attracted and influenced by news due to these fundamental features which makes count statistical evidence of fake news content is an important and noteworthy feature. In the following, we formally define the syntax-based X_i^{sy} of fake news.

Table 1: Syntax-based features

Syntax-based features	**Description**
char count	Total no. of characters with and without spaces
word count	Total no. of words in a given sentence
title word count	Count the number of words in a given title
Stop word count	Count the total no. of stop words in a given sentence
upper case word count	Count the number of uppercase words in a given sentence
word density	Number of occurrences of the chosen keyword over the total no. of words in a given text.

Definitions 1: Syntax-based evidences

For a given news A ,X^{sy} consists of character count (x_{cc}), word count ($x_{wc,}$), word density (x_{wd}), title word count ($x_{twc,}$), and title uppercase (x_{up}), stop word count (x_{stp}) .

$X^{sy} = \{x_{cc}, x_{wc}, x_{wd}, x_{twc}, x_{up}, x_{stp}\}$

3.1.2 Sentiment-based evidences:

Making a hypothesis, the sentiment is put forth on writing a news article that relies on decision-making factors in the process of classifying the news into fake or not fake. The elite sentiment-based features that linked to the judgment or intensity of certain emotions are defined below in Table 2.

Table 2: Sentiment-based features

Sentiment-based features	**Description**
Polarity	It refers to positive and negative statements. It lies in the range of [-1,1]
Subjectivity	Expressing an opinion, views, or a person's feelings. It lies in the range of [0,1]

Definitions 2: Sentiment-based evidences

The following sentiment-based features of news A are- polarity (x_{pol}), and subjectivity (x_{sub}). $X^{sen} = \{x_{pol}, x_{sub}\}$. Subjectivity is measures of sentiment being objective to subjective, Objective expressions are facts whereas subjective expressions are opinions, beliefs, or a person's feelings towards a specific topic. For example, of subjectivity and polarity for sentence, "Donald Trump is a great politician" is 0.9, 0.81 respectively.

3.1.3 Grammatical evidences:

To inspect real news and fake news, grammatical features is an important factor that is extracted through parts of speech (POS) tag evidence features. Out of all POS features, for targeted problem noun, verb, adjective, and pronoun are viable features to define its authenticity. These features are designed to apprehend the deceiver cues in writing style to differentiate fake news. Details are shown in Table 3.

Table 3: Grammatical features

Grammatical-based features	Example	Representation
Noun	Trump says nobody really knows if climate change is real.	Trump
verb		Is
adjective		Real
pronoun		if, nobody
Adverb		Really

Definitions 3: Grammatical evidences

For a given news A, defining the grammatical features references as: noun count (x_{nou}), verb count (x_{ver}), adjective count (x_{adj}), adverb count (x_{adv}) and pronoun count (x_{pro}).

$X^{gr} = \{x_{nou}, x_{ver}, x_{adj}, x_{adv}, x_{pro}\}$

3.1.4 Readability-based evidences

Readability is a measure with which a reader can apprehend the written text. In simple language, the readability of a text relies on its content material i.e. the complexity of its vocabulary and syntax of its content. The readability of the abstract is calculated using various readability indices (word and sentence score) through which one can identify the grade of any text. It helps us to determine if its target readers will be able to understand it completely. Details are given in Table 4. The parameters needed while computing readability measures score are described in Table 6 in Appendix- A.

Table 4: Readability Features

Readability-based Features	Description	Formulae
Flesch Reading Ease	Evaluate the difficulty pattern of the written text	$206.835 - (1.015 * ASL) - (84.6 * ASW)$
Automated Readability Index	Determined the level of understandability of English text	$4.71\left(\frac{x_{cc}}{x_{wc}}\right) + 0.5\left(\frac{x_{wc}}{x_{st}}\right)$
Gunning Fog index	Observing the writing problem	$0.4(ASL + PHW)$
Coleman Liau	Focuses on characters in the text	$(0.0588 * L) - (0.296 * S) - 15.8)$
Flesch-Kincaid score	Analyze the level of the written text	$3 + square\ root\ of\ Polysyllable\ Count$

The SMOG Index	Understand the formation of writing content	$(0.39 * ASL) + (11.8 * ASW) - 15.59$
Linsear write formula	Developed for the United States Air Force to calculate the readability of their technical manuals	$\dfrac{\left[\left(100 - \dfrac{100 * n_{wsy<3}}{n_w}\right) + \left(3 * \dfrac{100 * n_{wsy \le 3}}{n_w}\right)\right]}{\left(100 * \dfrac{n_{st}}{n_w}\right)}$

Definitions 4: Readability evidences

Defining the Readability features: Flesch Reading Ease(x_{re}), Automated Readability Index(x_{ari}), Gunning Fog (x_{gf}), Coleman Liau (x_{cl}), Flesch-Kincaid Index (x_{fki}), The SMOG Index (x_{smg}), Linsear Write formula. (x_{Lwf}) in a news A shown in Table 4.

$X^R = \{x_{re}, x_{ari}, x_{gf}, x_{cl}, x_{fki}, x_{smg}, x_{Lwf}\}$

3.2 Correlation among features

Correlation is designed to show the strength among the features i.e. how strongly one feature depends on another by defining the weightage. It computes the dependency among variables features and calculated correlation among considered features using coefficient equation (1). All used parameters are described in Table 6 in Appendix- A

$$\mathrm{r} = \frac{\sum_{i=0}^{n}(x_{i\_} - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=0}^{n}(x_i - \bar{x})^2 (y_i - \bar{y})^2}} \qquad (1)$$

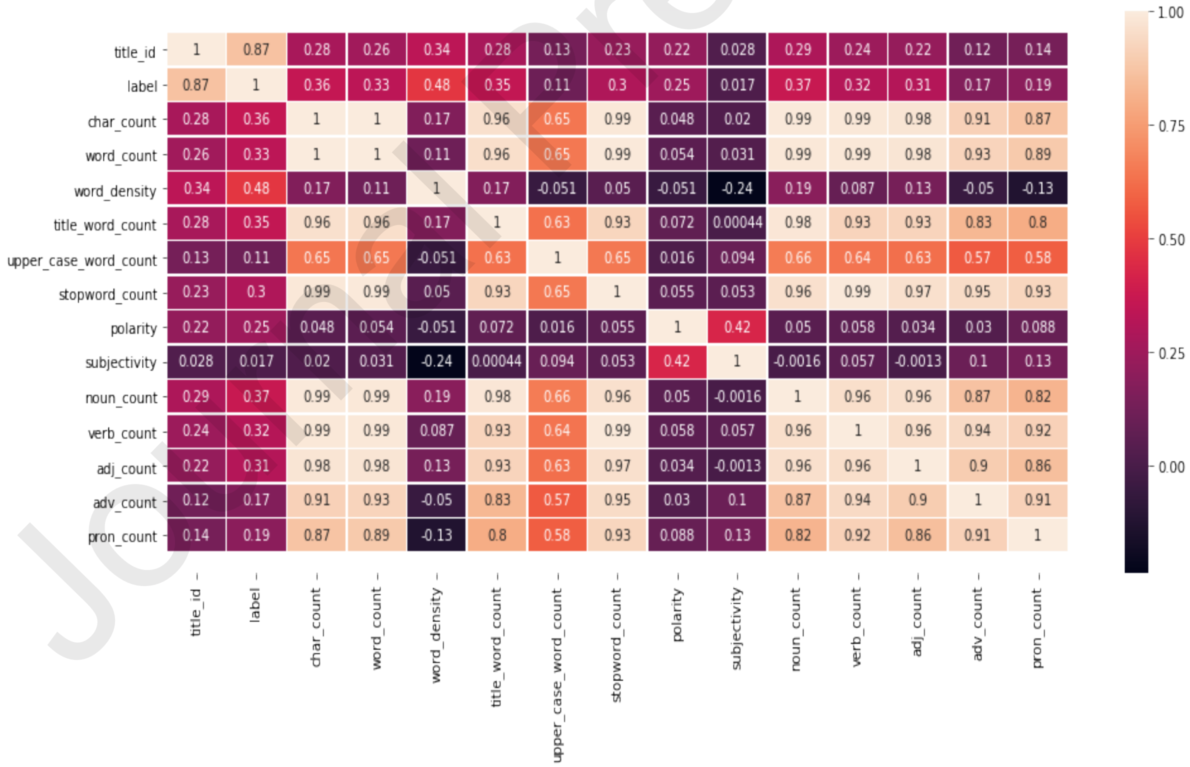
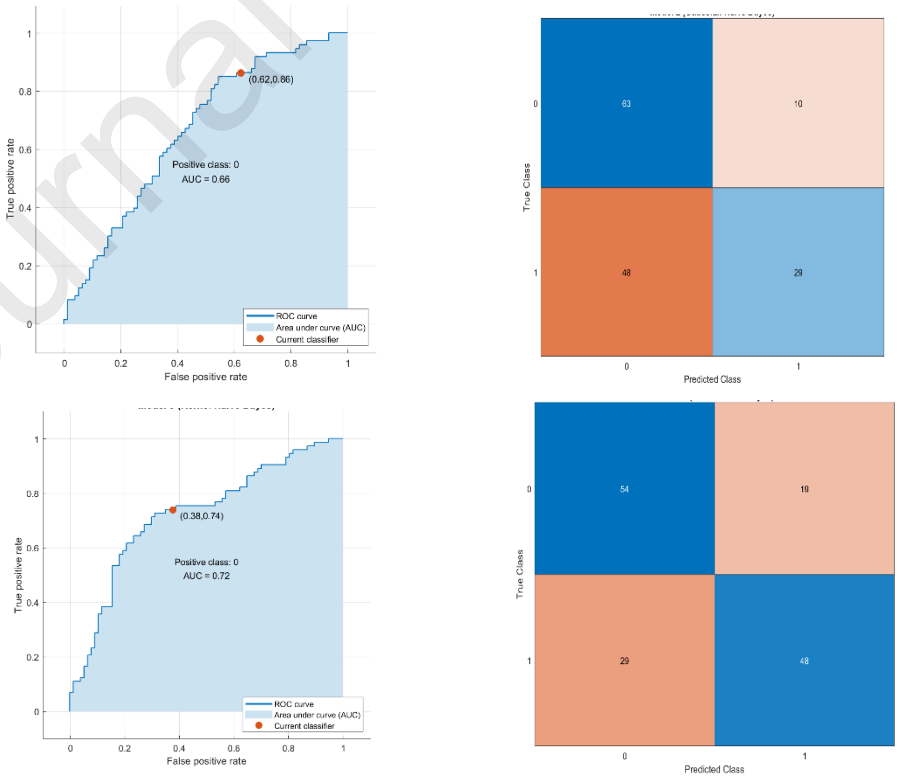


Figure 1: Correlation matrix of Linguistic-based features.

where $\bar{x}, \bar{y}$ are the mean and x, y are the feature vectors. In our scenario, we have computed correlation among all the features lying under syntax, sentiment, and grammatical features. The correlation coefficient ranges from -1 to +1. The correlation coefficient towards -1 depicts the negative correlation between the features, 0 means neutrals, and +1 defines the positively correlated features. Figure 1 shows the correlation matrix of our considered features. It is clearly shown that the 'class label' i.e. Fake/ Not-Fake news is having a 0.48 correlation coefficient with the 'word density' feature. On the other end, 'char count' is highly correlated with 'stop word count', 'noun count', and 'verb count' features. Similarly, for all other variables, the correlation value is illustrating in Figure 1.

3.3 Preliminary Machine learning Based Experiments

A number of machine learning based fake news detection research work exist in the literature (Bondielli et. al., 2019). Usually, in these research work Naïve Bayes, SVM, Decision Tree, and KNN as base learners and further AdaBoost and Bagging are used as ensemble algorithm (Gravanis et. al., 2019; Sharma et. al., 2019). Regardless of these works, initial efforts have been made in order to exploit knowledge of the machine learning algorithm to achieve better performance using all the extracted linguistic features. In all over work which is presented in the manuscript 'Horne2017_FakeNewsData' dataset has been used which is detailed in section 5.1, same dataset has been used for machine learning based preliminary experiments as well. Initially, fake news detection experiments using machine learning are performed using four base learners. Out of which, the performance of two Naïve Bayes models- Gaussian Naïve Bayes, Kernal Naïve and two SVM Models - Linear SVM, Gaussian SVM are validated. The receiver operating characteristic curve (ROC) of all the four applied models is shown in Figure 2 which shows achieved accuracy as 61.3%, 68.0%, 64.7%, and 70.7% for Gaussian Naïve Bayes, Kernal Naïve, Linear SVM, and Gaussian SVM respectively. Out of all applied base learners, Gaussian SVM base learners is able to achieve maximum accuracy of 70.7%.



(a) Gaussian Naïve Bayes (Accuracy- 61.3%)

(b) Kernel Naïve Bayes (Accuracy 68.0%)

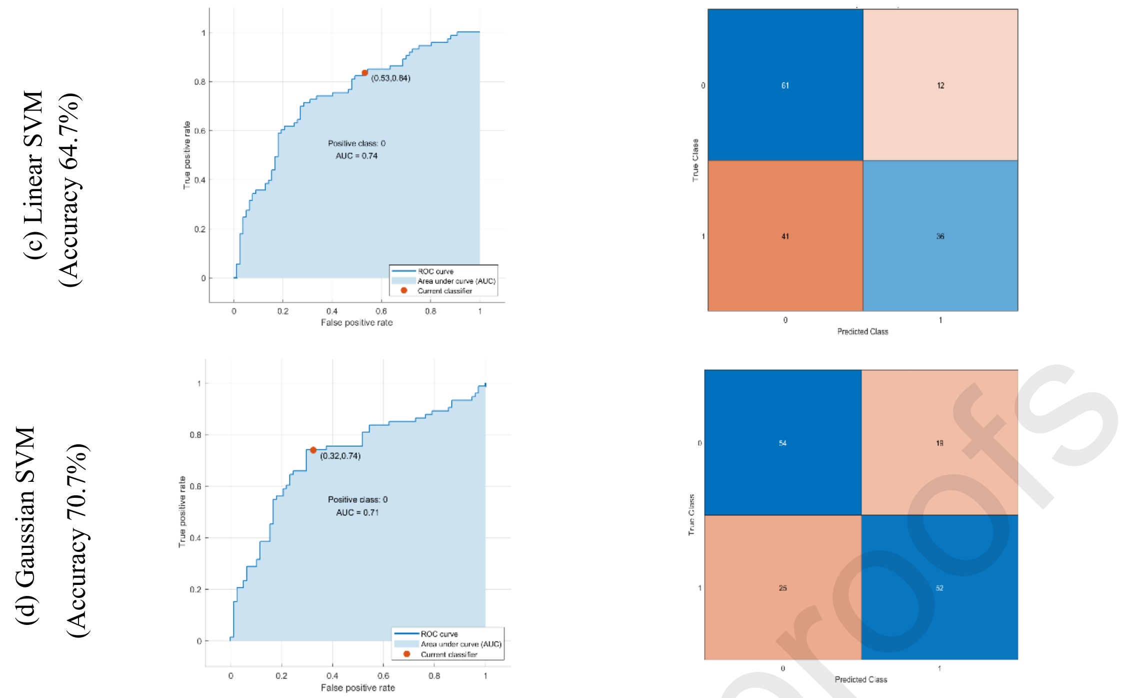


Figure 2: Machine Learning Base Learner performance evaluation outcome using ROC Curve and Confusion Matrix (a) Gaussian Naïve bayes (b) Kernel Naïve Bayes (c) Linear SVM (d) Gaussian SVM

Further, the Bagged Trees ensemble model and Boosted Trees model as ensemble models have been used to measure performance. The achieved accuracy by bagged trees ensemble model is 54% (see Figure 3) and boosted trees is 58.7% (see Figure 3).

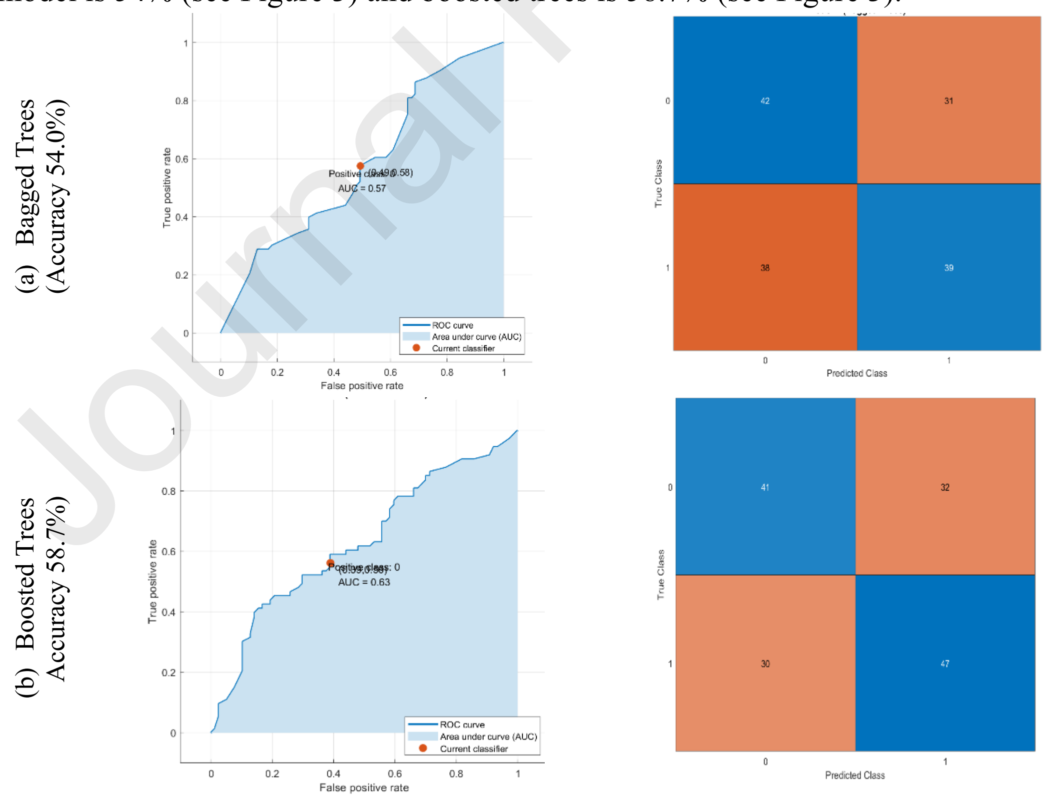
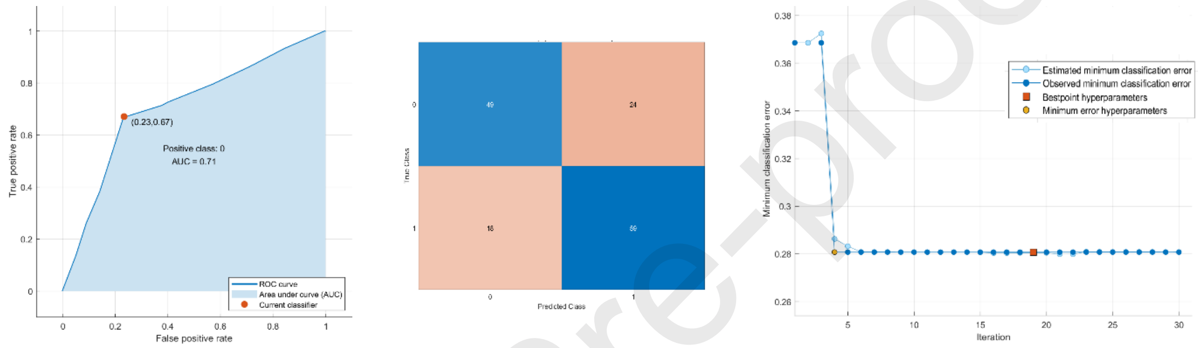


Figure 3: Machine learning ensemble classifier performance evaluation outcome in form of ROC Curve and Confusion Matrix. (a) Bagged Trees (b) Boosted Trees

Finally, the entire applied base learners shown in Figure 2 are used to build an ensemble model. The accuracy build of this ensemble model is better than all previously achieved accuracy which is 72% and the misclassification error plot of the ensemble model is shown in Figure 4.

Through the investigation of machine learning algorithms for the targeted problem transformed our research work direction with regard to the deep neural network. Girgis et. al. used deep learning models to address the challenge using RNN and LSTMs model to differentiating whether the news is truthful or deceptive (Girgis et al., 2018). After applying so powerful deep models as well, achieved accuracy by authors was in the range of 20% - 27%. So at first, this seems as erratic to explore deep neural network but we reconnoitred it which has been introduced as the proposed methodology in the manuscript for fake news detection.



(a) ROC Curve (b) Confusion Matrix (c) Misclassification Error

Figure 4: Ensemble Model Performance Result learners with achieved accuracy 72%

4. Methodology:

The outcome of all preliminary experiments of machine learning moved direction towards the neural network. The neural network (NN) is able to learn non-linear, complex relationship, and try to identify the important information from the inputs (Mahanta, J. 2017). The second objective of this research work is to introduce an effective linguistic feature-based fake news detection neural network model and the last objective is to measure the impact of extracted linguistic features in comparison to deep learning based model.

4.1 Model Description

In order to attain both objectives, a neural network model is implemented and the same model is classified into three models based on the varying linguistic feature set. The base structure of the proposed neural model is $f=\left\{X_i^{sy}, X_i^{sen}, X_i^{gr}, X_i^{R}\right\}_i^n \in \mathrm{X}\rightarrow\mathcal{Y}$ which is built to provide accurate labels as Fake / Not-Fake to the targeted news items. Literature suggests that readability is a rarely used feature for fake news using the neural network model (Reyes & Palafox 2019). All other features set are commonly used for classification. This was the main concept behind feature driven model categorization. Therefore, the feature driven neural model is divided among three models- Model 1 contains syntax based features, sentiment based features, and grammatical features, Model 2 contains readability features, and Model 3 contains all the lingual features (discussed in section 3.2) of news articles which fed to learn the sequential neural network model. So, the base concept of the learning model is the same except the change in inputted features set. Figure 5 shows the applied neural network model concerning inputted features based model classification. The process will start from inputting the fake news dataset which will enter to data pre-process phase. In data pre-processing, the dataset will tokenize and remove all punctuations. This pre-processed dataset is used to extract all features detailed in section 3.1. The considered NN model is a conventional sequential neural network model. A sequential neural network is considered as the best model for predictive modelling problems where some sequence of input features predicts a category. The specified process comprises of three models differentiating on the feature set. Model 1 works on syntax, semantic, and grammatical feature dimensions those are represented as f_i which is collection of 13 features in the count. Neural network architecture is the same for Model 2 and Model 3 as well and the single difference in both the models is of input deep linguistic feature dimensions. Model 2 uses readability features f_j which contain 7 dimensions, and Model 3 works on the entire considered linguistic feature f_k containing 20 dimensions.

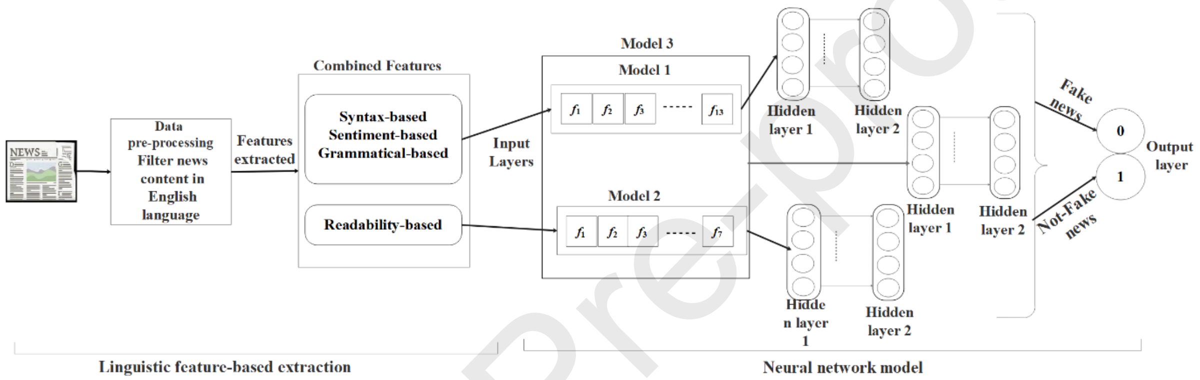


Figure 5: Fake news Detection based on Linguistic features Process Flow

The first model is applied to syntax-based, sentiment-based and grammatical-based features to find out the efficacy of specified features for fake news classification. On similar grounds, Model 2 is enforced on readability-based features and finally, the third model is an amalgam of all the features used in Model 1 and Model 2 as shown in Figure 5. Our problem is formulated as a binary classification problem and considered features are the factors that influence the spread of fake information on social media. The proposed model is based on deep linguistic Analysis which helps the researcher to relate the language structure. The writing style (word density and word count), grammatical usage (POS tag), and readability ability (ARI, Gunning fog), sentiment analysis extracts subjective information from news content and have important weightage in fake news identification and classification.

Model 1 input dimensions/feature sets are

$f_i = \{x_{cc}, x_{wc}, x_{twc}, x_{up}, x_{stp}, x_{wd}, x_{pol}, x_{sub}, x_{nou}, x_{ver}, x_{adj}, x_{adv}, x_{pro}\}.$

Model 2 input dimensions/feature set

$f_j = \{x_{re}, x_{ari}, x_{gf}, x_{cl}, x_{fki}, x_{smg}, x_{Lwf}\}.$

Model 3 input dimensions/feature set are an amalgam of features of Model 1 and Model 2 denoted as

$f_k = \{x_{cc}, x_{wc}, x_{twc}, x_{up}, x_{stp}, x_{wd}, x_{pol}, x_{sub}, x_{nou}, x_{ver}, x_{adj}, x_{adv}, x_{pro}, x_{re}, x_{ari}, x_{gf}, x_{cl}, x_{fki}, x_{smg}, x_{Lwf}\}$

Neural model architecture is the same for all three specified models as shown in Figure 5. The neural model contains two hidden layers and these layers are using a rectified linear unit (ReLu) as activation function along with a uniform kernel initializer. Kernel initializer generates tensor with a uniform distribution. W_i, where $i = 1$ to 13 are initially arbitrary features weights assigned to compute the first activation function for hidden layer 1, see equation (2), (3).

$$\prod_1^4 Z^{[j]}(x) = \sum_{i=1}^{13} W_i f_i + b1 \quad (2)$$

$$\prod_1^4 A^{[j]}(x) = ReLu\ Z^{[j]}(x) \quad (3)$$

Where $A^{[j]}(x) = \begin{cases} 0\ for\ x < 0 \\ y\ for\ x \geq 0 \end{cases}$

After performing various parameter tuning, we have found that the best results are achieved using two hidden layers. First, the hidden layer has 4 neurons which are further used and the ReLu activation function to get a better result. $W_{j,}$ where $j = 1$ to 4 is the weights assigned to compute the second activation function for hidden layer 2 with 4 neurons.

$$\prod_1^4 Z^{[k]}(x) = \sum_{j=1}^{4} W_j A_j + b2 \quad (4)$$

$$\prod_1^4 B^{[k]}(x) = ReLu\ Z^{[k]}(x) \quad (5)$$

The input at the output layer (Inp_{out}) is computed as the sum of the weighted connection (W_k) to output of the hidden layer and bias ($b3$), as in (6)

$$Inp_{out} = W_k * B^{[k]}(x) + b3 \quad (6)$$

So, the calculated output at the output layer () using SoftMax function is calculated, as in (7)

$$\hat{y}_{(i)} = \frac{e^{\hat{y}_i}}{\sum_j^k e^{\hat{y}_j}} \text{ for } i = 1,\ldots,k \quad (7)$$

However, the calculated output is compared with target answer to compute the predefined error function value i.e. using Adam optimizer, where E denotes error, as in (8).

$$E(\hat{y} - y) = \frac{1}{2}(\hat{y} - y)^2 \quad (8)$$

Two hidden layers with bias compute the sum of the weighted features. Then, the weighted connection with the SoftMax function flows into the output layer. The output layer with a bias calculates the output.

4.2 Algorithms:

It is clearly depicted in Figure 5 that the research work has been divided into two sections- 1) Linguistic Feature extraction, 2) Feature based Sequential Neural Network. On a similar ground, the detailed process of the proposed Linguistic-based Sequential Neural Network model is summarized in Algorithm 1 and feature based sequential neural network phase is described in Algorithm 2. All the variables and equations are discussed in Appendix-A and Section 4.1 respectively. The overall implementation has been done using python programming language and several packages have been used in the overall process. Algorithm 1 is about feature extraction using the news dataset. Step1 shows the initialization of the storage pool of the targeted news dataset. Further, for each record feature extraction phase will repeat i.e from step 2 to step 7 will repeat. Syntax based evidence, sentiment based evidence, grammatical based evidence, and readability based evidence extraction is shown in step 4, step 5, step 6, and step 7 respectively. The python numpy vector of all the extracted evidence is input for algorithm 2.

Algorithm 1: Linguistic feature-based extraction

Input: News A_i^n

Output: X^{sy}, X^{sen},X^{gr},X^R

1. **Initialize:** storage pool for news dataset $\mathcal{A}$.
2. For each, $\forall A_i^n \in \mathcal{A}$ do
3. $X^{sy} \Leftarrow$ Syntax-based evidence, $X^{sen} \Leftarrow$ Sentiment-based evidences,
   $X^{gr} \Leftarrow$ Grammatical-based evidences, $X^R \Leftarrow$ Readability-based features
4. **Syntax-based Evidences**
   Compute x_{cc}, x_{wc}, x_{twc}, x_{wd}, x_{up},x_{stp}
   $X_i^{sy} = \{x_{cc}, x_{wc}, x_{wd}, x_{twc}, x_{up}, x_{stp}\}$
5. **Sentiment-based Evidences**
   Compute x_{pol}, x_{sub}
   $X_i^{sen} = \{x_{pol}, x_{sub}\}$
6. **Grammatical-based Evidences**
   Compute x_{nou}, x_{ver}, x_{adj}, x_{pro}, x_{adv}
   $X_i^{gr} = x_{nou}, x_{ver}, x_{adj}, x_{adv}, x_{pro}\}$
7. **Readability-based Evidences**
   Compute: ASL, ASW, PHW, L, S, n_{st}, x_{cc}, x_{wc}, n_w,n_{wsy}
   Compute:
   $x_{re} = 206.835 - (1.015 * ASL) - (84.6 * ASW)$
   $x_{ari} = 4.71\left(\frac{x_{cc}}{x_{wc}}\right) + 0.5\left(\frac{x_{wc}}{x_{st}}\right)$
   $x_{gf} = 0.4(ASL + PHW)$
   $x_{cl} = (0.0588 * L) - (0.296 * S - 15.8)$
   $x_{fki} = (0.39 * ASL) + (11.8 * ASW) - 15.59$
   $x_{smg} = 3 + Square\ root\ of\ Polysyllable\ Count$
   $x_{Lwf} = \frac{[(100 - \frac{100 * n_{wsy} < 3}{n_w}) + (3 * \frac{100 * n_{wsy} \leq 3}{n_w})]}{(100 * \frac{n_{st}}{n_w})}$
   $X_i^R = \{x_{re}, x_{ari}, x_{gf}, x_{cl}, x_{fki}, x_{smg}, x_{Lwf}\}$
8. increment in for loop
9. end loop
10. end Process

The outcome of Algorithm 1 is basically the input for Algorithm 2. Algorithm 2 is about building a sequential neural network learning model. Algorithm 2 initial lines describe the collected input dimensions/ features of news content. All input dimensions are already discussed in detail in Section 4.1. Step 1 and Step 2 of Algorithm 2 is about the partitioning of the overall dataset i.e. 70:30 dataset partitions for training and test set. Although, 5-fold cross validation has been applied to get the outcome. The Neural Network model is described from step 3 to step 10 which shows the process of applying learning neural network model by taking input dimensions (extracted features from Algorithm 1). ReLu activation function is used for hidden layers. The process will learn according to the defined number of iterations per epoch. Finally, the SoftMax activation function is used to classify the outcome in Fake/Not-Fake.

Algorithm 2: Feature-based Sequential Neural Network Model

Input: For News $A_i^n \in \mathcal{A}$, the detection label $Y_i^n \in \mathcal{Y}$

Input dimensions:

$f_i = \{x_{cc}, x_{wc}, x_{twc}, x_{up}, x_{stp}, x_{wd}, x_{pol}, x_{sub}, x_{now}, x_{ver}, x_{adj}, x_{adv}, x_{pro}\}$

$f_j = \{x_{re}, x_{ari}, x_{gf}, x_{cl}, x_{fki}, x_{smg}, x_{Lwf}\}$

$f_k = \{x_{cc}, x_{wc}, x_{twc}, x_{up}, x_{stp}, x_{wd}, x_{pol}, x_{sub}, x_{now}, x_{ver}, x_{adj}, x_{adv}, x_{pro}, x_{re}, x_{ari}, x_{gf}, x_{cl}, x_{fki}, x_{smg}, x_{Lwf}\}$

Process: $\mathcal{X} \Rightarrow$ Feature standardization (f_i,f_j,f_k)

split input feature and fake news class variable.

1. float test size = 0.3
2. train test split ($\mathcal{X}, \mathcal{Y}$; test_ size)

Model

3. For number of training iterations **do**
4. Update the features for all three specified models according to Eq. (2) of section 4.
5. Compute and update the ReLu activation function for hidden layer 1 as discussed in Eq. (3)
6. Now, Update the features with 4 neurons for hidden layer 2 according to Eq. (4)
7. Further compute the ReLu activation function for the hidden layer 2 as discussed in Eq. (5)
8. Then, compute the input at the output layer as discussed in Eq. (6)
9. Finally, calculate the output at the output layer using SoftMax function according to Eq. (7)
10. At last, the output is compared with target answer to compute error as discussed in Eq. (8)
11. end for
12. end Process

4.3 Long Short Term Memory based Fake News detection Deep Learning Model

The linguistic feature based learning model results are compared with LSTM deep learning model. A dense representation of words is provided to LSTM network. Then, long short-term memory (LSTM) network is used to train the deep learning model for fake news detection. LSTM is a special variety of recurrent neural network (RNN) which is having capability to learn based on long and short term dependencies. It is adopted for the sequence modelling or sequence classification of the data. LSTM network learns system based on what specific fake information/data is to be forgotten or what fake information/ data is important to keep. LSTM network flows information through three different gates: 1) Forget gate, 2) input gate, and 3) output gate. These gates are added into the cell of the LSTM network. The network can store or acquit memory over the gating mechanism. For each time step t, the LSTM cell receives inputs from current input x_t, the previous hidden state h_{t-1}, and the previous memory cell c_{t-1}. These gates are updation works as follows: Input Gate i_t determines how much information is added to the updated cell state from the current input using equation (9).

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + V_i C_{t-1} + b_i) \ldots\ldots (9)$$

Forget gate f_t controls the information that is to be discarded or eliminated from the current memory cell. Forget gate information updation is performed using equation (10).

$$f_t = \sigma(w_j x_t + U_j h_{t-1} + V_j C_{t-1} + b_j) \ldots\ldots. (10)$$

Memory gate generates the new memory by giving an input x_t , the output of this network will element-wise multiple the new memory gate, and add to the old memory to form the new memory and is computed as in equation (11).

$$C_t = f_t C_{t-1} + i_t tanh\,(W_c x_t + U_c h_{t-1} + b_c) \ldots. (11)$$

Last gate is Output gate which is controlled by the new memory, that decides amount of cell memory or output to be pulled out. Output gate information is updated using equation (12).

$$O_t = \sigma(W_o x_t + U_O h_{t-1} + V_o C_t + b_o) \ldots\ldots (12)$$

and, finally the new hidden state is updated as depicted in equation (13).

$$h_t = O_t tanh\,(C_t) \ldots\ldots.. (13)$$

Where W*, U*, V* are the weight matrix for the corresponding gates and b* are bias terms that are learned from the network. σ is a logistic sigmoid function squishing value [0,1] similar to tanh squishing values lies in -1 and 1. Sigmoid function helps to forget or update the data.

5. Experimental setup and Results

This section is fragmented into subsections which discusses datasets, system environment setup, hyperparameter tuning results of all three models along with the best found outcomes of proposed deep linguistic feature-based neural network.

5.1 Dataset Used/Description

Two datasets are used to evaluate the performance of the proposed algorithm. Both datasets are available as Horne2017_FakeNewsData[1] repository. This repository contains two popular and independent news datasets, first one is Buzzfeed Political News Data was analysed for Buzzfeed News in articles and another one is Random Political News Data. The detailed descriptive view of dataset is shown in Table 5. Dataset contains detailed information of all news which increases the size of word embedding vector for all the performed tasks.
These datasets contain fake or real news that spread across social media and these news contents are filtered only in the English language ignoring the other regional language. The labelling procedure is done manually to label it as fake and real because the received dataset was initially in two separate folders for both labels. The datasets contain title and description of both category news and does not have class imbalance problem i.e. both the classes are equally distributed.
Data pre-processing is used to refine the news title, description content by removing errors and impurities. Even, it is requisite to make it suitable for the proposed algorithm. While pre-processing punctuation, ASCII characters are removed from the sentences and filtered for only English comments by ignoring other languages.

Table 5: Descriptive details of Dataset

Dataset Name	**News Categories**	**News Count**	
		Titles	**Description**
Buzzfeed Political News	Fake News	48	48
	Real	53	53
Random Political News	Fake	75	75
	Real	75	75

5.2 System environmental setup:

Python and Matlab are used for overall implementation purposes. The used libraries and their associated process are listed below:

Framework: The algorithm was modelled using Google Collaboratory for Python 3.
Machine Learning Models: Matlab
Linguistic Deep Learning Model: keras, sklearn for feature extraction and model selection.

Readability Features: selenium, unit test library is applied to calculate readability score.
Natural language processing: nltk, Text Blob libraries.
Visualization: matplotlib, seaborn libraries.

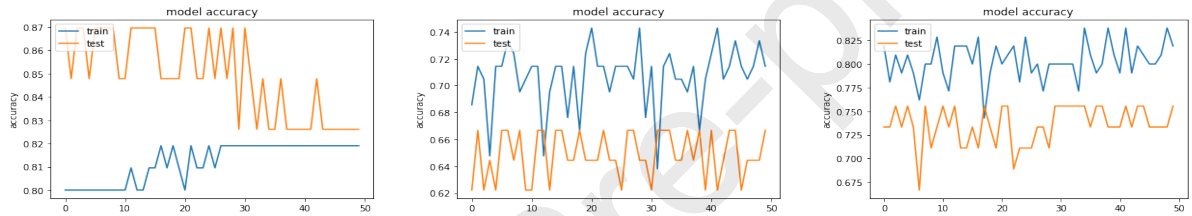
5.3 Results:

The results are examined in numerous contexts. The most expected outcome of the complete process was to determine the best performing model for fake news detection which circuitously interprets the role of linguistic features as well in order to classify news as fake/ not fake. We also monitored and showcased the gradual performance progressed with epochs.

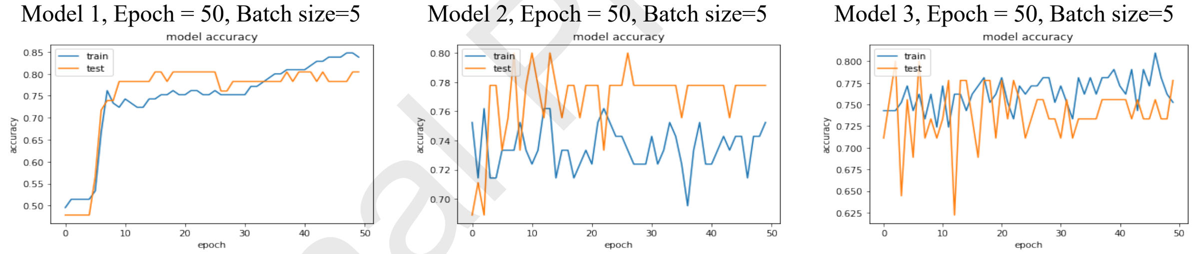
[1]https://github.com/BenjaminDHorne/fakenewsdata1

These results are interpreted to finalize the model based on early convergence and define the best batch size for all the proposed linguistic features-based models. The aim of this work was to depict that a sequential neural network model that is not computationally expensive is able to handle rich linguistic features effectively. As we already mentioned in our methodology section that model 1 employed syntactic, sentimental, and grammatical evidence, model 2 employed readability linguistic features, and model 3 is a combination of all the derived features to measure the fake news. Models comparison has been done on three sequential neural network parameters- Epochs, Batch size, and linguistic feature. Henceforth, results are presented to cover all three aspects.

Figure 6 and Figure 7 presents all three models' accuracy and loss curves for Epoch 50, batch size 5 and 10 respectively. It is noticed while comparing the outcome of all three models that syntactic features are dominating fake news detection capability over readability features. Even, combined feature model is also not able to achieve that high accuracy. Model 1 i.e. syntactic feature-based model is able to achieve 82% average accuracy, Model 2 i.e. readability features based model average accuracy is 72%, and combined average accuracy is around 80.22%. Increased batch size helped in an accuracy improvement.

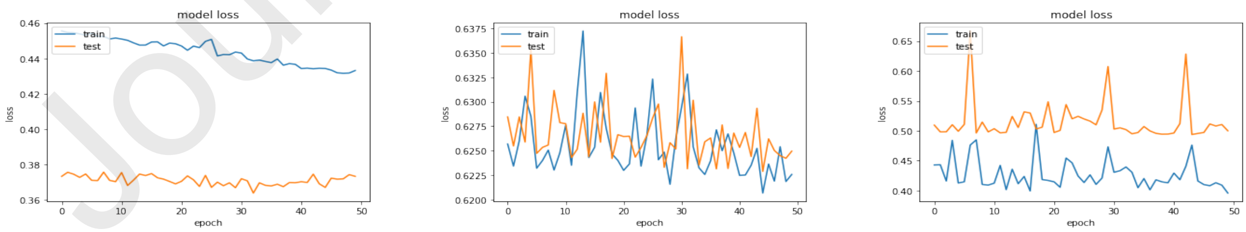


Model 1, Epoch = 50, Batch size=5 Model 2, Epoch = 50, Batch size=5 Model 3, Epoch = 50, Batch size=5

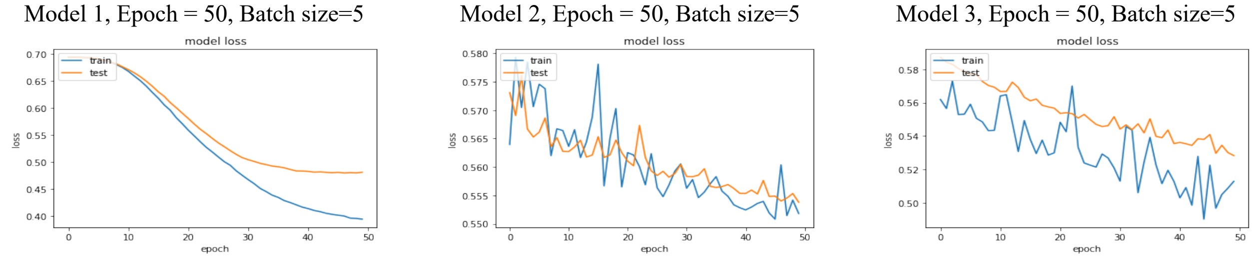


Model 1, Epoch = 50, Batch size=10 Model 2, Epoch = 50, Batch size=10 Model 3, Epoch = 50, Batch size=10

Figure 6: Accuracy plot of Model 1, Model 2, and Model 3 with epoch=50



Model 1, Epoch = 50, Batch size=5 Model 2, Epoch = 50, Batch size=5 Model 3, Epoch = 50, Batch size=5

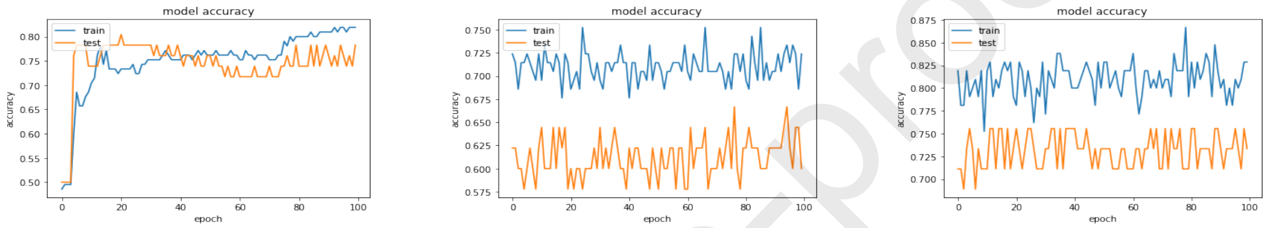


Model 1, Epoch = 50, Batch size=10 Model 2, Epoch = 50, Batch size=10 Model 3, Epoch = 50, Batch size=10

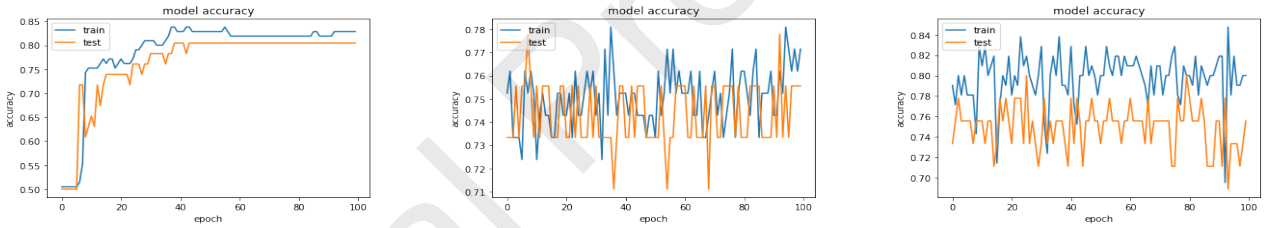
Figure 7: Loss plot of Model 1, Model 2, and Model 3 with epochs=50

Further, syntactic, readability, and combined features-based model outcome is validated for 100 epochs and batch size 5 and 10 to dig into the fake news detection pattern according to progress defined in epochs. Accuracy has been drastically increased by 3-4% in all three defined models. Average accuracy is 84.12%, 77.67%, and 84.52% for syntactic, readability, and combined features respectively.

These results show the improvement in combined features based fake news detection model as compared to the syntactic feature model. Accuracy and loss plots for the same are shown in Figure 8 and Figure 9 which clearly depicts the above noted results. Finally, we observed that the combined model behaves remarkably better as compared with other models.

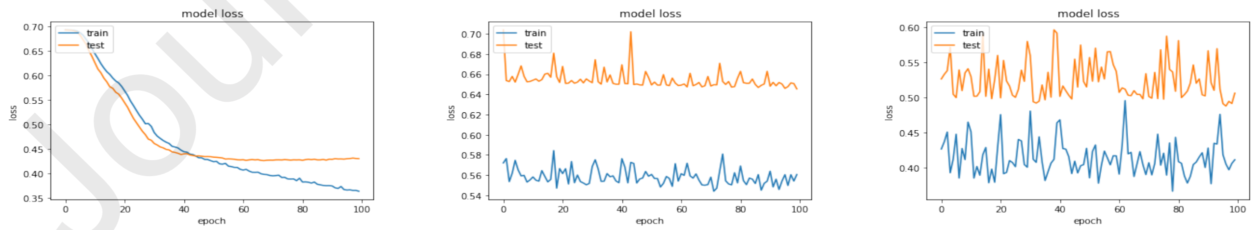


Model 1, Epoch = 100, Batch size=5 Model 2, Epoch = 100, Batch size=5 Model 3, Epoch = 100, Batch size=5

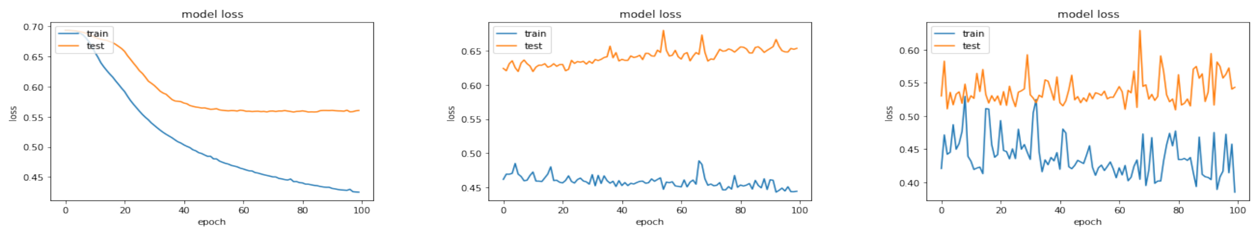


Model 1, Epoch = 100, Batch size=10 Model 2, Epoch = 100, Batch size=10 Model 3, Epoch = 100, Batch size=10

Figure 8: Accuracy plot Model 1, Model 2, and Model 3 for epoch=100, Batch size=10



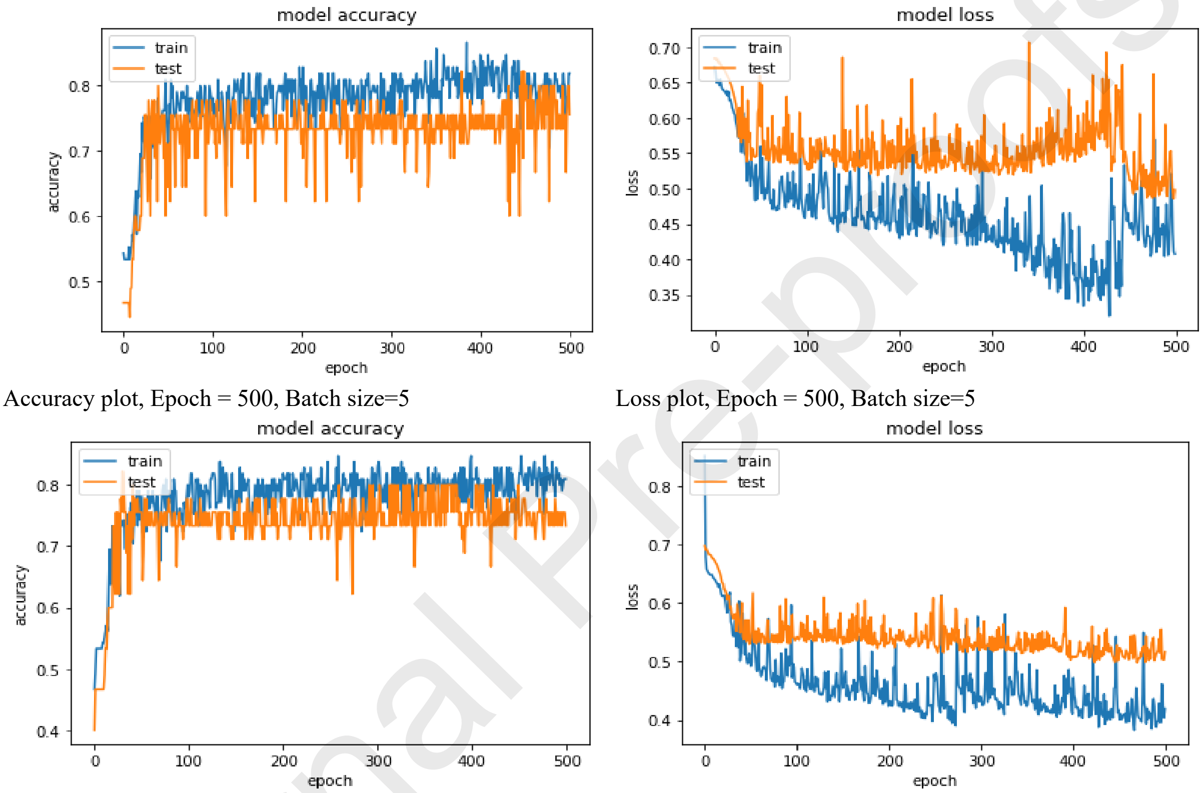
Model 1, Epoch = 100, Batch size=5 Model 2, Epoch = 100, Batch size=5 Model 3, Epoch = 100, Batch size=5



Model 1, Epoch = 100, Batch size=10 Model 2, Epoch = 100, Batch size=10 Model 3, Epoch = 100, Batch size=10

Figure 9: Loss plot Model 1, Model 2, and Model 3 for epoch=100, Batch size=10

Therefore, we showcased model accuracy and loss outcome of combined model i.e. model 3 which contains all the features for epoch size 500 and batch size 5 and 10. The average achieved accuracy is 86% and loss has been also been remarkably reduced as clearly depicted in Figure 10 which presents the accuracy and loss plot of both batch size for 500 epochs. These results, therefore, suggest that using the proposed linguistic feature-based sequential neural network model, we are likely to obtain superior results in less number of training epochs.



Accuracy plot, Epoch = 500, Batch size=5 Loss plot, Epoch = 500, Batch size=5

Accuracy plot, Epoch = 500, Batch size=10 Loss plot, Epoch = 500, Batch size=10

Figure 10: Accuracy and Loss plot for Model 3 for epoch=500, Batch size=10

Finally, LSTM model results for 30 Epoch are presented in figure 11 which shows validation accuracy as 86.5%. The architecture is trained using a sequence input layer into the network and sets the number of hidden units as 80 and word embedding layers having 50 dimension. Validation accuracy is comparable to sequential neural network based learning model. Sequential model is able to achieve 86% accuracy. But training time compared of LSTM based deep learning based model is 118 minutes 11 seconds which is much more than 45 minutes of linguistic features based sequential neural network learning model.

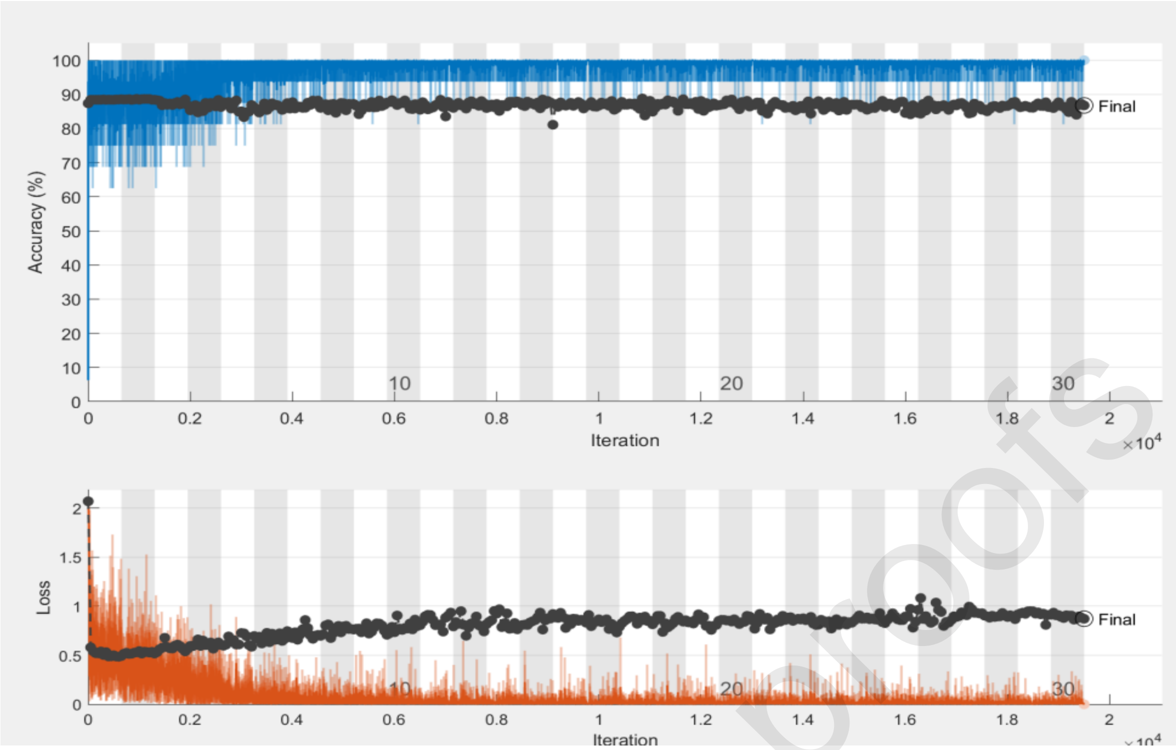


Figure 11: Accuracy and Loss plot for LSTM Deep Learning Model size=10 (Blue colour represents training accuracy plot, Orange colour represents loss plot, Black in both plot represents validation accuracy and loss plot)

The results concludes that sequential Neural network learning model is able to achieve effective accuracy in considerably less time as compared to LSTM deep learning model. Whereas, if we compare results with machine learning base and ensemble models than sequential neural network results contain remarkable performance.

6. Conclusion

The world of social media for sharing news content has grown at a phenomenal pace. This has impacted the reach of news enormously but also elicited difficulty to trust in it. On one side, social media is beneficial as it facilitates news generators by providing convenient means to promote. On the other side, it has revealed a set of challenges related to the authenticity of news content. Identifying fake news has become a crucial task and became a persuasive reason to work in this direction. Initially, in this research work, the linguistic features are extracted based on literature. In order to extract out linguistic features, various computational techniques have been used and syntactic, grammatical, sentimental, and readability features fetched out for the news dataset. Further, Preliminary experiments are performed to validate the efficiency of Machine learning algorithms: base learners and ensemble algorithms. The Maximum achieved accuracy by measuring all algorithms was 72% of the ensemble algorithm. This transformed research direction towards the Neural network model and linguistic features based sequential neural network model is built to classify news as fake or real. One research objective was to measure the importance of extracted feature sets as well and readability is considered as the most rarely used feature out of all extracted features according to literature study. Therefore, the same NN model is categorized into three separate models depending on the feature set. Extensive experiments and a comparison study on the targeted dataset have shown that the combined feature model performed superior as compared to differentiates feature sets. The Combined feature based sequential neural network model is able to achieve 86% accuracy for the test set. In future work, researchers may work on extensive features/parameters to improve the model performance. In parallel, a different version of approaches may be adopted to solve fake news detection problems. In the future, we intend to focus on extending this work with more linguistic features, dig into memory-based i.e. temporal data based fake news detection model, examine the latent semantic feature-driven fake news detection model, and explore various variants of convolution neural network for image-driven fake news detection.

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Appendix A.

Table 6: Details of the preliminaries symbol

Symbol	Description	Symbol	Description
$\mathcal{A}$	set of news article	x_{re}	Flesch Reading Ease
A_i^n	news articles from *i*=0 to *n*	x_{ari}	Automated Readability Index
	set of features	x_{gf}	Gunning Fog index
$\mathcal{Y}$	label set	x_{cl}	Coleman Liau
X^{sy}	syntax-based evidence	x_{fki}	Flesch-Kincaid index
X^{sen}	sentiment-based evidence	x_{smg}	SMOG index
X^{gr}	grammatical-based evidence	x_{Lwf}	Linsear write formula
X^{R}	readability-based evidence	n_{st}	no. of sentences
x_{cc}	character count	n_{sy}	no. of syllables
x_{wc}	word count	n_w	no. of words
x_{wd}	word density	ASL	average sentence Length
x_{twc}	title word count	ASW	average number of syllables per word
x_{up}	upper case word	PHW	percentage of hard words
x_{stp}	Stop word count	L	average no. of letters per 100 words
x_{pol}	Polarity	S	average no. of sentences per 100 words
x_{sub}	Subjectivity	Y_i^n	labels from *i*= 0 to *n* news article
x_{nou}	no. of noun	$\mathcal{X}$	feature standardization set
x_{ver}	no. of verb	f_i	feature set of model 1
x_{adj}	no. of adjective	f_j	features set of model 2
x_{pro}	no. of pronoun	f_k	features set of model 3
x_{adv}	no. of adverb		