Journal of Current Science and Technology, May-August 2022 Vol. 12 No. 2, pp. 224-242

ISSN 2630-0656 (Online)

Cite this article: Sharma, N., & Veenadhari, S. (2022, May). Sentiment analysis using attention-based convolution autoencoder (SAABCA). *Journal of Current Science and Technology, 12*(2), 224-242. DOI:

Journal of Current Science and Technology

Journal homepage: https://jcst.rsu.ac.th

Sentiment analysis using attention-based convolution autoencoder (SAABCA)

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Received 29 December 2021; Revised 2 March 2022; Accepted 4 March 2022;
Published online 25 August 2022

Abstract

Sentiment analysis (SA) has been a commonly studied issue in the disciplines of NLP, data mining and data analysis. Deep neural network (DNN) algorithms have lately been used to do SA with significant improvements. However, these algorithms can handle sequencing of any lengths, employing it in the extracting features of a Deep Neural Network increases the dimensionality of the feature space. In this paper, a sentimental analysis using attention-based convolution autoencoder (SAABCA) model is proposed to tackle such challenges. Moreover, the Attention mechanism (AM) is used on the outcomes of layers. SAABCA employs convolutional and pooling methods to decrease feature dimensions and recover position-invariant feature points. The efficacy of model is measured by its ability to identify sentiment orientation, that is the most popular and essential job in SA. As contrasted to seven previously recommended DNNs for sentiment analysis, additional state-of-the-art effectiveness is shown on several review classifications and tweet polarity classifications. The findings indicate that the suggested technique accuracy is 94% for Kindle Dataset, 97% for Movie Dataset and 98% for Airline Twitter Dataset.

Keywords: *Sentiment Analysis, Deep Learning, Autoencoder, Attention based Convolution Autoencoder.*

Abbreviations

SA	Sentiment Analysis
AM	Attention Mechanism
DNN	Deep neural network
SAABCA	Sentimental Analysis using Attention-based Convolution Autoencoder
NLP	Natural Language Processing
SVM	Support Vector Machine
CNN	Convolutional Neural Networks
CBAM	Convolution Based Attention Mechanism
LSTM	Long Short Term Memory
HAN	Hierarchical Attention Networks
CRNN	Convolution Recurrent Neural Network
ReLU	Rectified Linear Unit
CAE	Convolutional Autoencoder

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1. Introduction

SA is an internet-based method for identifying and collecting information from subjectively input. For its numerous scientific and corporate applications. SA had lately been a major study area in information retrieval and natural language processing (NLP). SA can be used at different domains for study like tourism and hospitality (Luo, Huang, & Wang, 2021), academia (Sidhu, & Khurana, 2022), health care (Rahman, & Islam 2022), business (Softic, & Lüftenegger, 2022). As a result, nowadays, numerous approaches including technologies for defining the polarities of a text, file, reviews have been established (Chaturvedi et al., 2018). Sentiment recognition is a binary classifier issue which is crucial like most SA applications (Gan, Wang, & Zhang, 2020). To get excellent polarities either True or False classification results, most previous approaches for sentiment classification built simplistic algorithms on carefully specified significant functions. Conventional different classifiers such as SVM (Poornima, & Priya, 2020), K-nearest neighbor (Seçkin, & Kilimci, 2020), Nave Bayes, and Random Forest are often used in sentiment analysis models. This method has two major disadvantages: the training of the model on sparse and high-dimensions feature space. This reduces the effectiveness of the algorithm, (ii) the featuring implementation rate is a time-consuming and labor-intensive job. To overcome this disadvantage Attention Based-Convolution Autoencoder were used using word embedding is a semi supervised approach (Chuhan et al., 2018). CNN have performed very well in a wide range of computer applications. These designs eliminate this necessity of handcrafted features, allowing network to learn essential characteristics while doing the necessary job, resulting in state-of-the-art precision. As a result, Convolution Neural Network have rapidly established themselves as the standard for most polarity detection applications. Technique has indeed been utilized as a normalization technique to improve the generalization of DNN. The vanished-gradient issue in convolutional models is improved by batch normalizing. Considering these methods, the efficiency of extremely deep CNNs continues to peak. Attention-based techniques, which enable a system to concentrate on the most important portions of the data, have recently been created data. Such attention methods were tested in the field on problems like information retrieval and nonverbal cues, but their use to improve predictions in sentiment analysis has yet to be shown (Kaul, Manandhar, & Pears, 2019). Self-attention blocks, including those seen in SE nets use squeezing and excitation blocks to re-calibrate the output of networking filtering. A traditional autoencoder generates a low-dimensional set of inputs initially, subsequently up-samples from it to reproduce the original input. Convolution encoder has great success in SA (Mack, Arcucci, Molina-Solana, & Guo, 2020). For sentence-level SA, recursive autoencoder (RAE) algorithms have subsequently been presented. They utilize word embedding to demonstrate evey word, and recursive auto encoders to learn compositional vector representations of phrases as well as sentences. Because the RAE method has difficulty capturing words, a more sophisticated method called PRAE (Phrase Recursive Auto Encoders) has been proposed (Fu, Liu, Xu, & Cui, 2017). Specific supervised learning models, such as SVM, are also used to forecast online sentiments (Roy, Biba, Kumar, Kumar, & Samui, 2017), but they have some drawbacks, such as the cost and time required to annotate sufficient samples for training. To overcome these drawbacks, this semi-supervised methodology for DSA depending on the variational autoencoder model was developed (Wu et al., 2019). Which consists of an encoding module for converting sentences to hidden vectors, a sentiment prediction module for predicting sentence sentiment scores, and a decoding module for reconstructing the input sentences using the outputs of the previous two modules. The primary factors that need to be tuned in different machine learning approaches are reaction time, accuracy, and training etc. For advances in all three areas, more precise data collection, improved representational and signal processing techniques, and optimal and effective translating methods are all necessary. Machine Learning technologies including SVM with linear kernel, LDA, Radial Basis Functions and ICA are already being used, Deep Learning for classifying objectives has, nevertheless, received little attention in recent years (Balas, Roy, Sharma, & Samui, 2019), and it still isn't extensively utilized despite its promising potential. It is hoped that the capabilities of Deep Learning will be fully realized as more applications are developed. To overcome all of these drawbacks, the proposed method used an autoencoder, which outperformed previous methods. We use this encoder-decoder architecture to predict Sentiments, emotions, feedback in a systematic order, resulting in the more precise decoding. The suggested approach is consistent against different DNN-based document classification and SA techniques in the trials. In accordance with the minimum performance metrics in SA and NLP categories, the suggested model surpassed previous techniques on both lengthy reviews as well as short tweets.

The below are the objectives of the proposed work:

- A unique sentiment analysis deep learning model has been proposed.
- Used two types of social texts to test our framework: lengthy evaluations and brief retweets.
- Used six current deep models for text categorization and SA to compare the effectiveness of the suggested scheme.

2. Literature Review

This sections gives the recent study in the field of sentiment analysis having different methods and the comparison is done by considering the most used parameters like accuracy, F-1 score, Precision, Recall (Luc Phan et al., 2021). SA can be done classified as machine learning algorithms (M.A et al. 2021) as well as lexicon based approaches (Hossen, & Dev, 2021). Various machine learning based method is discussed by the researchers. Supervised (Guellil et al., 2021). Unsupervised (Jigneshkumar Patel, Prakash Verma, & Patel. 2021), naïve based (Gautam et al., 2021; Dey et al., 2020), SVM (Kumar, & Subba, 2020), Bayesian based (Ruz, Henríquez, & Mascareño, 2020). Lexicon based approaches is discussed in (Rice, & Zorn, 2021) a method called corpus based, (Li, Li, & Jin, 2020) discussed another type of lexicon based approach called dictionary approached. Wang, Yu, Lai, and Zhang (2016) predicted the text by CNN_LSTM. A local CNN-LSTM Learning algorithm is presented in this research to identify the VA evaluations of documents. The suggested approach outperforms regression- and traditional Neural Network based methods reported in earlier research by collecting all localized (regional) data inside phrases and lengthy dependence between phrases. The result indicate that the Recall of the Positive and negative sentiment is 0.8833 and 0.9457 respectively. Precision is 0.942 and 0.890 and F1 measure is 0.9116 and 0.917 and accuracy of the suggested model is 0.91450. Chatterjee et al. (2018) trained semantics as well as emotion local features, this method employs 2 concurrent LSTM's level on 2 distinct word embedded matrices. To forecast emotional classes, the result of the LSTM level is put into a deep network including one hidden level. The result indicate that the Recall of the Positive and negative sentiment is 0.8303 and 0.9515 respectively. Precision is 0.946 and 0.852 and F1 measure is 0.8826 and 0.8979 and accuracy of the suggested model is 0.891. Rezaeinia, Rahmani, Ghodsi, and Veisi (2019) presented a novel technique for enhancing the precision of pre-trained word representations for emotion prediction is presented. Based on a mix of four methods, including the method enhanced the reliability of pre-trained word embedding's. They evaluated suggested approach 20 times with various DNN to verify its correctness. The approach enhances the reliability of SA tasks throughout all categories as well as databases, according to the results of the experiments. The result indicate that the Recall of the Positive and negative sentiment is 0.877 and 0.938 respectively. Precision is 0.93 and 0.8887 and F1 measure is 0.904 and 0.911 and accuracy of the suggested model is 0.9080. Yang et al. (2016) introduced hierarchical attention networks (HAN) for text categorization in this study. The study got improved visualization as a secondary consequence of utilizing the extremely informational elements of a text. By combining significant phrases and sentences, proposed model gradually generates a text vector. The result indicate that the Recall of the Positive and negative sentiment is 0.8762 and 0.9388 respectively. Precision is 0.9352 and 0.8843 and F1 measure is 0.9043 and 0.910 and accuracy of the suggested model is 0.9075. Wen and Li (2018) presented a recurrent convolution neural network with attention and its variations. The topology that sends the RNN feed's hidden layer to CNN may train n gram characteristics on bilateral consecutive vectors. The result indicate that the Recall of the Positive and negative sentiment is 0.8718 and 0.9463 respectively. Precision is 0.942 and 0.881 and F1 measure is 0.9053 and 0.912 and accuracy of the suggested model is 0.909. Basiri et al. (2021) suggested a Bidirectional Attention based CNN-RNN Deep Model (ABCDM). ABCDM will recover both present and upcoming settings by evaluating temporal data flow in bidirectional using 2 autonomous LSTM and GRU levels. The Data is taken from Tweets and Movie reviews in these experiments. The result indicate that the Recall of the Positive and negative sentiment is 0.908 and 0.956 respectively. Precision is 0.957 and 0.9131 and F1 measure is 0.932 and 0.9356 and accuracy of the suggested model is 0.9340. Liu, and Guo (2019) presented an attention-based bidirectional long short-term memory with convolution layer. The greater sentence depictions are extracted by the words embedded vector by the convolutional operation in AC-Bi-LSTM, and Bi-LSTM is utilized to retrieve both the previous and following contextual views. In terms of classification accuracy, the findings clearly indicate that LSTM surpasses other text classifiers. The result indicate that the accuracy of the suggested model is 0.9075. Onan (2019 a or b) proposed an word embedding model that is used to extract topic from bibliometric datasets. The model was designed in two stages, i.e., word vector formation and clustering. For this word2vec, POS2vec, word-position2vec and LDA2vec were used. Whereas in clustering phase ensemble of k-mean, self-organization maps and DIANA algorithms were used. Onan (2020) presented twitter sentiment analysis using deep learning approach. The model is designed with hybridization of CNN-LSTM network. Onan (2019 a or b) proposed a recurrent neural network for opinion mining. For result analysis GloVe word embedding was hybridized with classification and achieved approx. 98% of accuracy. Text genera classification was performed by Onan (2018). The author used random forest classification and obtained approx. 94.43%. Onan (2019 a or b) investigated for better prediction performance using heterogeneous consensus clustering that is designed for undersampled data. Onan (2019 a or b) presented text analysis for sarcasm identification. The model evaluated using word2vec, fastText and GloVe and acheived approx. 87% of F_measure. Onan (2018) presented swarm intelligence hybridized LDA algorithm for biomedical text classification and obtained approx 87% of accuracy. Association mining was used for student information system was also presented by Onan, Korukoğlu, and Bulut (2016). Onan, and KorukoGlu (2017) proposed k-mean and cuckoo search algorithm for text classification and obtained accuracy of approx. 90%. Onan and Toçoğlu (2021) hybridized the N-gram with ensemble classification for student higher education system.

Table1 Comparative chart of previous researches

Ref.	Method	Accuracy	Advantages
Wang et al. (2016)	CNN_LSTM	91.450	Enhance forecasting accuracy
Chatterjee et al. (2018)	LSTM-DPP	91.450	Surpasses lexicon-SA model, regression-SA model, and NN-SA methods
Rezaeinia et al. (2019)	Pre-trained CNN models	90.80	Improved the accuracy of pre-trained matrices in SA
Yang et al. (2016)	Hierarchical Attention Networks (HAN)	90.75	Outperforms prior approaches
Wen and Li (2018)	The ARC model's	90.9	Useful for choosing key words in a phrase
Basiri et al. (2021)	Convolutional Neural Network-RNN Deep algorithms	93.40	Outperforms prior approaches
Liu, and Guo (2019)	Bi-LSTM	90.76	Surpasses other text classifiers
Onan (2015)	Genetic Rank Aggregation	94.71	Aggregated the feature list using genetic algorithm obtained from different filter based feature selection techniques
Onan (2016)	Bagging ensemble of random forest	93.80	The keywords were extracted as feature and further classified.
Onan (2020)	CNN-LSTM	93.85	Used word embedding to reduce the overfitting issues.
Onan (2015)	Fuzzy rough set	99.71	Feature ranking was adopted to find enumerations in search space.

Onan et al., (2016)	Bagging	88.1	It was observed that ensemble of correlation feature set and bagging classification outperforms best.
Onan and Tocoglu (2021)	Bidirectional LSTM	95.30	Word-embedding with LSTM outperforms better.

3. Methodology

A quick outline of attention based core architectural elements and mechanism is given in Figure 1. In Section 3.1, Attention mechanism (AM) of DenseNet are discussed, followed by the Attention-based dense block and Attention-based DenseNet in Sections 3.2 and 3.3, correspondingly. Section 3.4 describes the stacked convolutional auto-encoders and section 3.5 give a classification.

3.1 Attention mechanism of DenseNet

CBAM represents the convolution based AM settings. It's a type of attention mechanism module that incorporates both spatial and channel considerations. It can lead to better outcomes than a channel-only attention method. A middle feature map $f \in r^{C\times H\times W}$ is feed as an entering feed of the CBAM, and 1-D channels map $m_C \in r^{C\times 1\times 1}$ and a 2-D spatially maping which is represented as $m_S \in r^{1\times H\times W}$ are evaluated consecutively, the attention architecture is summarized as eqn (i):

$$f' = m_c(f) \otimes f \qquad \text{(i)}$$
$$f'' = m_s(f') \otimes f'$$

Where, symbol $\otimes$ represents product of each element function.

And f'' is the outcome of CBAM.

Initially, we employ average-pooling and max-pooling layers to accumulate the spatial features of a feature map, and two separate spatial situation identifiers are developed: f_{avg}^{C} signifies average-pooled features, while f_{max}^{S} indicates average pooled features. Signifies and average pool features are fed into a common network for producing the $m_C \in r^{C\times 1\times 1}$ channel attention map. The concealed activation size is set at $r^{C/n\times 1\times 1}$, here r specifies the reduction ratio, to eliminate oversize variables. In an essence, the channel attention is calculated as follows:

$$m_C(f)=\sigma\left(MLP(Avgpool(f))\right)+(MLP(Maxpool(f))) \qquad \text{(ii)}$$

$$= \sigma\left(W_1\left(W_0\left(f_{avg}^{C}\right)\right)\right)+\left(W_1\left(W_0\left(f_{avg}^{C}\right)\right)\right)$$

Where, σ = sigmoid function,
$W_0 \in r^{C/n\times C}$ and,
$W_1 \in r^{C\times C/n}$ indicates the weight of MLP.

W0 and W1 are used in those inputs, and W0 is also used in the ReLU activation algorithm. Those who pooled operational operations all along channels line might effectively highlight instructive locations, as shown. To construct a spatial attention mapping $m_s(f)rHW$, a convolution layer is applied towards the sequence feature descriptor. This specifies when and how to concentrate. The technique is outlined in detail below.

A feature map's channel features are pooled by employing two pooling layers and two 2 dimensional maps: $f_{avg}^{s}r_1HW$ depicts average-pooled features throughout the channel, and $f_{max}^{s}r_1HW$ indicates max-pooled features all through channel. In brief, the spatial attention is calculated as follows in eqn (iii):

$$m_s(f)= \sigma\left(E^{7\times 7}([Avgpool(f)];[Maxpool(f)])\right) \qquad \text{(iii)}$$
$$=\sigma(E^{7\times 7}(f_{avg}^{s};f_{max}^{s}))$$

Here, σ and $E^{7\times 7}$ indicates convolution function with the 7×7 size of filter.

3.2 Attention-based dense block

Huang et al. (2019) developed interconnections from every layer to all subsequent layers are not interrupted. To pay special attention to the scale properties of objectives, we integrate the CBAM and DenseNet to enhance the feature of every layer. Ultimately, the *k*th layer joins all of the previous layers' feature maps, $x_0, x_1 \ldots\ldots x_{k-1}$, as input in eqn (iv):

$$x_k=H_k([x_0, x_1 \ldots\ldots\ldots\ldots x_{k-1}]) \qquad \text{(iv)}$$

Where, $x_0, x_1 \ldots\ldots\ldots\ldots x_{k-1}$ implies interlinked functions,

$H_k(.)$ is Batch normalizing (BN) rectified linear unit (ReLU)33 convolutional layer (Conv) CBAM is a composites functional made up of four operational function in a row.: Inflation rate, limiting factor of layers, compaction, as well as other aspects of attention-based dense block are just like DenseNet.

3.3 Attention-based DenseNet

The image is the attention-based feed DenseNet. A CNN with a 77% filter is denoted by d 0^1.

$$d_i^q = \odot d_{i-1}^p,\ W_i^d \qquad \text{(v)}$$

Where, d_i^q signifies the i_{th} attention-based featuring mapping term.

$\odot$ implies the set of operations,

W_i^d is the group of independent variables in the i_{th} DenseNet depending on attention Mechanism.

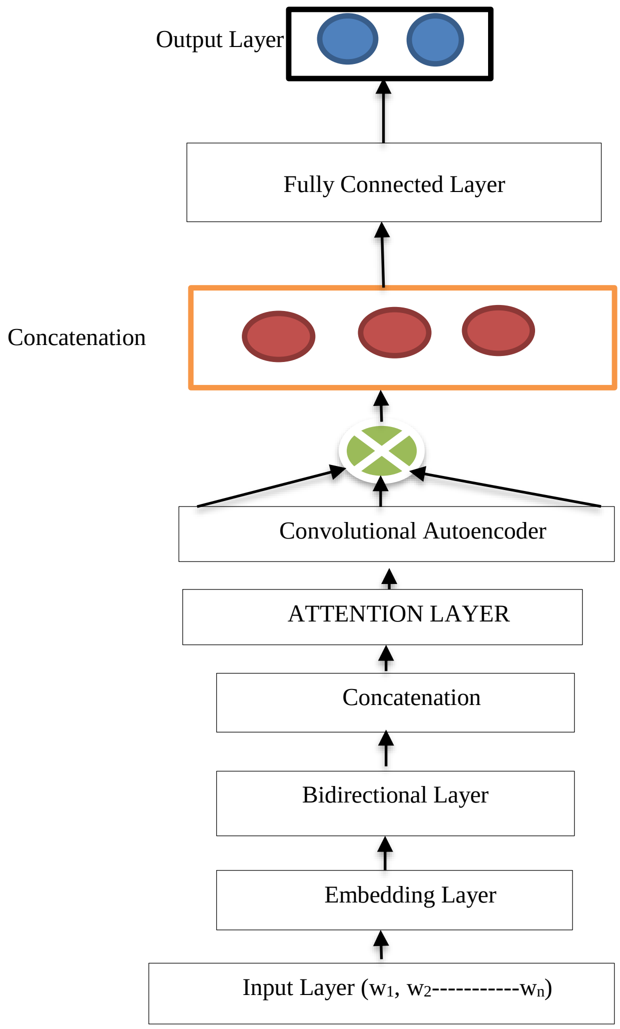


Figure 1 Proposed Network Architecture

3.4 Stacked convolutional auto-encoders

Auto Encoders were popular learning algorithm that is based on the principle of sparse coding and has a strong benefit in information extracting features. Conventional AEs are made up of an encoding and a decoding that use a back propagation procedure to achieve best result for matching the forecast outcome to the actual truth. The two-dimensional architecture is ignored by conventional Auto Encoders. Rather than a fully-interlinked layers, the convolutional auto-encoder utilizes convolutional layer. The idea is similar with that of an auto-encoder. It down-samples the input symbol to make the unexpressed dimension depiction narrower and pushes the auto-encoder to understand a compressed version of the symbol. Traditional AEs will lead the network to create numerous duplicate variables while analyzing high-dimensional input including images, particularly for image processing, color photos with three channels Due to a massive network layer characteristic of traditional auto encoders, traditional AEs are unable to maintain spatial locality, slowing the network training rate.

Figure represents the framework of a CAE, that consists of N-attention-based dense blocks linked by a convoluting function and a pooled process; the outcome is similar as the feed data in the form of image, which can be pre-trained by employing the supervision training technique, so there is a convolution operation in between feeds and outcomes.

3.5 Parameter training and classifier

Figure shows construction of an ADN; The i_{th} ABDB in ADN is identical to that in CAE, and the first half of CAE's attention-based dense blocks are retained in ADN. If Nis not even integers, we round it up, and ADN generates attention-based dense blocks with a N/2 limit. Finally, the SoftMax function is used to perform the final estimation.$\theta = arg\underset{\theta}{min} - \{\sum_{i=1}^{m} G_i \log O_i\}$ Here, N denotes quantity of pictures in the database, G_i denotes image's grounding true value, and Oi denotes the neural network's outcome following SoftMax. Learning by using Adam optimization additionally backpropagation method and describe a set of implementation variables is studied.

3.6 Proposed Flowchart

The suggested technique is comprised of three main components, which are outlined below (Figure 2). The suggested model will first construct a word vector, then use an autoencoder to discover lexicon and deep aspect level features, which will then be passed into a random forest classifier for polarity determination. The entire process is described in algorithm 1.

Algorithm 1: SAABCA

Input: Data {*D*}
Output: *CR* {classification Result, -1 = Negative, +1 = Positive}
1: Begin
2: *PD*←Pre-process (*D*) Where, *PD* = Pre-processed Data
3: TD_v←TD(*PD*) Where, TD = term-frequency feature vector
4: IDF_v←IDF(*PD*) Where, IDF = inverse document-frequency feature vector
5: PS_v←PS(*PD*) Where, PS = Polarity-frequency feature vector
6: Divide into feature sets as (FV_1, FV_2, FV_n)
7: While $cost_{\text{func}}$ reaches convergence do
8: OF_v = optimize {FV_1, FV_2, FV_n }
9: Minimize($cost_{\text{func}}$)
10: End
11: Train {CBAM}
12: *CR* ←Classify{ OF_v }
13: Return *CR*
14: End

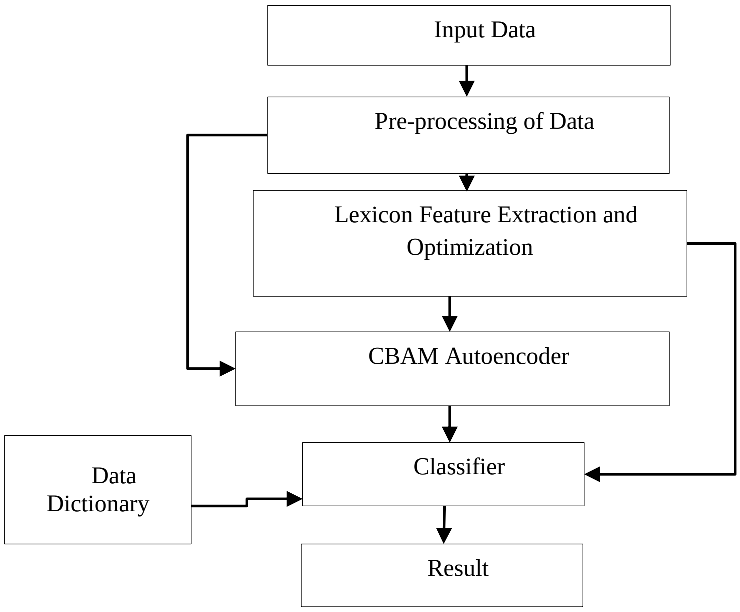


Figure 2 Proposed Flow Diagram

3.6.1 Data Gathering

This stage prepares a dataset for various domains acquired from various domains. For further processing, the data is gathered from a variety of publicly accessible data sources.

3.6.2 Data Pre-processing

It is essential to filter the original information obtained from various sources. Data pre-processing is the phrase for this stage. During pre-processing, any unneeded words in the reviews, like commas and specific denotion, are deleted since they don't add to any emotion values in the phrase or document. The acquired dataset is evaluated item by entities, and superfluous entities like URLs, specific symbols, commas, and other punctuation marks are deleted, leaving a clean dataset for future processing.

3.6.3 Lexicon Feature Extraction and Optimization

After Preprocessing of data, lexicon feature extraction and optimization is carried out. The main target of this project is to give a systematic method for extracting and choosing appropriate features using lexicon in order to categorise subjective data effectively and quickly. As a result, our study advances the process of feature extraction and selection. It is the method of extracting meaningful information from obtained clean data. Lexicon characteristics, for example, are extracted. Feature extraction is seen in Figure 3 below. Different lexical characteristics are retrieved, but they must be optimized to acquire just the most relevant ones. This step produces an optimized feature vectors that serves as a label or class for the information and is connected towards both negative and positive scores. A data dictionary is used to determine the score. The feature extraction process used in this step is TF-IDF. TF-IDF is formed by combination of Term Frequency (TF) and Inverse Document Frequency (IDF) that is used to determine the statistical probability of word frequency in a data set in a variety of activities, such as textual analysis. It is mathematically evaluated as:

$$TFIDF(t,d,D)= TF(t,d).\ IDF(t.D) \qquad \text{(vi)}$$

Where t depicts the word, d depicts each document and D depicts the number of documents.

$$\text{TF(t,d)}= \frac{f(t,d)}{|D|} \qquad \text{(vii)}$$

Where, f(t,d) is total number of times t appears in document d and $|d|$ is the total number of times in d "document".

$$\text{IDF(t,d)}= \log \frac{|D|}{|\{D\ I\ t\epsilon d\}|} \qquad \text{(viii)}$$

Where $|D|$ are total number of documents and $\{D\ I\ t\epsilon d\}$ is total number of documents with term t in it.

3.6.4 CBAM Autoencoder and classification

After Feature extraction Auto encoding is done using CBAM Autoencoder (Convolution Block Attention Module) to discover lexicon and deep aspect level features. We propose a basic yet efficient attention module (CBAM) that may be used to improve feature extraction and classification process, discussed in above section. The module is split up into two: channel and spatial. At every and every segmentation block of networks, our module (CBAM) refines the intermediary extracted features map adaptively. Classification techniques are applied to categories information values into distinct groups. In this article, a classifier is used to classify review data into distinct opinion polarity using a stacking of convolution auto-encoder and lexical features. Prior to fed the data into classifier, the dataset is transformed into a word vector and goes in the lexical feature extraction and a stacked convolution auto encoder in this part. Text must be transformed into word vectors before being fed into the network for feature extraction. The extracted word vectors are used as a starting value in the model. The classifier is trained for polarity decision using lexical features and deep aspect level data. The whole procedure is shown in Figure 4.

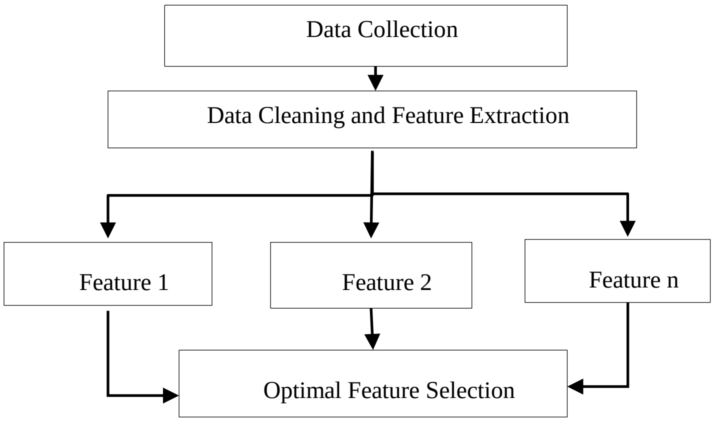


Figure 3 Feature Extraction for Proposed Work

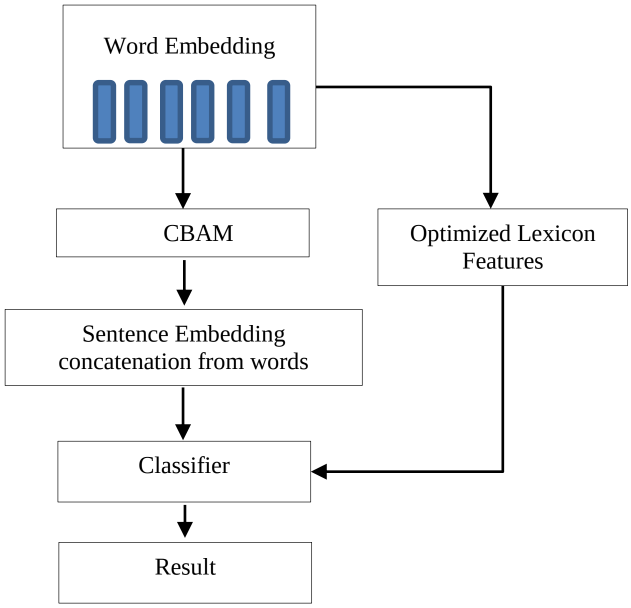


Figure 4 Feature Classification

4. Results and Discussion

The empirical and analytical explanation of the suggested approach for sentiment analysis is provided in this section. To analyze the performance, the simulation is run using the MATLAB environment. The research focuses on the extraction of deep aspect level features and lexical features for sentiment analysis of reviews as simulated results. Reviews from many domains are harvested and gathered from datasets like kindle, movie, and twitter for simulation execution. Performance parameters used in this paper for comparison are discussed as in below section.

4.1 Dataset Description

In this paper, the SAABCA model is evaluated on three datasets, kindle review, movie review and twitter review that are discussed below:

- Kindle Store review dataset was prepared by He and McAuley (2016). The dataset contains 982,619 reviews created rom product reviews from Amazon.
- Movies review dataset was prepared by McAuley, Targett, Shi, and Van Den Hengel (2015) that contains 1,697,533 reviews.
- Airline Twitter review dataset was prepared by Data.word (2015) that contains 14,641 tweets for problems faced by US airlines.
-

4.2 Performance Evaluation Parameters

Text categorization and sentiment analysis tasks frequently employ these criteria. The following formula is used to compute these criteria:

Accuracy = Accuracy refers to the condition of a SAABCA's efficiency being right or exact in all circumstances.

$$\frac{TP+TN}{TP+TN+FP+FN} \qquad \text{(ix)}$$

Precision = Precision refers to the correctness of the data being examined. It's a metric for determining if a positive occurrence is accurate or not. Presented by:

$$\frac{TP}{TP+FP} \qquad \text{(x)}$$

Recall =**:** The frequency of positive experiences is measured by recalls. The Recall formula is as follows:

$$\frac{TP}{TP+FN} \qquad \text{(xii)}$$

F1 score = It is defined as the inverse of accuracy and recall multiplied by two, as provided by the equation.:

$$\frac{2}{1/precision+1/Recall} \qquad \text{(ix)}$$

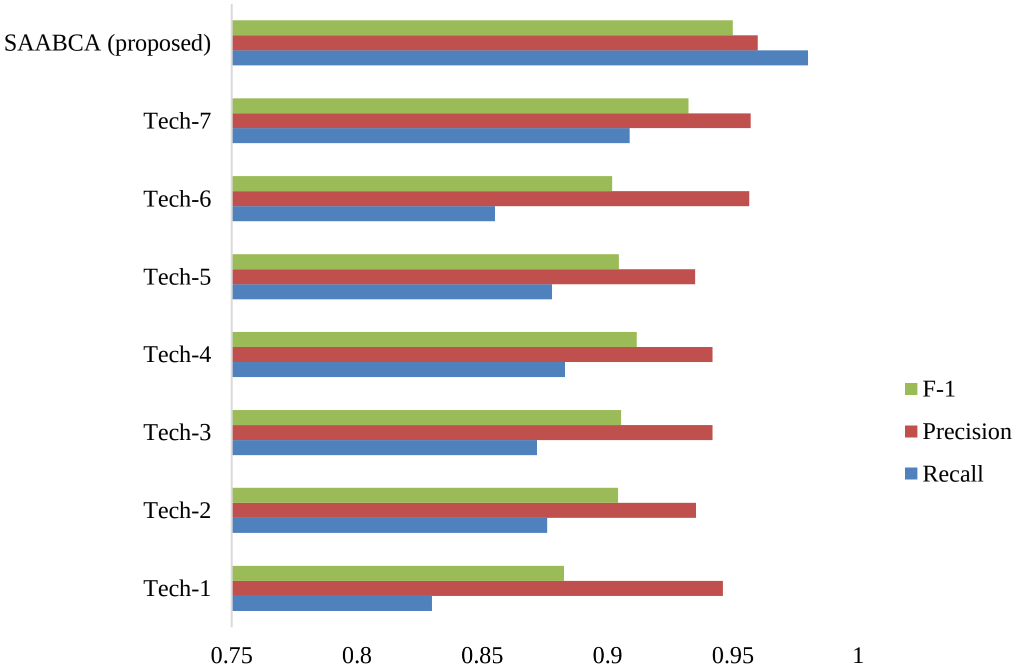
Where TP, TN, FP, FN are true positive, true negative, false positive and false negative instances respectively.

4.3 Result Analysis

Baseline analyses are analyzed in this section. For beginnings, SAABCA is contrasted to the neural approaches listed above for SA with Kindle dataset, Movie reviews and Tweets. Lastly, the desired outcomes by the methods presented in Table 2-4 are conducted to evaluate the performance of SAABCA. The result obtained from the performance on different reviews and tweet polarity classification when compared to seven previously suggested DNNs for sentiment analysis are given below. The Comparison of the 7 Techniques along with the proposed methods is :

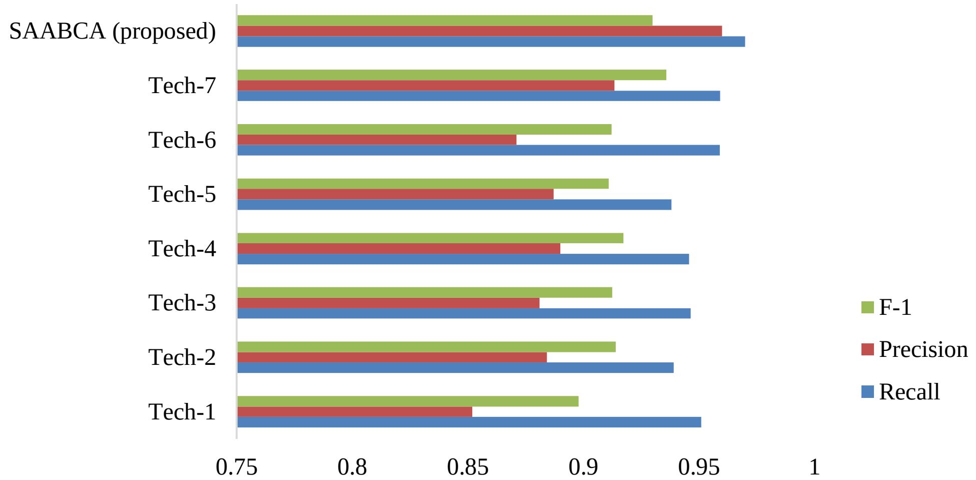
1. SS-BED(Tech-1)
2. HAN(Tech-2)
3. ARC(Tech-3)
4. CRNN (Tech - 4)
5. IWV(Tech-5)
6. AC-BiLSTM(Tech-6)
7. ABCDM(Tech-7)
8. SAABCA(Proposed)

Figure 5 and Figure 6 shows the comparison of the result obtained from Kindle Dataset. The lowest recall in positive and negative class is 0.8300 and 0.9381 respectively from all seven algorithms, whereas the highest value of recall in positive and negative class is 0.98 and 0.97 respectively for our proposed SAABCA algorithms. Similarly, the lowest precision in positive and negative class is 0.9350 and 0.852 respectively from all seven algorithms, whereas the highest value of precision in positive and negative class is 0.96 and 0.96 respectively for our proposed SAABCA algorithms. Similarly, the lowest F-1 measure in positive and negative class is 0.8826 and 0.898 respectively from all seven algorithms, whereas the highest value of precision in positive and negative class is 0.95 and 0.93 respectively for our proposed SAABCA algorithms. Compared with minimum accuracy(SS-BED), SAABCA is 5% more for accurate i.e. 0.94. Figure 7 and Figure 8 shows the Comparison of the result obtained from Movie Reviews Dataset. All seven algorithms have the lowest recall in PC and NC of 0.7374 and 0.906, correspondingly, but our suggested SAABCA algorithms have the maximum recall in positive and negative classes of 0.91 and 0.95, respectively. Similarly, all seven algorithms have the lowest precision in the positive classes(PC) and negative classes (NC) of 0.8992 and 0.8215, correspondingly, but our suggested SAABCA algorithms have the maximum precision in the PC and NC of 0.93 and 0.935, respectively. Similarly, the lowest F-1 measure in positive and negative class for all seven algorithms is 0.847 and 0.8674, respectively, but the greatest precision value in positive and negative class for our suggested SAABCA algorithms is 0.96 and 0.94, respectively. When compared to the minimal accuracy (CRNN), SAABCA is 11% more accurate, or 0.97. Figure 9 and Figure 10 shows the Comparison of the result obtained from Airline Twitter Dataset All seven algorithms have the lowest recall in PC and NC of 0.935 and 0.749, respectively, but our suggested SAABCA algorithms have the maximum recall in PC and NC of 0.95 and 0.975, correspondingly. Similarly, the lowest precision in the positive and negative classes for all seven algorithms is 0.9368 and 0.7575, respectively, but the maximum precision in the positive and negative classes for our proposed SAABCA algorithms is 0.95 and 0.97, respectively. Similarly, the lowest F-1 measure in the positive and negative classes for all seven algorithms is 0.7543 and 0.768, respectively, but the maximum precision value in the positive and negative classes for our proposed SAABCA algorithms is 0.965 and 0.94, respectively. SAABCA is approx. 8% more accurate than the minimal accuracy (IWV), i.e., 0.98. Figure 11 shows the accuracy comparison of different techniques named as Tech-1 to Tech-7 and proposed method using Kindle Dataset. The minimum accuracy is 89.11% for Tech-1. Compared with minimum accuracy Tech-1, i.e. SS-BED, SAABCA is 5% more for accurate i.e. 0.94. Proposed SAABCA have accuracy of 94%, which shows the effectiveness of the suggested technoques. Figure 11 also shows the accuracy comparison of different techniques named as Tech-1 to Tech-7 and proposed method using Movie Dataset. The minimum accuracy is 85.86% for Tech-1. SAABCA is approx. 8% more accurate than the minimal accuracy Tech-1 is 0.97. Proposed SAABCA have accuracy of 97%, It demonstrates the usefulness of the suggested approach. The accuracy comparison of different techniques named as Tech-1 to Tech-7 and proposed method using Tweet Dataset is also represented in Figure 11. The minimum accuracy is 89.9% for Tech-5. SAABCA is approx. 11% more accurate than the minimal accuracy tech-5, i.e. IWV, i.e., 0.98. Proposed SAABCA have accuracy of 98%, it demonstrates the usefulness of the suggested approach



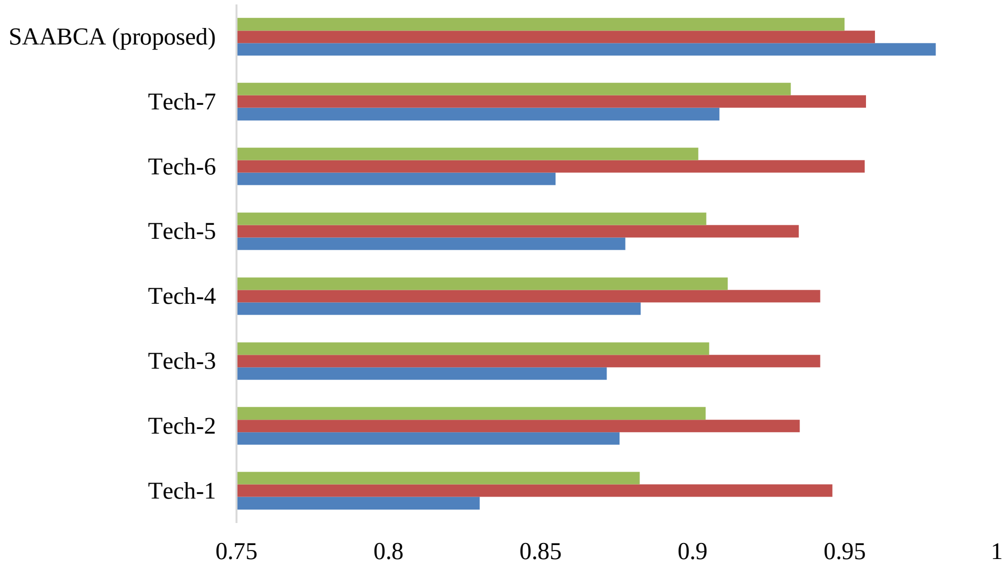
	Tech-1	Tech-2	Tech-3	Tech-4	Tech-5	Tech-6	Tech-7	SAABCA (proposed)
F-1	0.8826	0.9043	0.9055	0.9116	0.9045	0.9019	0.9323	0.95
Precision	0.946	0.9353	0.942	0.942	0.935	0.9566	0.9571	0.96
Recall	0.83	0.876	0.8718	0.883	0.8779	0.855	0.9089	0.98

Figure 5 Result of Positive Reviews on Kindle Dataset and its comparison with different techniques



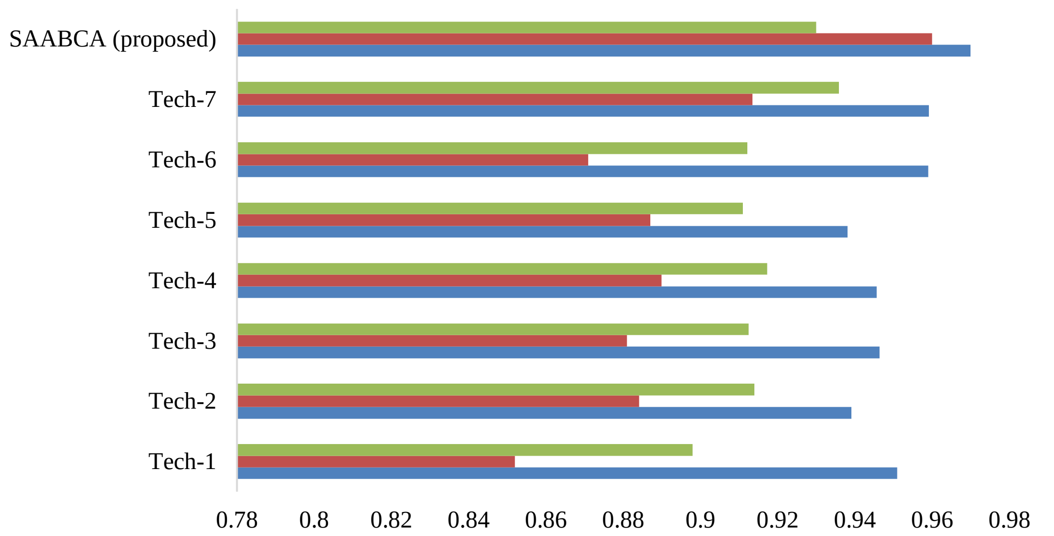
	Tech-1	Tech-2	Tech-3	Tech-4	Tech-5	Tech-6	Tech-7	SAABCA (proposed)
F-1	0.898	0.91404	0.9125	0.9173	0.911	0.9122	0.9359	0.93
Precision	0.852	0.8842	0.881	0.89	0.8871	0.871	0.9135	0.96
Recall	0.951	0.9391	0.9464	0.9457	0.9381	0.959	0.9592	0.97

Figure 6 Result of Positive Reviews on Kindle Dataset and its comparison with different techniques



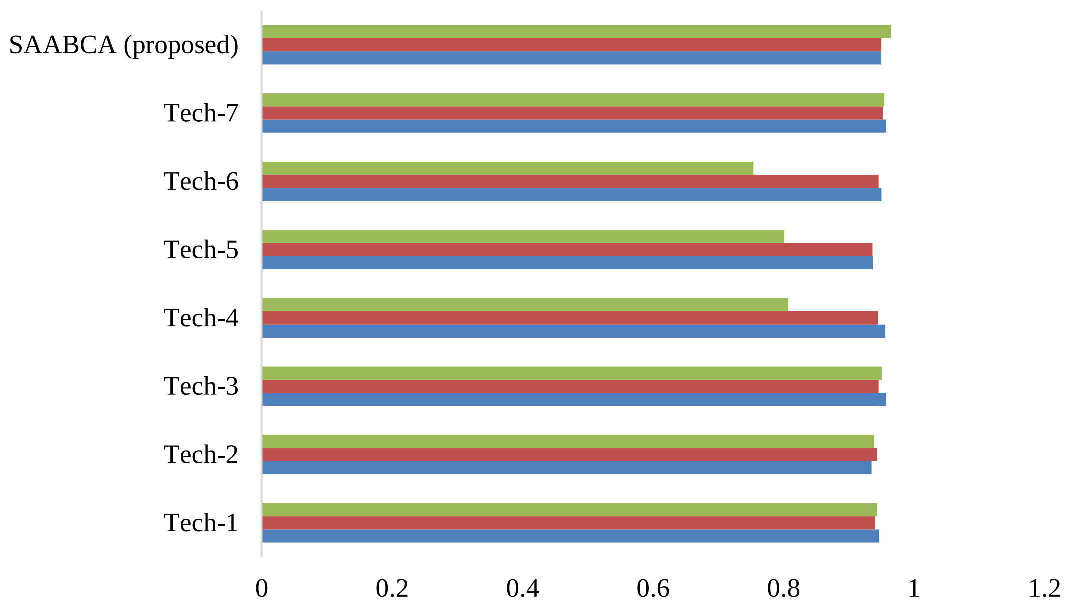
	Tech-1	Tech-2	Tech-3	Tech-4	Tech-5	Tech-6	Tech-7	SAABCA (proposed)
F-1	0.8826	0.9043	0.9055	0.9116	0.9045	0.9019	0.9323	0.95
Precision	0.946	0.9353	0.942	0.942	0.935	0.9566	0.9571	0.96
Recall	0.83	0.876	0.8718	0.883	0.8779	0.855	0.9089	0.98

Figure 7 Result of Positive Reviews on Movie Dataset and its comparison with different techniques



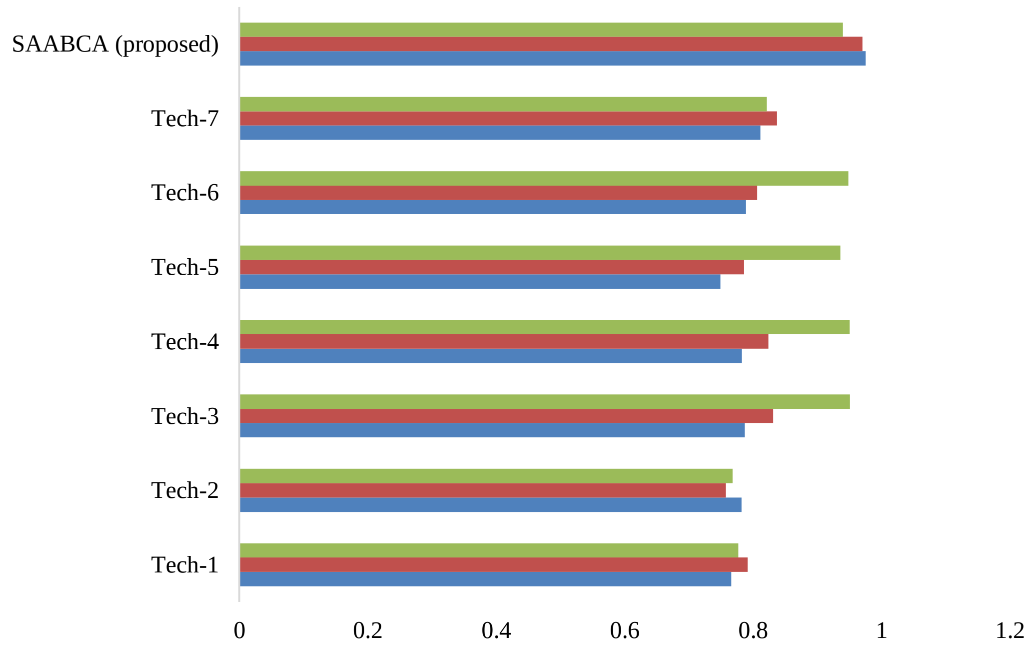
	Tech-1	Tech-2	Tech-3	Tech-4	Tech-5	Tech-6	Tech-7	SAABCA (proposed)
F-1	0.898	0.91404	0.9125	0.9173	0.911	0.9122	0.9359	0.93
Precision	0.852	0.8842	0.881	0.89	0.8871	0.871	0.9135	0.96
Recall	0.951	0.9391	0.9464	0.9457	0.9381	0.959	0.9592	0.97

Figure 8 Result of Positive Reviews on Movie Dataset and its comparison with different techniques



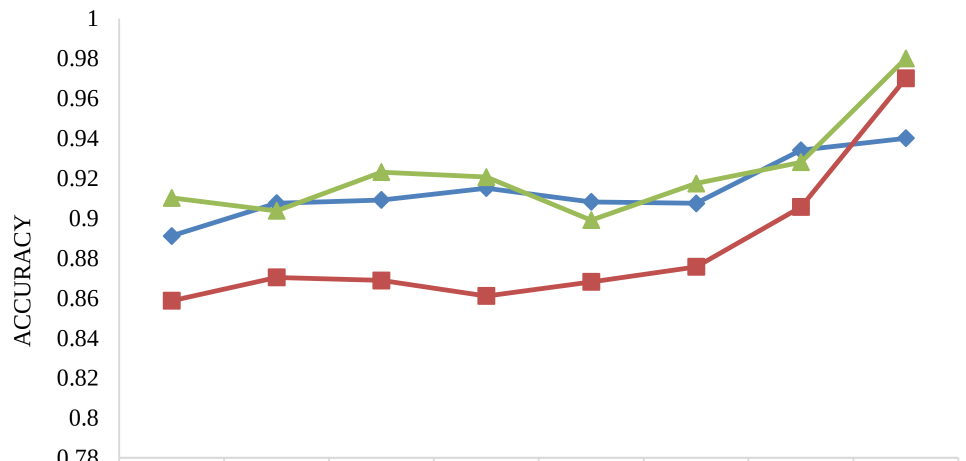
	Tech-1	Tech-2	Tech-3	Tech-4	Tech-5	Tech-6	Tech-7	SAABCA (proposed)
F-1	0.9437	0.9391	0.951	0.8071	0.8013	0.7543	0.955	0.965
Precision	0.9404	0.9435	0.9461	0.945	0.9368	0.946	0.9521	0.95
Recall	0.9471	0.935	0.9579	0.9562	0.937	0.9504	0.9575	0.95

Figure 9 Result of Positive Reviews on Airline Dataset and its comparison with different techniques



	Tech-1	Tech-2	Tech-3	Tech-4	Tech-5	Tech-6	Tech-7	SAABCA (proposed)
F-1	0.777	0.768	0.951	0.9504	0.9356	0.9481	0.821	0.94
Precision	0.7914	0.7575	0.831	0.8235	0.786	0.8061	0.837	0.97
Recall	0.7659	0.7817	0.787	0.7825	0.749	0.789	0.8113	0.975

Figure 10 Result of Positive Reviews on Airline Dataset and its comparison with different techniques



	Tech-1	Tech-2	Tech-3	Tech-4	Tech-5	Tech-6	Tech-7	SAABCA (proposed)
Kindle	0.8911	0.9075	0.9091	0.915	0.9081	0.9074	0.934	0.94
Movie	0.8586	0.8703	0.8688	0.861	0.8681	0.8756	0.9056	0.97
Tweet	0.9101	0.9036	0.923	0.9205	0.899	0.9173	0.928	0.98

Figure 11 Comparison of Accuracy using kindle, movie and twitter dataset

5. Conclusion

Sentiment analysis has seen a substantial increase in research efforts in recent years, owing to its importance in industries including online product acquisition, advertising, and brand management. On social networks and internet commerce platforms, user-generated data is abundant. Manufacturers, salespeople, and marketers are increasingly turning to this source for global feedback on their actions and goods. For this many Deep neural networks and machine learning models including RNN, CNN, auto encoders models, in particular, are increasingly widely used in the field of artificial intelligence for Sentiment Analysis. Many problems exist in present approaches, and classifier accuracy should be improved. This research proposes a unique sentimental analysis approach for SA that uses an attention-based convolution autoencoder (SAABCA). Several experiments were conducted utilizing various reviews and tweet datasets to determine the efficacy of the proposed approach. Furthermore, a comparing the review and twitter dataset findings reveals an increase in the model's accuracy. This study focused on sentiment analysis and polarity detection at the document level. We'd want to see how effective our proposed SAABCA is for future sentiment classification tasks including ratings forecasting and relevance prediction, as well as other levels of sentimenst analysis like phrase and AS-SA. Finally, although SAABCA was written in English, it may easily be adapted to other languages.

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