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Twitter Sentimental Analysis using Deep Learning Techniques

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ABSTRACT

There is a rapid growth in the domain of opinion mining as well as sentiment analysis which targets to discover the text or opinions present on the disparate social media plat- forms via machine-learning (ML) with polarity calculations, sentiment analysis or subjectivity analysis. Sentimental analysis (SA) indicates the text organization which is employed to cate- gorize the expressed feelings or mindset in diverse manners like favorable, thumbs up, positive, unfavorable, thumbs down, negative, etc. SA is a demanding and notable task that comprises i) natural-language processing (NLP), ii) web mining and iii) ML. Also, to tackle this challenge, the SA is merged with deep learning (DL) techniques since DL models are efficient because of their automatic learning ability. This paper emphasizes re- cent studies regarding the execution of DL models like i) deep neural networks (DNN), ii) deep-beliefnetwork (DBN), iii) convolutional neural networks (CNN) together with, iv) re- current neural network (RNN) model. Those DL models aid in resolving different issues of SA like a) sentiment classification, b) the classification methods of i) rule-based classifiers(RBC), KNN and iii) SVM classification methods. Lastly, the classification methods' performance is contrasted in respect of accu- racy.

Keywords : Sentiment analysis, Opinion mining, Deep learning.

I. INTRODUCTION

A. Sentimental Analysis

SA is contextual mining of text which recognizes and ex- torts subjective information from the source material, and it also assists a business to comprehend the social sentiment of their service, brand or product whilst observing online chats. SA manages sentiments, subjective text, and opinions [1,40]. SA renders the understandable information connected to the public views, as it examines diverse reviews and tweets. It is a verified effectual tool for the prediction of numerous imperative events like general elections and also box office movies [2]. Pub- lic reviews are utilized to assess a specific entity, i.e., product, person or location which existson disparate websites like Yelp and Amazon. Therefore, SA is utilized for the determination of the expressive directions of user reviews automatically [3]. The requirement for SA is elevated owing to the increased requisite of analyzing and also structuring of the concealed information which comes as of the social media in the sort of un- structured data [4]. As imperative resources of real-time opinion, Twitter, texts and the other social networks have fascinated substantial interests of the research in- dustry and community [5]. SA (opinion mining (OM)) of brief informal texts on social media summarizes opinions as a) positive, b) neutral or c) negative statement of the opinion holder [6,41,42]. A million numbers of tweets are created daily on multifarious issues. Linguistic flexibility in expression and Topical diversity in content are 2 notable challenges in examining tweets. Numerous twitter sentiment analyzers depend on diverse sentiment lexicons either to feed features to classifier models or to ascertain sentiment scores [7].

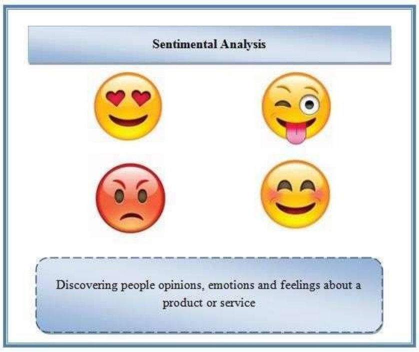


Fig. 1. Diagram for sentimental analysis

B. Features of Sentimental Analysis

Sentiments depend upon a certain range of values of fea- tures like bi-grams and also tri-grams with their polarities and also on their combinations [8, 9]. Their influences are iterative and slow in nature. So for continuing the work on the neural network's hidden layer, a kernel function is be- ing employed which evaluates the existence of class label. The conditional dependencies betwixt the various edges and nodes of an acyclic graph are executed with the aid of 'Bayesian networks', which assist in the extortion of data at the contextual level.

For the best SA of paragraphs and sentences, 'Hidden Markov model' [10-12,43-48] is employed. The optimiza- tion of words together with sentences brings faster learning which enhances data accuracy for social media. Data to- kenization at word root levels assists to create positive and negative facets of data. All those approaches are working harder to diminish the errors in OM and SA to attain a better level of data accurateness for social media [13].

C. Techniques for sentimental analysis

SA has 2 categories of techniques, a) ML Approach and b) Lexicon based approach [14-17].

Machine Learning Approach

ML is the utmost prominent methodology gaining the attention of researchers owing to its accuracy and adapta- bility [18]. In SA, mostly the supervised learning alternatives of this methodology are employed. It encom- passes 4 stages: i) Data collection, ii) Pre-processing, iii) Training data, iv) Classification as well as plotting results. Multiple tagged corpora are proffered on the training data. The Classifier presented numerous feature vectors from the former data. A model is built centered upon the training data-set which is implemented over the new/hidden text for classification. In the ML technique, the key for classifier accuracy is the selection of pertinent features. Normally, i) unigrams (one-word phrases), ii) bi-grams (two successive phrases), iii) tri-grams (three successive phrases) are cho- sen as feature vectors. There are various proposed features like a) number of negative words and positive words, b) the length of the document, c) SVM (Support Vector Ma- chines), and d) NB algorithm (Naïve Bayes) [19-22]. Accu- racy differs from 63% to 80% relying on the combination of chosen features. Fig.2 delineates the working of an ML approach.

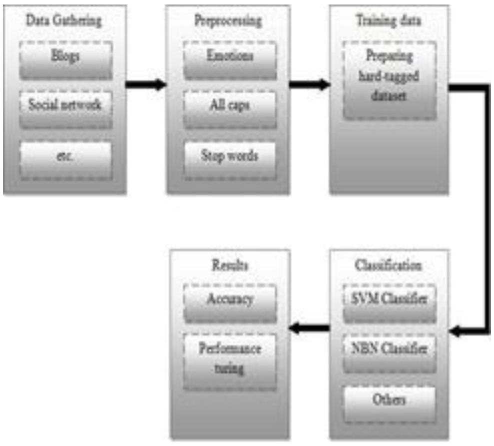


Fig. 2. General structure for ML approach

Lexicon-based Approach

This technique is guided by the utilization of a diction- ary comprising pre-tagged lexicons. The input text is transmuted to tokens by utilizing the Tokenizer. All newly arriving tokens are then matched for the lexicon in the dictionary. If a positive match is encountered, the score gets added to the total pool of a score for the inputted text e.g. if ‘dramatic’ is positively matched in the dictionary then increment this text’s total score else decrement or tag that word as negative. Albeit, this technique is amateur in nature, its variants are established to be valuable. Fig. 3 delineates the operations of a lexical technique.

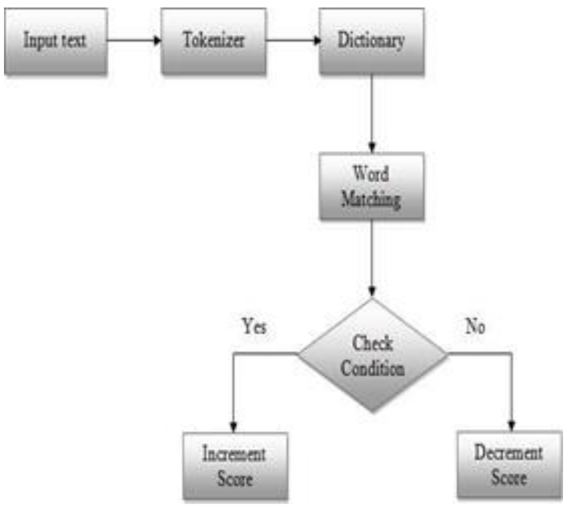


Fig. 3. General structure for a Lexicon-based approach

D. Deep Learning

ML technology powers several aspects of modern commu- nity i.e. as of web searches, content filtering in social net- works to suggestions in e-commerce websites, in addition, it exists increasingly on consumer products like smartphones and cameras. ML systems are utilized to i) recognize objects in images, ii) match news articles, iii) transcribe speech to text, iv) products or posts with con- sumer’s interests, and v) choose pertinent results of a search. These applications exploit a class of techniques termed DL.

DL is a representation-learning methodology with multi-leveled representation, attained by composing sim- pler but non-linear (NL) modules where each transmutes the representation in one level (beginning from the raw input) to a representation in a higher abstract level. With the compilation of such adequate transmutations, excep- tionally complex functions are learned. DL comprises un- supervised learning together with supervised learning.

E. Sentimental Analysis with Deep Learning

Recently, DL algorithms delivered impressive performance in NLP applications encompassing SA across numerous datasets. Such models don’t need any pre-defined features which are hand-picked by an engineer, but they could learn sophisticated features as of the dataset by themselves. Alt- hough every single unit in these Neural Networks (NN) is fairly simple, by means of stacking layers of NL units at the back of one another, those models are competent to learn highly sophisticated decision boundaries. Words are signified in a high-dimension vector space, and the feature extortion is left to the NN. As an outcome, those models could map words with identical syntactic as well as seman- tic properties to adjacent locations in their coordinate sys- tem, in a way which is evocative of comprehending the words' meaning. Architectures like RNNs are also compe- tent to effectively comprehend the sentences' structure.

These make DL models the best fit for tasks like SA.

II. LITERATURE SURVEY

This phase talks about the characteristic research works related to SA utilizing DL field. SA tasks are performed effectually by executing disparate models like DL models, which have been extended recently. Those models encom- pass RNN, CNN, DNN, RBC, KNN, SVM classifier, along with DBN. This section delineates the efforts of disparate researchers toward executing DL models and ML approach for executing the SA.

A. Sentimental Analysis Using Convolutional Neural Networks (CNN)

Shiyang et.al [23] suggested an approach to comprehend real situations with the SA of a Twitter data centered on DL techniques. With the suggested method, it was viable to forecast user satisfaction on a product, happiness with a certain environment or destructive situation after disasters. Lately, DL was competent to resolve problems in voice recognition or computerized vision. CNN worked fine for image analysis together with classification. An impera- tive reason to employ CNN for image analysis and image classification was that the CNN could extort an area of features as of global information precisely and also it was competent to regard the relations amongst those features. The above solution could attain the utmost accuracy in analysis together with classification. For NLP, texts' data features could also be extorted piece by piece. Regarding the relations amongst those features without considering the context or complete sentence might incor- rectly interpret the sentiment. And, it was the most effectu- al method to perform image classification. CNN comprised a convolutional layer to extort information by a large piece of text, so SA with CNN exhibited that it attained augmented accuracy performance in twitter sentiment clas- sification when contrasted to some traditional methodolo- gies like the SVM and NB methods.

Xiao et.al [24] recommended a hybridized NN model architecture termed LSCNN with data augmentation technology (DAT), which outperformed numerous single NN models. The recommended DAT augmented the gener- alization competency of the recommended model. Experi- ment outcomes exhibited that the recom- mended DAT in combination with the NNs model could attain astounding performance without any handcrafted traits on SA or brief text classification. It was tested on a Chinese news headline corpus and Chinese on- line com- ment dataset. It outperformed numerous modern models. Evidence confirmed that the recommended DAT could attain more precise distribution representation from data for DL, which augmented the generalization traits of the extorted features. The combination of the LSCNN fusion model and DAT was appropriate to brief text SA, specifi- cally on the small-scale corpus.

Jinzhan et.al [25] suggested a methodology for la beling the words of the sentences via integrating deep CNN (DCNN) with the sequential algorithm. Firstly, the aspects embraced by a) words vectors, b) part of speech vectors, c) dependent syntax vectors was extorted to train the DCNN, and then the sequential algorithm was em-ness of SA, it was suggested to construct the tuples em- bracing aspect, sentimental shifter, sentiment intensity, sentimental words after attaining the sentimental labels for every word existent in the sentence. Then, an algorithm was built for inherent aspect recognition by considering the 2 key facets of the aspects as i) a topic- the matching de- gree of aspects and ii) sentimental words- the human lan- guage habit. The experiment delineated that the algorithm could effectually detect the inherent aspect. The issue of inherent aspect recognition on SA and sentiment labeling was resolved. As a fresh tool for SA, this methodology could be employed to the enterprise management information analysis, like a) product online review, b) product online reputation, c) brand image and d) consumer preference management, and could also be utilized for the SA of huge text data.

Gichang et.al [26] recommended a methodology for recognizing keywords differentiating negative and posi- tive sentences by utilizing a weakly supervised learning methodology centered on a CNN. In this model, all words were signified as a continual-valued vector whereas, all sentences were signified as a matrix whose rows matched to the word vector utilized in the sentence. Subsequently, the CNN was trained utilizing those sentence matrices as inputs, in addition, the sentiment labels as an output. After training, the word attention scheme was implemented to recognize higher-contributing words to classify outcomes with the class activation map utilizing the weights. To vali- date the recommended methodology, the classification accurateness and the rate of polarity words amongst higher scoring words was assessed utilizing 2 movie review da- tasets. Experiential outcome confirmed that the recom- mended model could correctly categorize the sentence polarity and successfully recognize the matching words with the higher polarity scores.

Tao et.al [27] suggested a divide & conquers methodology which initially categorized the sentences into disparate types, then executed the SA separately on sen- tences as of each type. Especially, it was ascertained that the sentences tend to be utmost intricate if it comprised more sentimental words. Thus, it was suggested to employ an NN centered sequence model to categorize opinionated sentences into 3 types as per the count of targets transpired in a sentence. Each pool of sentences was then supplied to a one-dimension CNN separately for sentimental classifica- tion. This approach was appraised on 4 sentimental classi- fication datasets and contrasted with extensive baselines. Experiential outcomes exhibited that: (1) sentence type categorization could augment the performance of sentence- level SA; (2) the suggested approach attains modern out- comes on numerous benchmarking datasets.

Table 1. Analysis of convolutional neural networks

Researcher Name and year	**Model Used**	**Purpose**	**Data Set**	**Limitations**
Yazhi et.al [28]	CNN	SA	Movie Review and IMDB	Less convolutional layer utilized.
Zhao and Gui [29]	DCNN	Twitter sentiment classifica- tion	5 datasets that are 1) STSTd data set, 2) SE2014 dataset, 3) STSGd data set, 4) SED, and 5) SSTd.	Paved atten- tion on pre- trained word embeddings.
Shiyang et.al [23]	CNN	Compre- hend situations in the real world.	STS and MR Gold Dataset	Only utilized smaller training dataset.

B. Sentimental Analysis Using Recurrent Neural Networks (RNN)

Wenge et.al [30] recommended an SA model centered on RNN, which took a part of a document as input and then the subsequent parts were utilized to forecast the senti- mental label distribution. The recommended methodology learned words representation and also the sentimental dis- tribution.

Experiential studies were executed on commonly utilized datasets and the outcomes had proved its propitious potential.

Wen et.al [31] suggested an approach termed DRI-RCNN ('Deceptive Review Identification by RCNN') to recognize deceptive reviews by utilizing DL and word contexts. The fundamental idea was that, since truthful and deceptive reviews were provided by writers with and without real experience correspondingly, the re- view writers should have disparate context knowledge on their targeted goals under description. To distinguish the deceptive and truthful context knowledge embraced on the online reviews, each word of a review was signified with 6 elements as a re-current convolutional vector (RCV). The primary and secondary components were 2 numerical word vectors attained from training deceptive together with truthful reviews, respectively. The 3rd and 4th compo- nents were left neighboring truthful and deceptive context vectors attained by means of training a RCNN on word vectors and contextual vectors of left words. Also, the 5th and 6th components were right neighboring truthful and deceptive contextual vectors of right words. Further-

more, ReLU (Rectified Linear Unit) and max-pooling filter was employed to transfer RCVs of words on a review to a review vector by extorting positive maximal feature elements in RCVs of words in the review. Experiment outcomes on the deception dataset and the spam dataset delineated that the suggested DRI-RCNN approach per- formed better on considering the modern techniques in deceptive review recognition.

Fei et.al [32] suggested an LSTM-centered design that was responsive to the words that existed in the vocabu- lary; therefore, the keywords influence the semantics of the complete document. The suggested model was assessed in a brief-text SA task on 2 datasets like IMDB and SemEval- 2016. Experiential outcomes delineated that the design outperformed the baseline LSTM by 1%~2% in respect of accuracy and was effectual with notable performance en- hancement over numerous non-RNN latent semantic de- signs (specifically in handling brief texts). It also integrated the idea to an alternative of LSTM named the gated re- current unit (GRU) model and attained fine performance, which confirmed that this methodology was adequate to augment disparate DL models.

C. Sentimental Analysis Using Deep Belief Networks (DBN)

Shusen et.al [33] presented a 2-step SSL (semi-supervised learning) methodology termed fuzzy DBNs (FDBN) for sentimental classification. Primarily, the common DBN was trained by the SSL by utilizing the training dataset. Then, a fuzzy membership function (FMF) was designed for all classes of reviews centered on the DL archi- tecture. As the DBN training maps every review to the DBN output space, the dissemination of the entire training samples on the space was valued as prior knowledge, in addition, was encoded by sequences of FMFs. Secondly, grounded on the fuzzy membership functions and the DBN attained in the primary step, an FDBN architecture was built and the supervised learning stage was employed to increase the FDBN's classification performance. FDBN inherited the powerful abstraction competency of DBN and delineated the attractive fuzzy classification competency for handling sentimental data. To take over the upsides of both FDBN and active learning, an active FDBN (AFD) SSL method was suggested. The experiential validation on 5 sentimental classification datasets delineated the ef- fectiveness of AFD and FDBN methods.

Yong et.al [34] suggested a word positional form together with a word-to-segment matrix representation to integrate the position information to DBNs for senti- mental classification. Subsequently, the performance was assessed by the total accuracy. Therefore, these experien- tial outcomes exhibited that by including positional infor- mation on ten small text data sets, the matrix representation was utmost effective. On considering the linear positional contribution form, it further suggested that the positional information should be regarded for SA or NLP tasks.

Analysis Using Deep Neural Network (DNN)

Harika et.al [35] presented a scheme to spot the sentimental online Hindi product's reviews centered on its multiple modality natures (text together with audio). For every au- dio input, 'Mel Frequency Cepstral Coefficients' (MFCC) features were extorted. These features were utilized to build a sentiment design utilizing DNN and GMM (Gauss- ian Mixture Models) classifiers.

From outcomes, it was perceived that DNN classifier prof- fered better outcomes in contrast to GMM. Further features of text were extorted from the transcription of the audio input by utilizing Doc2vec vectors. SVM classifier was utilized to build a sentimental model utilizing those textual features. From experiential results, it was perceived that integrating the text and audio features brought enhance- ment in the performance for spotting the sentiment of online products' reviews.

Xiao et.al [36] suggested a contents extension structure (i.e), integrating posts and connected comments to a microblog conversation intended for features extortion. A convolution auto-encoder was employed which could extort contextual information as of microblog conversation which was utilized as features intended for the posts. A custom DNN, which was integrated with numerous layers of RBM ('Restricted Boltzmann Machine'), was executed to initialize the NN structure. The RBM layers could take probability distribution samples of the inputted data to learn concealed structures for fine higher level features' representation. A Class RBM ('Classification RBM') layer which was integrated on RBM layers was employed to attain the final sentimental classification label intended for the posts. Experiential outcomes exhibited that with proper parameters and structures, the performance of suggested DNN on sentimental classification was better on consider- ing recent surface learning models like NB or SVM, which confirmed that the suggested DNN model was relevant for shorter document classification with the suggested feature dimension extension methodology.

Shusen et.al [37] suggested an SSL algorithm termed 'active deep network' (ADN). Primarily, suggested the SSL framework of ADN. ADN was built by RBM with un-supervised learning centered on labeled and maximal unlabeled reviews. After that, the built structure was modi- fied by means of gradient-descent centered supervised learning having an exponential loss function. Secondly, in the SSL framework, then active learning was employed to recognize reviews that were marked as training data, after that, utilized the chosen labeled and all unlabeled reviews for training ADN architecture. Furthermore, to integrate the information density with AND suggested IADN (in- formation ADN) methodology, which could employ the information density of the entire un-labeled reviews in selecting the manually labeled reviews. Experiments on 5 sentimental classification datasets confirmed that IADN and ADN outperformed the classical SSL algorithms and DL techniques employed for sentimental classification.

D. Sentimental Analysis Using Rule-Based Classifiers

[38] presented an effectual OM together with SA of Web reviews utilizing disparate rule centered ML algorithms. To utilize SentiWordNet that created

score count words from the 7 categories namely i) strong-positive, ii) posi-

tive, iii) weak-positive, iv) neutral, v) weak-negative, vi) negative and vii) strong-negative words. The present- ed approach was tested on online books and political re- views and delineated the efficacy via Kappa measures, which had 97.4 % accuracy and lesser error rate. The weighted mean of disparate accuracy measures namely Precision, TP-Rate and Recall depicted higher efficacy rate and less FP-Rate. Comparative experiments on disparate rule centered ML algorithms were performed via a 10-Fold cross-validation training design for sentimental classification.

E. Sentimental Analysis Using SVM Classifier

Vo et.al [39] suggested a model utilizing an SVM algo- rithm with the Hadoop M (Map)/ R (Reduce) for English document category emotion classification in the Cloud era parallel network environment. Cloud era was also a disseminated system. This English testing dataset (ETD) had 25,000 documents, encompassing 12,500 posi- tive and also 12,500 negative reviews. This ETD had 90,000 sentences, embracing 45,000 positive sentences together with 45,000 negative ones. This model was exper- imented on the ETD and attained 63.7% accuracy of sentimental classification on this ETD.

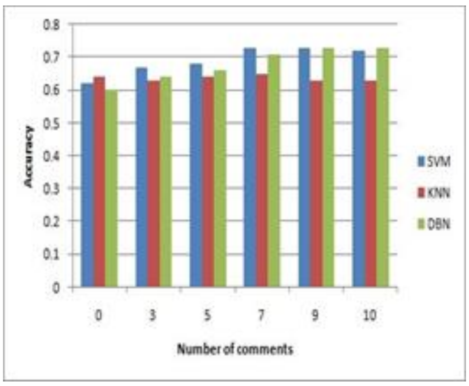


Fig. 4. Compare the performance of the different classi- fier in terms of accuracy with the number of comments

Discussion: The above figure 4 [36], contrasted the dis- parate classifier's performance in respect of accuracy. The accuracy range was varied based on the number of com- ments (n). From the above figure, it was clear that, when n=0, the SVM classifier offered 0.62 accuracy and when n= 10, it offered 0.72 accuracy. Similarly, KNN offered 0.64 accuracy for n= 0, but for n=10, it offered 0.63 accu- racy. Likewise, DBN offered 0.6 and 0.73 accuracies when n= 0 and 10 respectively.

III. PROBLEM STATEMENT

We use the dataset from Kaggle which was crawled and labeled positive/negative. The data pro- vided comes with emoticons, usernames and hashtags which are required to be processed and converted into a standard form. We also need to extract useful features from the text such uni- grams and bigrams which is a form of representation of the "tweet". We use various machine learning algorithms to conduct sentiment analysis using the extracted fea- tures. However, just relying on individual models did not give a high accuracy so we pick the top few models to generate a model ensemble. Ensembling is a form of meta learning algorithm tech- nique where we combine different classifiers in order to improve the prediction accuracy. Finally, we report our experimental results and findings at the end.

Methodology and Implementation

1.1 Pre-processing

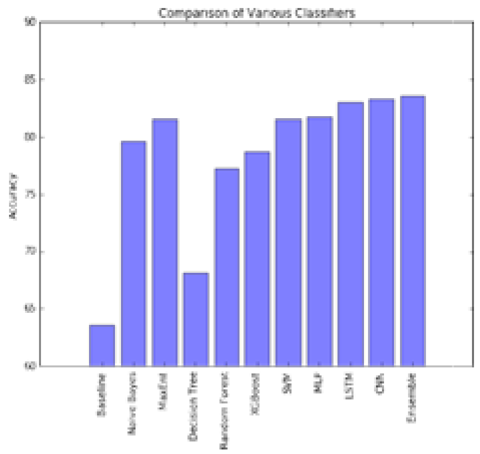
Raw tweets scraped from twitter generally result in a noisy dataset. This is due to the casual nature of people's usage of social media. Tweets have certain special characteristics such as re- tweets, emoticons, user mentions, etc. which have to be suitably extracted. Therefore, raw twitter data has to be normalized to create a dataset which can be easily learned by various classifiers. We have applied an extensive number of pre-processing steps to standardize the dataset and reduce its size. We first do some general pre-processing on tweets which is as follows.

- Convert the tweet to lower case.
- Replace 2 or more dots (.) with space.
- Strip spaces and quotes (" and ’) from the ends of tweet.

URL

Users often share hyperlinks to other webpages in their tweets. Any particular URL is not important for text classification as it would lead to very sparse features. Therefore, we re- place all the

URLs in tweets with the word URL. The regular expression used to match URLs is ((www\.[\S]+)|(https?://[\S]+)).



User Mention

Neural methods performed better than other classifiers in general. Our best LSTM model achieved an accuracy of 83.0% on Kaggle while the best CNN model achieved 83.34%. The model which used features from our best CNN model and classifies using SVM performed slightly better than only CNN. We finally used an ensemble method taking a majority vote over the predictions of 5 of our best models achieving an accuracy of 83.58%.

Every twitter user has a handle associated with them. Users often mention other users in their tweets by @handle. We replace all user mentions with the word USER_MENTION. The regular expression used to match user mention is @[\S]+.

Emotion

Users often use a number of different emoticons in their tweet to convey different emotions. It is impossible to exhaustively match all the different emoticons used on social media as thenumber is ever increasing. However, we match some common emoticons which are used very frequently. We replace the matched emoticons.

IV. CONCLUSION

The provided tweets were a mixture of words, emoticons, URLs, hastags, user mentions, and sym- bols. Before training the we pre-process the tweets to make it suitable for feeding into models. We implemented several machine learning algorithms like Naive Bayes, Maximum Entropy, Decision Tree, Random Forest, XGBoost, SVM, Multi- Layer Perceptron, Recurrent Neural networks and Convolutional Neural Networks to classify the polarity of the tweet. We used two types of features namely unigrams and bigrams for classification and observes that augmenting the feature vector with bigrams improved the accuracy. Once the feature has been extracted it was represented as either a sparse vector or a dense vector. It has been observed that presence in the sparse vector representation recorded a better performance than frequency.

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