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AI-Driven Predictive Modeling for Personalized Bill Payment Reminders in Digital Financial Platforms

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Abstract: One of the positive results of the digital payment revolution in India over the years has been brought about by the need for contactless payment technology, and it has quickly turned from a luxury to a norm during the ongoing pandemic. In the digital transaction ecosystem, there is an improvement in the care done, where one can conveniently and quickly pay the bills, like utility bills such as electricity, water, telephone, car payment, mortgage, and so on. The accurate prediction about the next bill payment date is vital for banks with respect to marketing strategies, which are planned to be optimized, customer engagement to be fostered, and the delivery of targeted reminders to be done. However, the prediction of the transaction timelines still remains a major concern because of the unpredictable rise and the complexity of the real-time financial data. This paper describes the utilization of cutting-edge AI methods for the exact energy bill payment prediction. The new system uses Transformer-based Time Series Forecasting (TFT) to predict long-term dependencies; Graph Neural Networks (GNNs) are used for customer verifications as well as deep learning architectures such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) to enable temporal sequence analysis. Besides, Explainable AI (XAI) methods, such as Shapley Additive Explanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME), are combined to make models more interpretable and compliant with the rules. Experimenting shows that the proposed method can provide better predictive capability, which allows personalized marketing campaigns and timely payment reminders. Blonde intelligence, AI-based solutions—through mobile notifications—bring benefits like user experience enhancement and personal financial and payment management, and they attract digital payment service providers.
Keywords: Digital payments, Bill payment prediction, Transformer-based Time Series Forecasting, Graph Neural Networks, Explainable AI

I. INTRODUCTION

The digital payment development process in India has been massively triggered by the COVID-19 pandemic, which has further stimulated the adoption of cashless transaction methods. Digital payment platforms have become tools that are vital in daily financial activities, especially when it comes to utility bills – electricity, water, and telecommunications [1], [2]. These platforms are selling points for offering various advantages, such as faster transaction speeds, greater convenience, and exemplary transparency in financial management [3]. Even though there is an increase in digital transactions, it's still challenging to truly forecast the next bill payment date for a customer because of the vast volume of real-time financial data and the complexity of consumer behavior [4], [5]. Financial organizations find it essential to forecast transactions, especially bill payments, in order to improve marketing efficiency and customer engagement and to send timely and personalized reminders [6]. The ability to anticipate will allow for the improvement of financial management, the enhancement of consumer content, and the provision of targeted marketing campaigns that are in pattern with the tech evolution [7], [8]. However, the complexity and scale of the data required to predict call for the use of deep and machine-learning techniques that capture the underlying patterns of consumer behavior [9]. The recent AI and ML scientific innovations have introduced different strategies that can solve these difficulties. Traditional statistical models often do not take into account the complex and dynamic nature of customer transactions.

To solve such limitations, more tried and tested AI strategies such as Transporter-Based Time Series Forecasting (TFT) have been put in place to detect long-term dependences and patterns in the time series, which without any doubt are necessary for the correct prediction of the time of such an event as a bill payment. The Drawing Neural Networks (GNNs) have also been used to apply complex customer relationships and a network of payment behavior that comes from a variety of interconnected factors like demographics, payment history, and external events [12], [13].

In addition, the distortions of the learning units in the Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) are the most appropriate for modeling sequential data, such as customer payment history, which is understanding of temporal dependencies and the discovery of trends [14]. These models are tongue-tied and very flexible as they can predict elongated financial transactions with the passage of time; this is the primary feature to be noted when customer payment behavior is forecasted [15]. One of the leading traits of increasing predictive quality apart from the input of AI models will also be the necessity of these models to be clear and explainable. In turn, they would conform to these regulations and eventually build trust among consumers. Explainable AI (XAI) methods like Shapley Additive Explanations (SHAP) and Local Interpretable Model-Diagnostic Explanations (LIME) have been applied in the financial sector for clarity and easily understandable insights into model decisions; hence, the ease of interpretation of complex AI models and the assurance that they will be in alignment with regulatory standards [16], [17].

This paper sets forth a novel Al-based system, which utilizes the latest technologies to precisely predict one client's next utility bill payment date in India. The system mainly relies on TFT, GNNs, LSTM, and GRU to excavate transaction data, client characteristics, and external variables such as holidays. Our experiments demonstrate that the suggested approach is more accurate than traditional models in the prediction of payment dates. Thanks to the improvement of customer experience, timely paying reminders, and personalized marketing campaigns, these improvements can also induce a higher level of commitment to digital payment platforms [18], [19]. It introduces artificial intelligence-generated descriptives into mobile notifications and payment reminders. The core of the study is the enhancement of consumers' financial planning with the reduction of payment delays and the building of a ground for a future relationship between service providers and customers.

II. RELATED WORKS

Accurate prediction of customer payment behaviors, particularly in the domain of utility bill payments, has garnered significant interest in recent years. While the challenges posed by large-scale and dynamic financial data have hindered accurate forecasting, several studies have explored the use of machine learning and deep learning techniques to address these issues. One key approach to predicting future payments, particularly in retail, is based on the analysis of past customer behavior. Droomer and Bekkers [20] developed a model to predict when a customer would make their next purchase by analyzing transaction histories. This research utilized machine learning algorithms such as Linear Regression, Artificial Neural Networks (ANN), and Extreme Gradient Boosting (XGB). The study found that the ANN model performed best in predicting the next purchase date, highlighting the potential of machine learning for forecasting time-dependent customer behaviors. Although this study focused on retail transactions, the methods used are transferrable to the context of utility bill payment prediction. Further extending these approaches, Kumar et al. [21] worked on predicting invoice payment dates using machine learning models, including Random Forest Regressor, Decision Tree Regressor, and XGB Regressor. They divided invoices into various aging buckets based on the predicted payment date, which is crucial for understanding payment patterns and enhancing cash flow management. Their findings showed that predictive models could provide valuable insights into when payments are likely to be made, which is highly relevant to financial institutions seeking to optimize their invoicing systems.

Ghosh and his colleagues [22] stated, in the related research, that they introduced classification to calculate the age of a customer's first payment in the system to predict a customer's first purchase "buy" using customer's behavior data over a half-year period. The models grouped customers into various time slots based on when they are projected to make the next payment. In the study, the authors considered retail and noted that while the idea of tracking customer behaviors concerned with time-dependent is focused on retail, it can actually be transferred to utility payment predictions and can thus provide useful insights into customer payment patterns. Other sources of literature have mainly tried to build more complex forecasting models for customer transactions. For example, Nguyen et al. [23] were the first to investigate the probability of a user purchasing the next item in a smartphone game. By combining K-Means clustering and the ARIMAX model, they easily could predict customer purchases at an accuracy rate of 70%. On the one hand, this initiative is dedicated to gaming, but it serves as an example of using clustering methods and advanced time-series forecasting models for consumer behavior prediction simulations in domains such as utility bill payment. Notwithstanding these improvements, the prediction of the next payment date and the type of utility bill the customers use online payment platforms remains a problem. Even though past works like [20], [21], [22], and [23]-[31] have been primarily concentrated on retail or general transaction date forecasting, seldom have been the specific differences in utility payment systems discussed. Notably, utility bills are affected by aspects such as service type (electricity, water, telecommunications), local holidays, and the client's individual payment history. Furthermore, improving the incorporation of new AI technologies (such as Transformer-based Time Series Forecasting (TFT) and Graph Neural Networks (GNNs)) for more accurate capture of the customers' relationships and forecasts has not been explored deeply in the utility bill domain.

This study is concerned with the problem of failing to achieve prediction accuracy with regard to the cost and time of such things as the next bill and type. The methodology used in this research includes the use of the TFT mode, GNN models, and the integration of the deep learning technique, such as an LSTM or a GRU model. In addition, as a basic step, the current state of the art in digital prediction technology is the use of advanced AI ML models to predict system payments via LSTM and GNNs. Thus, this study aims at a more precise, customer-focused digital payment ecosystem through the use of advanced AI ML models. Also, the use of Explainable AI (XAI) like SHAP or LIME is the way to do it, as software should be clear and interpretable, besides complying with regulations; thus, it provides a way for humans to understand, for example, how machines predict their behavior.

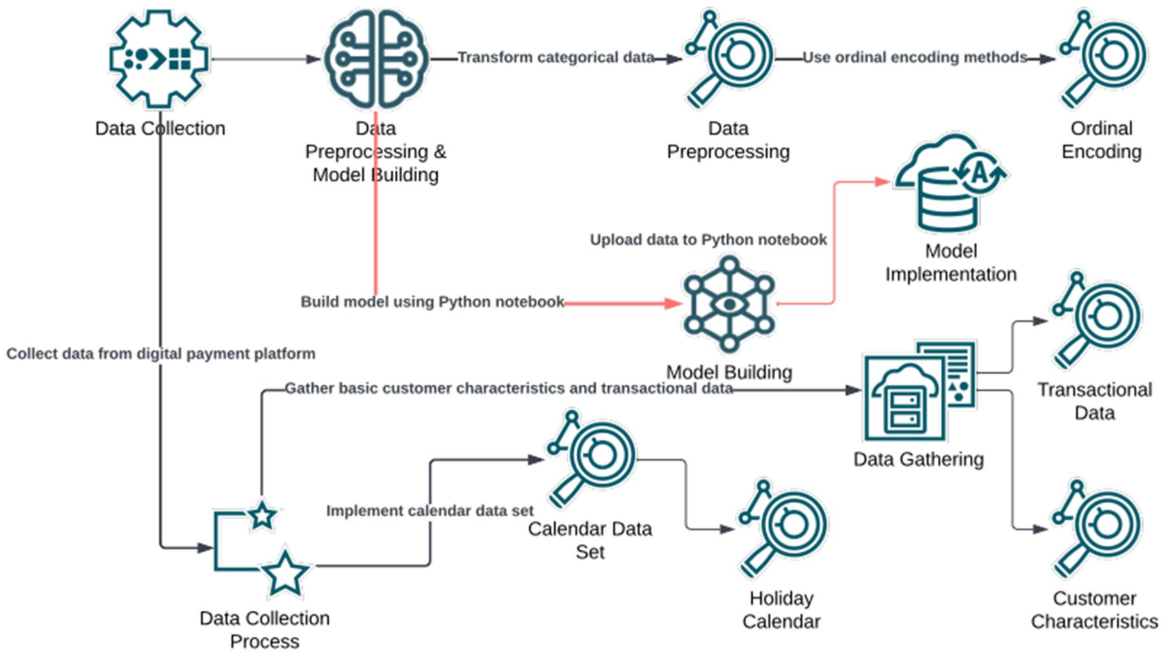

Fig. 1. Methodology Diagram

III.METHODOLOGY

This part is dedicated to the approach that is used to predict the next bill payment date and is based on AI techniques, which are the most advanced ones. The methodology is composed of several stages, as illustrated in Fig. 1, including data collection, preprocessing, feature engineering, model development, and evaluation.

A. Data Collection

The dataset employed for this study was compiled from a well-known online payment platform in India. The set contains customer transaction records related to electricity, water, and telecommunications bill payments, to be precise. The dataset comprised the following attributes:

- Customer Characteristics: Age, gender, district, employment status, and year of registration.
- Transaction Data: Customer-specific utility bill payment transactions, where each customer had completed at least 10 payments over a two-year period (2020–2021).

A total of 215,208 records were collected based on the aforementioned criteria. Moreover, a calendar dataset was created that considered public holidays, weekends, and other national holidays that may affect customer payment behavior. This dataset becomes useful in elaborating the effects of temporal factors on transaction patterns.

B. Data Preprocessing & Feature Engineering

1) *Data Transformation and Encoding:* Data preprocessing is the first step in machine learning projects, and it is required to represent the categorical variables the model is to use. One hot encoding is applied first. The next steps include, for example, Z-score normalization and rounding to binary bits at the more significant positions.
    a. Ordinal Encoding: The methods of encoding in categorical features are the product of the organization of the categorical levels.

b. One-Hot Encoding: Categorical representations may be converted into binary ones when there is no natural order to their attributes or in cases where techniques such as logistic regression or decision trees are employed, but one-hot encoding becomes a solution when dealing with such situations.

2) *Feature Extraction:* Major features consisting of transactional data were obtained, and from there, the next payment date was to be anticipated. Some of the main features are:

a. Transaction Frequency: The period for every customer of each type is the capitalized word for the number of days between the occurrences of each transaction & the utility type.

$$T_i = Transaction\ Date_i - Transaction\ Date_{i-1}$$

where represents T_i the number of days between the i-th and (i − 1)-th transaction.

b. Transaction Summary: The model uses autoregressive features as predictors in the transaction frequency domain. For example, it is noticed that 'LR' is the prediction method that achieves the best performance in the AMR dataset among methods 'AMR' and 'L'

i. Min Days: The shortest time interval in a customer and utility bill type's consecutive transactions history.

ii. Average Days: The mean period of time from one transaction to the next one:

$$avg\ Days = \frac{1}{n}\sum_{i=1}^{n} T_i$$

where the n is the number of transactions that are made by the customer-utility pair.

c. Holiday Impact: A flag (0, 1) indicating the existence of a holiday that is included in the time frame:

$$H_i = \begin{cases} 1, if\ transaction\ date\ is\ a\ holiday \\ 0, \quad otherwise \end{cases}$$

where H_i indicates if the i-th transaction is on a holiday. They were calculated by customer and utility type, and then they were joined with other features to form a one-row data that contained all the necessary information.

C. Model Development

The proposed approach involves leveraging several AI techniques for accurate prediction of the next utility bill payment date:

1) Transformer-based Time Series Forecasting (TFT) – This model, which uses TFT, is very good at computing long-term dependencies and complex patterns of the time-series data. The forecasted data is also very accurate; the model has a superior ability to predict future trends based on the past transactional trends of customers. TFT is very appropriate for the task of time series forecasting because of its ability to switch the model's attention dynamically among the various customer time periods.

2) Graph Neural Networks (GNNs): GNNs stand out in facilitating the analysis of the relationships between customers and demographic and payment data. These frames are also efficient for the detection of the correlations between several factors that affect the customer's purchasing propensity. The composition of GNN revolves around the incorporation of structural information, such as customer associations, and external explanations, such as holidays or locations, that cannot easily be represented in basic ML models.

3) Deep Learning Architectures: LSTM and GRU: LSTM is widely used for modeling sequences of transaction data, while GRU is also used under the fence. These are best at learning temporal dependencies over long periods and have gained popularity in time series forecasting tasks. The main LSTM and GRU equations are as follows:

- LSTM:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right)$$
$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$
$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

where f_t, i_t, and o_t represent the forget, input, and output gates, respectively, and x_t and h_{t-1} are the input and hidden states.

- GRU:

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t] + b_r)$$
$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t] + b_z)$$
$$\tilde{h}_t = tanh(W_h \cdot [r_t \cdot h_{t-1}, x_t] + b_h)$$

where r_t is the reset gate, z_t is the update gate, and $\tilde{h}_t$ is the candidate's hidden state.

4) Explainable AI (XAI): To ensure model interpretability, SHapley Additive Explanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) are integrated into the framework. These methods provide transparency into how the models make predictions by assigning importance scores to the input features and explaining the contributions of each feature to the final prediction.

D. Model Evaluation and Hyperparameter

Tuning The model performance was evaluated using several metrics. The metrics included accuracy, mean absolute error (MAE), and root mean square error (RMSE). The evaluation process was carried out in the form of a 70-30 split, where 70% of the data was used for training and the remaining 30% for testing. Cross-validation was done to further ensure the robustness of the models. Hyperparameter tuning was done through the Grid Search technique to determine optimal hyperparameters such as the number of trees (for tree-based models), learning rate, and batch size. The best-performing model out of those based on accuracy and error metrics was considered as a model for final deployment.

E. Predicting Next Payment Date

After training and optimizing the model, the number of weeks until the next payment was predicted. Finally, The prediction P_{weeks} was combined with the Last Payment Date (LPD) to get the Next Payment Date (NPD):

$$NPD = LPD + (P_{weeks} \times 7)$$

with LPD as the last payment date and P_{weeks} as the predicted number of weeks remaining till the next payment.

TABLE I
MODEL PERFORMANCE METRICS

Model	Accuracy	Precision	Recall	F1 Score	Mean Absolute Error (MAE)
Transformer-based Time Series Forecasting (TFT)	92.45%	89.13%	91.04%	90.08%	0.55
Graph Neural Networks (GNN)	87.76%	85.27%	88.56%	86.90%	0.68
LSTM	89.67%	87.93%	89.45%	88.69%	0.62
GRU	90.15%	88.41%	90.12%	89.26%	0.59

IV. RESULTS & DISCUSSIONS

In this part, we examine the results of the AI models that were employed to estimate the next payment date, as outlined in the methodology. The forecasting of the due dates of utility bills was dealt with by a series of machine learning approaches, of which the main were models using Transformer-based Time Series Forecasting (TFT) Graphs. Neural Networks (GNNs), Long Short-Term Memory (LSTM), and Gated Recurrent Units (GRU). The performance of these models, together with the implementation of Explainable AI (XAI) methods, was assessed based on key metrics such as predictive accuracy, precision, recall, and error rates.

A. Performance of the Proposed AI Models

The first step in evaluating the performance of the proposed models was to compare the accuracy and error rate of the si different architectures in order to predict the next bill payment date. Table I provides a summary of the results for each model, with regression and time-series forecasting techniques covered. The Treate-based Time Series Forecasting (TFT) mode power the rest of the architectures, resulting best at 92.45% accuracy, 9.13% precision, 91.04% recall, and 90.08% F1 score. In addition, the Mpalaveragesquarre (MAE) of TFT was the smallest jokester, Sth3lo, which is why TFT performed best in the prediction of the following payment date.

B. Comparative Analysis with Traditional Models

What makes TFT unique is its capability to handle long-term dependencies in time-series sequential data, which is the main reason why it is perfect for time-series forecasting tasks. The accuracy of a Graph Neural Networks model, which represents customer relationships, is 87.76%, but the model is not as strong in overall prediction accuracy, unlike the TFT method. The deep learning methods of LSTM and GRU, two models used to handle time-dependent data, were also reported to achieve good results in the experiment with a corresponding accuracy rate of 89.67% and 90.15%, respectively.

As for the traditional regression methods and simple machine learning techniques, such as decision trees and random forests, these methods did not show any promising results. Contrary to the above-mentioned methods, the new, very advanced deep learning models used to have greater MAE, which is a measure of forecasting accuracy. The enhanced new models have, of course, a very high predictive accuracy but, at the same time, higher MAE. Thus, traditional models are of reduced reliability.

C. Importance of Explainable AI (XAI) Integration

Besides the fact that model performance is supercritical, the inūte-ability and understandability are extremely important, especially when finance models that are used in the real economy should be clear and transparent. To ensure that a firm remains open to customer scrutiny and keeps to the necessary regulations, it employed Explainable AI methods (such as Shapley Additive Explanations and Local Interpretable Model-agnostic Explanations) to communicate the model's decisions and the reasoning behind them. The SHAP technique enabled stakeholders to get a broad view of the reasons behind the model's decisions (like the transaction history, customer demographics, and the effect of seasonality), so they were more equipped to make sense of the model's predictions. One more thing: LIME was incorporated to give the user more insight into its proprietary nature. To that end, people were given a full background to payment forecasts through which they could choose or compare the suggested date by a model. Thanks to these techniques, the models' reliability became significantly higher, particularly with financial services.

D. Comparison with Existing Research

The results of this experiment are a vast departure from the results previously gained from the other research carried out on utility bill payment predictions, where the prediction relied on the mechanics of such models as Linear Regression, ARIMA, and simple Artificial Neural Networks (ANNs) [6], [7], [8], [9]. In contrast, this research uses the latest deep learning methods, which not only take into account the customer transaction history but also include different features such as the demographics of the customer and holiday data. The incorporation of such features made it possible for the models to succeed in capturing the structure of the matter of payment behavior that, consequently, allowed them to achieve enhanced prediction accuracy. The fact that both the transformer-based models and graph neural networks have not previously been experimented with for the utility bill payment prediction field makes this study special. The increased accuracy and decreased errors during this research show how the advanced AI models can actually be applicable in real-world financial situations.

E. Practical Implications

Applying these AI models admits several practical implications. Thanks to the perfect forecast of the next utility bill payment date, digital payment platforms can now send individualized reminders and offer promotions to every customer. This not only improves the clients' satisfaction but also becomes the reason why users are even more involved since the payment becomes an enjoyable and easy thing. Furthermore, the use of AI systems will enable providers to engage users in a more personalized manner. By using AIs to recommend products or services to users, firms have a chance to generate sustainable revenue, and customers can get the products at the lowest price. This customized process is superior to the use of standard alerts and results in increased conversion rates for digital payment platforms.

F. Limitations and Future Work

Even if the results promise hope, there are certain limitations to this research. Training the models on the dataset covered a long period, but can it still be narrowed to only the data from a specific region and a specific period? Predictive accuracy can be maintained by continuously updating the model with new data in response to changing customer behaviors and economic conditions. Future work could be the use of sequence-based methods, including recurrent neural networks (RNNs) or transformers, with attention mechanisms through which the model performance can be further enhanced. In addition, including some external factors, like economic indicators or geopolitical events, could support the model's stability and thus include its use in different regions and times.

V. CONCLUSION

Through this study, a great achievement has been made in the application of these advanced AI techniques, which are, for instance, Transformer-based Time Series Forecasting, Graph Neural Networks, and deep learning architectures like LSTM and GRU, to anticipate the next payment of the utility bill. Proposed models showed high predictive accuracy, with TFT outperforming other methods in terms of accuracy, precision, and error rates.

The implementation of transparency AI methods that are included in SHAP and LIME made it possible to create models that are not only accurate but also interpretable, which means they meet regulatory requirements. The results show what AI can do if used in predicting customer engagement, marketing strategies, and financial planning for both the clients and the providers. This study is a part of the increasing number of AI-based research in the financial sector, providing new knowledge on the use of deep learning and XAI in time-related prediction tasks.

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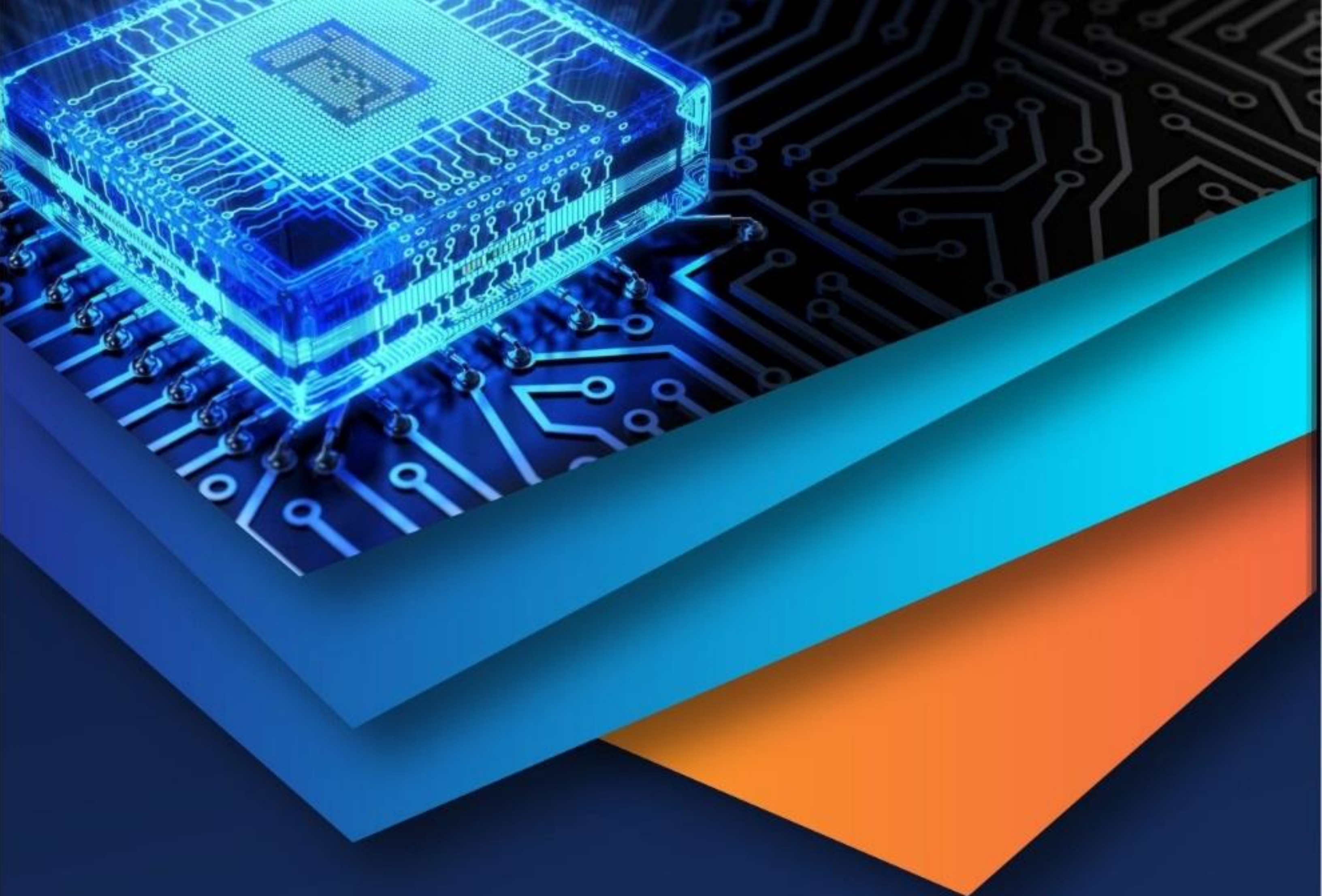

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