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Original Article

Leveraging Deep Learning Models for Automated Aspect Based Sentiment Analysis and Classification

R. Bharathi[1], R. Bhavani[2], R. Priya[3]

[1, 2, 3]*Department of Computer Science & Engineering, Annamalai University, Chidambaram, TamilNadu, India*

[1]*Corresponding Author : bharathirm17765@gmail.com*

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Abstract - *Aspect-based Sentiment Analysis (ABSA) is a subdomain of Sentiment Analysis (SA) that focuses on detecting the sentiment toward features of a product or particular aspects, experience, or service. ABSA targets to go beyond simple sentiment classification of a sentence or document and present a more granular study of sentiment towards different aspects. ABSA has several real-time applications, which include social media monitoring, customer feedback analysis, and product reviews. Many difficulties exist in ABSA, including dealing with language variability and complexity, sentiment subjectivity, and managing multiple aspects in a single sentence. Recently, Deep Learning (DL) methods continued to be an active area of research and proved a promising model in ABSA. This study focuses on designing and developing ABSA models using DL concepts. The presented ABSA model aims to identify the sentiments in the direction of particular aspects or features of a product, service, or experience. The presented approach initially accomplishes diverse phases of data pre-processing to convert the input data meaningfully. In addition, the word2vec model is applied as a feature extraction approach. For sentiment analysis, three DL models are employed, namely Hopfield Network (HN), Convolutional Neural Network (CNN), and Bidirectional Long Short Term Memory (BiLSTM) approaches. The experimental validation of the DL models occurs utilizing a benchmark dataset. The simulation values highlighted that the CNN model exhibits improved sentiment classification results over other DL models.*

Keywords - *Natural language processing, Aspect based sentiment analysis, Sentiment analysis, Deep learning, Word2vec.*

1. Introduction

The proliferation of web technologies has allowed new means of communication using user-generated content based on the website review form, blogs, e-commerce web applications, social networks, etc. [1]. With tremendous growth, there is strong interest from organizations and individuals in data mining technologies to use this source of subjective data. In computer sciences, one of the most productive research areas is SA which intends to extract and detect user opinions [2]. SA has many real-world applications and is prominent in natural language understanding. The common SA focus on forecasting the negative or positive polarity of the given sentences [3]. From the seminal work of Aspect-based SA, the study of SA is possible at three levels - entity or aspect, document, and sentence. A focus on the documents or sentence level believes that a single topic is expressed in the sentence or document, which is not the case in various circumstances [4]. A more thorough analysis, thus, necessitates investigation at the aspect level and entity for detecting entities and relevant aspects and categorizing sentiments linked with these aspects and entities [5].

ABSA aids in understanding the issue of SA as it directly emphasizes sentiments instead of language structure [6]. Where an aspect is relevant to an entity, and the fundamental concept of an aspect is not limited to judgment but even extends towards ways of thinking, thoughts, perspectives, point of view, an underlying method, or social influence towards an occurrence [7]. Three Machine Learning models, namely Gaussian Naive Bayes, Logistic Regression and Support Vector Machines, are used for SA and applied to the mobile reviews dataset [8-10]. Later, ABSA offers a chance to examine sentiments (public) over time across different content presented in media. Differences are found between ABSA and SA, like (a) managing comparative sentences and sentiment-shifting words [11].

DL is mostly preferred ML method to deal with several natural language processing (NLP) research difficulties (b) connecting part of the text to aspect (i.e., extraction of opinion target expression), and (c) text paraphrasing and aspect-term extraction (i.e., parts of texts deliberating the same aspect, e.g., power consumption and life of the battery are both denoting similar aspect) [12-14]. NLP research demanding variable input data lengths was suggested to use recurrent neural networks (RNN). The NLP researchers are attracted to RNNs working on NLP issues of textual material [15]. This research focuses on designing and developing ABSA models using DL concepts. The presented approach initially accomplishes diverse phases of data pre-processing to convert the input data meaningfully. In addition, the word2vec model is applied as a feature extraction approach. For sentiment analysis, three DL models are employed, namely Hopfield Network (HN), Convolutional Neural Network (CNN), and Bidirectional Long Short Term Memory (BiLSTM) approaches. The experimental outcome of the DL models takes place using a benchmark dataset.

2. Related Works

Huang et al. [16] present an Adaptive Semantic Relative Distance (ASRD) technique that depends on syntactic evaluation that utilizes ASRD to determine the suitable local context for every texting and enhance the exactness of SAs. Gao et al. [17] define the structure of a short-text ABSA approach dependent upon CNN and BiGRU. The primary stage is to attain the database and execute pre-processed. Afterwards, that sci-kit-learn is utilized for performing TF-IDF computations to obtain the feature word vector weight and gain the factor-level feature ontology word of estimated text. During the SAs section, a hybrid method dependent upon CNN and BiGRU (CNN+BiGRU) has been generated that utilizes corpus words and feature words as the vector input and forecasts the emotional polarity [18, 19].

Zhong et al. [20] examine a Knowledge Graph Augmented Networking (KGAN) that proposes efficiently including exterior data with apparent contextual and syntactic data. The KGAN primarily learns the syntactic and contextual depictions from parallel to remove the semantic feature. Dai et al. [21] present a human cognition-based model for ABSA that introduces the learning in word semantics to sentence syntax. In [22], the author concentrates on the capability of graph convolutional and presents an Aggregated GCN for enhancing the representation capability of target nodes. For extracting further connected node data, the author also executes the sub-dependency of nodes for aggregating the node feature and utilizes the attention mechanism to capture the sentiment dependency among distinct node feature data.

In [23-25], 2 DL techniques can be presented for addressing vital ABSA tasks: aspect-sentiment classification and aspect-category identification. Initially, an identification method was presented dependent upon CNN and stacked independent LSTM. Second, a classification method was presented dependent upon stacked bi-directional independent LSTM, multiple attention mechanism, and position-weighting mechanism layers. Bie and Yang [26] present an overall ABSA and a novel multitasks multiview network (MTMVN) structure. In the meantime, the representation learned in the branch network of essential tasks can be assumed to be that global view, but the representations of the two sub-tasks can be assumed that two local views with various emphases.

3. The Proposed Model

In this study, we have aimed to develop ABSA models using DL concepts. The presented ABSA model focuses to identify the sentiments in the direction of particular aspects or features of a product, service, or experience. It involves three stages: pre-processing, word2vec feature extraction, and DL-based sentiment classification. Figure 1 illustrates the workflow of automated aspect-based SA by employing CNN, Bi-LSTM and Hopfield method.

3.1. Data Pre-processing

Text pre-processed was completed for cleaning textual information so that the information it implies ready that model to the next step. The pre-processed systems utilized contain [27]:

Tokenization: During this step, phrases, symbols, words, and other vital entities (mentioned in tokens) can be divided into the text for more examination. Tokenization breaks down typescripts from the text (sentence) as word units. Besides, in this step, the words or features that could not be valid can be chosen. In this case, every punctuation mark and some entities that are not letters are eliminated.

Removing spaces, special characters, and punctuation: Removing spaces, special characters and punctuation like URLs, emoji, and hashtags enhances the accuracy of analysis by eliminating noise in the data.

Handling negation: Recognizing negation words like "not" and reversing the meaning of words that carry it out. For instance, "not good" would become "not_bad."

Create N-grams: An N-gram integrates adjectives that frequently perform to signify texting sentiment information that only contains one word. Bi-grams contain two words, and trigrams comprise three words. This case utilized the kind of trigram token.

Filter Stopword: An essential word can be obtained in the token outcomes.

At this point, it can utilize the stoplist technique (discarding lesser essential words) or wordlist (saving essential words).

Stemming or Lemmatization: The stemming system is required along with the minimization of the count of distinct terms of documents. The stemming is also utilized to group words that take a base word and the same meaning, then a distinct procedure as it obtains specific affixes.

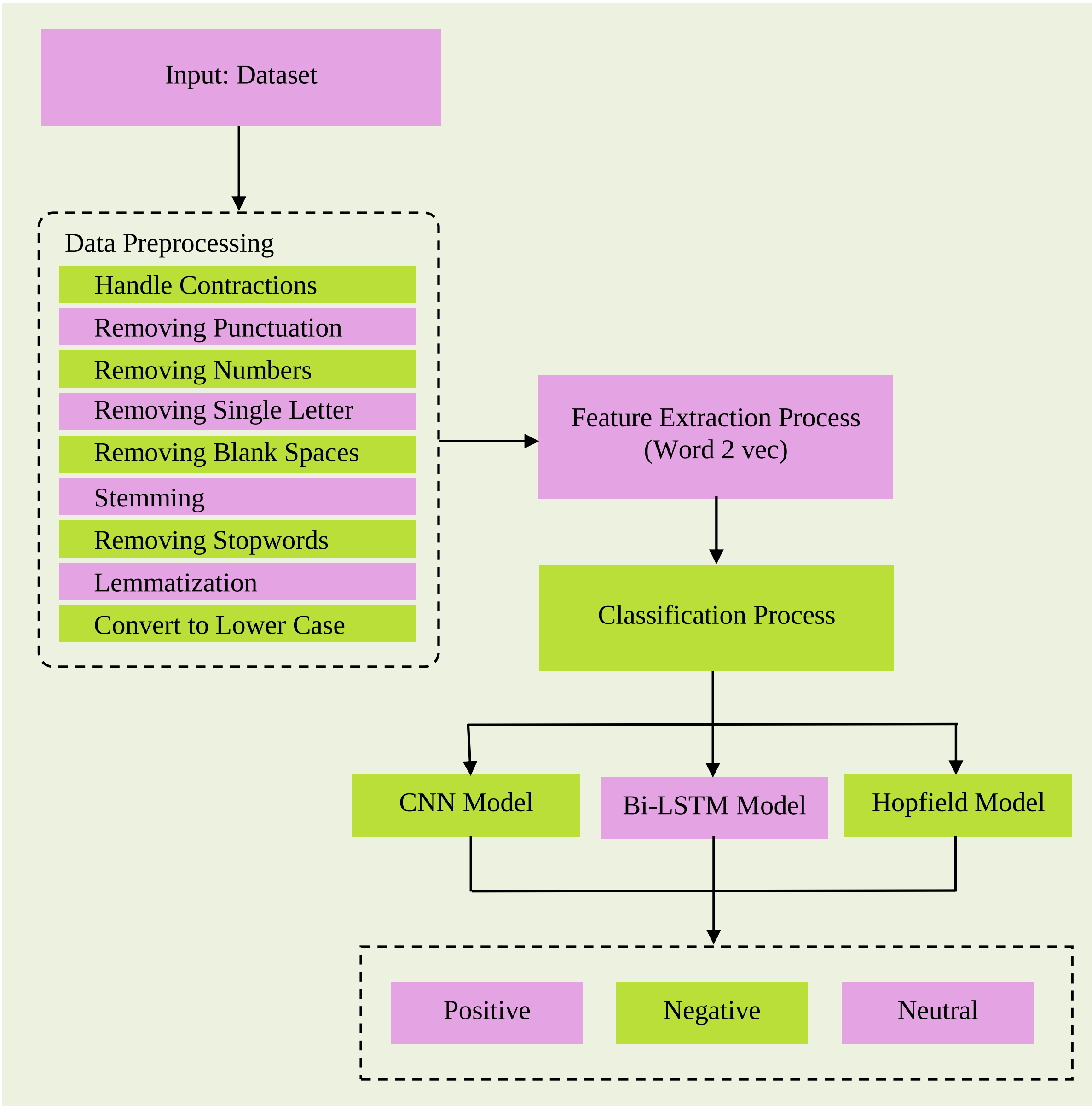


Fig. 1 Workflow of automated aspect-based SA by implementing CNN, Bi-LSTM and Hopfield method

Stopword Removal: This step removes lesser essential words like conjunctions or articles, such as "the", "is", "that", "is", and so on.

Transform Case: During this stage, the letters can be altered from lowercase to uppercase for every word in the sentence.

3.2. Word2vec Feature Extraction

The word2vec model is applied as a feature extraction approach at this stage. Based on the $Word2Vec$ model, the initial module of the method handles the detection of word representation [28]. Assume that a corpus D includes a vocabulary $T = \{t_1, t_2, t_3, \ldots, t_m\}$and a set of texts, $D = \{d_1, d_2, d_3, \ldots, d_n\}$, which contains unique terms extraction in D. The word depiction of the term t_i are exposed by the skip-gram method of Word2Vec to compute the likelihood dispersion of other terms in the given context t_i. Especially, t_i represents a vector $\vec{v_i}$ that includes the probabilistic value of each term in the vocabulary. However, the resultant set of vectors for each term from the corpus is higher dimension and is ineffective for the classifier from the SA. Accordingly, this initial component discovers a series of vectors. $V_T = \{\vec{v_1}, \vec{v_2}, \vec{v_3}, \vec{v_m}\}$ signifying the series of terms from the vocabulary T.

3.3. Sentiment Classification

This research passes the extracted features into three DL models for sentiment classification: HN, CNN, and BiLSTM.

3.3.1. Hopfield Network

The Hopfield technique is an RNN model in which the neuron takes a binary state $+1$ or -1. Because of this, the order parameter measuring the model's state can be represented as magnetization, and the neuron state is represented as spins [29].

The structure of the Hopfield network is demonstrated in Figure 2. A Hopfield networking stores binary patterns, or memories, by setting the connection weight among neurons so that while an upgrade rule can be employed, the structure will be moving across an energy landscape to its attractor that corresponds to storage patterning. Nevertheless, numerical simulation can be employed owing to its asymmetric connection and complex network topology.

$$E = -\sum_{ij} w_{ij} A_{ij} s_i s_j, \quad (1)$$

In Eq. (1), w_{ij} denotes the coupling among neurons i and j that might be negative or positive based on the stored pattern. The state of the neuron takes the value. $s_i = \pm 1$ and A_{ij} shows the element of the adjacency matrix.

Several good update rules could accomplish a desired behaviour, namely the Metropolis-Hastings algorithm.

$$s_i(t + \triangle t) = -s_i(t) \quad (2)$$

with

$$probability = \frac{1}{1 + \exp \frac{\triangle E}{T}}, \quad (3)$$

Where, T denotes a temperature parameter making the system stochastic, and $\triangle E'$ shows the energy variation connected to flipping the neuron state. To decrease the uncertainty and complexity, the outcomes that occur here are for a temperature significantly closer to 0, $T = 10^{-5}$.

3.3.2. CNN Model

CNN is a simplified convolutional network used for sentence classification. Initially, the sentence was transferred to a matrix; every sentence matrices rows are word vector depiction [30]. The dimensional of the word vector is d. Once the sentence's length is s, then the dimensional of sentence matrices can be defined by the din. As per Collobert and Weston, the sentence matrix was considered similar to the image matrix, it is implemented convolutional on a matrix with a linear filter. Figure 3 demonstrates the architecture of the CNN technique. It is the filter that parameterized the w-weighted matrix with h region size; the sentence matrices $A \in \mathbb{R}^{s \times d}$, $A[i:j]$ denotes the sub-matrix of A in row i to row j and d is the dimensional of word vector. The outcome $0 \in \mathbb{R}^{s-h+1}$ is evaluated as follows

$$A = \pi r^2 o_i = w \cdot A[i: i + h - 1] \quad (4)$$

For $i = 1 \;\; s - h + 1$ refers to the dot product between the filter and sub-matrix. Like other neural network models, activation function f and bias $b \in \mathbb{R}$ are added to 0_i:

$$c_i = f(0_i + b) \quad (5)$$

Then, a pooling function is used to get a fixed-length vector for all the feature maps. We used dropout as a means of regularization in the softmax layer. We also implement 12 norm constraints that effectively overfit while training the neural network.

3.3.3. Bi-LSTM Model

The classical RNN model could not capture long-distance semantic connections but could transfer semantic data between words [31]. During the parameter training, the gradient gradually reduces until it disappears. Consequently, the length of the series data is limited. LSTM overcomes the problems of gradient vanishing by presenting the Memory cell, Input gate i, Output gate 0, and Forget gate f. At the last moment, Forget gate f defines the data to forget in Memorycell. The input is $h(t\text{-}l)$ and (t). The output value is between 0 and 1:

$$f_t = \sigma\left(W_f x_t + U_f h_{t-1} + V_f c_{t-1} + b_f\right) \quad (6)$$

Where W_f denotes the weight connection of x_t and forgets gate f. h_{t-1} and x_t denotes the input of the LSTM unit. c_{t-1} shows the state of Memorycell at the last moment. U_f denotes the weight connection of h_{t-1} and forget gate f. $\sigma(\cdot)$ shows the sigmoid activation function. V_f denotes the weight connection of c_{t-1} and forgets gate f. b_f is the biased term. Input gate i defines the data to be updated in Memorycell at the current time:

$$\begin{cases} i_t = \sigma(W_i x_t + U_i h_{t-1} + V_i c_{t-1} + b_i) \\ c\_in_t = .tanb(W_c x_t. + U_c h_{t-1} + V_c c_{t-1} + b_c) \\ c_t = f_t c_{t-1} + i_t c_i n_t \end{cases} \quad (7)$$

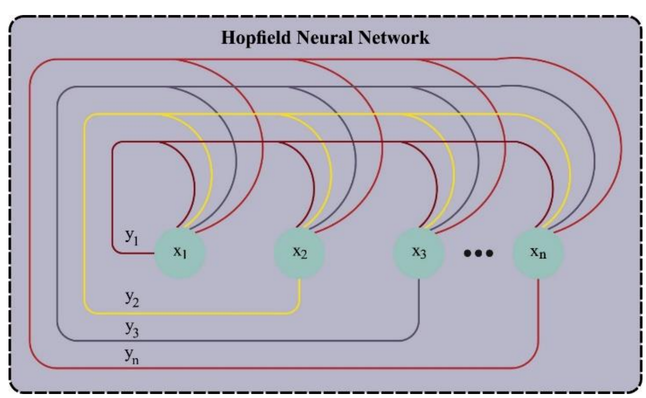


Fig. 2 Structure of Hopfield neural network

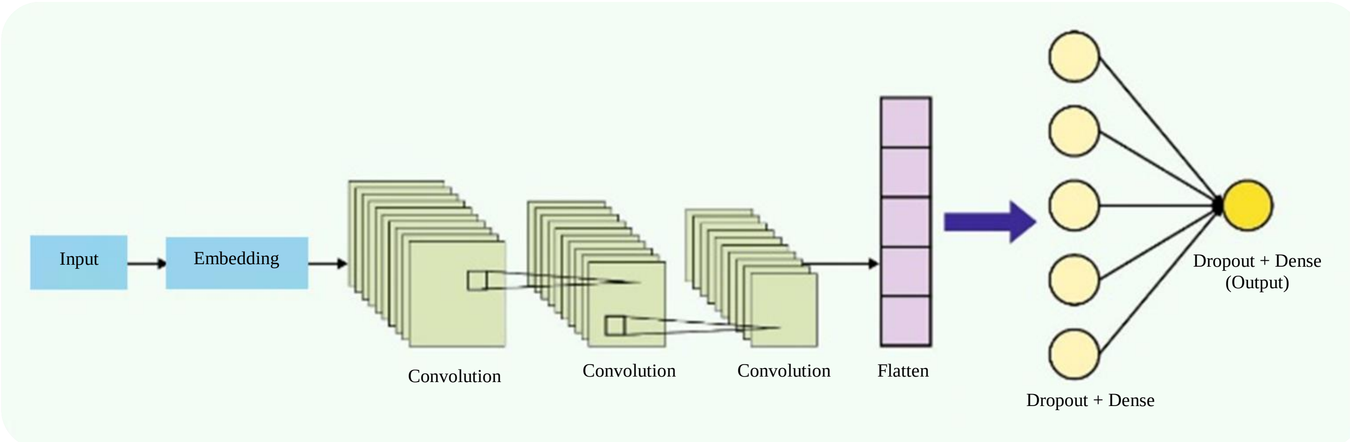


Fig. 3 Structure of CNN model

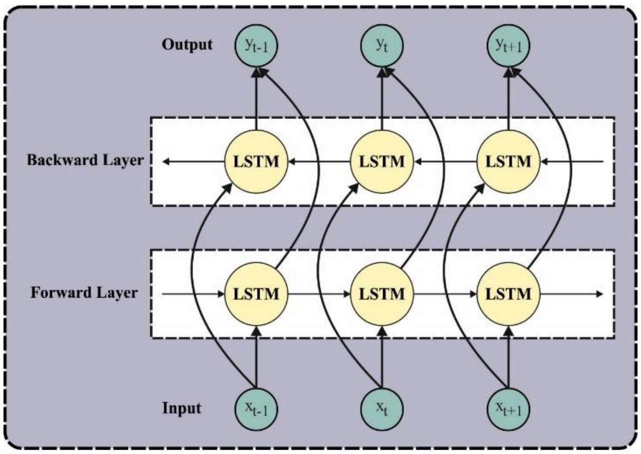


Fig. 4 Architecture of BiLSTM

Where U_i indicates the weight connection of h_{t-1} and i_t. W_i denotes the weight connect of x_t and i_t. W_c implies the weight connection of x_t and c_in_t. V_i shows the weight connection of c_t-1 and i_t. tanh is the tanb activation function. U_c is the weight connection of c_in_t and h_{t-1}. b_i and b_c are biased terms. f_t and i_t refers to weights of c_{t-1} and c_in_t.

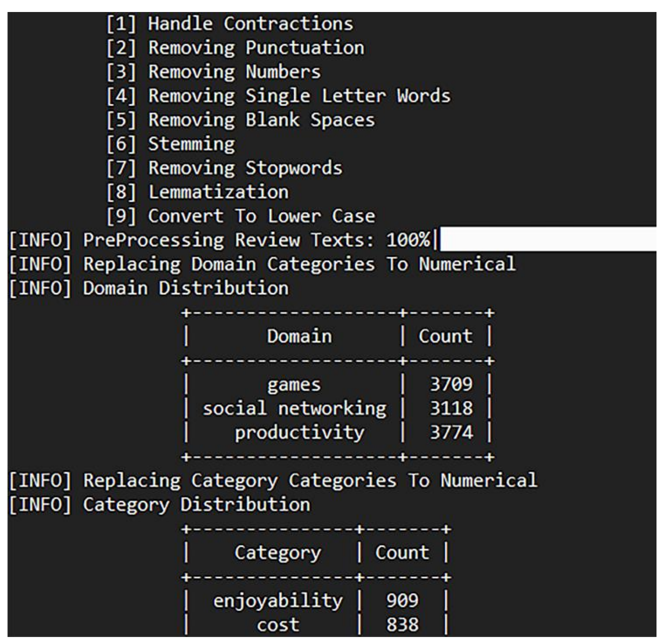
Output gate 0 defines the output value of the LSTM unit, and it can be calculated as follow:

$$\begin{cases} o_t = \sigma(W_o x_t + U_o h_{t-1} + V_o c_{t-1} + b_o) \\ h_t = 0_t \cdot tanb(c_t) \end{cases} \qquad (8)$$

Where U_o shows the weight connection of h_{t-1} and 0_t. W_o denotes the weight connection of x_t and $0_t.0_t$. b_o indicates the bias term and V_o represents the weight connection of c_{t-1}. The BiLSTM structure model is illustrated in Figure 4. It is a kind of RNN that processes data in 2 directions while working with two hidden layers (HLs). It is an important point of divergence with LSTM. Bi-LSTM has established optimum outcomes in NLP.

4. Results and Discussion

The dataset used here is AWARE: Dataset for Aspect-Based SA of Apps Reviews [32]. It has five csv files they are: AWARE_Comprehensive.csv, AWARE_Games.csv, AWARE_metadata.csv, AWARE_Productivity.csv and AWARE_Social_Networking.csv. We take three csv files from those five csv files (AWARE_Productivity.csv, AWARE_Social_Networking.csv and AWARE_Games.csv). Each has 14 attributes. We combine these csv files based on review, domain, category and rating. There are three domains; they are games, social networking and productivity. There is 12 category, they are enjoyability, cost, safety, usability, general, compatibility, efficiency, reliability, learnability, effectiveness, security and aesthetics. We have used 70% of the data for training, and for testing, we have used 30%. Sample outcomes for pre-processing are shown in Figure 5, and for feature extraction it is shown in Figure 6.



```
          [1] Handle Contractions
          [2] Removing Punctuation
          [3] Removing Numbers
          [4] Removing Single Letter Words
          [5] Removing Blank Spaces
          [6] Stemming
          [7] Removing Stopwords
          [8] Lemmatization
          [9] Convert To Lower Case
[INFO] PreProcessing Review Texts: 100%|
[INFO] Replacing Domain Categories To Numerical
[INFO] Domain Distribution
                 +-------------------+-------+
                 |       Domain      | Count |
                 +-------------------+-------+
                 |       games       |  3709 |
                 | social networking |  3118 |
                 |    productivity   |  3774 |
                 +-------------------+-------+
[INFO] Replacing Category Categories To Numerical
[INFO] Category Distribution
                 +---------------+-------+
                 |    Category   | Count |
                 +---------------+-------+
                 |  enjoyability |  909  |
                 |      cost     |  838  |
```

Fig. 5 Sample pre-processing output

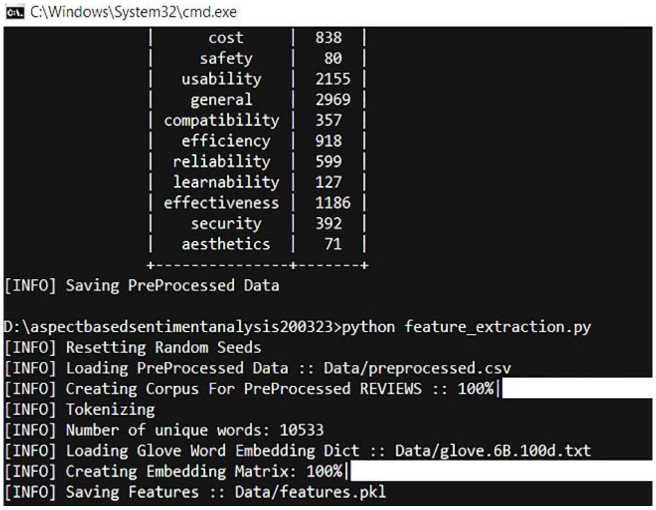


Fig. 6 Sample output of feature extraction (word2vec)

Figure 7 illustrates the classifier outcomes of the CNN algorithm. Figure 7(a) depicts the confusion matrices the CNN system offers. The figure denoted that the CNN algorithm has identified and classified all 3-class labelling accurately. Likewise, Figure 7(b) illustrates the PR evaluation of the CNN technique. The figures described that the CNN approach had obtained maximum Precision-Recall (PR) performance under three classes.

Moreover, Figure 7(c) illustrates the Receiver Operating Characteristic (ROC) examination of the CNN method. The figure exhibited that the CNN model has led to able outcomes with maximal ROC values under three classes. In addition, Figure 7(d) determines the accuracy investigation of the CNN system. The figure reports that the CNN technique attains improved accuracy values over improved epochs. The improved validation accuracy over training accuracy demonstrates that the CNN model learns effectively on the testing data. Finally, Figure 7(e) illustrates the loss investigation of the CNN algorithm. The results indicate that the CNN approach attains closer training and validation loss values. It is experimental that the CNN system learns effectively on the testing data.

Figure 8 showcases the classifier outcome of the Bi-LSTM methodology. Figure 8(a) depicts the confusion matrix the Bi-LSTM approach offers. The outcome denoted that the Bi-LSTM system accurately identified and classified all 3-class labelling. Likewise, Figure 8(b) illustrates the PR investigation of the Bi-LSTM approach. The figures demonstrated that the Bi-LSTM approach had obtained higher PR performance under three classes. Moreover, Figre 8(c) exemplifies the ROC examination of the Bi-LSTM approach. The figure demonstrated that the Bi-LSTM system has led to capable outcomes with higher ROC values under 3 class labels. In addition, Figure 8(d) establishes the accuracy examination of the Bi-LSTM approach. The figure informs that the Bi-LSTM technique attains improved accuracy values over improved epochs. Also, the improved validation accuracy over training accuracy demonstrates that the Bi-LSTM algorithm learns effectively on the testing data. Finally, Figure 8(e) illustrates the loss investigation of the Bi-LSTM methodology. The outcomes inferred that the Bi-LSTM approach attains closer training and validation loss values. The Bi-LSTM methodology learns effectively on the testing data.

Figure 9 illustrates the classifier outcome of the Hopfield approach. Figure 9(a) represents the confusion matrices the Hopfield approach offers. The figure indicates that the Hopfield algorithm has accurately identified and classified all 3-class labelling. Likewise, Figure 9(b) depicts the PR evaluation of the Hopfield system. The figures described that the Hopfield system had attained more excellent PR performance under three classes. Likewise, Figure 9(c) depicts the ROC outcome of the Hopfield model. The figure represented that the Hopfield model has led to able outcomes with maximum ROC values under three classes. Followed by, Figure 9(d) determines the accuracy analysis of the Hopfield approach. The figure reports that the Hopfield technique attains a higher accuracy over growing epochs. Additionally, the growing validation accuracy over training accuracy demonstrates that the Hopfield model learns effectively on the testing data. At last, Figure 9(e) illustrates the loss investigation of the Hopfield system. The outcomes stated that the Hopfield approach attains closer training and validation loss values. It can be noted that the Hopfield approach learns efficiently on the test dataset.

Table 1 and Figure 10 provide the overall ABSA outcomes offered by the three DL models. The CNN model obtains $accu_y$ of 92.08%, $prec_n$ of 88.44%, $reca_l$ of 86.20%, F_{score} of 87.21%, and AUC_{score} of 95.12%. Meanwhile, the Bi-LSTM approach gains $accu_y$ of 89.46%, $prec_n$ of 82.33%, $reca_l$ of 79.54%, F_{score} of 80.70%, and AUC_{score} of 92.48%. Concurrently, the Hopfield technique attains $accu_y$ of 75.69%, $prec_n$ of 63.79%, $reca_l$ of 49.70%, F_{score} of 46.81%, and AUC_{score} of 75.21%.

Comparative ABSA results of the various models in terms of the difference in terms of different measures are in Table 2 [33]. In Figure 11, a detailed comparative $accu_y$ examination of different models is demonstrated. The results indicate that the ML-RBF model reaches a reduced $accu_y$ of 69.77%. At the same time, the HM, SVM, and RAKEL models obtain slightly closer $accu_y$ of 75.69%, 72.77%, and 77.77% respectively. Meanwhile, the Bi-LSTM and DenseNet models accomplish reasonable $accu_y$ of 89.46% and 85.76%. Although the ResNet-SCSO algorithm reaches near-optimal $accu_y$ of 91.25%, the CNN model gains a maximum $accu_y$ of 92.08%.

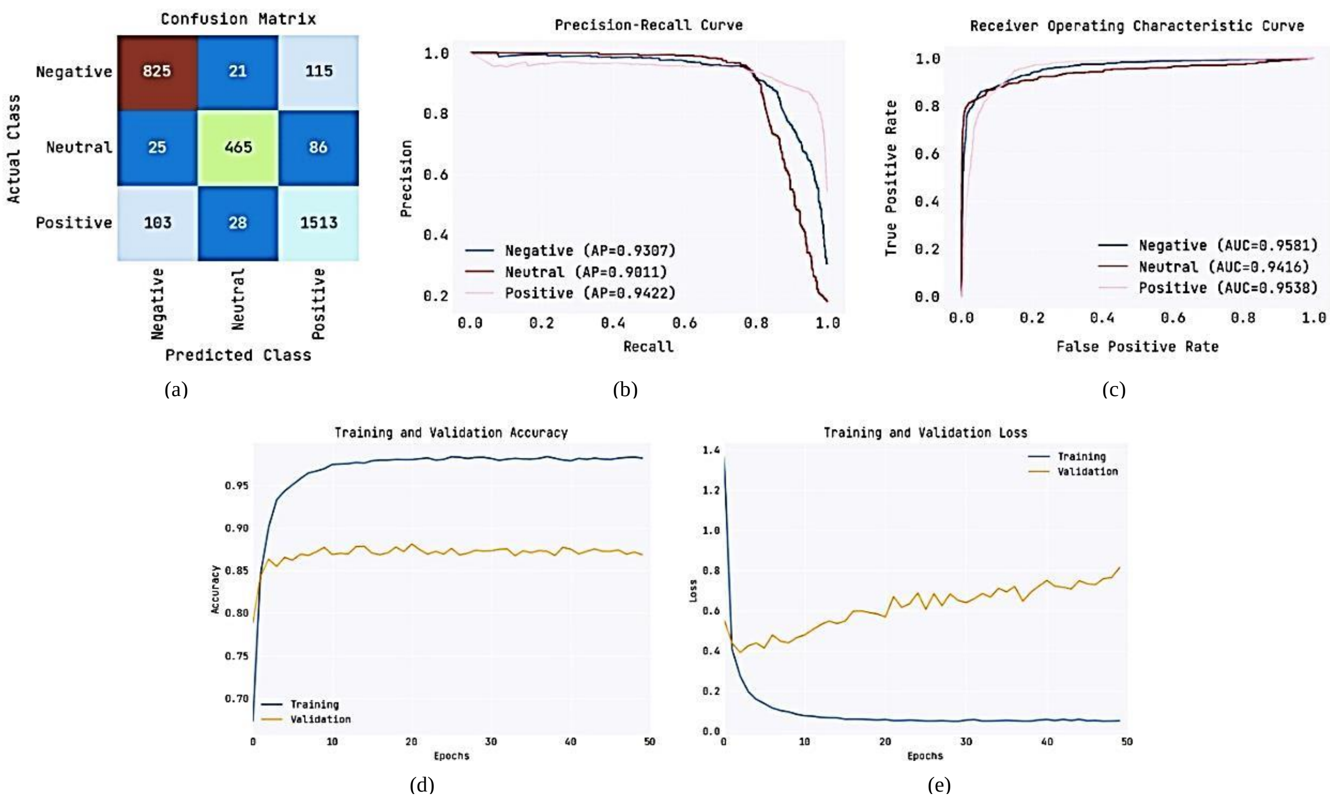


Fig. 7 Results of CNN model (a) Confusion matrix (b) Precision-recall (PR)-curve (c) Receiver operating characteristic (ROC) curve (d) Accuracy graph (e) Loss graph

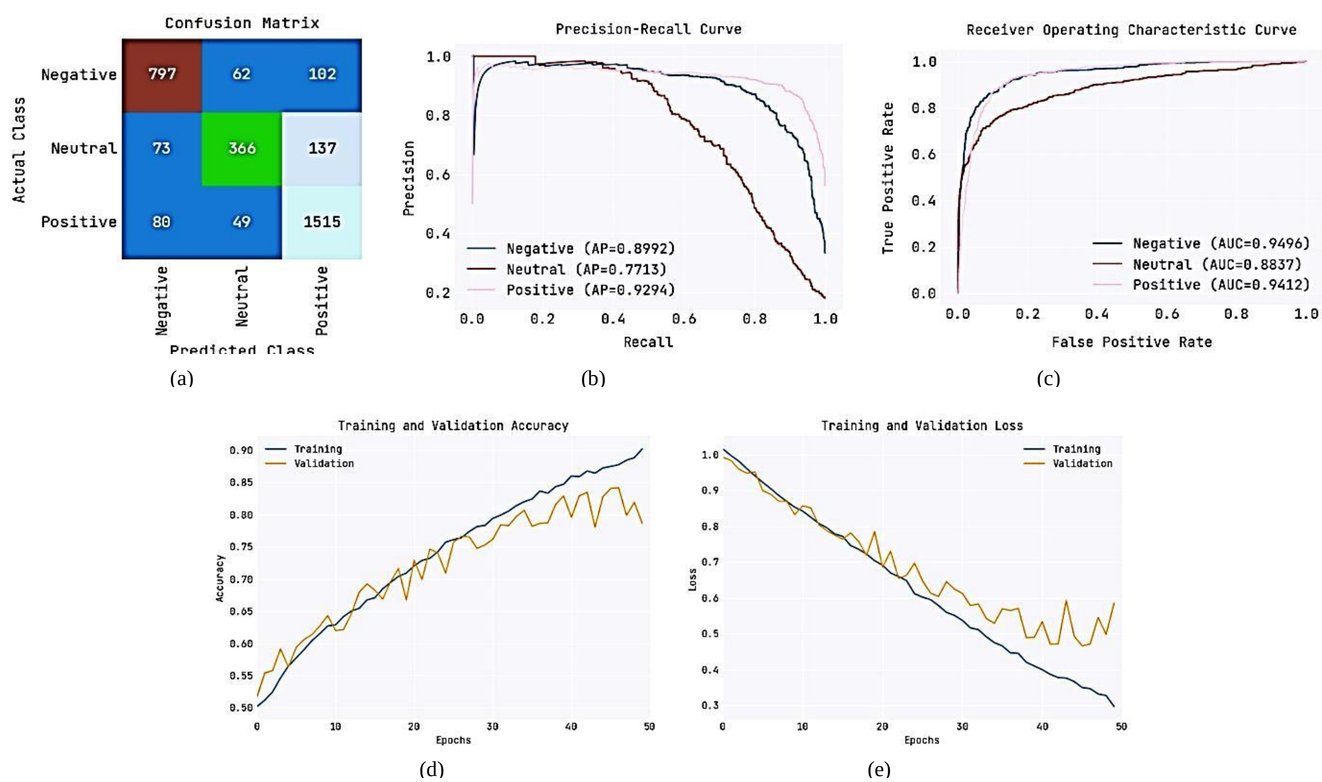


Fig. 8 Results of Bi-LSTM model (a) Confusion matrix (b) Precision-recall (PR)-curve (c) Receiver operating characteristic (ROC) curve (d) Accuracy graph (e) Loss graph

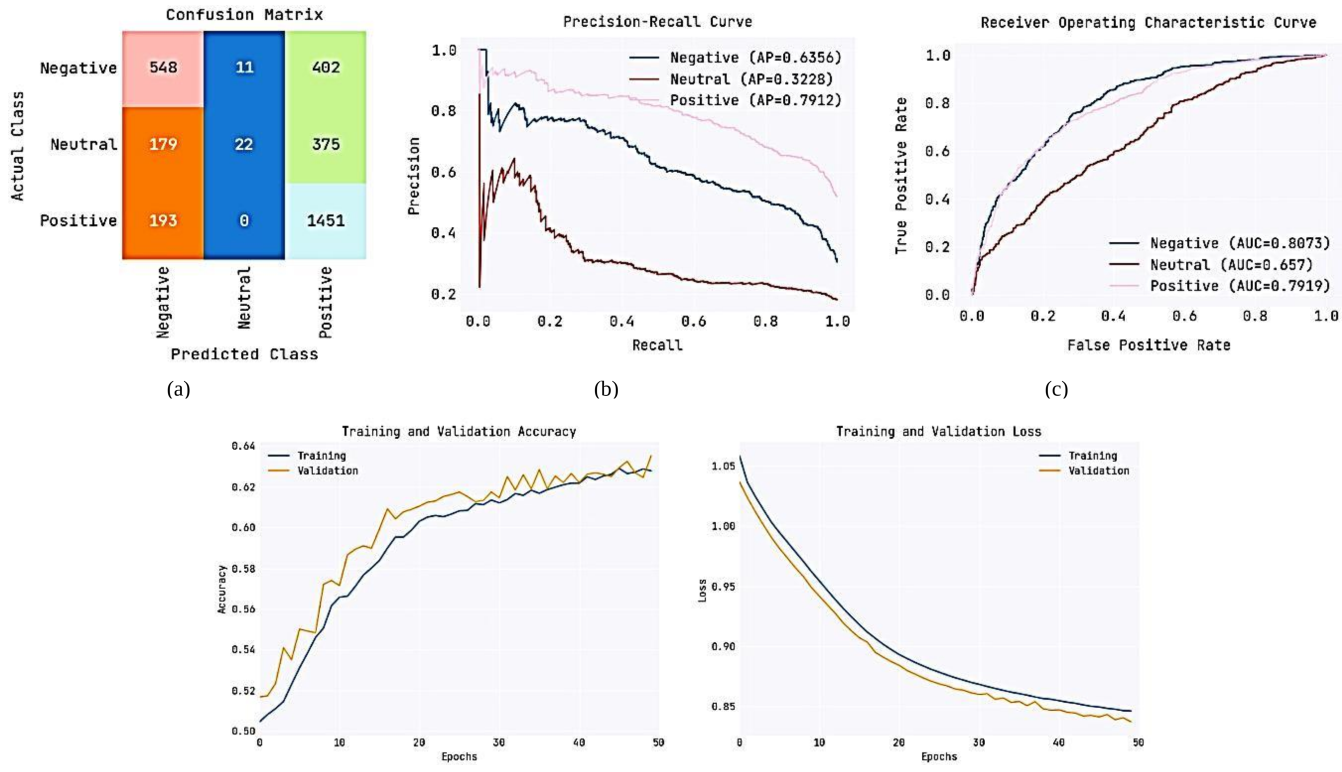


Fig. 9 Results of Hopfield model (a) Confusion matrix (b) Precision-recall (PR) – curve (c) Receiver operating characteristic (ROC) curve (d) Accuracy graph (e) Loss graph

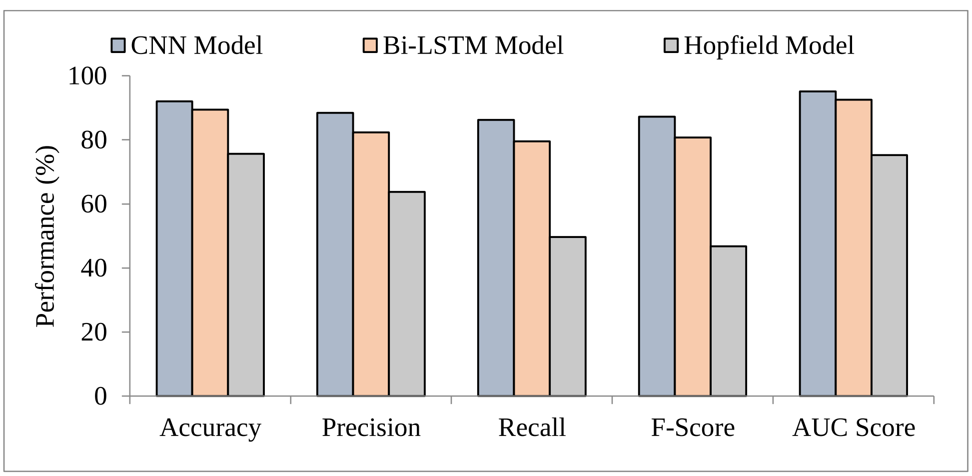


Fig. 10 ABSA outcome of three DL techniques with various measures

In Figure 12, a detailed comparative $\mathrm{prec_n}$, $\mathrm{reca_l}$, and $\mathrm{F_{score}}$ Inspection of different approaches is demonstrated. The outcomes inferred that the HM technique gains lesser $\mathrm{prec_n}$, $\mathrm{reca_l}$, and $\mathrm{F_{score}}$ of 63.79%, 49.70%, and 46.81%. At the same time, the ML-RBF, SVM, and RAKEL algorithms obtain somewhat closer $\mathrm{prec_n}$, $\mathrm{reca_l}$, and $\mathrm{F_{score}}$. In the meantime, the Bi-LSTM and DenseNet approaches accomplish reasonable $\mathrm{prec_n}$, $\mathrm{reca_l}$, and $\mathrm{F_{score}}$. Eventually, the ResNet-SCSO system reaches near-optimal $\mathrm{prec_n}$, $\mathrm{reca_l}$, and $\mathrm{F_{score}}$ of 87.88%, 85.40%, and 86.56%, the CNN approach gains maximal $\mathrm{prec_n}$, $\mathrm{reca_l}$, and $\mathrm{F_{score}}$ of 88.44%, 86.20%, and 87.21%. These results showcased that the CNN model appears to be effective over other models on the ABSA.

Table 1. ABSA outcome of three DL techniques with various measures

Metrics	CNN Model	Bi-LSTM Model	Hopfield Model
Accuracy	92.08	89.46	75.69
Precision	88.44	82.33	63.79
Recall	86.20	79.54	49.70
F-Score	87.21	80.70	46.81
AUC Score	95.12	92.48	75.21

Table 2. Comparative outcome of various methods with distinct measures

Methods	Accuracy	Precision	Recall	F-Score
CNN Model	92.08	88.44	86.20	87.21
Bi-LSTM Model	89.46	82.33	79.54	80.70
Hopfield Model	75.69	63.79	49.70	46.81
ML-RBF	69.77	68.66	74.83	78.03
SVM	72.77	71.66	77.83	81.03
RAKEL	77.77	76.66	82.83	86.03
DenseNet	85.76	86.88	83.40	86.16
ResNet-SCSO	91.25	87.88	85.40	86.56

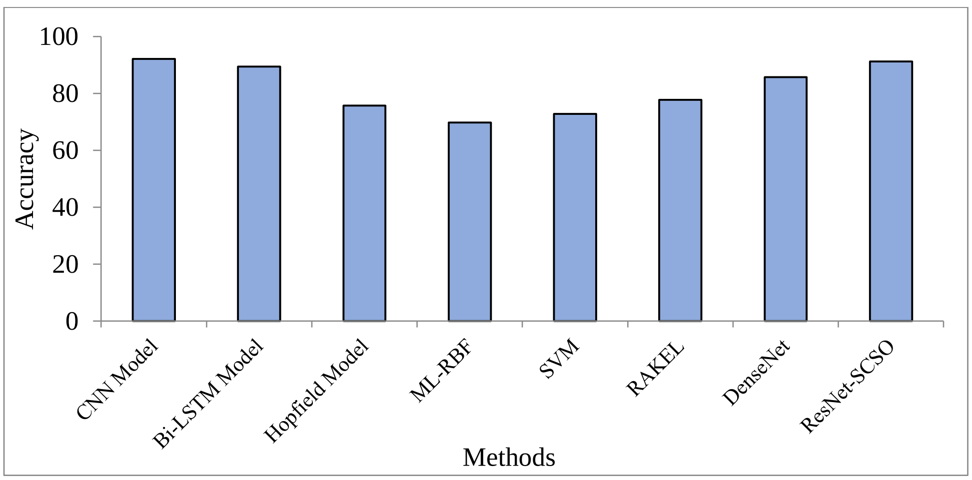


Fig. 11 $Accu_y$ the outcome of various methodologies

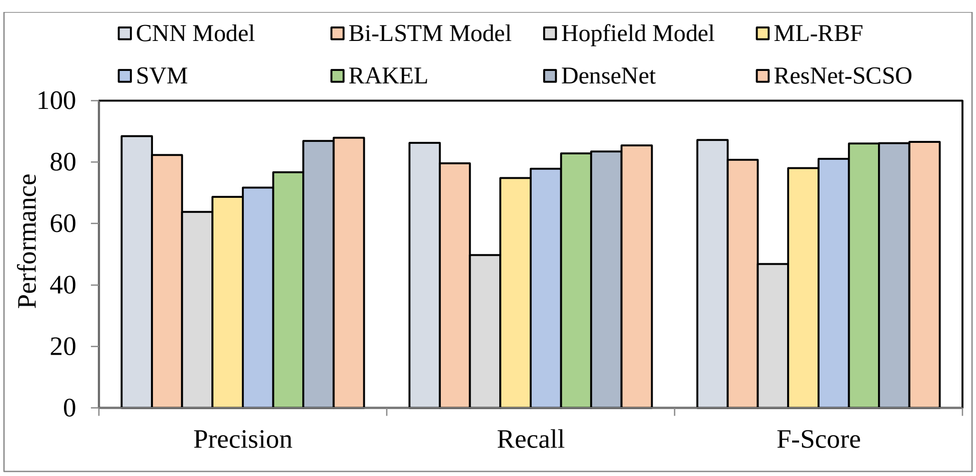


Fig. 12 $Prec_n$, $reca_l$, and F_{score} the outcome of various methodologies

5. Conclusion

In this research work, we have aimed to develop ABSA models using DL concepts. The automated ABSA model focuses to identify the sentiments in the direction of particular aspects or features of a product, service, or experience. This approach initially accomplishes diverse phases of data pre-processing to convert the input data meaningfully. In addition, the word2vec model is applied as a feature extraction approach. Three DL models are employed for sentiment analysis: HN, CNN, and BiLSTM. The experimental validation of the DL models occurs utilizing a benchmark dataset. The simulation values highlighted that the CNN model exhibits improved sentiment classification outcomes over other DL methods. In future, a hybrid DL model can be derived to boost the classification outcomes of the DL methods.

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