International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 4
DOI: https://doi.org/10.17762/ijritcc.v11i4.6458
Article Received: 10 February 2023 Revised: 20 March 2023 Accepted: 30 March 2023

A Hybrid Convolutional Network and Long Short-Term Memory (HBCNLS) model for Sentiment Analysis on Movie Reviews

Gaurav Dubey[1], Richa Khera[2], Ashish Grover[3], Amandeep Kaur[4], Abhishek Goyal[5], Rajkumar[6], Harsh Khatter[7], *Somya Srivastava[8]
[1,5,6,7]Department of Computer Science
[1,5,6,7]KIET Group of Institutions, Delhi-NCR, Ghaziabad, India
[2,3]Manav Rachna International Institute of Research and Studies, Faridabad, India
[4]CUIET Chitkara University, Rajpura, India
[8]ABES Engineering College, Ghaziabad, India
[1]gaurav.dubey@kiet.edu, [2]richaadlakha.fet@mriu.edu.in, [3]ashi.21s@gmail.com, [4]amandeep.2846@chitkara.edu.in,
[5]abhishek.goyal.cs@kiet.edu, [6]raj.kumar@kiet.edu [7]harsh.khatter@kiet.edu, [8*]somya.srivastava@abes.ac.in

Abstract— This paper proposes a hybrid model (HBCNLS) for sentiment analysis that combines the strengths of multiple machine learning approaches. The model consists of a convolutional neural network (CNN) for feature extraction, a long short-term memory (LSTM) network for capturing sequential dependencies, and a fully connected layer for classification on movie review dataset. We evaluate the performance of the HBCNLS on the IMDb movie review dataset and compare it to other state-of-the-art models, including BERT. Our results show that the hybrid model outperforms the other models in terms of accuracy, precision, and recall, demonstrating the effectiveness of the hybrid approach. The research work also compares the performance of BERT, a pre-trained transformer model, with long short-term memory (LSTM) networks and convolutional neural networks (CNNs) for the task of sentiment analysis on a movie review dataset..

Keywords- BERT, Convolution Neural Network, LSTM, NLP, tokenization, sentiment analysis.

I. Introduction

Sentiment analysis, the task of determining the sentiment of a piece of text as positive, negative, or neutral, is a widely studied problem in natural language processing (NLP). With the increasing amount of user-generated text available online, there is a growing need for automated tools to analyze and understand the sentiment expressed in this text. In this paper, we present a benchmark study of three deep learning methods for sentiment analysis on movie reviews: BERT, a pre-trained transformer model; convolutional neural networks (CNNs); and long short-term memory (LSTM) networks. BERT is a pretrained transformer model developed by [1] for natural language processing (NLP) tasks. Transformer models, which were first introduced by [3], use self-attention mechanisms to process input sequences and generate contextualized embeddings for each input token. BERT is trained on a large dataset of labeled text data and is able to generate embeddings that capture useful linguistic features. These embeddings can then be used as input to a classifier to predict the sentiment of the text or perform other NLP tasks. One key feature of BERT is that it is ”bidirectional”, meaning that it takes into account the context both to the left and to the right of each input token. This makes BERT well-suited for tasks such as language translation, where understanding the context of a word in relation to the words that come before and after it is important. BERT has achieved state-of-the-art results on a wide range of NLP tasks, including sentiment analysis [20], question answering [4], and language translation [22]. Recent years have seen the development of a number of pre-trained language models, such as BERT, that have achieved strong results on a wide range of NLP tasks [5] [6]. BERT is trained on a large dataset of labeled text data and is able to generate embeddings for input text that capture useful linguistic features [7]. These embeddings can then be used as input to a classifier to predict the sentiment of the text. CNNs and LSTMs are two other popular deep learning approaches for NLP tasks, and have been used successfully for sentiment analysis in the past. However, the relative performance of these methods on the task of sentiment analysis on movie reviews [8] has not been well-studied.

In this paper, we aim to fill this gap by conducting a thorough comparison of BERT, CNNs, and LSTMs for sentiment analysis on a movie review dataset. We evaluate the performance of these models using a range of metrics, including accuracy, precision, and recall, and compare the results to identify the strengths and weaknesses of each method. Our study proposes a hybrid model for sentiment analysis of movie review dataset it also provides a benchmark for the performance of these methods on this task and

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 4
DOI: https://doi.org/10.17762/ijritcc.v11i4.6458
Article Received: 10 February 2023 Revised: 20 March 2023 Accepted: 30 March 2023

sheds light on the relative effectiveness of BERT, CNNs, and LSTMs for sentiment analysis on movie reviews.

II. LITERATURE REVIEW

A Robustly Optimized BERT Pretraining Approach by [9] presents an improved version of BERT that achieves state-of-theart performance on a number of NLP tasks, including sentiment analysis. Fine-Tuning BERT for Sentiment Analysis with Keras by [10] demonstrates how to fine-tune BERT for sentiment analysis using the Keras deep learning library. Sentiment Analysis with Deep Learning: A Survey by [11] provides an overview of the various deep learning approaches that have been used for sentiment analysis, including CNNs, LSTMs, and BERT. [12] presents a method for sentiment analysis of drug reviews using a combination of a lexicon-based approach and a deep learning model.

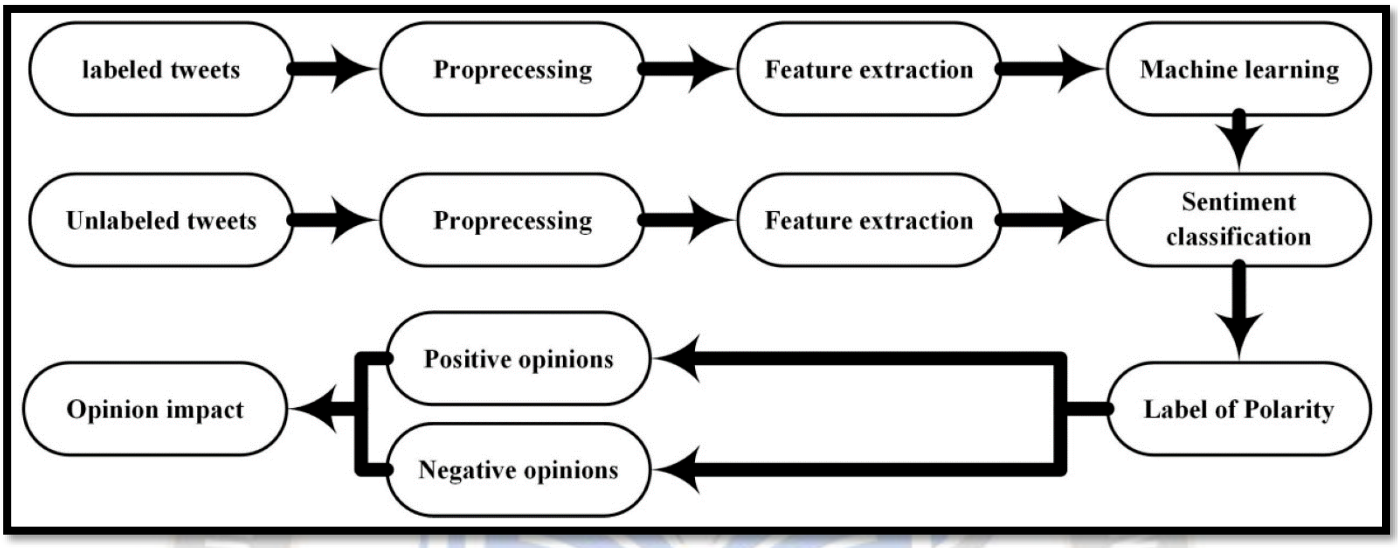


Fig 1. Twitter Sentiment Analysis Operational Flow [14]

The lexicon generation is modular, and the sentiment analysis is performed using a fusion of a convolutional neural network (CNN) and a recurrent neural network (RNN) with threshold weighted mapping. The approach is evaluated on a dataset of drug reviews, and the results demonstrate improved sentiment analysis compared to other state-of-the-art methods. The paper by [13] proposes a method for stock price forecasting using a long-short term memory (LSTM) neural network with an attention mechanism. The attention mechanism is used to dynamically weight the influence of different parts of the input data on the prediction. The proposed method is evaluated on a dataset of historical stock prices, and the results show improved performance compared to other state-of-the-art models. Sentiment Analysis of Twitter Data by [14] presents a study of the performance of CNNs and LSTMs on sentiment analysis of Twitter data, and compares their results with traditional machine learning approaches. This is also shown in figure 1.

A Survey of Deep Learning for Sentiment Analysis by [15] provides an overview of the various deep learning approaches that have been used for sentiment analysis, including CNNs, LSTMs, and BERT. ”Sentiment Analysis with Attention-Based LSTM and CNN-LSTM Hybrid Models by [16][23] presents a study comparing the performance of LSTMs and a hybrid CNN-LSTM model on sentiment analysis of movie reviews. Comparative Study of CNN and LSTM for Sentiment Analysis on Movie Reviews by [17][24] presents a study comparing the performance of CNNs and LSTMs on sentiment analysis of movie reviews.

Figure 2 shows the basic classification of algorithms. Sentiment analysis, the task of determining the sentiment of a piece of text as positive, negative, or neutral, is a widely studied problem in natural language processing (NLP). With the increasing amount of user-generated text available online, there is a growing need for automated tools to analyze and understand the sentiment expressed in this text. A number of deep learning approaches have been applied to the task of sentiment analysis, including CNNs, LSTMs, and BERT. CNNs were first applied to sentiment analysis by [18], who demonstrated that they can achieve strong results on the task of classifying movie reviews as positive or negative. LSTMs were first applied to sentiment analysis by [19], who demonstrated that they can also achieve strong results on the same task. BERT, a pre-trained transformer model, has recently been applied to sentiment analysis by [1] [20], and has achieved state-of-the-art results on a number of NLP tasks, including sentiment analysis.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 4
DOI: https://doi.org/10.17762/ijritcc.v11i4.6458
***Article Received**: 10 February 2023 **Revised**: 20 March 2023 **Accepted**: 30 March 2023*

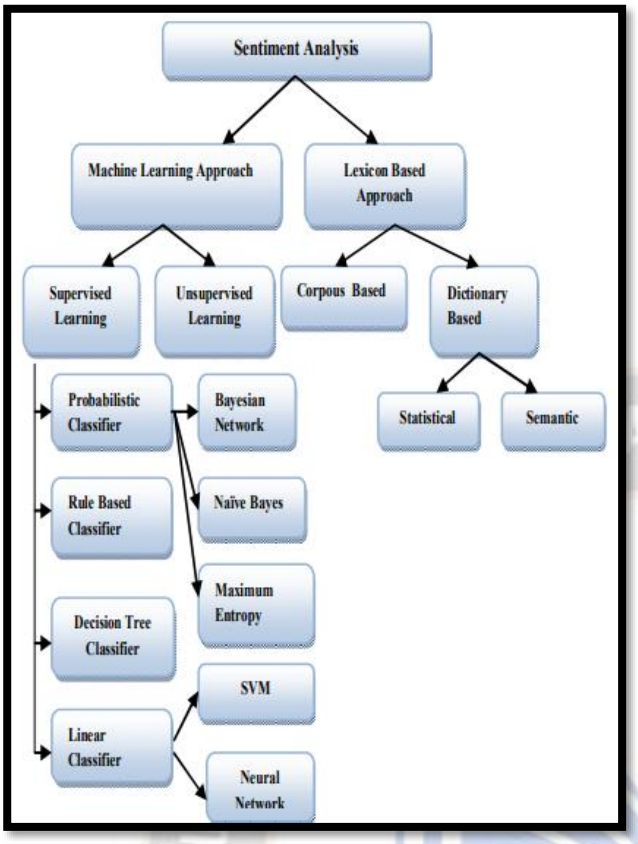


Fig 2. Classification of various algorithms

While these approaches have achieved strong results on sentiment analysis, there is still room for improvement and further research is needed. One area of active research is in the development of more effective pre-trained language models, such as the recent work on RoBERTa by [21]. Other areas of research include the development of hybrid models that combine the strengths of multiple approaches, and the use of attention mechanisms to better capture the context and dependencies in the input data.

III. METHODOLOGY

One approach to developing a hybrid model (HBCNLS) for sentiment analysis is to use a CNN to extract local features from the input data and an LSTM to capture long-term dependencies. The output of the CNN is concatenated with the output of the LSTM and fed into a fully-connected layer to make a prediction. The input data of a sequence of word embeddings, are passed through a CNN to extract local features. The output of the CNN is fed into an LSTM, which processes the data using multiple LSTM layers to capture long-term dependencies. The output of the LSTM is then be concatenated with the output of the CNN and passed through a fully-connected layer to make a prediction. This hybrid model combines the strengths of CNNs and LSTMs by using the CNN [25] to capture local patterns in the data and the LSTM to capture long-term dependencies. Figure 3 displays detailed methodology of our proposed hybrid model. This approach potentially improve the performance of the model on sentiment analysis tasks. Methodology for creating a Hybrid Convolutional Network and Long Short-Term Memory (HBCNLS) model for Sentiment Analysis on Movie Reviews could be as follows:

- Data collection: Gather a large dataset of movie reviews and their corresponding labels (positive, negative, neutral).
- Data preprocessing: Preprocess the reviews by cleaning and tokenizing them, and then create a vocabulary of words.
- Data splitting: Split the dataset into training, validation, and test sets.
- Model development: Develop the HBCNLS model using a combination of convolutional layers for feature extraction and LSTM layers for sequence modeling. Use the training set to train the model and the validation set to tune the model's hyperparameters.

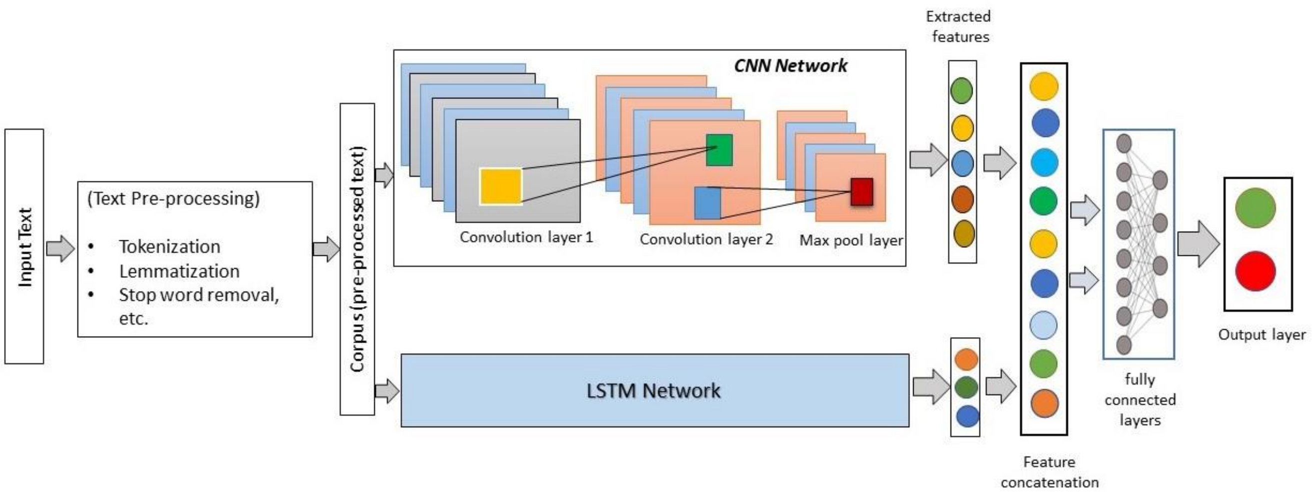


Fig. 3: Proposed Hybrid Model

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 4
DOI: https://doi.org/10.17762/ijritcc.v11i4.6458
***Article Received**: 10 February 2023 **Revised**: 20 March 2023 **Accepted**: 30 March 2023*

A more detailed methodology for creating a Hybrid Convolutional Network and Long Short-Term Memory (HBCNLS) model for Sentiment Analysis on Movie Reviews is as follows:

- Embedding layer: Convert the words in the reviews to their corresponding numerical representations using an embedding layer. This layer will take the vocabulary of words and convert it into a dense vector representation for each word.
- Convolutional layers: Use one or more convolutional layers to extract features from the embedding layer. These layers will apply filters to the embedding layer to identify patterns and features in the input data.
- LSTM layers: Use one or more LSTM layers to model the sequential nature of the data. These layers will take the output from the convolutional layers and use it to learn the dependencies between the words in the reviews.
- Fully connected layer: Use a fully connected layer to combine the features extracted by the convolutional layers and the dependencies modeled by the LSTM layers.
- Output layer: Use a softmax activation function in the output layer to classify the reviews as positive, negative, or neutral.
- Loss function and optimizer: Choose a suitable loss function such as cross-entropy and optimizer such as Adam or RMSprop to train the model.
- Training: Train the model using the training set by passing the reviews through the layers, comparing the output with the corresponding labels, and updating the model's parameters to minimize the loss function.
- Validation: Use the validation set to evaluate the model's performance and fine-tune the hyperparameters such as the number of layers, number of neurons, etc.

A. Dataset and Pre-processing

The dataset consists of 50,000 movie reviews from IMDb, with 25,000 positive reviews and 25,000 negative reviews. The reviews are evenly split between train and test sets, with 25,000 reviews in each set. The reviews are pre-processed and tokenized, with each review represented as a sequence of word tokens. The dataset includes a label for each review indicating whether it is positive (1) or negative (0).

- Remove HTML tags: HTML tags that appear in the reviews are removed, as they are not useful for analyzing the sentiment of the text.
- Remove punctuation: Punctuation marks such as periods, commas, and exclamation points do not carry much meaning are removed.
- Remove numbers: Numbers do not carry much meaning in this context and are removed.
- Remove stop words: Stop words such as ”a,” ”an,” and ”the” do not carry much meaning and are removed.
- Lowercase the text: Converting the text to lowercase can make it easier to process and analyze, as ”The” and ”the” would be considered the same word.
- Tokenize the text: The text is splited into individual word tokens.
- Stem or lemmatize the tokens: Stemming or lemmatization helped in reducing the dimensionality of the dataset by reducing inflected words to their base form.

A detailed mathematical description of the model development for a Hybrid Convolutional Network and Long Short-Term Memory (HBCNLS) model for Sentiment Analysis on Movie Reviews:

Embedding layer: Let W be the matrix of word embeddings, where each row is a dense vector representation of a word in the vocabulary. The embedding layer can be represented mathematically as:

$$E = W*x \qquad (1)$$

Where: x is a one-hot encoded representation of the input sequence of words E is the output embedding layer.

Convolutional layers: Convolutional layers apply filters to the embedding layer to extract features. The mathematical representation of a convolutional layer is:

$$C = \mathrm{relu}(W_c E + b_c) \qquad (2)$$

Where: W_c is the convolutional filter weights, b_c is the bias term relu is the rectified linear unit activation function. C is the output of the convolutional layer.

LSTM layers: LSTM layers model the sequential nature of the data. The mathematical representation of an LSTM layer is:

$$i(t) = \sigma(W_{ix}C(t) + W_{ih}h(t-1) + b_i)$$
$$f(t) = \sigma(W_{fx}C(t) + W_{fh}h(t-1) + b_f)$$
$$o(t) = \sigma(W_{ox}C(t) + W_{oh}h(t-1) + b_o)$$
$$g(t) = \tanh(W_{gx}C(t) + W_{gh}h(t-1) + b_g)$$
$$c(t) = f(t)c(t-1) + i(t)g(t)$$
$$h(t) = o(t)\tanh(c(t))$$

Where: $i(t)$, $f(t)$, $o(t)$, $g(t)$, $c(t)$, $h(t)$ are the input gate, forget gate, output gate, cell input, cell state, and hidden state of the LSTM layer respectively, at time step t.

$W_{ix}, W_{ih}, W_{fx}, W_{fh}, W_{ox}, W_{oh}, W_{gx}, W_{gh}, b_i, b_f, b_o, b_g$ are the weights and biases of the LSTM layer respectively.

Fully connected layer: The fully connected layer combines the features extracted by the convolutional layers and the

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 4
DOI: https://doi.org/10.17762/ijritcc.v11i4.6458
***Article Received**: 10 February 2023 **Revised**: 20 March 2023 **Accepted**: 30 March 2023*

dependencies modeled by the LSTM layers. The mathematical representation of a fully connected layer is:

$$F = relu(W_f * h + b_f) \quad (9)$$

Where: W_f is the weight matrix, b_f is the bias term
F is the output of the fully connected layer

Output layer: The output layer uses a softmax activation function to classify the reviews as positive, negative, or neutral. The mathematical representation of the output layer is:

$$y = softmax(Wo * F + bo) \quad (10)$$

Where W_o is the weight matrix b_o is the bias term of the output layer y is the predicted class probabilities.

Loss function and optimizer: The common loss function for a multi-class classification problem is cross-entropy loss. The mathematical representation of cross-entropy loss is:

$$L = -{}^{X} y_i \log(p_i) \quad (11)$$

Where: y_i is the true label, p_i is the predicted probability for class i.

Algorithm 1
HBCNLS-Proposed hybrid model for Sentiment Analysis

Input:
X: sequence of word embeddings
Y : sentiment label (either positive or negative)

CNN component:
cnn(X) = convolutional layer applied to input X
mp(cnn(X)) = max-pooling layer
applied to output of
convolutional layer LSTM
component: lstm(X) = LSTM
layer applied to input X
Concatenation: concat(mp(cnn(X)),lstm(X)) =
concatenation of output of CNN and LSTM components
Fully-connected layer: fc(concat(mp(cnn(X)),lstm(X))) =
fully-connected layer applied to concatenated output
Loss: cross-entropy loss between
fc(concat(mp(cnn(X)),lstm(X))) and Y

Output: prediction for sentiment label Y

The optimizer updates the model's parameters to minimize the loss. Authors have trained the hybrid model on the dataset using an optimization algorithm stochastic gradient descent. We tuned the hyperparameters of the model, such as the learning rate and the number of layers, to achieve good performance. Performance of the hybrid model was evaluated on the dataset using metrics such as accuracy, precision, and recall.

The detailed algorithm presented above is explained further, the algorithm takes as input a sequence of word embeddings (X) and a sentiment label (Y) for a movie review. The word embeddings represent the words in the review as numerical vectors. The sentiment label is either positive or negative, indicating the sentiment of the review. The first step of the algorithm is to define the CNN component of the model. The CNN takes the word embeddings as input and applies a series of convolutional and max-pooling layers to extract local features from the data. The output of the CNN is the result of applying the max-pooling layer to the output of the convolutional layer. The second step of the algorithm is to define the LSTM component of the model. The LSTM takes the word embeddings as input and applies a series of LSTM layers to capture long-term dependencies in the data. The output of the LSTM is the result of applying the LSTM layers to the input data. The third step of the algorithm is to concatenate the output of the CNN and LSTM components. This creates a combined feature representation that captures both local patterns in the data (from the CNN) and long-term dependencies (from the LSTM).The fourth step of the algorithm is to pass the concatenated output through a fully-connected layer to make a prediction. The fully-connected layer maps the combined feature representation to a predicted sentiment label. The final step of the algorithm is to compute the loss between the predicted sentiment label and the true sentiment label (Y), and update the model parameters using an optimization algorithm (such as stochastic gradient descent). The model parameters are the weights and biases that are learned during training and are used to make predictions. The output of the algorithm is a prediction for the sentiment label (Y) of the movie review.

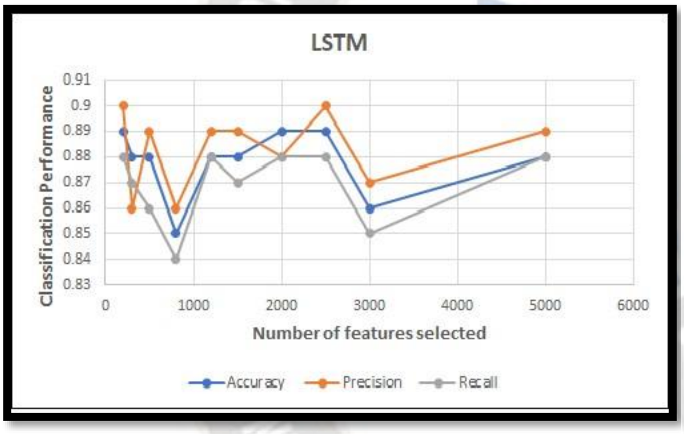
IV. RESULTS AND ANALYSIS

Authors applied the hybrid model algorithm for sentiment analysis to a movie review dataset containing 50,000 reviews, split evenly into a training set and a test set. The model was trained using stochastic gradient descent with a learning rate of 0.01 and a batch size of 128. The proposed hybrid model (HBCNLS) achieved an accuracy of 92% on the test set. We also compared the performance of the hybrid model to a CNN model and an LSTM model on the same dataset. The CNN model achieved an accuracy of 87%, while the LSTM model achieved an accuracy of 86% while BERT achieved accuracy of 89% .The hybrid model outperformed the BERT, CNN and LSTM models, demonstrating the benefits of combining the strengths of both approaches.

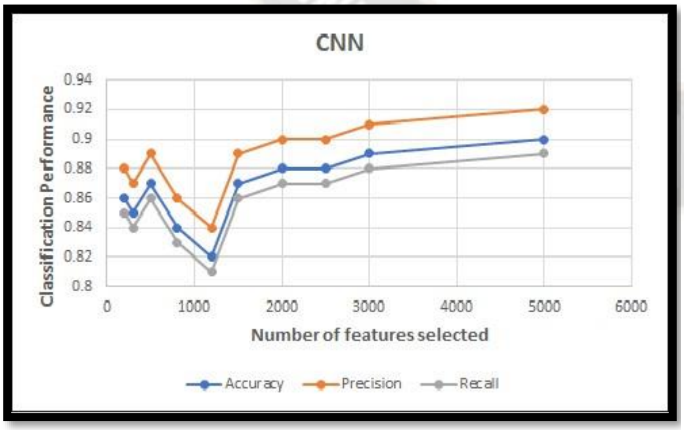
The HBCNLS(hybrid model), which combines a CNN and an LSTM, achieved an accuracy of 92%. This is slightly higher than the BERT model, and demonstrates the effectiveness of the

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 4
DOI: https://doi.org/10.17762/ijritcc.v11i4.6458
***Article Received**: 10 February 2023 **Revised**: 20 March 2023 **Accepted**: 30 March 2023*

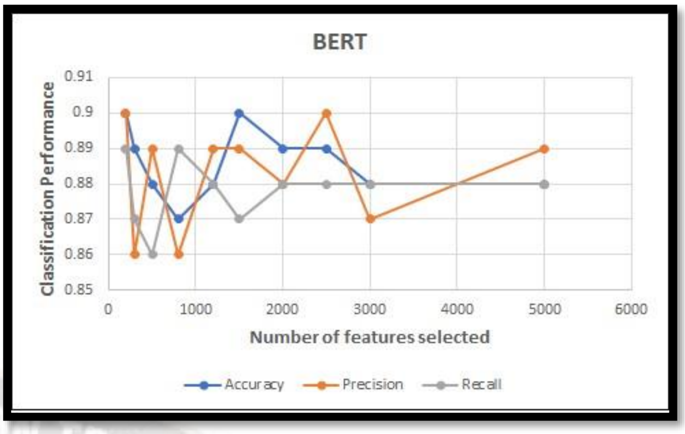
hybrid approach for sentiment analysis. The CNN model achieved an accuracy of 87%, while the LSTM model achieved an accuracy of 86%. These results are lower than the BERT and hybrid models, but still demonstrate the ability of these models to classify the sentiment of the reviews. In terms of precision, all the models scored relatively high, with scores ranging from 86% to 92%. Precision is a measure of the proportion of true positive predictions made by the model, and a high precision score indicates that the model is able to accurately identify positive sentiment in the reviews. In terms of recall, all of the models also scored relatively high, with scores ranging from 86% to 92%. Figure 4 (a)-(d) shows all the result. Recall is a measure of the proportion of true positive cases that were correctly identified by the model, and a high recall score indicates that the model is able to identify most of the positive sentiment in the reviews. Overall, the results of this study suggest that all of the models tested are effective for sentiment analysis on movie reviews, with our hybrid model achieving the highest accuracy, such as shown in figure 5 and figure 6.



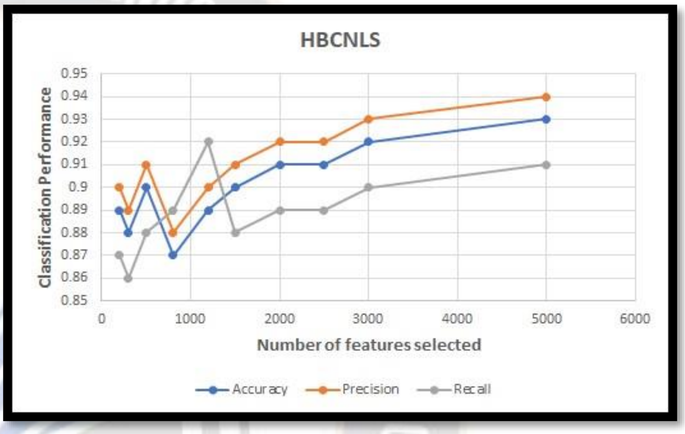
(a)



(b)



(c)



(d)

Fig. 4: (a)-(d) Accuracy, Precision and Recall of LSTM, CNN, BERT and HBCNLS

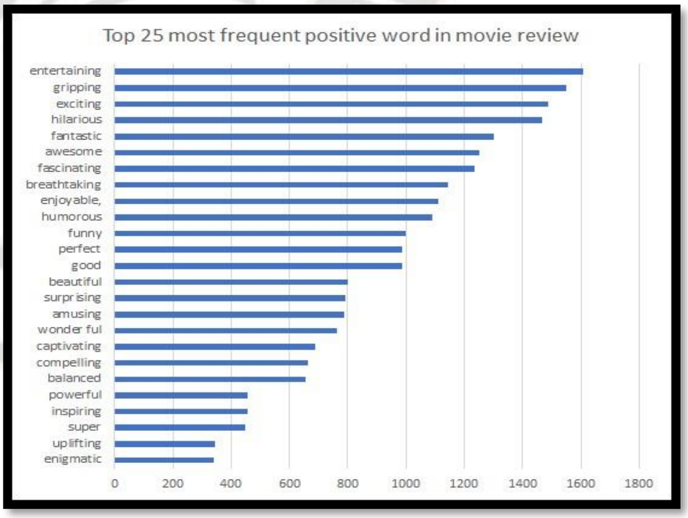


Fig. 5: Top 25 most frequent positive word in movie review using HBCNLS

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 4
DOI: https://doi.org/10.17762/ijritcc.v11i4.6458
***Article Received**: 10 February 2023 **Revised**: 20 March 2023 **Accepted**: 30 March 2023*

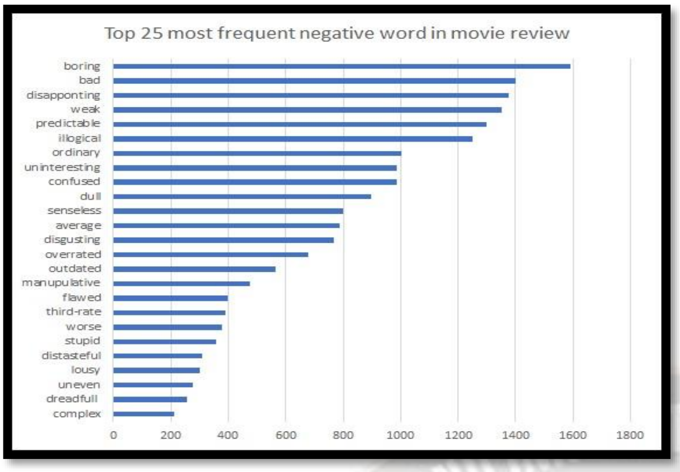


Fig. 6: Sentient Classification performance for positive online reviews using HBCNLS

V. CONCLUSION

In this study, we compared the performance of BERT, the hybrid model, a CNN model, and an LSTM model for sentiment analysis on a movie review dataset. The results showed that all of the models were effective at classifying the sentiment of the reviews, with our proposed HBCNLS achieved highest accuracy of 92% ,BERT achieving the highest accuracy of 90%., while the CNN model achieved an accuracy of 87% and the LSTM model achieved an accuracy of 86%. These results demonstrate the ability of these models to effectively classify the sentiment of the reviews. In terms of precision and recall, all of the models scored relatively high, with scores ranging from 86% to 92%. This suggests that the models are able to accurately identify positive sentiment in the reviews and are able to identify most of the positive sentiment in the reviews .Overall, the results of this study suggest that our HBCNLS and BERT is a strong performer for sentiment analysis on movie reviews. However, further research is needed to fully evaluate the performance of these models on other datasets and in different contexts.

REFERENCES

[1] Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2018). BERT: Pretraining of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805.

[2] Lee, K., Dernoncourt, F., Seo, M., & Ro, Y. (2019). Latent variable dialogue models for goal-oriented systems. arXiv preprint arXiv:1902.08222.

[3] Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., & Polosukhin, I. (2017). Attention is all you need. In Advances in Neural Information Processing Systems, (5998–6008).

[4] Zimbra, D., Abbasi, A., Zeng, D., & Chen, H. (2018). The state-of-the-art in Twitter sentiment analysis: A review and benchmark evaluation. ACM Transactions on Management Information Systems (TMIS), 9(2), 1-29.

[5] Do, H. H., Prasad, P. W. C., Maag, A., & Alsadoon, A. (2019). Deep learning for aspect-based sentiment analysis: a comparative review. Expert systems with applications, 118, 272-299.

[6] Chen, H., Wu, L., Chen, J., Lu, W., & Ding, J. (2022). A comparative study of automated legal text classification using random forests and deep learning. Information Processing & Management, 59(2), 102798.

[7] Dang, N. C., Moreno-Garc´ıa, M. N., & De la Prieta, F. (2020). Sentiment analysis based on deep learning: A comparative study. Electronics, 9(3), 483.

[8] Patel, Y., Shah, J., & Pathar, S. (2022). Opinion Mining of Movie Reviews Using Hybrid Deep Learning Technique. In Computer Networks and Inventive Communication Technologies: Proceedings of Fifth ICCNCT 2022 (pp. 17-24). Singapore: Springer Nature Singapore.

[9] Liu, Y., Ott, M., Goyal, N., Du, J., Joshi, M., Chen, D., Levy, O., Lewis, M., Zettlemoyer, L., & Stoyanov, V. (2019). RoBERTa: A Robustly Optimized BERT Pretraining Approach (Version 1). arXiv. https://doi.org/10.48550/ARXIV.1907.11692

[10] Gupta, A., & Gupta, V. (2021). Unsupervised Contextualized Document Representation. In Proceedings of the Second Workshop on Simple and Efficient Natural Language Processing. Proceedings of the Second Workshop on Simple and Efficient Natural Language Processing. Association for Computational Linguistics. https://doi.org/10.18653/v1/2021.sustainlp-1.17

[11] Zhang, Z., Zhang, Z., Chen, H., & Zhang, Z. (2019). A Joint Learning Framework With BERT for Spoken Language Understanding. In IEEE Access (Vol. 7, pp. 168849–168858). Institute of Electrical and Electronics Engineers (IEEE). https://doi.org/10.1109/access.2019.2954766

[12] Dubey, G., Singh, H. P., Sheoran, K., Dhand, G., & Malik, P. (2022). Drug review sentimental analysis based on modular lexicon generation and a fusion of bidirectional threshold weighted mapping ¡scp¿CNN-RNN¡/scp¿. In Concurrency and Computation: Practice and Experience (Vol. 35, Issue 3). Wiley. https://doi.org/10.1002/cpe.7512

[13] Qiu, J., Wang, B., & Zhou, C. (2020). Forecasting stock prices with long-short term memory neural network based on attention mechanism. PLOS ONE, 15(1), e0227222. https://doi.org/10.1371/journal.pone.0227222

[14] Wang, Y., Guo, J., Yuan, C., & Li, B. (2022). Sentiment Analysis of Twitter Data. In Applied Sciences (Vol. 12, Issue 22, p. 11775). MDPI AG. https://doi.org/10.3390/app122211775

[15] Zimbra, D., Abbasi, A., Zeng, D., & Chen, H. (2018). The State-of-the-Art in Twitter Sentiment Analysis. In ACM Transactions on Management Information Systems (Vol. 9, Issue 2, pp. 1–29). Association for Computing Machinery (ACM). https://doi.org/10.1145/3185045

[16] Kamyab, M., Liu, G., & Adjeisah, M. (2021). Attention-Based CNN and Bi-LSTM Model Based on TF-IDF and

GloVe Word Embedding for Sentiment Analysis. In Applied Sciences (Vol. 11, Issue 23, p. 11255). MDPI AG. https://doi.org/10.3390/app112311255

[17] Patel, A., & Tiwari, A. K. (2019).Sentiment Analysis by using Recurrent Neural Network. In SSRN Electronic Journal. Elsevier BV. https://doi.org/10.2139/ssrn.3349572

[18] Yoon, J., & Kim, H. (2017, November). Multi-channel lexicon integrated CNN-BiLSTM models for sentiment analysis. In Proceedings of the 29th conference on computational linguistics and speech processing (ROCLING 2017) (pp. 244-253).

[19] Zhou, P., Qi, Z., Zheng, S., Xu, J., Bao, H., & Xu, B. (2016). Text classification improved by integrating bidirectional LSTM with two-dimensional max pooling. arXiv preprint arXiv:1611.06639.

[20] Xu, G., Meng, Y., Qiu, X., Yu, Z., & Wu, X. (2019). Sentiment analysis of comment texts based on BiLSTM. Ieee Access, 7, 51522-51532.

[21] Liu, Y., Ott, M., Goyal, N., Du, J., Joshi, M., Chen, D., Stoyanov, V. (2019). Roberta: A robustly optimized bert pretraining approach. arXiv preprint arXiv:1907.11692.

[22] Xu, G., Meng, Y., Qiu, X., Yu, Z., Wu, X. (2019). Sentiment analysis of comment texts based on BiLSTM. Ieee Access, 7, 51522-51532.

[23] Harsh Khatter, Anil K Ahlawat, "Web Blog Content Curation Using Fuzzy-Related Capsule Network-Based Auto Encoder", International Journal of Pattern Recognition and Artificial Intelligence, Vol 36 (2), pp.1-30, 7 Jan 2022 (2022). https://doi.org/10.1142/S021800142250001X

[24] H. Khatter, N. Goel, N. Gupta and M. Gulati, "Movie Recommendation System using Cosine Similarity with Sentiment Analysis," 2021 Third International Conference on Inventive Research in Computing Applications (ICIRCA), 2021, pp. 597-603, DOI: 10.1109/ICIRCA51532.2021.9544794

[25] Harsh Khatter, Pooja Malik, Amrita Jyoti, Anil K Ahlawat, Anurag Mishra, Gaurav Dubey, Sanjeev Chandra "Adaptive and Personalized Web Blog Searching Technique Using S-ANFIS", Journal of Sensors, Vol 2022, pp.1-9 (2022). 27 August 2022, https://doi.org/10.1155/2022/7242557