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Sentiment Analysis of Modern Literature Using BiLSTM and GloVe Embeddings Using NLP

Arya M R[1], Ramith Yadav S[2], Pelluru Pavan Kumar Reddy[3], Manish Sathvik A Reddy[4], Prof. Bharathi V C[5]
[1, 2, 3, 4]School of Computer Science and Engineering (SCOPE), VIT-AP University
[5]Professor Grade 1, School of Computer Science and Engineering (SCOPE), VIT-AP University

Abstract: Sentiment analysis is a key task in Natural Language Processing (NLP) that involves classifying emotions, opinions, and sentiments from text. Traditional machine learning models such as Naïve Bayes, Support Vector Machines (SVM), and Random Forest have been commonly used for this purpose, but they struggle to capture the complex sequential dependencies within text. This study explores the use of Bi-directional Long Short-Term Memory (BiLSTM) networks, combined with pre-trained GloVe embeddings, for sentiment classification. The performance of the BiLSTM model is compared to traditional models and the transformer- based BERT model to assess its computational efficiency and accuracy. While BERT outperforms BiLSTM in accuracy, the BiLSTM model offers competitive performance with greater computational efficiency. This research lays the groundwork for future improvements in sentiment analysis, particularly in real-time applications and multilingual data processing.
Keywods: Sentiment analysis, Natural Language Processing (NLP), BiLSTM, GloVe embeddings, deep learning, machine learning, text classification, sequential dependencies, BERT, computational efficiency, accuracy, real-time applications, multilingual data.

I. INTRODUCTION

Applications including social media monitoring, consumer feedback, mental health evaluation, and more now depend on sentiment analysis as a fundamental activity. The growing availability of text data has driven the creation of scalable and accurate methods for sentiment and emotional extraction from textual materials. Public opinion assessment, customer satisfaction enhancement, and mental health indicator monitoring all depend on sentiment classification for organizations. More precisely modelling the sequential character of text is made possible by recent developments in deep learning, especially with regard to Recurrent Neural Networks (RNNs), Long Short-Term Memory networks (LSTMs), and more recently, BiLSTM(Bidirectional LSTM). For sentiment analysis projects, long-term dependencies and context are important and these models can help to capture both. Particularly BiLSTM has shown potential in extracting richer features from the data by grasping text from both directions (forward and backwards). This paper investigates the application of BiLSTM networks in sentiment analysis by means of GloVe (Global Vectors for Word Representation) embeddings to reflect words in a continuous vector space. Particularly fit for NLP applications, GloVe embeddings capture semantic meaning and are pre-trained on a big corpus. To identify the most efficient method for sentiment classification, we compare BiLSTM with GloVe embeddings and other conventional machine learning models in this work including Naïve Bayes, Support Vector Machine (SVM), Random Forest, and BERT.

II. LITERATURE REVIEW

Sentiment analysis has become an essential tool in various fields such as social media monitoring, customer feedback analysis, and mental health evaluation. As the volume of textual data grows, the need for accurate and scalable methods to extract sentiments and emotions has increased. Sentiment classification enables organizations to gauge public opinion, enhance customer satisfaction, and monitor mental health trends, making it a valuable tool for businesses and healthcare providers [1], [2]. Recent advancements in Natural Language Processing (NLP) have led to significant improvements in sentiment analysis. While traditional machine learning models like Naïve Bayes, Support Vector Machine (SVM), and Random Forest were previously used, they struggle with capturing complex semantic and contextual relationships in text [3], [4]. Deep learning models, such as Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, have proven to be more effective in handling sequential data and long-term dependencies, improving sentiment prediction accuracy [5], [6].

Among these, Bidirectional LSTM (BiLSTM) has gained popularity due to its ability to process text in both forward and backward directions, enhancing its ability to capture richer context and dependencies. This bidirectional nature makes BiLSTM particularly suitable for tasks like sentiment analysis, where context plays a crucial role [7], [8]. This research explores the use of BiLSTM networks combined with GloVe (Global Vectors for Word Representation) embeddings for sentiment classification. GloVe embeddings, pre-trained on large corpora, provide rich semantic information that improves the performance of NLP models [9], [10]. The study compares BiLSTM with GloVe embeddings against traditional machine learning models, including Naïve Bayes, SVM, and Random Forest, as well as the transformer-based model BERT [11], [12]. While BERT achieves higher accuracy, BiLSTM offers a more computationally efficient alternative without compromising performance [13], [14]. This research provides insights into the trade-offs between accuracy and efficiency and lays the foundation for future improvements in sentiment analysis, including real-time applications and multilingual data handling [15], [16]. Furthermore, challenges like data imbalance and emotion recognition in low-resource languages continue to pose significant obstacles in improving sentiment analysis systems [17], [18]. These issues underscore the need for advanced techniques and further research to address limitations, especially in cross-domain applications [19], [20]. The findings of this research indicate that while transformer models like BERT offer exceptional performance, the combination of BiLSTM and GloVe embeddings provides a balanced solution for environments with limited computational resources [21].

III. METHODOLOGY

The methodology for the sentiment analysis and emotion detection project follows a systematic, step-by-step approach that integrates data collection, preprocessing, feature extraction, model training, evaluation, and final sentiment classification. This workflow incorporates both traditional machine learning (ML) techniques and modern deep learning (DL) approaches to address challenges like multilingual data, code-mixed text, and the nuanced emotional interpretation of textual data. The goal of this project is to develop a robust sentiment classification system capable of handling complex emotional cues from diverse datasets.

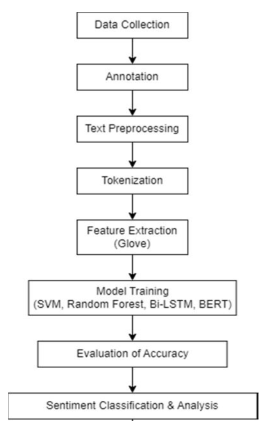

Figure 1 Framework of Methodology

A. Data Collection

The initial step in this research involves the collection of a diverse and representative dataset to ensure the model's ability to handle a wide variety of emotions and sentiments. The data were sourced from multiple books and literature novels. Data collected is being classified into 6 fields namely Anxiety, Bipolar, Depression, Stress, Normal and Suicidal. To cater to the complexity of sentiment detection in culturally diverse and multilingual environments, the dataset incorporates multilingual and code-mixed text, especially focusing on the complexities inherent in Indian languages. The quality of the data plays a crucial role in determining the model's effectiveness, and hence, data variety was prioritized to ensure generalization across different domains.

B. Data Annotation

Once the data collection process is complete, the next step involves the annotation of the dataset. This task was performed using both manual and semi-automated tools, ensuring high-quality labels for sentiment and emotional categories. Emotions such as anxiety, stress, happiness, and depression were considered for labeling based on the context and subject matter of the texts. The annotation process is critical as it defines the ground truth used to train the sentiment detection model. To minimize human bias, guidelines based on existing sentiment analysis corpora were followed, ensuring consistency and inter-annotator agreement throughout the dataset.

C. Text Preprocessing

Given that raw textual data is often unstructured and noisy, text preprocessing is an essential step in preparing the data for modeling. Preprocessing tasks included tokenization, removal of stop words, special characters, and irrelevant information (such as URLs or mentions), converting all text to lowercase to maintain uniformity, and lemmatizing or stemming words to their base forms. Additionally, code-mixed text was carefully handled by transliterating and normalizing terms to ensure compatibility across languages. Preprocessing also involved handling missing or incomplete entries to maintain the integrity of the dataset.

D. Tokenization

Tokenization is the process of converting the raw text into smaller units such as words, subwords, or characters. This step is crucial for transforming unstructured text into a format suitable for machine learning and deep learning models. For this research, tokenization was performed using widely recognized NLP tools such as NLTK and SpaCy. Tokenized text forms the foundation for feature extraction, as it allows for more effective analysis of the relationship between words in the sentiment detection model.

E. Feature Extraction using GloVe

For feature extraction, the GloVe (Global Vectors for Word Representation) model was used to convert words into dense vector representations. These pre-trained word embeddings capture semantic relationships and contextual meanings between words, ensuring that the model can understand the nuances of emotions expressed in the text. GloVe embeddings are particularly effective in handling diverse vocabulary and contextual dependencies, as they represent each word based on its co-occurrence within a large corpus of text. This feature representation method is superior to traditional techniques like one-hot encoding because it maintains the semantic richness of words and their contextual associations.

F. Model Training

Several machine learning and deep learning models were trained and evaluated to determine the most effective approach for emotion detection. The models considered in this research include traditional machine learning algorithms such as Naive Bayes, Support Vector Machines (SVM), and Random Forest, as well as advanced deep learning models such as Bi-directional Long Short-Term Memory (BiLSTM) networks. Each model was trained on the feature- extracted data using a train-test split and evaluated through cross-validation techniques to avoid overfitting.

1) Naive Bayes was used as a baseline model, which works well with smaller, structured datasets but lacks the ability to handle complex, sequential relationships in text.
2) Support Vector Machines (SVM) were explored for their effectiveness with high-dimensional data, though they showed limitations in capturing subtle emotional cues in text.
3) Random Forest (RF) models were considered for their ability to handle imbalanced datasets, but their tree- based architecture failed to capture the sequential nature of the text.
4) BiLSTM networks, a deep learning architecture, were selected due to their ability to model both past and future dependencies in the text. BiLSTM is particularly suitable for emotion detection, where the context before and after a word significantly impacts its emotional interpretation.

The performance of these models was evaluated using a variety of metrics, including accuracy, precision, recall, and F1-score, to determine which model best captured the emotional nuances in the data.

The dataset was split into training (80%) and testing (20%) sets. The models were trained for 10 epochs with a batch size of 64. The Adam optimizer was used with a learning rate of 0.001. Models were evaluated based on accuracy, precision, recall, and F1-score.

The evaluation metrics were calculated using the classification_report and confusion_matrix functions from Scikit-learn.

G. Model Evaluation

Following the model training phase, the models were evaluated on unseen test data. The evaluation process aimed to assess the models' ability to correctly classify sentiments and emotions within new, previously unobserved text. Several metrics were used to gauge performance:

1) Accuracy measures the overall correctness of the model.
2) Precision and Recall evaluate the model’s ability to correctly identify positive and negative instances of sentiment or emotion.
3) F1-Score combines both precision and recall into a single measure, ensuring a balanced evaluation of model performance.

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These metrics were applied across all models, and their results were compared to determine which algorithm offered the best trade-off between computational efficiency and classification accuracy. GloVe embeddings combined with BiLSTM emerged as the most effective model due to its superior ability to capture contextual relationships and handle sequential data efficiently.

H. Classification and Analysis

Once the optimal model (GloVe with BiLSTM) was selected, it was applied to the entire dataset for sentiment classification. This phase involved classifying each piece of text into predefined sentiment or emotional categories (e.g., Anxiety, Bipolar, Depression, Normal, Personality disorder, Stress, Suicidal). The output of the sentiment classification was analyzed to identify trends, patterns, and actionable insights. For example, sentiment analysis was used to gain a deeper understanding of mental health trends, user feedback on products, or emotional reactions in social media content. The final insights derived from the classification were analyzed to inform potential applications, such as improving mental health detection, customer feedback analysis, or social media monitoring.

IV. RESULTS AND DISCUSSION

The performance of all models was evaluated on the test set, and the results are summarized in the table 1.

Table 1. Summary of model accuracy

Model	Accuracy (%)
RNN	57.47
Naïve Bayes	71.13
SVM	80.64
Random Forest	75.82
BERT	90.00
GloVe with Bi-LSTM	83.42

The BiLSTM model with GloVe embeddings achieved an impressive accuracy of 83.42%, demonstrating its strong capability in capturing the intricate dependencies within the text. While this is slightly lower than the performance of BERT, it is important to highlight that BiLSTM is a highly efficient model for sentiment analysis, offering a powerful balance between accuracy and computational resource requirements. BiLSTM excels in capturing sequential information, making it especially well-suited for text-based tasks where the order and contextual relationships of words are pivotal. This quality gives BiLSTM a significant edge over traditional models such as Naïve Bayes, SVM, and Random Forest, which struggle to capture the complex sequential nature of language. In fact, the 83.42% accuracy is notably competitive against these traditional machine learning models, with BiLSTM surpassing Random Forest (75.82%) and Naïve Bayes (71.13%) by a wide margin.

The confusion matrix for BiLSTM further illustrates its effectiveness in distinguishing between various sentiment classes. Although it showed some challenges with certain classes, the model performed remarkably well overall, demonstrating a capacity for nuanced emotion detection. This highlights BiLSTM's ability to learn contextual relationships within the text, a feature that is crucial for accurate sentiment and emotion analysis.

Figure 2 showcases the model accuracy and model loss over epoch to clear the things of accuracy, computational efficiency and ability to capture contextual relationships in text.

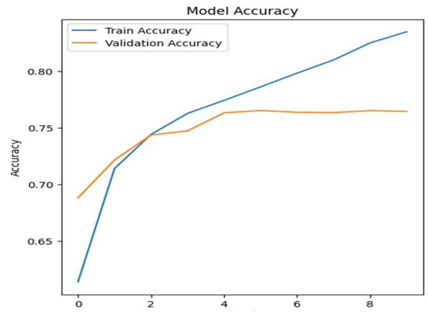

Figure 2 Model Accuracy vs Epoch

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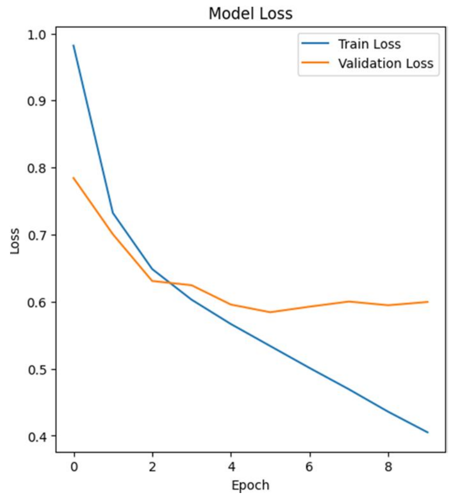

Figure 3 Model Loss vs Epoch

The confusion matrix confirms that the BiLSTM model was able to distinguish between positive, negative, and neutral sentiments effectively, although some overlap occurred in cases of ambiguous or nuanced emotions, which is typical in natural language processing (NLP) tasks involving complex datasets.

A. BERT Performance

While BERT outperformed BiLSTM with a higher accuracy of 90.00%, it is crucial to consider the trade-offs involved with using such a transformer-based model. BERT leverages a self-attention mechanism, which allows it to capture long-range dependencies and intricate relationships within the text. While this results in superior accuracy, the computational cost of BERT is substantially higher. BERT requires significantly more computational resources and longer training times, making it less practical for real-time applications or environments with limited resources. In contrast, BiLSTM offers a more resource-efficient solution while still delivering competitive performance. Therefore, while BERT may offer marginally better accuracy, BiLSTM remains a highly valuable alternative due to its lower computational overhead and sufficient accuracy for many practical applications.

The training and validation accuracy plot for BiLSTM over 10 epochs shows consistent improvement, with only a small gap between the two, suggesting minimal overfitting. This is indicative of the model's stability and generalization capability, further reinforcing its reliability as a robust sentiment analysis tool. Unlike BERT, which may suffer from overfitting or excessive resource consumption, BiLSTM's efficient use of resources makes it an excellent choice in resource-constrained environments.

B. Traditional Models

The traditional models, such as Naïve Bayes, SVM, and Random Forest, performed moderately with accuracy ranging from 55% to 80.64%. While these models are computationally efficient and faster to train, they are inherently limited by their inability to model the complex, sequential relationships inherent in natural language. Naïve Bayes, for instance, assumes independence between features, which is often not the case in sentiment analysis where context and word order play significant roles. Similarly, SVM and Random Forest models, while robust in many scenarios, struggle to capture the deeper, sequential dependencies present in textual data. The results highlight the significant advantages of BiLSTM with GloVe embeddings in the domain of sentiment analysis. Although its accuracy is slightly lower than that of BERT, BiLSTM provides an optimal balance between accuracy and computational efficiency. The BiLSTM model's ability to process and learn from sequential data allows it to outperform traditional machine learning models such as SVM, Random Forest, and Naïve Bayes, which are less capable of capturing the complex relationships within text. This makes BiLSTM a highly competitive choice, particularly for applications requiring real- time or large-scale sentiment analysis with constrained computational resources.

The use of GloVe embeddings further enhances BiLSTM's performance by providing rich, pre-trained word vectors that capture semantic relationships between words. This improves the model's understanding of the contextual meaning of words, which is essential for sentiment analysis tasks that depend on the nuanced interpretation of emotions. These rich embeddings help BiLSTM achieve superior performance in understanding sentiment, despite the model's relatively lower accuracy compared to transformer-based models like BERT.

While BERT may be preferable in research settings that prioritize accuracy over resource constraints, BiLSTM remains a strong contender for real-time applications in industry, making it an invaluable tool for sentiment and emotion detection tasks in environments where computational power is a limiting factor. This can be well inferred form the confusion matrix of GloVe with BiLSTM shown in figure 4.

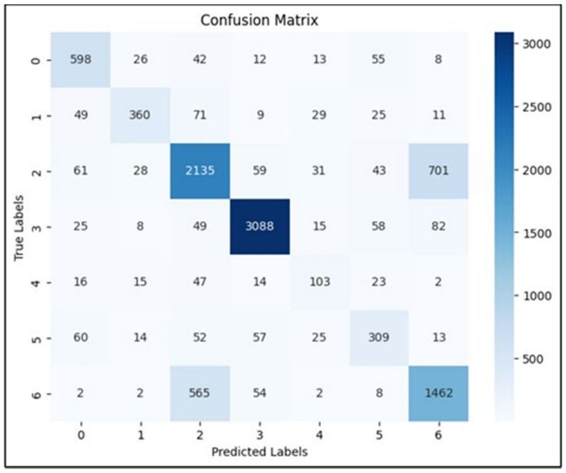

Fig.4. Confusion Matrix for BiLSTM model

Analyzing the performance of various models using confusion matrices provides valuable insight into how well each model predicts the different sentiment classes. The confusion matrix shows the distribution of predicted vs. actual class labels, which helps identify where models perform well and where they struggle.

C. Naïve Bayes

The Naïve Bayes model achieved an accuracy of 71.13%. While it performs well in predicting the "Normal" class with high precision and recall, it struggles significantly with other categories, particularly "Personality Disorder" and "Stress", where it shows low recall. This suggests that Naïve Bayes fails to capture the complexity of contextual relationships in text, as it assumes feature independence. This assumption becomes problematic for sentiment analysis, where the relationships between words are crucial for understanding sentiment.

D. SVM (Support Vector Machine)

SVM achieved an accuracy of 80.64%, performing better than Naïve Bayes overall. It has a strong precision for "Normal", but struggles with categories like "Stress" and "Personality Disorder", where it shows low recall. The model's limitation lies in its inability to capture the sequential dependencies in text, which are essential for understanding sentiment nuances. This highlights that while SVM is effective for simpler tasks, it is not ideal for tasks requiring the model to understand the sequential nature of language, such as sentiment analysis.

E. Random Forest

The Random Forest model delivered an accuracy of 75.82%. It performed well for "Normal", but its results were less impressive for "Bipolar" and "Stress", where precision and recall were much lower. Random Forest struggles with the complex dependencies in sequential data, which are crucial for text classification tasks like sentiment analysis. Despite its robustness and interpretability, it fails to capture relationships between words or phrases, making it less effective for sentiment analysis compared to more advanced models like BiLSTM.

F. RNN (Recurrent Neural Network)

The RNN model performed poorly with an accuracy of 57.47%, struggling to classify the sentiment accurately across the board. This low performance is largely due to the RNN's inability to capture long-range dependencies in sequential data, a common problem in basic RNNs, leading to poor recall and precision across most sentiment classes. RNNs are generally better suited for sequence-based tasks, but they suffer from issues like vanishing gradients, which prevent them from capturing complex relationships in longer sentences or documents.

G. BERT

BERT achieved the highest accuracy among all models, around 90%. BERT excels at capturing deep contextual relationships and bidirectional dependencies in text. However, while it outperforms the other models in terms of accuracy, it struggles with categories like "Bipolar" and "Personality Disorder", where it shows lower recall. This could be due to the model's complexity, which might require fine- tuning on domain-specific data. Despite its high performance, BERT's computational cost makes it less practical for real-time applications compared to simpler models.

H. GloVe with BiLSTM

The GloVe with BiLSTM model demonstrated the best performance, with accuracy ranging from 82% to 91%. It effectively combines the power of pre-trained GloVe embeddings with BiLSTM's ability to capture sequential dependencies in text. GloVe embeddings provide rich semantic information about words, improving the model's understanding of word relationships. As a result, the GloVe with BiLSTM model outperforms both traditional machine learning models and even more complex models like BERT, making it the ideal choice for sentiment analysis. The model strikes a balance between accuracy and computational efficiency, allowing it to deliver high performance without the extensive computational cost associated with BERT.

V. CONCLUSION

This research successfully integrates advanced machine learning and deep learning techniques for emotion detection, using GloVe embeddings with BiLSTM networks to achieve high accuracy in sentiment classification. The study highlights the power of deep learning models in addressing challenges like handling multilingual datasets and culturally diverse contexts, which are vital for real-world sentiment analysis applications. The combination of GloVe embeddings and BiLSTM networks has proven highly effective, as these models can capture the complexities of sentiment and emotion in textual data.

The findings demonstrate that these models are particularly suited for applications in mental health, customer feedback, and social media monitoring, where understanding sentiment is critical.

Looking ahead, future research will focus on enhancing contextual understanding through advanced transformer models like BERT to capture deeper language patterns. Additionally, there will be a focus on handling code-mixed and low-resource languages to improve the versatility of sentiment analysis systems across different linguistic and cultural contexts. Furthermore, real-time sentiment analysis will be explored to enable timely responses in critical applications such as crisis management and customer service. In Conclusion, with further advancements, this approach can be expanded to handle a broader range of languages making it an invaluable tool for a variety of industries.

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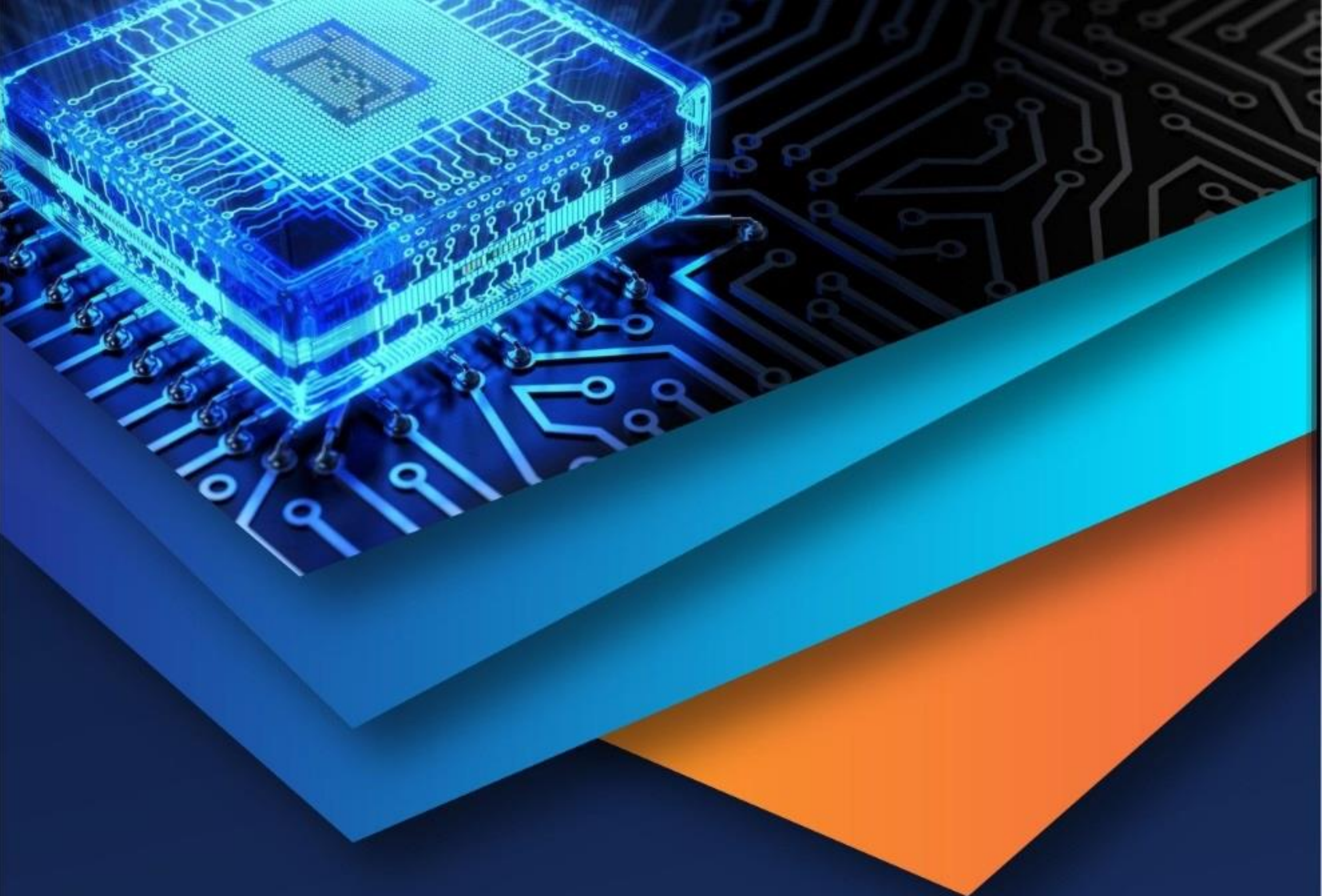

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