Sentimental Analysis using Deep Learning Techniques

Kalaivani A , Thenmozhi D

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 platforms via machine-learning (ML) with polarity calculations, sentiment analysis or subjectivity analysis. Sentimental analysis (SA) indicates the text organization which is employed to categorize 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 recent studies regarding the execution of DL models like i) deep neural networks (DNN), ii) deep-belief network (DBN), iii) convolutional neural networks (CNN) together with, iv) recurrent 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), ii) KNN and iii) SVM classification methods. Lastly, the classification methods' performance is contrasted in respect of accuracy.

Index terms: Sentiment analysis, Opinion mining, Deep learning.

I. INTRODUCTION

A. Sentimental Analysis

SA is contextual mining of text which recognizes and extorts 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]. Public 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 industry 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].

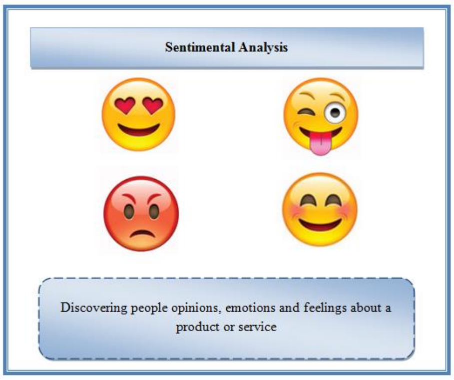

Fig. 1. Diagram for sentimental analysis

B. Features of Sentimental Analysis

Sentiments depend upon a certain range of values of features 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 being 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 optimization of words together with sentences brings faster learning which enhances data accuracy for social media. Data tokenization 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].

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Kalaivani A, SSN College of Engineering, Chennai, INDIA
kalaiwind@gmail.com
Thenmozhi D SSN College of Engineering, Chennai, INDIA
kalaiwind@gmail.com

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 adaptability [18]. In SA, mostly the supervised learning alternatives of this methodology are employed. It encompasses 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 chosen 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 Machines), and d) NB algorithm (Naïve Bayes) [19-22]. Accuracy differs from 63% to 80% relying on the combination of chosen features. Fig.2 delineates the working of an ML approach.

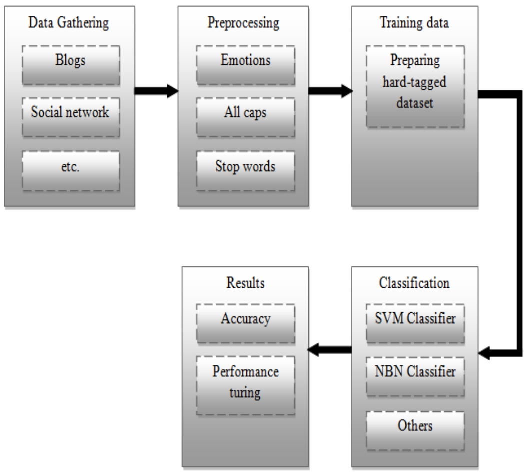

Fig. 2. General structure for ML approach

Lexicon-based Approach

This technique is guided by the utilization of a dictionary 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.

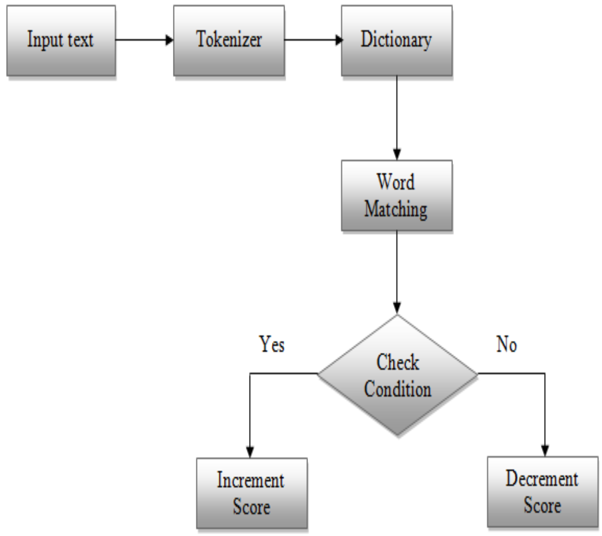

Fig. 3. General structure for a Lexicon-based approach

D. Deep Learning

ML technology powers several aspects of modern community i.e. as of web searches, content filtering in social networks 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 consumer'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 simpler 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, exceptionally complex functions are learned. DL comprises unsupervised 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. Although 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 semantic properties to adjacent locations in their coordinate system, in a way which is evocative of comprehending the words' meaning. Architectures like RNNs are also competent to effectively comprehend the sentences' structure. These make DL models the best fit for tasks like SA.

In this paper, Section II delineates the detailed literature review and Section III proffers the

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conclusion.

II. RELATED WORK

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 encompass 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 imperative 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 incorrectly interpret the sentiment. And, it was the most effectual 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 classification when contrasted to some traditional methodologies 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 generalization competency of the recommended model. Experiment outcomes exhibited that the recommended 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 comment 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, specifically on the small-scale corpus.

Jinzhan et.al [25] suggested a methodology for labeling 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 employed to attain the sentimental annotation of the sentence. Experiential outcome verified that this methodology was effectual for sentimental labeling. Considering that the recognition of the implicit facets augmented the completeness of SA, it was suggested to construct the tuples embracing 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 degree of aspects and ii) sentimental words- the human language 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 positive 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 validate the recommended methodology, the classification accurateness and the rate of polarity words amongst higher scoring words was assessed utilizing 2 movie review datasets. Experiential outcome confirmed that the recommended 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 sentences 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 classification. This approach was appraised on 4 sentimental classification 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 outcomes 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 classification	5 datasets that are 1) STSTd data set, 2) SE2014 dataset, 3) STSGd data set, 4) SED, and 5) SSTd.	Paved attention on pre-trained word embeddings.
Shiyang et.al [23]	CNN	Comprehend 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 sentimental label distribution. The recommended methodology learned words representation and also the sentimental distribution. 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 review 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 components 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. Furthermore, 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 performed 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 vocabulary; 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 enhancement over numerous non-RNN latent semantic designs (specifically in handling brief texts). It also integrated the idea to an alternative of LSTM named the gated recurrent 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 architecture. 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 effectiveness 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 sentimental classification. Subsequently, the performance was assessed by the total accuracy. Therefore, these experiential outcomes exhibited that by including positional information 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.

D. Sentimental 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 audio input, 'Mel Frequency Cepstral Coefficients' (MFCC) features were extorted. These features were utilized to build a sentiment design utilizing DNN and GMM (Gaussian Mixture Models) classifiers.
From outcomes, it was perceived that DNN classifier proffered 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 enhancement 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 considering 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 modified 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 (information 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.

E. 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) positive, iii) weak-positive, iv) neutral, v) weak-negative, vi) negative and vii) strong-negative words. The presented approach was tested on online books and political reviews 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.

F. Sentimental Analysis Using SVM Classifier

Vo et.al [39] suggested a model utilizing an SVM algorithm 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 positive 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 experimented on the ETD and attained 63.7% accuracy of sentimental classification on this ETD.

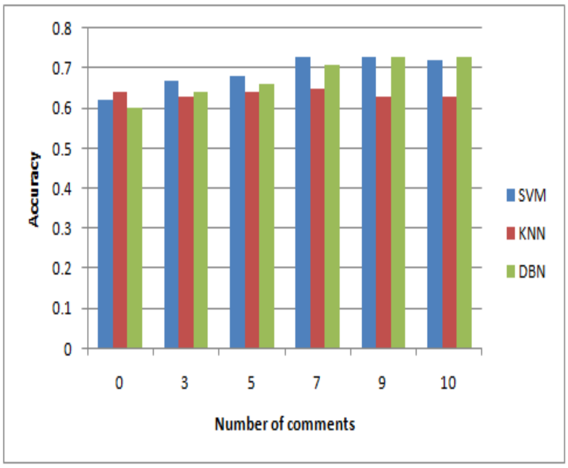

Fig. 4. Compare the performance of the different classifier in terms of accuracy with the number of comments

Discussion: The above figure 4 [36], contrasted the disparate classifier's performance in respect of accuracy. The accuracy range was varied based on the number of comments (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 accuracy. Likewise, DBN offered 0.6 and 0.73 accuracies when n= 0 and 10 respectively.

III. CONCLUSION

A primary task in SA is to categorize the polarity of the provided text at the sentence, document, or aspect/feature level- to ascertain whether the expressed opinions in a sentence, a document or else an entity aspect/feature is negative, neutral or positive. This paper as well offers a literature survey on the different DL techniques associated with SA. The SA importance is also delineated. In addition, the disparate types of classification process and their limitations are discussed briefly. This literature work en lightens the various prevailing methods of SA proposed by diverse researchers, which assist the forthcoming researchers in this specific area.

For future work, the current research problem that was discussed above can be addressed, and also explores DL approaches that have the potentiality to make the SA easier. It will be motivating in the upcoming years to contrast the performance and accuracy demand with those of more traditional methods.

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