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SENTIMENT ANALYSIS OF AMAZON REVIEWS WITH AW-LSTM: UNLEASHING THE POWER OF ATTENTION MECHANISMS WITH LSTM

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Abstract: Sentiment Analysis on Amazon reviews helps to understand the opinions of users about various products listed on that platform. Various existing techniques were applied to analyze the sentiment of users about the products and existing methods have the limitation of overfitting and imbalance data problems. This research proposes the Attention Weighting – Long Short-Term Memory (AW-LSTM) model to focus on features in the network and improve the performance of sentiment analysis. The AW-LSTM model is tested on the Amazon review dataset and compared with existing techniques in sentiment analysis. In attention weighting, word embedding, global pooling,the importance of word order, and short sentence processing were performed. Global pooling technique helps to samplethe input data that helps to handle imbalance data problems. The importance of word order helps to analyze the meaning of the sentence and Named Entity Recognition (NER) based short sentence process extract information from a short sentence. The advantages of the AW-LSTM model improve the performance of the sentiment analysison Amazon review dataset. The AW-LSTM model has accuracy of 93.28 % and the existing BERT has 88.48 % accuracy in sentiment analysis of the Amazon review dataset.

Keywords: Amazon review, Attention Weighting, Long Short-Term Memory, Named Entity Recognition, and Sentiment Analysis.

1. INTRODUCTION

Sentiment analysis on user reviews to classify thesentiment polarity of users such as neutral, positive, and negative. Sentiment analysis is required in someapplications such as marketing, social media analysis, and e-commerce for analysis of the sentiment of customers. Sentiment analysis is considered a hot topic in Natural Language Processing (NLP) research. Deep learning techniquesprovide efficient performance in NLP tasks includingsentiment analysis. Sentiment analysis on reviews is considered as a classification task, where features extracted from input text are applied to the classifier and predicts sentiment types as outputs [1]. Sentiment analysis examines an individual's emotions, thoughts, attitudes, perceptions, and opinions based on the post shared on social network platforms. The sentiment analysis model classifies a given text as neutral, positive, or negative [2]. Various tools and methods that can specify the input text polarity, have been developed in recent years. Polarity detection is binary or multi class classification task that represents an important dowel in most applications. Shallowmodels were trained in most earlier sentiment analysis methods that were carefully designed to extract features of polarity classification [3]. Cloud blogs are present in excessive size that require processing of huge volume of information in various forms like reviews, opinions, and attitudes. Sentiment analysis is an effective technique to extract relevant information from big data that classify the polarity and predict sentiments [4]. The sentiment analysis field is widely used to analyze text data and extract sentiment component. E-commerce websites generate a large amount of text data like tweets, feedbacks, comments and customer's review. Sentiment analysis provides great help to retailers in better understanding the expectations of customers and shaping the policies [5].

The online reviews of text messages explicitly express consumers' opinions on various products, brands, or firms. Some techniques classify the data into two classes (positive or negative), others include sentiment classes. These techniques can understand sentiment polarities from huge volumes of texts and are previously applied in the review of opinions [6, 7]. RNNs are sequence neural networks applied to sequence data for classification and they are difficult to train due to vanishing gradient problem. LSTM network provides solution/mitigation to this problem and the GRU model controls data and functions like LSTM that perform without considering any extra memory unit. The bidirectional variants of these networks are special variants that allow the system to predict better about the current state [8, 9].Extracting the features from a large volume of information is difficult to process [10].

The objectives and contribution of this research are discussed as follows:

1. The AW-LSTM model is applied to focus on feature types to improve the classification in sentiment analysis. Focusing on feature types in the network helps to solve overfitting problem.
2. The Global pooling technique used in attention weighting helps to sample the minority class and reduces the imbalance data problem. The NER technique is applied to extract information from a short sentence and considers important order of words to improve classification performance.
3. The AW-LSTM model has higher efficiencythan the existing attention weight method and SVM based models on Amazon review sentiment analysis.

This research paper is organized as follows: the Literature survey is given in Section 2 and the AW- LSTM model is explained in Section 3. The results and discussions are presented in Section 4. The conclusion of this research work is given in Section 5.

2. Literature Survey

Customer feedback is important for product development to gather information about new ideas. Amazon website consists of many customer reviews related to various products. Some of the recent researches related to sentiment analysis on Amazon reviews are surveyed in this section.

Alharbi [11] applied four variants of RNN modelsnamed as Update Recurrent Unit (URU), Gated Recurrent Unit (GRU), LSTM, and Group LSTM. Tokenization, stop word removal and lemmatization were applied as pre-processing techniques. The URUmodel consisted of GRU and LSTM cell for theclassification process. Word embedding was appliedwith four variants of RNN models as a feature extraction method for sentiment analysis using FastText by skip-gram, Word2Vec and Glove. The three feature extraction techniques and five different algorithms were tested for sentiment analysis on Amazon dataset comprising of balanced and unbalanced datasets. The FastText feature extractionand Group LSTM method provide higher performance in sentiment analysis on Amazondataset.

Chatterjee [12] applied the correction method andstatistic-based outlier method for sentiment analysis and outlier detection on Amazon customer reviews [26]. This method was called SODCM. It found the anomaly detection in the review and rectified the starratings to enhance the efficiency of sentiment analysis without data loss. The SODCM method wastested on the collected data and publicly available dataset for performance analysis. The SODCM method had higher efficiency in anomaly detection, outlier detection and sentiment analysis on the Amazon dataset. The SODCM method had the advantage of pipeline preserving the outliers to correct and prevent data loss.

Vizcarra [13] developed a method consideringthe semantic processing based on excerpts fromknowledge of sentiment analysis. The knowledge-based method applied a disambiguate process, graphtheory algorithm, similarity measures, and knowledge graph. The knowledge-based method ofsentiment analysis was tested with two datasets asTwitter and Amazon datasets. The knowledge-basedmethod shows higher efficiency in sentiment analysis than existing methods such as polarity, sentiment, andpolarity sentiment hybrid methods. The disambiguation in the knowledge- b a s e d methodincreases the efficiency of the classification process. Geetha and Renuka [14] applied the deep learning model [23] and BERT base Uncased model for thesentiment analysis of Amazon data. The WordPieceTokenizer was applied as pre-processing beforeapplying in the BERT model [22]. Dropout regularizationof softmax classifier was applied for the classificationprocess in Amazon data. The BERT model providedimproved efficiency with high accuracy and goodprediction than existing models. The hyper-parameter was set in the developed model to improvethe efficiency of the sentiment analysis. The BERT model provides higher efficiency than machinelearning models [24] [25] in sentiment analysis. The BERTmodel has lower efficiency in handling large textsequences and this tends to vanish gradient problems.Shobana and Murali, [15] extracted the contextual and semantic features of word information using Skip-gram architecture. Adaptive ParticleSwarm Optimization (APSO) was used to weightparameters optimization in LSTM to improve theclassification performance. The APSO-LSTM model was evaluated using four datasets which are Amazon,Trip Advisor, Twitter, and Book review. The APSO-LSTM model has higher performance on fourdatasets than existing methods.

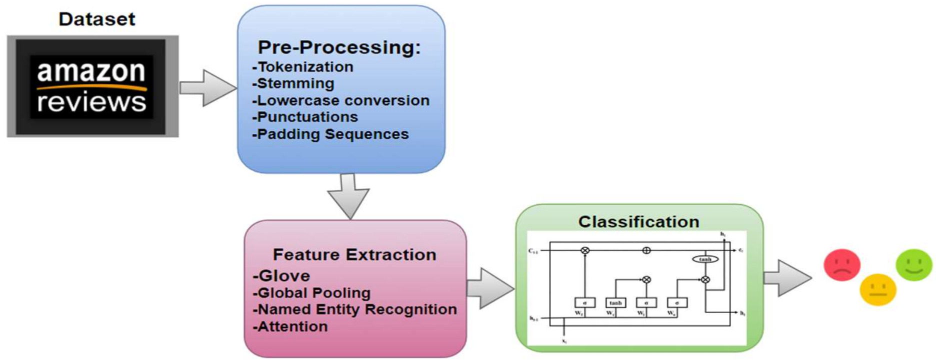


Figure. 1 The attention weighting method in LSTM for sentiment analysis in Amazon review dataset

3. Proposed Method

This research proposes the Attention weighting method to solve data imbalance, overfitting, and relevant feature selection for sentiment analysis in Amazon review dataset. The Glove, Simple word embedding, Global pooling, the importance of word order information, and short sentence processing were applied for attention weighting. The attention weight is applied to LSTM with input data for sentiment analysis such as positive, neutral, and negative from Amazon review data. The flow ofAttention weighting in LSTM for sentiment analysison the Amazon review dataset is shown in Fig. 1.

3.1. Pre-processing

The pre-processing methods such as Tokenization, stemming, lower casing, Punctuation removal, and sequence padding were applied to structure the data.

Tokenization: Tokenization is a basic task in most NLP tasks and words or phrases are considered as token and split from a document or sentence. Spacesare trivial to split words in English. Additional knowledge is considered such as named entities and opinion phrases. Some stop words such as ‘a’, ‘the’ are removed in tokenization and retain usefulinformation. Many tokenization tools such as Tokenizer, OpenNLP, and Standford Tokenizer apply pre-processing as a fundamental technique.

Stemming: Removing ending letters to detect thestem or root form of input text is stemming. Stemming reduces dimensionality and merges many words. Stemming is widely used to yield good results.Porter Stemmer is a widely used algorithm for stemming.

Lowercasing: Lowercasing words is a common pre-processing technique. This technique reduces dimensionality and merges the same words.

Removing Punctuation: Removing punctuation isa classic technique for pre-processing text in data mining and information retrieval. Some sentiments are denoted as punctuation marks. For example, intense positive or negative sentiments are denoted by an exclamation mark.

3.2 Feature Extraction:

The Glove is an upbeat word embedding technique developed for competing of Stanford's researchers. Global vectors are coined for Glove thatis based on factorization matrix techniques on word-context matrix. This is an unsupervised learning method based on word vector representation. Co- occurrence knowledge ($words \times context$) is used to construct a large matrix. For instance, a largecorpus consists of some 'context' of a word that occurs for each 'word' (the rows).

3.1.1. Simple Word-Embedding Model

A class model having no additional compositional parameters, is considered to analyze the word embedding capacity in raw modelling to encode sequences of natural language, termed asSWEMs. Element-wise average is computed as the simplest strategy over word vectors for a given sequence, as in equation (1).

$$z = \frac{1}{K}\sum_{i=1}^{K} v_i \qquad (1)$$

Average pooling operation is present in equation (1) that considers mean over each K dimension of word embedding, results in z representation with embedding same dimension, termed as SWEM-aver.Every sequence element is considered as z in the additional operation of the account.

3.2.2 Global Pooling

Consider 10 feature maps in size of 6 × 6 in the last convolutional layer. The output of 10 feature points of 10 feature maps is calculated using averageor global value. Data points are concatenated into a 1× 10 feature vector and is given as input to Softmax for classification. The Global Average Pooling (GAP) is applied for fully connected operators in theamazon review classification. GAP performsparameter reduction and dimension reduction thatenhances the ability of generalization. This helps to overcome the overfitting problem without a dropout parameter and the GAP layer does not require any parameter for optimization.

In the LSTM layer, consider k^{th} feature map with a size of $m \times n$ is denoted as x_{ij}^{k}, equation (2) performs GAP.

$$y_{GAP}^{k} = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1} x_{ij}^{k} \qquad (2)$$

Where GAP layer output is denoted as y_{GAP}^{k}.

3.2.3. Short Sentence Processing

Generally, the SWEM method is less effective inextracting information from short sentences than from long documents. This is because for shorter text sequences, word-order features are more important in semantic information of limited word embedding alone. sensitive to overfitting problems.

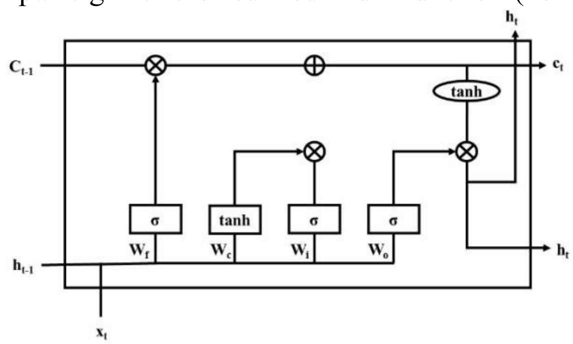
3.2.4 Attention weighting: It is a mechanism used in neural networks, particularly in natural language processing tasks, to focus on specific parts of the input sequence when making predictions. In the context of a model, like an Attention-Weighted Long Short-Term Memory (AW-LSTM) network, attention weighting assigns different importance scores to different elements of the input sequence. This allows the model to "pay attention" to certain parts of the input more than others, emphasizing their contribution to the final output.

3.3 Long Short-Term Memory

Hochreiter and Schmidhuber developed the LSTM unit and since then this model has undergone some changes like forget gate addition. Storage of information is carried out in the memory cell of LSTM [16–20]. Memory is managed by input, outputand forget gates and the LSTM unit performs tasks such as keeping important features inflow or propagating. LSTM model is very successful in various applications like sentiment analysis, machinetranslation, and handwriting recognition. sensitive to overfitting problems.

Figure. 2 The architecture of the LSTM unit

The weighted sum of Input signals is calculated and a function (non-linear) at a time t for



each of j^{th} LSTM unit is preserved in c_t^i memory. The activation of the LSTM unit or output h_t^j , is given in equation(3).

$$h_t^j = \sigma_t^j \tanh\left(c_t^j\right) \tag{3}$$

Where memory content exposure amounts are controlled in the output gate σ_t^j. Equation (4) denotes the output gate.

$$\sigma_t^j = \sigma(W_0 x_t + U_0 h_{t-1} + V_0 c_t)^j \tag{4}$$

Where logistic sigmoid function is denoted as σ and a diagonal matrix is denoted as V_0. The existing memory forgetting is updated in the memory cell c_t^j that has limited extent and new memory content c_{-t} is added, as in equation (5).

$$c_t^j = f_t^j c_{t-1}^j + i_t^j c_{-t}^j \tag{5}$$

Equation (6) denotes the new memory content.

$$c_{-t}^j = \tanh(W_c x_t + U_c h_{t-1})^j \tag{6}$$

Forget gate f_t^j is modulated for forgetting the existing memory. The input gate i^j is modulated in new memory content and memory cell is augmented, as in equations (7 & 8).

$$f_t^j = \sigma\left(W_f x_t + U_f h_{t-1} + V_f c_t\right)^j \tag{7}$$

$$i_t^j = \sigma(W_i x_t + U_i h_{t-1} + V_i c_t)^j \tag{8}$$

Diagonal matrices are V_i and V_f.

3.4 Working Procedure of AW-LSTM:

The proposed sentiment analysis algorithm integrates an Attention-Weighted Long Short-Term

Memory (AW-LSTM) model, GloVe word embeddings, and Named Entity Recognition (NER) to predict sentiments from input text. Tokenization and preprocessing are initially performed, followed by the application of NER to enhance feature extraction, especially for short sentences. The GloVe embeddings capture word semantics while preserving word order information. The attention mechanism is then applied to produce weighted vectors, emphasizing key words in context. The AW-LSTM model, initialized to capture sequential dependencies and word order, processes batches during training epochs, predicting sentiments with consideration for both context and sequence. The algorithm optimizes through parameter updates, evaluates performance on validation/test sets, and facilitates sentiment prediction for new text instances, culminating in the final output of predicted sentiments for the given input text. The algorithm's design ensures the effective utilization of word order information throughout the sentiment analysis pipeline shown in Algorithm 1.

Algorithm 1: AW-LSTM Sentiment Analysis Pipeline with Attention Mechanism and Named Entity Recognition

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Inputs: - T (Text)
Outputs: - S' (Predicted Sentiments)

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1. Tokenize text T into tokens Ti; preprocess Ti (tokenization, stemming, lowercasing, punctuation removal, sequence padding).
2. For short sentences in T, apply Named Entity Recognition (NER) to extract significant entities and enhance feature extraction.
3. Use GloVe for word embedding on Ti to get vector representations Vi.
4. Apply attention weighting to Vi to produce weighted vectors Wi.
5. Initialize AW-LSTM model parameters θ.
6. For each training epoch, process batches B:
   a. Extract features ViB, apply attention to get WiB.
   b. Pass WiB through LSTM layers to predict sentiment S'B.
   c. Calculate loss L between S'B and true labels SB, backpropagate to update θ.
7. Optimize model (adjust learning rate, hyperparameters, apply dropout).
8. Evaluate model on validation/test set using accuracy, precision, recall, F1-score.
9. For new text Tnew:
   a. Preprocess, tokenize to Tnewi.
   b. Apply NER for short sentences, feature extraction, attention mechanism.
   c. Predict sentiment S'new using trained model.
10. Final Output: S' (Predicted Sentiments for T).

4. RESULTS

Sentiment analysis technique on Amazon review dataset helps to analyze opinions of customers about their products. This research involves applying the attention weighting LSTM model to improve the performance of sentiment analysis. The AW-LSTM model is tested on the Amazon review dataset and compared with existing techniques for performance analysis.

Table 1. The AW-LSTM model performance for various learning rates

Learning Rate	Precision (%)	Recall (%)	F-measure (%)	Accuracy (%)
0.00005	84.22	86.15	85.17	92.65
0.00004	84.65	86.54	85.58	92.71
0.00003	85.63	86.78	86.2	92.83
0.00002	85.91	87.32	86.61	93.28
0.00001	85.54	87.12	86.32	93.02

The AW-LSTM model is evaluated for various learning rate values in terms of performance metrics, as given in Table 1 and Fig. 3. The AW-LSTM model has higher performance in 0.00002 learning rate due to optimal weight value in the LSTM network. The attention weighting technique helps the model to focus on specific features for the classification that improves the classification performance. The performance of AW-LSTM model is considerably the same for various learning rates of the model in classification. The AW-LSTM model has 93.28 % accuracy in 0.00002 learning rate and 92.65 % accuracy in 0.00005 learning rate.

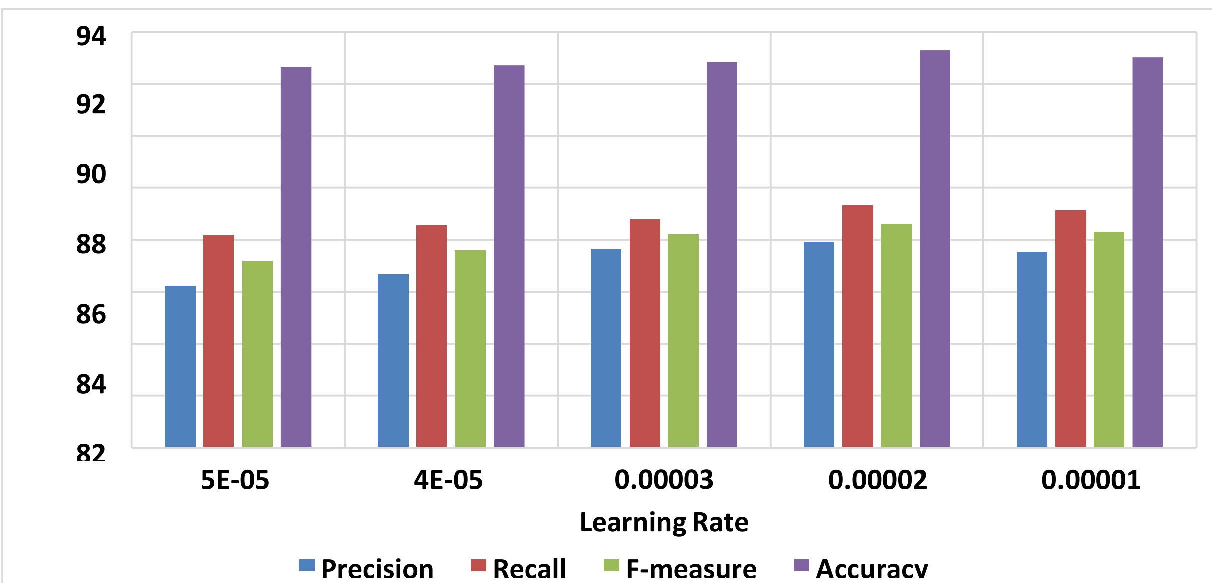

Figure. 3 The AW-LSTM model performance on various learning rates

Table 2. F-measure (%) of AW-LSTM for various categories

Categories	AACOSVM	EFAN	EBC	AW-LSTM
DVD	78.3	63.1	55.2	80.4
Books	75.6	65.4	59.7	78.0
Kitchen	74.5	66.9	58.2	76.0

Electronics	76.9	63	51.9	77.3
Avg	76.33	64.6	56.25	77.925

The F-measure value of the AW-LSTM model ismeasured for various categories and compared with existing methods, as shown in Fig. 4 and Table 2. The AW-LSTM model has higher efficiency than EFAN and AACOSVM models in sentiment analysis of theAmazon review dataset. The AW-LSTM model has the advantage of considering information from short sentences using Named Entity Recognition (NER). The AW-LSTM model also focuses on the order of words to extract the meaning related to the sentences. The Global pooling-based sampling technique is usedin attention weighting to handle the imbalance data problem. The existing Enhanced Feature Attention Network (EFAN) method has a limitation of overfitting the network and the AACOSVM method has an imbalance data problem and local optima trap. The AW-LSTM model has an average value of F- measure of 77.92 % and the AACOSVM method hasa 76.33 % F-measure.

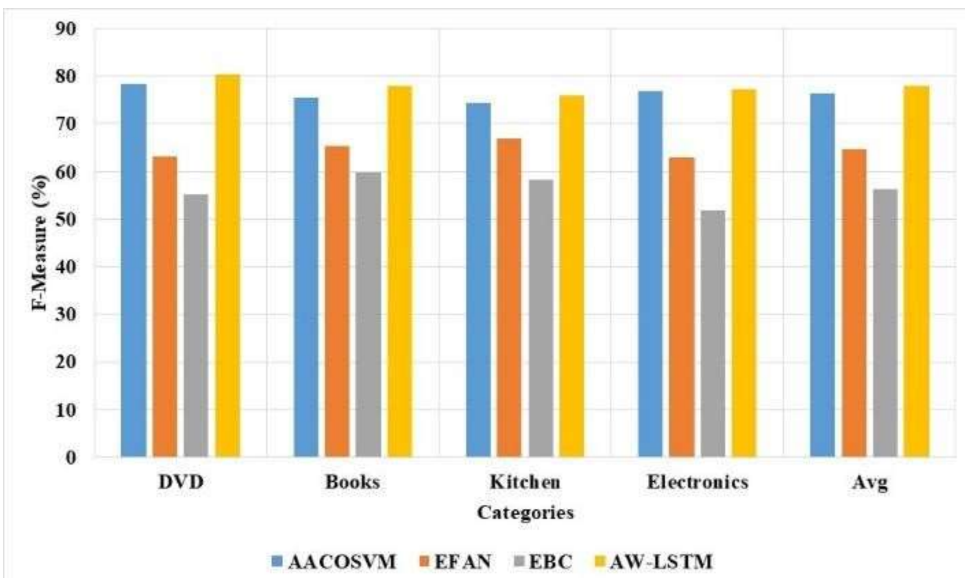

Figure. 4 The AW-LSTM model and existing models F-Measure for various categories

Table 3. Accuracy (%) of AW-LSTM model for various categories

Categories	AACOSVM	EFAN	EBC	AW-LSTM
DVD	77.8	62.6	54.4	88.2
Books	75.1	65.1	59.3	84.1
Kitchen	73.8	66.4	57.9	87.0
Electronics	76.6	62.5	51.4	89.4
Avg	75.83	64.15	55.75	87.1

The AW-LSTM model is evaluated in terms of accuracy for sentimental analysis and compared withthe existing methods, as given in Fig. 5 and Table 3. The AW-LSTM model has higher efficiency than the existing attention-based model and ACO-SVM based models. The AW-LSTM model extracts information from short sentences using NER, considers the order of importance, and embedding of information. The existing ACO-SVM method has a limitation of localoptima trap and imbalance data problem. The EFANmethod has created an overfitting problem in the network for classification. The AW-LSTM method has average accuracy of 93.28 % and the existing AACOSVM model has average accuracy of 75.83 %in sentiment analysis.

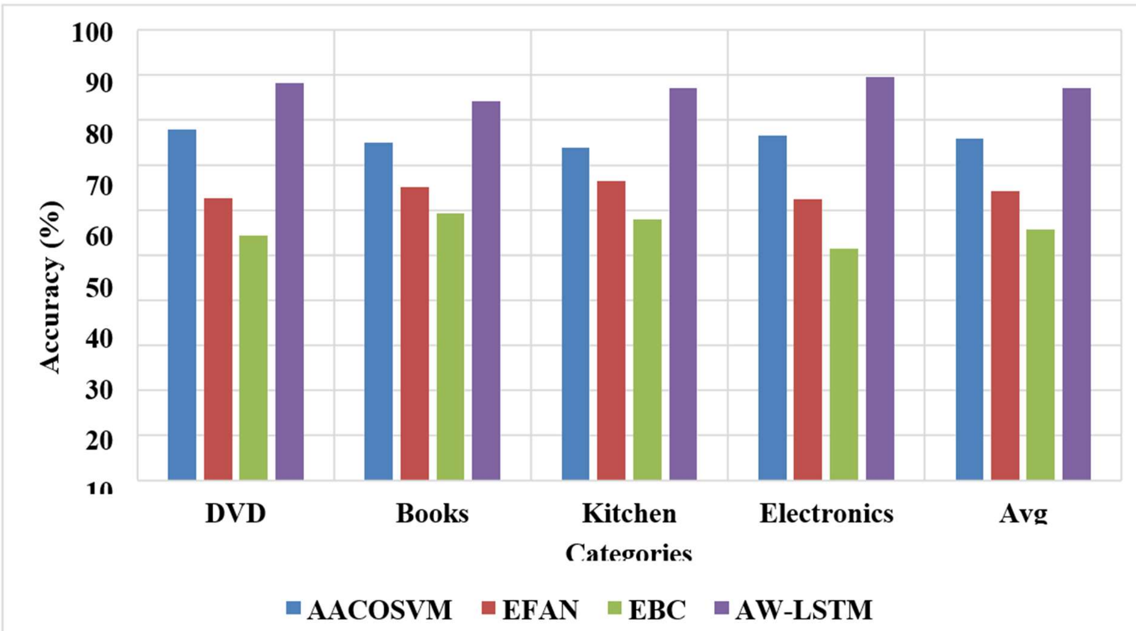

Figure. 5 The AW-LSTM model and existing models' accuracy in various categories

Table 4. Classifier comparison of AW-LSTM models

Model	Precision (%)	Recall (%)	F-measure (%)	Accuracy (%)
NB	79.32	73.57	76.34	80.12
SVM	82.68	84.31	83.49	81.33
LSTM	80.57	79.28	79.92	83.97
BERT	88.09	86.22	87.14	88.48
AW-LSTM	89.54	88.45	88.99	93.28

The AW-LSTM model is evaluated on sentimentanalysis on the Amazon review dataset and comparedwith existing classifiers, as shown in Table. 4. The AW-LSTM model has a higher performance than the existing standard classification models. TheAW-LSTM model applies attention weighting to focus on specific features to improve classification performance. The existing BERT model has a limitation of lower performance in handling long textsequences in the network. The LSTM model has a limitation of vanishing gradient problem and the SVM model has a limitation of imbalance data problem. The AW-LSTM model has the accuracy of 93.28 % and BERT has 88.48 % accuracy in sentiment analysis of Amazon review dataset.

5. Conclusion

Sentiment analysis on Amazon review data helpsto understand the opinions of customers related to theproduct. The existing methods in amazon sentiment analysis have limitations of local optima trap, imbalance data and overfitting problem. This research proposes the AW-LSTM model to focus on relevant information and improve the classification performance. The attention weighting method applies Global pooling technique that solves imbalance data problem. The attention weighting method extracts information from short sentences using NER which resulted in performance improvement. The existing ACO-SVM based method has the limitation of local optima trap and imbalance data problem. The AW- LSTM model has an accuracy of 93.28 % and BERThas 88.48 % accuracy in sentiment analysis. Thefuture work of this AW-LSTM model proposes to apply the feature selection technique to select unique features and improve the recall value of the model inthe classification.

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