ZKG INTERNATIONAL

ISSN: 2366-1313

AN APPLICATION (SYSTEM) FOR DETECTION OF IMPLICIT SENTIMENT ANALYSIS USING DEEP LEARNING TECHNIQUES

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ABSTRACT:

In an era increasingly dominated by digital commerce, the analysis of customer sentiment expressed in product reviews holds pivotal importance for businesses seeking to understand consumer preferences and enhance user experiences. Implicit sentiment analysis, a task aimed at discerning sentiment polarity without explicit cues, presents a significant challenge in natural language processing. This study addresses the imperative need for efficient implicit sentiment analysis methods by proposing a comprehensive approach that integrates advanced pre-processing techniques and a bidirectional Long Short-Term Memory (Bi-LSTM) neural network architecture. Leveraging a dataset comprising diverse product reviews, including best-selling books, the study meticulously examines the efficacy of various pre-processing steps such as tokenization and padding in enhancing sentiment classification accuracy. Furthermore, it evaluates the performance of the Bi-LSTM model, considering a range of metrics including accuracy, precision, recall, and F1-score, offering comprehensive insights into the model's classification capabilities. The findings highlight the effectiveness of the proposed pre-processing methods and the Bi-LSTM architecture in accurately capturing implicit sentiment cues in product reviews, thereby contributing to advancements in sentiment analysis research and offering valuable implications for businesses aiming to leverage customer feedback for informed decision-making.

Keywords: Bidirectional Long Short-Term Memory (Bi-LSTM), Natural language processing.

I INTRODUCTION

In today's digital era, online platforms have not only transformed the shopping experience but have also fundamentally altered how consumers make purchasing decisions. With an extensive range of products readily available, consumers often turn to reviews as a guiding force in their buying journey. However, navigating through these reviews presents its challenges, as they encompass not only feedback on the products themselves but also on the services provided by the manufacturers.

Amidst this backdrop, sentiment analysis has emerged as an indispensable tool for businesses aiming to extract valuable insights from the vast troves of unstructured data generated across social media platforms. While traditional machine learning and natural language processing methods have laid the groundwork for sentiment analysis, the ascendancy of deep learning methodologies has captured widespread attention owing to their unparalleled performance in handling complex textual data.

In light of this paradigm shift, our thesis endeavours to contribute to the burgeoning field of sentiment analysis by delving into the application of sophisticated deep learning models. Leveraging a comprehensive deep learning architecture such as the Long Short-Term Memory (LSTM) framework, we aim to dissect its intricacies, elucidate its key features, and assess its performance metrics in the context of sentiment analysis. By immersing ourselves in the realm of deep learning, we aspire to furnish businesses with the requisite tools and insights essential for navigating the dynamic landscape of sentiment analysis in the digital age.

Our approach goes beyond mere exploration; it is a concerted effort to bridge the gap between theoretical advancements and practical applications. By harnessing the capabilities of deep learning, we aspire to empower businesses with actionable insights gleaned from the intricate nuances of sentiment expressed across diverse textual data sources. Through meticulous experimentation and rigorous analysis, we seek to unlock the transformative potential of deep learning in deciphering sentiments, thereby facilitating informed decision-making and strategic manoeuvring in the ever-evolving digital marketplace.

ISSN: 2366-1313

In essence, our thesis serves as a beacon illuminating the path toward leveraging cutting-edge technologies to unravel the intricacies of sentiment analysis. As we embark on this intellectual journey, we remain steadfast in our commitment to unravelling the complexities of sentiment analysis and equipping businesses with the tools necessary to thrive in an era defined by data-driven insights and informed decision-making.

II. LITERATURE SURVEY

Sentiment analyses are done with the help of the machine learning algorithms to classify the textual data detecting the polarity of the reviews about online products (amazon, IMBD, and any other dataset) using either machine learning methods or deep learning methods or in some cases integrating them. In the field of the sentiment analysis using the machine learning algorithms, the researchers in focused on increasing the accuracy of the review classification. They used the unigram and weighted unigram techniques. The definitions are a unigram is one word, a bigram is a sequence of two words, a trigram is a sequence of three words, and so forth. This was done to train the machine with the help of the classifiers and the applied algorithms such as maximum entropy (ME), naïve bias (NB), and support vector machine (SVM). ME classifiers are under the class of exponential models and are categorised as a probabilistic classifier. ME does not take into consideration the independent elements of each other. It is mainly used to work out large quantities of text classification problems and is widely used in the sentiment analysis. However, NB method is a technique for the constructing classifiers for models that designates a class label to the problem examples. They are represented in a vector form varying on the features of the value being characterised, where these labels come from the finite sets. NB is not a standard algorithm but it depends on the used principles. The value of a feature does not relate to the value of another feature making them independent, given the class variable. On the other hand, SVM algorithms are mostly used for classification problems; however, sometimes it could be used in the regression as well. In this algorithm, each feature of the data is plotted in n-dimensional space; the more features present more dimensions. The plot would have with the value of each feature corresponding to a specific coordinate. The classification is performed with finding the hyper plane that distinguishes between the two classes. On the other hand, utilised the technique of “ensemble” machine learning algorithm that combines the predictions from the output of the classifiers NB and SVM together to produce more accurate predictions compared to an individual model. Dealing with the issue of performance, speed execution and accuracy created a better accurate system in contrast with the old systems.

On the other hand, in the field of sentiment analysis using deep learning approaches, a dataset consisting of 10,662 records was used to produce the sentiment analysis from IMDb dataset. This method combined the deep learning and the unsupervised machine learning which in return gave better results and a better analysis with respect to other existing methods. The deep learning aspect used a Convolutional Neural Network (CNN) classifier, on the other hand, the machine learning aspect of the analysis used the K-mean method, which falls under the category of the unsupervised learning. CNN was used to train and to learn from the data, and after the feature extraction, the K-mean clustering algorithm was used to categorize the reviews into the positive or negative clusters. The results showed that the accuracy was acceptable with a low error rate. It was also shown in the research that K-mean algorithm is more effective for the larger datasets. Paper suggested a method to perform a sentiment analysis and to mine customers’ reviews from the large datasets of 400,000 reviews. The research involved two parts; first, word2vec was used to convert reviews into another form as vector representation finding similar features for different aspects, and then a technique called common bag of words (CBOW) along with skip-gram was used to integrate with different machine learning techniques, that is, SVM, NB, logistic regression, and “Random Forest” utilising 10-fold cross validation. The results demonstrated that CBOW along with “Random Forest” (with word2vec representation) gave the most superior results; thus, CBOW performed better than the skip-gram. The result showed only the results of the unbalanced dataset because the classification accuracy for the balanced dataset was unacceptably lower than the unbalanced dataset. However, the best accuracy was “Random Forest” with CBOW equal to 90.6622%. In another analysis [3], the dataset of Electronica

ISSN: 2366-1313

Shopping site was used; only reviews in the English language were considered.

III SYSTEM ANALYSIS

EXISTING SYSTEM

In the realm of sentiment analysis for reviews, two main approaches emerge: handcrafted features and machine-learned features. Handcrafted features involve manually incorporating factors to influence sentiment, with lexicon-based methods being a prominent example. These methods assign sentiment scores to words based on predefined lists of positive and negative words. On the other hand, machine-learned features rely on algorithms to automatically classify sentiment, with traditional machine learning techniques like Support Vector Machine (SVM), Naive Bayes (NB), Random Forest, and Decision Tree being widely employed. These algorithms are trained on labelled datasets to classify sentiment efficiently. Deep learning, a subset of machine learning, employs complex neural networks to identify patterns in text data. Notable examples include Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Deep Belief Networks (DBN), Attention Mechanism, Bidirectional Recurrent Neural Networks (BIRNN), and Capsule Networks. While handcrafted features offer interpretability and transparency, machine-learned features often provide superior performance, especially with the advent of deep learning techniques, which excel at capturing intricate patterns in textual data. Consequently, the choice between these approaches depends on the specific requirements and constraints of sentiment analysis tasks.

Limitations of Existing system

- **Limited Vocabulary Coverage:** Lexicon-based approaches rely on predefined lists of positive and negative words. These lists may not encompass the entirety of language nuances, resulting in limited coverage of vocabulary. Consequently, sentiments expressed through nuanced or domain-specific language may be overlooked.
- **Inability to Capture Context:** Lexicon-based methods do not consider the context in which words are used. A word's sentiment may vary depending on

ISSN: 2366-1313

the context of the sentence or document. For example, the word "sick" may convey a positive sentiment in slang contexts but a negative sentiment in a healthcare context.

- **Difficulty Handling Negation and Modifiers:** Lexicon-based approaches struggle to handle negations and modifiers effectively. For instance, phrases like "not bad" or "very good" may alter the sentiment of individual words, but lexicons may not account for such nuances.

PROPOSED SYSTEM

Deep learning, a subset of machine learning, employs advanced neural network techniques like CNN, RNN, GRU, DBN, Attention Mechanism, BiRNN, and Capsule Networks for sentiment analysis. Despite their power, these methods face challenges such as the need for large amounts of labeled data, which can be difficult to gather, especially in niche areas. Over fitting is also a significant concern with small datasets, impacting the model's ability to generalize well to new data. Additionally, the high computational demands of deep learning models can limit their scalability

Long Short-Term Memory (LSTM) networks. Specialized form of RNN, address some Of these issues With their unique architecture, which includes memory cells and gating mechanisms that effectively capture long-range dependencies and sequential patterns. This design enhances their ability to handle sequential data more efficiently, reducing the risk associated with over fitting and lowering the computational load compared to other deep learning models.

Proposed system Advantages:

- Long Short-Term Memory networks are highly effective for sentiment analysis in natural language processing (NLP) due to their ability to handle long-term dependencies in text. Their architecture allows them to retain and forget information selectively; capturing both local and global contextual clues, which is crucial for understanding the sequential nature of language and the temporal relationships between words and phrases.
- Additionally LSTMs are robust to noisy data, such as misspellings and slang, and

excel in feature extraction and representation learning. This capability reduces the need for manual feature engineering. Leading to more accurate sentiment analysis outcomes and making LSTMs a powerful tool for interpreting sentiments in text.

IV IMPLEMENTATION

Architecture:

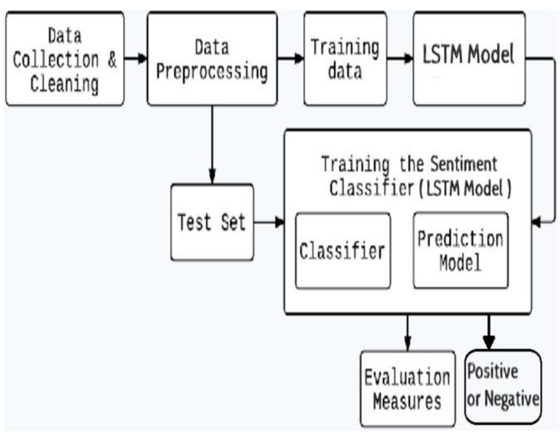

Fig-1. Architectures of the system model

- **Dataset:** The dataset utilized in this research comprises 400,000 sentences extracted from Amazon customer reviews, with a test split of 10%. These reviews, sourced from Xiang Zhang's Google Drive directory, are annotated with star ratings to facilitate sentiment analysis. Structured in compliance with the supervised learning format, each sentence is associated with a single class label, either __label__1 or __label__2, corresponding to negative (1- and 2-star) and positive (4- and 5-star) sentiments, respectively. Notably, the dataset excludes reviews with neutral sentiment, focusing solely on polarized opinions. While predominantly in English, the dataset includes a subset of reviews in other languages like Spanish, adding linguistic diversity. This dataset's substantial size and balanced class distribution make it suitable for training deep learning models to perform sentiment analysis on product reviews.

- **Pre-processing:** In the pre-processing phase of the study, the initial step involved reading the dataset, which consists of 400,000 sentences extracted from Amazon customer reviews, with a 10% split reserved for testing. Following data acquisition, text cleaning procedures were applied to enhance data quality and consistency, including the removal of special characters, punctuation, and stop words, thereby preparing the text for analysis. Visual exploration of the cleaned text was facilitated through the generation of a word cloud, offering insights into the frequency distribution of words across the corpus. Subsequently, the text underwent tokenization, breaking it down into

ISSN: 2366-1313

individual words or tokens, followed by padding sequences to ensure uniform length, preparing the data for input into the LSTM model. Finally, the pre-processed dataset was divided into training and testing sets, enabling model evaluation and validation. These pre-processing steps collectively laid the foundation for robust sentiment analysis of product reviews using deep learning techniques.

Text Cleaning:

In the realm of sentiment analysis for Amazon reviews using LSTM, text cleaning emerges as a critical pre-processing step, wielding significant influence over the quality and interpretability of the textual data. Beyond the rudimentary elimination of non-alphanumeric characters, special symbols, punctuation marks, and extraneous whitespace, a comprehensive approach to text cleaning is paramount for extracting meaningful insights from the reviews.

LSTM:

The described sentiment analysis model starts with a Tokenizer layer that Converts input Sequences into 64-dimensiotial vectors. It then processes these sequences through two ISTM layers, the first with 64 units and the second with 32 units, capturing sequential dependencies. A Spatial Dropout1D layer with a dropout rate of 0.2 followed prevent over fitting. Dense layers With ReLU activation functions refine the features, culminating in final Dense layer.

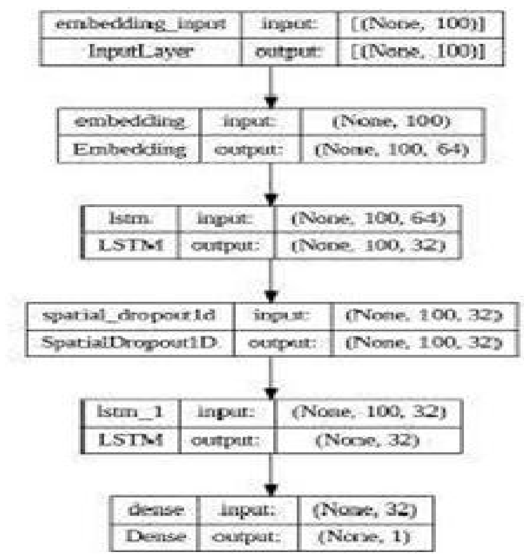

Fig.2. Proposed Model Architecture

With a sigmoid activation for binary classification. The model, with 377,985 trainable parameters, is compact and efficient, suitable for deployment on various platforms, including mobile and edge devices, due to its moderate complexity and lack or non-trainable parameters.

- **Tokenizer Layer:** Tokenization is essential for LSTM-based sentiment analysis Of Amazon reviews, converting text into

ISSN: 2366-1313

tokens that capture key linguistic elements. It simplifies feature extraction, Stop words, and Creates vocabulary index for numerical data conversion, crucial for model training. The Tokenizer layer then transforms these tokens into dense vectors, standardizing input sequences. This process enables LSTM models to effectively analyze sentiment, providing valuable insights for businesses and consumers.

- **LSTM Layer (1st):** The first LSTM layer processes embedded sequences recurrently, capturing sequential dependencies in the data with 64 LSTM units or memory cells. The parameter return sequences=True ensures that this layer outputs the full sequence for each time step, rather than just the final output.
- **Spatial Dropout1D Layer:** Spatial Dropout ID, tailored for 1D sequence data like text, drops 20% of input units during training to prevent over fitting. This dropout rate, set at 0.2, randomly disables features, enhancing the model's generalization.
- **LSTM Layer (2nd):** The second LSTM layer processes sequential information from the previous layer with 32 units. Unlike the first layer, it does not use return sequences, returning only the last output of the Sequence.
- **Dense Layers**: Dense layers are fully connected layers that handle the final classification or regression task. The first Dense has 128 units With ReLU activation, adding non-linearity to the model, while the second Dense layer has 64 units with RcLU activation, further relining the features from the previous layer.

Summary of the Bi-Directional LSTM Model Architecture:

```
Model: "sequential_1"
_________________________________________________
Layer (type) Output Shape Param #
=================================================
embedding_1 (Embedding) (None, 100, 64) 320000
lstm_2 (LSTM) (None, 100, 64) 33024
spatial_dropout1d_1 (None, 100, 64) 0
(SpatialDropout1D)
lstm_3 (LSTM) (None, 32)     12416
dense_1 (Dense) (None, 128)    4224
dense_2 (Dense) (None, 64)      8256
dense_3 (Dense) (None, 1)       65
=================================================
Total params: 377985 (1.44 MB)
Trainable params: 377985 (1.44 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________
```

Fig.3. Model Summary

The model size and parameters provide valuable insights into the complexity and requirements of the sentiment analysis model developed in this study. With a total of 377,985 pararneters, equivalent to approximately 1.44 megabytes in size the model demonstrates a moderate level of

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complexity. These parameters are trainable, indicating that they can be adjusted during the training process to optimize model parameters. The absence of non-trainable parameters suggests that the model does not incorporate any fixed features or pre-trained embeddings relying solely on the information learned from the training data. Overall, the modest size of the model and its trainable parameters make it computationally efficient and suitable for deployment in various computing environments, including resource-constrained platforms such as mobile devices or edge devices.

V RESULT AND DISCUSSION

Random Forest

The random forest model for sentiment analysis Of Amazon reviews shows significant limitations, with a modest accuracy of 53.43%. Despite a high training accuracy of 91.73%, the model's testing accuracy is only 53.43% indicating overfitting. Cross-validation results align with the testing accuracy, further supporting this finding. The classification report shows balanced but suboptimal performance, with precision, recall, and F1-scores of for both positive and negative sentiments. The confusion matrix and average F1-scores also reflect the model's struggle to accurately capture sentiment, suggesting it does not effectively handle class imbalances or generalize well. These results highlight the model's in- adequacy for real-world sentiment analysis tasks, indicating a need for more advanced techniques to improve accuracy and reliability.

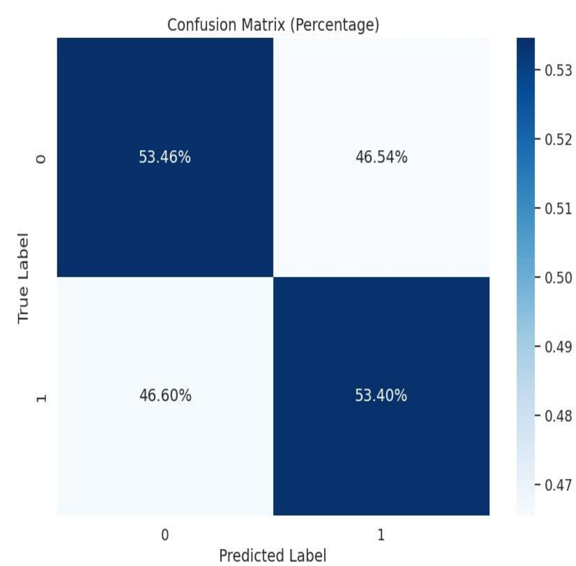

Fig. 4. Confusion Matrix of Random Forest

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Logistic Regression

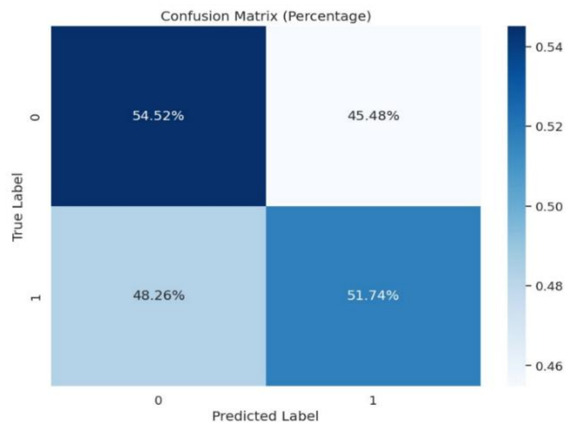

Fig.5. Confusion Matrix of Logistic Regression

The logistic regression model for sentiment analysis of Amazon reviews achieved a training accuracy of 53.13% and a testing accuracy of 53.08%, only slightly better than random chance. This indicates limited predictive capabilities, with precision, recall, and F1 scores low for both positive and negative sentiments, reflecting the model's difficulty in accurately identifying sentiment categories. The confusion matrix shows significant misclassifications, with 55% of positive reviews correctly identified and 53% of positives actually being negative. Overall, the model's performance underscores the need for more advanced techniques, like deep learning, to achieve better accuracy and reliability in sentiment analysis.

Proposed Bi-LSTM

The evaluation of the proposed Bi-LSTM model for sentiment analysis yielded promising results. The model achieved a -training accuracy of 94.09% with a loss Of O. 15 50, and a validation accuracy Of 94.32% With a loss Of O. 1503, indicating strong generalization to unseen data. The classification -report showed a balanced performance with precision, recall, and F1 -scores of for both positive and negative sentiment classes, validating the model robustness and reliability. The confusion matrix revealed I true negatives and 188,921 true positives, with a relatively small number of false positives (12,440) and false negatives (11,079). These metrics underscore the model's efficacy in sentiment analysis tasks and its potential for practical deployed in real-world applications.

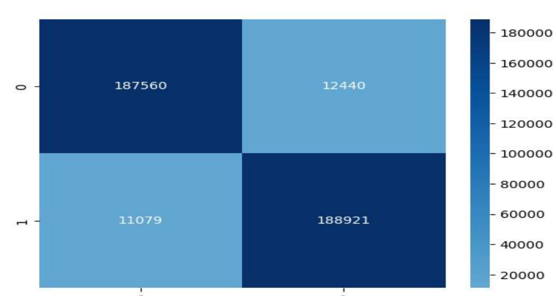

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Fig.6. Confusion Matrix of the Proposed Model

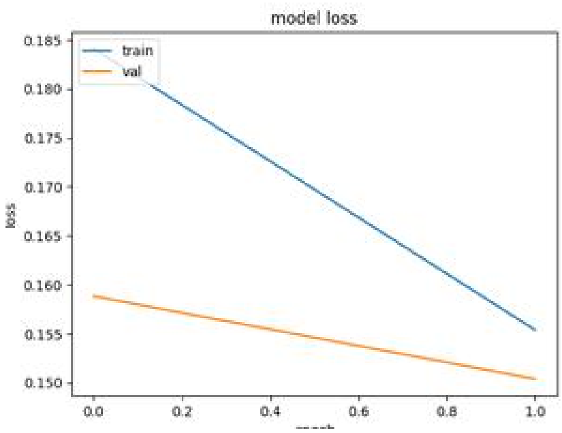

Fig.7. Model train ys validation loss

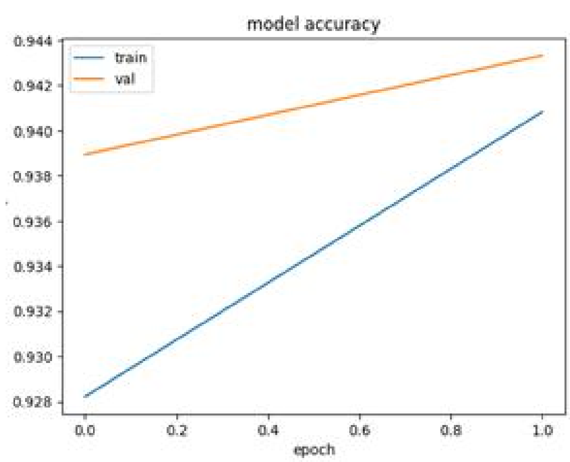

Fig.8. Model train vs validation Accúracy

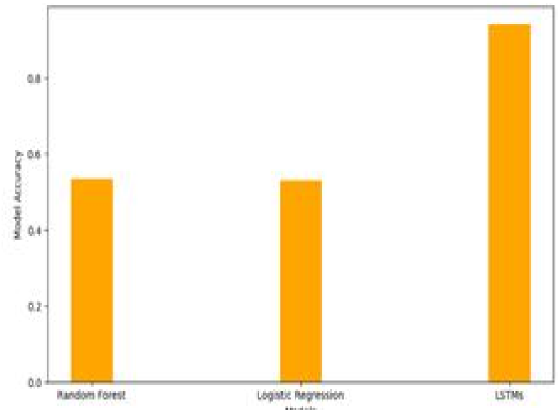

Fig.9. Modal Accuracy Comparison Graph

Table 1: MODEL PERFORMANCE ON AMAZON REVEIWS DATASET

METHOD	ACCURACY
Random Forest	53.43
Logistic Regression	53.07
Proposed Bi-LSTM model	94.32

VI CONCLUSION

In conclusion, this study has demonstrated the effectiveness of deep learning techniques, specifically LSTM-based models, in sentiment analysis of customer reviews. Through meticulous pre-processing, including tokenization and padding, and leveraging Tensor Flow and Keras frameworks, a robust sentiment analysis model was developed and trained on a substantial dataset. The model exhibited

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commendable performance metrics, including high accuracy, precision, recall, and F1-score, indicating its ability to accurately classify sentiment polarity in Amazon reviews. Additionally, the evaluation of the model included comprehensive analyses such as the classification report and confusion matrix, providing detailed insights into its classification behaviour. Overall, the results validate the efficacy of the developed model in accurately discerning sentiment in text data, underscoring its potential for real-world applications in market research, customer feedback analysis, and product recommendation systems. Moving forward, further research can explore enhancements to the model architecture, incorporation of advanced techniques like attention mechanisms, and extension to multilingual sentiment analysis for more comprehensive insights into customer sentiments across diverse linguistic contexts. Density estimation in diverse real-world scenarios.

FUTURE ENHANCEMENTS

1. Multimodal Sentiment Analysis: Integrating additional modalities such as images or videos along with textual data could enhance the depth and accuracy of sentiment analysis. Future research could explore multimodal approaches to sentiment analysis, leveraging advanced techniques like deep learning and attention mechanisms to analyse diverse forms of user-generated content on e-commerce platforms.

2. Fine-grained Sentiment Analysis: While the current study focuses on binary sentiment classification (positive/negative), future research could delve into fine-grained sentiment analysis, which involves distinguishing between multiple sentiments classes (e.g., positive, neutral, negative). This would provide more nuanced insights into customer sentiments and preferences, enabling businesses to tailor their strategies and offerings more effectively.

3. Domain Adaptation and Transfer Learning: Adapting sentiment analysis models to specific domains or transferring knowledge learned from one domain to another could enhance model generalization and performance. Future studies could explore domain adaptation techniques and transfer learning approaches to sentiment analysis, enabling models to better handle domain-specific nuances and variations in language usage across different product categories or markets.

VII REFERENCES

ISSN: 2366-1313

[1] A. S. Rathor, A. Agarwal, and P. Dimri, "Comparative study of machine learning approaches for Amazon reviews," *Procedia Computer Science*, vol. 132, pp. 1552–1561, 2018.

[2] J. Sadhasivam and R. B. Kalivaradhan, "Sentiment analysis of amazon products using ensemble machine learning algorithm," *International Journal of Mathematical, Engineering and Management Sciences*, vol. 4, no. 2, pp. 508–520, 2019.

[3] K. Q. Anh, Y. Nagai, and L. M. Nguyen, "Extracting customer reviews from online shopping and its perspective on product design," *Vietnam Journal of Computer Science*, vol. 6, no. 1, pp. 43–56, 2019.

[4] B. S. Lakshmi, P. S. Raj, and R. R. Vikram, "Sentiment analysis using deep learning technique CNN with KMeans," *International Journal of Pure and Applied Mathematics*, vol. 114, no. 11 2, pp. 47–57, 2017.

[5] B. Bansal and S. Srivastava, "Sentiment classification of online consumer reviews using word vector representations," *Procedia Computer Science*, vol. 132, pp. 1147–1153, 2018.

[6] N. M. Ali, A. El Hamid, M. Mostafa, and A. Youssif, "Sentiment analysis for movies reviews dataset using deep learning models," *International Journal of Data Mining & Knowledge Management Process (IJDKP)*, vol. 9, no. 2/3, 2019.

[7] G. Xu, Y. Meng, X. Qiu, Z. Yu, and X. Wu, "Sentiment analysis of comment texts based on BiLSTM," *IEEE Access*, vol. 7, pp. 51522–51532, 2019.

[8] S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," Neural Computation 9(8), pages 1735-1780, 1997.

[9] H. Sak, A. Senior, F. Beaufays, "Long Short-Term Memory Recurrent Neural Network Architectures for Large Scale Acoustic Modeling," INTERSPEECH 2014, 14-18 September, Singapore, 2014

[10] X. Li, X. Wu (2015). "Constructing Long Short-Term Memory Based Deep Recurrent Neural Networks For Large Vocabulary Speech Recognition," 2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Australia, 2015.

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