SEYBOLD Report
ISSN: 1533 - 9211
DOI: 10.5281/zenodo.7074332

SENTIMENT ANALYSIS ON SOCIAL MEDIA REVIEWS USING ENHANCED RNN TECHNIQUES FOR DIVERGENCE CLASSIFICATION

[1]M. Subathra, [2]Dr.J. Vandarkuzhali, [3]Dr. K. Meenakshisundaram
[1]Ph.D Research Scholar, [2]Assistant Professor, [3]Associate Professor and Head,
Department of Computer Science, Erode Arts and Science College (Autonomous), Erode, India
[1]iamsubathra@gmail.com, [2]kuzhalijv@gmail.com, [3]lecturerkms@yahoo.com

Abstract

Sentimental Analysis is growing rapidly across various domains as a direct outcome of natural language processing and machine learning approaches for assessing and classifying emotions from data. Analyzing sentiment over product reviews is the clumsy task, which provides a variety of information regarding customer lifestyle. Hence high level of impedance involved while classifying the sentiment from the social media reviews documents. Existing researches have been focused on summarization of text, reduction of features, and prediction of sentiment separately. In this research work, all the approaches are integrated to provide a novel sentimental analysis framework for classifying reviews of a customer. The proposed work is consisting of three folds. Initially, pre-processing is done which includes tokenization, stemming, lemmatization, stop words, lower case conversion. Second, Selection of features is done with help of Effective Moth Flame Optimization Algorithm (EMFO), hence as a result standard features only exist which determines fittest individuals. Finally, the accurate sentiment prediction is done with help of Enhanced Recurrent Neural Network (ERNN). The proposed Heed BiGRU incorporate with BiGRU Layer and Attention layer. The proposed work is experimented by utilising the datasets, which is widely consisting of product reviews from social media platforms. To analyse the proposed customer sentimental analysis method, the evaluation metrics like accuracy, precision, recall and f-score are used and, also comparison has been made with existing state-of-art model. Proposed work outperforms well than other methods in terms of all performance metrics.

Keywords: Sentimental analysis, Deep learning, Bidirectional Gated Recurrent Units, Heed Mechanism, Effective Moth flame Optimization.

I. Introduction

The rapid increase in the rate of internet user's day by day leads to evolution of e-commerce and social media sites like Amazon, Flipkart, Facebook, Twitter etc. Nowadays reviews and rating have become an important source of information for consumers. Sentiment analysis is one of the major research types of NLP (Natural Language Processing) for tracking the opinion towards a particular product as positive or negative. It studies people's sentiments towards certain entities, like hotels, airlines, online shopping, Business Process Outsourcing (BPO) organization etc, highly increasing the number of customers for e-business made an impact on product reviews. Reviews are useful in making decisions for both the customer and

DOI: 10.5281/zenodo.7074332
ISSN: 1533 - 9211
manufacturer. Sentiment is a state of mind, thought, or judgment provoked by a sentiment of the customer who is writing a review.

Nowadays, the first thing a person does before making a purchase is to read the reviews and opinions left by other users on social media platforms like Facebook, Twitter, and several other blogs and product review websites. Prior to making a purchase choice, almost 95% of customers read customer reviews [4]. This opened the door for brand-new fields of study like sentiment analysis and opinion mining. Businesses can gain information from sentiment analysis by receiving quick feedback on their products and gauging the success of their social media marketing campaigns. The manufacturer can use this to manage their reputation and find new prospects.

Neural networks, which use an architecture modelled after the neurons in the human brain, are able to solve practically any categorization issues that are machine-leaning in nature. Recurrent neural networks (RNN) produce outstanding results when classifying text [6]. To improve the accuracy of sentiment analysis in this work, RNN (recurrent neural networks deep-learning method) [7][8] is utilized. Extract characteristics from words or phrases that strongly convey a good or negative judgement. Deep learning, however, offers the ability to address many of the issues that sentiment analysis now faces.

Using the EMFO Method, the semantic word vectors from each word of the input review were extracted from the lexical words. The combined features were sent into an HBiGRU to train it and predict whether the review's emotion labels would be favorable or negative. The investigation on the data demonstrates that the HBiGRU technique is more accurate at predicting sentiment classification.

The organization of the rest of the paper is as follows: In Section- 2 Related works and the Proposed Methodology in Section 3 and Experiment Results in Section 4 and finally, the Concluding remarks in Section-5.

II. RELATED WORKS

Ying et al., proposed a better Bayesian algorithm to address the issue of text classification. First, the text was classified using the Bayesian algorithm, and accuracy was calculated and compared to other approaches to determine how well each algorithm performed. The model may then successfully predict the text given its features by altering the threshold value to increase prediction accuracy [21].

Jiwei Li et al., demonstrated a method of displaying multidimensional feature vector spaces, as the output of vector-based models is highly challenging to understand. These techniques, such as the saliency heatmap for displaying word compositions in neural networks for NLP, were exhibited. According to the authors, visualisation models can demonstrate asymmetries of negation, aid in understanding how neural models might construct meanings, and help to explain some elements of LSTMs' impressive performance in NLP tasks.

Meenakshisundaram.K et al., presented the LSTM (Long Short-Term Memory) model, which enhanced the recurrent neural network. The input gate, forget gate, and output gate are all under the control of the LSTM unit. An additional RNN vaiation is LSTM.[16].

David Zimbra et al., claimed that the outcomes from Twitter Sentiment Analysis (TSA)

DOI: 10.5281/zenodo.7074332

approaches are not what was expected. They have examined Twitter analysis in this article since its inception. They have outlined the difficulties posed by TSA methods and how to overcome those difficulties. The authors also examined TSA benchmark methodologies, benchmark evaluation procedures, and typical reasons for categorization errors. They concluded by summarising the important points and presenting TSA with benchmark evaluation techniques.

Barkha Bansal et al., reviews were transformed into vector representations using the word2vec model for categorization. They tested their approach using a dataset from Amazon that includes more than 400,000 customer evaluations in the mobile phone category. They divided up how they presented their work. First, they showed that word2vec can identify semantic traits that are comparable and unique to the domain in question. To categorise the customer reviews, second, features suppressed in CBOW (continuous bag of words) and skip-gram forms were subjected to appropriate machine learning algorithms (SVM, Naive Bayes, Logistic Regression, and Random Forest).

Wang et al., extensive research has been done on them. Although RNN can handle sequential data in deep learning, it has issues with gradient disappearing or exploding. Through the design of "gates," the introduction of long short-term memory networks (LSTM) and the gated recurrent unit (GRU), which is more succinct, can successfully address the aforementioned issues. In order to understand context dependency more thoroughly than GRU, GRU may extract feature information in both forward and backward directions.

Uma.K.K et al., [21]is a considered grey wolf feature selection optimization. To extract emotions from emoji, a brand-new Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN) based model is suggested. CNN-style deep learning is used to classify the sentiments. The researcher demonstrates that the CNN and LSTM model's performance in detecting sentiment targets has significantly improved. A new general accuracy function selection and classification is proposed using optimized deep learning approach. This new method is proposed to solve the misclassification problem in social media review data set. In addition, the work is defined with a mew general accuracy feature selection using convolution neutral network clubbed with evolutionary optimized technique proposed by **Uma et al.,** [19].

III. Proposed Methodology

In the proposed Method develops HBiGRU which is method for prediction of different product reviews of customer in an improved way. Combination of the BiGRU method and the Heed mechanism is named as HBiGRU. It solves the problems of complex calculation and high space cost of text sentiment analysis method. Our HBiGRU method incorporates text vectorization input layer, hidden layer, and output layer. Among them, the hidden layer contains of four layers as BiGRU layer, Heed layer, dropout layer, and dense layer. The word vector obtained by text preprocessing passes through the input layer and enters the BiGRU layer of the neural network to extract features. The word vector obtained by text preprocessing is extracted by input layer and neural network BiGRU layer, and then the key information of the word vector is highlighted by Heed mechanism, through dropout layer to prevent over fitting,

SEYBOLD Report
ISSN: 1533 - 9211
DOI: 10.5281/zenodo.7074332

then through dense layer, and finally into softmax layer for text reviews classification. The proposed work consists of Pre-processing, Effective Moth Flame Optimization Algorithm (EMFO) and HBiGRU.

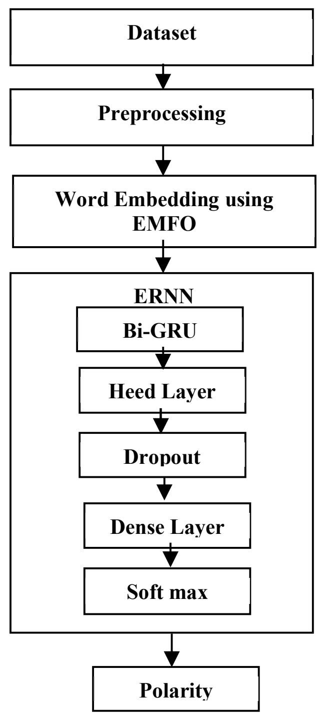

Figure 1: Flow Diagram for proposed Methodology

3.1 Pre-Processing

Data preprocessing is the process of cleaning and removing non-textual substances [10] from the collected dataset to improve the accuracy and performance of the proposed method. Some preprocessing techniques are Tokenization, Stopword Removal, Stemming and Lemmatization and Contraction and Expansion.

3.2 Word Embedding technique

Word embedding is a method of feature extraction to boosting the accuracy of machine learning, deep learning, and Natural Language Processing (NLP) tasks by converting each word, into a corresponding vector representation using EMFO pre-trained models and own trained dataset.

3.3 Deep Learning Approach

The traditional GRU works on the process of both convolution and sub-sampling and the working is done with help of sequence of layers. At last, all the layers are connected with fully connected layer, and then Softmax activation is applied in order to determine the output. Using Effective Moth Flame Optimization Algorithm, once initial population is generated, each vector has been assigned a sentiment score with respect to its semantic information which is done by fitness function. At the final state, consisting of best individuals with respect to given context. This best individual is given as input to HBiGRU.

The proposed HBiGRU is the combination of the BiGRU model and the Heed

DOI: 10.5281/zenodo.7074332

mechanism, with EMFO in which the Heed mechanism can assign different weight information to different word vectors, highlighting the importance of words. The HBiGRU is used to classifying the given product reviews as positive, negative or neutral emotion. The process of identifying features from the subjective data is known as feature extraction. This extraction of features which consisting of people emotions of categories like positive, negative and neural. This model helps to capture emotion behind the particular feature and predict that by using sentiment score and evaluate by different evaluation metrics. The final result, predicted that accuracy is improved with respect to the given approach.

Input Layer

In general, input layer consisting of all the features of input in a vector form. Here applied the input such as the output that got from EMFO infused dataset, which is the best features and indirectly represent fittest individual from the given population. It is noteworthy that the input data of dataset obtained from EMFO technique.

Hidden Layer

Bi-GRU (Bidirectional Gated Recurrent Units)

Gated recurrent units (GRUs) are considered to be a gating mechanism in recurrent neural networks. However, GRUs has been shown to demonstrate better performance on smaller to medium quantity datasets. Calculate the word vector output by the BiGRU layer. The text word vector is the input vector of the BiGRU layer, and the purpose of the BiGRU layer is mainly to extract the deep features of the text from the input text vector. The word vector of the t[th] word of the j[th] sentence input at time i is c_{ijt}. After feature extraction from the BiGRU layer, the relationship between contexts can be learned more fully and semantic coding can be performed. Specific calculation formula:

$$h_{ijt} = BiGRU(c_{ijt}) \tag{1}$$

Next, calculate the probability weight that each word vector should be assigned. In order to highlight the importance of different words to the sentiment classification of the entire text, the Heed layer is introduced. The input of the Heed layer is the output vector h_{ijt} of the previous layer that has been activated by the BiGRU neural network layer. The weight coefficients are specifically calculated by the following formulas:

$$U_{ijt} = \tanh\,(w_w h_{ijt} + b_w) \tag{2}$$

$$\propto_{ijt} = \frac{\exp\,(U_{ijt}^T U_w)}{\sum_{nt} \exp\,(U_{ijt}^T U_w)} \tag{3}$$

$$s_{ijt} = \sum_{i=1}^{n} \propto_{ijt} h_{ijt} \tag{4}$$

Among them, h_{ijt} is the output vector of the previous BiGRU neural network layer, w_w is the weight coefficient, b_w is the bias coefficient, and U_w is the randomly initialized Heed matrix. The Heed mechanism matrix is the cumulative sum of the product of the different probability weights assigned by the Heed mechanism and the state of each hidden layer and is

DOI: 10.5281/zenodo.7074332

obtained by using the softmax function for normalization.

Heed Mechanism

The essential idea of the Heed mechanism source can be assumed to be composed of a series of data pairs. Key value queries have three basic elements: Query, Key, and Value. The calculation process of the Heed value can be summarized as follows. Firstly, obtain the weight coefficient of each Key's corresponding Value by calculating the correlation between each Query and each Key, and then perform a weighted summation of the weight and the corresponding key value. Therefore, the essential idea of the Heed mechanism can be described as a mapping from a query to a series of key-value pairs, which is expressed as follows:

$$Heed(Query, Source) = \sum_{i=1}^{l_x} Similarity(Query, Key_i) * Value_i \quad (5)$$

Where $l_x = \|Source\|$ represent the length of the data source. Among them, K (Key) represents keywords, Q (Query) represents query, F represents function, V (Value) represents weight value, S represents similarity, a represents weight coefficient, and A (Heed Value) represents Heed value.

In the first stage, the weight coefficient of each Key corresponding to Value is obtained by calculating the correlation between each Query and each K. In the second stage, a similar softmax function is introduced to normalize the weights, which can highlight the weights of important elements. a_i is the weight coefficient corresponding to Value, and the specific calculation is shown in the following formula,

$$a_i = Soft\max(s_i) = \frac{e^{S_i}}{\sum_{j=1}^{l_x} e^{S_j}} \quad (6)$$

In the third stage, the weight and the corresponding key value are weighted and summed to get the final Heed value.

Dropout Layer

In order to avoid the occurrence of overfitting, a dropout layer is added between the Heed layer and the fully connected layer. In the neural network, some nodes are randomly ignored, and nodes are randomly selected each time, which can effectively prevent the learned model from performing well on the training data and poor performance on the test data. The following describes the main workflow of the dropout layer and how it works in a specific neural network,

Forward propagation: Input the output result of the Heed layer to the dropout layer. The dropout layer randomly ignores the preset nodes in the internal hidden layer (the ignored nodes are backed up and saved), and then the remaining nodes are propagated forward to obtain the predicted label.

Back propagation: Compare the original label with the value obtained from the predicted label and adjust the parameters through back propagation.

Update the parameters: The adjusted value is only updated on the nodes that are not ignored, and the other ignored nodes are not updated. Repeat the corresponding operation on the training dataset in the next iteration process until the number of iterations is reached and the model is

ISSN: 1533 - 9211
DOI: 10.5281/zenodo.7074332
trained.

Output Layer

The input of the output layer is the output of the dense layer. The softmax function is used to calculate the input of the output layer to classify the text. The specific formula is as follows:

$$y_j = soft\max\,(w_1 s_{ijt} + b_1) \quad (7)$$

Where w_1 represents the weight coefficient matrix to be trained from the Heed mechanism layer to the output layer, b_1 represents the bias to be trained, and y_j is the output prediction label.

In datasets, preset parameters, and number of iterations N as input. The text vectorized input layer processes the dataset in the form of word vectors and classifies the dataset with the AT-BiGRU model. Let the word vector corresponding to a word in the text be x_t in the form of the word vector corresponding to the dataset. Processing of each comment in the dataset:

For hop =1 to h

$$\overrightarrow{h_t} = GRU(x_t, \overrightarrow{h_{t-1}})$$

$$\overleftarrow{h_t} = GRU(x_t, \overleftarrow{h_{t-1}})$$

$$h_t = w_t\overrightarrow{h_t} + v_t\overleftarrow{h_t} + b_t$$

$$U_{ijt} = \tanh\,(w_w h_{ijt} + b_w)$$

$$\propto_{ijt} = \frac{\exp\,(U_{ijt}^T U_w)}{\sum_{nt}\exp\,(U_{ijt}^T U_w)}$$

$$s_{ijt} = \sum_{i=1}^{n} \propto_{ijt}\, h_{ijt}$$

End for.

$y_j = soft\max\left(w_1 s_{ijt} + b_1\right) is$ Calculated by softmax is compared with the original label, and the objective function is

$$Loss = -\sum_j \hat{y}^j\, log y^{(j)} \quad (8)$$

Through the above training steps, using formula (8), feature extraction is performed on the words from 1 to h, and the corresponding weights are assigned to the cumulative sum. The dense layer further extracts feature and finally performs classification in the softmax output layer. Then, the results of the multiplication of each comment tag value and log y_j are accumulated. The sum of the accumulated values is negative, and the opposite is taken to minimize the loss and reduce the calculation error. Adam is used as the training device to make the model training and convergence faster. In the process of backward error propagation along time, the weights and offsets are adjusted and updated according to the errors until the iterations are reached or a fixed precision is reached.

IV. Results and Discussions

The social media product reviews are taken from the dataset. In the pre-processing step, the dataset is a converted into a suitable form to be given to the deep learning models. The data

DOI: 10.5281/zenodo.7074332

preparation includes Stop Words removal, Punctuation removal, stemming, lemmatization and count vectorization. In Recurrent Neural Networks, all the sentences in the dataset are split into words and converted using the embedding layer into word embedding. Next, the word embedding is applied along with Improved Bi-GRU and Heed Mechanism layer is performed. These layers finally connect to the output layer. The accuracy of the neural networks that are trained using those layers.

The proposed HBiGRU model produces high accuracy when compared with previous method. And also, compared the result with various state-of-art method which is present in [24]. In this HBiGRU method, epoch size as 45 is used to test the working efficiency. Table 1 shows performance result of HBiGRU for product review dataset.

Performance Measures

When evaluating the performance indicators of word vectors, the confusion matrix method is used. TP means that the positive class is predicted as a positive class number, TN predicts a negative class as a negative class number, FP predicts a negative class as a positive class number, and FN means that a positive class is predicted as a negative class number.

Accuracy rate is expressed as the ratio of the number of correctly classified samples on the test dataset to the total number of samples. The formula is expressed as

$$\text{Accuracy}=\frac{T^p+T^n}{T^p+F^p+T^n+F^n} \quad (9)$$

Precision can be defined as

$$\text{Precision}=\frac{T^p}{T^p+F^p} \quad (10)$$

Recall rate can be expressed as

$$\text{Recall}=\frac{T^p}{T^p+F^n} \quad (11)$$

F1 value is the harmonic mean value of precision rate and recall rate, expressed as

$$\text{F1}=\frac{2T^p}{2T^p+F^p+F^n} \quad (12)$$

It can be seen from equation (12) that the value of F1 will increase with the increase in accuracy and accuracy. Generally speaking, the accuracy rate is for the prediction result, which means the correct number of samples whose prediction is positive. The recall rate is for the training set, which represents the number of positive examples predicted to be correct in the sample, including the positive class prediction in the sample as the positive class (TP) and the positive class prediction in the sample as the negative class (FN).

Table 1. Performance Results of HBiGRU for product Review dataset

Model	Accuracy	Precision	Recall	F1-Score
LSTM	89.65	82.25	82.69	85.63

DOI: 10.5281/zenodo.7074332

BiGRU	92.23	86.69	89.52	89.23
EMFO with HBiGRU	95.29	90.86	91.23	94.56

Above Table 1 shows performance result of HBiGRU for product review dataset. The HBiGRU method on product review has better Accuracy, Precision, Recall, F1-score than other methods and it achieves highest accuracy 95.29% respectively.

V. CONCULSION

The proposed HBiGRU is for text classification in sentiment analysis. Evaluation experiments were performed using review data, and the proposed model exhibits higher performance than the existing CNN, LSTM, MLP, hybrid models. The proposed method achieved higher accuracy which increased as the size of training data and the number of training epochs increase. This can provide an alternative solution to the long-term dependency problem in existing models and the data-loss problem that occurs as the size of training data increases. Recently, the field of text classification research has focused on extracting accurate semantics and features from special fields (e.g., medical, engineering, and emotional) and areas requiring specialized knowledge, rather than simply increasing accuracy. Experimentation purpose that are tested with metrics of accuracy, precision, recall and F1-score. The proposed work achieves better results for product review and datasets.

References

[1] Alshammari.N.F and A. A. AlMansour, "State-of-the-art review on twitter sentiment analysis," in 2019 2nd International Conference on Computer Applications & Information Security (ICCAIS), pp. 1–8, IEEE, 2019.

[2] Ain, Q.T.; Ali, M.; Riaz, A.; Noureen, A.; Kamran, M.; Hayat, B.; Rehman, A. Sentiment analysis using deep learning techniques: A review. Int. J. Adv. Comput. Sci. Appl. 2017, 8, 424.

[3] Abhilash Mittal, Sanjay Patidar. Sentiment Analysis on Twitter Data: A Survey: Proceedings of the 7th International Conference on Computer and Communications Management July 2019 pp.9 https://doi.org/10.1145/3348445.3348466

[4] Aliaksei Severyn and Alessandro Moschitti. Twitter sentiment analysis with deep convolutional neural networks. In Proceedings of the 38th International ACM SIGIR Conference on Research and Development in Information Retrieval, pages 959–962. ACM, 2015.

[5] Bermingham.A and A. F. Smeaton, "Classifying sentiment in microblogs: is brevity an advantage?," in Proceedings of the 19th ACM international conference on nformation and knowledge management, pp. 1833–1836, 2010.

[6] Baziotis.C, N. Pelekis, and C. Doulkeridis, "Datastories at semeval-2017 task 4: Deep lstm with Heed for message-level and topic-based sentiment analysis," in Proceedings

SEYBOLD Report
ISSN: 1533 - 9211
DOI: 10.5281/zenodo.7074332
of the 11th international workshop on semantic evaluation (SemEval-2017), pp. 747–754, 2017.
[7] Cicero dos Santos and Maira Gatti. Deep convolutional neural networks for sentiment analysis of short texts. In Proceedings of COLING 2014, the 25th International Conference on Computational Linguistics: Technical Papers, pages 69–78, 2014.
[8] CHEN G N, DAI Z B, DUAN J T, et al. Improved naive bayes with optimal correlation factor for text classification[J]. SN Applied Sciences, 2019,1(9): 1-10. Go.A, R. Bhayani, and L. Huang, "Twitter sentiment classification using distant supervision," CS224N project report, Stanford, vol. 1, no. 12, p. 2009, 2009.
[9] Huy Nguyen and Minh-Le Nguyen. A deep neural architecture for sentence-level sentiment classification in twitter social networking. arXiv preprint arXiv:1706.08032, 2017.
[10] Jianqiang .Z., G. Xiaolin, and Z. Xuejun, "Deep convolution neural networks for twitter sentiment analysis," IEEE Access, vol. 6, pp. 23253–23260, 2018.
[11] Pedregosa.F, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. Scikit-learn: Machine learning in Python. Journal of Machine Learning Research, 12:2825–2830, 2011.
[12] Ramachandran.D and R. Parvathi, "Analysis of twitter specific preprocessing technique for tweets," Procedia Computer Science, vol. 165, pp. 245–251, 2019.
[13] Severyn.A and A. Moschitti, "Unitn: Training deep convolutional neural network for twitter sentiment classification," in Proceedings of the 9th international workshop on semantic evaluation (SemEval 2015), pp. 464–469, 2015.
[14] Sharma.A and U. Ghose, "Sentimental analysis of twitter data with respect to general elections in india," Procedia Computer Science, vol. 173, pp. 325–334, 2020.
[15] Su. M.-H., C.-H. Wu, K.-Y. Huang, and Q.-B. Hong, "Lstm-based text emotion recognition using semantic and emotional word vectors," in 2018 First Asian Conference on Affective Computing and Intelligent Interaction (ACII Asia), pp. 1–6, IEEE, 2018.
[16] Richard Socher, Alex Perelygin, Jean Wu, Jason Chuang, Christopher D Manning, Andrew Ng, and Christopher Potts. Recursive deep models for semantic compositionality over a sentiment treebank. In Proceedings of the 2013 conference on empirical methods in natural language processing, pages 1631–1642, 2013.
[17] Wang, Y.; Wang, M.; Xu, W. A sentiment-enhanced hybrid recommender system for movie recommendation: A big data analytics framework. Wirel.Commun.Mob.Comput. 2018.
[18] Xi Ouyang, Pan Zhou, Cheng Hua Li, and Lijun Liu. Sentiment analysis using convolutional neural network. In Computer and Information Technology; Ubiquitous Computing and Communications; Dependable, Autonomic and Secure Computing; Pervasive Intelligence and Computing (CIT/IUCC/DASC/PICOM), 2015 IEEE International Conference on, pages 2359–2364. IEEE, 2015.

DOI: 10.5281/zenodo.7074332

[19] Xin Rong. word2vec parameter learning explained. arXiv preprint arXiv:1411.2738, 2014. [20] Google image search. [21] David Meyer. How exactly does word2vec work? 2016.

[20] Yang.C, K. H.-Y. Lin, and H.-H. Chen, “Emotion classification using web blog corpora,” in IEEE/WIC/ACM International Conference on Web Intelligence (WI’07), pp. 275–278, IEEE, 2007.

[21] YING Y, MURSITAMA T N, SHIDARTA, et al. Effectiveness of the News Text Classification Test Using the Naïve Bayes’ Classification Text Mining Method[J]. Journal of Physics: Conference Series, 2021, 1764(1).

[22] Zhao Jianqiang, Gui Xiaolin, and Zhang Xuejun. Deep convolution neural networks for twitter sentiment analysis. IEEE Access, 6:23253– 23260, 2018.

[23] K.K. Uma, K. Meenakshisundaram” Sentence Level Sentiment Analysis using Deep Learning Method” International Journal of Recent Technology and Engineering (IJRTE) ISSN: 2277-3878, Volume-8 Issue-3, September 2019.

[24] K. Meenakshisundaram, K.K. Uma,” Retainable Short Term Memory Based Sentiment Analysis on Trending Data” CiiT International Journal of Digital Signal Processing, Vol 11, No 12, December 2019.

[25] Uma. K.K, Meenakshisundaram.K” A Novel Optimizer Technique for Sentiment Polarity in Social Web Environment” International Journal of Applied Engineering Research ISSN 0973-4562 Volume 14, Number 1 (2019) pp. 118-125 © Research India Publications. http://www.ripublication.com .