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International Journal of Artificial Intelligence and Machine Learning

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Research Paper Open Access

Attention LSTM framework for Aspect-enabled Sentiment Analysis

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Abstract

Sentiment analysis is the automated analysis of the input data and identifies the person's attitude from the text. Aspect-enabled Sentiment Analysis demonstrates the relationship between the opinion aims of a particular document and the polarity values between the texts while aspects are implied, it is a very complex job to analyse and compute the corresponding polarity. In modern days, various techniques and enhancements have been involved in efficiently solving these kinds of issues. At the same time, the correlated aspects through the pre-defined groups could scuffle when the involvement of the low-performed aspects. The Attention LSTM framework is incorporated in this proposed work for performing the sentiment analysis the attention LSTM framework could focus on various sentence parts while the different kinds of aspects are involved in the input text and the IMDB movie review dataset is used for aspect-enabled sentiment analysis. Experimental results show that the proposed technique has produced 94.5% accuracy and the relevant techniques of SVM, RNN, and LSTM in various performance metrics.

Keywords: Sentiment analysis, Aspect, polarity, Attention LSTM, Accuracy, Classification.

1. Introduction

Sentiment analysis is called opinion mining which is the subset of the Natural Language Processing which goals for automatic discovering and extracting the particular data from the text. Sentiment Analysis has several related applications which range from politics to business and it is the most popular research area in Modern days. It could be utilized for identifying the sentiments of the specific product, the opinion of the politicians, patients with the medical situation, and other related applications. The improvements in sentiment analysis, various factors like language ambiguity, and sarcasm detection while the input text has tones it is unable to detect in the specific techniques where similar words have different meanings according to the expressed tones(Namitha et al., 2023).

The sentiment analysis has the contextual difference according to the context where it is positive in one culture and negative in another context. Quality is the main aspect of the efficiency of sentiment analysis techniques which need a huge amount of quality information for effective training. Additionally, it could be the big issue of collecting the relative information specifically for the complex topics, the quality information matters have the noise, bias, and data loss would minimize the accuracy. The granularity model has to examine the entire text with a particular aspect(Gu et al., 2024). Every level of analysis could manage the problems of different levels. The machine learning and lexicon-enabled techniques are utilized for identifying the polarity in the text as the machine learning technique is categorized as the supervised model(Ganpat et al., 2023) which could train the machine with the labelled information, unsupervised model has the training process that is trained with the classified data or labelled data that permits the algorithm should work without the constraint.

The aspect-enabled sentiment analysis (Shelke et al., 2021)has been involved in achieving improved results through the enhanced classification process while the observation of the behavioural classification process for estimating the analysis difficulty and the sentiment analysis difficulty could reduce the resource utilization. The network management has the latest way of connecting user-enabled content like blogs, and reviews while the development of the data mining technique utilizes the particular data resource as the semantic analysis is the most regularly used research area to classify and extract the opinion mining. The input text has extracted the emotions conveyed within the paragraph text and trusts that research could be managed in the sentence, word, and document aspects. Every document has a single entity as the opinion as it accepts the document signifies the single topic whereas the sentence level analysis has a different entity as the sentence embraces a single possibility. There are several aspects of a similar product, the link for each text portion demonstrates the text which demonstrates the other side of the text. The main characteristics of the sentiment analysis are to enhance the component-enabled aspects and have several operations like word identification, categorization, and equal word suggestion(Kanwal et al., 2023).

The interactive elements have increased in social media and those contents permit the users to deliver false news while the posted content has an emotional state around something. The content is available in social media given blogs, reviews, and news, this amount of data is available in the form of un-structural information, and it is useful for the organization to make various thoughtful understanding that data is very substantial for making decisions in the form of email, reviews, and documents. Data Mining is used to identify the people and the views are important to several stakeholders like businesses and the government, sentiment analysis and big data have various challenges such as the complexity of the unstructured information in natural language(Chong et al., 2014).

Attention technique(Wang et al., 2019) has the enhanced output as the aspect classification, neural network-enabled attention methodology could enhance the capability of reading the comprehension effectively. The correlation of the aspect with the sentiment polarity is analyzed for capturing useful data in the specific aspect. The NLP-related problems have solutions through the LSTM model(Mahadevaswamy et al., 2023) while the target data attained improved performance in a target-reliant sentiment classification. The target vector is computed through the mean value of the sentence vectors with the target phase holds to demonstrate the semantics of the optimal values. Aspect-enabled sentiment classification is reflected as a classification issue for the fine-grained classification process. Aspect-enabled sentiment analysis is the process of identifying the sentiment across the particular aspects of an entity from the text data as the demonstration of every extracted aspect with the equivalent aspect. The text data is collected from several sources and the normalization process is implemented into the text data by removing the inconsistencies while the extraction process of every entity recognition for extracting aspects into the text data.

The sentiment analysis is to provide a Natural Language Processing (NLP) which focuses on discovering and extracting subjective data from text data like emotions, and sentiments that involves analyzing text to demonstrate the sentiment orientation whether positive, negative, neutral could be applied to several domains including social media, customer reviews. The sentiment analysis has accurately captured the context for determining sentiment which handles ambiguous language and very hard to detect, the linguistic various could impact sentiment analysis. The customer opinions and sentiment are used to enhance the services, the understanding of market trends in the customer sentiment is involved to finalize the business decisions as the tracking sentiment on social media for monitoring brand reputation in public opinion. The main contribution of the paper is:

- ✓ A novel framework for aspect-enabled sentiment analysis is proposed, which demonstrates the relationship between opinion targets and polarity values in text data. This framework can effectively analyze complex sentiment relationships within documents.
- ✓ The Attention LSTM framework is incorporated to perform sentiment analysis, allowing the model to focus on different parts of sentences when various aspects are involved in the input text. This approach enables the model to capture nuanced sentiment expressions and improve overall performance.

✓ The proposed framework effectively handles correlated aspects through pre-defined groups, addressing the challenge of analyzing low-performing aspects. By leveraging the relationships between aspects, the model can better understand the sentiment expressed towards specific targets.

✓ Experimental results on the IMDB movie review dataset demonstrate the effectiveness of the proposed technique, achieving an accuracy of 94.5%. The performance of the proposed framework is compared to relevant techniques, including SVM, RNN, and LSTM, showcasing its superiority in various performance metrics.

✓

2. Related works

Theaspect-enabled sentiment analysis is for identifying and categorization the emotions to perform the sentiments into the automatic processing of the input text. The sentiment analysis is the main research area which could be determined in various levels like the document level, sentence level, and paragraph level. The most efficient machine learning methodologies like SVM(Gupta et al., 2019), Naïve Bayes(Wongkar et al., 2019), deep learning techniques like LSTM(Rajesh et al., 2023), RNN(Naidu et al., 2022), and Ensemble-enabled functionalities joined with the classifiers that could have the categories(Ankit et al., 2018). Sentiment analysis has a huge amount of research work developed while the multi-modal, and multi-lingual have involved aspect-enabled sentiment analysis. The aspect is segregated into the dissimilar tasks of extraction and estimation while the classification of the positive and the negative reviews provides the conflict values using the aspect parameters. The Machine Learning techniques have utilized the text representation while the vector model has no values in the semantic representation(Singh et al., 2017).

An organized technique is utilized in social media through individuals to analyse opinion mining to pre-process and the classification process. The reviews and the aspect identification with the classification process as each aspect has the associated score that the polarity of the entire sentence should be analyzed(Tian et al., 2022). The reviews have been categorized into testing and training while the model is trained, this data is to identify the polarity in future reviews. The transactional information has the numerical data which is well structured and it is more essential to make decisions where the unstructured data is accessible in the form of reviews. Aspect-enabled sentiment analysis(Jiang et al., 2023) yields the reviews and analyzes the aspects related to it. Every individual aspect produced the score while using the score the polarity of the entire sentence should be quantified, then the reviews are categorized into the training, and testing while the framework is trained and is capable of identifying the polarity in the future reviews. The machine learning technique(Jemai et al., 2021) is utilized to categorise the sentiment analysis while the language is involved in the social media to identify the opinion comprising the data pre-processing.

The system could be more resource in the aspect-enabled sentiment analysis utilising the notion for data retrieval, specifically stimulated through the post-retrieval functionality, after conducting the repeated experiments which will improve the automation of the estimated analysis for enhancing the sentiment classification process according to the aspects. The sentence classification is very tough in the existing techniques in aspect-enabled sentiment analysis, it is significant to identify the complex sentences for analyzing the alternating approach despite extracting the prompt sentiment(Bordoloi et al., 2023). The resource-intensive functionalities(El Madhi et al., 2023) have a classification strategy to minimize the cost of the specific framework and data retrieval as the predictors are described according to the ambiguity, distribution, and complexity.

The CNN-Recurrent technique (Myska et al., 2019) has utilized the independent enabled sentiment analysis which is implemented using the technique of RNN through the stacked dense layers. The computational complexity has been balanced through the classification effectiveness evaluation with the multi-lingual datasets. The multi-lingual character (Wehrmann et al., 2018) methodology has presented the parallel convolutional layers using various filters for analyzing the trigram features, the stacker's layers are involved in the sentiment analysis from different languages. Deep learning methodology (Singhal et al., 2016) has been implemented for various languages for sentiment analysis to utilize the word embedding concept through translation. CNN architecture has been used to analyze tweets in multiple languages. The sentiment words are used to enhance the training data size from various language datasets to provide effective sentiment analysis.

The deep learning-enabled techniques (Nankani et al., 2020; Dashtipour et al., 2016) have been implemented for enhancing sentiment analysis in multi-languages. The techniques of prediction are segregated into the pre- and post-retrieval process on the existence of query values.

The existing techniques have detected the polarity of the whole sentence; the aspect classification model is used to provide the solution for the problems into the group of features through the sentiment lexicons.Aspect-enabled sentiment analysis has several challenges as the aspect extraction process has discovered the particular aspects in text data, and the category specification of the aspect type like attribute, features could be challenging. Every extracted aspect with the matching sentiment in the identification of aspects is not demonstrated in the text data where the contrast in text data management could affect the sentiment expressed across the aspect. The sarcasm detection in text data could be challenging which affects the sentiment discovered from the aspect as well as the sentence handling process which has multiple aspects required to identify the sentiments from every aspect. The proposed model has specific benefits in several aspects of the NLP process to achieve enhanced performance in long-term dependency as the attention functionality produces the input sequence into the related outputs to make the most interpretable on several tasks.

The attention LSTM framework for Aspect enabled Sentiment analysis has a crucial role in identifying relevant phrases in a sentence could convey sentiment based on particular aspects. Aspect-enabled sentiment analysis is the methodology of identifying the sentiment according to the particular aspect of the entity, it knows the sentiment may vary on several aspects to provide a better understanding of emotions and opinions. The particular aspect being addressed through the text data as the sentiment analysis of every aspect has provided a more opinion understanding which enhance the insight by understanding opinions across particular aspects, the decision-making has been enabled to discover areas for the enhancement to help the business by satisfying the customer requirements and preferences. The problems regarding the aspect have the solution to understand this proposed technique to involve the benefits of aspect-enabled sentiment analysis. The model captures nuanced sentiment expressions for the particular phrases while the model could exactly capture sentiment across distinct aspects, it could differentiate sentiment in several aspect to provide a detailed understanding of user opinions. By leveraging attention mechanisms, the proposed model can efficiently evaluate sentiment towards exact aspects, enabling applications like customer feedback analysis.

3. Proposed Framework of Attention LSTM

The Attention LSTM framework is the LSTM model which integrates attention functionality for enhancing the performance of LSTM models while the conventional LSTM model is framed for handling sequential data to maintain the hidden state which captures data from the prior time values while the Attention LSTM model reduces the restrictions by integrating the attention functionality which permits the proposed model focusing on particular input values to produce the outputs as the attention functionality calculates weights which affect every component into the computation of the weighted sum of the input values. Attention LSTM is appropriate for sequential data processing to capture temporal dependency than the SVM model as the integration of the attention model than RNN model with enhanced performances. Aspect-enabled Sentiment analysis utilizes the reviews and enables the aspect combined into the framework as every individual aspect has value in the entire word should be identified. The reviews have been categorized as the testing and training model; the trained framework is capable of identifying the polarity of the feature reviews. The working model of the proposed framework is demonstrated in Figure 1 as the testing and the training modules are delivered into the deep learning model with the Sentiment analysis enabled. The language which is utilized by every individual while the systematic process is required for review contains pre-processing and the classification process. The data is converted into clean by removing the noisy data, inconsistencies, and unwanted values, and eliminating the duplicate or irrelevant data from the dataset. Data Visualization technique is utilised to curate data into an easier form for understanding and processing through outliers, it is the process of transforming data into a visual representation like a graph, to manage data easier to understand the useful values. Data splitting is the process of segregating the data into various subsets, the initial part is utilized for testing purposes and another part is utilized for the training process in the specific model. In the training split, every epoch is used for validation to determine the performance of the proposed framework. Attention LSTM functionality is used to improve the proposed framework to focus on the essential input components, enhancing the accuracy and effectiveness of the computational metrics. It is involved in prioritizing the related data and it permits to specifically attend to other parts of the input data for assigning several weights to dissimilar components. The aspect-enabled classification is performed as the Positive, Negative, Neural, and Conflict aspects are classified from the dataset.

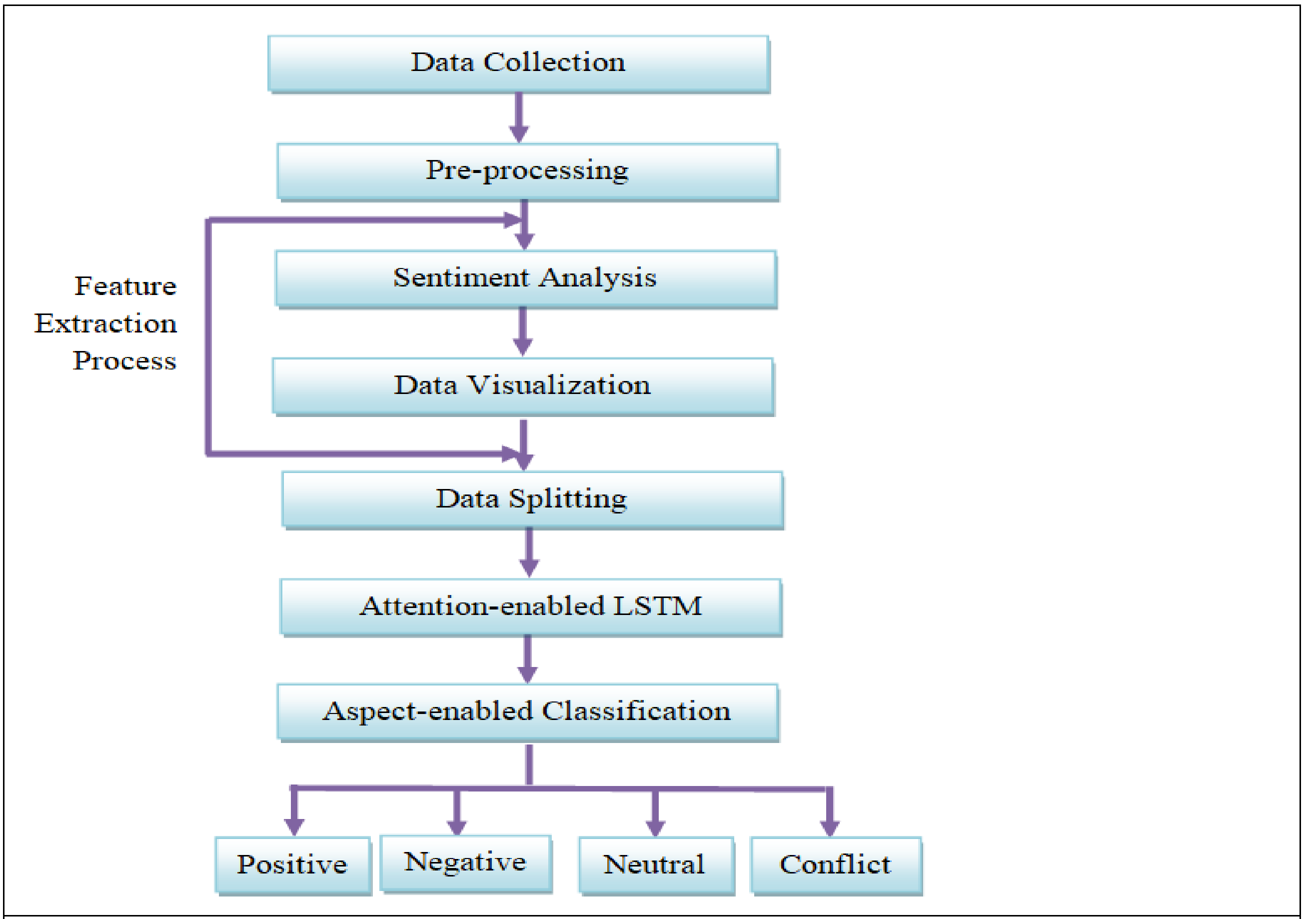

Fig. 1. Working Model

The proposed framework has the prediction of the polarity for the particular document with the specific aspect, the neural network framework has accurately predicted the entire polarity of the sentence with the negative and positive values. The most complex scenario for predicting the emotional aspect connected with others is through the vector value of the aspect-enabled relationships. The opinion mining techniques have text-enabled analysis and could identify well-known opinions, the proposed framework aims to identify the aspects and sentiments of every aspect.The criteria for selecting an aspect are that the specific aspect appears regularly in the input data, the selection of a specific topic for the analysis process, the high sentiment intensity as the association with the sentiments. The identification of the aspects which belong to particular categories like features as the aspects have the sentiments associated with the emotions while the domain knowledge is used to discover aspects which are related to the particular domain. The proposed model has effectiveness which includes enhanced accuracy, the Long-term dependency is handled in a better way, and the robustness to the irregular data to filter the unwanted data. The attention functionality delivers better insights as the input sequence has the production of outputs from the input sequence to make the model interpretability. The proposed functionality has the flexibility to be applied in several tasks like NLP, it can be parallelized effortlessly than the related models to make it suited for several applications, it could minimize the training time to be focused on the related parts of the input sequence and the generalization process has the adaptation into the latest patterns.

Data collection is the initial step for the proposed technique as web scraping method is enabled for collecting the reviews while the categories $+ve$ and $-ve$ reviews have been split, which helps to differentiate several aspects. The pre-processing is completed to fetch the useful information from the dataset, the data is involved in the classification, the semantic features are collected from the particular domains and the final score is computed according to the basic features. Pre-processing has been used to transform the data into the structured form as the empty data like empty cells, and rows are cleaned from the raw data and restored the useful information which is demonstrated in Figure 2. Pre-processing helps to improve the data quality by the extraction of important data as cleaning and organizing the raw data to enable it for training the proposed framework, and the transformation of raw data into an understandable form. It is used for identifying and removing the empty rows, and empty data from the dataset as the bias value is not changed even after removing the specific data from the dataset.

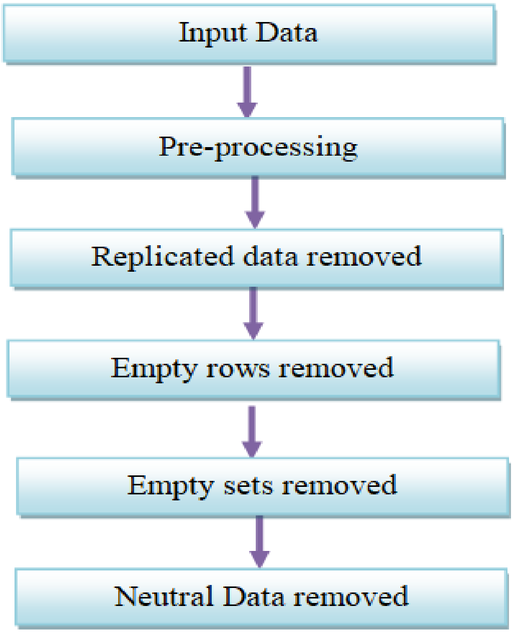

Fig. 2. Steps for Pre-processing

The reviews are analyzed manually, the gathered reviews are segregated into the specified category for implementing the pre-processing process. The proposed framework has involved the analysis module particularly adapted for extracting the emotions from the input text. The lexical features are normally categorized as negative and positive according to the semantic representation. Social media texts are most effective for calculating the negative and the positive scores while it has the generalization for various domains, it has a reasonably fast online streaming process to enable the performance. The web scraping functionality is incorporated through Python while the features are extracted from input text and delivered to the classification process, the semantic features are segregated from the particular domain and the final score is evaluated according to the features extracted in the pre-processing state. The transformation tool is framed for processing the corpus to utilize the end vector for training using the neural network-based classifier. The classification process is evaluated through the hyperparameters for achieving the simplification process, the feature extraction procedure is initiated as the feature vectors are transformed into the initial network layer for extracting the semantics regarding the words demonstrating the vocabulary Vo^{Ch} for representing the character. The input words $(Wo_1, Wo_2, Wo_3, \ldots, Wo_n)$ are converted into vectors in Eq. (1).

$$Vo_n = \{r^{wo}, r^{wch}\} \qquad (1)$$

While r^{wo} demonstrates the embedding, r^{wch} denotes the character embedding, and the semantic data in the word-enabled embedding is extended for capturing the shape and morphological data. The word embedding is initiated for the encryption process to matrix embedding through the vector of every column and the matrix-vector product is computed in Eq. (2).

$$R^{Wo} = Vo^{Wo}\, Wo^{Wo} \qquad (2)$$

The features are extracted from a specific domain automatically, it executes well in small text from the huge corpus for creating words and executes faster in large datasets. The deep learning framework utilizes the word meaning for categorizing the bigger entities to identify the word meaning. In the proposed technique, the vectors are used for training the datasets which consist of 3.5 million words with a huge corpus for obtaining the exact relationships. The similarity within words transformation and the relationship within the dissimilar words in the dataset. The sentiment analysis of the dataset utilizes several hashtags for managing needed information like the #ihateit and several adverb data, suffixes. The Convolution creates the local values within the characters and manages the character-enabled embedding with the Max function. The embedded character in the column vector (R^{Ch}) is computed in Eq. (3).

$$R^{Ch} = Vo^{k}\, W^{Ch} \qquad (3)$$

Where Vo^{k} demonstrates the $|Vo^{Ch}|$ size, the Convolution layer is involved in the Character-enabled embedding in Eq. (4).

$$[K^{WCh}]_j = \max_{n}[Wt^{o} X_n + a^{o}]_j \qquad (4)$$

Where K^{WCh} is the Character-enabled embedding, Wt^{o} is the weight vector value, a^{o} is the bias value. The matrix with each character window utilized the local features in the input word, a sentence has some words and is converted into the word level combined with embedded characters while the adjacent state contains the sentence representation when feature extraction is completed within the distinct size, the sentence has the useful data while the issues have the solution through the neural network for computing the balanced feature vectors of large sentences. The

character-enabled feature extraction has produced the features of every sentence, the max operation for creating the feature vector with a link and the matrix-vector of every work in a sequence is computed in Eq. (5).

$$X_n = \{u_a, \dots, u_b\} \qquad (5)$$

Where u_a, u_b is the word sequence, the value of a is computed in Eq. (6).

$$a = \frac{2n - u^{l} - 1}{2} \qquad (6)$$

The value of b is computed in Eq. (7).

$$b = \frac{2n + u^{l} - 1}{2} \qquad (7)$$

The vector value has the comparison of a global vector with the sentence into the layers while the representation value of each sentimental score$\big(Ss(x)\big)$ is computed in Eq. (8).

$$Ss(x) = Wt^{3}\, h\,(Wt^{2} r_x + \alpha^{2})\alpha^{3} \qquad (8)$$

Where the learning parameter is denoted by $Wt^{2} \in \Re^{N}$, the vector is demonstrated by $Wt^{3} \in \Re^{N}$. The proposed model has trained within the group for reducing the probability of negativity, a sentence is delivered to the model has the parameter and every sentimental value is computed in the time series. The computed scores are transferred into the distribution-enabled probability ($\Pr(\theta)$)and the SoftMax operation is enabled in Eq. (9).

$$\Pr(\theta) = \frac{e^{Ss_{\theta}(x)_i}}{\sum_{i \epsilon T} e^{Ss_{\theta}(x)_i}} \qquad (9)$$

Where $e^{Ss_{\theta}(x)_i}$ is the standard exponential function, the gradient descent(θ) is computed in Eq. (10).

$$\theta = \sum -\log Pr(x, \theta) \qquad (10)$$

The vector representation of the word into the framework for creating the sentence vector will have the data related to the aspect while the location data is utilized for obtaining the improved result, the weighted embedding vector and the Gaussian distribution have the probability density function used for preventing the data interference which is utilized to acquire the position weights.The objective of the proposed classifier is determined as reducing the cross-entropy prediction loss on every target aspect in Eq. (11).

$$PL = \frac{1}{|D_f|} \sum_{a \epsilon D_f} \sum_{t \epsilon T} \sum_{s \epsilon A} \log Pr_{s,t}^{a} \qquad (11)$$

Where A is the aspect predicted value, $Pr_{s,t}^{a}$ is the polarity-based probability function, a is the categorization of the sentence with the target value t. The SoftMax function is computed in Eq. (12).

$$Pr_{s,t}^{a} = SoftMax\left(Wt^{p} X_{s,t}^{a} + bi_{s}^{a}\right) \qquad (12)$$

The overfitting is avoided by including the dropout layer through the probability value of 0.50 in the embedding layer, the training procedure of the proposed framework after 10 epochs to identify that it produces the enhanced performance on the development group. The Attention-enabled LSTM is proposed to detect the aspect through the sentiment classification, the attention procedure could capture the important sentence given the specific aspect and the proposed framework is demonstrated in Figure 3.

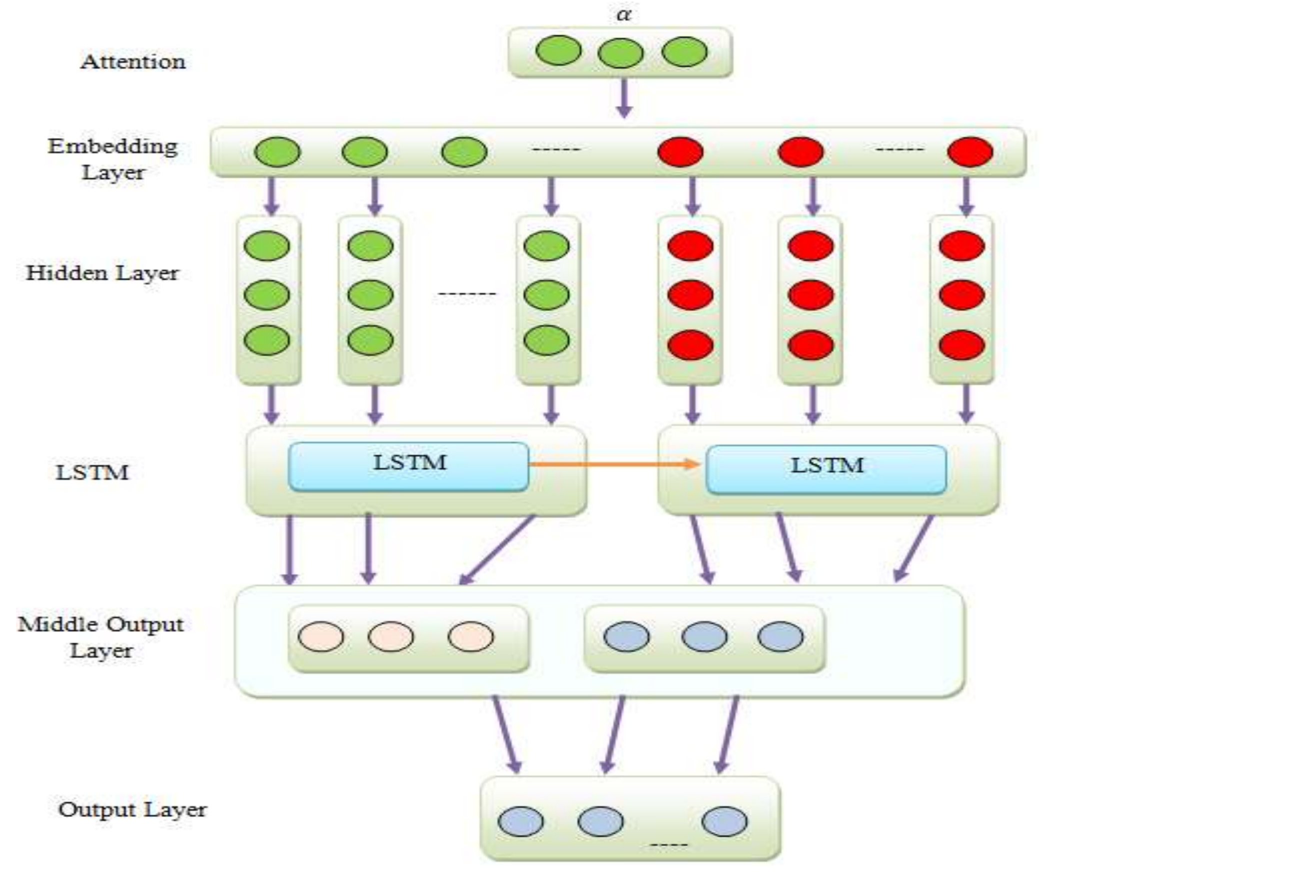

Fig. 3. Attention LSTM model

Let $H \epsilon \Re^{N}$ is the matrix with hidden vectors $[hi_1, hi_2, \ldots, hi_N]$ from the LSTM model in the total length of N sentences. Additionally, the aspect embedding from the vector will generate the weight vector $w_N \epsilon \Re^{N}$ with the weighted hidden representation. The final representation is computed in Eq. (13).

$$hi^{*} = \tanh\left(Wt_{p} r + Wt_{x} hi_{N}\right) \qquad (13)$$

The attention process permits the framework for capturing the most useful sentence aspect while dissimilar aspects are involved. hi^{*} is utilized for the feature demonstration of the given input sentence while the linear layer is utilized for converting the sentence vector through the SoftMax function in Eq. (14).

$$\beta = SoftMax(Wt_s hi^* + bi_s) \qquad (14)$$

The way of utilizing the aspect data in the proposed model is having the embedding aspect in the role of calculating the attention weight. The aspect data is appended into the input vector through the framework while the output hidden representations $(hi_1, hi_2, \dots, hi_N)$ could have the data from the input vector. Hence, the attention weights are computed in the dependence within the words and the aspect could be developed. The proposed framework could be trained into the backpropagation while the object function with the cross-entropy with the sentence distribution in Eq. (15).

$$Lo = -\sum_p \sum_q \alpha_p^q \log \hat{\alpha}_p^q + \rho||\theta||^2 \qquad (15)$$

Where p is the sentence index, q demonstrates the class index, ρ denotes the regularization, $and\ \theta$ produces the parameter group. The main parameter group demonstrates the embedding word with the common parameters, the dimension has dissimilar models. The aspect embeddings are included in the LSTM input unit, the dimensionality will be improved accordingly with added parameters. The useful filters are involved to match the specific sentence in the classification process with the dissimilar filters participating in the various attributes while the classification-related issues on similar sentences effectively catch the features.

The Attention LSTM framework is used to handle sequential data like text to capture long-term dependencies where the attention technique permits the model for focusing on related data in the input data, enhancing the capability of capturing complex patterns. Attention LSTM is used to enhance the performance on several NLP tasks like sentiment analysis. The Attention LSTM framework is used to efficiently handling sequential data like text, the proposed model captures complex patterns. The correlated aspect demonstrates the relationships within several features of an entity as the correlations is identified using the text data analysis to reveal patterns while the predefined groups demonstrate the aspect clusters need to be created according to the prior knowledge, the groups could be involved for organizing and framing the aspect-level sentiment analysis to understand complex opinions. The relationships within the Predefined groups and the correlated aspects have to discover the correlated aspect by analyzing text data for discovering relationships within aspects, the correlated aspects have been assigned to predefined groups according to the characteristics, every aspect into the predefined groups needs to analyze sentiment. The predefined groups and correlated aspects have to provide the improved framework to understand complex opinions, the patterns and associations within aspects have been revealed to enable the targeted sentiment analysis to particular aspects.

4. Performance analysis

The proposed framework is implemented in the system with the specifications of 8 GB RAM and, an Intel Core i5 processor while the implementation is performed through the Python language with the Anaconda Spyder software, several performance metrics are involved for validating the proposed framework through the iteration process and the semantic features are extracted with the refined information where the specific domain reviews minimize the false negative rates which generate the enhanced accuracy. A suitable statistical analysis is critical to enhance the accuracy of the proposed Attention LSTM framework through the cross-validation process and performance metrics like precision, recall, f1-score, and accuracy have been involved to assess the reliability and robustness of the improved accuracy. The experimental setup for this study involves a comprehensive approach to data preprocessing, hyperparameter tuning, and training methodology. Data preprocessing includes normalization to ensure that the text data is clean and consistent. Hyperparameter tuning is performed using a grid search approach to identify the optimal combination of parameters for the model. The training methodology involves using a recurrent neural network with an attention mechanism, optimized using the Adam optimizer and cross-entropy loss function. The model is trained on a large dataset and evaluated using metrics such as accuracy, precision, recall, and $F1_{measure}$. To ensure reproducibility, the code and data used in the experiment are made available, the detailed documentation of the experimental setup enables other researchers to replicate the study and build upon the findings. By providing a transparent and thorough description of the methodology, this study aims to contribute to the advancement of research in this field and provide reliable insights. IMDB movie review dataset (http://ai.stanford.edu/~amaas/data/sentiment/) has 51,500 movie reviews for sentiment analysis while this dataset has the binary sentiment enabled classification model with the testing and training framework for predicting the total positive reviews and negative reviews.The IMDB movie review dataset is the most common benchmark dataset to perform the aspect-enabled sentiment analysis process as the Data pre-processing has the process of segregating the individual words as the removal process has to remove the common words. The stemming process is used to minimize words from the base form so that words are treated as similar words, remove special characters and punctuation which don't include more value in the analysis and finally convert all text values to lowercase for ensuring the analysis is case-sensitive. Figure 4 demonstrates Various Polarity (%) in the dataset as the movie reviews based on the positive, negative, neutral, and conflict in the Training and Testing using the proposed framework.Polarity value demonstrates the sentiment carried from the text data like the document, paragraph as the value may be positive, negative, or neutral while it should be identified through the proposed Attention LSTM technique. The polarity identification is the complex task to deal with the variation in the specific language and it is depended on the text involved in the context.

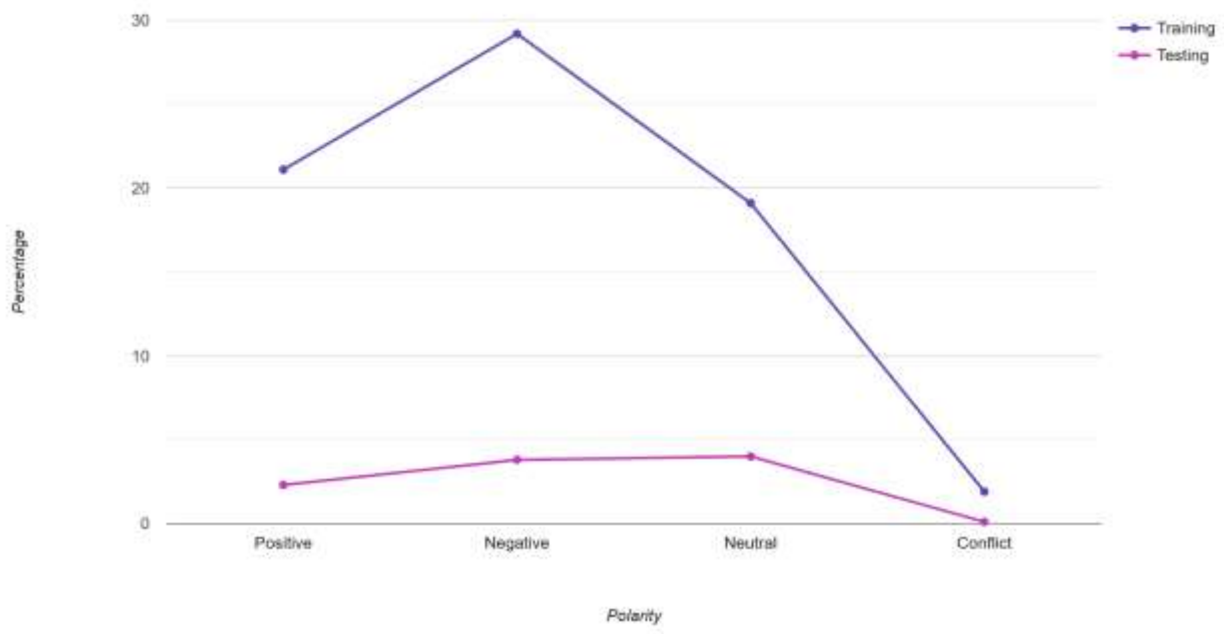

Fig. 4. Various Polarity (%) in the dataset

Table 1 demonstrates the Polarity (%) in the dataset for training and testing in the IMDB movie review dataset for the proposed framework.

Table 1. Performance evaluation for the proposed technique in several iterations

States	Positive	Negative	Neutral	Conflict
Training	21.1	29.2	26.7	1.0
Testing	2.3	3.8	4.0	0.0

Accuracy is the parameter which measures the correct prediction of the outcome, it is computed by dividing the total correct predictions by the total predictions where the measurement is utilized for determining the best for discover the relationship within the patterns in the training dataset, the accuracy is computed in Eq. (16).

$$Accuracy = \frac{TrP + TrN}{TrP + TrN + FaP + FaN} \qquad (16)$$

Where TrP denotes the True Positive value, TrN demonstrates the True Negative value, FaP is the False Positive value, FaN is the False Negative value. Precision is the parameter which manages the quality of the positive prediction which has the total true positive value by the total positive predictions. Precision value is computed in Eq. (17).

$$Precision = \frac{TrP}{TrP + FaP} \quad (17)$$

Recall is the parameter which computes the exact identification of the true positives from the entire actual parameters in the dataset. Recall value is computed in Eq. (18).

$$Recall = \frac{TrP}{TrP + FaN} \quad (18)$$

F1-measure is the computation of the harmonic mean within the recall and the precision, the evaluation parameter is the multi-class evaluation and F1-measure is computed in Eq. (19).

$$F1_{measure} = \frac{(Precision\ x\ 2\ x\ Recall)}{(Precision + Recall)} \quad (19)$$

Figure 5 illustrates the performance evaluation for the metrics as the proposed technique has improved performance than the related techniqueswhere the classification in the Backpropagation to make deep learning enabled framework efficiently.The confidence intervals for sentiment analysis through predictions which includes the resampling process for generating an estimate distributions-based prediction. The computation of confidence intervals for polarity scores in aspect ratings with statistical techniques like the percentile-based intervals. The dataset distribution insights have the computation of descriptive statistics like mean, standard deviation to understand the polarity scores. The proposed framework achieves an accuracy of 94.5% with a 95% confidence interval of (93.2%, 95.8%) on the IMDB dataset. The proposed framework performs significantly better than the baseline model ($p < 0.01$) and achieves a higher F1-score (0.92) compared to alternative approaches (SVM: 0.85, RNN: 0.88).

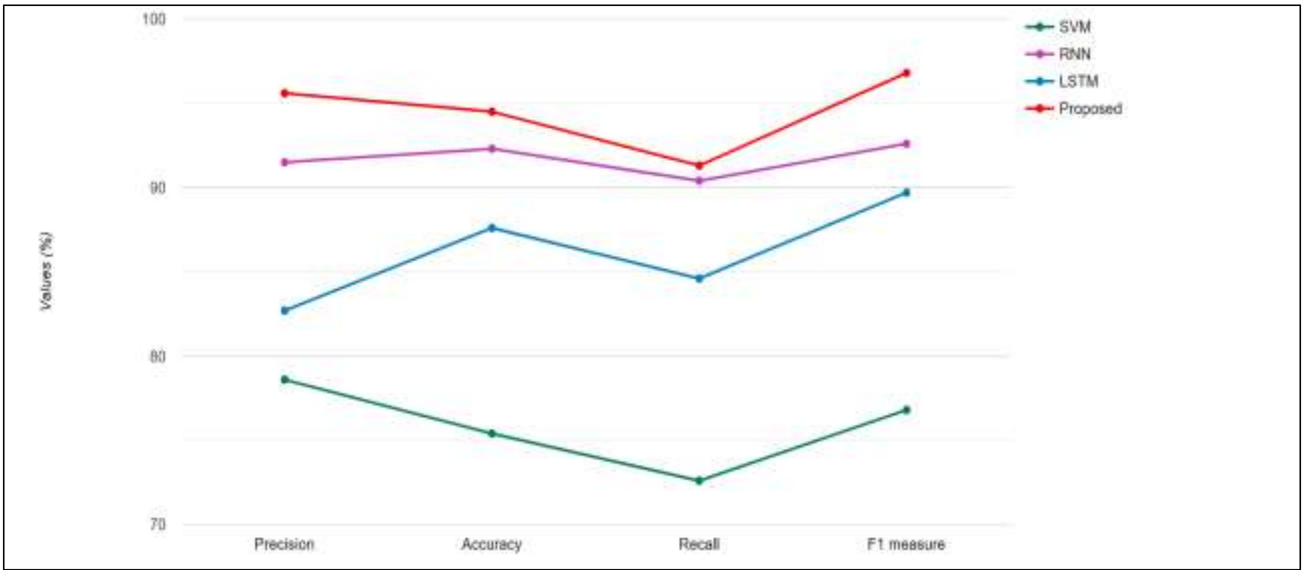

Fig. 5. Performance metrics comparison

Figure 6 denotes the value of loss in various iterations. Loss value is the summation of the errors which demonstrates the performance of the model, the iteration is demonstrated as the total steps through the segregated packets of the training data which is required to finish in a single epoch. An epoch is the completed pass within the dataset, a batch is the dataset processed for updating the weights after completing every batch.

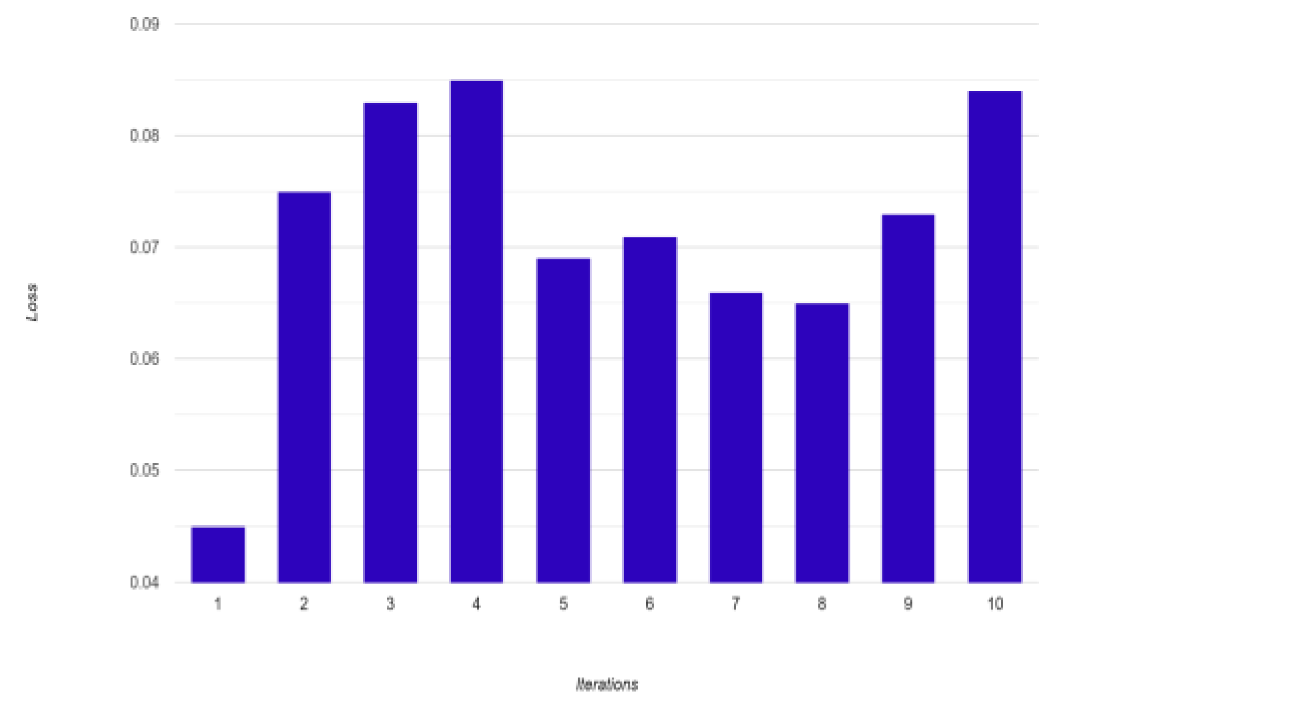

Fig. 6. Loss comparison in several iterations

Table 2 demonstrates the performance evaluation of Precision, Recall, F-measure, and Accuracy which demonstrates that the Recall has a minimum amount than other parameters in different iterations.

Table 2. Performance evaluation for the proposed technique in several iterations

Iterations	Precision	Accuracy	Recall	F-measure
Iteration 1	98.5	96.2	90.5	98.2
Iteration 2	94.4	95.2	91.6	97.4
Iteration 3	92.4	92.5	90.5	95.8
Iteration 4	95.8	94.6	93.6	96.4
Iteration 5	96.2	95.6	91.3	96.9
Iteration 6	96.3	92.9	90.4	95.4
Iteration 7	94.8	95.2	92.4	96.4
Iteration 8	94.5	92.7	91.2	97.2
Iteration 9	97.5	95.6	90.2	97.5
Iteration 10	95.6	94.5	91.3	96.8

Elapsed time is computed as the time taken from starting to ending of the particular task and it is also known as the time required to complete the task within the specified iteration. Figure 7 demonstrates that the proposed technique has a higher amount of elapsed time at the beginning and the ending iteration level in the process of aspect-enabled sentiment analysis process.

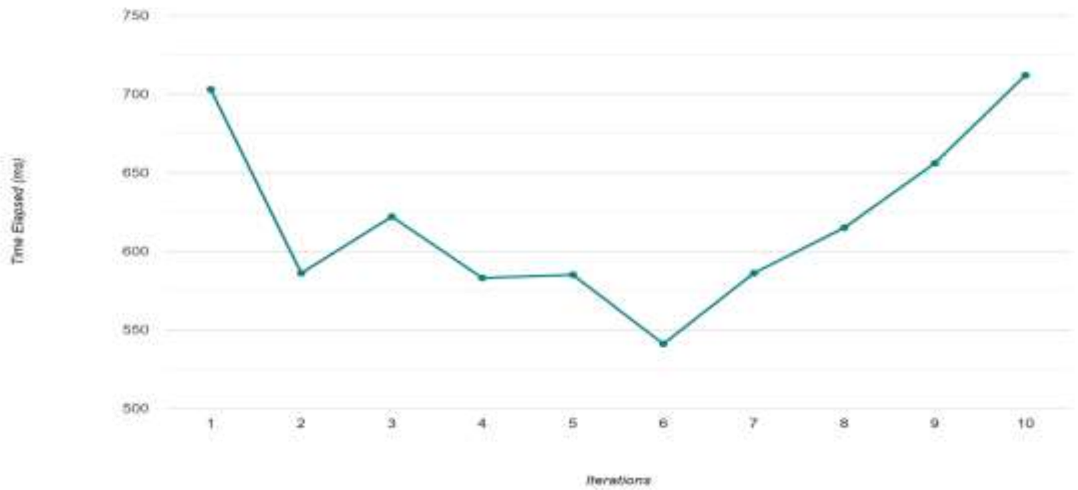

Fig. 7. Elapsed Time

The group of classified aspects are involved in determining the polarity of every aspect in the input sentence the task as positive, negative, neutral, and conflict. From the input dataset, the location and polarity for every existence in each aspect word. The proposed framework has the aspect embedding vector to process the training while the uniqueness within the word embedding and the aspect, also captures the useful data given the input aspect. Table 3 demonstrates the experimental results based on the iterations of the IMDB movie review dataset.

Table 3. Experimental results based on the iterations on the IMDB movie review dataset

Iteration	Loss	Time Elapsed (ms)	Accuracy
1	0.405	703	0.81
2	0.075	586	0.92
3	0.083	622	0.92
4	0.085	583	0.91
5	0.069	585	0.92
6	0.071	541	0.93
7	0.066	586	0.91
8	0.065	612	0.92
9	0.073	656	0.92
10	0.084	712	0.92

The thorough comparison with the relevant state-of-the-art techniques for aspect-based sentiment analysis is completed as the proposed technique has achieved the better result than the relevant techniques for the IMDB movie review dataset. The scalability is the measurement of the capability for handling huge dataset with minimized complexity. The Robustness is the capability of handling noise, missing values, outliers and the Interpretability is the capability of providing insights into its decision-making procedure, Comparison with other state-of-the-art methods for aspect-based sentiment analysis is demonstrated in Table 4.

Table 4. Comparison with other state-of-the-art methods for aspect-based sentiment analysis

S. No.	Technique	Computational time	Scalability	Robustness	Interpretability
1.	SVM (Gupta et al., 2019)	23 sec	Medium	Low	Low
2.	Naïve Bayes (Wongkar et al., 2019)	20 sec	Low	Medium	Medium
3.	LSTM (Rajesh et al., 2023)	21 sec	High	Medium	Medium
4.	RNN (Naidu et al., 2022)	22 sec	High	Low	Medium
5.	Proposed Model	18 sec	High	High	Medium

The proposed technique has the Aspect based sentiment analysis for the IMDB movie review dataset as the main limitation has the capability of accurately detecting aspects while the performance may face the degrade of the sarcasm, figurative language that are prevalent in movie reviews. The generalizability to several language is another limitation that relies on language-specific annotated datasets into a cross-lingual contexts as the proposed technique should need substantial retraining for accommodating languages with specific grammatical and sentiment expression patterns. The techniques for adapting the model with dissimilar datasets by incorporating linguistic resources as multiple languages for improving the generalizability and robustness to enhance the capability to handle outlier data like sarcasm. The error types could deliver an enhanced insight as the aspect detection errors could identify specific aspect types while the model has hard to accurately classifying sentiment like Sarcasm, several sentiment phrases, Figurative languages. The Aspect-sentiment Alignment errors could occur as wrongly align aspects with sentiment-bearing phrases to wrong aspect in mis-attributing sentiment. The improving amount of training data for particular aspect types could help for the performance of the model, the sentiment lexicon for including several nuanced sentiment expressions could improve the capability of accurate sentiment classification. The understanding of the contextual expressions using the deep learning model could minimize aspect-sentiment alignment errors.

5. Conclusion

This paper demonstrates the efficient classification technique for sentiment analysis by Attention LSTM framework while the sentiment features are classified and various techniques are trained for the performance analysis. The input data is gathered using the LSTM model and domain-explicit reviews minimize the negatives and increase the accuracy, the hyper-parameters using the attention model to become the optimized results. The performance analysis shows that the recommended technique outperforms the related techniques with more accuracy and other performance metrics. In Future, the parallel computing process will involve the computational speed-up and evaluate the meta-heuristics-based features, the improved work will be used to manage the web-related ontology functionality for incorporating the sentiment analysis in online social networks. The future work of the Aspect-enabled sentiment analysis has the integration of several modalities like text, images for analyzing the aspect, the model needs to be constructed to process low-resource languages from the annotated datasets, to develop the model for enhancing the trustworthiness and transparency. The external ontologies could be incorporated to enhance the robustness, the applications like feedback analysis, social media monitoring have to be improved and develop the model which could compare the aspects on several entities like products.

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