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**Feed Forward Neural Network based Effective Feature Extraction technique for better Classification accuracy**<sup>1</sup>Adilakshmi Vadavalli, <sup>2</sup>Subhashini R<sup>1</sup>School of computing, Sathyabama Institute of science and Technology, chennai Email: adilakshmi.vadavalli@gmail.com<sup>2</sup>School of computing, Sathyabama Institute of science and Technology, chennai Email: subhaagopi@gmail.com**Article History:** Received: 11 January 2021; Revised: 27 February 2021; Accepted: 27 March 2021; Published online: 10 May 2021

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**Abstract**—Discovery of trustworthy information from so- cial media (i.e. Facebook, Twitter, and Instagram) is one of the crucial and challenging tasks in data processing. With the advent of internet and social network usage large chunks of dark data is being generated. Nevertheless, In- sights are generated and decision are taken by organiza- tions using this data. So the most important question is how reliable is your data and equally how reliable are the users who generate the data. Twitter is a most famous micro blogging social media. The earlier analysis shows that the maximum information which are being tweeted via twitter is mostly assumed to be true in form and there are no checks that have been carried out for its creden- tials. But the spread of misinformation dynamics makes it even more crucial to ascertain the trustworthiness of the data from a humanitarian perspective. Thus, using an auto- matic and effective Feature Extraction technique and Feed forward neural network classification the tweets and the twitter users are classified as either True or False and re- liable or Unreliable respectively. The case study is exper- imented on a real- world data set which demonstrates the effectiveness of the proposed approach while comparing with the existing truth discovery methods.

**Index Terms**—Socail media, Truth discovery, Feed forward neu- ral network, Effective feature extraction, Tweetclassification

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## I. INTRODUCTION

Social Media is one of the largest information portals, which is used to build consensus between the people around the world. When compared to other social media including Facebook, Instagram, Whatsapp, etc, twitter has attained a significant attention in recent days. It pro- vides an easy and quick channel access for the users to share and market their information. In twitter, the users can post their tweets (i.e. experiences) about the social events that are influenced by the topics covered around the world. Moreover, it is a social sensing application, where an ideal scenario has been created with rich set of information gathered from disparate data sources. A major challenge that exists in the social media sensing is truth discovery, where the reliability of the sources and truthfulness of claims are at stake. In this process, the source reliability estimation and truth computation techniques are highly used, and they depend on each other which are executed alternatively. Moreover, the tweets are enriched with the additional information for describing the spatial, temporal and publication context. Thus, the collection of tweets pro- vides more useful information for understanding the people's opinion and preferences about different topics. Generally, multiple data sources provide conflicting in- formation about the same object, so detecting the trust- worthy information by reliable source is complicated in social media. In order to solve this issue, a rich set of approaches have been proposed in the traditional works, which includes machine learning, data mining, and net- work sensing. These schemes are used to address the mis- information spread and data sparsity issues. Moreover, the techniques such as iterative methods, optimization based methods, and probabilistic graphical model based methods are also developed for truth discovery. In being able to classify the data as reliable or not feature extraction plays a key role. In this paper a genuine attempt has been made to use an Effective Feature Extraction technique followed by a Feed Forward Neural Network based tweet classification algorithm to classify genuinely the data and the reliability of the users.

**The objectives of this work are listed as follows:**

- To clean and process the data of the given twitter data set by Normalizing, filling the missing values and eliminating the irrelevant information.
  - To extract the relevant features from the text of tweets, an Effective Feature Extraction (EFE) technique is developed by using certain parameters of interest.
  - To exactly discover the truth of tweets posted by the user, using a Feed Forward Neural Network — Tweet Classification (FFNN-TC) mechanism and also ascertain the reliability of the users based on the extract text
- On Twitter usually most of the messages are like chat and conversations. And most of the people usually share the related information. The keywords which are used in Twitter vary frequently and are termed as the trending sub-jects. This is considered as persistent news.

The following are the properties which are making twitter as an interesting social medium.

The twitter is a Micro blogging social media which permits the user to post brief writing updates, along with the special aspect which is not permitting more than the 140 letters in a single text message. This restriction became the smart property which permits the user to post the text very fast in real time. It makes the users to respond to one's post in the twitter, and at the same time it makes the user to proceed with the immediate response to the tweets as well. This leads the people to spread the news and in-formation as fast as possible. The spreading of news in the fast way will cause the positive influence and also the negative influence in the society depending on whether the spreading information is true or false.

- The frankness and the easiness in the access of posts from the various sources generally create the interest among the people much more than the other social media sites. In Facebook mutual consent is needed for access or response to the one's information posted in the social me-dia. But in twitter the user is allowed to follow others, and they can reply their messages even without the mutual con-sent. This may increase the chances of spreading the false messages in the twitter. This is the reason for selecting the twitter data set for this research.

- The vast usage of the hash tags allows people to easily search for the particular tweet. These hash tags are the labels which are normally utilized in the social media and in the micro blogging services. This made the users to find the specified tweet which they want. This hash tag also allows the users to classify their tweets. Henceforth, other users in the twitter may have an idea about what the tweet can be related with.

The remaining sections present in the paper are organized as follows: Section II investigates the traditional feature extraction and classification techniques used for truth discovery on social media. The description about the proposed tweet classification system is presented with its working flow illustration in Section III. The experimental results of existing and proposed techniques are analyzed and evaluated in Section IV. Finally, the paper is concluded with its future work in Section V.

**I. RELATED WORK**

This surveys the existing techniques and methodologies which are related to truth discovery on the social media data.

In this paper [1] a new probabilistic model is designed for extracting the local and global topics by using a unified framework. The contributions have been mainly focused on reducing the cause of long tail effect by avoiding the local topics. Here, each tweet was simultaneously associated by determining the type of topic. Then, a Global and Local Topic Model (GLTM) was developed to learn the global topics that were distributed around all locations. In order to analyze the performance of this framework, a Geo tag twitter data set was used during experimentation. Moreover, this model has the ability to deal with the long tail effects by eliminating the local topics. But this work was required to obtain more reliable ground truths by using the crowdsourcing technique. In this paper [2] a Semi Supervised Span Detection (S<sup>3</sup>D) model was developed which includes two modules such as real time mode and operating in batch mode. In this detection module, four different types of lightweight detectors have been utilized such as blacklisted domain detector, near duplicate detector, reliable ham detector and multi-classifier based detector. Here, a min hash algorithm was utilized to detect the near duplicate tweets, which was highly efficient for detecting the spam tweets. Then, a reliable ham tweet was considered to detect tweets by satisfying the following conditions: the tweet does not have any spam words and was posted by a trusted user. Finally, multi-classifier based detector was developed based on the Naïve Bayes (NB), Random Forest (RF), and Logistic Regression (LR) classification techniques. This framework was

computationally efficient for all the spam detectors, so it has the ability to detect the labeling tweet streams in real time. However, the user level spam detection mechanism should be incorporated with this S<sup>3</sup>D technique, which was the main limitation of this work. In this paper the authors [3] intended to extract various hidden features that were related to the tweets generated by the user. Generally, the sentiment analysis was performed to analyze the degree of emotions based on different user communities. During a time series analysis, the tweets posted by the users were calculated. Here, the time was measured based on the day, hour and month at regular intervals. The lexical based method was used to analyze the nature of tweet and the lexical identifier could measure the words as positive, negative or neutral with the scores. Typically, the main challenge in the tweet analysis was to segregate the tweet with its features.

In this paper [4] the authors conducted a real time sentiment analysis for streaming the twitter data to predict the potential prices of company stocks. Also, Lambda architecture was designed to predict the price of stock market, which was developed based on the data processing architecture. It includes three layers such as batch layer, serving layer and speed layer. In order to exactly classify the sentiment of each tweet, the sentiment analysis was performed that categorized the class as positive, negative or neutral. Here, the Recurrent Neural Network (RNN) have been used to extract various forms of sentiments from the large set of data. Still, the accuracy and performance of this technique could be improved by implementing a deep learning models. In this paper the authors [5] intended to examine whether the twitter trends were secure against the manipulation of malicious users. Here, an influence model was utilized to analyze the dynamics of hash tag and identify the manipulation from diffusion. The parameters such as popularity, coverage, reputation, potential coverage, and transmission have been considered in this analysis. Moreover, the Support Vector Machine (SVM) classification technique was used to accurately predict the factor that could be trending. In this paper the authors [6] developed a data analytics methodology based on clustering and association rule discovery algorithms. Here, a new distance measure, namely, TASTE was used to discover the groups of tweets with good cohesion. Moreover, the Tweets Characterization Methodology (TCHARM) architecture was constructed, which includes the stages of data collection, processing, cluster analysis, and association rule mining. In this paper the authors [7] designed an event detection system by using an incremental clustering approach for detecting the newsworthy events form the twitter data stream. Here, a new architecture named as Twitter News+ was formed with the modules of searching and event clustering. In which, the fast retrieval of tweets were facilitated for providing a binary decision of an input tweet. A word level Longest Common Subsequence (LCS) approach was used to identify the representative tweets for each event.

In this paper [8] the authors introduced a new framework, namely, T-Hoarder for displaying the summarized and analytical information based on a certain event in a web page. Here, different parameters such as speed limit, time recovery limit, and tweets samples were considered. The functional divisions of T-Hoarder were as follows: data collection, storage, data processing, and visualization. In this paper [9] the authors aimed to solve the spam drift problem by developing a Learning from unlabeled tweets (L fun) approach. The intention of this approach was to reduce the impact of spam drift with better detection rate and f-measure values. In this work, both the data analysis and experimental evaluation tests have been conducted to analyze the efficiency of spam drift detection. Also, a parametric and non-parametric approach was utilized to extract the mean value of the features. But it required to incorporate the incremental adjustments for adjusting the training data. In this paper [10] the authors implemented a pattern based approach for performing sentiment analysis in twitter. In this analysis, the SENTA tool was used to help the users for selecting the large number of features to increase the efficiency of classification. The stages involved in this approach were processing, tokenization, POS tagging, lemmatization, negation vector generation, and polarities detection. Also, these techniques was used to quantify the sediments present in the tweet. In this paper [11] the authors employed an ensemble heterogeneous classification methodology for discovering the health related knowledge in social media. In this study, different types of classification techniques were surveyed, which includes Random Forest (RF), Support Vector Machine (SVM), Multi nominal Naïve Bayes (MNB), and Bernouli Naïve Bayes (BNB). Also, the sensitivity parameter was utilized to evaluate the performance of the feature extraction techniques for attaining the best features from each feature type. In this paper [12] the authors formed an estimation theoretic approach for discovering the theme relevant truth on twitter. This analytical model considered the theme relevance feature for providing the suitable solutions for the truth discovery problem. Moreover, a bi-dimensional estimation problem was solved by estimating the correctness and theme relevance of claims. Then, the analytical model could be used to derive the solutions, which were consistent with the observed twitter data. In this paper [13] the authors developed a generalized social spammer detection framework by integrating multiple view information and social regularization. Also, an empirical in-depth analysis was conducted on a real world twitter data set, which determined the feature distributions between the spammers and legitimate

users. The benefit of this technique was, it considered multiple view information for spammer detection based on single view methods, optimization methods, and combination methods. Still, it required to improve the performance of spammer detection by implementing a simple strategy for complementing the missing values.

In this paper [14] the authors implemented a user interest model based event evolution strategy for discovering the events in a social data streams. A cosine measure based event similarity detection method for assessing the correlation between the events. In this approach, a set of tweets were classified into different classes such as positive, negative or neutral. However, it required to increase the accuracy of classification by extracting the most relevant features. In this paper [15] the authors deployed a semantic abstraction method for improving the generalization of tweet classification. In this approach, the features such as location and temporal mentions were extracted from the linked open data. Then, the incident related tweets were segregated with respect to different incident types and neutral class. Moreover, the temporal expression extraction and replacement were performed in tweets by using Heidel time framework. In this paper [16] the authors developed a twitter sentiment classification method for addressing the issues of public health concerns. In this paper, a two-step classification model based on the combinations of clue based search and machine learning was developed for classifying the tweet sentiments. Here, the sentiment timeline and news timeline were correlated in a quantitative and qualitative manner. Still, it required to increase the efficiency of discovery by implementing better classification technique, which was the limitation of this model. In this paper [17] the authors propose a neural network classification algorithm for Mobile learning. With the usage of e-learning through mobile devices, the authors develop an opinion mining system for extracting the reviews and opinion of users if they are positive or negative.

The following literature survey details out the different methods used for classification of toxic comments and sentences.

In this paper [18] the authors propose a Scalable and Robust Truth discovery technique for addressing the three major challenges like the misinformation spread, data sparsity and scalability. The proposed model has been evaluated on three real world data sets. In this [19] toxic comments on large pool of text has been identified and classified using convolution based neural network. It has been combined with a selection algorithm to evaluate. All the different layers namely, convolution layer, pooling layer, embedding layer, fully connected layer are explained in detail. It has been compared against bag of words text. The training of the data set is done using back propagation algorithm. In this [20] the authors have tested on Wikipedia talk page data on three different models namely for comment abuse classification namely recurrent neural network, long short term memory and Convolution neural networks. Word embedding and character embedding have been used extensively. A hand tagged data set has been used.

The authors in this paper [21] used a one layered convolution neural network classifier for sentence classification. They have been tested on 9 real world data sets. In their dense feature space a support vector machine is used as a baseline. The effect of input word vectors has been effectively explained. Even the effect of number of feature maps for each filter size has also been explained. This paper [22] proves to be an interesting article on discussing the different evaluation metrics for discriminating and obtaining an optimum classifier. Five New metrics have been proposed which when used improve the efficiency of classification algorithm. Advantages of generative classifiers and classifiers has been explained in detail. This paper [23] aims to prove that the classification performance accuracy improves with the depth of the convolution layer network. 29 layers have been used to improve the accuracy of the algorithm. Look up table and 2D sensors have been used. The strategy has been tested on 8 different data sets. The main advantage of the system is its improved accuracy and the disadvantage lies in the complexity of the design. This paper [24] aims to eliminate the drawbacks of the curse of dimensionality by learning a distributed representation of words. It learns to neighbor sentences by exponential semantics. The model describes three main features namely a distributed representation, a probability function for words and generalization of sequence of words. This algorithm strategy uses N-Gram model, learned distributed feature vector combined with neural architecture. It uses parallel processing for catering to large scale data set. It uses two phases of computation namely forward phase and a backward/update phase. A variant of the above model is an energy minimization network. The main disadvantage of this approach is that it slows down the training process. From all these studies, it is examined that the existing techniques have both advantages and disadvantages. The main limitations observed are listed as follows:

- The existing work required to obtain more number of reliable ground truths by using the crowdsourcing techniques.
- The user level spam detection mechanism should be effectively incorporated.
- The main challenge in the tweet analysis is to segregate the tweet with its features.

- It is necessary to improve the performance of detection by implementing a simple strategy for complementing the missing values.
- It is required to increase the efficiency of truth discovery and the trustworthy user information by implementing better classification technique.

## II. PROPOSED METHODOLOGY

Most of the existing literature concentrate on predicting the relevancy and sentiment analysis of the tweets ignoring the reliability of the users. This paper presents the detailed description about the proposed methodology with its clear working flow and procedure. The main intention of this paper is to classify the truthfulness and relevancy of the tweets to the topic of interest which is posted by the users. Hence, forth, the user’s trustworthiness is also assessed. The entire concept is based on the truth discovery principle that truthful tweets are provided from reliable users and in turn reliable users consistently provide true information. In this proposed method the trustworthy information is discovered by using the MIB data set [25]. This data set contains the group name, description, accounts, tweets, and the year. As shown in Figure 1, this truth discovery system has the following stages of processing, feature extraction, classification and output description. Initially the data sets are taken from the real time data collected from the twitter. The processing is used to eliminate missing values and standardize the data which are taken from several users in a different format. From the data sets the text of the tweets is extracted by using the Effective Feature Extraction (EFE) algorithm. Using the extracted features it undergoes a classification process. For the classification process the Feed Forward Neural Network —Tweet Classification (FFNN-TC) technique is developed for truth discovery. Finally, the classified label is discovered as true or false tweet. Based on the weight assigned to the user, they are classified as reliable or Unreliable.

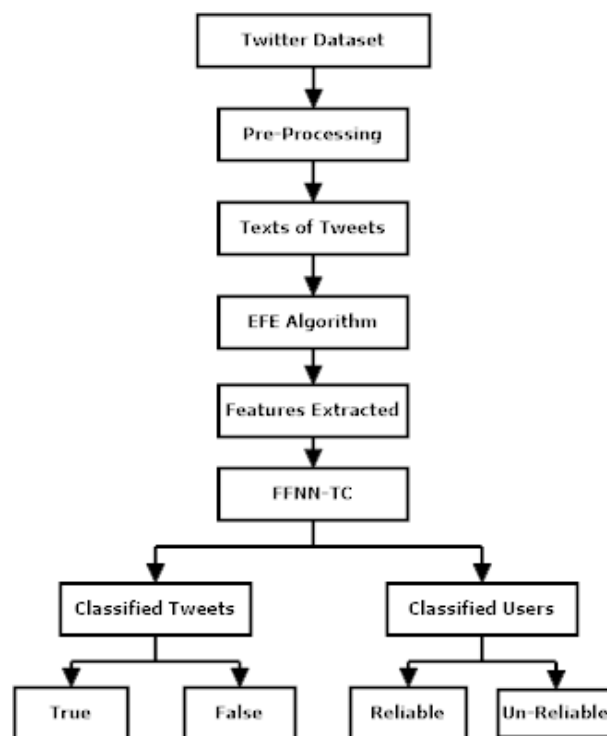


Fig. 1. Flow of the proposed truth discovery tweet classification system

Normally in social media platform like twitter, Face- book, etc. there are various elements which was perceived. The trustworthiness of the information is accessed by the following factors:

- The generation of reactions for a particular topics and while discussing the topic the posted emotions by the users. For example the used emotion symbol may symbolize the positive or negative of that particular information.
- The broadcasting of the information depends upon the inevitable usage level of the specified information. For ex- ample the queries raised by the user for a specified post.
- The citation of the external sources. For example the citation of other website URL link which have the

contents of information related to the post and also whether the source is popular (standard) or not also determines the reliability of the source.

- The aspects of the information which is propagated. For example in the specified platform like twitter or Face- book the number of followers that belong to every user.

For the characterization of every topic in the proposed work the feature set is extracted according to the need. The extracted features here are mostly related to the Twit- ter platform, and these features can be applied to the social media platforms as well.

A. Data Processing

Typically, the twitter data set contains different opinions that are expressed by several users in varying ways. Typically, the twitter data set processing includes the following steps:

All URLs, targets and hash tags are removed at first Then, the spelling errors and the sequence of repeated characters are corrected

Then the symbols, numbers, punctuation marks, non- tweet words and stop words are also removed

Finally, all acronyms present in the tweet are expanded

B. Feature Extraction

In this stage, the features present in the data set are extracted, which contain many distinctive properties. The opinion about the individuals are determined by computing the positive and negative polarity in a sentence. Generally, the classification techniques requires the key features of the text or documents, which are considered as the feature vectors used for classification. The following list of attributes are extracted in this work:

C. Algorithm 1 Description:

It is difficult to extract the Number of Hash tags, Number of Retweets, Number of replies, Used URL, Sentimental basis tags and emotion basis tags used in the twitter for the specified twitter post. For achieving this the Effective Feature Extraction technique is used to extract the Number of Hash tags, Number of Retweets, Number of replies, Used URL, sentimental basis test and the emotion basis test labeled separately by using NLP functions as shown in

Table 1. Extracted Attributes

Sl. No	Attributes
1	Date
2	Time
3	Tweet_text
4	Type
5	Media Type
6	Hashtag
7	Tweet ID
8	Tweet URL
9	twf_favourites_is_this_like_Question Mark
10	ReTweets

Algorithm1 (Effective feature extraction)

D. Classification

After extracting the features, the classification technique is employed to classify the label. In this paper, a Feed Forward Neural Network — Tweet Classification (FFNN- TC) technique is developed for truth discovery as shown in algorithm2. This technique incorporates the features from the relevant tweets with the word of embedding vectors. The weights of the tweet ids in turn give us whether the user is reliable or not.

E. Algorithm 2 Description:

The extracted Number of Hash tags, Number of Retweets, Number of replies, Used URL, Sentimental basis tags and emotion basis tags are classified with the help of the Feed Forward Neural Network — Tweet Classification (FFNN-TC) technique. This classification algorithm is based on the Artificial Neural Network. This algorithm does not contain the backward loop and cycle. It only processes the forward nodes through the hidden nodes. In this algorithm, there are no possibilities to know the path of the node because the hidden nodes does not contain the indexes.

**Input:** Data set ( $TW_{tws}$ )

**Output:** Features

$TW_{tws} \leftarrow$  Over all Data set  $TW_{hash} \leftarrow$  Hash Tags in tweets  $feat_{hash}$  be number of Hashtags

Table 2. **Algorithm 1: Effective Feature Extraction (EFE)**

$$Feat_{hash} = \sum_{i=1}^{len(TW_{tws})} TW_{hash}$$

$hash$

$TW_{tws} \leftarrow$  Tweet text in tweets  $feat_{retw}$  be number of retweets  $feat_{repl}$  be number of replies

For  $j=1$  to  $len(TW_{tws})$

If  $TW_{tws}$  contains “RT@”

$feat_{retw} = 1$  Else  $feat_{retw} = 0$  End For

Let  $i$  be the presence of URL For  $j=1$  to  $len(TW_{tws})$

If  $TW_{tws}$  contains “https://” or “http://”

$feat_{url} = 1$  Else  $feat_{url} = 0$  End For

$feat_{users}$  be reference to other users For  $j=1$  to  $len(TW_{tws})$

$feat_{users} = \text{count}("@")$

End For

$feat_{spcl}$  be presence of URL For  $j=1$  to  $len(TW_{tws})$

If  $TW_{tws}$  contains “” or “”

$feat_{spcl} = 1$  Else  $feat_{url} = 0$  End For

$len(tws) i=1$

$feat_{pos} \leftarrow$  apply part of speech tagging to extract the tag of each and every word as  $wrds(feat_{wrds})$  in the review using nltk toolkit and select only nouns, adverbs and adjectives.

for  $m=1$  to  $No\ of\ words\ in(wrds(feat_{wrds}))$

extract the synset of  $wrds_m$  using the senti-wordnet dictionary.

if ( $wrds_m$  is either (NN. || Adv. || Adj. ) ) && if (size ( $wrds_m$ )  $\geq 1$ )

$$Pos_S = \sum_{i=1}^n PositiveScore(wrds_i) \text{ in Synset}$$

$$Neg_S =$$

$n i=1$

NegativeScore ( $wrds_i$ ) in Synset

End for

Label Annotation

If  $NN\_score >$  and If  $feat_{hash}$  is available

$feat_{label} = 1$

Else If  $NN_{score} > 0$  then  $feat_{label} = 1$  End if

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Table 3. **ALGORITHM 2: Feed Forward Neural Network — Tweet Classification (FFNN-TC)**

Initialize network

$netw_{ini}$  be the initialized network  $netw_{hid}$  be the hidden layer  $netw_{out}$  be the output layer

$netw_{hid} \leftarrow$  for  $i=1$  to  $\text{len}(TW_{tws})+1$  for  $i=1$  to  $netw_{hid}$

$netw_{ini} \leftarrow netw_{hid}$

End For End For

$netw_{out} \leftarrow$  for  $i=1$  to  $\text{len}(netw_{hid})+1$  for  $i=1$  to  $netw_{out}$

$netw_{ini} \leftarrow netw_{hid}$

End For End For Activate

Let  $neu_{wei}$  be weights of neuron Let  $neu_{net}$  be activation of network for  $i=1$  to  $\text{len}(neu_{wei})$

$neu_{net} += neu_{wei} * netw_{ini}$  End for

Forward propagate  $neu_{inp}$  be neuron inputs  $neu_{out}$  be neuron outputs for layer in  $neu_{net}$  for neuron in layer:

$neu_{net} = \text{activate}(\text{neuron}(neu_{wei}))$

$neu_{inp} \leftarrow neu_{out}$

End For Predict

$feat_{pre}$  be predicted results

$feat_{pre} = \text{Forward propagate}(\text{network}, \text{row})$

$feat_{pre} = \max(feat_{pre})$

### III. PERFORMANCE ANALYSIS

In the existing algorithm, either tweets or tweeters alone are taken. But in our proposed approach both the tweets and tweeters for the particular event is considered. For the analysis of the performance, the particular subsets of features achieves the mission of involuntary valuation of trustworthiness. To perform this, the following subsets of features are grouped as follows:

**Text subset:** The features of the text of the messages is considered. The features include:

- Average length of the tweets
- Sentiment-based features
- Features related to URLs
- Hashtags
- User mentions

**Network subset:** The characteristics of the user's social network is considered in these subsets. This subset features includes the following terms:

- Features related to the author's messages



- Particular user’s number of friends
- Particular user’s number of followers

**Propagation subset:**The considered features are based on the propagation along with the following features:

- The fraction of re-tweets
- The total number of tweets

**Top-element subset:** The ration of tweets considered correspondingly the following:

- Contain the most frequent URL
- Most frequent hashtag
- User mention or author

The performance measures to evaluate the proposed

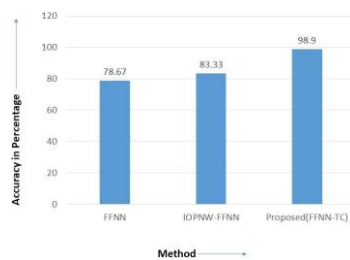


Fig. 2. Comparison of Accuracy

algorithm shows the 78.67% of accuracy. The IOPNW- FFNN algorithm shows the 83.33% which is second most accuracy value among the considered algorithm. The pro- posed FFNN-TC shows the superior accuracy value which is 98.9%.

**PRECISION, RECALL AND F-SCORE COMPAR- ISON:**

The accuracy of the measure is further validated using the parameters like, precision, recall and F-score. Especially in a statistical analysis of binary classification, F- measure is a test accuracy. More over the F-score is interpreted as a weighted average of the precision and recall. method includes True Positive (TP), True Negative (TN),

$$Precision = \frac{TP}{(TP + FP)} \quad - (4)$$

False Positive (FP), False Negative (FN), accuracy, sensitivity, specificity, precision, Recall and F-measure.

**SENSITIVITY, SPECIFICITY:**

Sensitivity is the proportion of true positives that are cor- rectly identified by the classification technique. Similarly, specificity is the proportion of true negatives that are cor- rectly identified.

$$Sensitivity = \frac{TP}{TP + FN} \times 100\% \quad - (1)$$

$$Specificity = \frac{TN}{TN + FP} \times 100\% \quad - (2)$$

**ACCURACY COMPARISON:**

Accuracy is measured by identifying the correctness of the classified results.

$$Accuracy = \frac{TP+TN}{TP+FN+TN+FP} \times 100\% \quad (3)$$

Figure 2 shows the comparison of existing method to the

$$F\ measure = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (6)$$

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

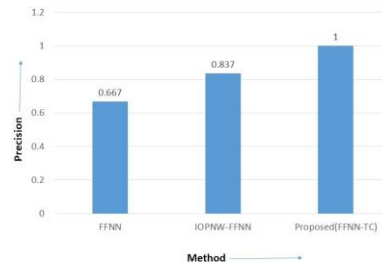


Fig. 3. Comparison of Precision

proposed algorithm. The following existing methods are taken as baseline for the comparison such as simple FFNN (Feed Forward Neural Network) without feature extraction and IOPNW-FFNN(Input Output Positive Negative Weight Feed Forward Neural Network) [17]. The FFNN The Figure 3 shows the comparison of the precision among the exiting algorithms such as FFNN, IOPNW- FFNN to the proposed algorithm FFNN-TC. In this plot the FFNN algorithm shows the least precision value among the others which is 0.667. The second most precision value is belongs to the IOPNW-FFNN which is 0.837. Thus, the proposed algorithm shows the better precision that is 1.

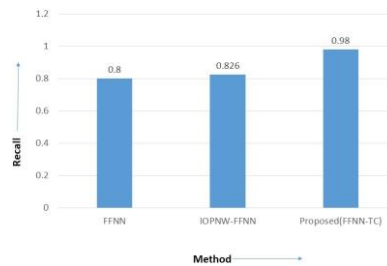


Fig. 4. Comparison of Recall

The comparison of recall value among the FNN, IOPNW-FFNN, and proposed FFNN-TC is shown in figure 4. The FNN algorithm shows the minimum recall value among all the algorithms. The IOPNW-FFNN algorithm shows the second most value which is 0.826. The proposed algorithm shows the uppermost value in the comparison which is 0.98. Finally, the comparison defines the proposed algorithm is having superior features among all the existing algorithms. negative parts that were correctly labeled by the classifier. FP defines the negative parts that were incorrectly labeled as positive and FN indicates the positive parts that were mislabeled as negative.

The TP, TN, FP, FN values listed for existing FFNN algorithm and the proposed algorithm in the above table 4.

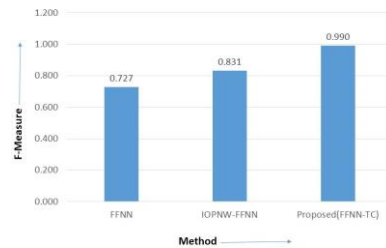


Fig. 5. Comparison of F-Measure

The comparison of F-measure is plotted in the figure 5. Here the maximum F-measure value is attained by the proposed algorithm FFNN-TC which is 0.990. The second most value is shown by the IOPNW-FFNN which is 0.831. Among all the three the FFNN shows the minimum value that is 0.727

TP, TN, FP and FN

TP refer to the positive part tuples that were correctly labeled by the classifier whereas TN represents the negative.

Table 4. Comparison of TP, TN, FP and FN value between Existing and Proposed algorithm.

Algorithm	TP	TN	FP	FN
FFNN	5684	6306	1245	1516
Proposed	1189	1001	0	23

#### IV. CONCLUSION AND FUTURE WORK

A Unique Effective Feature Extraction (EFE) method was established for the extraction of the features from the text of tweets. Truthfulness of the tweets posted by the user and trustworthiness of the sources was discovered using the Feed Forward Neural Network — Tweet Classification (FFNN-TC). The evaluation of the outcome on the real- world data set was demonstrated while comparing it with other truth discovery methods with the concern of efficiency as well as the effectiveness. The applicability of the strategy of feature extraction and the effectiveness of the classification techniques based on various parameter’s has been put forward for the given users and the corresponding texts. A set of 10 attributes are used in effective feature extraction algorithm. It can be further extended to include 25 different features to enhance the performance of classification algorithm. The work can further be extended to make an automatic dynamic system for discovering the truthfulness of the twitter tweets on a given topic and to as- certain the reliability of the user on streaming data. Also, deep learning algorithms can be used in place of feed for- ward neural network to enhance the classification performance of the algorithm.

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