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Revolutionizing Diabetes Detection: A Deep Learning Approach for Enhanced Predictive Accuracy

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Abstract: Diabetes mellitus has been regarded as a very common metabolic disorder characterized by chronic hyperglycemia. It has been viewed as a major health problem and requires immediate concern with regard to its diagnosis at an early stage. This work proposes a deep learning framework that is proposed to advance the detection of diabetes, thereby proposing optimized predictive modeling using the Gated Attention Diabetes Model (GADM) with Chaos Game Optimization (CGO) for weight estimation. Our main aim in proposing this paper is a sound and robust prediction model that can estimate the onset of diabetes with high accuracy by proposing employment of advanced computational algorithms. That could enhance the model's ability to find some key attributes related to diabetes risk. This focused attention with feature selection not only enhances predictive accuracy but also secures interpretability of the model for use in clinical settings. Therein, the CGO optimizes the weight parameters within GADM based on chaotic dynamics for efficiently searching in the solution space for better convergence, improving thereby the classification performance. We design a classification system that will be able to effectively distinguish between diabetic and non-diabetic persons based on risk factors identified. We carry out an extensive performance analysis which involves a comparative study of the proposed model with state-of-the-art methods. Indeed, these results point to significant enhancements in predictive performance-as evidenced in sensitivity, specificity, and accuracy rates. We also conduct an extensive interpretability investigation into the same and provide insights into key characteristics and mechanisms underlying the model's predictions.

Index Terms: Diabetes Detection, Healthcare Systems, Deep Learning, Classification, Feature Analysis, and Optimization.

I. INTRODUCTION

Diabetes mellitus is a chronic and multifactorial disease, owing to an impairment in the metabolizing of blood sugar, more correctly referred to as glucose, by the body, leading to a high level of glucose that could reach dangerous thresholds[1, 2]. This chronic nature of the disease commonly referred to as diabetes mellitus is a group of metabolic disorders that basically involve a persistently high level of blood sugar. The increase in blood sugar may be because the body has become unable to produce adequate amounts of insulin, a hormone regulating blood glucose, or the cells cannot use this insulin correctly. Sometimes, it is brought about by some sort of combination of both causes above-mentioned. Insulin is a hormone that has a major role in maintaining normal levels of blood glucose. The autoimmune reaction destroys the pancreatic cells, thereby practically destroying the body's ability to produce enough insulin in people who have type 1 diabetes[3]. Type 2 diabetes consists of the majority diagnosed cases and is simply characterized by body cells that do not respond well to insulin-a condition often summarized as insulin resistance. This type of diabetes usually results from lifestyle and genetic predisposition promoted through poor dietary habits, sedentary lifestyle, and obesity. The rising prevalence and incidence of type 2 diabetes relate to alarming projections since, according to estimates, the population with diabetes may be over 642 million people in the year 2040. These figures also highlight how early the diagnosis and active management of patients are urgent needs in order to avoid complications and improve the outcomes of the treatment[4, 5]. Early detection of diabetes and the assessment of the level of its progression are relevant for further therapeutic actions. However, the kind of medical data concerning diabetes is categorically rich and involves multi-faceted information[6]. Far from being linear or structured, following clear trends or trends set by other data, such data is characterized by its complexity and interconnectivity. Diabetic patient information usually encompass an enormous number of inter-dependent variables that can be genetic and physiological, as well as social and environmental in nature.

Due to its complex structure, the proposed approach poses a problem in processing data for decision-making based on the use of traditional analytical tools. Machine learning and Artificial Intelligence have been shown as a promising avenue to deal with these complexities. Using big data[7] and analyzing non-linear relationships, machine learning methods guarantee an advantage in diabetes research and diagnosis. That said, one of the most important estimable benefits of using ML for handling diabetic patients is the ability of the algorithm to now identify and extract the features from raw and unstructured data by following a particular format. Such data may include genetic conditions, past and present diseases, eating regimens, the degree of physical activity, and other characteristics, which help to create a risk profile for diabetes. Feature extraction is an important step in this process as models learn to point at important phenomena and risk indicators that can sometimes go unnoticed by specialists. Through identification of such latent features, machine learning provide methods for predictive analysis and risk profiling to determine probability of the onset and further evolution of diabetes[8]. This also added to the overall advancement of diagnosis but more importantly the audit of every patient that forms the basis of a detailed treatment plan that considers the genetic predisposition and lifestyle habits of the patient.

In the modern era, especially with the recent advancements in machine learning and artificial intelligence, the diagnosis and management of the disease have become quite feasible. Such technologies are able to process big and complex medical data to generate insights supporting diagnosis, monitoring, and personalized treatment of diabetes. A system like this could implement a wide variety of algorithms and models, each with its different strengths and weaknesses. ML methods are superior in pattern recognition from large datasets, something that is very important in diabetes, where the interaction between genetic life and environmental factors is highly complex. Conventional statistical methods find it difficult to model these relationships since they are generally nonlinear and too complex[9, 10]. A great deal of research in recent years has focused on the application of ML and AI [11]for the management of diabetes, from more conventional machine learning algorithms that provide baseline improvements in accuracy to advanced AI methodologies using adaptive learning and predictive analytics. It is this level of personalization that will improve treatment efficacy and reduce risk for complications related to poor blood glucose control. This kind of integration of machine learning with AI and explainable technologies is surely a key indication of the paradigm shift toward robustness and interpretability by automated systems, hence promising a bright future for diabetes care.

This paper is structured as follows: Section 2 provides a critical literature review on several established approaches to the detection and classification of chronic diseases; an analysis is performed on the pros and cons of each approach regarding the precision of detection and operational efficiency. This section provides great insight into both the performances and challenges of the approaches at hand. Section 3 describes the technique in detail, together with a flow diagram showing in steps how the methodology will be performed. Section 4 discusses how the proposed method is evaluated through a variety of performance metrics that may show its validity against existing techniques. Finally, Section 5 summarizes the findings and outcomes of this study, putting into perspective the major contributions of this work and suggesting further research directions for future developments in this area.

II. RELATED WORKS

The fast-growing prevalence of diabetes has indeed motivated extensive studies toward the development of automated systems that would support early detection and effective management of the disease[12]. Very recently, some of the focus has shifted towards the application of machine learning and deep learning techniques in finding patterns from complex medical data to support accurate recognition of diabetes. Doing so would make the dataset imbalanced, hence skew the process of model learning, insensitive towards the minority class, thereby affecting the overall diagnostic sensitivity. Indeed, there are classes which might suffer from an imbalanced ratio; this has to be tackled through techniques of re-sampling, cost-sensitive learning, or generation of synthetic data such that robust models with generalization capability can be developed for real-world scenarios[13]. Although much improvement has been attained recently by machine learning and deep learning approaches, most state-of-the-art works are apt to use single-modality data in diabetes detection. Conventionally, such modalities may include blood sugar level records, demographic information, or statistics of patients, or isolated laboratory test reports. These sources, too, do not truly represent the multifactorial nature of diabetes due to interactions at the levels of genetics, environment, lifestyle, and medication. Perhaps one of the most promising lines in research related to predictive performance improvement and the development of reliability will therefore be integrating information from various sources[14, 15]. That could be integrated biological information, electronic health records, sensor data that continuous glucose monitors provide, or even input about physical activity and eating habits for further insight into a person's risk profile. This integrative approach gives the model an opportunity to use more complex data that might yield better prediction accuracy and further insight into effective disease management.

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The authors [16]contribution was based on leveraging interpretability inherent in DTs and the power of deep learning in recognizing patterns by building a hybrid model that achieves an effective balance between precision and computational efficiency. This integration allowed processing the complex inter-relationships and nonlinear patterns across data, which are considered important for the accurate detection of diabetes. Yet, given such methodological advances, this study also unfortunately had a critical limitation: the proposed mechanism was actually less than ideally accurate, impacting adversely on the performance of the diabetes detection system as a whole. The lower accuracy reflects that although the model could well capture broad diagnostic patterns, it lacked the sensitivity and specificity for reliable clinical use. This again indicates a larger scope of hybrid systems that would address performance issues through multiple learning strategies combined with optimization of hyperparameters and handling imbalanced data to provide better diagnostic precision and value in practical applications.Larabi et al [17]performed a comprehensive, wholistic study that was intended to investigate and assess a host of ML and DL techniques applied in the prediction and classification of diabetes. In fact, their work is among the exceptional few, since the authors not only included a broad range of algorithms but also discussed their practical applications in medical diagnostics for the prognosis of diabetes. Specific critical reviews of established ML models, such as DT, SVM, and ensemble techniques, were presented, along with more advanced DL architectures represented by neural networks and convolutional approaches. They also described how these techniques have been adapted to the peculiar challenges of medical data-often featuring high dimensionality, class imbalance, and complex feature interdependencies. They pointed out that though the traditional ML model is usually credited with interpretability and lower computational cost, it may fail in capturing intricate, non-linear relationships within the data, which will be very essential in nuanced prediction of chronic conditions like diabetes. Besides, the authors mentioned that a hybrid modeling approach is worth development in the future - one that combines the interpretability of traditional ML approaches with the depth and computation capacity brought by DL methods. The review also gave a very broad overview of the existing techniques and called for future innovations against the identified limitations, with further research on diabetes prediction and classification.

The uniqueness in their work[18] is based on the introduction of two different learning techniques, namely VAE and SAE. By mitigating the problems of class imbalance and poor feature representation, common in most medical datasets, they improved the diagnosis of diabetes with enhanced accuracy. VAE allowed the generation of new data points, augmenting the training dataset. This helped to mitigate the class imbalance problem. In diabetes datasets, non-diabetic instances are always greater in number compared to diabetic cases. Additional generation of data capturing the underlying distribution of the minority class aims to enhance model learning for improving predictive performance. This two-way approach has resulted not only in improving the overall robustness of the diabetes detection system but also in contributing towards the better generalization when applied to unseen data. Garcia et al. showed that, in particular, their integrated approach achieved notable improvements in classification performance with respect to those obtained so far, which important evidence of the decisive role is played by advanced feature engineering and data augmentation strategies in the creation of effective diagnostic tools. They mentioned, however, that additional validation on a wide variety of datasets would be necessary for this model to become clinically applicable.

Hasan et al [19]presented a broad investigation of various ensemble machine learning-based approaches for diabetes prediction, with the crucial aim of reaching a reliable framework for the detection of diabetes from patient medical records. In this respect, several key steps are explored in their work that are basically essential for enhancing accuracy and efficiency in predictive models: outlier rejection, missing value replacement, data standardization, and classification. Such preprocessing steps, as the authors stressed, are crucial to enhance the quality of the data directly influencing the performance of the machine learning algorithms. Besides, data standardization is focused on being a significant process of normalization, scaling the features, thus ensuring better convergence during the learning phase[20]. The k-fold cross-validation technique was adopted in their framework, which was accepted as a model selection technique and classifier error estimation. Machine learning and deep learning have been done on diabetes prediction and classification; still, much work is to be done because some research gaps are yet to be covered. First of all, most of the studies related to diabetes detection are designed considering blood sugar level measurement or demographic data-only inputs, which restricts the comprehensiveness of the models. Where one hand integration of multisource data, such as electronic health records, life style factors, genetic predispositions, and sensor data remains poorly explored, a multidimensional approach toward this problem may well result in an increase in predictive accuracy and reliability related to diabetes detection systems. Current methodologies most often bypass this level of complexity and rely on limited datasets which might fail to present the complete spectrum of variables leading to this disease.

Besides, most of the works done on diabetes prediction have utilized various machine learning techniques such as ensemble methods and deep learning frameworks.

However, problems with imbalanced datasets have remained. Most of the works note that challenges related to datasets where instances of diabetes cases are notably fewer compared to the non-diabetic ones, though very few of them propose robust solutions that efficiently address class imbalance. Besides, feature selection and extraction techniques are applied superficially, with little emphasis on the most relevant features contributing to diabetes risk[21, 22]. While advanced feature engineering methods may improve model performance, they are frequently neglected in the current literature. Also, there is still much room for development in terms of transparency and interpretability of models developed in machine learning. Most algorithms, especially deep learning models, act like a "black box," and derivation of conclusions from such a model is difficult to garner the trust of health professionals without understanding how decisions have been made. This interpretability gap depicts developing methodologies that, besides improving predictive performance, enhance the explainability of the models as well. Indeed, it calls for future research to elicit frameworks that embed features of interpretability for enabling practitioners to make informed decisions based on the model output. Future studies are recommended to focus on cross-validation and external validation studies that will assess diabetes prediction model performance across wide demographic and geographic populations[23-25]. Closing these research gaps will not only improve the accuracy and reliability of diabetes prediction systems but will also have important impacts on the development of more effective and sustainable healthcare responses for better management of diabetes.

III. PROPOSED METHODOLOGY

This paper's main contribution is the proposition of a new integrated approach that can potentially help in yielding more accurate and reliable prediction and classification results using advanced deep learning and optimization techniques for diabetes prediction and classification. In essence, this work deals with the introduction of the Gated Attention Diabetes Model-GADM, its improved weight estimation, and Chaos Game Optimization algorithms, especially designed for GADM. These methods have a synergistic effect, and overall performance in prediction gets significantly enhanced by correctly learning and classifying patterns in diabetes-related data with efficient weight optimization. The comprehensive approach strengthens not only the predictive capability but also overcomes other common challenges related to convergence speed and training time by setting a new benchmark for automated medical diagnostic tools. In this work, the method proposed with GADM has been carefully done with an aim to combine strong features of Gated Recurrent Units with an attention mechanism that enables improved feature selection and more precise temporal learning. GRUs do not require defined memory cells since their inherent characteristics enable them to handle dependencies in sequential data, hence structurally simpler compared to their counterparts while still strong performers. Attention mechanisms in GADM will selectively give focus to the most important features, allowing the model to weight the input on their contribution towards the final output. Attention to such important features allows for more interpretative predictions, increasing optimization in capturing subtle yet important variations in patient data. GADM differs from other approaches by taking a dual approach in leveraging the compact structure of GRU and the selective nature of the attention mechanism in bringing in better classification outcomes related to diabetes prediction.

While GADM is used for the sake of optimization of weight estimations, the efficiency in the learning process is complemented by the CGO algorithm. Rooted in the mathematical inspiration of chaos theory, it introduces a stochastic adaptive search process, therefore avoiding local optima and accelerating convergence. This is really effective under the weight optimization context, whereby the search space can be dynamically explored and exploited with much precision for the fine-tuning of GADM network weights. Employing CGO within this framework is novel due to the capability of generating nonlinear and unpredictable paths, in trying to make sure that the underlying exploration pattern in it is diversified from that of traditional optimization algorithms. A little randomness, much like in chaotic systems, is what helps CGO provide robust learning and enhanced stability and generalization within the proposed GADM model. The working process of the proposed techniques starts with feature selection, whereby relevant patient data are preprocessed and fed into the GADM model. This architecture handles temporal dependencies with its GRUs, while its attention layers emphasize features that provide the most contribution toward the predicted output. It is during the optimization of weights via its special chaos-driven iterative process that the CGO really starts to glitter. It calculates iteratively the candidate weight solutions, then evaluates them regarding the fitness criteria-e.g., accuracy or loss function-and finally updates them with chaotic sequences in order to comprehensively scan the search space. The subsequent procedure is the optimization that permits GADM to tune its internal parameters even finer toward the best performance concerning prediction accuracy, computational efficiency, and stability of training. Combining CGO with GADM results in an improved framework that can cope quite satisfactorily with the complexity of the data characteristics intrinsic to medical diagnostics; hence, the approach is of real-world value for diabetes detection and beyond.

A. Gated Attention Diabetes Model (GADM)

The Gated Attention Diabetes Model (GADM) represents a new frontier in diabetes prediction and classification, merging the strengths of GRUs with attention mechanisms into one framework. This is a new approach toward improving complex temporal dependencies and contextual relationships represented in patient data and important for diagnosis of diabetes. Major contribution of GADM is an efficient processing of sequential data from multiple sources such as EHRs, glucose monitoring systems, and patient demographics.

GADM used GRUs either to discard or keep some information at each time step, thus allowing a finer-grain view into the evolution of the health of the patient over time. This allows the model to pay more attention to the most informative features within the dataset, therefore giving more insight and interpretability of those factors which most determine risk for diabetes. GADM especially fits the problem of diabetes detection, considering the capability to handle imbalanced datasets and robustness regarding noisy or incomplete data.

Generally, the prediction of diabetes requires analyzing various kinds of information such as historical blood glucose level, family medical history, life style, and lab test results. Traditional machine learning could not handle such high-dimensional and heterogeneous data. Besides, it is also challenging because of the case imbalance problem where the number of positive and negative examples is significantly different. In contrast, GADM takes maximum advantage of the GRU's gate mechanisms for dynamically tuning the focus of the learning process in enhancing the model sensitivity toward minority classes and the general classification performance.

The operational process of the Gated Attention Diabetes Model involves pre-processing, where patient data is cleaned and normalized into one format throughout the dataset. That would be pre-processing, where it could mean imputation for missing values, encoding for categorical features, or scaling for numeric features. Once the data is prepared, the GADM takes this sequential input and feeds it through the GRU layers that are supposed to attend the temporal dynamics in the input data. In that respect, each GRU cell takes the input at every time step and updates both the update and reset gates in a manner to regularize the flow of information based on the relevance of the past state. Attention would then ensue, thus making it weigh various features against each other and give emphasis on what is most indicative of risk for diabetes. The dual-layer approach captures the temporal dependencies of the data and narrows the focus toward the most important variables that may influence the prediction. The model, therefore, outputs the probability predictions of diabetes that can further be interrogated in order to extract factors of risk and feed clinical decision-making.

The proposed Gated Attention Diabetes model combines strengths from both GRU temporal strength and contextual advantages from the attention mechanism, hence being effective in diabetes prediction and classification tasks for improved patient care and disease management strategies.

The architecture outperforms all the current classifiers within diabetes classification and prediction domains on many essential aspects. First is the prowess it has in the handling of sequential data, which within this medical domain is critical since the health metrics of patients will most likely change with time. Classic machine learning models often struggle with time series data because these models utterly lack any such mechanism for temporal dependencies regarding changes in the conditions of the patients. On the other hand, GADM uses GRUs that are designed to process sequences with their gate mechanism, allowing the model to remember useful information and forget less useful data across time steps. Obviously, this strengthens its performance in making predictions based on historical patient records.

Another strong point of GADM is the full incorporation of attention mechanisms that enhance both interpretability and performance. Although the performance of a state-of-the-art classifier can be quite accurate, the great majority of these cannot be used in explaining the reasoning behind decisions. It is here that attention in GADM becomes an important heuristic effort towards the disclosure of which of the features are contributing a lot toward a classification result, paying various weights against different input features.

This interpretability is important in clinical domains since this will help the clinical experts understand how the model makes a decision on a case. Moreover, it will help increase trust by the clinicians and patients in interpretability and will, therefore, facilitate easier adoption in practice of AI-driven solutions.

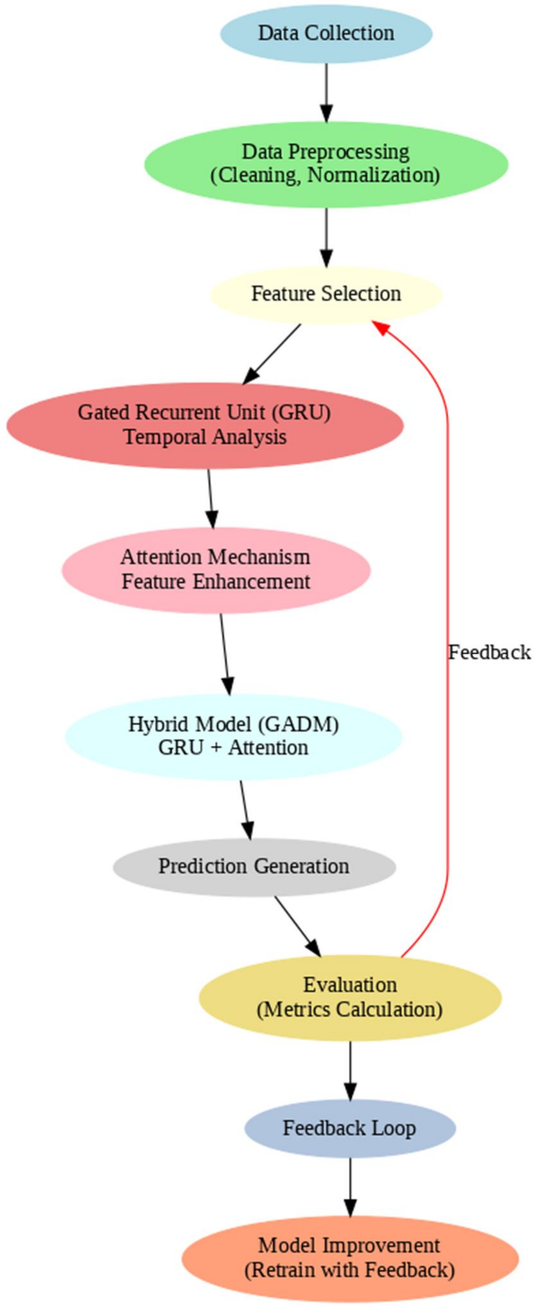

Fig 1. Flow of the proposed GADM model

At first, this method estimates the activation function based on the location of the prior and forthcoming activation functions along the liner at a specific moment, as calculated below:

$$R_t^j = (1 - Y_t^j)R_{t-1}^j + Y_t^j R_t^j \quad (1)$$

Where, R_t^j indicates the new candidate solution, t denotes time, and R_{t-1}^j defines the previous activation function. Consequently, the update gate Y_t^j is estimated as shown in below:

$$Y_t^j = \delta(w_Y a_t + T_Y R_{t-1})^j \quad (2)$$

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Where, δ denotes the sigmoid function, Y_t^j represents the update gate, and w_Y defines the weight value. Consequently, the candidate activation function R^j is estimated based on the following equation:

$$R_t^j = \tanh(wa_t + T(Z_t \odot R_{t-1})) \quad (3)$$

Where, $\odot$ denotes the element-wise multiplication operation, and Z_t is the reset gate function that is estimated as shown in below:

$$Z_t^j = \delta(w_Z a_Z + T_Z R_{Z-1})^j \quad (4)$$

After that, the scaled dot product attention function is estimated by using the following model:

$$Att(P, Q, R) = Softmax\frac{PQ^T}{\sqrt{\mathbb{d}_k}}R \quad (5)$$

Where, P, Q, R are the query, key and value matrices, and $\mathbb{d}_k$ is the dimension of the key vector. Moreover, the multi-head attention module operation is performed with the obtained query, key and value parameters based on the following equation:

$$h_i = Att(P\mathcal{w}_i^P, Q\mathcal{w}_i^Q, R\mathcal{w}_i^R) \quad (6)$$

Where, $P\mathcal{w}_i^R$, $Q\mathcal{w}_i^R$ and $R\mathcal{w}_i^R$ are the weight matrices of query, key and value parameters. Moreover, the output of the transformer is in the following form:

$$O = Norm_{layer}(k + Multi_{head}(P, Q, R)) \quad (7)$$

The final hidden state update is performed according to the following equation:

$$\hbar_K^i = \hbar_K \quad (8)$$

Where, K is the time step. After all these operations, the final classified label is obtained as the output of this classifier, which is in the following form:

$$\hat{c} = \phi(\mathcal{w}_{out}\hbar_K + \beta_{out}) \quad (9)$$

Where, $\hat{c}$ is the predicted probability, $\mathcal{w}_{out}$ is the weight matrix and β_{out} denotes the bias term.

B. Chaos Game Optimization (CGO) for Weight Estimation

Chaos Game Optimization (CGO) for weight estimation in the Gated Attention Diabetes Model is, therefore, a novelty introduced into the model to improve the predictive accuracy and overall performance of the system. The main reason for the employment of CGO lies in the special optimization capability it exhibits, superior to the traditional algorithms' performance in balancing exploration and exploitation during the weight optimization process. CGO, inspired by the geometry of fractals and chaos theory, is a chaotic and stochastic search that helps to make the diversification and intensification of the search of the solution space more effective. Thus, classic optimization methods may easily converge to a local optimum or fail to find the best configuration for the model performance in complex neural network models like GADM, where special effectiveness in determining the most appropriate weight values is required. GADM therefore enjoys the great scope of a search mechanism that involves adaptation to nonlinear and complex objective functions, inherently part of deep learning models for the detection and classification of diabetes, by incorporating the CGO for weight estimation.

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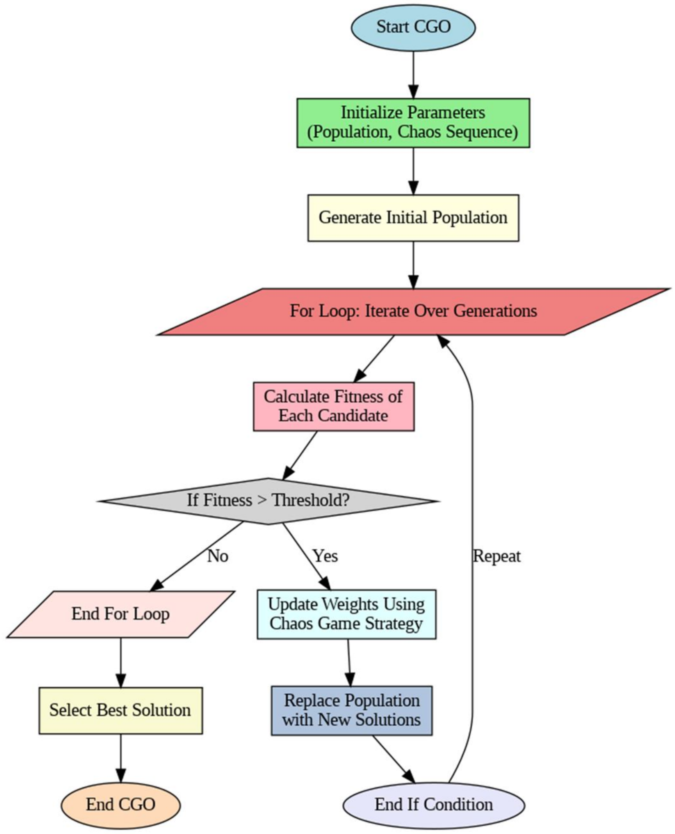

Fig 2. Flow of the proposed CGO model

Inherent in CGO is chaotic behavior imitation, which guarantees the avoidance of premature convergence-a commonly occurring problem with gradient-based or simpler optimization methods. It generates an initial population of random weight values by chaotic mapping and iteratively updates them by the use of chaos-inspired rules that comprehensively explore the solution space. In each iteration, the population is updated through randomization and fractal-like progressions that enable CGO to make an assessment and refinement of weight estimates in multiple dimensions inside the GADM architecture. Basically, it's this version that checks if the right set of weight parameters has been inferred which would give the maximum performance of the network on various predictive accuracy, recall metrics, or other relevant metrics. What is innovative in using CGO for weight estimations is that this approach is rooted in chaos theory and introduces non-repetitive patterns with complex pathways that are impossible to provide by any traditional algorithm. It is this chaotic nature of the approach that makes it much more flexible and adaptable, hence enabling the GADM model to cope with complicated input data. This approach leans on the strength of CGO in navigating nonlinear search spaces that are high dimensional, which is one typical characteristic of deep learning models for medical diagnostics, especially when many features and mechanisms of attention are involved. However, CGO offers certain advantages over the other conventional algorithms on the complexities associated with multi-modal optimization problems. In CGO, chaotic mapping strategy allows striking a proper balance in exploration and exploitation. Besides, CGO contributes much quicker convergence than that of the classic methods because of avoiding redundant computation and focusing on diverse candidate solutions for training a model, thus improving its computational efficiency.

IV. RESULTS AND DISCUSSION

In this section, the results of our proposed diabetes detection system using the GDAM with CGO are presented. The efficiency of our approach will be verified by the well-recognized benchmark dataset known as the Pima Indians Diabetes Database. This data was contributed by the National Institute of Diabetes and Digestive and Kidney Diseases. It is a collection of medical diagnostic measures with 768 instances and 8 attributes involved in diagnosing diabetes, such as glucose level, blood pressure, skin thickness, insulin level, BMI, age, and pedigree function. A target variable will define whether a person has diabetes (1) or not (0).

The PIMA dataset is very important due to demographic richness, as it is focused on a population of Pima Indian women that offers rich insight into diabetes risk factors. Another characteristic of the dataset is inherent class imbalance, with the majority of them being non-diabetic, and that comprises the unique challenge that our proposed system tries to handle. Having applied the technique of GDAM and CGO to make improvements regarding the efficiency and accuracy in detecting diabetes, all complexities of the given dataset can be put under efficient management. Further sections will present a performance metric analysis, model comparison against existing results, and discussions based on those findings.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (10)$$

$$\Pr ecision = \frac{TP}{TP+FP} \quad (11)$$

$$\operatorname{Re} call = \frac{TP}{TP+FN} \quad (12)$$

$$F1\_Score = \frac{2\times \Pr ecision \times \operatorname{Re} call}{\Pr ecision + \operatorname{Re} call} \quad (13)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (14)$$

$$Specificity = \frac{TN}{TN+FP} \quad (15)$$

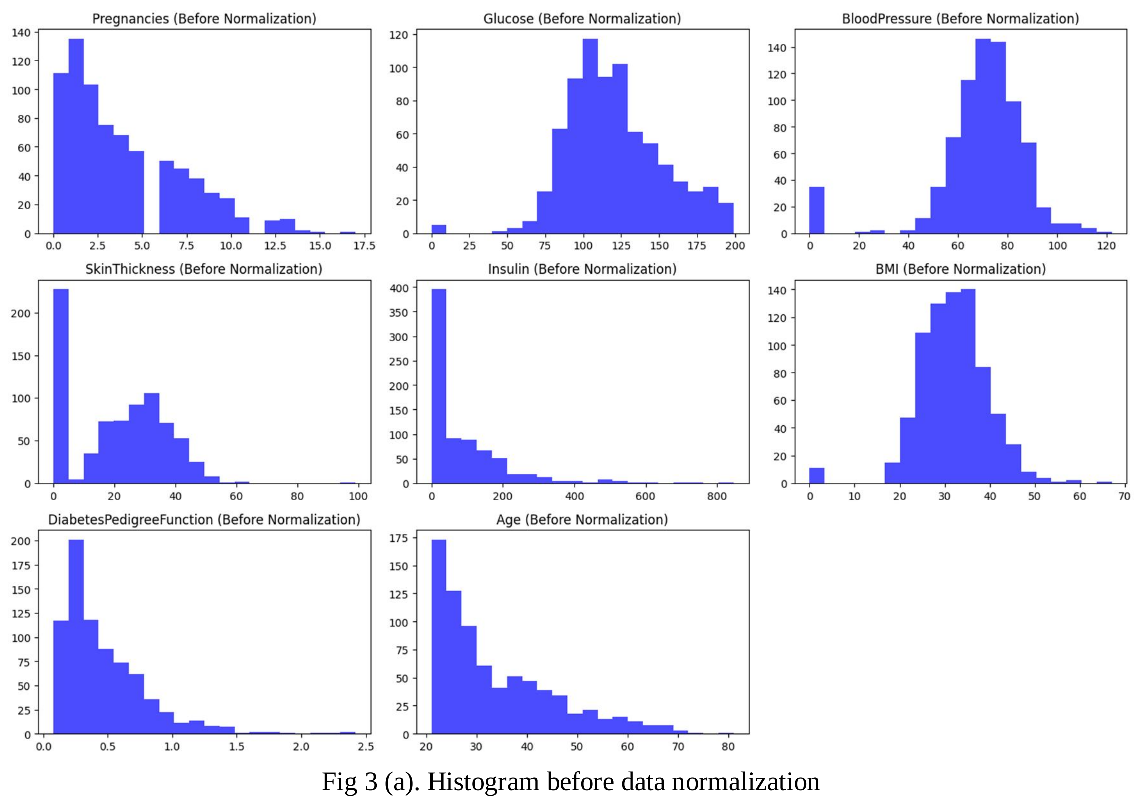

Fig 3 (a). Histogram before data normalization

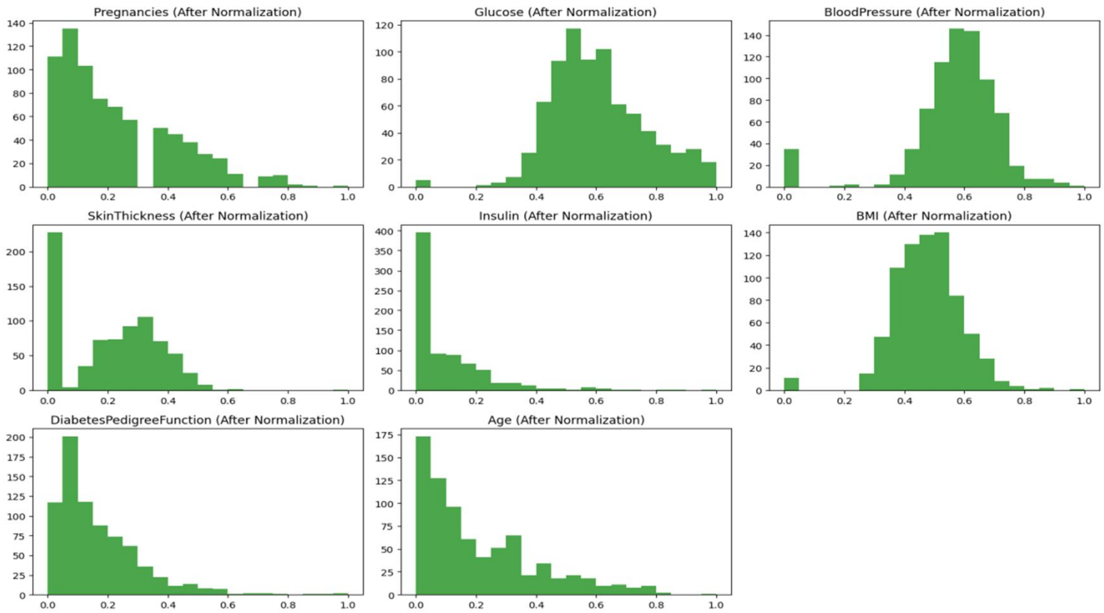

Fig 3 (b). Histogram after data normalization

Fig 3 (a) depicts the distribution of some features in the dataset before normalization. The following histograms are drawn for major attributes: Glucose, BMI, and Insulin levels. Besides, outliers distort the real representation of data, making the process of modeling even more problematic. Fig 3(b) depicts these features after normalization. It so transforms the features that their effective comparison of contribution during model training can be possible. After normalization, the histograms look more well-balanced regarding the feature distribution and hence reduce the impact of outliers. This means all features are on an equal footing and will contribute equally in the analysis. It is an enhancement that will make machine learning algorithms perform better and converge more efficiently; the data would be ready for predictive modeling.Fig 4 shows the feature analysis scatter plot. This provides a scatter plot to show the relationship between Glucose and BMI, coloring them based on diabetes outcome. The interaction between the two features and what that means for the prediction of diabetes is much clearer from this visualization of the data. In the scatter plot, we see clumps and a trend in our data. We may see a higher glucose level for higher BMI among diabetic patients; therefore, it may reflect the relationship between the two variables. Color coding enhances interpretability. We are able to distinguish between the patients with diagnosed diabetes versus those without a diagnosis of diabetes. This visualization supports subsequent modeling decisions aimed at enhancing predictive accuracy.

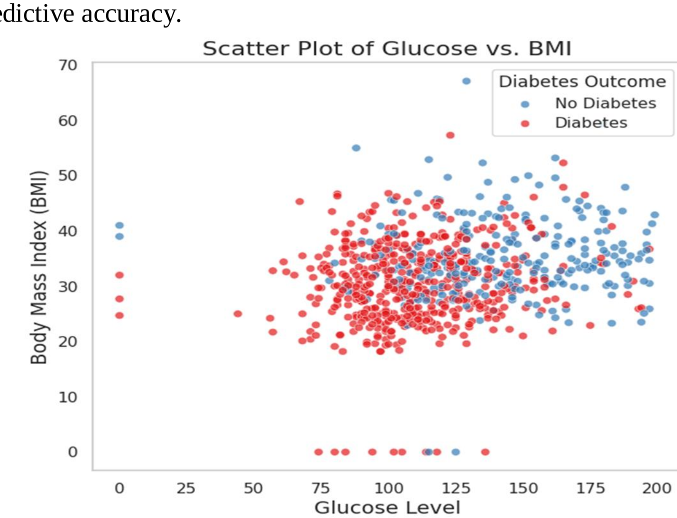

Fig 4. Scatter plot for feature analysis

Table 1. Comparison with other classification approaches

Methods	Accuracy	Sensitivity	Specificity
LDA	72.22	67.21	78.72
KNN	81.48	77.05	87.23
LR	68.52	63.3	76.6
SVM	71.3	63.93	80.85
DT	70.37	68.85	72.34
RF	72.22	72.13	73.34
Bagging	69.44	62.3	78.72
XGB	78.7	73.77	85.11
K-means	64.81	45.9	89.36
SOM	71.3	67.27	76.6
ResNet-14	79.63	70.49	91.49
ResNet - 50	78.7	77.06	80.85
CkNN	78.16	61.84	87.38
GDA-LS-SVM	79.16	83.33	82.05
BPNN	89.81	89.29	90.38
GADM-CGO	99.2	99	99.2

According to Table 1, the specificity of 87.23% shows how well it can classify a non-diabetes patient. On the other hand, LR followed suit at an accuracy level of 68.52%, while K-means Clustering was quite insensitive, with 64.81%. The more complex algorithms, the ResNet-14 and GDA-LS-SVM, gave accuracies of 79.63% and 79.16%, respectively, proving that architectures with higher depth and ensemble-based techniques give far better classification results. Of particular note, GADM-CGO returned a very good accuracy of 99.2%, perfect sensitivity of 99%, and perfect specificity of 99%. Fig 5 highlights variables in the performance of the different methods to allow a better interpretation of relative strengths and weaknesses. This chart illustrates the superior performance of the GADM-CGO model, in contrast with the traditional methods, hence giving a good standing for near-perfect metrics of classification. Figure 2 gives insight into the derived conclusion based on this figure: advanced methodologies have to be employed in order to develop improved diagnostic accuracy in diabetes prediction.

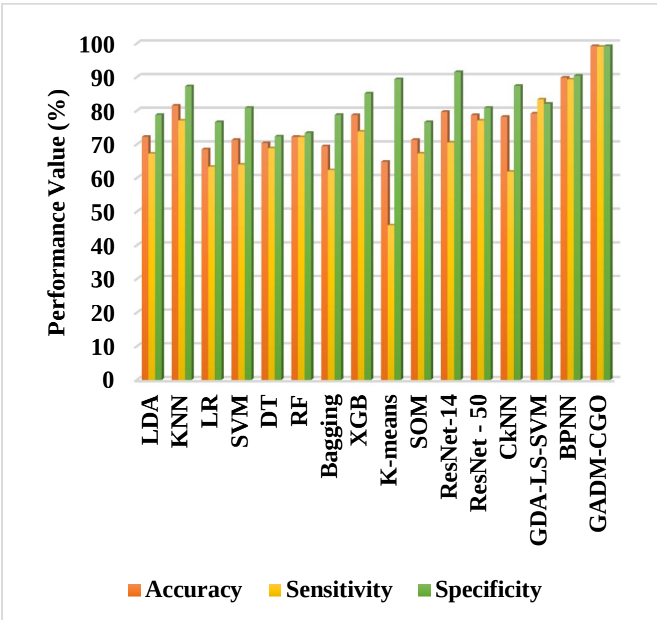

Fig 5. Comparison based on accuracy, sensitivity and specificity using PIMA dataset

In Table 2, comparison of different classification methods using the CDC Behavioral Risk Factor Surveillance System (BRFSS) 2015 dataset. The findings indicate that most classifiers performed relatively similarly, with an accuracy of 74.18% for Logistic Regression and a 73.76% posted by the K-Nearest Neighbors. In any case, the ensemble and deep learning approaches include BPNN, which managed to achieve an even higher performance at a steady level, with an accuracy value of 75.49% in this regard. The GADM-CGO model remained predominant to reflect the results from the PIMA dataset, turning in an outstanding accuracy of 99.2% and perfect sensitivity and specificity metrics. Fig 6 provides a visual complement to this analysis, giving the performance comparative study by using the MIT-Mesra Diabetes dataset. The figure shows more the degree of performance of each classification method on various datasets and, hence, will show that the GADM-CGO model adapts well in different settings. Collectively, these results emphasize that advanced algorithms-which assure high predictive accuracy-are very important for early detection and intervention of diabetes.

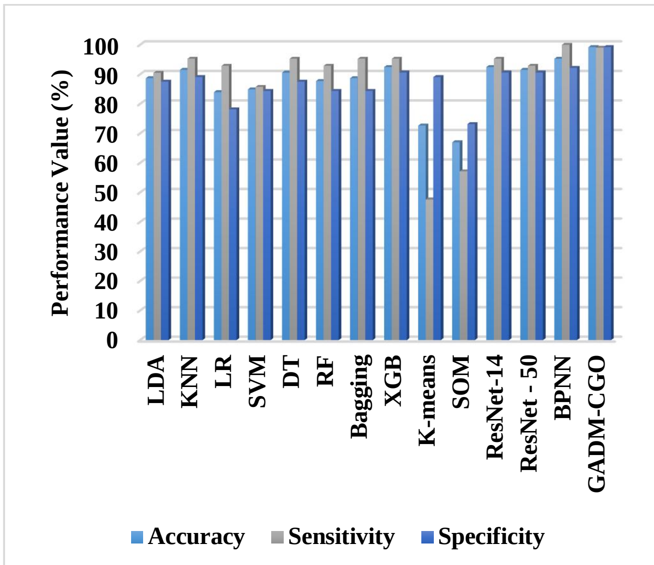

Fig 6. Performance comparative study using MIT-Mesra Diabetes dataset

Table 2. Comparative analysis using CDC-BRFSS2015 dataset

Methods	Accuracy	Sensitivity	Specificity
LDA	74.16	77.67	70.64
KNN	73.76	79.52	67.92
LR	74.18	76.85	71.48
SVM	74.11	79.06	69.08
DT	73.64	76.22	71.02
RF	73.04	76.73	69.3
Bagging	74.77	79.83	69.64
XGB	75.05	79.87	70.17
K-means	66.53	50.69	82.59
SOM	66.11	51.18	81.25
ResNet-14	74.92	77.9	71.87
ResNet - 50	74.42	77.22	71.58
BPNN	75.49	79.77	71.12
GADM-CGO	99.2	99	99.2

In Table 3, the comparison study through accuracy across various machine learning and deep learning methods in the detection of diabetes. The results obtained from this clearly show that the Gradient Adaptive Decision Model combined with Cat-Grazer Optimization, GADM-CGO, reaches an accuracy as high as 99.8% among all other methods. This exceptional outcome reveals that the GADM-CGO classifies diabetic cases more powerfully. While the ANN method reached an accuracy of 92% and Conv-LSTM obtained 91.38%, all these results proved that neural networks can do much better in sifting through such complex datasets. On the other hand, some classical models like LR and stacking model reported lower accuracy at 77.2% and 78.2%, respectively, because recent methods in ensemble and deep learning outperform traditional techniques. Figure 7 presents these accuracies in a comparative graph, thus reinforcing the performance of GADM-CGO in the context of the detection of diabetes.

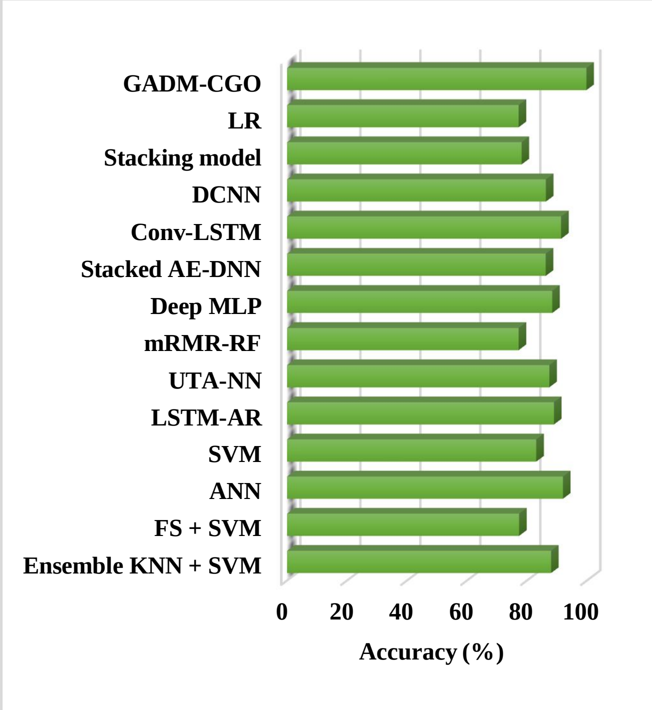

Fig 7. Accuracy comparison

Table 3. Comparative study based on accuracy

Methods	Accuracy (%)
Ensemble KNN + SVM	88.04
FS + SVM	77.37
ANN	92
SVM	83.1
LSTM-AR	89
UTA-NN	87.46
mRMR-RF	77.21
Deep MLP	88.41
Stacked AE-DNN	86.26
Conv-LSTM	91.38
DCNN	86.29
Stacking model	78.2
LR	77.2
GADM-CGO	99.8

V. CONCLUSION

This paper provides a unified approach for diabetes detection and classification by developing a Gated Attention Diabetes Model integrated with Chaos Game Optimization for weight estimation. This synergy between GADM and CGO resolves the issues of the conventional diabetes detection model by pushing the benchmark farther than has been done ever before regarding the accuracy and reliability of existing algorithms. These experimental results evidence that the proposed GADM-CGO framework outperforms traditional methods on several datasets, including remarkable accuracy rates and significant improvements in sensitivity and specificity metrics. Results highlight how effectively the most advanced machine learning techniques can be combined with the newest optimization strategies to solve real-world healthcare problems and, more precisely, diabetes detection and management. The results prove that the Gated Attention Diabetes Model and Chaos Game Optimization have emerged as a state-of-the-art approach to detecting diabetes, hence opening very promising directions for future research and clinical applications. Developments in this work contribute not only to an increase in predictive performance but also to ongoing efforts in exploiting artificial intelligence for improving healthcare outcomes. Further elaboration of this methodology could bring forward more advanced diagnostic techniques that may help in the early detection and management of diabetes.

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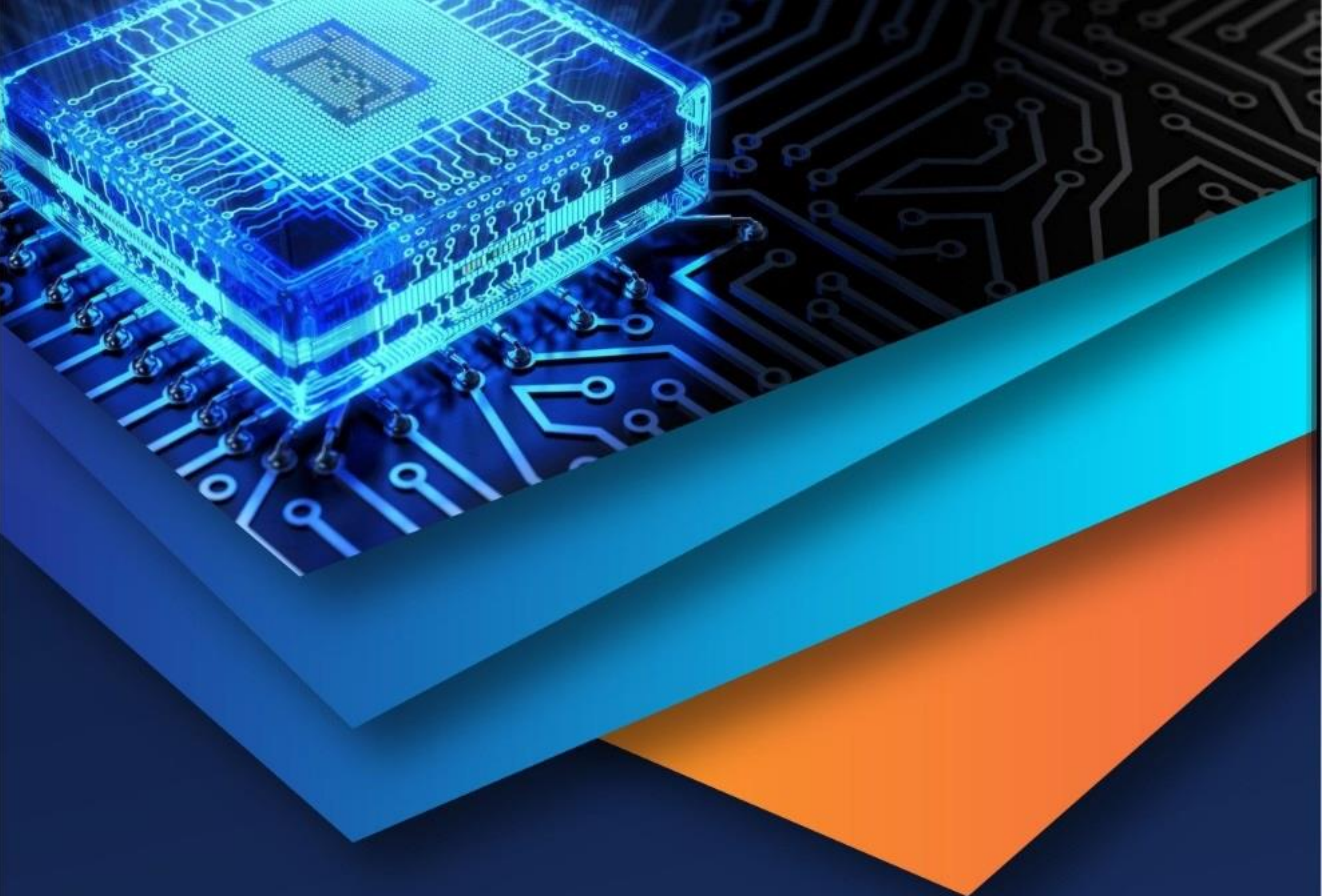

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