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SENTIMENT ANALYSIS FOR IMPROVING QUALITY OF PRODUCTS AND SERVICES BY USING DEEP LEARNING

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ABSTRACT

In Today's internet world, sentiment analysis is an essential and more demanding task because it allows different commerce and organizers to know customer opinions regarding multiple business aspects. Such opinions significantly support the business. It could easily understand the feelings and needs of each customer. In the current decade, social media networks like Twitter are becoming a beneficial resource that extracts millions of posts to know the customer feelings since it is possible to succeed. In this paper, we recommend the latest approach called deep-learning, which easily enables different types of commerce and corporations to recognize customer feelings on sentiment analysis to improve the quality of their stocks or facilities and easily succeed in today's businesses activities. Therefore, with the help of a convolution neural network (CNN), we researched various sizes of a Twitter dataset consisting of millions of tweets to evaluate the efficiency of such a method for categorising each Twitter post as positive, negative and neutral.

Keywords: convolution neural network (CNN), sentiment analysis (SA), deep learning (DL), naive bayes (NB), support vector machine (SVM).

1. INTRODUCTION

The most popular micro blogging platforms are Twitter, which was established in 2006 by Jack Dorsey, Noah Glass, Biz Stone, and Evan Williams, have recently become more popular social media across the whole world. Around 500 million tweets are generated across the world per second, and approximately 6,000 tweets have been tweeted on average, Twitter keeps up a huge correspondence to more than 350,000 tweets post per each minute, mainly per each day 500 million tweets and approximately 200 billion tweets for every year and more 321 million active users are using because today's internet is growing bigger and bigger, its horizons are becoming wider [1].

Nowadays, in internet world every business and organization has been a wide range of opinions across social media networks. Such opinions are very useful and important regarding to know each customer's feelings therefore it motivates the way to take decisions, among several other topics, regarding purchasing a product, casting a vote in a major election, and selecting a vacation destination [2]. This data is still valuable and helpful to companies as it allows them to understand in real time the customer opinions on their goods, the revenue outlook, and customer satisfaction. Organizations may find possibilities to develop the excellence of their goods or services with this knowledge.

A great example of the significance of opinions is an Amazon.com store Lenovo laptop that received negative reviews as it looked like the laptop used in the feature. Such organizations need to respond immediately in such cases to solve the issues, so that such views do not harm their credibility. In this context, it is helpful to know public opinion through social media like Twitter as real-time [3]. Twitter is really a current internet decade popular social media platform in which people share posts nearly real time. Hence, corporation reflect on this social media network especially twitter become a vast resource for customer opinions that enables them to learn, amongst other things, the overall opinion of their services and products.

Moreover, it takes a lot of time and work for people to evaluate and interpret such opinions. For such purposes, a technology recently has arisen which handles this data efficiently. Such technique is referrers to as study of opinion or extraction of opinion. Many scholars have described the study of sentiment. Although, this concept mostly apply in the research area would be the one suggested. This described it as tries to follow: "Sentiment analysis is the area of research which examines the thoughts, feelings, perceptions, attitudes, and feelings of people regarding concepts such as goods, services, organizations, persons, problems, incidents, themes, and their qualities".

Many techniques are developed in recent decades for the evaluation of customer sentiments. Many of these methods are focusing on two major methods, semantic manner and ML. While achieving better outcomes by using both methods, many studies in the research has shown that positive results are gaining from ML but not enough accuracy. Moreover, an innovative approach defined as deep learning also gained researchers interest in more recent years since it has greatly exceeded conventional techniques [4]. Many of the sentiment analysis methods implement deep learning, which is focusing on English and improves accuracy and generates good results.

2. RELATED WORKS

Several scholars have been introduced many strategies to perform sentiment analysis in the recent research. Such studies utilized only two key methods, semantic direction and ML. Therefore, such strategies utilizing sentiment lexicons to evaluate polarization with

respect to the first methodology. SentiWordNet is really the literature's most widely utilized lexicon. This Word Net-based lexicon involves multiple meanings of a word. This also offers to each context a positive and negative value. Many studies are using this method have generated interesting outcomes even though, several other studies had not produced excellent outcomes due to two major causes: First: Sentiment lexicons being primarily focused on English, that requires researchers to interpret the English lexicons into the original language, and Second: A word could be set of alternate meanings on the environment they are being used [5].

R.S Shankar and D R Babu [6] Illustrates how automated essay scoring, assists writers in determining their level of competence. For several aspects of the task, expansion is still to be addressed; however, there are many opportunities for growth, with regard to the wide array of languages in the world. One of the advantages of this system is that it's almost impossible to miss critical grammatical errors. Additionally, it is self-evident how ML can perform if the agent is properly prepared with a large set of suitable data and a sufficiently powerful algorithm facilitates the learning phase. Although statistically significant differences between instructor and AES grading were observed, this study suggests that utilizing this interface will be much more prudent. RS Shankar *et al,* [7] reported that essay writing still plays a good role in measuring a person's learner autonomy, which is why it has been used in most competitive assessments. Currently, this assessment is carried out manually. This entails considerable human initiative and time. This assessment methodology is automated in this project. Since machines cannot comprehend measurement metrics, provide them with keywords that serve as features. Initially, the student-written essay is linked to the keywords specified by the administrator. If the degree of resemblance is less than 20%, the article does not meet the norm. The function extraction methods are critical in the text mining phase. Finally, an effective automated tool focused on function methods and different properties such as word count is built in this project work. Numerous numerical functions, a spell checker, and so forth. The proposed system's success was evaluated using broad topics such as corruption, demonetization, and so on. Finally, it computes the grades for each student in a certain class based on the submitted essays. To evaluate the proposed system's efficiency, accuracy and error are used as measurement metrics. The suggested system's success is often evaluated when comparing it to manual judgment. Observing the system-generated scores for each pupil is preferable to manual judgment. As a result, it is established that the proposed method is 85 percent effective.

R Shiva Shankar *et al*, [8] stated that the business's forecast of day attrition had become an enormous challenge. Employee attrition is a significant problem for companies, especially as educated, technical, and key workers quit for better opportunities outside of the company. The suggested method analyses previous and current employee data to forecast potential attrition and investigate the causes of employee turnover. The findings of this study demonstrate that data extraction algorithms will be used to develop effective and precise statistical models of employee attrition. Attrition diagnosis is more than simply separating attrition from non-attritions. They can show the turnover risk for each employee utilizing preliminary data analysis to data extraction methods and provide them with results to develop retention strategies. RS Shankar *et al.*, [9] Reviewed the Online Student Feedback Analysis System is a web-based system that gathers feedback from individual students and automatically generates composite feedback. It has been used to gather feedback from students on the course's major components, including plans, material, implementation processes, punctuality, expertise, appreciation, and learning experience. They have designed a framework to distribute input to each department, or educational institute in a fast and simple manner Feedback is obtained using Qualitative scores.

Recent techniques for data mining for reviews make use mainly qualitative data. Thus, a full assessment cannot be produced. Student feedback mining system (SFMS) employs text analytics and sentiment analysis to offer instructors an in-depth understanding of the students. They gathered input from students and then cleaned the data using text analysis. Comments are gathered and rendered as a cluster about each topic. Use the sentiment classifier to classify comments and use the method of visualization to reflect students' opinions. This novel input mechanism enhances the teaching experience for the students. This technology speeds up the process of giving reviews via the online system. Since the current system takes longer to collect input from students, an online feedback system is introduced. Avoid paper usage and save time and effort of the workers in charge or faculties. The proposed method has been designed with safety concerns since only the genuine individual will see the aggregate input of a batch of students and learn about the collective opinion.

Researchers have been using classification algorithms like SVM, Bayesian Networks, and DT are, among many others. Both datasets are required for this methodology, a training set as well as an assessment set. The training set can be utilized for learning the methodology from both the domain characteristics. Meanwhile, the assessment set is being used to verify the constructed model from either training set. The efficiency of the ML methodology focuses on the efficiency of the approach chosen for extracting features.

While, Latest research process focused on deep learning methods, for example, suggested a strategy to study small documents on sentiments [10]. The strategy focuses on a CNN implemented on two corporate tweets, movie blogs and Tweets. First, get features vectors across the domain information also the language. Second is the creation of a DNN. For concept of mining and sentiment analysis, the researchers have been using a CNN such recommendation was decided in many other domains, including restaurants, hotels, computers, mobiles, and cams. Developed a DL framework that applies to two

activities, specifically Twitter sentiment analysis text-level and sentence-level. At last, three variants are choosing to demonstrate the efficiency of the technique, SVM, NB, and DNN. Lastly, by utilizing a deep learning method, a strategy to aspect retrieval for SA is used. The writers have compiled a series of language trends in order to integrate them through neural networks. R.S Shankar *et al* [11, 12, 13, 14, 15], has done their work on various SA using various datasets to get best accuracy. In the other direction, the strategies to sentiment analysis concentrate on analyzing the views of blogs, forums, and websites for transportation and marketing. Though, recently, a higher special interest having emerged in social networks like Twitter since for its research it becomes possible to obtain a large amount of information across various topics. Films, technological goods, tourist industry, and nutrition are one of the most researched sectors in the field of sentiment analysis.

3. CHALLENGES IN SENTIMENTAL ANALYSIS

SA is a latest field of research with several research challenges that could be dealt with in order to add insight to the decision-making methods. Since much of the research is about classifying customer feelings, this study intensity across the sentiments could be very effectively improves the categorization of social media posts, where it is possible to suggest a mixture of wide-ranging of feeling parameters [16]. The appreciation of sarcasm and irony detection in phrases paired with several other characteristics is also an attribute that influences the recognition of viewpoint strength. Embedding people feelings in ontology will help answer intelligent opinions and questions that have not been thoroughly investigated so far. A semantic paradigm utilizing profound learning will assist to reduce the interaction between the individual and add value to the mining area of opinion. A hybrid strategy to rule-based learning together with methods of ML will yield more reliable results. Although positive and promising outcomes have been displayed in this field, more work is still needed because of the decision-making, product sales, and prediction model are focused on social media data sentiment.

4. PRE-PROCESSING MODULE

In this research spotlight as classification of sentiments that is, categorize into three major components:

a) Pre-Processing,

b) Word embedding, and

c) Recommended Convolution Neural Network (CNN) Classifier model

Step 1: for Twitter posts of CSV file do
Step 2: delete HTML, dt=deleting (row review).gettext ()
Step 3: deleting symbols/non-letters with resubmitting by regular expressions.
Step 4: change to a lowercase letters and splits the words= letters_only.lower ().split ()
Step 5: change the stop-words to a set
Step 6: stop=set (stop-words (english))
Step 7: eliminate stop-words
Step 8: give (important words)
Step 9: end for

The title "convolution neural network" means that the network operates a statistical method named convolution. This is a specific sort of linear mechanism. Convolution arrangements are just neural networks that apply convolution in the area of common matrix multiplication might be one of their layers.

A CNN has a single input and s single output layer but many hidden layers which generally have a list of convolution layers that convolve based on multiplication [17]. The RELU layer means is activation function which is consequently succeeded by further convolutions such as pooling, fully connected and normalization layers, associated to as hidden layers since their inputs and outputs are hidden with the activation function and closing convolution layer. The closing convolution has generally involved back propagation in order to achieve high accurately weight the end result. Therefore, each layer is joined together as convolutions simply by tradition. Statistically, this is a cross-correlation and sliding dot product.

Figure-1 displays the system's functionality. Primary, the document will be tokenized and standardized. After that, word2vec could utilize to get the vectors of the function [18]. The final step is to train a CNN for the classification of tweeting as positive or negative. The following sections offer a good complete description of these components.

The first phase of the recommended approach is to pre-process the posts. Twitter is a social media platform in which consumers will be using informal language because 140 characters are limited. There have been also various problems, including spelling mistakes, idiomatic expressions, acronyms, and word duplication, that need to be resolved until recognizing a tweet's polarization. Figure-2 shows a few of these difficulties with such a twitter post. To address this issue, we incorporated the tweet processing method was proposed [19].

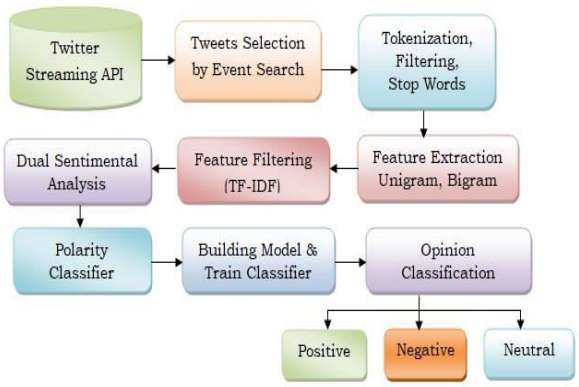

Figure-1. Sentiment analysis on twitter data system overview.

The tokenization procedure is the very first step of the pre-processing section. The document is separated into tokens in this phase, which could be phrases or punctuation. The Tokenize method has been shown to accomplish this procedure. The tool becomes Twitter-oriented which helps, among others, to find Twitter objects such as hash tags, comments and responses, and URLs. Applied Twitter APIs as its library mechanism to gather tweets for sentiment report from the popular social networks and make a model based on NB and SVM.

We give training to each classifier and categorized each twitter posts as follows:

a) We developed a classifier for NB to classify subjective tweets and objective tweets. The main subjective on training dataset is phrases, which are calling as subjective or objective, and we used the set of features like Unigram, Bigram, and Object-oriented to achieve efficient training.

b) The subjective posts are listed in the +ve or -ve category for the SVM classifier. The sentiment training dataset seems to be positively or negatively tagged words, and we used set of training features are Unigram, Bigram and object-oriented.

c) After analyzing the customer emotions, the system might draw a graph. Figure-1 demonstrates the working of newly build classifier for sentiment analysis which measuring can be focused on various features like Unigram, Bigram, and object-oriented.

NAIVE BAYES

The purpose of the whole technique is the conditional probability between terms, phrases and classes of predicting to their class-based statistics [20]. A particular purpose of this scheme is the presence of terms, which is becomes separate Naive Bayes classifier does not determine the dependency of terms in any class. We have been using the Naive Bayes Multinomial. Naive Bayes allocate a tweet d to class c. The equation is as continues to follow: in which: i) f: defines a function. ii) ni (d): the amount of functionalities fi can be observed in tweets.
There are m set of features.

Step 1: for Testing Class do
Step 2: Training the naive Bayes classifier
Step 3: Naïve bayes gauss nb=gaussianNB ().fitting the (training classes)
Step 4: predict the targeting variables for test classes clf.predict (test class)
Step 5: set up the models on accuracy
Step 6: Give prediction on accuracy and matrix of testing classes
Step 7: end for

Which is a probability classifier and it completely allows those characteristics applied individualistic to every classifier with Bayes theorem. In this approach, the collected CSV file is provided as the trained set for the model. The algorithm includes Gaussian Naive Bayes to handle on real-time data i.e. twitter posts; it could spread each class as Univariate Distribution. Ultimately, the forecasting is made for specified test class and predicts the accuracy level.

SVM

A further approach that has been common with ML is Machine Vector Support. We even utilized the SVM Scikit-Learn classifier based on linear kernel. The training dataset for the Vector Machine Aid is made up of two vector sets of m dimension. M is really a function. The vector element represents the truth or falsity of this feature [21]. For example, a feature is a term identified in a tweet using the Information Gain technique. While the function is active, the value of the feature is 1. On the other hand, that value is 0. Bigram and Object-oriented apps are the same thing.

Step 1: for Testing Class do
Step 2: train the classifier with Naive Bayes
Step 3: linear SVC=SVM. Linear SVC(C, class weight, dual).fit (train classes)
Step 4: linear SVC. Predict (testing class)
Step 5: given the prediction on accuracy score and matrix of testing class
Step 6: set up the models on accuracy
Step 7: Give prediction on accuracy and matrix of testing classes
Step 8: end for

Approximately all Machine-learning algorithms for sentiment analysis follows regular steps to categorize the emotion as explained below:

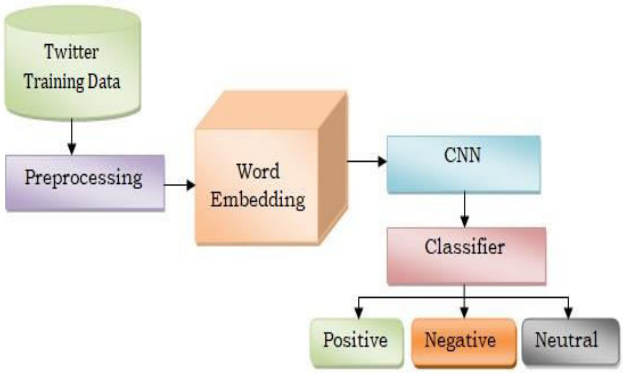

Figure-2. Sentiment analysis with CNN.

This second phase involves normalizing the document. Next, with the help of Tokenize we detected objects then eliminated since they do not support essential data to polarity identification. First, it describes the item are eliminated from the tweets. Notices and answers to consumers: such things become labeled by @. URLs: all things begin by http:/ Hash tags: the # symbol is only omitted in this situation because the remainder of the

document is an essential part to examine. In this phase, two remarks and single hashtag are detected by Tokenize. The module after which eliminates the references like ("@bufalo58" and "@SamsumgChile") and "# ChaoSamsumg".

Second, hashtags will be divided based on upper case letters (strings containing one or more terms). Taking into consideration the above instance, #ChaoSamsung is divided into two sentences "Chao" and "Samsung."

Third, acronyms and synonym notes are expanded.

We were using the NetLingo dictionary (http:/www.netlingo.com) for such a reason.

For e.g., "que" rather than "q," "por que" rather than "xq," and "cellular" instead of "celu".

Word Embeddings

We utilize word2vec in this strategy to know encoding words. Such a tool executes the Constant Bag-of-Words Method (CBOW) and Skip-gram Model for word recognition computational vector. Word integrating is an essential part of CNN infrastructure because it enables lexical and linguistic knowledge to be accessed from the messages, which is also very useful for characterization of sentiments.

Convolutional Neural Network (CNN) Model

We will be using a popular deep convolutionary neural network CNN for the categorization of messages across positive and negative groups. The structure of the CNN includes concatenated data vectors as inputs which are shown in Figure-3. Tensor flow (https:/www.tensorflow.org) has been utilized to incorporate this method [22].

5. EXPERIMENTS

The primary goal of this technique seems to be to identify each product and service their feedback through customer opinions, which significantly helps in many businesses and organizations to develop them more improvement and success way [23]. Hence, our strategy needs a product and service-related repository like stock maker datasets. Throughout this context, we got many posts through Tweet.

The collecting mechanism for that kind of posts is categorized below.

a) Use of Twitter4J (http:/ twitter4j.org/) library to gather twitter posts. A collection of keywords relating to technical items has been identified to achieve appropriate tweeting.

b) Duplicated messages, retweets, other language twitter posts and twitter posts containing just URLs have been eliminated.

c) The overall 70,000 number of positive messages as well as 63,000 negative messages.

d) Finally, just 50000 positive messages and 50000 negative messages are collected, which have been reviewed weekly to acquire those appropriate to our research.

We utilized-known parameters: accuracy, recall, and F-measure to determine the efficiency of our recommended model. First: Accuracy is the ratio of positive instances that are forecasted to be true positives. In the other side, second: recall is the ratio that was accurately prophesied as just that of overall positive events. F-measure: harmonic mean would be the consistency and recall [24].

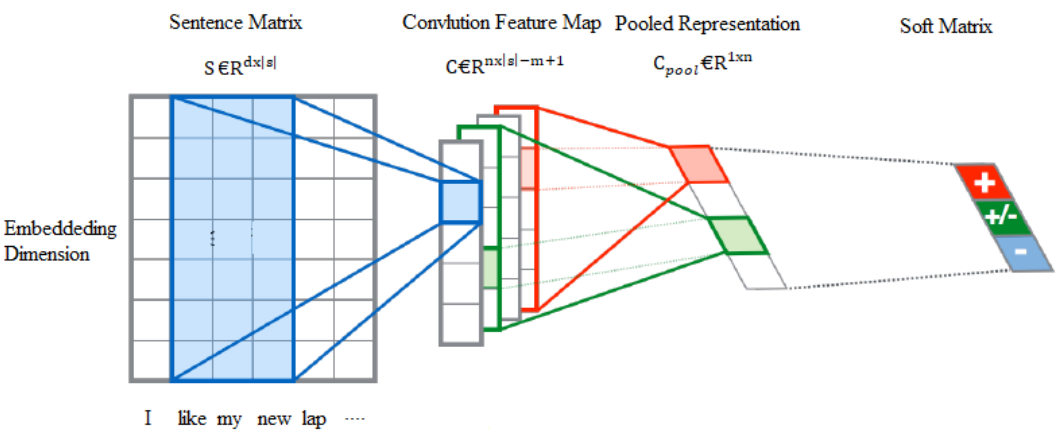

Figure-3. The architecture of deep learning model.

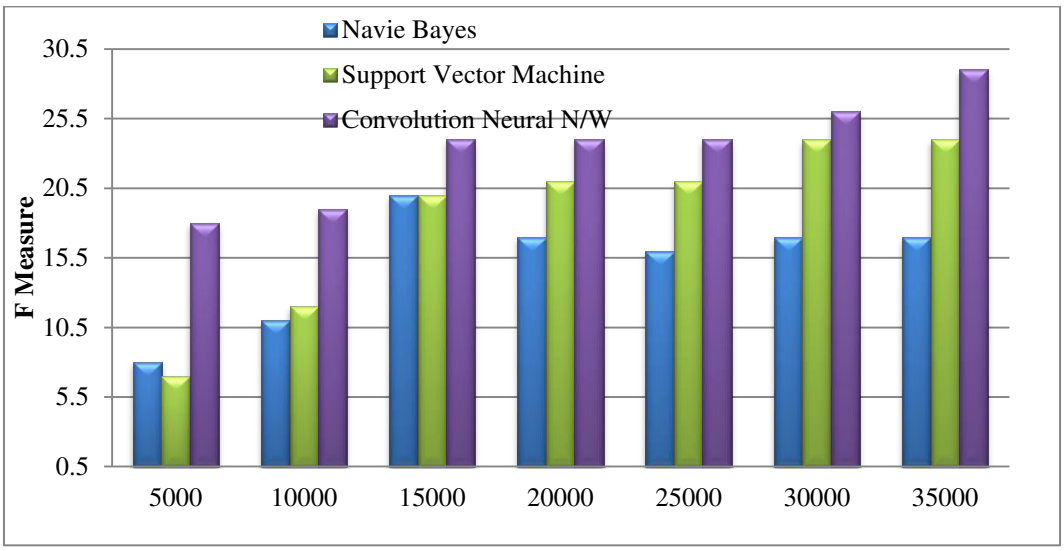

Figure-4. F-Measure Results on SVM, NB and CNN.

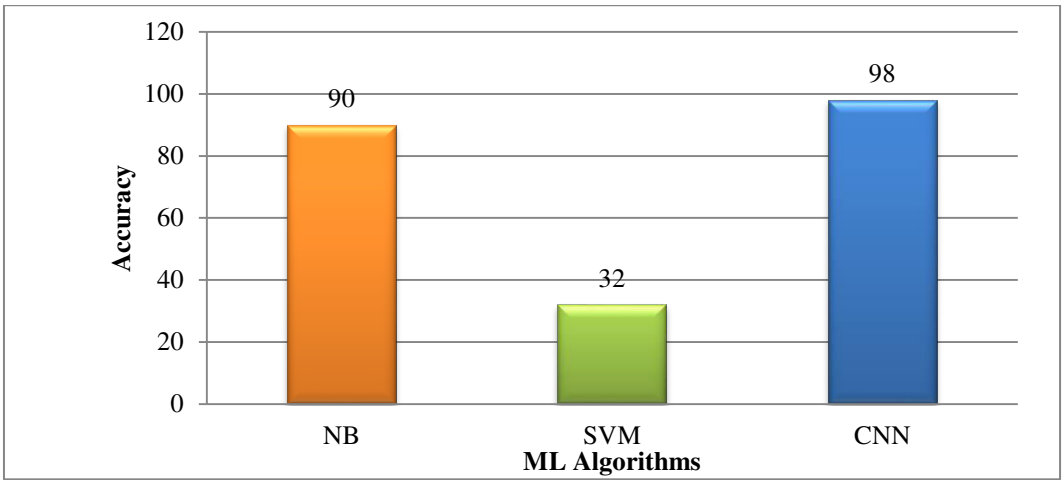

Figure-5. Accuracy on ML algorithms with CNN.

Comparison with Traditional Learning Methods

The recent study on the analysis of sentiments could be categorized into various viewpoints: the methodology employed interpretation of the message, level of detail of the study of the document, level of rank, etc. There have been four fundamental strategies from a technical perspective, including ML, lexicon-based, analytical, and rule-based strategies. The ML strategy is commonly utilized because it can perform computation and negotiate with smaller and larger data sets. Using the lexicon-based strategy, the polarity of feelings from the examined data is measured to obtain lexical option support on a dictionary or corpus approach. Semantic perspective is a test of the message's subjectivity and viewpoint. The rule-based method categorizes depending on the sign of positive and negative terms, such method applies various classification principles like dictionary polarization, words of denial, and words of advocate, phrases, hash tags, and conflicting feelings. Much of the current classification approaches characterize the information incorrectly, and due to a shortage of dictionary and corpus in much other language, some sentimental research is performed on English text [25].

Various classification methods have contrasted to the equal function vectors in this research, including SVM, NB, and CNN (Figures 3, 4 and 5). The standard dimensions for each method have been utilized for a meaningful association without performing an extra modulation mechanism. This research has been conducted to test with something like a CNN potential influence of the recommended solution. With help of various scales of the corpus tested these algorithms.

Every set, which is separates in two datasets:

a) 80% of the information will be utilized as a training set and

b) 20% of the information could be used as a test set.

The F-score is frequently applied in the area of document classification performance. More beginning works concentrated fundamentally upon the F1 score [26]. However, with the generation of massive scale search

engines, the performance aims are adjusted to place larger importance on each precision or recall.

The F-score is also applied in ML. However, the F-measure doesn't get the true negatives into concern. Measures such as the kappa could be superior to evaluating a binary classifier's performance as shown in Figures 4 and 5. The F-score has been popularly employed in natural language processing research, such as evaluating named entity recognition and word segmentation.

Moreover, as dataset scales linearly increase, SVM generates more desirable outcomes over NB. In addition, from the other direction, findings have suggested the coevolutionary neural network achieved faster results over conventional models (SVM and NB) with the various subgroups of the Twitter repository [27, 28]. Such outcomes demonstrate which deep learning approaches outperformed conventional methods of ML of sentiment analysis [29, 30, 31 and 32]. It is essential to keep in mind that we did not compare our findings with those published in related works whereas in Spanish there will be a shortage of deep learning strategies to sentiment analysis.

6. CONCLUSIONS

We addressed a Twitter sentiment analysis strategy in this research. The primary aim of this recommendation would provide the foundation for awareness of consumer satisfaction and to recognize possibilities for product and service enhancement. The recommendation is focused on a deep learning framework to create an emotion detecting neural network. Our methodology achieved promising outcomes with 88.7 percent accuracy, recall, and F-measure. The findings further indicate that CNN has surpassed conventional models including SVM and NB. The test results recommend that accurately trained CNNs can exceed the baseline ML algorithms for sentiment analysis. In our CNN model, the sentences of reviews are labeled into three categories such as positive, negative and neutral. All the tests are done applying various parameter contexts for all CNN models, and it must be recognized that CNN model becoming two convolution layers with filter volumes 3 and 4 gives the most useful models and is able to accomplish 95% an accuracy.

REFERENCES

[1] Chambers Nathanael, Victor Bowen, Ethan Genco, Xisen Tian, Eric Young, Ganesh Harihara and Eugene Yang. 2015. Identifying political sentiment between nation states with social media. In Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing. pp. 65-75.

[2] Chang Chih-Chung and Chih-Jen Lin. 2011. LIBSVM: a library for support vector machines. ACM transactions on intelligent systems and technology (TIST). 2(3): 1-27.

[3] Collobert Ronan, Jason Weston, Léon Bottou, Michael Karlen, Koray Kavukcuoglu and Pavel Kuksa. 2011. Natural language processing (almost) from scratch. Journal of machine learning research 12, no. ARTICLE: 2493-2537.

[4] Davidov Dmitry, Oren Tsur and Ari Rappoport. 2010. Enhanced sentiment learning using twitter hash tags and smileys. In Coling 2010: Posters. pp. 241-249.

[5] Davidov Dmitry, Oren Tsur and Ari Rappoport. 2010. Semi-supervised recognition of sarcasm in Twitter and Amazon. In Proceedings of the fourteenth conference on computational natural language learning. pp. 107-116.

[6] Shankar, R. Shiva and D. Ravibabu. 2019. Digital Report Grading Using NLP Feature Selection. In Soft Computing in Data Analytics, pp. 615-623. Springer, Singapore.

[7] Shankar R. Shiva, D. Ravi Babu, K. V. S. S. Murthy and Vmnssvkr Gupta. 2017. An approach for essay evaluation using system tools. In 2017 International Conference on Innovative Research in Electrical Sciences (IICIRES), pp. 1-9. IEEE.

[8] Shankar R. Shiva, J. Rajanikanth, V. V. Sivaramaraju and K. V. S. S. R. Murthy. 2018. Prediction of employee attrition using datamining. In 2018 IEEE international conference on system, computation, automation and networking (icscan), pp. 1-8. IEEE.

[9] Shankar R. Shiva, L. V. Srinivas, D. Ravibabu and Ch Raminaidu. 2018. NOVICE RETROACTION REPORT. ARPN Journal of Engineering and Applied Sciences. 13(24): 9746-9753.

[10] Dong Li, Furu Wei, Chuanqi Tan, Duyu Tang, Ming Zhou and Ke Xu. 2014. Adaptive recursive neural network for target-dependent twitter sentiment classification. In Proceedings of the 52nd annual meeting of the association for computational linguistics (volume 2: Short papers). pp. 49-54.

[11] Eisner, Ben, Tim Rocktäschel, Isabelle Augenstein, Matko Bošnjak and Sebastian Riedel. 2016. Emoji2vec: Learning emoji representations from their description. arXiv preprint arXiv: 1609.08359.

[12] Shankar RS, Priyadarshini V, Neelima P, Raminaidu CH. 2021. Analyzing Attrition and Performance of an Employee using Machine Learning Techniques. In 2021 5th International Conference on Electronics,

Communication and Aerospace Technology (ICECA) Dec 2 (pp. 1601-1608). IEEE.

[13] Kambhampati Kalyana Kameswari, J Raghaveni, R. Shiva Shankar, Ch. Someswara Rao. 2019. Predicting Election Results using NLTK. International Journal of Innovative Technology and Exploring Engineering (IJITEE). 9(1): 4519-4529.

[14] Jyothirmayee S, Dilip Kumar V, Someswara Rao C, Shiva Shankar R. 2019. Predicting stock exchange using supervised learning algorithms. International Journal of Innovative Technology and Exploring Engineering. 9(1): 4081-90.

[15] Shankar RS, Murthy KV, Rao CS, Gupta VM. 2018. An approach for extracting tweets from social media factors. In2018 ieee international conference on system, computation, automation and networking (icscan) (pp. 1-7). IEEE.

[16] Shankar RS, Neelima P, Priyadarshini V, Babu DR. 2014. An Object Oriented Approach for Evaluating the Error Correction Coding. International Journal of Engineering Research. 3(4).

[17] Kalchbrenner, Nal, Edward Grefenstette and Phil Blunsom. 2014. A convolutional neural network for modelling sentences. arXiv preprint arXiv: 1404. 2188.

[18] Kim Yoon. 2014. Convolutional Neural Networks for Sentence Classification. r08r25. https://arXiv. org/abs/1408.5882.

[19] Kouloumpis, Efthymios, Theresa Wilson and Johanna Moore. 2011. Twitter sentiment analysis: The good the bad and the omg. In Proceedings of the International AAAI Conference on Web and Social Media. 5(1).

[20] Nakov, Preslav, Alan Ritter, Sara Rosenthal, Fabrizio Sebastiani and Veselin Stoyanov. 2019. SemEval-2016 task 4: Sentiment analysis in Twitter. arXiv preprint arXiv: 1912.01973.

[21] Medhat Walaa, Ahmed Hassan and Hoda Korashy. 2014. Sentiment analysis algorithms and applications: A survey. Ain Shams engineering journal. 5(4): 1093-1113.

[22] Cambria, Erik, Dipankar Das, Sivaji Bandyopadhyay, and Antonio Feraco. 2017. Affective computing and sentiment analysis. In A practical guide to sentiment analysis, pp. 1-10. Springer, Cham.

[23] Rosenthal, Sara, Noura Farra and Preslav Nakov. 2019. SemEval-2017 task 4: Sentiment analysis in Twitter. arXiv preprint arXiv: 1912.00741.

[24] Wan Yun and Qigang Gao. 2015. An ensemble sentiment classification system of twitter data for airline services analysis. In 2015 IEEE international conference on data mining workshop (ICDMW), pp. 1318-1325. IEEE.

[25] Jianqiang Zhao and Gui Xiaolin. 2017. Comparison research on text pre-processing methods on twitter sentiment analysis. IEEE Access. 5: 2870-2879.

[26] Tokle Sumit, Shamantha Rai Bellipady, Rajeev Ranjan and Shirshu Varma. 2014. Energy-efficient wireless sensor networks using learning techniques. Case Studies in Intelligent Computing: Achievements and Trends. 407-426.

[27] Bouazizi, Mondher and Tomoaki Ohtsuki. 2017. A pattern-based approach for multi-class sentiment analysis in Twitter. IEEE Access. 5: 20617-20639.

[28] Hua Wen, Zhongyuan Wang, Haixun Wang, Kai Zheng and Xiaofang Zhou. 2016. Understand short texts by harvesting and analyzing semantic knowledge. IEEE transactions on Knowledge and data engineering. 29(3): 499-512.

[29] Rajput Nikhil Kumar, Bhavya Ahuja Grover and Vipin Kumar Rathi. 2020. Word frequency and sentiment analysis of twitter messages during coronavirus pandemic. arXiv preprint arXiv: 2004.03925.

[30] Vilares David, Carlos Gómez-Rodríguez and Miguel A. Alonso. 2017. Universal, unsupervised (rule-based), uncovered sentiment analysis. Knowledge-Based Systems. 118: 45-55.

[31] Thomas Darrin. 2017. Sentiment analysis of the conflict of age's series. In International Forum Journal. 20(1): 31-43.

[32] Cortis Keith, André Freitas, Tobias Daudert, Manuela Huerlimann, Manel Zarrouk, Siegfried Handschuh, and Brian Davis. 2017. Semeval-2017 task 5: Fine-grained sentiment analysis on financial microblogs and news. Association for Computational Linguistics (ACL).