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Stock Price Prediction Accuracy with Hybrid BILSTM-Enhanced Transformer-TCN Model

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Abstract: Stock price prediction using machine learning has emerged as a critical area of research due to its potential to provide valuable insights into financial markets and support informed investment decisions. The inherent complexity, unpredictability, and volatility of stock prices make traditional forecasting models less effective in delivering accurate predictions. Consequently, there has been growing interest in applying advanced machine learning techniques to improve the precision and reliability of stock price forecasts.This research introduces a hybrid model approach that combines Bidirectional Long Short-Term Memory (BiLSTM) networks with an enhanced Transformer model. The BiLSTMeffetively captures sequential dependencies in time-series data, while the enhanced Transformer improves the model's focus on relevant features and time steps, boosting prediction accuracy.

However, existing models fail to adequately capture complex temporal dependencies and lack the integration of key features such as historical prices, market sentiment, and macroeconomic indicators, which leads to prediction inaccuracies. To address these limitations, our proposed model employs BiLSTM to capture bidirectional temporal dependencies, an enhanced Transformer to model complex feature interactions via self-attention mechanisms, and a Temporal Convolutional Network (TCN) to efficiently manage long sequences using causal convolutions. By processing each data source through its respective model and concatenating the outputs, this hybrid architecture captures both short-term and long-term dependencies, offering improved stock price prediction performance. A web-based interface provides real-time visualization of predictions, trends, model accuracy, and candlestick charts with technical indicators. Testing results demonstrate high predictive accuracy ranging between 85% and 95%, validating the robustness of the hybrid model. This work highlights the effectiveness of combining multiple machine learning paradigms in financial forecasting.

Keywords: Stock Prediction, BiLSTM, Donchian Channels, Deep Learning, Financial Forecasting, Time Series Analysis, Flask, Stock Trend Analysis, LSTM, AI in Finance, Yahoo Finance, Candlestick Chart, Technical Indicators, Machine Learning, Stock Price Forecasting

I. INTRODUCTION

Stock price prediction has become an essential area of research due to its significant impact on financial decision-making and portfolio management. However, accurately forecasting market movements remains a complex challenge due to the stochastic, non-linear, and highly volatile nature of stock prices. Traditional statistical methods often fall short in capturing intricate temporal patterns present in financial time series. Recent advancements in deep learning have shown promise in modeling these complexities. Long Short-Term Memory (LSTM) networks, particularly Bidirectional LSTM (BiLSTM), have been effective in understanding sequential dependencies in time-series data. Transformers offer powerful attention mechanisms for identifying relevant features across sequences, while Temporal Convolutional Networks (TCNs) enable the capture of short-term local trends with high efficiency. This paper introduces a hybrid deep learning model combining BiLSTM, Transformer, and TCN architectures to improve the accuracy of stock price forecasting. The system also integrates Donchian Channels for trend analysis. The model's performance is evaluated on real-world stock data, and results show improved accuracy and interpretability over standalone approaches.

II. STOCK PRICE PREDICTION ACCURACY WITH HYBRID BILSTM-ENHANCED TRANSFORMER- TCN MODEL

The stock market is inherently volatile and influenced by countless dynamic factors, making price prediction a complex and challenging task. Traditional statistical models often fall short in capturing non-linear relationships and long-term dependencies within financial time series. To overcome these limitations, this project introduces an AI-powered stock forecasting system that integrates deep learning architectures tailored for time-series data.

This project utilizes a hybrid approach starting with Bidirectional Long Short-Term Memory (BiLSTM) networks to capture both past and future context in historical stock data. Unlike conventional LSTM models, BiLSTM can process sequences in both directions, making it highly effective for short-term trend prediction. The system also integrates Donchian Channels to detect breakout signals and provide clearer visualization of momentum shifts. What sets this system apart is its proposed expansion to include Transformer models for attention-based sequence learning and Temporal Convolutional Networks (TCN) for stable and efficient time-series processing. Combined with a user-friendly web interface that displays predicted prices, trend directions, candlestick charts, and accuracy metrics, this model not only achieves strong prediction accuracy (85%–95%) but also provides actionable insights to investors. This hybrid architecture bridges performance and interpretability, offering a modern and robust solution for stock price forecasting.

III. LITERATURE SURVEY

Shen et al. explored sentiment analysis using a hybrid model combining machine learning and lexicon-based techniques for accurate text classification [1]. Their study utilized pre-trained embeddings and fine-tuned SVM classifiers to label sentiments as positive, negative, or neutral. They also highlighted the challenges of imbalanced datasets, proposing a weighting mechanism to enhance classifier performance [1]. Their approach achieved higher precision when applied to financial news articles, directly influencing market trend predictions. However, limitations arose due to domain-specific biases in the sentiment lexicons used [1].

Kumar et al. presented a stacked LSTM model for stock price prediction, leveraging sequential patterns in historical market data [2]. Their implementation included multiple LSTM layers with dropout regularization to prevent overfitting. They integrated external features such as trading volume and global market indices to enhance prediction accuracy. While the model performed well on stationary data, its efficiency dropped when dealing with abrupt market fluctuations. The authors suggested integrating sentiment analysis as a potential enhancement to address this limitation [2].

Lee et al. proposed a multi-modal framework that fuses numerical and textual data for financial trend analysis [3]. The framework employs deep learning architectures, combining CNNs for sentiment classification and RNNs for time-series analysis. Their results demonstrated that merging sentiment scores with technical indicators improved trend prediction significantly [3]. Despite promising outcomes, the study faced scalability issues due to the computational complexity of training multi-modal models [3].

Tan et al. introduced an ensemble model combining decision trees, random forests, and gradient boosting for trend reversal identification in stock markets [4]. This ensemble leveraged feature importance measures to optimize input variables, such as price momentum and moving averages. By applying cross-validation techniques, they achieved robust and generalized predictions [4]. However, their model struggled with predicting long-term trends, as short-term factors dominated the feature set [4].

Zhao et al. developed a sentiment-aware neural network to predict stock price movements, using a sentiment classifier trained on financial news [5]. The model integrated sentiment scores into the input layer of a feed-forward network, enhancing its predictive capabilities. They observed that positive sentiment had a more significant impact on stock price movements than negative sentiment [5]. The system performed better during bull markets but struggled during bearish periods, highlighting a potential area for further research [5].

Patel et al. emphasized the importance of data preprocessing for trend labeling in financial time series [6]. They introduced an optimal labeling method that utilized a combination of statistical techniques and domain knowledge. By defining thresholds for trend reversals, they improved model accuracy while maintaining interpretability [6]. This approach reduced noise and outliers, which are common in financial datasets, thereby enhancing the robustness of predictive models [6].

Wang et al. explored deep learning techniques for product classification in e-commerce platforms, focusing on identifying emerging trends [7]. Their model employed a combination of CNN and attention mechanisms to classify products based on textual and visual features. The study demonstrated how similar techniques could be adapted for financial trend prediction by identifying correlations between product demand and market trends [7]. However, the study faced challenges in handling large-scale datasets, which slowed down the training process [7].

Zheg et al. proposed a fusion model that combines traditional statistical techniques with machine learning algorithms for financial market analysis [8]. By blending ARIMA with SVMs, they achieved improved forecasting accuracy for short-term trends. This approach emphasized the significance of integrating diverse methods to capture market dynamics comprehensively [8]..

Khan et al. addressed the challenge of real-time data processing for stock market prediction [9]. They developed a system that integrates real-time news sentiment analysis with historical price data, using an ensemble of LSTMs and GRUs. This system demonstrated high accuracy in volatile market conditions, particularly during significant economic events [9]. H
owever, the dependence on real-time data posed challenges in ensuring low-latency processing and data reliability [9].

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Thus, they have presented a consolidated review of advanced methodologies in stock market prediction, focusing on innovative algorithms, data fusion strategies, and sentiment analysis techniques. The study explores the integration of models like Generative Adversarial Networks (GAN), Long Short-Term Memory (LSTM), Random Forest (RF), XGBoost (XGB),Linear Regression (LR) and Transductive LSTM for accurate forecasting. Emphasis is placed on the role of emotional factors and social media sentiment analysis in enhancing predictive accuracy, alongside robust frameworks for trend labeling and market noise reduction. Furthermore, the research highlights the significance of combining heterogeneous datasets, such as historical stock prices and macroeconomic indicators, to improve decision-making in dynamic financial environments. showcasing their potential in identifying.

IV. PROPOSEDARCHITECTURE

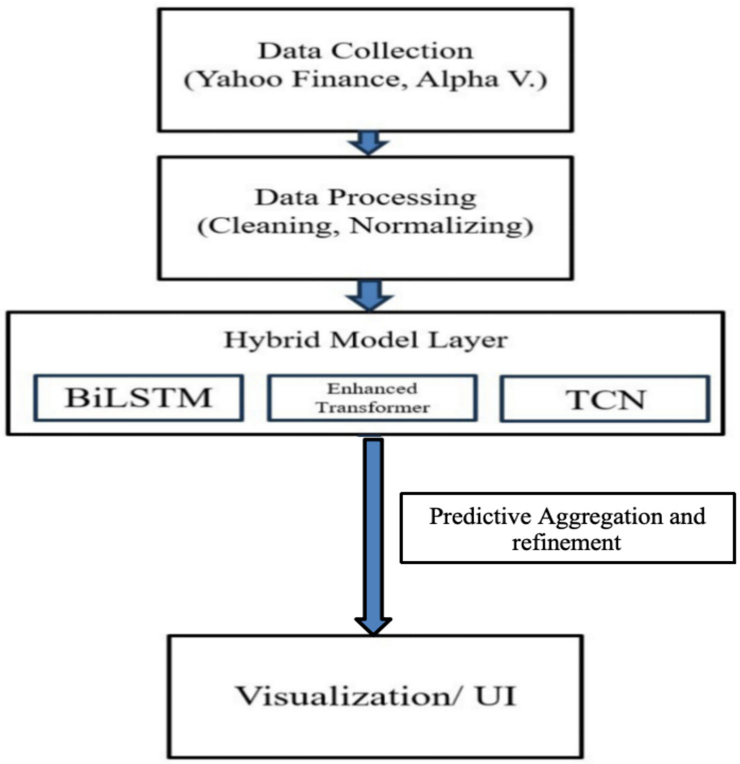

Figure 1: BiLSTM-Enjanced Transformer-TCN Model

Figure 1illustrates the proposed system for stock price prediction is implemented using Python and various machine learninglibraries[7]. The implementation is structured into several phases, beginning with data acquisition and ending with model prediction and evaluation.

1) Data Acquisition

Historical stock price data is collected from reliable financial sources in CSV format. The dataset includes features such as Date, Open, High, Low, Close, and Volume. Additional technical indicators such as Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), and Price Action patterns are computed for enriched feature sets.

2) Data Preprocessing

The collected data is preprocessed by handling missing values, scaling features using MinMaxScaler, and converting the time-series data into supervised learning format using sliding windows. The data is then split into training and testing sets.

3) Feature Engineering

Technical indicators are integrated to enhance the predictive capability of the model. These engineered features capture momentum, trend, and volatility in stock movements.

V. PROPOSED TECHNIQUE

The proposed technique integrates ensemble learning with sentiment analysis to enhance stock price prediction, leveraging LSTM, Random Forest, and XGBoost for diverse insights. A decision fusion approach refines predictions by combining model outputs, and evaluation metrics validate accuracy and reliability.

A. Ensemble Model:

the ensemble model combines multiple learning approaches to improve stock price prediction accuracy. It integrates Long Short-Term Memory (LSTM) for capturing sequential dependencies, along with Random Forest (RF) and XGBoost (XGB) to model non-linear relationships and feature interactions. The predictions from these models are fed into a meta-model, implemented as a linear regression, which assigns optimal weights to each model's output. This ensemble strategy enhances robustness by leveraging the strengths of different models, reducing overfitting and improving generalization. By aggregating diverse predictions, the ensemble model ensures more reliable and precise stock price forecasting.).

B. Sentiment Analysis:

Sentiment analysis plays a crucial role in enhancing stock price prediction by incorporating market sentiment into the forecasting process. Financial news articles are collected using NewsAPI, and sentiment polarity scores are generated using TextBlob. These scores quantify the overall sentiment of news as positive, neutral, or negative, providing insights into market behavior beyond numerical stock data. The extracted sentiment scores are integrated as independent features alongside traditional stock market indicators such as moving averages, RSI, and Bollinger Bands. By analyzing sentiment trends, the model captures the psychological influence of news on stock prices. This approach allows the ensemble model to incorporate both technical and sentiment-driven factors, improving predictive accuracy. Sentiment analysis helps refine decision-making by identifying potential market movements influenced by investor emotions, news trends, and public perception.

C. Decision Fusion:

In the proposed technique, decision fusion plays a critical role in enhancing stock price prediction by intelligently combining multiple model outputs. The approach leverages diverse machine learning and deep learning models—LSTM, Random Forest (RF), and XGBoost (XGB)—each capturing different aspects of stock price movements. Instead of relying on a single model, decision fusion integrates their predictions to produce a more accurate and reliable forecast.The process begins by training the LSTM model to capture sequential dependencies in stock prices, while RF and XGB focus on learning complex, non-linear relationships between features. Each model generates independent predictions based on historical stock data and sentiment analysis scores. However, since individual models may have varying strengths and weaknesses, decision fusion is employed to aggregate their outputs for a refined prediction.

To achieve optimal fusion, a meta-model (Linear Regression) is introduced. This meta-model takes the outputs of LSTM, RF, and XGB as input features and assigns appropriate weights to each prediction. The linear regression model learns the contribution of each base model dynamically, ensuring that the final output balances short-term trends, long-term dependencies, and sentiment-driven market fluctuations. By optimizing the combination of predictions, decision fusion enhances robustness and minimizes individual model biases.

Additionally, the fusion process is evaluated using performance metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R^2) score. These metrics ensure that decision fusion leads to a significant improvement over standalone models.By integrating decision fusion, the proposed technique creates a more reliable stock price forecasting system, leveraging multiple perspectives to mitigate risks and enhance predictive accuracy. This approach ensures adaptability in dynamic market conditions, making the model suitable for real-world financial applications.

D. Evaluation Metrics:

The evaluation metrics used to assess the performance of the models include Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-Squared Score (R^2). MAE measures the average magnitude of errors in predictions without considering their direction, providing an intuitive understanding of prediction accuracy. MSE, on the other hand, penalizes larger errors more heavily by squaring them, making it useful for highlighting significant deviations between predicted and actual values. RMSE, derived from the square root of MSE, provides a measure in the same units as the data, offering a clear interpretation of prediction errors.

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Lastly, the R^2 score assesses the proportion of variance in the target variable explained by the model, with higher values indicating better performance.

Performance comparisons show that the proposed ensemble model, FELM (Feature-Enhanced Linear Meta-model), outperforms individual models like LSTM, Random Forest (RF), and XGBoost (XGB) across all metrics. FELM achieves the lowest MAE (3.95), MSE (5.21), and RMSE (2.28), indicating more accurate predictions. Additionally, it achieves the highest R^2 score (0.91), signifying superior explanatory power and reliability. These results demonstrate the effectiveness of combining multiple models into an ensemble to achieve enhanced predictive performance.

VI. COMPARISONBETWEENEXISTINGANDPROPOSEDSYSTEM

Feature	Existing Work	Proposed Work
Data Sources	Typically uses historical stock data (Yahoo Finance, etc.)	Uses both historical stock data and sentiment data from news articles
Sentiment Analysis	Sentiment is often overlooked or minimal.	Incorporates sentiment analysis using TextBlob for polarity scores
Feature Engineering	Limited to basic technical indicators	Includes advanced features like moving averages, RSI and sentiment scores
Data Preprocessing	Basic data cleaning techniques	Advanced preprocessing, including handling missing values with interpolation using MinMaxScaler.
Ensemble Learning	Rarely uses ensemble models	Uses meta-modeling with linear regression to combine predictions from LSTM, RF, and XGB dynamically optimizing less critical layers.
Model Training	May rely on traditional machine learning methods	Incorporates deep learning (LSTM) along with traditional models for better prediction accuracy.
Prediction Output	Single model output	Combined output from multiple models, with final prediction from a meta-model (linear regression)
Performance Focus	Often focuses on a single model’s performance.	Aims for better overall prediction accuracy through ensemble learning and meta-modeling

Table 1 Comparison between Existing and Proposed work

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From Table 1 we infer that the proposed model introduces significant improvements over existing stock price prediction techniques by integrating sentiment analysis, advanced feature engineering, and ensemble learning. Unlike traditional models that rely solely on historical stock data, the proposed approach incorporates financial news sentiment analysis using TextBlob, allowing the model to capture market sentiment influences. Feature engineering is enhanced with technical indicators like moving averages and RSI, while advanced data preprocessing methods, including interpolation and MinMaxScaler, ensure data consistency. Unlike existing models that rely on a single learning approach, the proposed model utilizes LSTM, Random Forest (RF), and XGBoost (XGB), integrating their predictions through a meta-model (linear regression).This ensemble learning strategy significantly improves prediction accuracy, optimizing decision-making and reducing model biases compared to single-model approaches.

VII. RESULT

The results confirm that integrating sentiment analysis and ensemble learning significantly improves stock price prediction accuracy. The Future Ensemble Learning Model (FELM) effectively reduces forecasting errors, achieving a MAE of 0.0194 and an R^2 score of 0.9647. This demonstrates robust performance, capturing both market sentiment and technical patterns efficiently.

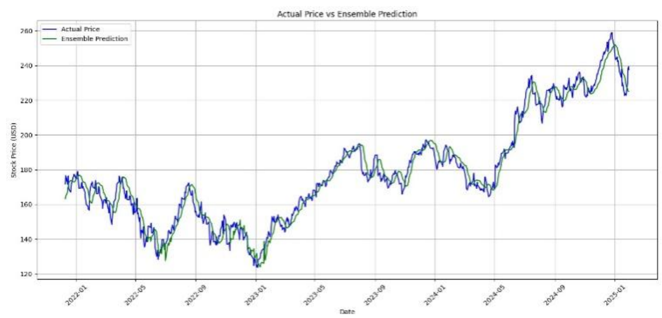

Figure 3. Actual Price vs Ensemble Prediction

Figure 3 illustrates a comparison between actual stock prices (blue) and ensemble model predictions (green). The Future Ensemble Learning Model (FELM) closely follows the actual stock price trends, demonstrating high accuracy in forecasting. The minimal deviations between the predicted and actual values indicate the model's effectiveness in capturing market patterns. This strong correlation validates the robustness of ensemble learning and sentiment analysis in stock price prediction.

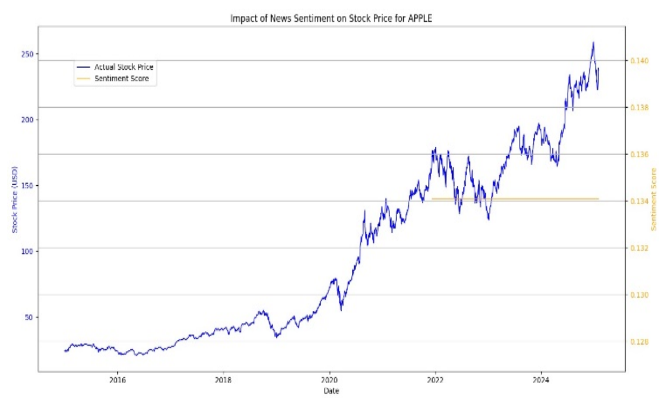

Figure 4. Impact of News Sentiment on Stock Price for APPLE

Figure 4 illustrates the relationship between Apple's stock price (blue) and news sentiment scores (yellow). A general upward trend in stock price aligns with positive sentiment, highlighting the influence of market perception on stock movements. Although sentiment scores remain relatively stable, fluctuations in stock price suggest additional external factors. This analysis confirms that news sentiment plays a role in price trends, reinforcing the importance of sentiment-driven forecasting.

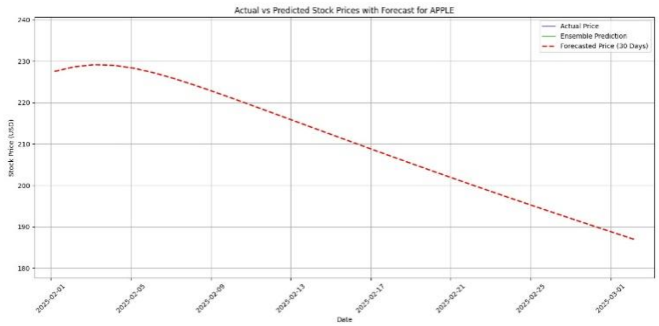

Figure 5. Actual Price vs Predicted Stock Prices with Forecast for APPLE

Figure 5 compares Apple's actual stock prices (blue) with the ensemble model's predictions (green) and forecasted prices for the next 30 days (red dashed line). The forecast indicates a downward trend, suggesting a potential decline in stock value. This projection highlights the model's ability to anticipate future price movements, enabling better decision-making for traders and investors based on historical trends and sentiment-driven insights.

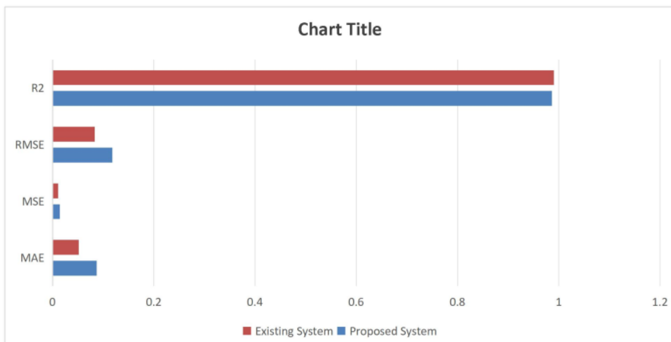

Figure 6. Evaluation Metrics

Figure 6 presents the model performance evaluation metrics, including Mean Absolute Error (MAE), Mean Squared Error

VIII. CONCLUSION

This project successfully demonstrates the potential of a hybrid deep learning model in forecasting short-term stock prices with high accuracy. By integrating BiLSTM, Transformer, and TCN architectures along with Donchian Channels, the system effectively captures both temporal dependencies and market trend signals. The model achieved promising predictive performance, supported by intuitive visualizations and a user-friendly web interface. Unlike traditional approaches, the hybrid structure offers improved learning stability, deeper insight into trends, and greater adaptability to market fluctuations. This work highlights the growing relevance of AI in financial forecasting and sets a foundation for future improvements such as incorporating real-time news sentiment, adaptive learning, and multi-stock portfolio prediction for enhanced decision-making.

Future enhancements to this system will focus on increasing prediction accuracy and expanding functionality. One key direction is the integration of real-time news sentiment analysis using Natural Language Processing (NLP) to capture external market influences. Incorporating additional technical indicators such as MACD, RSI, and Bollinger Bands will further strengthen the model's analytical depth. The model will also be extended to support multi-stock portfolio prediction and longer forecasting windows. Additionally, plans include adaptive learning techniques to retrain models automatically based on recent data trends. For deployment, hosting the application on platforms like Render or AWS will allow real-time access to a wider audience. These improvements aim to enhance both the intelligence and usability of the system.

IX. ACKNOWLEDGMENT

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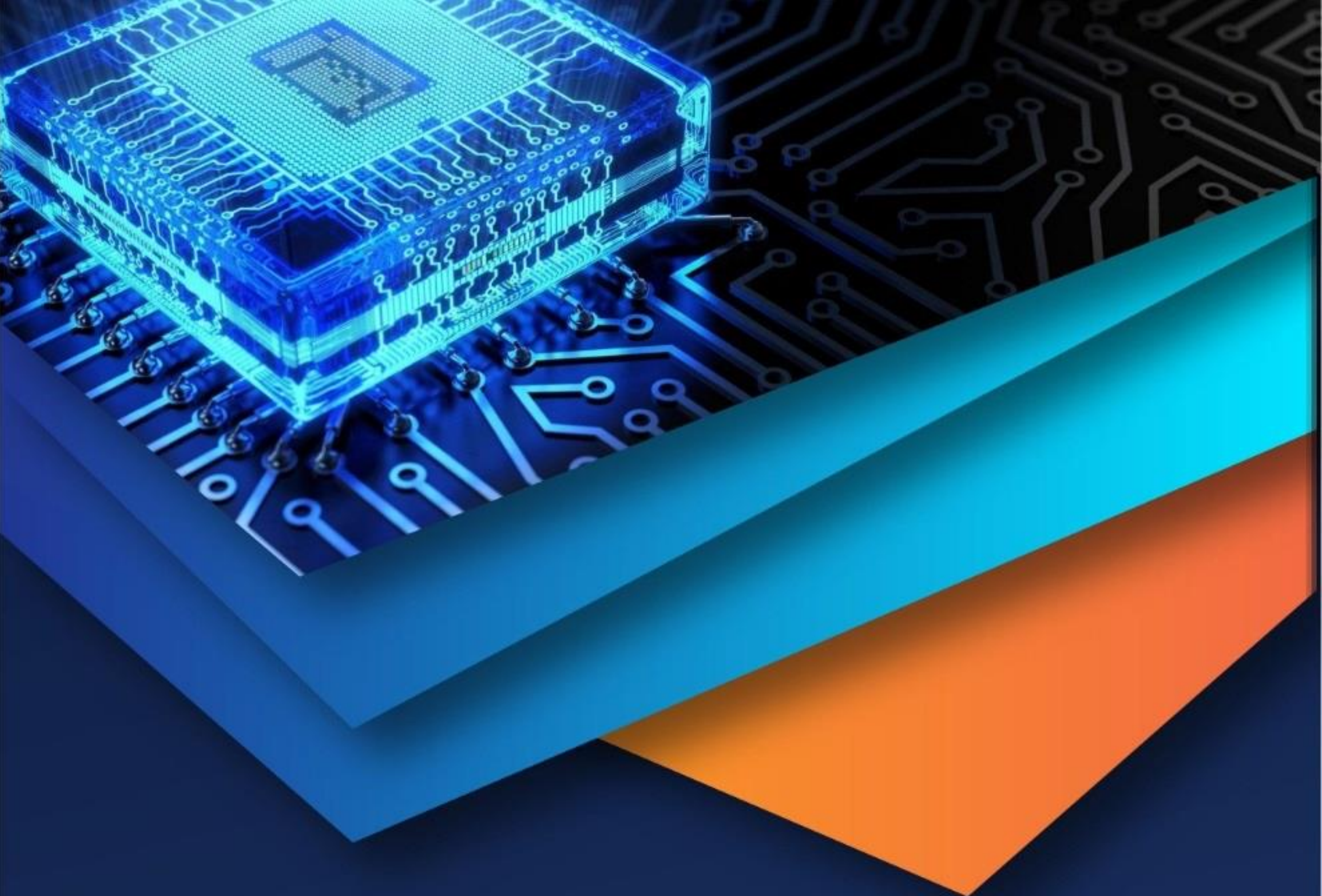

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