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Hybrid CNN Classification for Sentiment Analysis under Deep Learning

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Abstract**:** ***Sentiment Analysis (SA) is a popular field in Natural Language Processing (NLP) which focuses on the human emotions by analyzing the lexical and syntactic features. This paper presents an efficient method to find and extract the strong emotions for the sentiment classification using the proposed hybrid Convolutional Neural Networks - Global Vectors - Complex Sentence Searching - ABstract Noun Searching (CNN-GloVe-CSS-ABNS) model. The strong emotions are mostly found in the abstract nouns than the adjectives and adverbs present in the sentences. This research aims in extracting the complex sentences with abstract nouns for the sentiment classification from the twitter data. To extract the complex sentences, the proposed Complex Sentence Searching (CSS) algorithm was used. On the other hand, another proposed algorithm named, ABstract Noun Searching (ABNS) algorithm was used for identifying the abstract nouns in the sentences based on their position in the sentences. The results of this study presents that the proposed CNN-GloVe-CSS-ABNS model outperforms the other proposed models as well as the existing models, by producing an of accuracy 94.87 per cent in sentiment classification.***

Keywords**:** ***Convolutional Neural Network, Deep Learning, Natural Language Processing, Sentiment Analysis.***

I. INTRODUCTION

The Natural Language Processing (NLP) is playing a vital role in text classification applications, such as Sentiment Analysis (SA), ranking, classifying the customer feedback in business, information retrieval and web search [1], [2]. SA is an automated action to determine whether a sentence contains objective or subjective content and furthermore, it can also be used to determine the text's sentiment polarity. Nowadays, we have so many social network (Twitter, blogs, facebook, etc) organizations providing huge dataset for analyzing and surveying people's emotions in real time. Twitter, with over 319 million monthly active users, is widely being considered as a potential data source for organizations and individuals to study the human emotions on various areas of political, social and economic interest. Text data set generally contains texts of various grammatical nature namely, adjective, verb, adverb, abstract nouns etc. Among the texts of various grammatical nature, it is generally felt that only the abstract nouns express the strongest and intense emotions [3]. Moreover, there is only a limited amount of research being done with reference to abstract nouns. Abstract nouns always denote the internal emotions like pleasure, anger etc. and does not points out the externally expressed emotions like crying, smiling etc. In other words, internal emotions are emotions that cannot be felt by the five human senses. It expresses a quality (patience, beauty), a state (death, slavery), a feeling or an action (pleasure, laughter). Both the adjectives and abstract nouns can express the emotions but it is only the abstract nouns which denote the internal emotions than the adjectives. Hence abstract noun emotional words are generally chosen to study the strong internal emotional intentions [4]. An abstract noun can be formed from an adjective (ignorance from ignorant) or from verbs (pleasure from please) or from some common nouns (slavery from slave) [5]. To state an example for abstract noun, in the sentence, "It was a pleasure trip for me and I enjoyed a lot", where, "pleasure" is an abstract noun word. In recent years, there has been a growing interest in using deep learning (DL) techniques for SA, because of its automatic feature extraction and enhanced sentiment classification accuracy level than the machine learning (ML) techniques. In our proposed work, pre-processing technique was used on twitter dataset to make the unstructured data format into structured data format. Then the complex sentences were extracted using the proposed CSS algorithm after tagging the structured data. Afterwards, another proposed algorithm called ABNS was applied to the extracted complex sentences of twitter dataset for identifying the sentences with abstract noun. The proposed Complex Sentence Searching (CSS) and ABstract Noun Searching (ABNS) algorithms were applied with different ML and DL classifiers namely SVM and CNN along with two vectorization methods namely Word2Vec and GloVe in four different combinations (SVM-Word2Vec-CSS-ABNS; SVM-GloVe-CSS-ABNS; CNN-Word2Vec-CSS-ABNS; CNN-GloVe-CSS-ABNS). The results of the experiment have shown that the DL model of CNN-GloVe-CSS-ABNS performed better when compared to the other models.

The rest of the paper is organized as follows. Section 2 describes the motivation and challenges. Section 3 presents the related works on this topic. A comprehensive research method is highlighted in section 4. Result and discussion are done in section 5. Finally, the section 6 presents the conclusion part of our research.

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II. MOTIVATION AND CHALLENGES

Twitter has been the main source for many researchers to do the SA on different kinds of people for studying their emotions towards the social, political, and economic aspects of their life. When analyzing the sentiment words, generally, the researcher will consider adjectives, adverbs and nouns, for assessing the emotions than any other words. But, when the adverb, adjective and abstract noun words were analyzed, it was strongly felt that the strongest and intense emotions were being expressed by the abstract noun words than the adjective and adverb words. The same has also been reported by Lenci *et al*., in their research paper [3].

The major challenge for SA analysis using abstract noun, was the unavailability of the abstract noun database. Apart from this, difficulties were faced in identifying the abstract noun emotion words from the twitter data sentences, the same was also reported by other researchers [6]. For example, the word 'love' will be considered as a verb if it is found in the beginning of a sentence, but the same word will act as an abstract noun if it is in the middle of a sentence. So, merely mapping the word with the abstract noun database can lead to wrong predictions, and also finding the place of the abstract noun word in a sentence do poses considerable challenges.

III. RELATED WORKS

In an Adverb-Adjective-Noun (AAN) based SA research, the researchers have examined all the categories of nouns and found that only abstract class of noun is useful in opinion analysis. In this paper the researchers have classified the abstract nouns into two sets namely, positive abstract noun such as joy, victory, faith etc and negative abstract noun such as sorrow, pain, failure, etc. Scoring of noun can be either + 1 or -1 depending upon the SentiWordnet positive and negative polarity decision [7]. Abstract noun is also referred as ‘container noun’ [7], ‘carrier noun’ [8], ‘unspecific’ or ‘metalanguage noun’ [9] and ‘shell noun’ [10], [11]. Determining the abstract noun words through semantic links with other lexemes was by establishing their synonyms and antonyms, which are the characteristics of the abstract nouns [12]. Some researchers have suggested that the abstract nouns can be identified from their word building, i.e. by their semantic suffixes. For example, these English words will end by -tion, -ity, -ety, -ism, -ing, -ness etc. However, this approach must be applied with caution for two main reasons. First, it cannot be universally applicable as there are a number of words which convey different meanings, some might be abstract and some might be concrete. For example, words like population, abbreviation, are abstract in nature when they denote a process, and concrete when they denote a result. Under such cases, additional semantic information are needed to aid a formal criterion. Secondly, a lot of abstract nouns do not have these suffixes if they are derived from foreign words or are substantiated verbs (for example, sense, and treason). Hence to avoid such issues, it is better to find synonyms (e.g. sense = perception, treason = treachery), thereby turning to semantic criteria again [6]. Moreover, the fact that most of the abstract nouns derived from verbs and adjectives encourages linguists to apply nominalization and transformation to confirm their abstractness [13].

In the research [14], the researcher has developed a model for retrieving the sentiment and emotions from the twitter dataset. In this model, positive and negative polarities were used to express the sentiments and Minsky’s [15] conception was applied for finding the emotions, which consists of four affective emotions with six levels of activations. Emotions and sentiments were modelled as a fuzzy set. To tune the intensity of the emotions, the fuzzy modifier was used. In this research, the abstract nouns in simple sentences were used for the SA by adopting Plutchik’s [16] flower model to measure the intensity of emotions. The research shows that the best result (+ 0.81, - 0.69) was from the lowest threshold value (± 0.1) for the tweet and the least value (0.25) was from the highest threshold (±0.6) value for tweet with negative polarity. However, this model could not able to perform good for twitter negative polarity.

Neural Networks have become increasingly popular for SA as it becomes possible to train more complex models for larger datasets [17]. With the advent of neural networks, these days many studies have started exploring the application of DL in sentiment classification to overcome manual feature extraction [18]. Recently, DL methods are well established in machine learning [19], [20] and have started to overtake traditional models of NLP.

CNN a most preferred DL technique has been successfully applied in sentence-level sentiment classification in many studies [21], [22],[23]. It was found that combining the CNN model with another DL model can result in better performance. Convolution and recurrent neural networks can be used for extracting useful information in the text analytic tasks. This is mainly because of the effective feature extractions and also better passing of features from one layer to another layer within the network, as well as from one network to another network. Researchers in their research have used three datasets to display the advantages of extracting and fusing multilevel as well as multitype features from different neural networks. In this, multilevel features were from different layers of the same network, and multitype features were from different network architectures. It was found from the research that the model based on multilevel and multitype weighted features fusion out performed many existing works with a greater accuracy [24]. In another research, a network architecture was introduced to analyze sentences meaning through character-level representations by using a combination of long short-term memory (LSTM), CNN and conditional random field (CRF) [25]. CNN and Bidirectional Long Short-Term Memory (BLSTM) models were used to design four kinds of memory network models in a study done for text sentiment classification [26].

In a research [27] that focused on tweets of two halal products, i.e., halal tourism and halal cosmetics, twitter data over a span of 10 years were extracted using the twitter search function, and an algorithm to filter the data. Later, DL algorithm was used to calculate and analyze the tweet’s sentiments. In addition, to improve the accuracy and construct prediction models CNN, LSTM and RNN were utilized.

From the results, it was found that the Word2vec feature extraction method combined with a stack of the CNN and LSTM algorithms achieved the highest accuracy of 93.78%. In another research [28], word embeddings were constructed using GloVe on a large twitter corpus, then combined with ngram features and sentiment intensity scores were fed into a CNN. The researchers evaluated this model on five twitter data sets from the literature and found good results. However, the research did not mention on whether the twitter corpus was constructed or collected and whether the tweets contained sentiments or not. Also, the paper did not mention any experiments on the combination of the GloVe word embedding with the manually engineered features and even the comparisons made with previous works were also not comprehensive at all.

CNN architecture with multiple convolution layers, dense and low-dimensional word vectors (initialized to random values) as inputs were used to study the human sentiments in movie reviews and Twitter datasets [29]. When CNN was applied to high dimensional text for text classification and to obtain several state-of-the-art performances on some benchmark data sets for sentiment categorization, the model becomes more complex and expensive to train [30].

From the array of literatures surveyed, it was found that the CNN performed well in SA. Moreover, there were limited or no works related to SA focusing on sentences with abstract nouns. In SA research, there were always struggles to identify the abstract nouns with precision. Hence, our motivation was to perform sentiment classification with focus on abstract noun sentences.

IV. RESEARCH METHOD

The Fig.1 shows the overall architecture diagram of this research on the abstract noun based sentiment classification. The research was focused on evaluating the following proposed ML and DL hybrid models for abstract noun sentiment classification.

- SVM-Word2Vec- CSS-ABNS
- SVM - GloVe-CSS -ABNS
- CNN-Word2Vec-CSS-ABNS
- CNN-GloVe-CSS-ABNS

Publicly available twitter dataset from sentiment140 project [31] which was created by the graduate students of Stanford University was used for our research. This dataset contains 8,00,000 positive and 8,00,000 negative labelled data for training. Later the dataset was pre-processed by converting the unstructured data into the structured data. The pre-processing of data includes the removal of special symbols, URLs, slangs, languages other than English, replacement of the abbreviations with their original words, and finally the tokenization.

After pre-processing, all the structured sentences got tagged with Stanford POS tagger. Next, to extract the complex sentences, our proposed CSS algorithm was applied. Then to the extracted the complex sentences, the proposed ABNS algorithm was applied to identify the sentences with abstract noun emotion words accurately in the identified complex sentences, by checking all the possibilities like noun singular, noun plural, proper noun singular, proper noun plural etc,. A manually created abstract noun database was used for verifying the identified possible abstract noun words from the ABNS algorithm by mapping, as there was no existing database for the abstract noun words. Then the identified complex sentences with abstract noun were later got converted into the vector values by using GloVe and Word2Vec word embedding methods in accordance to the mentioned proposed models. GloVe and Word2Vec - CBOW (Continuous Bag of words) [32] methods used for our research were pre-trained word features applied for initializing the parameters of the embedding layer, with 300-dimensional vector for each word representation. After that, CNN and SVM were used with respect to each proposed model to perform the feature extraction and the classification of abstract noun complex sentences into positive and negative values (binary values). The CNN consists of four layers including input layer, convolutional layer, max-pooling layer and fully connected layer with softmax output. The max-pooling was utilized to reduce the number of parameters in the feature extraction process and finally the positive and negative abstract noun classification was done in the fully connected softmax layer with the dropout regularization to avoid over fitting problems.

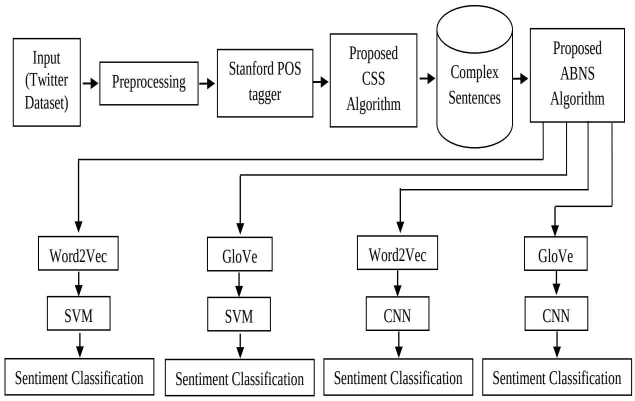

Fig.1. Overall architecture of this research

A. Proposed CSS algorithm

The sentences with conjunctions (CC) are considered as complex sentences. The CSS algorithm (Algorithm 1) identifies complex sentences with one CC and then stores that in the complex sentences database. On the other hand, the algorithm rejects the sentences with more than one conjunctions. For our research long sentences with multiple conjunctions were not considered for our sentiment classification, which will be taken as a subsequent research work. All the notations used in this paper are presented in Table.1.

Algorithm 1: Proposed CSS algorithm for complex sentence extraction

Input: POS tagged twitter dataset tw_p, Each sentence in tw_p is h.
Output: Complex Sentences C
Start
1. **FOR** each sentence $h_i \in tw_p, \forall$ i=1 to h
2. // Initialize CC=0 //
3. **IF** h == CC **THEN**
// Count number of CC in h //
4. **IF** Count (CC) ==1**THEN**
5. **ACCEPT** h as C
6. **STORE** in C_DB // Complex Sentences Database //
7. **ELSE REJECT** h as C
8. **END FOR**
End

Table.1. Summary of the notations used in this paper

S.No s	Notation	Description
1.	tw	Tweet Dataset
2.	h	Each Sentence in the twitter dataset
3.	C	Complex Sentences
4.	NN	Noun Singular
5.	NNS	Noun Plural
6.	NNP	Proper Noun singular
7.	NNPS	Proper Noun Plural
8.	Det	Determiner
9.	Adj	Adjective
10.	Adv	Adverb
11.	LW	Last Word
12.	NW	Next Word
13.	ARW	Any Random Word
14.	PW	Previous Word
15.	CC	Conjunction
16.	PRP	Preposition
17.	V	Verb
18.	ABN_DB	Abstract Noun Database

B. Proposed ABNS algorithm

The ABNS algorithm (Algorithm 2) was developed for the effective identification of the sentences with abstract noun words from the identified complex sentences. An illustration of the ABNS algorithm is presented in the Fig.2. This algorithm has the ability to identify the abstract nouns based on the position of the text's POS tag. For example, "It is more a pleasure shopping in Spencer Plaza but the crowd irritated me very much". The above mentioned example is a complex sentence (C), and the POS tags of the sentence is elaborated below.

It/Pronoun **is**/V **more**/Adv **a**/Det **pleasure**/NN **shopping**/NN **in**/PRP **Spenser**/NN **plaza**/NN **but**/CC **the**/Det **crowd**/NN **irritated**/Adj **me**/Pronoun **very**/Adv **much**/Adv.

When the ABNS algorithm does the search operation on the above sentence, Step 5 from the proposed ABNS algorithm, identifies the previous word (PW) of the conjunction (CC) as True (NN) and the Last Word (C) as false (Adv). Since one of the conditions in Step 5 was true then it checks the next condition in Step 6. As the **plaza**/NN was not available in the ABN_DB, it was not considered as an abstract noun word. Next, the ABNS continues the search with the different conditions. The search was on the ARW part, where, any random word has to be tagged with the NN or NNS or NNP or NNPS. In this, ARW identified was **pleasure**/NN. In Step10, the PW (**pleasure**/NN) was **a**/Det and the condition was true. In Step11, the NW (**pleasure**/NN) was tagged with **shopping**/NN and the condition was true. As both the conditions were true, the algorithm then checks the ARW with the ABN_DB. As, **pleasure**/NN was in the ABN_DB the above sentence was classified as the abstract noun sentences by the algorithm.

Algorithm 2: Proposed ABNS algorithm for abstract noun extraction

Input: Each sentence h in the twitter dataset tw
Output: Classification of positive abstract noun and negative abstract noun sentences

Start

1. **FOR** each sentence $h_i \in tw_{labelled} \forall$ i=1 to h
2. C = Complex Sentences; // Sentence with one Conjunction //
3. **IF** h == C **THEN**
4. **ACCEPT** C
//Perform the search operation for abstract noun on C //
5. **IF** ((PW(CC) or LW(C)) == NN or NNS or NNP or NNPS)**THEN**
6. **IF**((PW(CC) or LW(C)) ==ABN_DB)**THEN**
7. **ACCEPT** the C as an Abstract Noun Sentence
8. **ELSE** Reject the C
9. **IF**ARW (C) == NN or NNS or NNP or NNPS **THEN**
10. **IF**(PW (ARW (C))==Det or Adj or Adv) **THEN**
11. // NN must not in theAbstract_Noun_Database (ABN_DB) //
12. **IF** (NW (ARW (C)) == Adj or NN)**THEN**
13. **ELSEIF**ARW (C)== ABN_DB **THEN**
14. **ACCEPT** the C as an Abstract Noun Sentence
15. **ELSE** Reject the C
16. **END FOR**

End

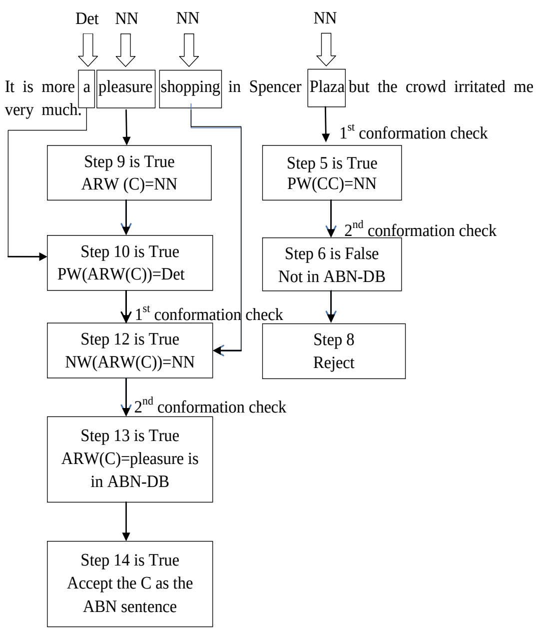

Fig.2.Illustration of Abstract Noun Searching Algorithm

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C. Hybrid ML Models

For our research two proposed hybrid ML models were developed namely, Hybrid SVM-Word2Vec-CSS-ABNS; and Hybrid SVM-GloVe-CSS-ABNS. In this framework, after the complex sentences got extracted by CSS algorithm, the proposed ABNS algorithm was applied on the extracted complex sentences which accurately identified and extracted the complex sentences with abstract noun. Then, the complex sentences with the abstract noun features were applied on Word2Vec / GloVe for word embedding and later the converted numerical data obtained during word embedding process in Word2Vec / GloVe proceeds to the SVM classifier. SVM is a supervised machine learning algorithm for classification and regression, which can solve the linear and non-linear problems (inseparable data). For addressing the non-linear problems, SVM uses the Kernel as a similarity function. In our research, we used the radial basis function (RBF) kernel to solve the non-linear problem in the complex sentences with abstract noun. RBF kernel was applied on the features of the abstract noun complex sentences such as ngram feature, sentiment polarity features, word vector feature and twitter related features to classify them into positive abstract noun and negative abstract noun sentences.

D. Hybrid DL Models

For our research apart from the ML models, two proposed hybrid DL models namely, Hybrid CNN-Word2Vec-CSS-ABNS, Hybrid CNN-GloVe-CSS-ABNS were also developed.

The Fig.3 shows the proposed hybrid CNN-GloVe-CSS-ABNS internal framework for abstract noun complex sentence classification. In the CNN algorithm, let consider "t" and "V" be the twitter sentence length and vocabulary size, respectively in the word vector "R" such as $t \in R$, $V \in R$.

In the embedding layer, GloVe word embedding model convert the words in the twitter tokens to the word vector with the help of the word vector table $Q \in R^{sx|V|}$, where "s" is a dimensional word vector and "V" is a vocabulary size. Each word "e" gets mapped to a word embedding vector $e_i \in R_s$. Then the abstract noun specific feature vector gets concatenated with the word embedding vectors as the new feature vector " v " of tweet "t".

$$v = e_1 \oplus e_2 \oplus e_{3....} \oplus e_n \qquad (1)$$

Where, $\oplus$ is the concatenation operator and $e_n \in R$.

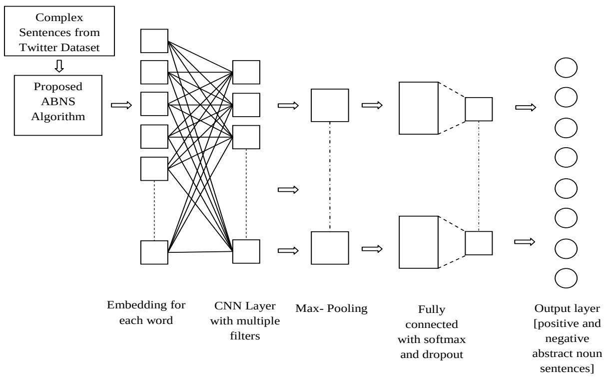

Fig.3. Proposed hybrid CNN-GloVe-CSS-ABNS Internal framework for abstract noun sentence classification

In the convolutional layer, convolution consists of multiple filters which were applied on the input data to obtain the different activation local sentiment feature vector "z_i" with variable window size "p". The feature vector consists of the bias term $b \in R$ and the transition matrix $E \in R^{P_u xPS}$, where p_u is the number of hidden units in the convolutional, p is a variable window size and s is a dimensional word vector. These are generated for each filter in convolutional layer. In vector " v ", the vector position is beginning from "i" to "i : i+p-1" and the new vector "z_i" as follows:

$$z_i = a(E.v_{i:i+p-1}+b) \qquad (2)$$

where "b" is the bias term and E is a transition matrix are generated for each filter in CNN. Rectified linear units (ReLU) is a non-linear active function in CNN denoted by "a". After the convolution layer computation, the new vector "z" was generated:

$$z = [z_1, z_2, \ldots\ldots z_{s-p+1}] \qquad (3)$$

Next, the k-max pooling layer is also a non-linear layer but specifically used for down sampling which reduce the parameters and speedup the computational process. The k-max pooling layer is applied on the new vector "z" generated by the convolution layer.

$$v' = \max\{z_1, z_2 \ldots \ldots z_{s-p+1}\} \qquad (4)$$

where v' is the output vector for pooling layer. It selects the maximum value as the input to the fully connected layer with the softmax layer. Finally the softmax layer gives the probability value of the positive and negative abstract noun sentences which was obtained from the softmax function:

$$f = sotmax(Ev' + b) \qquad (5)$$

Where " f " is the output vector of softmax layer, v' is the output vector for pooling layer, "E" is the transition matrix of softmax layer, "b" is the bias factor of softmax layer. The CNN to avoid over fitting problem, the dropout regularization is used in the fully connected layer to terminate the problem of the lot of hidden units and the connection between them.

E. Experimental Setup

For our research, 10-fold cross validation was done for all the proposed models. In the proposed CNN models, the hyper parameters such as word embeddings, dropout, learning rate, batch size, epochs were used. In this, only one convolutional layer and 300 word embedding dimensions were used. The activation function ReLu was used in the convolutional layer. The dropout rate of 0.5 for the regularization was applied on the fully connected layers before the output. Mini-batch (size = 10) gradient descent with the learning rate of 0.001 was also used. For our experimental twitter dataset, the total number of training epochs were 10. In the experiment, we found that the activated function Leaky ReLU was better than the performance of ReLU in CNN. On the other hand, in the proposed SVM models, SVM with the kernel function which internally maps the input vectors (Word2Vec / GloVe) to the higher dimensional feature spaces was used.

To enhanced the classification of SVM, SVM parameter of kernel got tuned into a RBF kernel, C=1 and gamma=0.0 and also verified with the cross validation to avoid over-fitting. Finally, the precision, recall, F-measure were used to evaluate all the proposed hybrid models.

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To evaluate our proposed hybrid models, F-measure was calculated from the confusion matrix. The confusion matrix (Table 2) calculates the actual and predicted classes of the twitter dataset which shows the accuracy of the SVM and CNN classifiers.

Table.2. Confusion matrix

		PREDICTED		
		Positive-Abstract	**Negative-Abstract**	TOTAL
ACTUAL	**Positive-Abstract**	TP	FN	P
	Negative-Abstract	FP	TN	N
TOTAL		P'	N'	P+N = P'+N'

Where,

P: Positive; The predicted value is positive abstract noun (Example: Pleasantness)

N: Negative; The predicted value is negative abstract noun (Example: Unpleasantness)

TP: True Positive; It indicates the predicted and the actual value of abstract noun value is 1(True).

TN: True Negative; It indicates the predicted and the actual value of abstract noun value is 0 (False).

FN: False Negative; It indicates the predicted one is false but the actual is an abstract noun. In this, the values did not match. So, it is false negative.

FP: False Positive; It indicates the predicted one is true but the actual is not an abstract noun. In this, the values did not match. So, it is false positive.

P, R, and F-Score were measured by using the given equations:

Precision = TP / (TP+FP)

Recall / Sensitivity = TP / (TP+FN)

Specificity = TN / (FP+TN)

V. RESULT AND DISCUSSION

Table.3, presents the precision, recall and the F- measure of the abstract noun sentence's sentiment classification performance for all the proposed hybrid models of ML and DL. From the results, it was observed that DL hybrid model of CNN-GloVe-CSS-ABNS performed better for the precision, recall and F-measure than the other proposed hybrid models while tested on the twitter dataset. The DL hybrid model of CNN-GloVe-CSS-ABNS achieved an increased accuracy of 14.13%, 13.6% and 5.45% respectively, when compared with our other proposed hybrid models of SVM-Word2Vec-CSS-ABNS, SVM-GloVe-CSS-ABNS and CNN-Word2Vec-CSS-ABNS.

The precision, recall and F-measure values of few existing models experimented on twitter data set are presented in Table 4. It was found from our review that there was no research work available in sentiment classification by using sentences with abstract nouns. The existing papers have relied on sentences focusing nouns, adjectives, adverbs etc for sentiment classification. On the other hand, there is only limited studies focused on abstract nouns, even here the research focus was only on the abstract noun words alone without considering the sentence as a whole. In addition, our proposed work was focused on complex sentences which was in contrary to the existing works which relied on only words from simple sentences. While comparing our best performed DL hybrid model of CNN-GloVe-CSS-ABNS with the existing models presented in table 4, shows that our aforesaid model has achieved 19.87%, 13.57%, and 7.21% improvement in accuracy over the Text Processing pipeline, Random Forest and GloVe-DCNN models respectively.

The Fig.4, presents the graphical representation of the overall accuracy of our proposed models (CNN-GloVe-CSS-ABNS, CNN-Word2Vec-CSS-ABNS,SVM-GloVe-CSS-ABNS and SVM-Word2Vec-CSS-ABNS) with the existing works in table 4 (Text Processing pipeline, Random Forest and GloVe-DCNN). The graphical comparison of results have distinctly captured that all the proposed models have an edge over the existing works and among all the proposed models, the hybrid CNN-GloVe-CSS-ABNS approach has distinctly outperformed the other models in predicting the accuracy.

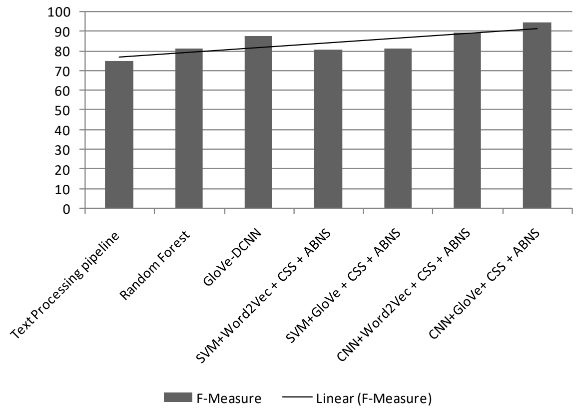

Fig.4. Comparison of the overall accuracy of proposed models with the existing models

The experimental results clearly describe that hybrid CNN-GloVe-CSS-ABNS model has produced the best sentiment classification. This is mainly because, the CNN has the capability to automatically retrieve the important features in an effective way than the SVM [28]. The classification of the positive and negative abstract noun was a difficult task on the twitter dataset apart from challenges like non availability of database for abstract nouns, varying position of the abstract nouns in the sentences leading to its wrong identification and non-availability of POS tag tool to precisely identify the abstract nouns. Through the proposed work we could able to overcome these challenges. The proposed ABNS algorithm has proved effective in identifying the abstract nouns and the research do have created its own abstract noun database for conforming the ABNS identified abstract nouns by mapping with the database. But in other researches, the researchers have followed other techniques like nominalization transformation [13] and oracle Alchemy-API [33] where there were some lacunas in precisely identifying the abstract nouns when compared to our proposed ABNS approach.

Table.3 Performance of the proposed hybrid models

Model	Pos %			Neg %			Avg %		
	P	R	F	P	R	F	P	R	F
SVM-Word2Vec- CSS-ABNS	86.09	82.64	84.32	75.20	79.26	77.17	80.64	80.95	80.74
SVM-GloVe-CSS-ABNS	86.41	84.39	85.38	75.25	79.20	77.17	80.83	81.79	81.27
CNN-Word2Vec-CSS-ABNS	95.41	87.39	91.22	91.29	84.25	87.62	93.35	85.82	89.42
CNN-GloVe- CSS -ABNS	93.32	94.63	**93.97**	96.13	95.42	**95.77**	94.72	95.02	**94.87**

*Where, P = Precision, R = Recall, F = F-measure

Table.4 The reviewed results of the existing models

Research	Dataset	Approach	Pos%			Neg %			Avg %		
			P	R	F	P	R	F	P	R	F
[14]	Sentiment140 (Twitter) [30]	Text Processing pipeline model using ML (ABN words were analysed for sentiment classification)	87.00	76.00	81.00	72.00	67.00	69.00	79.50	71.50	75.00
[34]	Twitter Dataset	Random Forest (Sentences with nouns were analysed for sentiment classification)	82.00	78.90	80.50	80.60	83.50	82.00	81.30	81.30	81.30
[28]	Twitter SED (The Sentiment Evaluation Dataset)	GloVe-SVM Contextual semantic approach followed for sentiment classification	86.82	90.22	88.42	84.30	79.61	81.74	85.56	84.92	85.08
		GloVe-DCNN (Contextual semantic approach followed for sentiment classification)	87.29	92.39	89.77	88.71	82.25	85.35	88.00	87.32	87.66

*Where, P = Precision, R = Recall, F = F-measure

VI. CONCLUSION

Although CNN extracts the higher level features, it is difficult to identify the abstract nouns which lead to the development of our proposed hybrid model of CNN to accurately identify and extract the abstract noun words in the twitter sentences. Our proposed hybrid model jointly combines CNN and proposed CSS and ABNS algorithms with the pre-trained word vectors GloVe, proved very effective. In future works, we are planning to apply our proposed models in various other domains like marketing, health care etc. Moreover, as this proposed research is primarily focused on complex sentences with one conjunction (CC), this research has also paved way to explore complex sentences with multiple conjunctions as future research.

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