Computer
& Robotics

# Determining COVID-19 Tweet Check-Worthiness: Based On Deep Learning Approach

Hosniyeh SafiArian[a], Mohammad Jafar Tarokh[b,*] , Mohammad Ali Afshar Kazemi[c]

*Department of Management Information Systems, Science and Research  Branch, Islamic Azad University, Tehran, Iran*
*Department of Industrial Engineering,, Khaje Naser Toosi University ,Tehran, Iran*
*Department of Industrial Management,Centeral Tehran Branch, , Islamic Azad University, Tehran, Iran*

Recived 04/September 2021; Accepted 28/ December 2021

**Abstract**

When, we consider the ubiquity of Facebook, twitter, LinkedIn, it is easy to understand how social media is woven into the fabric of our day-to-day activities. It is a suitable tool to find information about  news , events , and different Issues. After corona virus outbreak, it is inspired users to understand pandemic news, mortality statistics and vaccination news. According to evidence, the diffusion of pandemic news on social medium has  increased from 2020 and user face a ton of COVID19 messages. The purpose of this paper is to determine the check-worthiness of news about COVID-19 to identify  and priorities news that need fact-checking. We proposed a method that is called CVMD. We extracted the feature of content. We use the deep learning approach for prediction it means that we model this problem with a binary classification problem. Our proposed method is evaluated by different measures  on twitter dataset and the results show that CVMD method has a high accuracy in prediction rather than other methods.

***Keywords**:* Check-Worthiness,Covid19 ,Deep learning,Diffusion ,Social media

## 1.Introduction

Nowadays, more people are spending sizable chunks of their time in virtual world such as Facebook, LinkedIn and Twitter [1]. They can be a way towards communication and interaction with people from all walks of life. Users can read news with ease and face a ton of messages. They want more likes, more retweets and more followers. Therefore, these medium have a direct impact on our life [2].

Emerging outbreak diseases, such as COVID-19, have a direct effect on using social media for sharing information. In the first few months of 2020, information and news reports about the coronavirus disease (COVID-19) were rapidly published and shared on social media and social networking sites [3].

Users can diffuse  many posts on social media  with out any content verification , as a result of all of this thousands or millions of other users face harmful information. To prevent the undesired consequences of misinformation spread, there is a need to develop tools to assess the validity of social media posts. after corona virus , users face  conspiracy theories about the virus and untested dangerous treatments. Compounded with the negative  effects from the virus alone, the social harms from misinformation spread can be very dangerous  [4].

In this paper, we present our method in tackling the check-worthiness. We make a proposed method for prediction by a set of binaries classify   and deep learning approach can be useful for it. It is called CVMD. Also, we evaluated the proposed method with other classifiers methods on twitter dataset.

This paper is organized as follows: in section 2 we discuss the work related to our research. Proposed method is presented in section 3. In section 4 we evaluate method. Finally, we explain some conclusions and  future works.

* Corresponding Author. Email: mjtarokh@kntu.ac.ir

## 2.Related Work

Check-worthiness and rumor are really important and hot topic on social media. Recently researchers try to identify worthiness and rumor by different methods. In this section, we present the related work into two parts , check-worthiness and rumor detection.

### 2.1.Check-Worthiness

There are many different methods for check-worthiness on social media.The first proposed method to do check-worthiness estimation, i.e., predicting which sentences in a given input text should be prioritized for factchecking, was the ClaimBuster system [5].It is proposed a method for check-worthiness problem. This method is based on some features, and is used SVM classifier for prediction. In [6] is presented a method by similar features. They used multi-classifier system based on a dynamic clustering of data for prediction.In [7] focused on other features , it means that extended the features used by ClaimBuster to include more context, such as the sentence's position in the debate segment, segment sizes, similari-ties between segments, and whether the debate opponent was mentioned.In [8] is proposed a method by embeddings, part of speech tags, and syntactic dependencies. This method used a GRU neural network with attention as a learning model.In [9]improved the work of ClaimBuster by using additional sentiment, tense, and paragraph structure features, to predict if a sentence should be fact-checked. In[10] is presented a method based on used word2vec embedding and a recurrent neural network. According this method, they can acquire 0.182 in mean average precision in a check-worthy sentence retrieval task.In[11] use of LSTM RNN that learned dual token embeddings, domain-specific embeddings and syntactic dependencies.In[12]is proposed base on a feed-forward neural network with two hidden layers which takes as input Standard Universal Sentence Encoder (SUSE) embeddings.

### 2.2.Rumour Detection

In recent years , rumour detection is one of those important topics to researchers focus on. This field is categorized by four segmentations: rumor detection, rumor tracking, rumor stance classification, and rumor veracity classification[13]. The authors[14] proposed a rumor detection model based on a sequential classifier where a tweet is classified as a potential rumor or non-rumor based on data.In [15] proposed a supervised machine learning approach to judge the relevance of new tweets to the known set of rumors.In [16] proposed a tweet latent vector representation of tweets and used the Semantic Textual Similarity (STS) [17]) to assess the relevance of new tweets to the known rumors. Some studies focused on capturing the temporal traits of rumors during their propagation. In [18] proposed a model based on time-series-fitting for the temporal properties of a single feature – tweet volume. In [19] Extended a model based on time-series to capture the variation of a set of social context features over time. In [20] paid attention to the structure of misinformation cascades on Facebook by analyzing comments with links to rumor debunking websites. Through utilizing a message propagation tree where each node represents a text message to classify whether the root of the tree is a rumor or not[21].

## 3.Proposed Method

Examining the retweeting behavior of users at the individual level can provide important information about the dissemination of information at the community level. Tweet $\boldsymbol{tw_i}$ is effective for the user $\boldsymbol{u_i}$ if and only if it leads to a retweeting behavior $\boldsymbol{RT_{tw_i}}$ by the user $\boldsymbol{u_i}$. Measuring the effectiveness of a tweet requires the growth of a model for predicting the individual behavior of users in facing different tweets. Today, the function of social networks has gone beyond entertainment and these networks also operate with applications such as education, information and problem solving. Users often follow related pages to access the latest news and information in their area of interest. According to these functions, in this paper, a method based on the concept of content value of each tweet is used to investigate the retweeting behavior of users. It should be noted that content value is a relative concept and varies for different users. Depending on the field of activity and the amount of information and expertise, a tweet can have different content value for different users. To evaluate the content value of each tweet according to the retweeting behavior of users, in this study, a content-based method is presented.

Definition 1: Retweeting behavior: If a microblog is considered as a graph $\boldsymbol{G} = (\boldsymbol{V}, \boldsymbol{E})$, V is a set of users and E is a set of communications as a following. The following relationship between two users $\boldsymbol{U_i}, \boldsymbol{U_j}$as $\boldsymbol{U_i} \rightarrow \boldsymbol{U_j}$ indicates the following of user j by user i. Retweet behavior is represented as a triad $\boldsymbol{U_j}, \boldsymbol{tw_i}, \boldsymbol{t}$ , which means retweeting the tweet belonging to user $\boldsymbol{U_j}$, at time t. Each user $\boldsymbol{U_i}$has two sets of retweeted tweets $\boldsymbol{RP_{u_i}}$ and a list of posted tweets $\boldsymbol{p_{u_i}}$. The retweeting behavior of user $\boldsymbol{U_i}$ when viewing a tweet $\boldsymbol{tw_i}$ is displayed as a binary value $y(tw_i, u_i) = \{0,1\}$ . $\boldsymbol{y(tw_i, U_i) = 0}$ indicates that tweet $\boldsymbol{tw_i}$ was not retweeted by $\boldsymbol{U_i}$, and $\boldsymbol{y(tw_i, U_i) = 1}$ indicates that $\boldsymbol{tw_i}$ tweet was retweeted by $\boldsymbol{U_i}$.

Definition 2: Problem of retweeting behavior prediction- For each tweet $\boldsymbol{tw_i} \in \boldsymbol{P}$ (P, set of tweets), $\boldsymbol{T} \in \boldsymbol{t}$ (T, time) and each user $u_i \in U$ (U, set of users) there is a function $\delta_t(tw, u_i)$ whose value is 1 if and only if a behavior (event) of retweeting $\boldsymbol{tw_i}$by user $\boldsymbol{U_i}$ at time $t' > t$ is occurred, otherwise the value of this function is zero. The problem of predicting the retweeting behavior of the user in the viewing a tweet is predicting the value of this function for $\forall tw \in P$and $\forall u_i \in U$.

### 3.1. Measuring the Content Value of a Tweet

There are several informal definitions of content value in various sources. In this study, the content value of a tweet refers to the amount of attention that a tweet brings to its audience. This attention is shown in the form of retweeting, replying or mentioning the event by the user. As mentioned, for this end, the proposed method is based on content-based measurement and tweet statistics, which are discussed below.

#### 3.1.1.Checking the Novelty of a Tweet

For examining the content of a tweet in order to measure the content value, a lot of work has been done in the field of news. Many features are provided for reviewing the content, including a series of features related to the message (length, questionable or not, etc.), tweeter (number of followers, year of registration, etc.), topic of the message. These methods perform classification, thematic ranking and similarity measurements by lexical analysis of words and statistical techniques. In the proposed method, new features are considered for online measurement of the value of information based on content and function of the problem. The novelty of a tweet is an important feature in its content value. By definition, a tweet $\boldsymbol{tw_i}$ is new to the user $\boldsymbol{U_i}$ if it is related to interests of $\boldsymbol{U_i}$ and unknown to him. Methods are mentioned for calculating unexpected information of web page retrieval in [22] and for unexpected news in [23].

$\boldsymbol{p_{u_i}} = \{\boldsymbol{tw_1}, \boldsymbol{tw_2}, \dots \boldsymbol{tw_n}\}$ is the set of tweets created by user $\boldsymbol{U_i}$. As stated in the definition of a tweet, the tweet must first be related to the user's interests. In order to determine the relationship of a tweet with the areas of interest to the user, in most of the work done, the TF-IDF method and the cosine of the angle between the words vector $\boldsymbol{tw_i}$ and $\boldsymbol{p_{u_i}}$ are used. This method has low accuracy due to the variety of words used. For this purpose, using the Latent Dirichlet Allocation topic modeling method, different topics in the texts can be categorized. Each topic contains a set of words $\boldsymbol{M_{topic\#}} = \{\boldsymbol{w_1}, \boldsymbol{w_2}, \dots \boldsymbol{w_n}\}$ ,the probability of which is specified in the relevant topic. To increase the accuracy of measuring the relationship between tweet $\boldsymbol{tw_i}$ and the set of tweets created by user $\boldsymbol{U_i}$, $\boldsymbol{p_{u_i}} = \{\boldsymbol{tw_1}, \boldsymbol{tw_2}, \dots \boldsymbol{tw_n}\}$, thematic similarity is measured using equation (1):

$$\mathrm{topic} - \mathrm{sim}(\mathrm{tw_i}, \mathrm{P_{u_i}}) = \frac{\mathrm{topic_{tw_i}} . \mathrm{topic_{P_{u_i}}}}{||\mathrm{topic_{tw_i}}|| . ||\mathrm{topic_{P_{u_i}}}||} \quad (1)$$

Using the LDA method, the topic of each tweet can be obtained in the form of a topic containing a group of words that are likely to occur in this topic. As a result, using this method, the topic of the tweet is found and the category of words related to this topic is determined. If the tweet $tw_i$ is first deleted by a standard method of resident words and the set $tw_i = \{w_1, w_2, \dots, w_m\}$is a set of words used in the tweet $tw_i$, and the set $M_{topic\#} = \{w_1, w_2, \dots, w_L\}$is a set of words related to the topic $tw_i$, the following relationship determines the novelty of the tweet:

$$\mathrm{Novelty} = \frac{\mathrm{topic} - \mathrm{sim}(\mathrm{tw_i}, \mathrm{P_{u_i}})}{\mathrm{sim}(\mathrm{M_{topic\#}} - \{\mathrm{M_{topic\#}} \cap \mathrm{tw_i}\}, \mathrm{P_{u_i}})} \quad (2)$$

In equation (2), $M_{topic\#} - \{M_{topic\#} \cap tw_i\}$is a set of related words that is not in the tweet. As can be seen in Equation (2), the more similar the topic-related words are to the topics discussed by the user, the less likely it is that the tweet will be novel. The novelty of the tweet is by definition directly related to the user-created tweets.

### 3.1.2 Checking the Location of a Tweet

In addition to the novelty of the tweet, the relation of a tweet with the user can be a key point in the content value of this tweet by the user. In this paper, in addition to calculating the lexical similarity between tweet $\boldsymbol{tw_i}$ and the tweets used by the user, a geographical similarity is considered. Typically, tweets that address regional issues are more effective than tweets from other regions. Therefore, in this paper, maxmind data set including 4 million names of cities and different regions along with additional information about the country, location, etc. is used to find words related to cities and geographical regions. To find words related to cities from the tweet $\boldsymbol{tw_i}$, all the words in the tweet are used except for the extra words (even hashtags with the # symbol removed). If $\boldsymbol{LOC_{tw_i}}$ is a set of cities plus the country and region used in the tweet and $\boldsymbol{LOC_{U_i}}$ is a set of cities, countries and regions used by the user $\boldsymbol{U_i}$ in all created tweets, the relationship (3) indicates the geographical relationship between the tweet $\boldsymbol{tw_i}$ and the user $\boldsymbol{U_i}$:

$$\underset{\mathrm{u_i \in U \& tw_i \in P}}{|(\mathrm{Loc_{tw_i}} \cap \mathrm{Loc_{u_i}})|} \quad (3)$$

In (Gou et al., 2011) it is shown that logical news and information can be disseminated more than positive events. Therefore, in order to analyze the content of a tweet to measure the content value, in this paper, the negativity of the tweet is determined. In the method used to measure the negative value of the tweet, an attempt was made to use a simple method for online execution. The University of Michigan Twitter dataset was used for this purpose. In this data set, 1,578,627 labeled tweets (label 1 for positive tweets and 0 for negative tweets) were collected. Using the Python NLTK natural language processing tool kit and the naïve bayes method, sentiment analysis was conducted. To obtain the separator, 1/10 of the data was used for testing and the rest for training. As a preprocessing, two steps of tokenization and normalization are performed on the data set. Emoticons and abbreviations (OMG, ASAP, WTF…) are considered as separate tokens in the tokenization step. In the normalization phase, uppercase words are converted to lowercase letters (for example I LOVE it !!!!) and the repetition of letters in tweets (for example I am happyyyy !!) is removed.

### 3.1.3 Checking the Growth of a Tweet

Another parameter that determines the content value of a tweet is the growth of the tweet's topic. Tweet topics taken from posts outside the microblog environment can have a direct impact on the retweeting behavior of the tweet. In this work, using the LDA method mentioned above, topics related to a tweet are extracted. The growth rate of the tweet topic over a period of time (24 hours) is calculated using Equation (4):
In (4), $\boldsymbol{M_{topic\#}}$is a set of words related to the topic of the tweet $\boldsymbol{tw_i}$and # $\boldsymbol{tw_{w_i}^{t-24}}$ is number of tweets from the last 24 hours that contain the words $\boldsymbol{tw_i \epsilon M_{topic\#}}$ for all tweets $\forall \boldsymbol{tw_i \epsilon p}$ .

$$\boldsymbol{Topic_{growth}} = \left[\frac{\mathbf{1}}{\mathbf{24}} \left(\frac{\sum_{w_{i \in M_{topic\#}}} \#\boldsymbol{tW_{w_i}^{t}} - \sum_{w_{i \in M_{topic\#}}} \#\boldsymbol{tw_{w_i}^{t-24}}}{\sum_{w_{i \in M_{topic\#}}} \#\boldsymbol{tw_{w_i}^{t-24}}}\right.\right] \times \mathbf{100} \quad (4)$$

### 3.1. 4 Tweeter Credibility

The tweet feature is also used to complete the content value of the tweet. This feature was selected to complement the content in such a way that it can be used online and efficiently. Many features have been used to predict retweeting behavior in numerous articles, however, in selecting these features, two aspects of operational capability and relevance to content value were considered. According to the retweeting statistics of a post, a feature is introduced which in this article is called the weight of a tweet. The weight of the tweet is directly proportional to the credibility of the tweeter and the users who retweeted the tweet. If $U_{tw_i}^{RT} = \{u_1, u_2, \ldots, u_R\}$is the set of users who retweeted the tweet $\boldsymbol{tw_i}$ by time t, equation (5) determines the weight of the tweet:

$$\boldsymbol{weight}(\boldsymbol{tw_i}, \boldsymbol{t}) = \left[ \sum_{u_j \in U_{tw_i}^{RT}} \boldsymbol{log}\left(\frac{\#\boldsymbol{f}(\boldsymbol{u_j})}{\#\boldsymbol{E}(\boldsymbol{u_j})}\right) + \boldsymbol{log}\left(\frac{\#\boldsymbol{f}(\boldsymbol{Au_{tw_i}})}{\#\boldsymbol{E}(\boldsymbol{Au_{tw_i}})}\right) \right] \times (\boldsymbol{t} - \boldsymbol{t_{tw_i}})^{-\boldsymbol{\beta}} \tag{5}$$

$\#f(u_j)$ and $\#E(u_j)$ are the number followers of the user $\boldsymbol{U_j}$ and the number of followings by the user $\boldsymbol{U_j}$, respectively. t indicates the calculation time and $\boldsymbol{Au_{tw_i}}$ indicates the tweeter of tweet $\boldsymbol{tw_i}$. Due to the mutual following relationship, it is not possible to determine the user or tweeter credibility only based on #. The higher the number of followers of user $\boldsymbol{U_j}$ than the number of followings by user $\boldsymbol{U_j}$, the greater the credibility of user $\boldsymbol{U_j}$.

One of the most important and decisive aspects for the content value is the age of the tweet. According to the evaluation data set of this article, the rate of retweeting a tweet is very similar to the power point in terms of its age. β is the power of the time elapsed since the creation of the tweet $\boldsymbol{tw_i}$, which is applied to the weight of the tweet according to the power point. Since a tweet is created, the weight and content value of that tweet decreases over time.

### 3.2 Effective Learning Using a Deep Learning-Based Method

In this paper, using different architectures, a deep learning model is presented to develop a predictive system for predicting user's retweeting behavior. In the training step, a deep auto-encoder algorithm is trained using normal network data to generate the initial parameters. The basic parameters include weight and bias, and this algorithm trains a deep representation of normal observations. These parameters are used as an initial step in training a standard deep feed forward neural network (DFFNN) to learn existing feature coefficients as well as predict future user behaviors in facing a post. In the experimental step, the standard deep feed forward neural network is used to learn the coefficients and form a classification. The various hidden nodes in this technique learn the representation of deep features professionally and receive the most important features by transforming the high-dimensional data to the low-dimensional ones based on the reduction of the hidden layer. The details of the proposed method are described in detail in the following.

#### 3.2.1 Phases of learning and Testing of Retweeting Behavior Prediction System Based on Deep Learning

The Deep Feed Forward Neural Network[24] and the Deep Auto-Encoder[25] discussed in the different resources are the basic mechanisms for predicting retweeting behavior of users based on deep learning. The structure of the deep feed forward neural network and deep auto-encoder network is shown in Figure1[26].

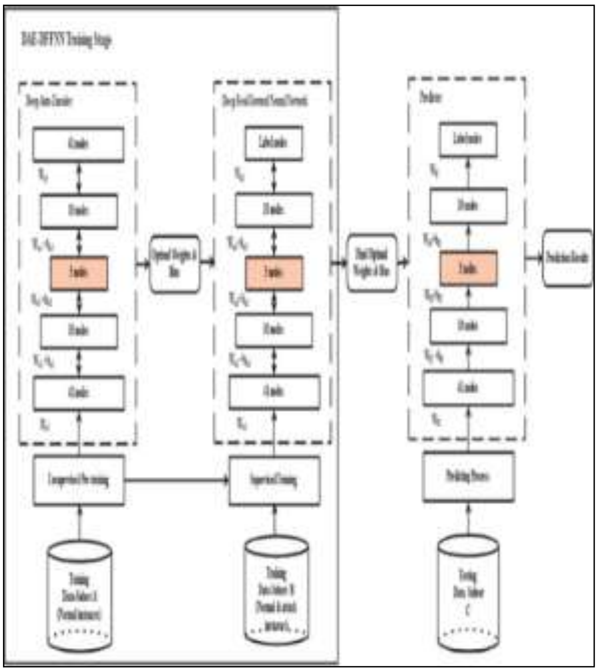

Fig1: The structure of the DAE-DFFFN network

In the learning phase, the normal learning dataset without label E, the learning dataset with label F, in which EGF is a deep auto-encoder with a single-layer bottleneck containing just normal data (E) that they don’t have any unusual vectors for learning, is trained and it covers the most important features for displaying normal patterns. This training with all the data, where the input to the network (Z (i)) passes by three hidden layers, including a bottleneck for building (Zˆ (i)), is done where We, Wn and Wf are the weights of deep feed forward neural network, the deep auto-encoder and Final Prediction Model described in Figure 1.

In the encoding step, the input layer is processed in the first hidden layer. In the bottleneck step, a low-dimensional nonlinear transformation of the input feature is performed to extract features effective in users' retweeting decision. Then, in the decoding step, the last hidden layer in the bottleneck feature is used to approximate the input repetition Then the back propagation of stochastic gradient descent is used to reduce the loss function or the cost function, ie the mean square error between (x (i)) and (xˆ (i)). A key process for unsupervised learning of predicting user retweeting behavior based on the proposed deep learning is presented in Figure 2:

```
Input: training dataset (A) with n umber of samples (n) of
  (x^(i)), where i ∈ (1, ...., n).
Output: parameters θ = (W, b)
Begin
  Initialize (W, b);
    repeat
      For each record (x^(i)), do
        compute the activation (z^(i)) in/at hidden layer and
        give output (x̂^(i)) to outhe tput layer.
        compute the training error (E(x^(i), x̂^(i)).
        Back-propagate E and update parameters
        θ = (W, b);
    End
until converged
end
```

Fig2: Unsupervised learning phase for predicting republishing behavior of users based on deep learning

After the training model for the starting point and initialization of weight and bias parameters for learning for the deep network of supervised learning and setting network model using labeled learning datasets (F ((x (i)), (y (i)) ))) is used. The similar steps as before learn and validate the method of predicting user retweeting behavior based on the proposed deep learning on data set B, which includes data on retweeting and non-retweeting behaviors to test the accuracy of the proposed method.

In the test phase, next the parameters are automatically trained in the learning phase, the sample of the new dataset $(\boldsymbol{G} \subsetneq [\boldsymbol{E}, \boldsymbol{F}])$ based on the model is tested.

## 4-Evaluation

In this Section, we explain in details how the datasets were collected and how the experiment were conducted. We collected Three different datasets from twitter about Covid-19 and performed different experiments on them to see to what extent we can determine COVID-19 tweet check-worthiness in the Twitter social network and maximize diffusion.

### 4-1 Dataset

In this section we will describe in more detail which datasets are used. Twitter is a suitable media that generate many million tweets per day. We select three datasets. Having three different dataset allows us to test our methods on different conditions to evaluate how well our methods can be generalized. The detail of dataset is showed in table 1:

Table 1
The detail of dataset

| Dataset | Description | # Tweets | # User | # Retweet |
|---|---|---|---|---|
| Covid 19 | Outbreak Corona virus in China | 45801 | 466679 | 7800981 |
| mortality | Mortality rate in corona virus | 670098 | 572789 | 8700964 |
| vaccination | Producing vaccine | 254209 | 5764001 | 1409341 |

### 4-2 Evaluation Metrics

We use Specificity, accuracy and F1-measures to evaluate the performance of the method. The Specificity, accuracy and f-measure are calculated according to equation 6 ,7 , 8 ,9and 10 :

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{6}$$

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FN} + \text{FP} + \text{TN}} \tag{7}$$

$$\text{Precison} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (8)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (9)$$

$$\text{Fmeasure} = \frac{2 * (\text{Precison} * \text{recall})}{\text{Precison} + \text{recall}} \quad (10)$$

In equation 6 , 7 ,8 ,9and 10 variables are showed by table 2.

Tabel2
The variable of recall and precision

| | Prediction Condition | | |
|---|---|---|---|
| True Condition | Condition Positive | TRUE Positive | False Negative |
| | Condition Negative | False Positive | TRUE Negative |

### 4.3. The Result of Evaluation

In this section, the proposed method is compared with other methods based on Specificity, accuracy and F-measure. As shown in table (3), the CVMD performed best. In terms of Specificity, Perceptron has the best performance after CVMD on average. In this section, the Random Forest method has the worst performance.

Table 3
Comparison of the Specificity criteria of the proposed method with other methods

| Specificity Measure | Average | First Dataset | Second Dataset | Third Dataset |
|---|---|---|---|---|
| CVMD | 0.684246633 | 0.6002189 | 0.7590701 | 0.6934509 |
| Perceptron | 0.5539615 | 0.569076 | 0.5239064 | 0.5689021 |
| Random Forest | 0.4048449 | 0.45689 | 0.3678907 | 0.389754 |
| SVM | 0.424366767 | 0.3709853 | 0.478659 | 0.423456 |

As can be seen in table (4) ,the CVMD method has performed best in accuracy, also the second most great performance is SVM while the worst performance is Random Forest.

Table 4
Comparison of the accuracy criteria of the proposed method with other methods

| accuracy Measure | Average | First Dataset | Second Dataset | Third Dataset |
|---|---|---|---|---|
| CVMD | 0.767603923 | 0.760981 | 0.7987642 | 0.7430666 |
| Perceptron | 0.495917 | 0.58998 | 0.4768 | 0.420971 |
| Random Forest | 0.399862967 | 0.45689 | 0.3856009 | 0.357098 |
| SVM | 0.593193667 | 0.580123 | 0.562678 | 0.63678 |

According to table (5), the F-measure of different methods are compared. The F-measure is weighted average of precision and recall. Proposed method has best performance while Random Forest has worst performance.

Table 5
Comparison of the F-measure criteria of the proposed method with other methods

| F- Measure | Average | First Dataset | Second Dataset | Third Dataset |
|---|---|---|---|---|
| CVMD | 4.63 | 4.76 | 4.61 | 4.53 |
| Perceptron | 2.91 | 3.1 | 2.98 | 2.65 |
| Random Forest | 1.81 | 1.78 | 1.99 | 1.67 |
| SVM | 2.54 | 2.89 | 2.06 | 2.68 |

## 5.Conclusion

The social media is a convenient way to find new information about events and news. Nowadays, users face the tone of information however they don't know which is true or false. In this paper, we proposed a model based on content. In other words, we made a model based on different features of content. It is called CVMD .We tried to use a deep learning model for prediction. In the evaluation part , we compared with proposed model with other models and CVMD model has best accuracy and performance.Our proposed method can be extended from views in long term. YouTube is a kind of important social media that users can see movies. This content has different features rather than text. This can be a new project that we should focus on. Also users change their ideas for diversity issues.

This is a sort of dynamic feature that we should pay attention to it for new model in the future.

**Reference**


[1] Shearer, E., & Mitchell, A. (2021). News use across social media platforms in 2020.

[2] Appel, G., Grewal, L., Hadi, R., & Stephen, A. T. (2020). The future of social media in marketing. Journal of the Academy of Marketing Science, 48(1), 79-95.

[3] Shearer, E., & Mitchell, A. (2021). News use across social media platforms in 2020.

[4] Cuan-Baltazar, J. Y., Muñoz-Perez, M. J., Robledo-Vega, C., Pérez-Zepeda, M. F., & Soto-Vega, E. (2020). Misinformation of COVID-19 on the internet: infodemiology study. JMIR public health and surveillance, 6(2), e18444.

[5] Hassan, N., Arslan, F., Li, C., & Tremayne, M. (2017, August). Toward automated fact-checking: Detecting check-worthy factual claims by claimbuster. In Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (pp. 1803-1812).

[6] Patwari, A., Goldwasser, D., & Bagchi, S. (2017, November). Tathya: A multi-classifier system for detecting check-worthy statements in political debates. In Proceedings of the 2017 ACM on Conference on Information and Knowledge Management (pp. 2259-2262).

[7] Nikolov, A., Martino, G. D. S., Koychev, I., & Nakov, P. (2020). Team alex at clef checkthat! 2020: Identifying check-worthy tweets with transformer models. arXiv preprint arXiv:2009.02931.

[8] Hansen, C., Hansen, C., Simonsen, J. G., & Lioma, C. (2018). The Copenhagen Team Participation in the Check-Worthiness Task of the Competition of Automatic Identification and Verification of Claims in Political Debates of the CLEF-2018 CheckThat! Lab. In CLEF (Working Notes).

[9] Gencheva, P., Nakov, P., Màrquez, L., Barrón-Cedeño, A., & Koychev, I. (2017, September). A context-aware approach for detecting worth-checking claims in political debates. In Proceedings of the International Conference Recent Advances in Natural Language Processing, RANLP 2017 (pp. 267-276).

[10] Zuo, C., Karakas, A., & Banerjee, R. (2018, September). A hybrid recognition system for check-worthy claims using heuristics and supervised learning. In CEUR workshop proceedings (Vol. 2125).

[11] Hansen, C., Hansen, C., Simonsen, J. G., & Lioma, C. (2019, September). Neural Weakly Supervised Fact Check-Worthiness Detection with Contrastive Sampling-Based Ranking Loss. In CLEF (Working Notes).

[12] Favano, L., Carman, M. J., & Lanzi, P. L. (2019). TheEarthIsFlat's Submission to CLEF'19CheckThat! Challenge. In Working Notes of CLEF 2019-Conference and Labs of the Evaluation Forum (Vol. 2380, pp. 1-11). CEUR-WS. org.

[13] Zubiaga, A., Aker, A., Bontcheva, K., Liakata, M., & Procter, R. (2018). Detection and resolution of rumours in social media: A survey. ACM Computing Surveys (CSUR), 51(2), 1-36.

[14] Derczynski, L., Bontcheva, K., Liakata, M., Procter, R., Hoi, G. W. S., & Zubiaga, A. (2017). SemEval-2017 Task 8: RumourEval: Determining rumour veracity and support for rumours. arXiv preprint arXiv:1704.05972.

[15] Qazvinian, V., Rosengren, E., Radev, D., & Mei, Q. (2011, July). Rumor has it: Identifying misinformation in microblogs. In Proceedings of the 2011 Conference on Empirical Methods in Natural Language Processing (pp. 1589-1599).

[16] Hamidian, S., & Diab, M. (2016, June). Rumor identification and belief investigation on twitter. In Proceedings of the 7th Workshop on computational approaches to subjectivity, sentiment and social media analysis (pp. 3-8).

[17] Guo, W., & Diab, M. (2012, July). Modeling sentences in the latent space. In Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers) (pp. 864-872).

[18] Kwon, S., Cha, M., Jung, K., Chen, W., & Wang, Y. (2013, December). Prominent features of rumor propagation in online social media. In 2013 IEEE 13th international conference on data mining (pp. 1103-1108). IEEE.

[19] Ma, J., Gao, W., Wei, Z., Lu, Y., & Wong, K. F. (2015, October). Detect rumors using time series of social context information on microblogging websites. In Proceedings of the 24th ACM international on conference on information and knowledge management (pp. 1751-1754).

[20] Friggeri, A., Adamic, L., Eckles, D., & Cheng, J. (2014, May). Rumor cascades. In Proceedings of the International AAAI Conference on Web and Social Media (Vol. 8, No. 1).

[21] Wu, K., Yang, S., & Zhu, K. Q. (2015, April). False rumors detection on sina weibo by propagation structures. In 2015 IEEE 31st international conference on data engineering (pp. 651-662). IEEE.

[22] Wu, B., & Shen, H. (2015). Analyzing and predicting news popularity on Twitter. International Journal of Information Management, 35(6), 702-711.

[23] Alshaabi, T., Dewhurst, D. R., Minot, J. R., Arnold, M. V., Adams, J. L., Danforth, C. M., & Dodds, P. S. (2020). The growing echo chamber of social media: Measuring temporal and social contagion dynamics for over 150 languages on Twitter for 2009–2020. arXiv preprint arXiv:2003.03667.

[24] Glorot, X., & Bengio, Y. (2010, March). Understanding the difficulty of training deep feedforward neural networks. In *Proceedings of the thirteenth international conference on artificial intelligence and statistics* (pp. 249-256). JMLR Workshop and Conference Proceedings.

[25] Gomede, E., de Barros, R. M., & de Souza Mendes, L. (2021). Deep auto encoders to adaptive e-learning recommender system. Computers and Education: Artificial Intelligence, 2, 100009.

[26] Muna, A. H., Moustafa, N., & Sitnikova, E. (2018). Identification of malicious activities in industrial internet of things based on deep learning models. Journal of Information security and applications, 41, 1-11.