Detection and Prediction of Rumor Microblogs from Social Networks using Ontology

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Abstract— Social network innovations have lead the people to communicate at any time easily. This type of accessibility would provide the users to transmit the information quickly. As its one side is admirable, the other side may leads to problems due to propagation of unverified information. Finding the veracity of such information in social networks has become a real challenge. Earlier rumor detection models concentrated on limited features. But, in many cases it is not possible to discriminate rumor message and normal message using the limited features.

In this paper, a novel RDS architecture which recognizes rumor contents in social networking sites is proposed. The Rumor Detection System (RDS) which makes use of Set of pre-defined rules, WordNet Ontology and Probabilistic algorithms namely (TreeAlignment & STL) for deriving rumor words and tagging a post as rumor or non-rumor. RDS captures small posts containing text based on certain threshold value. This threshold value is checked using the pre-defined set of rumor words (Table 1). We also take into consideration the social interactions of posts such as likes and dislikes. If post satisfies a certain threshold value, it is tagged as rumor post. We further compare the proposed system with existing systems which uses ICDM and CPNM techniques and it shows significantly better results higher than state-of-the-art techniques.

Keywords— Rumor, microblogs, Social Networking Sites (SNS), Rumor Detection System (RDS), Ontology

I. INTRODUCTION

In our day to day life social media plays a significant role. Nowadays majority of the people get news online. When the internet was not in existence the main sources of news events were newspapers and T V news channels. The quick development in social media platforms can propagate news in the society very fast. Most of the times the news or information posted in this media is unverified. According to recent studies 62 percent of people receive news from social media. Social networks consists several communities which may share malicious information such as virus and rumors which causes damage to the society. Rumor is untrue information which is broadcasted in different social networking communities. It is also defined as 'disinformation', which is intentionally intended to cheat and can have serious consequences. Currently, mathematical demonstration of rumor is a significant area of research. It is taken-up by most of researchers as a challenge to identify rumors in SNS. One of the DK classical model which is designed by Daley and Kendall in 1965 was the basic conventional rumor model [17]. This model categorizes users into three different classes, i) unknown about the rumor, ii) the users who has little idea of rumor and adopts precautionary measures iii) and can have knowledge of rumor, but do not diffuse it. Most prior rumor dissemination models primarily viewed as rumor circulatory that meets high frequency rate. Rumor spreading is strictly associated with individual psychological ability of user. Most of the previous studies in Social Network Sites are unable to find new rumor words. In our research work we would like to detect rumor words from short messages in social network sites. Many research studies overlook the combining of ontology to detect rumors from short messages.

II. PROBLEM STATEMENT AND RELATED WORK

Many of the Rumor Detection models could not able to detect rumor at an early stage in Social Networking Sites. Existing Rumor Detection models were built to detect rumor by comparing with the data sets collected from face book, twitter, weibo Sina and others. These Rumor Detection models use machine learning, Deep learning, Graph theory structure and other approaches (They require extensive training, which is time consuming process). Further emerging rumor is not detected and hence fails to predict at an early stage.

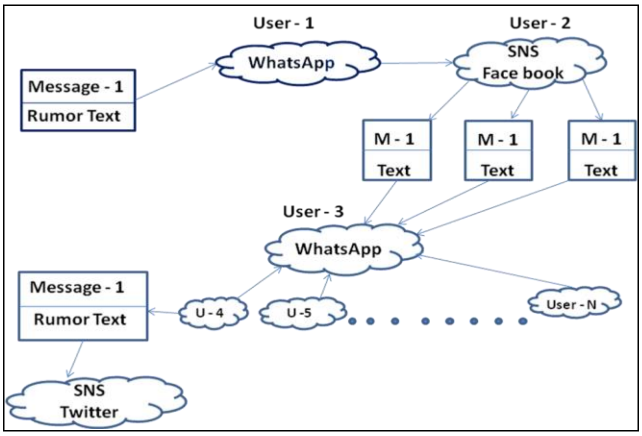

Fig 1: Rumor spreading scenario

The consequence of this rumor messages leads to social disaster. The propagation of rumor messages in various social networking sites is depicted in the below picture. Multi lingual rumor are also failed to detect by existing Rumor Detection models. Note: Many of the Rumor Detection models specifically built to surveillance rumor words in a specific situation or context in Social Networking Sites.

As shown in above fig.1, the messages will pass from one user to another user in the social media. The user may send to N number of his friends. If the message contains any rumor content, such content propagates in social networking sites and causes social disaster. To void this we must stop the post/ message at an early stage

The main goal to design rumor detection model is to find a message posted in social media is rumor or not. Jing Ma et al [18] developed models which classify the propagation as tree to evaluate likeliness among the trees to say the message is rumor or not. Nivetha et al [19] applied two-step process to find the rumor. In the first step inserting observing nodes to report the receiving data and step two to recognize rumor post applying the GSSS algorithm. Ma et al. [20] uses various RNN methods to the repost sequence. K. Wu et al [21] applied the hybrid kernel SVM classification to identify rumor, which combines the CA – LPT and the random walk graph kernel. Yu et al. [22] adopted the CNN model on the repost sequence to find the interactions with high features. Ruchansky et al. [23] combines three features: the article script, user reactions on the script, and the source user who was stimulating the post/message.

III. PROPOSED RD FRAMEWORK

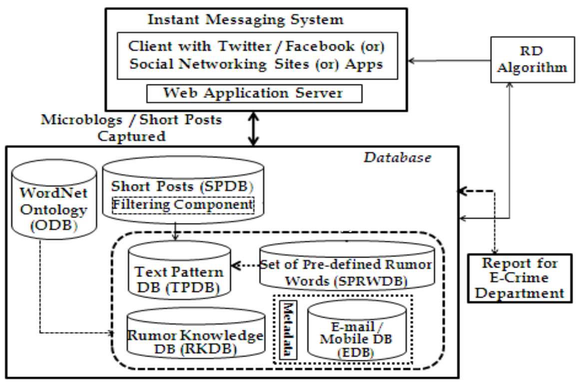

Fig 2: Framework for Rumor Detection.

The probabilistic learning method OBIE predicts the domain to which the rumor words belongs [16]. Different database tables namely SPDB, TPDB, EIDB, ODB, SPRWDB, RKDB, EDB and Metadata were used in the design of Framework shown in Fig. 2. In this Framework, the online messages/posts which were communicated among the user/friends (chat mates) are stored in SPDB (Short Posts database). ODB (Ontology Database) is a lexical database that identifies terms, Synonyms, Concepts, Taxonomy (concept hierarchy), relations, Axioms and Rules [23] [3].

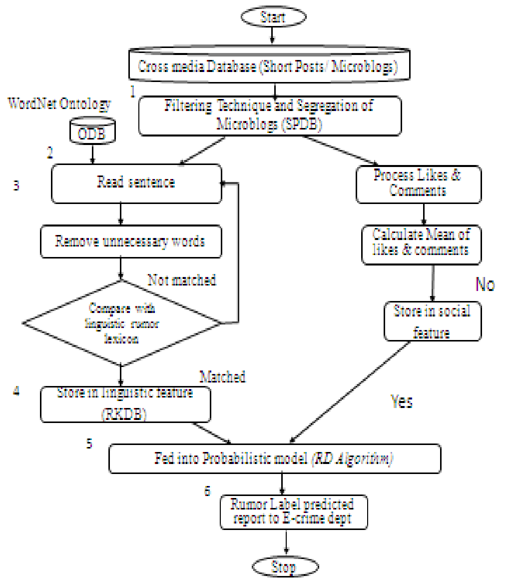

Fig 3: Flowchart for Rumor Detection

The steps involved in pseudo code algorithm for rumor detection is shown in Fig. 3, are illustrated as follows:

1. The first step is to capture the short posts or microblogs sent between users of Social Networking Site (SNS). These messages are saved in the database.
   a) In this step a single text post is taken. This text message is transformed to plain text removing stop-words (such as articles, preposition).
   b) Next, we will check social interface to calculate number of comments and like.
2. a) This is main step in which it will compare plain text with linguistic rumor lexicon (Table 1) to find out number of rumor words present in text and store result into RKDB.
   b) In this step, we calculate the mean value of comments and likes and stored it in feature set table.

$$M_{L,C} = \frac{\text{Total No. of Likes + Comments}}{2} \quad \text{....... (1)}$$

3. a) All the textual features are fed into the probabilistic model to predict whether a post is a rumor or no rumor. It uses maximum likelihood estimates for the detection.
   b) Social feature is fed into social model (EIDB) and compared with threshold value.
4. In the last step results are displayed to user if and only if user posts satisfies all the threshold values then only his/her posts will tagged as rumor and if the user is rumoured then will send recommendation to user regarding rumor management.

3.1 Root Taxonomy Construction STL Algorithm

Wang Wei and et al. had developed Similarity Taxonomy Learning (STL), this algorithm detects for the most alike topics of the current "root" and removes the words under the root which are not satisfy the condition of the difference of *KL* divergence. This algorithm starts with a primary value as the root node and search for the top *n* most identical values according to (*dis*)similarity measures. The parameters used in the algorithm are given below:

- *N* — the tot. no. of values (domains i.e. root words).
- *Mc* — the max. no. of sub-nodes (words) for a certain node (root node, i.e. domain/topic).
- *THs* and *THd* — the thresholds for similarity and divergence measures.
- *THn* — the noise factor, defined by the difference between two *KL* divergence measures *DKL (P||Q)* and *DKL (Q||P).*
- I — Maximum number of iterations.

The parameters *THs, THd, THn* are user-specified values, which can be changed to obtain desirable precision and accuracy. Particularly, in our experiment, we noticed that setting *THs, THd,* and *THn* within some narrow range results in negligible variation of precision values. The pair wise measures of Cosine similarity, JS divergence, and KL divergence are collectively denoted as the ***Ms*** Matrix. But we have used KL divergence for *dis* (similarity). The algorithm will terminate according to the conditions specified in the while loop. The pseudo code for STL algorithm is shown in Fig. 4.

Table 1**:** Depicts set of knowledge based pre-defined logical rules internally supported with WordNet Ontology for Linguistic rumor lexicon

RULE 1 (Pre-defined Knowledge based rules)	
Type of rumor (Domain)	words to be detected in a given context
Political rumor ➜	Assertive, wedding, won, humiliate, influential
Share Market rumor ➜	Falling down, drastically, rapidly, strikes, distress
Decease rumor ➜	Health services interrupt, collateral, disruption, weird, vicious
Anticipatory rumor ➜	Expectant, looking forward to, vigilant, anxious, impatient
RULE 2	
Social Interaction (Mean Value)	No. of likes, dislikes and comments
RULE 3(threshold value)	
The user-defined threshold value will be checked for stem words that may fit in to several domains, using precision & Mean Values. (RD algorithm)	

3.2. OBIE Model for Root word (Domain) Extraction using Treealignment algorithm

Ontology refers to intelligent information contains a set of words within a domain and predicts the association among those words within the specific domain and among the other successive domain(s). The hidden rumor words are explored from the short posts or microblogs using pre-defined logical rules (SPRWDB) given in Table I, and rumor domain words

Algorithm1. STL *(root)*
Require: Initialize *V, Ms, I, THs, THd, THn,* and *Mc.*
Ensure: A terminological ontology with "broader" and "Related" relation.

```
Initialize V, Ms, I, THs, THd, THn, and Mc;
while (i < I and V is not empty) do
Add current root into V ;
Select most similar Mc nodes (words) of root word (topic) from Ms;
Add similar nodes into Vtemp;
Remove nodes in Vtemp against//similarity and divergence
for (all nodes n ,in Vtemp) do
if (Sim(ni, root) > Sim(ni, Sibling(root))) then
Assert broader relations between root and topic ni;
else default
Assert related relation between root and topic ni;
end if
Move topic ni from Vtemp to V ;
Increment i by 1;
end for
Remove current root from V ;
end while
```

Fig. 4: Pseudo code of STL algorithm that finds root word from domain (topics) with the use of tunable pre-defined threshold value(s)

Algorithm 2 TreeAlignment (RootNode, node) for Domain (Topic) extraction using Ontology concepts
Require: Initialize RootNode, Node(s), and MinThreshold value
Ensure: Domain (topic) extraction from stem words.

```
for (int i:1 to numDomainTopic {
//traverse tree for DomainTopic i
NumLevels=2; //size of tree is 2(parent & child)
for (int j:1 to NumLevels){
RootNode[ ]Nodes=Empty // top most level 1
Node[ ]nodes=getNodesAtlevel(nodes);
//All the stem words from the TPDB at level 2
RootNode[]Nodes=Node[]nodes
//stem words assigned to RootNode
checkForRepetitiveData(Nodes);
{ call SCL (Root) }//check the stem words(TPDB)
//matched in other domain i.e SPRWDB using Ontology
checkFordisjunctiveData (nodes);
{ call SCL (Root, MinThreshold) } //check for stem
//words that belongs to more than one domain (topic)
}//end for
}//end for
```

Fig. 5. Pseudo code of Tree Alignment for classification of Domain(s) Rule 1 *(SPRWDB)* for rumor stem words *(TPDB)*

are identified i.e., Rule 1 using ontology, Rule 2 are found in our Rumor Detection Framework. The Ontology actively assists in forming of partial tree (constrained to 2-levels, i.e. *"parent-child"*) using algorithm in [15] [17]. During this Tree building phase, the stem words *(TPDB)*, participates in mapping with the Domain words *(SPRWDB)*, at the same time threshold value for each Domain is checked using RD algorithm shown in Fig. 7.

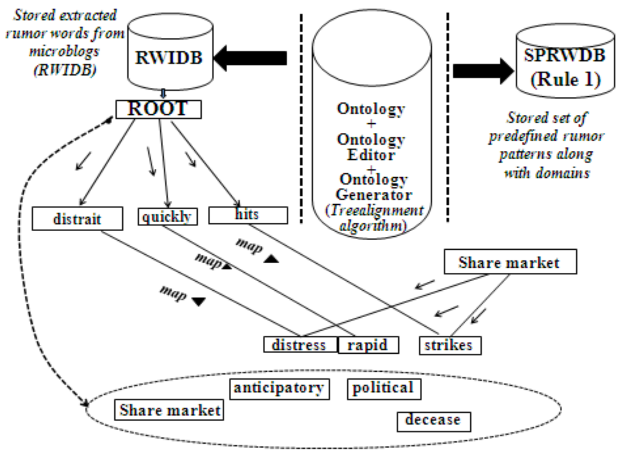

Fig 6. Prediction of Rumor Lexicon Domain from Stem words mapped with domains using Tree alignment algorithm

When the word distress in searched using the WordNet ontology the synonyms found are "suffering", "sorrow", "pain", "anguish", "distrait", "grief", "misery" and other equivalent words. Among them "distrait" is mapped to "distress" as shown in the fig. 6. Similarly the other words that are present in RWIDB are mapped with SPRWDB database. The ontology guides in construction of partial tree. In the tree building process the stem words RWIDB participate for mapping the words with domain words SPRWDB at the same time the threshold of the topic is evaluated using STL algorithm which is shown in fig. 4

3.3. Role of Rumor Detection (RD) Algorithm for the proposed Rumor Detection Framework.

Detection Framework, as already discussed in previous section that has initiated the overall progress starting from storing text messages in *SPDB* till finding the rumor keywords by providing a detailed report from *RKDB* and *EDB* databases to E-crime department on detection of rumor words. RDM schematic cum algorithmic steps of Fig. 3, are revisited again are shown in Fig. 6.

Algorithm 3 *Rumor Detection Algorithm (RD)*
Input: Short posts/microblogs stored in Text Database (SPDB) (Day to day) from IMS/RD Framework.
Output: Report to E-crime when Rumor messages are detected

```
1 Do {//Apply Ontology based IE technique for filtering unnecessary
//words and pick rumor words from SPDB (if found) and push to
//(TPDB) for Text which include stem words mapped with
 //pre-defined knowledge-based rules stored in (SPRWDB)
//rule 1 & rule discussed in section 3.
Push Messages to SPDB //instant messages stored in SPDB
2: Do{//Scan SPDB for relevant rumor words patterns if found
//store it in TPDB and perform mapping with SPRWDB
//(rule 1) using
// Ontology (OBIE) building taxonomy of stem words
3 Call TreeAlignment algorithm{ // algorithm discussed in Fig. 5
// initially all stem words (TPDB) mapped to empty root
//node using OBIE model forming tree
4 Call STL algorithm {//Check threshold values of stem
//words (TPDB) with root nodes stored in SPRWDB (rule 1) using
//algorithm 1 shown in Fig. 4 and finds rumor type(s)
//activity i.e. domain topic(s)
5 Scan TPDB
6 Push patterns to SKDB //stem words
} //end of call STL
7 Compare TPDB with SPRWDB{
8 If TPDB==SPRWDB Then Push patterns to SKDB
//stem words with Rumor Domain(s) stored
else
Do Nothing
9 End If
} //end compare
} //end call TreeAlignment
10 }until TPDB!=NULL //end of do
11 If TPDB==RKDB Then //Rumor words found with Domain
12 Check RKDB {//check the knowledge database using E-crime
// monitoring system program for type of cyber threat
// activity (i.e rumor linguistic stem words along with rumor
// category ( i.e domain) using Treealignment algorithm
13 if RKDB=='TRUE' then {// if Rumor words match then
14 Check EDB {//trace the profile details (emailid, phone
//number, ISP IP address and location details
15 Report to E-crime Department //detailed report
//including threat activity details traced from KDB/EDB
16 }//end of check EDB
17 }//end if
18 }//end of check RKDB
19 } //end of do
```

Fig 7. Pseudo code showing the Overall working of our proposed RD Framework for identifying rumor messages and reporting to E-crime dept

IV. IMPLEMENTATION AND EXPERIMENTAL RESULTS

4. 1. Evaluation method for data sets

Precision metric is used as given in Equation (1) [14] for evaluation of tweets in RD Framework. The rumor words extracted are based on two factors, the number of actual words available in the pre-defined database i.e. *SPRWDB* with respect to rumor domain, to that of the number of extracted rumor words from tweet chat session:

$$Precision\ (P) = \frac{\text{Correctly Extracted}}{\text{Total Extracted Correctly}} \quad \text{..................} \quad (1)$$

4.2. Preparation of data sets

Rumor related datasets in social media are not freely accessible due to restriction of privacy policies of FISA Act. Many of the rumor detection strategies tested their developed frameworks for detection of rumor from data collected through their local databases from social networking sites which includes Twitter, Facebook, Instagram, WhatsApp and other social media applications [2, 3, 5, 9-13]. To test our RDS architecture, we have used pre-defined rules that have rumor related words totaling of 50 words. Further, each of these words is supported with WordNet ontology that had created synonyms for the existing pre-defined words.

4.3. Tested using RD Framework and ICDM and SPNM

The real chatting session is intentionally conducted and the experimental results are demonstrated for the conversation happened between the two users, as shown in Table 2.

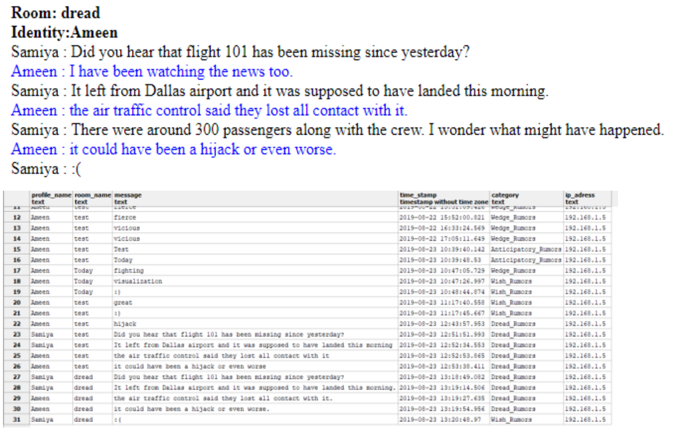

Fig. 8. Real Tweet, constitutes of Linguistic rumor lexicon words

Table 2: Depicts the domain of "***Share Market***" *rumour* words communicated between the users.

Domain of Rumor	User 1	User 2
Share Market	"Do to known the share market is <u>falling down</u> <u>rapidly</u>?"	"Why it is falling so <u>drastically</u>?" "Is there any <u>outbreak</u>?"
	"It might be due to recent U S <u>strikes</u> on Iran"	" It can <u>distress</u> the shareholder"
Rumor words to be detected:	Falling, rapidly, drastically, outbreak, strikes, distress	

For chatting session (Fig. 6), is tested using RD algorithm (Fig. 7), The rumoured words stored in pre- defined database are mapped with microblogs, if it matches it stores those rumoured posts separately into its log as shown in the above figure. Apart from that, Emoticon which is exactly mapped with our pre-defined database (SPRWDB) rule 2 is also shown. The accuracy rate obtained by ICDM and CPNM is 70% and 90% respectively, whereas 93% with RDS system as shown in Figure 9.

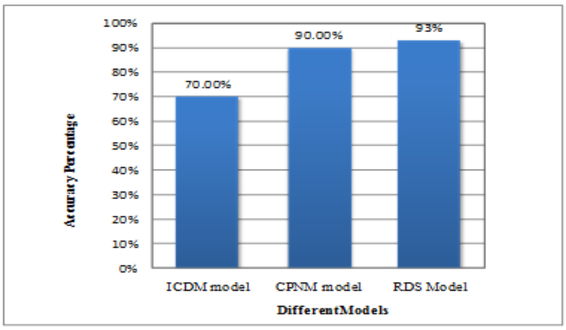

Fig. 9. Comparision of ICDM, CPNM with proposed RDS Model

V. CONCLUSION AND FUTURE WORK

Most of the rumor based existing systems consider only text part of the posts. However it is necessary to take into consideration social interaction as popular posts tend to grab more attention quickly. With the popularity of social media, people are used to sharing their daily activities and interacting with friends on social media platforms. Social media data are being considered more in the rumor detection systems as it is inexpensive, transparent and provides primary access to new opportunities. Thus, many researchers are focusing on leveraging social media interactions to improve effectiveness of social media analysis of rumor detection. The proposed strategy is to utilize these social media interactions content to detect rumours by employing a Rumor Detection System (RRD) model. Detecting user's rumor levels from user's social media content will improve the rumor detection performance efficiently. The proposed RDS strategy detects rumours by employing the probabilistic model. In RDS model two unique features (emoticons and social interactions) are added which were not done earlier, except ICDM which has used only one feature of pre-defined rules that to only textual words are considered. Experimental results show that proposed model can improve the detection per performance and achieved 93 percent of accuracy when compared to ICDM and CPNM models shown in Table 3.

Table 3: Comparison of efficiency & effectiveness using different model

Models \ Parameter	Text	Support for Social Interaction	Pre-defined rules	Report generation for e-crime dept.	Ontology support	Accuracy
ICDM	✓	×	×	×	×	0.70
CPNM	✓	×	×	×	×	0.90
RDS model	✓	✓	✓	✓	✓	0.93

REFERENCES

[1] Juan Cao, Junbo Guo, Xirong Li, Zhiwei Jin, Han Guo, and Jintao Li, "Automatic Rumor Detection on Microblogs: A Survey", 2018.

[2] J. Gottfried and E. Shearer, "News use across social media platforms2016," Pew Research Center, 2016.

[3] Mohammed Mahmood Ali, Mohammad S. Qaseem, Ateeq ur Rahman, "Rumour Detection Models & Tools for Social Networking Sites", International Journal of Engineering & Advanced Technology (IJEAT), Vol. 9, issue 2, 2019 Published on December 30, 2019.

[4] Yan Zhang, Weiling Chen, Chai Kiat Yeo, Chiew Tong Lau, Bu Sung Lee,"Detecting rumors on Online Social Networks using multi-layer autoencoder", IEEE Technology & Engineering Management Conference (TEMSCON), 2017.

[5] P. Suthanthira Devi, S. Karthika, "Veracity Analysis of Rumors in Social Media",International Conference on Computer, Communication, and Signal Processing (ICCCSP),2018.

[6] Somayeh Zamani, Masoud Asadpour, Dara Moazzami, "Rumor Detection for Persian Tweets", Iranian Conference on Electrical Engineering (ICEE) 2019.

[7] Liang'an Huo and Chenyang Ma," Optimal Control of Rumor Spreading Model with Consideration of Psychological Factors and Time Delay", Discrete Dynamics in Nature and Society Volume 2018, Article ID 9314907, 12 pages 9 July 2018 .

[8] Surekha Rawale, Sapana Birkure, Kajal Hiray , Prof. Deepti Deshmukh," Detection and Minimization Influence of Rumor in Social Network", International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056 Volume: 04 Issue: 11 | Nov - 2017.

[9] A.M. Meligy, H. M. Ibrahim and M. F. Torky," Recognizing and Stopping Rumors Patterns in Social Networks", Indian Journal of Science and Technology, Vol 10(28), July 2017.

[10] S.Nivetha, R.Priyadharshini, P.Balakumar, K.Kapilavail, "Detecting root of the rumor in social network using GSSS", International Research Journal of Engineering and Technology (IRJET).

[11] Ruixia Zhang 1 and Deyu Li," Identifying Influential Rumor Spreader in Social Network", Discrete Dynamics in Nature and Society 2019:1-10 · May 2019.

[12] Anjan Pal, Alton Y.K. Chua, and Dion H. Goh," Rumor Analysis &Visualization System", Proceedings of the International MultiConference of Engineers and Computer Scientists 2019 IMECS 2019, Hong Kong, , March 13-15, 2019.

[13] Laijun Zhao, Xiaoli Wang, Jiajia Wang, Xiaoyan Qiu, Wanlin Xie," Rumor-Propagation Model with Consideration of Refutation Mechanism in Homogeneous Social Networks", semantic scholar 2014.

[14] Massimo Ostillia, Eiko Yonekic, Ian X. Y. Leungc, Jose F. F. Mendesa, Pietro Li´oc, Jon Crowcroft, "Statistical mechanics of rumor spreading in network communities", International Conference on Computational Science, ICCS 2010.

[15] M. Nekoveea, Y. Morenob, G. Bianconic, M. Marsili," Theory of rumour spreading in complex social network", Elsevier, 2007.

[16] Rehana Moin, Zahoor-ur-Rehman, Khalid Mahmood," Framework for Rumor Detection in Social Media", International Journal of Advanced Computer Science And Application (IJACSA), 2018.

[17] D. J.Daley andD. G.Kendall, "Epidemics and rumours," *Nature*, vol. 204, no. 4963, p. 1118, 1964.

[18] Ma J.,Gao W., Wong K.: "Detect Rumors in Microblog Posts Using Propagation Structure via Kernel Learning", the ACL, pp. 708–717, 2017.

[19] NivethaS., Priyadharshini R. et al: "Detecting Root of the Rumor in Social Network Using GSSS", International Research Journal of Engineering and Technology, 2017.

[20] Ma J.,Gao W., et al: "Detecting Rumors from Microblogs with Neural Networks" Twenty-Fifth International Joint Conference on Artificial Intelligence, 2016.

[21] Cai G., Bi M., and Liu J.: "A Novel Rumor Detection Method Based on Labeled Cascade Propagation Tree", 13th ICNC-FSKD, 2017.

[22] YuF., LiuQ., WuS., WangL., and TanT.: "A convolutional approach for misinformation identification," in Proceedings of IJCAI, 2017.

[23] RuchanskyN., SeoS., and LiuY.: "CSI: A hybrid deep model for fake news detection," in Proceedings of 7 ACM on Conference on IKM, pp. 797–806, 2017.

[24] Mohammed Mahmood Ali, Mohd Tajuddin & M. Kabeer, ―SDF: Psychological stress detection from microblogs using predefined rules and ontologies‖, International Journal of Intelligent Systems and Applications in Engineering, Vol. 6, Issue 2, pp. 158-164, 2018.

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