



Journal Homepage: -www.journalijar.com
**INTERNATIONAL JOURNAL OF
 ADVANCED RESEARCH (IJAR)**

Article DOI:10.21474/IJAR01/11686
 DOI URL: <http://dx.doi.org/10.21474/IJAR01/11686>



RESEARCH ARTICLE

CLASSIFICATION OF VULGAR COMMENTS USING CONVOLUTIONAL NEURAL NETWORK WITH GLUON NATURAL LANGUAGE PROCESSING

Rufyda Jahan¹, Mohsinul Bari Shakir¹, Md. Mahdiul Imran², Surovi Zinia¹ and Md. Iftekharul Mobin¹

1. Department of Computer Science and Engineering, BRAC University, Dhaka, Bangladesh.
2. Department of Computer Science and Engineering, Independent University, Dhaka, Bangladesh.

Manuscript Info

Manuscript History

Received: 10 July 2020

Final Accepted: 14 August 2020

Published: September 2020

Key words:-

Vulgar Comments, Convolutional
 Neural Network, Natural Language
 Processing

Abstract

With the advancement of technology, the virtual platform and social media have become an important part of people's daily life. The social media allows users to communicate, to express their feelings and to discuss on various topics. But cyber bullying and vulgar or toxic comments become an alarming problem in social media. In this paper, a system has been proposed to detect and classify vulgar comments using convolutional neural networking with gluon natural language processing. The system can classify toxic, hate speech, insult, obscene, threat and normal text by training from a huge dataset obtained from Kaggle, extracting comments from YouTube, facebook through extension of browser. The system shows 95.4% accuracy to detect and classify the vulgar comments.

Copy Right, IJAR, 2020,. All rights reserved.

Introduction:-

Internet negativity has perpetually been a hot topic. The obscurity and therefore the sense of distance of people's web presence have inspired to expose themselves freely caused by lack of cyber security [1,2] and lack of proper social education. As a result, the popularity of internet specially social medium like facebook, twitter, what's app, youtube have risen too high nowadays. But the negative portion of social media has become a new trend of abuse, cybercrime, offensiveness. Vulgarity and Spam can be any bothersome and obliged conduct that could possibly break the security approaches of any arrange security. Nowadays, spam is any vulgar message or fake message sent by spammers to draw the authentic customers. There can be diverse objectives of spammers for sending these spam and disgusting messages like for publicizing any item, cyber tormenting, annoying, threatening. There are different sorts of vulgarism and spam as depicted beneath [3]:

Toxic email: Email Spam is a kind of spam sent through email. The connections present in sent sends may delude clients to locales having phishing or malevolent properties. The spammers play in all respects cleverly in the event of email spamming. They collect different email addresses from visit rooms, diverse, sites and so on. furthermore, pitch it to different spammers.

Vulgar comments: Comment Spam is a sort of post in which spammer posts harsh and hostile information in organizing destinations. In remark spam, spammer dissipates the spam as remarks on online journals, discussions, Wikipedia and so forth.

Instant messenger spam: Instant Messenger Spam gives its clients a majority of catalog of its everything clients having scientific information like name, age, sexual orientation and so on. Spammers searching for such vulnerable

Corresponding Author:- Rufyda Jahan

Address:- Department of Computer Science and Engineering, BRAC University, Dhaka, Bangladesh.

information, assembles all subtleties and by marking in, sends unconstrained and spontaneous messages which may contain any infections, noxious connections and so forth.

Junk fax :Junk fax is similar to email spam. The main distinction lies is that spam in junk fax is obtained as faxes through fax transmission. These are fundamentally utilized for swelling in commercials.

Spontaneous Text Messages : Spontaneous Text Messages is a type of Mobile Spam. This spam type focuses on the message box of any client on his cell phone in any case, this sort is less common than email spam.

Social Media Spam : Social Networking Spam is a sort in which spammed content is posted on social systems. Spam can be as remarks, tweets, talks, pictures and so forth. Fundamentally, above clarified types can be considered inside Social Networking Spam.

Nowadays, artificial intelligence is being used in sectors like medical [4-8], pattern analysis [9], agriculture [10-12], human assistantship [14], education, industry, home appliance [15] and so on and based on this, it has become a great medium to apply on Now, governments of different countries are trying to prevent cybercrime, bullying and most importantly vulgarity and spam from the internet. Our proposed system has designed in a way inspiring from Pavel, M. I. et. al [29], to classify the vulgar and spam comments from social media comment so that internet can be again user friendly to all sort of people.

Related Works:-

S. Srivastava et al [16] presented capsule network based aggressive comment classifier. The proposed worked was based on focal loss along with single model capsule network which achieves 98.46% accuracy on the on their first dataset and mentioned to apply on TRAC dataset which is Hindi-English combined dataset of aggressive and non-aggressive comment with RNN classifier where α and γ was 2 and 0.25 respectively.

C. Rădulescu et al [17] et al took an integrated approach to identify spams by combining Machine Learning, Natural Language Processing and URL examination methodologies. The combined methodology has shown better and more exact results than when each modularity was applied individually. M. McCord et al detected vulgar comments on Twitter in [18] applying the api method from tweeter. The authors used Random Forest Classifier algorithm to detect vulgar comments or response where they got 95.7 F1 score and 95.7%.

For identifying spam remarks applying Natural Language Processing Techniques Kandasamy et al [19] integrated three approaches- the implementation of URL analysis, supervised machine learning techniques, natural language processing to classify the vulgar and toxic comment from social media where they got 94% accuracy.

Carreras et al built up a strategy to demonstrate that the success rate of AdaBoost is much higherto classify vulgar comments than Decision Tree and Naïve Bayes Algorithm. The authors shows that toxic comments and cyber bullying began to turn into a significant issue of the World Wide Web from back in late 1990s. Techniques for web-indecent separating dependent on substance examination were additionally investigated to recognize vulgar pages [20].

S. Shubha et al [21] showed a classification framework to review comment implementing Machine Learning Bayes Sentiment Classification (MLBSC) which was proposed in their paper. The method firstly extract user comments and related comments are listed based on prior training. Then they

Evaluate label of class applying probabilistic Bayes classifiers. Finally they got 88.75% accuracy applying MLBSC on 70 testing comments.

Methodology:-

The proposed methodology is divided into two core part CNN [23,24,25] for text classification with feature extraction implementing natural language processing. Figure 1 shows the work diagram of the methodology.



Figure 1:- Proposed work diagram.

Data Acquisition

We have used two types of dataset in this research, one is acquired from Kaggle which is very popular publicly available dataset named “Wikipedia Talk Page Comments annotated with toxicity reasons” which content almost 1,60,000 comments with manually labelling and another one is our own made dataset extracting comments from YouTube, Facebook and tweeter for testing only. The dataset contains total six classes which are described down below, [27]

- a. Toxic: a common class for all comments which are vulgar, toxic and bullying type.
- b. Sever toxic: This class denotes the extreme toxic or vulgar comments.
- c. Threat: Articulations with the aim to cause antagonistic activity .
- d. Obscene: Rude, dirty, wicked types of languages are in this category.
- e. Identity: Racism, sexism, bullying for homophobia etc are in this category.
- f. Insult: Hate speech, verbal abuse and showing disrespect, commenting aiming the disability or religion of

specific people.

In the training dataset, these six categories are binarily individually labelled where one comment or sentence can belong to more than one category or no category if they are not toxic or vulgar. Figure 3. shows the training dataset before preprocessing.

Data Preprocessing

In preprocessing, first of all null data are removed so that it may not occur any trouble while the processing portion. A blank row of comment is counted as a null data and is removed. After that, the huge amount of data needs to be separated into vulgar and non vulgar part. To do this, we implement sampling technical, which simply search is every comment if there is class with value 1 which indicates it is in any of vulgar class. If at least one class is true, then it is vulgar, rest are non vulgar.

Feature analysis

In order to differentiate between vulgar and legitimate comments, we compute nine features for each comment. The features are assigned numeric values and they represent various differentiating characteristics of the two types of comments. The features are as follows:

1. *URL in the replies*: harassing comments may get an increment of responses regardless of the fact that spammers need to divert users to sites with a relatively small number of viewers in order to maximize the ranking of the website. That is the reason the quantity of connections in the remarks must be taken into records when distinguishing toxic comment.

2. *Spaces in the comments*: Vulgar comments may have lots of white spaces because replies or comments creates huge impact on the user who reads these comments.

3. *Sentences in the comment*: Total sentences in a toxic comment is lower than the total sentences in a rational statement despite the fact that use of words and sentences is generally consistent.

4. *Punctuation marks*: Presence of large number of punctuation marks, especially exclamation and dot characters is a defining feature of vulgar comments, as punctuation characters tend to attract the attention of the reader. In contrast, legitimate comments tend to contain only sentence delimiting punctuation marks. However, sometimes legitimate comments can contain larger than normal number of punctuation characters to express strong feelings.

5. *Word duplication*: Vulgar or toxic comments tend to have a lot of repetition of words compared to legitimate comments with contextual flow of word structure. To capture this property we take the ratio of the number of unique words to the total word count in the comment and define it as word duplication ratio RWD. The equation is expressed in the following way:

$$RWD = \frac{\text{Number of Unique words in a comment}}{\text{Total numbers of words in a comment}} \quad (1)$$

6. *Ratio of Stop Words*: Another feature that captures the difference between vulgar comments and the legitimate comments is the ratio of stop word, which is computed as the ratio of the number of stop words to the number of total word count in the comment.

$$RSW = \frac{\text{Number of Stop words in a comment}}{\text{Total numbers of words in a comment}} \quad (2)$$

7. *Non-ASCII Characters*: Vulgar comments may contain a moderate amount of Non-ASCII Characters compared to legitimate comments and non-toxic comments.

8. *Capital Letters*: People who write vulgar comments, use more capital letters than legitimate. Sometimes, vulgar or toxic comments are very often written fully using capital letters.

9. *New lines numbers*: Vulgar comments contain a huge number of new lines in order to draw attention with the facts by creating a visual effect for the reader..

Gluon Natural language Processing

Nature Language Processing (NLP) is a hypothesis propelled scope of computational procedures for the programmed analysis and portrayal of human language. Practically, It is a procedure which empowers a machine to process a characteristic language (like English) and perform all of the things that a human can do. Prior to going into profound ideas of NLP, a lot of deficient sentences which regularly shows up in a tweet, youtube and facebook comment are recognized. Subsequent to looking into on dataset, some regular sentences in spam remarked were found. They are 'include me at', 'take me out on the town', 'you'll giggle when you see this pic of you', 'You appear to be unique in this photograph', 'my companion sent me this pic with you in it', 'my companion demonstrated to me this pic of you', 'tail me back', 'markdown drugs', 'I discovered you in this video', and some other sensitive words that can't be written for unable circumstances. If these expressions are found in the facebook, email, YouTube then the user is classified as spam. In this thesis, three elements of NLP are applied which are (1) stop words removing, (2) tokenization and (3) stemming. For processing English there is no need of stop words like I, you, in, the, we, is, was, me, our, it, etc. o each of these words are expelled and just the keywords are removed. The following stage is to discover the root word or stem of the catchphrase. For this, stemming methods are utilized. A basic stemming calculation has been utilized in this paper. A lot of spam words that can show up in a tweet is distinguished, similar to 'pornography', 'Viagra' and so on. The stemmed watchwords are contrasted and the arrangement of recognized spam words. On the off chance that the words coordinate, at that point the client is viewed as spam. At this stage, in the event that the client isn't found as spam, at that point the third system of Machine Learning is utilized.

Gluon comes with a really propelled NLP toolbox, which makes working with content simple. It additionally fuses pre-prepared Language Models, the mystery sauce for Transfer Learning. Thing is, how might we anticipate that a model should make sense of whether content is lethal or not, on the off chance that it can't "communicate in" English by any means. To implement Gluon with NLP, first of all, an independent language model is trained before embedding matrix by a standard LSTM encoder. Then LSTM output is pooled which is generated by sequence of tokenization aiming to feed dense layer.

Tokenization: Tokenization [28] is one of the vital part of Natural Language Processing which is implementing for word segmentation. In the first step, we split constant content information like "I go, you do, we have", so on and encode them into numerical vectors [29]. After that, each words are converted into its numerical portrayal. Following that, words are mapping this tokenization to sectioned content information and basically restores the content as a numeric components to included words in the vocabulary. This concise clarification serves to give establishments to

the word2vec"method is applied. A method named word2vec is applied which is used to compare words that show up in comparable positions in the specific circumstances.

Stop Word Removing :Stop word [30] expulsion is a standout amongst the most usually utilized preparing strategy at the present time. Web indexes utilized this procedure to disregard each one of those words or character that has no esteem or less incentive in the season of creating precision structure the dataset. At the season of making the list, most motors are modified to evacuate some specific words that has less weight. Chiefly the rundown of words or characters that are not added to 20 the last informational index is known as the stop word list. This recovers both existence as it evacuates the words at ordering time and overlooked at looking time. We expel these arrangement of words as they convey no data for example pronoun, relational word, conjunctions. In English language there are normally more than five hundred stop words. In our methodology, using the NLTK library [31] we removed the stop words to make better classification.

Stemming :It is the procedure to diminish a group of comparable words and give them a root word which is called lemma. Stemming [32] is including word and giving a lot of words same sort of importance. We use stemming to characteristic language preparing. When we found a comparative kind of word we give a specific load to it for estimating and at that point when another word is discovered it is chosen as another kind. To get the best outcome the procedure of lemma is implemented.

CNN for text Classification

Convolutional Neural Networks is mainly popular for image classification because of the ability to exploit 2 statistical characters which are local stationary and compositional structure. In this thesis, CNN [8,9,10] is applied for text classification where main dataset represents the mentioned two statistical characters relying on the fact that neighboring words in a sentence present dependency, however, their processing is not straight forward. In image classification, pixels are some integer values with specific threshold value, but in the case of sentence or words, we need to encode first before fed to the networks [11]. To do so, we applied NLTK library [12] of python for using vocabulary which is structured as a list containing words which are shown in the set of comment's texts. Then we need to map each word to encode it integer ranging between one to size of vocabulary. The fluctuation in reports length (number of words in a record) should be tended to as CNNs require a consistent information dimensionality. For this reason the cushioning strategy is received, loading up with zeros the archive grid so as to achieve the most extreme length among all reports in dimensionality. In the subsequent stage the encoded reports are changed into lattices for which each column compares to single word. The created lattices go through the implanting layer where each word (push) is changed into a low-measurement portrayal by a thick vector. When all is said in done the word installing strategies have been prepared on a substantial volume dataset of words delivering for each word a thick vector with a particular measurement and fixed qualities. The word2vec implanting strategy for instance, has been prepared on 100 billion words from Google News delivering a vocabulary of 3 million words. The inserting layer coordinates the info words with the fixed thick vector of the pre-prepared implanting techniques that have been chosen. The estimations of these vectors don't change amid the preparation procedure, except if there are words not officially incorporated into the vocabulary of the inserting strategy in which case they are instated arbitrarily.

Result & Analysis:-

Implementing the dataset from Kaggle [22] and extract commenting from youtube, facebook and tweeter using chrome's comment extraction extension, almost 1,59,000 data are stored in training dataset with leveling the classes shown in Figure 2. The dataset is labelled based on toxic, severe toxic, Obsecene, threat, insult, identity hate speech and others; where 1 means presence of its class, 0 mean not in that class. A comment or text can belong to multiple classes. Figure 3 shows relation of each classes of the labelled dataset.

	id	comment_text	toxic	severe_toxic	obscene	threat	insult	identity_hate
6	0002bcb3da6cb337	COCKSUCKER BEFORE YOU PISS AROUND ON MY WORK	1	1	1	0	1	0
12	0005c987bdfc9d4b	Hey... what is it... \n@ talk \nWhat is it...	1	0	0	0	0	0
16	0007e25b2121310b	Eye! \n\nDon't look, come or think of coming ...	1	0	0	0	0	0
42	001810bf8c45bf5f	You are gay or antisemitian? \n\nArchangel WH...	1	0	1	0	1	1
43	00190820581d90ce	FUCK YOUR FILTHY MOTHER IN THE ASS, DRY!	1	0	1	0	1	0

Figure 2:- Data visualization.

	toxic	severe_toxic	obscene	threat	insult	identity_hate	other
toxic	1	0.308619	0.676515	0.157058	0.647518	0.266009	-0.967748
severe_toxic	0.308619	1	0.403014	0.123601	0.375807	0.2016	-0.298666
obscene	0.676515	0.403014	1	0.141179	0.741272	0.286867	-0.702812
threat	0.157058	0.123601	0.141179	1	0.150022	0.115128	-0.162925
insult	0.647518	0.375807	0.741272	0.150022	1	0.337736	-0.677324
identity_hate	0.266009	0.2016	0.286867	0.115128	0.337736	1	-0.280144
other	-0.967748	-0.298666	-0.702812	-0.162925	-0.677324	-0.280144	1

Figure 3:- Corelation between labeled dataset.

The CNN classifier classifies based on extracting the eight features and implementing gluon natural language processing where it rejects all unnecessary words by stopwords and tokenization, removing common sentence structures, numbers, barriers of url and so on. After the post comment analysis, a list of vulgar words is processing with NLP to classify the vulgar words from test dataset. Figure 4 shows the predicted output of the system.

	id	toxic	severe_toxic	obscene	threat	insult	identity_hate
0	00001cee341fdb12	0.605656	0.075524	0.354032	0.031793	0.329857	0.086772
1	0000247867823ef7	0.618192	0.053303	0.326704	0.023079	0.302790	0.060001
2	00013b17ad220c46	0.615244	0.054219	0.326017	0.023219	0.306833	0.060899
3	00017563c3f7919a	0.645400	0.041264	0.319742	0.018374	0.280795	0.048270
4	00017695ad8997eb	0.618311	0.052855	0.327208	0.022676	0.304501	0.058959

Figure 4:- Classification output.

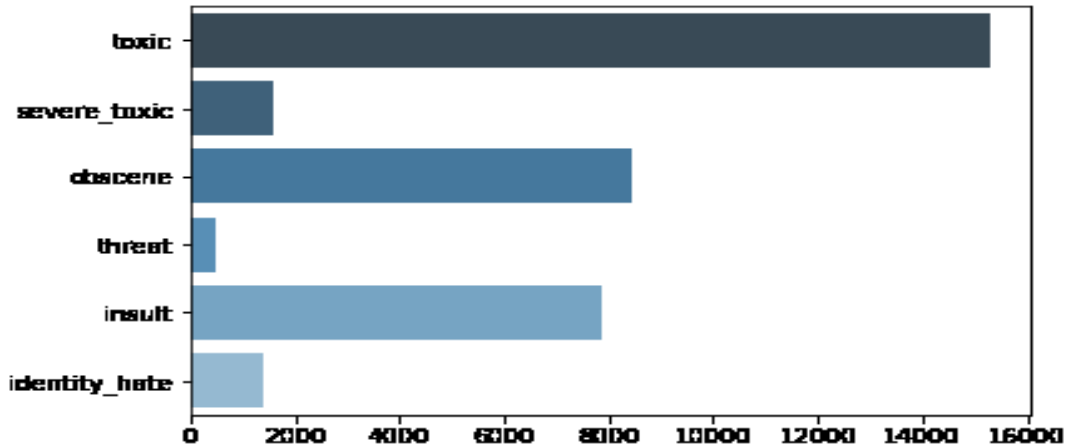


Figure 5:- Classification visualization.

Figure 5. displayed the multiclass output of classification to visualize where toxic levels in more than 15,000 comments, obscene is in more than 8,500 comments and so on. The architecture is got 95.4% accuracy with CNN and NLP. Table I shows the comparison of the model with other classifying algorithms where our proposed models gives the best accuracy.

Table I:- Result comparison with other Classifiers based on Accuracy.

Classifier	Accuracy
Random Forest	94%
Support Vector Machine	91%
Decision Tree Classification	89.75%
Proposed Model	95.4%

Table II:- Result comparison with other Classifiers based on Sensitivity.

Classifier	Sensitivity
Random Forest	86.08%
Support Vector Machine	82.55%
Decision Tree Classification	71.95%
Proposed Model	82.32%

Table III:- Result comparison with other Classifiers based on F1 Score.

Classifier	F1 Score
Random Forest	91.07%
Support Vector Machine	86.87%
Decision Tree Classification	83.45%
Proposed Model	95.4%

Conclusion:-

We led an inside and out examination on remarks to reveal some insight into various highlights of spam remarks. We were keen on structure a framework which distinguishes vulgar or spam and non-vulgar comments as for various attributes that are characterized. The combination of Gluon NLP with tokenization, stop words, stemming and nine numerical features and huge dataset made the result more error free. In our characterization tests, we showed that our usage of the spam discovery framework gives the best outcomes by utilizing the Gluon NLP and CNN classifier where we got 95.4% accuracy, 82.32% sensitivity and 95.4% f1 score which are higher than other regular algorithms. For the further process, we are planning to develop an advance real-time vulgar video and post detector to remove it instantly before appearing in publicly. To do so, we are adding a lot of data for deep learning and reinforcement modeling combining with server-side processing for practical implementation.

Reference:-

1. Hassan, M. A., Shukur, Z., Hasan, M. K., & Al-Khaleefa, A. S. (2020). A Review on Electronic Payments Security. *Symmetry*, 12(8), 1344.
2. Hassan, M. A., Shukur, Z., & Hasan, M. K. (2020). An Efficient Secure Electronic Payment System for E-Commerce. *Computers*, 9(3), 66.
3. Srivastava, S., Khurana, P., & Tewari, V. (2018, August). Identifying aggression and toxicity in comments using capsule network. In *Proceedings of the First Workshop on Trolling, Aggression and Cyberbullying (TRAC-2018)* (pp. 98-105).
4. Alam, M. A., Shakir, M. B., & Pavel, M. I. (2019, May). Early detection of coronary artery blockage using image processing: segmentation, quantification, identification of degree of blockage and risk factors of heart attack. In *Micro-and Nanotechnology Sensors, Systems, and Applications XI (Vol. 10982, p. 109820L)*. International Society for Optics and Photonics.
5. Pavel, M. I., Sadique, A. M., Ritul, R. A., Khan, S., & Nath, S. (2017). Cancer detection using image processing techniques based on cell counting, cell area measurement and clump detection, BRAC Univeristy.
6. Rumman, M., Tasneem, A. N., Farzana, S., Pavel, M. I., & Alam, M. A. (2018, June). Early detection of Parkinson's disease using image processing and artificial neural network. In *2018 Joint 7th International Conference on Informatics, Electronics & Vision (ICIEV) and 2018 2nd International Conference on Imaging, Vision & Pattern Recognition (icIVPR)* (pp. 256-261).
7. Rumi, R. I., Pavel, M. I., Islam, E., Shakir, M. B., & Hossain, M. A. (2019, December). IoT Enabled Prescription Reading Smart Medicine Dispenser Implementing Maximally Stable Extremal Regions and OCR. In *2019 Third International conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC)* (pp. 134-138).
8. Alam, M. A., Shakir, M. B., Hossain, M. A., Pavel, M. I., Shams, K. M. A., & Akib, F. R. (2018, March). Early detection, segmentation and quantification of coronary artery blockage using efficient image processing technique. In *Medical Imaging 2018: Imaging Informatics for Healthcare, Research, and Applications (Vol. 10579, p. 105791J)*. International Society for Optics and Photonics.
9. Azad, M., Khaled, F., & Pavel, M. (2019). A novel approach to classify and convert 1D signal to 2D grayscale image implementing support vector machine and empirical mode decomposition algorithm. *Int J Adv Res*, 7, 328-335.
10. Chowdhury, M. M. J., Pavel, M. I. & Sabuj, S. R. (2020). Chapter Eight AI-Enabled IoT Network In The Agricultural Food Chain Using Blockchain Technology. *Blockchain in Data Analytics*, 185.
11. Pavel, M. I., Kamruzzaman, S. M., Hasan, S. S., & Sabuj, S. R. (2019, February). An IoT Based Plant Health Monitoring System Implementing Image Processing. In *2019 IEEE 4th International Conference on Computer and Communication Systems (ICCCS)* (pp. 299-303).
12. Kamruzzaman, S. M., Pavel, M. I., Hoque, M. A., & Sabuj, S. R. (2019). Promoting greenness with IoT-based plant growth system. In *Computational Intelligence and Sustainable Systems* (pp. 235-253).
13. Pavel, M. I., Rumi, R. I., Fairouz, F., Jahan, S., & Hossain, M. A. Deep Residual Learning Approach For Plant Disease Recognition. In-press in *International Conference on Mobile Computing and Sustainable Informatics*.
14. Pavel, M. I., Chowdhury, I., & Akther, A. (2018). Raspberry Pi and Image Processing Based Person Recognition System for Visually Impaired People. *International Research Journal of Engineering and Technology*, 5(7), 809-813.
15. Milon, M. S. I., Pavel, M. I., Ehsan, M. S., Sadi, S. H., & Sabuj, S. R. (2020). Application of Smart Appliance Using Internet of Things. In *Innovations in Electronics and Communication Engineering* (pp. 359-368). Springer, Singapore.
16. Srivastava, S., Khurana, P., & Tewari, V. (2018, August). Identifying aggression and toxicity in comments using capsule network. In *Proceedings of the First Workshop on Trolling, Aggression and Cyberbullying (TRAC-2018)* (pp. 98-105).
17. Rădulescu, C., Dinsoreanu, M., & Potolea, R. (2014, September). Identification of spam comments using natural language processing techniques. In *2014 IEEE 10th International Conference on Intelligent Computer Communication and Processing (ICCP)* (pp. 29-35).
18. Mccord, M., & Chuah, M. (2011, September). Spam detection on twitter using traditional classifiers. In *international conference on Autonomic and trusted computing* (pp. 175-186). Springer, Berlin, Heidelberg.
19. Kandasamy, K., & Koroth, P. (2014, March). An integrated approach to spam classification on Twitter using URL analysis, natural language processing and machine learning techniques. In *2014 IEEE Students' Conference on Electrical, Electronics and Computer Science* (pp. 1-5).

20. Carreras, X., & Marquez, L. (2001). Boosting trees for anti-spam email filtering. In Proceedings of RANLP-01, 4th International Conference on Recent Advances in Natural Language Processing, (pp. 58-64).
21. Shubha, S., & Suresh, P. (2017, March). An efficient machine Learning Bayes Sentiment Classification method based on review comments. In 2017 IEEE International Conference on Current Trends in Advanced Computing (ICCTAC) (pp. 1-6).
22. "Toxic Comment Classification Challenge," Kaggle. [Online]. Available: <https://www.kaggle.com/c/jigsaw-toxic-comment-classification-challenge/data>. [Accessed: 30-Jan-2020].
23. Davison, B. D. (2000). Recognizing nepotistic links on the web. Artificial Intelligence for Web Search, 23-28.
- Patil, S., Gune, A., & Nene, M. (2017, August). Convolutional neural networks for text categorization with latent semantic analysis. In 2017 International Conference on Energy, Communication, Data Analytics and Soft Computing (ICECDS) (pp. 499-503).
24. Li, L., Xiao, L., Wang, N., Yang, G., & Zhang, J. (2017, December). Text classification method based on convolution neural network. In 2017 3rd IEEE International Conference on Computer and Communications (ICCC) (pp. 1985-1989).
25. Ju, R., Zhou, P., Li, C. H., & Liu, L. (2015, October). An efficient method for document categorization based on word2vec and latent semantic analysis. In 2015 IEEE International Conference on Computer and Information Technology; Ubiquitous Computing and Communications; Dependable, Autonomic and Secure Computing; Pervasive Intelligence and Computing (pp. 2276-2283).
26. Zhang, Y., & Wallace, B. (2015). A sensitivity analysis of (and practitioners' guide to) convolutional neural networks for sentence classification. arXiv preprint arXiv:1510.03820.
27. Seyyed, S. R., Fakhrahmad, M., & Sadredini, M. H. (2015, November). PTokenizer: POS tagger tokenizer. In 2015 2nd international conference on knowledge-based engineering and innovation (KBEI) (pp. 252-256).
28. Pavel, M. I., Razzak, R., Sengupta K., Niloy, M .D. K., Muqith M. B., Tan, S. Y. Toxic Comment Classification Implementing CNN Combining Word Embedding Technique. In-press in 2nd International Conference on Inventive Computation and Information Technologies.
29. Popova, S., Kovriguina, L., Mouromtsev, D., & Khodyrev, I. (2013, November). Stop-words in keyphrase extraction problem. In 14th Conference of Open Innovation Association FRUCT (pp. 113-121).
30. "Natural Language Toolkit," Natural Language Toolkit - NLTK 3.4.1 documentation. [Online]. Available: <https://www.nltk.org/>. [Accessed: 15-Jun-2018].
31. Gadri, S., & Moussaoui, A. (2015, May). Information retrieval: A new multilingual stemmer based on a statistical approach. In 2015 3rd International Conference on Control, Engineering & Information Technology (CEIT) (pp. 1-6).