Journal of Theoretical and Applied Information Technology
15th January 2024. Vol.102. No 1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

DEPTHWISE SEPARABLE CONVOLUTION RESNET MODEL FOR SENTIMENT ANALYSIS IN AMAZON E-COMMERCE WEBSITES

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ABSTRACT

In this era of modern world, exponential growth in e-commerce websites helps people buy necessary products online because of delivering to everyone’s doorstep. Consumers no need to get out of their home to buy products, through the websites they able to view wide variety of brands for each product. Since customers rely on e-commerce websites, the value of rating is important for business growth. To buy the products online, people solely rely on the review comments of products before purchasing the products. The reviews are sometimes lengthy, tedious and deceptive, in such situation sentiment analysis used which identify sentiment in reviews by investigating and extracting the views. This paper describes the depthwise separable convolution resnet model for sentiment analysis in amazon e-commerce website such that reviews are collected from publicly available dataset. On collecting the reviews, pre-processing of data by using Stemming, Lemmatization, Tokenization and Stop word removal for cleaning the data. In sentiment analysis, for reducing the dimensionality features are extracted to create a smaller set of features and feed this lower-dimensional data to classifiers to predict the sentiment polarity of the entire text. Thus review related features extracted by Latent Semantic Analysis (LSA) and Improved Term Frequency- Inverse Document Frequency (ITF-IDF) methods. From the review related features, aspect features are extracted by evaluating the weight matrices. Finally extracted features are fed to proposed model for the detection and classification of the consumers’ sentiment into positive, negative and neutral. The model is evaluated based on performance metrics and compared with existing techniques, proposed model obtains an accuracy of 98.2% which is higher than existing methods. Thus proposed approach helps manufacturers improve their products based on user feedback.

Keywords: *Latent Semantic Analysis, Term Frequency- Inverse Document Frequency, Stemming, Lemmatization, Tokenization, Stop Word Removal, Depthwise Separable Convolution Resnet Model*.

1. INTRODUCTION

In recent years, sentiment analysis is gained a lot of interest. Opinion mining is the process by which businesses leverage user comments, reviews, and tweets on social media sites to determine the perceptions that the public has of their goods and services [1]. These huge amounts of data become vital and useful information for forecasting consumer preferences and consumption trends, as well as sentiment indicated in reviews [2]. This helps businesses enhance their marketing plans and offerings [3]. Sentiment analysis’s primary goal is to interpret textual expressions of human emotions [4]. Customers are free to voice their opinions on the goods they have already accepted. Customers can use these reviews as effective tools to examine products on e-commerce sites before making a purchase [5]. Sentiment analysis is used in a wide range of fields, including education, finance, and politics.

This research discusses the e-commerce industry, the number of online buying has been mainly improved in recent years [6, 7]. As a result, client reviews of goods they have previously bought because e-commerce sites to produce a lot of records every day [8]. User opinions create an opportunity for interaction where users can exchange recommendations and guide about goods and services [9].Additionally, analyzing these viewpoints, internet dealers can better understand user expectations, enhance the buying experience, and boost revenue [10]. This work aims to identify user sentiment towards certain smartphone items by automatically analyzing textual data gathered from the most common e-commerce platform for amazon [11, 12].

This is accomplished by utilizing a deep learning algorithm with a creation related on a quantity of feelings language [13]. In order to conduct this study, firstly extracted an amount of data for amazon. Then, used a variety of natural language processing techniques, including stemming, lemmatization, stop word removal and tokenization [14, 15]. Finally, assessed the effectiveness and performance of the convolutional neural network (CNN) classification algorithm. According to the performance, CNN operated with a high accuracy rate [16, 17]. This research differs from other works in that used a scratching process to extract a large quantity of data for amazon e-commerce platform about smart phone products [18]. This aided us classify reviews using CNN, then deep learning algorithms typically require a large amount of records to train accurately [19]. In addition, the CNN algorithm is associated to other methods that also attained a very high accuracy rate [20].

Motivation: Communication plays important role in providing relationship between people since early times. Nowadays, each and every one of society uses social media since it evolved as effective tool. The rapid advancements in E-commerce websites made people to buy and sell products online. People uses social media websites to share their views online about the quality of products, which have positive or negative comments based on the experience faced by customers. Thus e-commerce websites like amazon are in a condition to detect and classify the comments based on the reviews collected. Here comes the sentimental analysis, which identifies the expressed feeling or opinions based on reviews. Thus based on the reviews the policy makers makes decision of improving quality, quantity etc. Sentiment analysis has received huge attention among researchers in numerous applications, hence an effective framework is needed for analysis. To improve the performance of feature extraction and classification variety of strategies employed using machine learning and deep learning models. The existence of spam, negation, fraudulent, emotions, sarcasm etc. makes the extraction process challenging. Based on the studies conducted shows that existing sentiment analysis based techniques are not sufficient to represent sentiments accurately. Thus proposed depthwise separable convolution ResNet model for sentiment analysis in e-commerce websites. The major objectives of the proposed methodology for sentiment analysis are discussed as follows:

- The text reviews gathered from datasets contains unwanted data which are removed through pre-processing using stemming, lemmatization, tokenization and by removing the stop words.
- Hybrid feature extraction process takes place to extract review related features (RRF) and aspect related features (ARF), means extracting the meaning of words expressed by analysing their feelings, attitudes, thoughts and judgements.
- Review related features extracted by using latent Semantic analysis (LSA), improved term frequency- inverse

document frequency (ITF-IDF) methods.

- Aspect related features extraction and classification of reviews into positive, negative and neutral class through depthwise separable convolution ResNet model.
- Finally comparing the classification performance by measuring the performance metrics for proposed and existing methods.

The organization of the paper is listed as follows: Section 2 discussed about recent deep learning approaches used for sentiment analysis. Section 3 elaborated in detail the proposed methodology for sentiment classification. Section 4 discussed about the result of proposed and existing method. Section 5 describes the conclusion and future scope.

2. RELATED WORKS

Alzahrani et al. [21] introduced to this research utilized deep learning with long short term memory (LSTM) approaches of sentiment analysis for reviews in e-commerce industry. The real time records from amazon, which includes reviews are cameras, computers, tablets, smart phones and TVs, was used to test and assess the system. In order to identify and categorize customer sentiment as either positive or negative, the fresh data are analyzed using the LSTM models. The conclusion that deep learning methods used in this instance produce the best categorization outcomes for the approaches of customers in the direction of the products. Therefore, the LSTM methods is high expensive and need more time and memory to train a model.

Every day, the amount of client grows and presents new challenges. Customer's inability to select a high-quality product by analysis every online review is the main issue. Furthermore, they take a lot of time and large amount of data, then product evaluations help e-commerce platform provide better services. Munna et al. [22] presented to this research focus on deep neural network (DNN) and natural language processing (NLP) to resolve these issues with Bangla text. In order to enhance the services and quality, this work suggested two deep learning models: one for sentiment analysis and another one for product analysis classification. Essentially, the accuracy of suggested methods for sentiment analysis is less accuracy than compare to product analysis classification. These models can surely assist customers in selecting the appropriate product and service providers in enhancing their offerings.

Gondhi et al. [23] presented to the relevance of ratings is increasing as more clients rely on online buying sites these days. People just use the product reviews as guidance when making purchases of these goods. Sentiment analysis must be done in order to evaluate these reviews, which can be beneficial to both the company and the customers. This research explains sentiment analysis steps and requirement then using the 2018 amazon review dataset and combine word2vec illustration with LSTM to get better overall performance. In the training phase, LSTM employed a gating mechanism. Compared to other baseline models, the suggested LSTM model performed better overall based on four performance measures: F1-score, recall, accuracy and precision. An issue with LSTMs is overfitting, particularly with small size datasets.

The recommendations assist customers in choosing products, and businesses can boost a product's use. Sentiment analysis is used to better comprehend a user's opinions, feelings and attitudes in the context of social data. Which is useful to integrating sentiment analysis into recommender approaches to increases suggestion reliability. Dang et al. [24] introduced to assess a recommendation strategy that combines collaborative filtering techniques with sentiment analysis. The suggested recommender system is built on an adaptable structure that incorporates enhanced methods for sentiment analysis-based deep learning models and feature extraction. The result of research performed with two popular datasets, demonstrate that collaborative filtering techniques and deep learning methods can greatly enhance the effectiveness of recommender systems. It has several disadvantages such as less privacy/security, lack of information loss and high cost.

Jahidul et al. [25] presented to this research uses a recurrent neural network (RNN) with LSTM for sentiment analysis. An alternative to using the RNN to prevent the vanishing and disappearing gradient issue is to utilize the LSTM model. A comparison is performed between the outcomes of altered RNN method and those of other traditional RNN methods. It is observed that the suggested model outperforms the other traditional RNN methods. In this case, the suggested model of altered RNN method has high accuracy. The e-commerce website can use the model to analyze customer feedback regarding the many product kinds that customers identical.

Challenges:

- Developing multi-lingual models
- Detecting emotions beyond positive or negative sentiment
- Incorporating contextual information
- Handling sarcasm and irony

Problem statement: Rise in growth of e-commerce websites caused online shopping more attractive by surpassing the experiences of in store purchasing. To make the e-commerce websites successful, feedbacks and experiences of customers is very important. New buyers rely on the feedback, reviews and ratings to measure the quality and value of products and services. In physical stores, customers directly interact with items where online customers rely only on experiences and information shared. The change in consumer behaviour might underscore the importance of customer's voice. Thus feedbacks and reviews are necessary for increasing the prospective buyers and inducing purchasing decisions. Satisfying customer needs is essential for running the business successfully. By listening to customer feedbacks, companies can able to identify the strength and weakness, failure of predicting customer voice leads to unfavourable effects on profit of the company. Not responding to customer expectations results in financial loses, reduces customer preservation and satisfaction. Hence responding to customer reviews enhances the growth of e-commerce websites.

Research Questions:

- What do Amazon customers like about products and services?
- What do Amazon customers don't like about products and services?
- Are we getting too many negative responses recently?
- Has the number of negative responses increased gradually?

3. PROPOSED METHODOLOGY

In digital e-commerce, sentiment analysis is considered as an effective technique that helps the purchaser's to take better choices on buying the products and to attain greater sales of the products. Therefore, this work intend to develop a lightweight deep learning model based sentiment analysis for obtaining the sentiments about the products expressed by purchased customers, particularly in the amazon e-commerce websites. The architecture of proposed methodology is shown in Figure 1.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

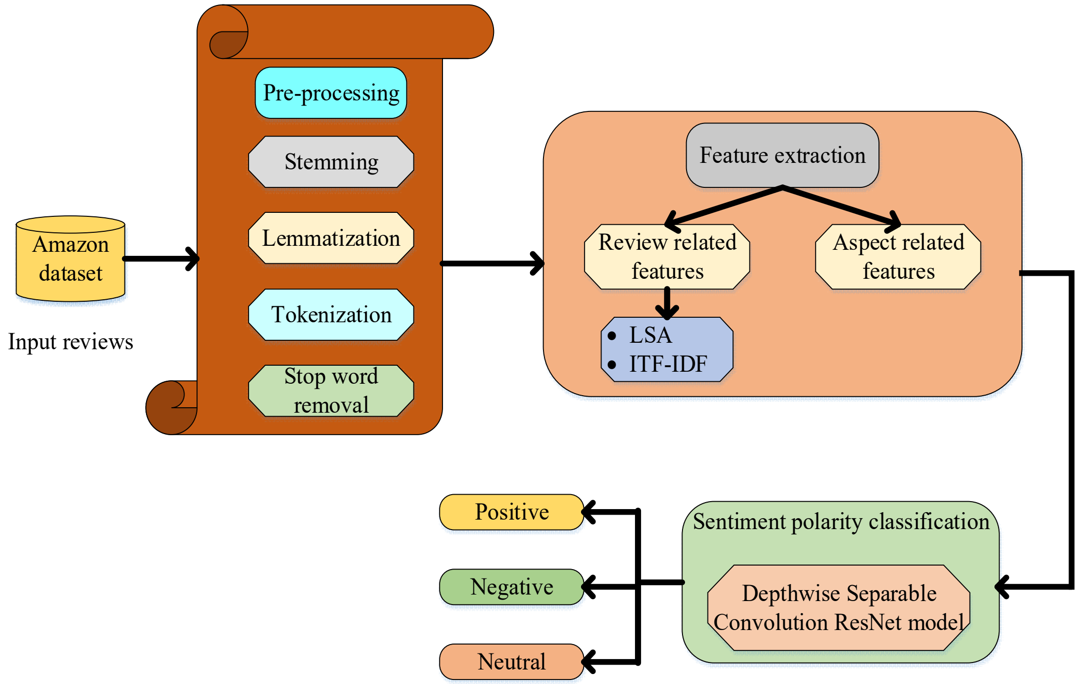

Figure 1: The Architecture Of Sentimental Polarity Classification

The proposed work covers pre-processing, feature extraction, and sentiment classification phases. Initially, the input text are pre-processed by using Stemming, Lemmatization, Tokenization and Stop word removal. Then, the pre-processing phase removes the unwanted data from input text reviews. For extracting the features efficiently, a hybrid feature extraction is employed to obtain features from both review's and aspects for creating the unique hybrid feature vector corresponding to each review. Initially, the review level feature extraction is performed by utilizing Latent Semantic Analysis (LSA), Improved Term Frequency- Inverse Document Frequency (ITF-IDF) methods. Further, Aspect related features extraction process is performed on review text. Finally, Depthwise Separable Convolution ResNet model used for sentiment polarity classification. The results of proposed method is compared with the metrics like Sensitivity, Specificity, Accuracy, Precision, and F1-score.

3.1 Pre-processing: Data pre-processing is the process of converting the raw data into clean dataset. The data's in the dataset is pre-processed to check noisy data, missing values and other inconsistencies before executing the algorithm [26]. Before analysing the text data or comments necessary to remove unwanted parts of data by converting the characters into lowercase, removing stopwords, punctuations, typo errors etc. Natural language processing and artificial intelligence techniques are used for processing the text data. The text data analysis is difficult due to the presence of reviews, blogs, tweets, type of text etc. Data pre-processing helps in cleaning the reviews hence processing is easy.

Stemming: Stemming is the process of reducing the dimensionality of input by changing the words into base or root form. Which combines together, variations of same word and makes easier to detect common features and meanings in the text. For stemming only the sentiment words are considered, while other category features are removed. For example words like sing, singing or sang are changed into root form sing. The transformation converts the words by eliminating the prefixes and suffixes. Therefore stemming leads to a form, but not words since

Journal of Theoretical and Applied Information Technology
15th January 2024. Vol.102. No 1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

deletion of end of words. For example software development creates job opportunities changed as softwar developmen create jo opportunitie.

Lemmatization: By using this technique, lemma of word is obtained by reducing the text data to normalized form. Removing the variation from the token and changed to original form as seeing into see, waiting into wait and falling into fall etc. The process of converting the words into original form. Lemmatization usually refers to doing things properly with the use of a vocabulary and morphological analysis of words, normally aiming to remove inflectional endings only and to return the base or dictionary form of a word, which is known as the lemma.

Tokenization: Tokenization is the process of splitting the data into smaller units called tokens, classified into n grams where, n=1,2,3,… n=1 represents unigram consist of single word as token hat is nice, good etc. n=2 represents bigram consist of combination of two words as tokens that is not appropriate, poor build etc. Most widely used tokenization is whitespace tokenization, where words are tokenized based on white space. The process of extracting the words from the text, by breaking down text into number of units or tokens, here each word is considered as tokens. Tokenization helps to solve the complex textual contents thus important for lexical evaluation and sentiment and semantic analysis.

Stop word removal: The words commonly used in English language are stop words such as articles, prepositions and conjunctions (an, a, from, where, the etc.). which has no specific meaning and no use in sentiment identification. In addition to the stop words, punctuation marks and characters separating text are also considered as stop words, which are removed from the text. Thus reduces noises and dimensionality of the data. Sometime many words appear repeatedly hence necessary to remove the stop words which has no specific importance. Due to the presence of these kinds of words in large number in text data, mining process is difficult and on classification produces unexpected results. Thus on removing the stop words, analysing text data is easier.

3.2 Feature extraction: The process of converting the textual data into numerical features called feature extraction of text data. To get better classification results feature extraction is necessary, although numerous approaches exist for feature extraction, precise, robust and effective feature extraction is still challenging. Thus introduced hybrid feature extraction technique, at first review related features (RRF) extracted by employing various methods to achieve the polarity for every term within the pre-processed text including negations and emotions. The aspect terms with their polarities are then extracted using the ARF method. Sarcastic and ambiguous reviews are also addressed and represented by the ARF.

Review related feature (RRF) extraction: RRF is sentence level feature extraction strategy which considers text as well as emotions to describe the feelings, opinions and negations in the input reviews. RRF extracted using latent semantic analysis (LSA), improved term frequency- inverse document frequency (ITF-IDF) methods.

Latent sentiment analysis [27]:The process of searching for hidden words in the text document, initially collect the pre-processed text from product reviews. Each document has a product review labelled identity document, ID label is adjusted to the number of product review. The result is extended through wordNet for semantic relations in English. WordNet used to detect the words having multiple meanings, wordNet expanded term list evaluated using semantic probabilities. Expectation maximization algorithm in probabilistic latent sentiment analysis evaluates the hidden words from relevant and similar reviewin document. PLSA is chosen to handle words containing polysemy and equipped with document training corpus from E and M step algorithms. PLAS better evaluate hidden words using the following algorithm. Initially determine the number of reviewand initialize probable parameters as $P(C)$,

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

$P(E|C)$ represents the probability document containing review, $P(F|C)$ represents probability of words contained in the review. Evaluation of words in document is given as follows,

$$P(E_a|F_b) = \sum_{l=1}^{L} P(C_l)P(C_l)P(E_a|C_l)P(F_b|C_l) \quad (1)$$

Then find the probability value of words using expectation and maximization algorithm, E-step evaluate the probability of reviews in document, given as follows,

$$P(C_l|E_a, F_b) = \frac{P(F_b|C_l)P(C_l|E_a)}{\sum_{l=1}^{L} P(F_b|C_l)P(C_l|E_l)} \quad (2)$$

The maximization step evaluate the update value from document given as follows,

$$P(F_b|C_l) = \frac{\sum_{a=1}^{n} N(E_a|F_b)P(C_l|E_a, F_b)}{\sum_{m=1}^{M} \sum_{l=1}^{L} N(E_a|F_m)P(C_l|E_a, F_m)} \quad (3)$$

$$P(C_l|E_a) = \frac{\sum_{b=1}^{n} N(E_a|F_b)P(C_l|E_a, F_b)}{n(E_a)} \quad (4)$$

The result of equation 3 and 4 gives probability of words in documents, which produces hidden reviews.

Improved Term Frequency- Inverse Document Frequency (ITF-IDF) [28]:The TF-IDF used to extract the features, thereby reduce the dimensionality by extracting only the subset of features. TF-IDF disregards feature distribution and gives equal weight to both terms, this is the limitation in this method. The improved TF-IDF evaluates the weights within same category and between two categories.

Inter-category Dispersion: Inter category distribution refers to distribution of features between enormous categories. The features have higher values when all are in same or fewer categories. Inter category dispersion is defined based on standard deviation equation,

$$G(t)\begin{cases} \dfrac{\sqrt{\dfrac{1}{h-1}\sum_{a=1}^{m}\left(B_a(t) - \vec{B}(t)\right)}}{\vec{B}(t)}, & \vec{B}(t) \neq 0 \\ 0, & \vec{B}(t) = 0 \end{cases} \quad (5)$$

Where, $B_a(t)$ represents number of documents which has the term t in category G_a

$\vec{B}_a(t)$ Represents mean frequency of occurrence of feature in all category.

m Represents total number of category.

Intra-category information entropy: Which states the importance of each term in every category. Based on information entropy feature term distribution is evaluated given by following equation,

$$F(t, G_a) = -\sum_{b=1}^{n} e_a \quad (6)$$

Where,

$$e_a = \begin{cases} \dfrac{No.E_b}{No.G_a}\log_2 \dfrac{No.E_b}{No.G_a}, & No.G_a \neq 0 \; and \; No.E_b \neq 0 \\ 0, & No.E_b = 0 \; and \; No.G_a = 0 \end{cases} \quad (7)$$

Where n represents number of reviews ion category G_a

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$No.G_a$ represents number of feature term in all reviews of category G_a

$No.E_b$ represents total number of feature term in all document of category G_a

Category distribution: Higher the analysis of inter category and intra category dispersion information entropy, higher the power for category dispersion given by following equation,

$$cd(t,G_a) = d(t) * F(t,G_a) \quad (8)$$

$$V_{ab}(t) = tB_{ab} * cd(t_b, G_a) \quad (9)$$

Where, tB_{ab} represents frequency of term t_b

$cd(t_b, G_a)$ Represents category discrimination of feature term to category G_a

In ITF-IDF method IDF is substituted with category distribution term, thereby overcoming the shortcomings of TF-IDF method.

Aspect related feature (ARF) extraction [29]: After RRF extraction, aspect related features are extracted to boost the results of sentiment analysis. The aim is to count the lemma's co-occurrences with aspect types, sentence categories and grammatical dependencies co-occurrences. ARF are find by evaluating weight matrix of each category, bypassing categorical approaches. The ARF extraction is shown in algorithm 1.

Algorithm 1: ARF extraction
Input: O: training set
Output: ARF extracted for each reviews
Initialize c, R, S, T, U
For each review $a = 1\, to\, length(O)$
$[Q, Q_c] \leftarrow get\, lemma\, dependencies(O(a))$

For each set $b = 1\, to\, length(Q)$
For each term $c = 1\, to\, length(Q(b))$
Count lemma/dependency occurrences b
If $(Q(b,c) \neq R)$

Let O represents training set consist of reviews from amazon websites, extraction of features based on co-occurrences rates and dependencies performed on the reviews collected. The algorithm identify the lemma's, dependencies and categories on reviews. The dictionary form of a word is represented as lemma, dependencies represents grammatical relation between the sentences. The dependency relation is given by the following instance, The price is okay and the appearance looks very attractive. Here price acts as governor, okay act as dependent, making dependency relation hence named as subject predicate relation, next very act as governor, attractive dependent hence termed as adverbial clause modifier.

List of lemmas and dependencies exist in set Q, each reviews consist of list of aspect categories Q_c. The reviews are handled by POS tagger, lemmatizer and dependency parser. The next is to count and add the lemmas, dependencies occurrences to vector R . Thus all input reviews aspect categories are detected and added to vector c. The co-occurrences frequency of lemma's and dependencies are saved to vector S, similarly occurrences frequency of lemmas and dependencies are saved to vector R. Then the weight matrices of occurrences and co-occurrences matrix are evaluated and stored in vector T. If the co-occurrences frequency exceeds zero weight frequency evaluated, thereby eliminating the need of thresholding. The weight matrix with highest co-occurrence frequency in vector T is moved to vector U. Thus aspect related features extracted without any constraints.

3.3 Depthwise Separable Convolution (DSC-ResNet) ResNet model:

The proposed DSC-ResNet model has stack of depthwise seperable convolutional layers with residual connections. The DSC-ResNet [30] model employs ResNet as its backbone, on comparing the other CNN models with less number of layers. ResNet uses Skip connections by skipping several layers in between to avoid the vanishing gradient problems. Thus construct a deep network with more layers to extract the features from the reviews. Initially the input features are extracted

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

by convolutional layer of kernel size 7x7, then the features are fed into four resnet blocks for refining the features, each block employs the depthwise and point wise convolution to obtain the feature maps. At the end global average pooling and cross entropy loss are applied for classification of reviews. The architecture of proposed DSC-ResNet model is shown in Figure 2.

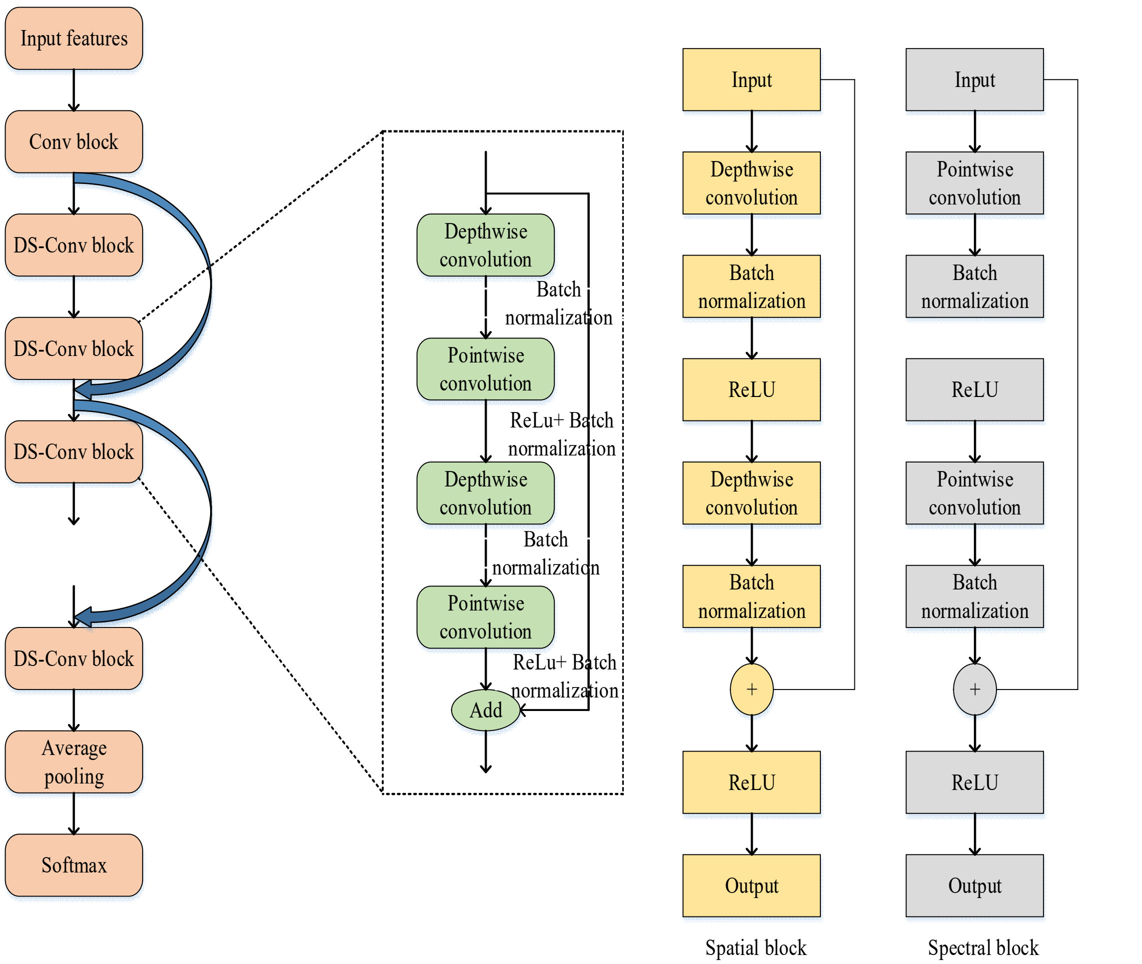


Figure 2: Depthwise Separable Convolution Resnet Model Architecture

The depth wise separable convolution factorizes normal convolution operation into two: point wise and depth wise convolution. Consider input features $FF \in P^{w \times h \times n}$ where, w, h represents spatial dimensions, n represents number of channel, perform normal convolution operation with kernel size $s \times s$ to get an output feature $FF' \in P^{w' \times h' \times n'}$ where, w', h', n' represents spatial dimensions and number of channels. The computational burden and number of parameters in normal convolution operation are reduced by using depth wise separable convolution operation. Which first uses depth wise convolution, that is uses one filter per channel to convolve with input feature, which is given as follows,

$$\hat{FF} = FF \otimes S \qquad (10)$$

Where $FF \in P^{w \times h \times n}$ is given as input, $S = P^{s \times s \times n}$ represents depth wise convolutional kernel during convolution operation, the output feature has the same number of channels as the input feature. After depth wise convolution, point wise convolution is applied with kernel size 1×1 to get an output given as follows,

$$FF^{'} = \hat{FF} \otimes \bar{S} \qquad (11)$$

Where, $\hat{FF} \in P^{w\times h\times n}$ represents depth wise convolution, $\bar{S} = P^{1\times 1\times n\times n^{'}}$ represents 1×1 convolution, $FF \in P^{w\times h\times n}$ represents output of entire depth wise separable convolution.

For normal convolution operation, with kernel size $s\times s\times n\times n^{'}$ the number of parameters optimized is represented as $PR_{norm} = s^2 \times n \times n^{'}$. By using depth wise separable convolution the number of parameters reduced is given as $PR_{DS} = s \;\; \times s\times n + n\times n^{'} = (s^2 + n^{'})\times n$. By using normal convolution operation, number of kernel and channels used are higher. Thus through depth wise separable convolution operation, number of parameters and computational burden are compressed, thereby improving the classification accuracy.

Depth wise separable ResNet model

The depth wise separable ResNet model architecture is given by the following equation,

$$G(FF,\theta) = soft\max(Convolution3x3(spatial\,\mathrm{Re}\,sNet(Convolution1x1(spectralresNet(convolution1x1(FF))))))$$

where, $spectral\,\mathrm{Re}\,sNet, spectral\,\mathrm{Re}\,sNet$ represents spectral and spatial residual modules, FF represents input features, θ represents model parameters, $Convolutional\,1x1$ represents convolution operation with kernel size 1, $Convolutional\,3x3$ represents convolution operation with kernel size 3, $soft\max$ represents softmax classifier layer.

Spectral residual module: The spectral residual module is given by the following equation,

$$Spectral\,\mathrm{Re}\,sNet(FF) = N_a(...N_2(N_1(l))....) \qquad (12)$$

$$N_k(l) = l + pconv(pconv(l)), \quad k = 1,2,..,a \qquad (13)$$

Where $pconv$ represents point wise convolution followed by batch normalization operation, point wise convolution performed by using 2-d convolution with kernel size one, thereby extracting the spectral features, l represents input features.

Spatial residual module: The spatial residual module is given by the following equation,

$$Spatial\,\mathrm{Re}\,sNet(FF) = M_b(...M_2(M_1(l))....) \qquad (14)$$

$$M_k(l) = l + dconv(pconv(l)), \quad k = 1,2,..,b \qquad (15)$$

Where $dconv$ represents depth wise convolution followed by batch normalization operation, depth wise convolution apply independent kernel to each input features, thereby extracting the spatial features by reducing the number of parameters, l represents input features.

The output of depth wise separable convolutional ResNet model is given by the following equations,

$$FF_{in}^{'} = FF_{conv}(FF_{in}) \qquad (16)$$

$$FF_{res} = FF_{in} \otimes FF_{in} \qquad (17)$$

Finally for classifying the features, cross entropy loss function is considered and is given by the following equation,

$$O = soft\max(FF_{average}(FF_{res})) \qquad (18)$$

$$cross\,entropy\,loss = -\frac{1}{t}\sum_{i=1}^{t} X_i \ln O_i \qquad (19)$$

FF_{res} Represents output of last convolution operation in resnet block, $FF_{average}$ represents global average pooling output.

$$soft\max(FF)=\exp(A_k)/\sum_{k=1}^{m}\exp(A_k) \tag{20}$$

Where, A_k represents global average pooling output, m represents number of class. O Represents classification result, X_i represents true label of ith feature.

4. RESULTS AND DISCUSSION

The Evaluation of proposed and existing methods used for sentiment analysis are suggested in this section. The suggested model analysed through publicly accessible benchmark datasets which is obtained from Kaggle.com i.e., Amazon reviews. The dataset contains total of 25000 reviews while 80% of the data are used for training and 20% of the data are used for testing. The simulation is performed through python programming and the system configuration is shown in table 1.

Table 1: System Configuration

System Configuration		
S No.	**Parameters**	**Configuration**
1	Installed RAM	16.00 GB(15.9 GB usable)
2	Processor	Intel® Core™ i7-3770 CPU @3.40 GHz,3.40GHz
3	System type	64-bit operating system,x64-based processor
4	Pen and touch	No pen or touch input is available for this display

4.1 Evaluation Metrics:

Accuracy indicates the capability of correctly classifying the reviews and is given as follows,

$$Accuracy=\frac{T_n+T_p}{T_n+T_p+F_n+F_p} \tag{21}$$

Precision denotes the positive values that are truly positive given by,

$$\Pr ecision=\frac{T_p}{T_p+F_p} \tag{22}$$

Recall, also known as sensitivity, is the measure of true positives to the sum of true positives and false negatives, which is given in the following equation,

$$\operatorname{Re}call=\frac{T_p}{T_p+F_n} \tag{23}$$

F-score analyses the accuracy of the proposed model based on precision and recall rates, given by the following equation,

$$F-score=2\times\frac{\Pr ecision\times Sensitivity}{\Pr ecision+Sensitivity} \tag{24}$$

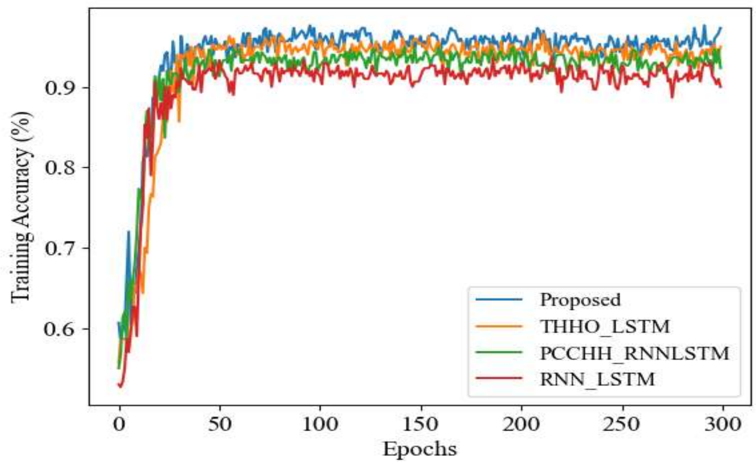
Specificity indicates the percentage of negatives that are correctly classified, given by the following equation,

$$Specificity=\frac{T_n}{T_n+F_p} \tag{25}$$

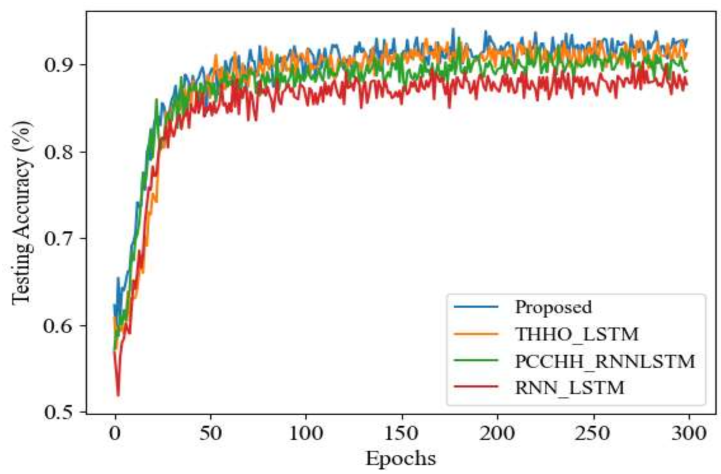
Where, T_p represent true positive, T_n represent true negative, F_p represent false positive, F_n represent false negative. Thus the performance metrics parameters are evaluated.

4.2 Comparison of different sentiment analysis methods:

The performance of the proposed DSC-ResNet model is compared with existing methods [31] such as Pearson correlation coefficient-based Harris Hawks Optimization – based Recurrent Neural Network-Long Short-Term Memory (PCCHH-RNNLSTM), Taylor–Harris Hawks Optimization driven long short-term memory (THHO-LSTM), RNN-LSTM. Figure 3 (a) & (b) shows the training and testing accuracy curve obtained for proposed and existing method.



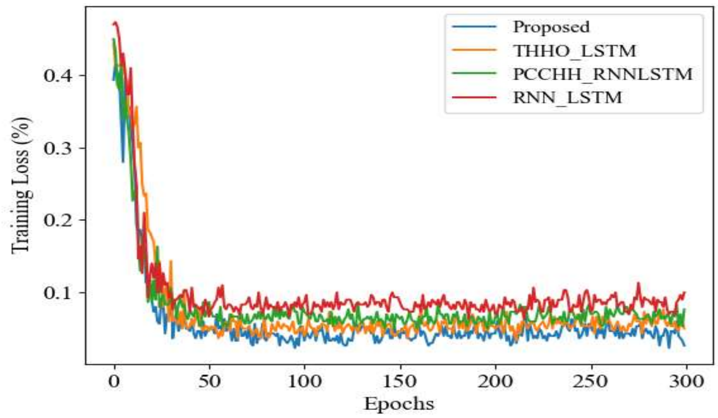
(a)



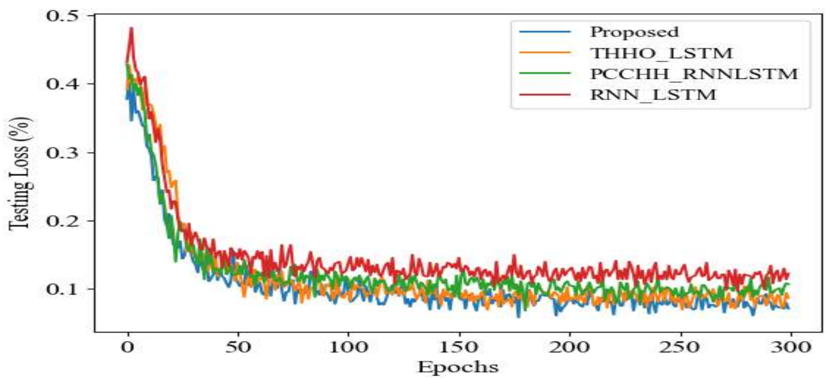
(b)

Figure 3 (A) & (B): Training And Testing Accuracy Curve

Figure 3 (a) & (b) shows the training and testing accuracy curve obtained for the proposed and existing methods by varying the epoch values from 0 to 300. For epoch value from 0 to 50, the training accuracy value shows sudden rise, after that accuracy shows gradual rise till epoch value 100. After that, the training accuracy remains constant till the epoch value is 300. Compared to the existing methods proposed method shows higher accuracy value than the existing methods. Similarly during testing period the accuracy curve shows sudden rise for epoch 0 to 50 and after that shows gradual rise and then remains constant till end. On comparing the training and testing curve, both shows similar results. This shows the proposed method improved performance.



(a)



(b)

Figure 4 (A) & (B): Training And Testing Loss Curve

Figure 4 (a) & (b) shows the training and testing loss obtained for proposed and the existing methods, loss value measured by varying the epoch from 0 to 300. During training and testing period, for epoch value from 0 to 50, loss curve shows sudden drop after that from 50 to 100 epoch's loss shows gradual drop and then which remains constant till the end of epoch 300. On comparing with existing methods, proposed method obtained less loss value. Also during training and testing period, loss curve shows similar changes this shows the proposed method better performance.

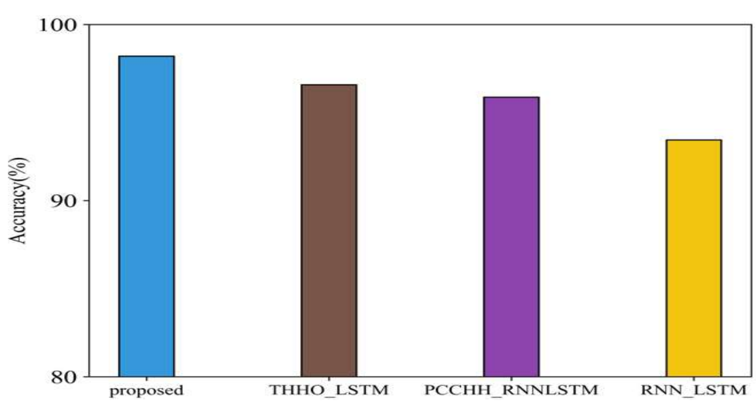


Figure 5: Accuracy

Figure 5 shows the accuracy value obtained for proposed and existing method. Accuracy defines how close the measurement is correct. Higher the accuracy much more the prediction is correct. The accuracy obtained for the proposed method is 98.2%, existing THHO-LSTM, PCCHH-RNNLSTM and RNN-LSTM methods obtained accuracy of 96.58%, 95.87% and 94.68%. The proposed method obtained higher accuracy than the existing methods.

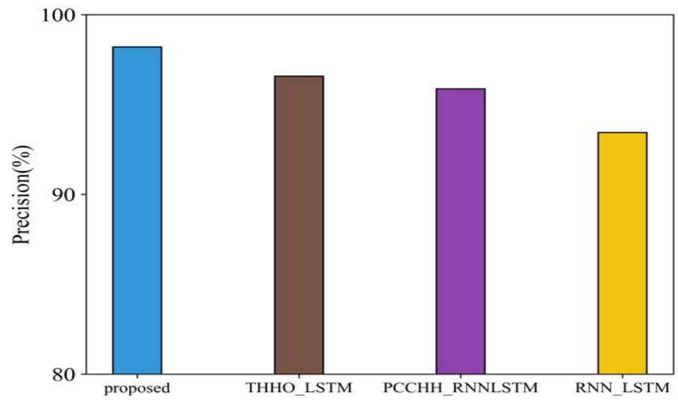


Figure 6: Precision

Figure 6 shows the Precision value obtained for proposed and existing method. Precision defines how close the measurement is between the repeated experiments. Higher the Precision much more the prediction is correct. The Precision obtained for the proposed method is 97.5%, existing THHO-LSTM, PCCHH-RNNLSTM and RNN-LSTM methods obtained Precision of 95.6%, 95.45% and 93.47%. The proposed method obtained higher Precision than the existing methods.

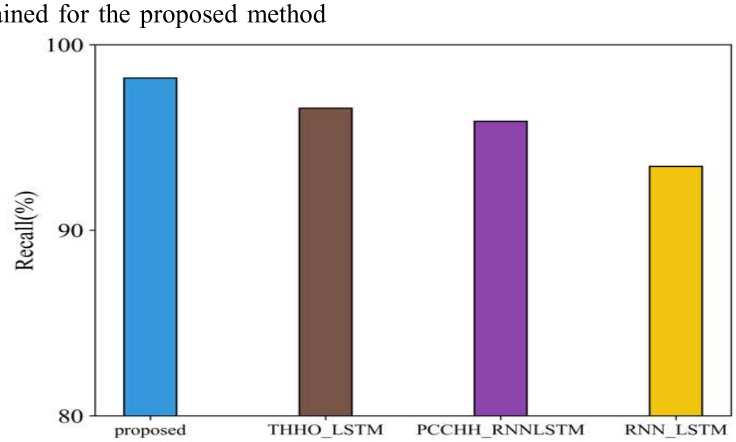


Figure 7: Recall

Figure 7 shows the Recall value obtained for proposed and existing method. In order to reduce the amount of False Negatives, recall is measured which defines how many false negatives exist. The Recall obtained for the proposed method is 97.76%, existing THHO-LSTM, PCCHH-RNNLSTM and RNN-LSTM methods obtained Recall of 95.9%, 95.65% and 93.9%. The proposed method obtained higher Recall than the existing methods

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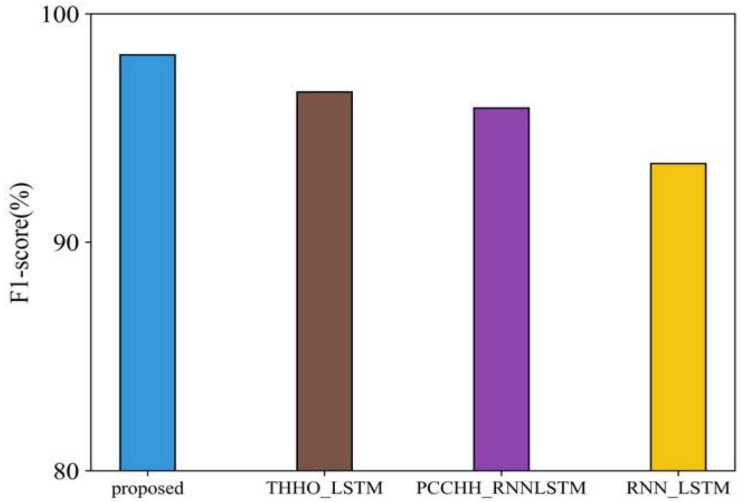

Figure 8: F1-Score

Figure 8 shows the F-score value obtained for proposed and existing method. Precision and recall measure the two types of errors that could be made for the positive class. Maximizing precision minimizes false positives and maximizing recall minimizes false negatives. F-Measure or F-Score provides a way to combine both precision and recall into a single measure that captures both properties. The F-score obtained for the proposed method is 97.2%, existing THHO-LSTM, PCCHH-RNNLSTM and RNN-LSTM methods obtained F-score of 95.8%, 95.25% and 93.42%. The proposed method obtained higher F-score than the existing methods.

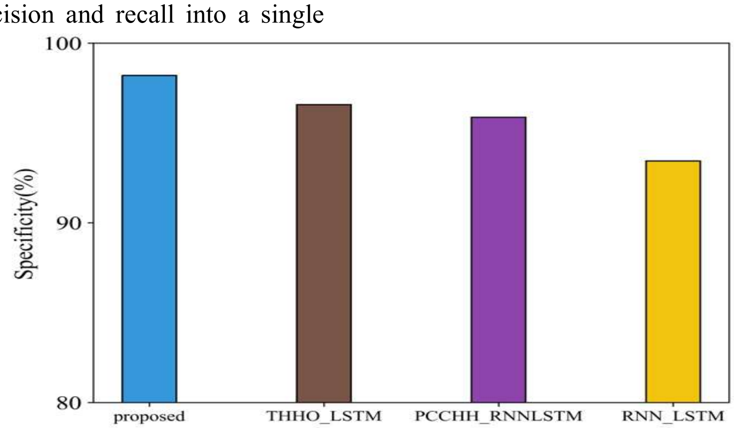

Figure 9: Specificity

Figure 8 shows the specificity value obtained for proposed and existing method. Specificity, or true negative rate, quantifies how well a test identifies true negatives that is how well a test can classify subjects who truly do not have the condition of interest. The specificity obtained for the proposed method is 97.55%, existing THHO-LSTM, PCCHH-RNNLSTM and RNN-LSTM methods obtained F-score of 95.6%, 95.12% and 93.6%. The proposed method obtained higher specificity than the existing methods.

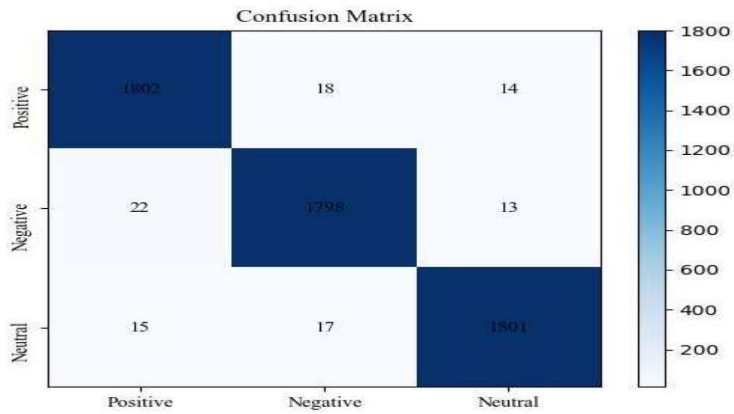

Figure 10: Confusion Matrix

Figure 10 shows the confusion matrix obtained for amazon dataset evaluated by using the proposed model. The dataset consist of three classes of reviews as positive, negative and neutral. On testing using proposed model 20% data considered for testing thus 5,500 utilized reviews for testing. On predicting through proposed model, which correctly predicted 1802 reviews as positive and only 22 incorrectly predicted as negative and only 15 incorrectly predicted as neutral. On predicting the negative reviews, which correctly predicted 1798 reviews as negative and only 18 incorrectly predicted as positive and only 17 incorrectly predicted as neutral. On predicting the neutral reviews, which correctly predicted 1801 reviews as neutral and only 14 incorrectly predicted as negative and only 13 incorrectly predicted as neutral. Thus the proposed method effectively performs the classification task.

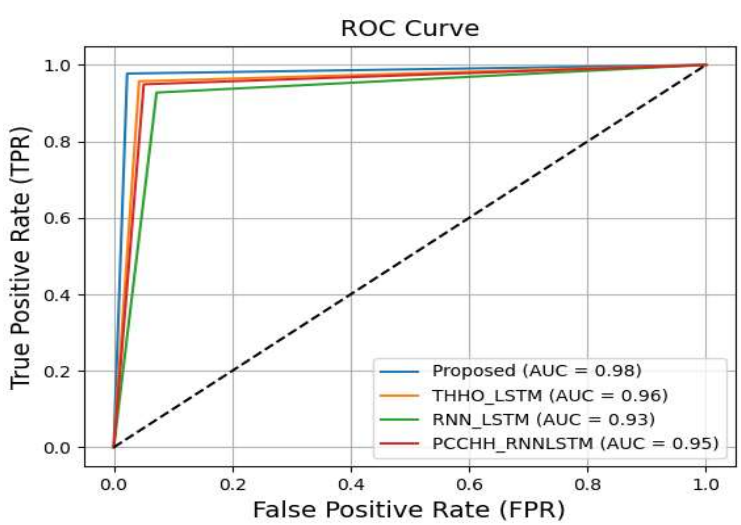

Figure 11: Roc Curve

Figure 11 shows the RoC curves obtained for proposed model, An ROC (receiver operating characteristic curve) curve is a graph showing the performance of a classification model. This curve plots two parameters such as True Positive Rate and False Positive Rate. The RoC value obtained for proposed method is 98%, existing methods obtained RoC of 96%, 95% and 93% respectively. The proposed method obtained higher accuracy than the existing methods.

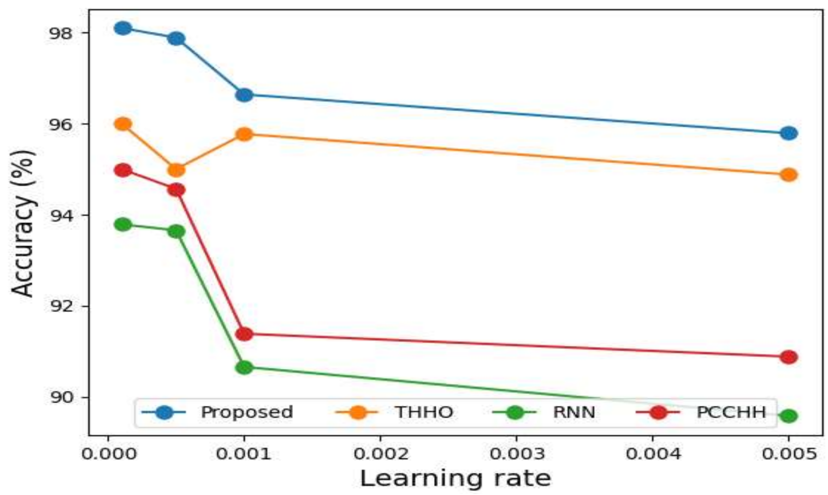

Figure 12: Accuracy Measurement By Varying The Learning Rate

Figure 12 shows the accuracy measurement by varying the learning rate from 0.001 to 0.005. The proposed method shows higher accuracy than the existing methods and values are given in table 2.

Table 2: *Accuracy Measurement By Varying Learning Rate*

Learning rate	Proposed	THHO	RNN	PCCHH
0.0001	0.981	0.96	0.937867	0.95
0.0005	0.978907	0.95	0.936554	0.945679
0.001	0.966413	0.957731	0.906544	0.913835
0.005	0.957899	0.948796	0.895767	0.908799

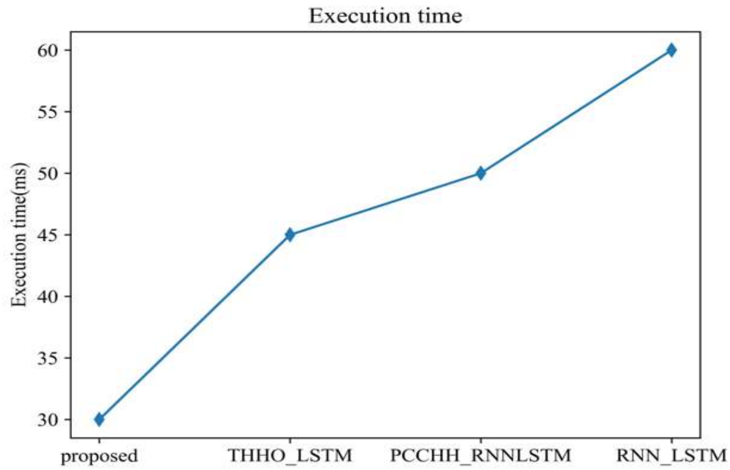

Figure 13: *Processing Time Comparison*

Figure 13 shows the processing time of proposed and existing method. The processing time obtained for proposed method is 30ms, existing methods taken 45ms, 50ms and 60ms to process. Overall proposed method obtained reduced processing time than the existing methods. Table 3 shows the overall performance comparison of proposed and existing methods.

Table 3: *Results Comparison Of Proposed And Existing Methods*

Metrics	RNN-LSTM	PCCHH-RNNLSTM	THHO-LSTM	**Proposed DSC-ResNet**
Accuracy (%)	94.68	95.87	96.58	**98.2**
Precision (%)	93.47	95.45	95.6	**97.5**
Recall (%)	93.9	95.65	95.9	**97.76**
F-score (%)	93.42	95.25	95.8	**97.2**
Specificity (%)	93.6	95.12	95.6	**97.55**
Execution time (%)	60ms	50ms	45ms	**30ms**

5. CONCLUSION AND FUTURE SCOPE:

Nowadays, sentiment analysis considered as tool for evaluating various type of data, thereby helping decision making process to improve the business of e-commerce Company. E-commerce websites creates a large amount of data that require processing and analysis to obtain relevant insights. In the present study, the experimental dataset containing reviews of products was collected from the Amazon websites. Initially data cleaning process performed through stemming, lemmatization, tokenization and stop word removal. Data cleaning to identify and remove the incorrect or incomplete data in dataset. Stemming work by cutting off the end or the beginning of the word, taking into account a list of common prefixes and suffixes that can be found in an inflected word. Lemmatization is the process of reducing the derived word to the root form that is lemmas. Tokenization refers to the process of converting a sequence of text into smaller parts, known as tokens. The idea of removing the words that occur commonly across all the documents in the corpus. Typically, articles and pronouns are generally classified as stop words. The input pre-processed reviews can be transformed into meaningful feature vectors, allowing efficient, reliable, and robust sentiment analysis. In sentiment analysis tasks, extracting features for dimensionality reduction is to create a smaller set of features and feed this lower-dimensional data to classifiers to predict the sentiment polarity of the entire text. Thus review related features are extracted using LSA and ITF-IDF method. The aspect related features extracted by evaluating the weight matrices. Finally, Depthwise Separable Convolution ResNet model used for sentiment polarity classification has been suggested to select features from user reviews and classify the reviews according to their polarity. The effectiveness of the suggested technique has been assessed by utilizing various parameters such as accuracy, recall, F-measure, precision and Specificity. The proposed model outperformed other models in sentiment analysis, according to the experimental data proposed method obtained an accuracy of 98.2%, precision of %, recall of %, f-score of % and specificity of %. As a future scope, investigating the proposed model's performance using diverse datasets, and exploring more NLP techniques to make the model language independent. Also, the proposed study will be extended to utilize real-time dataset in the future.

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