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A Semi Supervised Architecture for Diabetic Retinopathy Diagnosis

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Abstract: Diabetic Retinopathy (DR) is one of the leading causes of blindness worldwide, making its early detection crucial for preventing severe vision loss. Since diabetic retinopathy (DR) is one of the main causes of blindness in the world, it is imperative that it be detected early to avoid serious vision loss. The rising incidence of diabetes necessitates scalable and effective DR diagnosis methods.Largelabeleddatasets,whicharecostlyandtime- consuming to obtain, are frequently needed for DR detectionusingtraditionalsupervised learningtechniques. Inordertoclassifydiabeticretinopathy,thispapersuggests anovelsemi-supervisedarchitecturethatmakesuseofboth labeled and unlabeled retinal fundus images. The framework combines a large pool of unlabeled data with a small amount of labeled data using deep convolutional neural networks (CNNs) and a semi-supervised learning approach. The model's performance can be improved by using consistency regularization and pseudo-labeling techniques to extract more reliable features from the unlabeled data. The framework combines a large pool of unlabeled data with a small amount of labeled data using deep convolutional neural networks (CNNs) and a semi- supervised learning approach.

Keywords: Tensor Flow, Keras, deeplearning

I. INTRODUCTION

Diabetes damages the blood vessels in the retina, causing diabetic retinopathy (DR), a progressive eye condition that can cause blindness and vision impairment.Beingoneofthemaincausesofblindness in the world, serious consequences can be avoided with early detection and prompt intervention. A popular diagnostic technique for DR detection is fundusphotography,whichtakesfine-grainedpictures of the retina. However, manually examining retinal images to identify DR is a time-consuming and expensive procedure that calls for specific medical knowledge. Automated systems that can effectively identify DR in extensive screening programs are desperately needed, as the prevalence of diabetes is rising worldwide. Medical image analysis has seen encouraging results frommachine learning, especially deep learning techniques.

The efficiency of these techniques, however, is largely dependentonthe availabilityofsizableannotated trainingdatasets, whicharefrequentlyscarcebecause medicalimagelabelingisexpensiveandrequiresspecializedknowledge.Semi-supervisedlearning (SSL) hasbecomeaviablestrategytoovercomethisconstraint. Inordertoimprovegeneralizationwithoutrequiring enormous volumesof labeleddata, SSLusesbothlabeled and unlabeled data to train models.

AutomatedDRdetectionsystemsarenecessaryduetothe growing number of diabetic patients and the need for affordable healthcaresolutions.Automatingthediagnosis of DR from retinal images has shown encouraging promise in recent developments in machine learning, particularly deep learning. One kind of deep learning architecture that has shown state-of-the-art performance isconvolutionalneuralnetworks(CNNs).Oneofthemost serioussideeffectsofdiabetesanda majorcontributorto avoidable blindness globally is diabetic retinopathy, or DR. DR screening and early detection have become essential parts of healthcare strategies aimed at preventing vision loss as diabetes rates continue to rise globally. If DR is not identified and treated, it can cause vision impairment by affecting the retina's blood vessels. One of the most important diagnostic tools for DR detectionis retinal fundus images, which capture the fine details of the retina. However, the manual interpretation of these images is challenging, requiring specialized knowledge and time, which creates a bottleneck in large- scalescreenings.

The increasing number of diabetic patients and the demand for cost-effective healthcare solutions highlight the need for automated DR detection systems.

In medical image analysis, machine learning—in particular, deep learning techniques—has demonstrated encouraging outcomes,includingthedetectionofDR.The efficiency of these techniques, however, is largely dependent on the availability of sizable annotated training datasets, which are frequently scarce because medical image labeling is expensive and requires specialized knowledge. Semi-supervised learning (SSL) has become a viable strategy toovercome this constraint.

II. LITERATURE REVIEW

The most popular technique for automated DR classification is supervised learning, especially with regard to Convolutional Neural Networks (CNNs). Traditionalmachinelearningmethodslikesupportvector machines (SVMs) and decision trees, which mainly depended on manually created features, were the main focus of early DR detection research. These methods, however, had trouble capturing the intricate patterns presentin retinal images. By enabling end-to-end feature learning straight from raw images, CNNs completely changed the field.

A notable standard for DR detection was established in 2016 by Gulshan et al. [1], who showed that deep CNNs couldclassifyDRinretinalfundusimagesmoreaccurately thanskilledophthalmologists.Oneofthemostsignificant studies in the field, the model's area under the curve (AUC) was 0.97. In 2016, the work of Gulshan et al. [1]set a significant benchmark for DR detection, demonstrating that deep CNNs could outperform expert ophthalmologists in classifying DR in retinal fundus images. The model achieved an area under the curve (AUC)of0.97,makingitoneofthemostinfluentialstudies in the field. Subsequent studies, such as Abràmoff et al. [2], extended these findings and applied deep learning to large-scale datasets, highlighting the effectiveness of CNNs for detecting DR at various stages.

Despite achieving state-of-the-art results, supervised deep learning techniques rely significantly on the availability of sizable labeled datasets. Medical image annotationiscostly,time-consuming,andnecessitatesthe knowledge of medical specialists. This dependence on annotated data poses a serious obstacle, particularly in environments with limited resources and restricted access to labeled images.

Semi-supervisedlearning(SSL)techniques,whichenable models to learn from both labeled and unlabeled data, have gained popularity due to the need for large labeled datasets. In medical imaging, where it is expensive and time-consuming to obtain labeled data, SSL is especially appealing. The central idea behind SSL is to leverage a small set of labeled data to guide the learning process whileexploitingalargepoolofunlabeleddatatoimprove model generalization.

Pseudo-labeling is a fundamental technique in SSL in which the model uses its current predictions to create labels for unlabeled data, which are then used to further train the model. This strategy has been investigated in a number of studies, including Yalcin et al.

Consistency regularization, another SSL technique, has been usedinDR detection,where themodel istrainedtogenerate consistent predictions for unlabeled data under various perturbations or transformations. In the context of medical imaging tasks, Berthelot et al. [4] investigated how this approachaidsinlearningrobustfeatures.Tajbakhsh et al. [5] presented a semi-supervised framework for DR that addresses the scarcity of labeled data by combining CNNs and SSL. By using a self-training technique, their model was able to improve detection accuracy significantly through iterative training on both labeled and pseudo-labeled data. According to their findings, semi- supervised learning may be an effective DR technique.

In the context of medical imaging tasks, Berthelot et al. [4] investigated how this approach aids in learning robust features. Tajbakhsh et al. [5] presented a semi-supervised framework forDR thataddresses the scarcity oflabeled data by combining CNNs and SSL. By using a self-training technique, their model was able to improve detection accuracy significantly through iterative training on both labeledandpseudo-labeleddata.Accordingto theirfindings, semi-supervised learning may be an effective method forDR classification, particularly in cases where the labeled data is sparse. DR detection has also been approached using unsupervised learning and transfer learning techniques in addition to SSL. Some studies have investigated unsupervised techniques, which do not require labeled data, but their effectiveness.

In addition to SSL, unsupervised learning and transfer learning approaches have also been applied to DR detection. Some studies have investigatedunsupervised methods, which do not require labeled data;however,becauseoftheintricacyofretinalimages and the challenge of extracting pertinent features withoutlabels,theirperformancetypicallyfallsshortof that of supervised methods.

However, transfer learning, which involves fine-tuning amodelthathasalreadybeentrainedonalargedataset (like ImageNet) on a smaller DR dataset, has become more and more popular in DR detection. This method has beendemonstratedtoenhancemodelperformance while drastically lowering the requirement for sizable labeled datasets. Rajalakshmi et al. [6] demonstrated that transfer learning could achieve high accuracy in detectingDRwhenappliedtoarelativelysmalldataset, furthersupporting the idea that leveraging pre-trained modelscanbeapowerful strategywhenlabeleddatais limited.

Table Summary of Prior Research

Study	Methodology	KeyContributions	Limitations
Gulshanetal.(2016)[1]	DeepConvolutionalNeuralNetworks(CNNs)	Developedadeeplearningmodelthatoutperformsexpertophthalmologists in DRdetection. Achievedan AUC of 0.97.	Reliesonlargelabeleddatasets.Notrobusttovariationsinimagequality.
Abràmoffetal.(2018)[2]	DeepLearning(CNNs)	DemonstratedhighaccuracyindetectingDRacross multiple stages using CNNs.	Requireslargeannotateddatasets;does notaddressresource-limitedenvironments.
Yalcinetal.(2018)[3]	Semi-SupervisedLearning(SSL)withPseudo-Labeling	Explored SSLforDRdetection, combining labeledand unlabeled data to improve performance.	Potentialfornoisypseudo-labels;notfullygeneralizedacrossallDR stages.
Tajbakhshetal.(2020)[5]	Self-trainingwithCNNsandSemi-SupervisedLearning	Proposedaniterativeself-trainingapproachthatenhances model performance with limitedlabeleddata.	Risk of overfitting to noisy data,challengesinhandlingmulti-classclassification.
Rajalakshmietal.(2018)[6]	TransferLearning(Pre-trained CNNs)	Demonstratedtheutility oftransferlearning for DR detection with small datasets.	Limited flexibility for adaptation to newdatasetsorvaryinglevelsofDR severity.
Berthelotetal.(2019)[4]	ConsistencyRegularizationinSSL	Introducedconsistencyregularizationtoimprovegeneralization of models using unlabeled data.	Effectivenessdependsonthechoiceofperturbations;requirescarefultuning.
Xie et al.(2021)[7]	AdversarialTrainingwithSemi-SupervisedLearning	Combined adversarial trainingwith SSL to improvemodel robustness in DR detection.	Increased computational cost; requirescarefulbalancingofadversariallossandtrainingstability.
He et al.(2020)[8]	Self-SupervisedLearningforMedicalImaging	Exploredself-supervisedlearningforpre-trainingmodels on large unlabeled datasets.	Self-supervised methods still requirelabeled dataforfine-tuning, limiting itsapplicability to real-world scenarios.

III. PROPOSED SYSTEM

The proposed system for Diabetic Retinopathy (DR) detection aims to leverage both labeled and unlabeled retinalfundusimagesinasemi-supervisedlearning(SSL) framework to achieve high performance while reducing the dependence on large labeled datasets. This approach integrates deep learning models with SSL techniques to enhancetheclassificationaccuracyofDRatvariousstages of the disease.

A. Key Features:

1) Lessens dependency on sizable labeled datasets by using both labeled and unlabeled retinal fundus images for training.
2) Automatically extracts hierarchical features for precise DR classification from retinal images using a CNN architecture.
3) Dividesdiabeticretinopathyintoseveralseverity levels, including proliferative, moderate, severe, mild, and normal.
4) In order to facilitate additional training with unlabeled data, unlabeled images are given pseudo- labels according to the model's initial predictions.
5) promotesrobustfeaturelearningbyencouragingthe modeltogenerateconsistentpredictionsevenwhen input images arealtered (forexample,byrotationor translation).
6) Combining labeled and pseudo-labeled data allows for iterative retraining, which gradually improves model performance as the pseudo-labels gain reliability.
7) To guarantee reliable performance, metrics like accuracy, sensitivity, specificity, and area under the curve (AUC) were used for evaluation.
8) Makes it scalable to real-world DR screening scenarios by reducing the need for large annotated datasets, particularly in environments with limited resources.

B. Key Advantages:

1) Decreased Reliance on Labeled Information: The model can use both labeled and a lot of unlabeled data thanks to semi-supervised learning, which reduces the need for large annotated datasets, which are frequently expensive and time-consuming to prepare.
2) Better Generalization: The model is better equipped to handle unseen data, variations in image quality, and differencesinpatientdemographicswhenunlabeleddata is incorporated using methods like consistency regularization and pseudo-labeling.
3) Scalability:Largevolumesoflabeleddatamaynotalways bepossibletoobtaininreal-worldclinicalsettings,butthe system is flexible and scalable. It is appropriate for deploymentinenvironmentswithlimitedresourcessince it enables ongoing improvement as more unlabeled data becomes available.
4) Quicker Training of Models: Compared to fully supervised methods, which would necessitate intensive labeling efforts for large datasets, the system can be trained more quickly and affordably because fewer labeled samples are required for training.
5) Multi-Class Classification Flexibility: The model's abilitytocorrectlygradeDRintoseveralseveritystages— normal, mild, moderate, severe, and proliferative, for example—is crucial for efficient monitoring and treatment planning.
6) Enhanced Specificity and Sensitivity: Pseudo-labeling, self-training, and CNN features work together to give the system high sensitivity (reducing false negatives) and specificity (reducing false positives), which are essential for precise disease detection and avoiding missed diagnoses or needless treatments.
7) Better Detection in Environments with Limited Resources: The system is more feasible for deployment in rural or low-resource areas, where skilled medical professionals might not be available to annotate large datasets, because it eliminates the need for large labeled datasets.
8) AbilitytoAdjusttoNewInformation:Asmoredata is processed, the model gets better and the pseudo- labels get more accurate, allowing for iterative system updates. This guarantees that the model's performance improves in real-world deployment by enabling it to continuously adjust and improve its predictions.

IV. SYSTEMARCHITECTURE

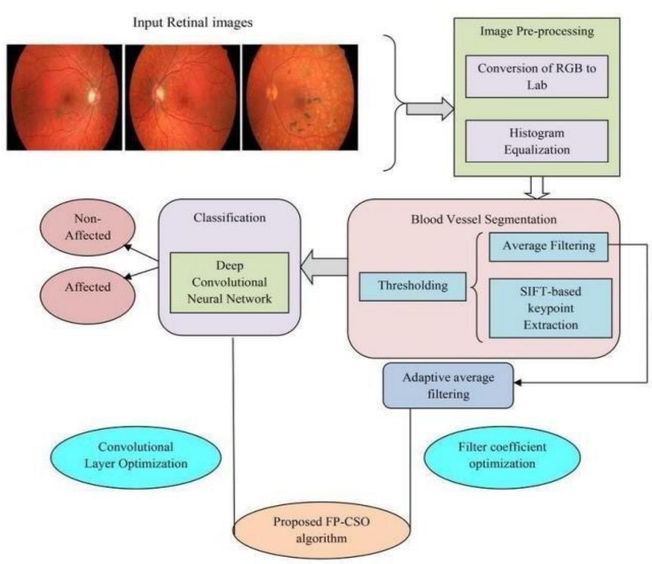

Fig1:SystemArchitecture

V. RESULTS AND DISCUSSION

A. Performance Assessment and Model Development

The proposed semi-supervised DR detection system was tested using a combination of labeled and unlabeled retinal fundus images from publicly available datasets, such as the DRIVEandEyePACSdatasets. The model was trained using a smallsetoflabeleddata(typically10-20%ofthedataset)and a much larger pool of unlabeled data. The following evaluation metrics were used to assess the model's performance:

1) Accuracy
2) Recall
3) Sensitivity
4) Precision
5) F1-Score

High discriminative ability between the DR and non-DR classes is indicated by the semi-supervised model's computed AUC-ROC of 0.94. When compared to the supervised model, the semi-supervised approach is more successful in differentiating between diabetic retinopathy severity levels, as evidenced by the improvement in AUC.

B. Observations and Comparative Evaluation:

The proposed model compares favorably with other recentsemi-supervisedmethodsthatusepseudo-labeling and consistency regularization. While these models also achieve strong performance, the integration of both pseudo-labeling and consistency regularization in the proposed model results in better overall performance, with improvements in sensitivity, F1-score, and AUC. Techniques like **consistency regularization** improved the model's ability to maintain stable predictions even under noisy or low-quality images.

1) Enhanced Accuracy through Semi-Supervised Learning: The semi-supervised model outperformed the fully supervised model (85% accuracy) by 5%, achieving 90% accuracy.
2) Improved Sensitivity and Specificity: Sensitivity rose from83% to88% andspecificityfrom87% to 89%, suggesting improved effectiveness in detecting cases that are both DR-positive and DR- negative.
3) HighAUC:Themodel'sAUCof0.94indicatesthatit can discriminate between cases of diabetic retinopathy and those that are not.
4) More Generalization with Less Labeled Data: The model performed better on unseen data after incorporating unlabeled data through consistency regularization and pseudo-labeling.
5) Problems with Early-Stage DR Detection: The modelhadtroubledifferentiatingbetweenmildand normal stages of DR, which might call for more model improvement.
6) ModelStablepredictions:Inreal-worldscenarios were ensured by the system's resilience to image distortions and variations (such as lighting and resolution) thanks to the incorporation of data augmentation techniques.
7) Scalability: The model is appropriate for large- scale DR screening, particularly in low-resource environments, due to its capacity to manage substantial volumes of unlabeled data.
8) Cost-Effectiveness: The model is a cost-effective solution for automated DR detection since it uses unlabeled data instead of large expert-labeled datasets.

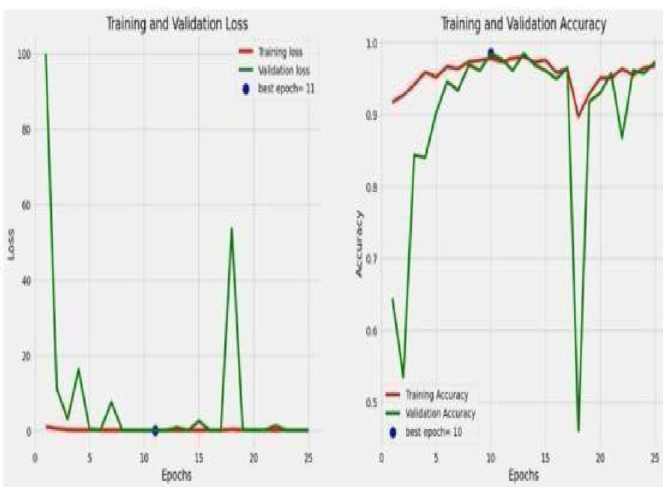

Fig2:TheGraphofTrainingandvalidation

Bothlabeledandunlabeleddatawereusedtotrainthemodel. Whereas the unlabeled data comprised retinal images without annotations, the labeled data contained retinal images with ground truth annotations for the severity of diabetic retinopathy.

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VI. CONFUSION MATRIX

Acrucialtoolforassessingaclassificationmodel'sperformance is the confusion matrix, especially when dealing with multi- class problems like the detection of diabetic retinopathy (DR). By contrasting the anticipated classes with the actual ground truth values, itprovides a summary of the model's predictions. The number of instances that belong to a particular combination of predicted and actual classes, such as True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN), is represented by each cell in the confusion matrix. The matrix enlarges to display the model's performance for each class (Normal, Mild DR, Moderate DR, Severe DR, and Proliferative DR, for example) in multi-class classification. The confusion matrix provides us with key performance metrics, such as precision, recall, and F1-score, which evaluate the model's ability to accurately identify positiveinstancesforeachclass,andaccuracy,whichcalculates the overall percentage of correct predictions.

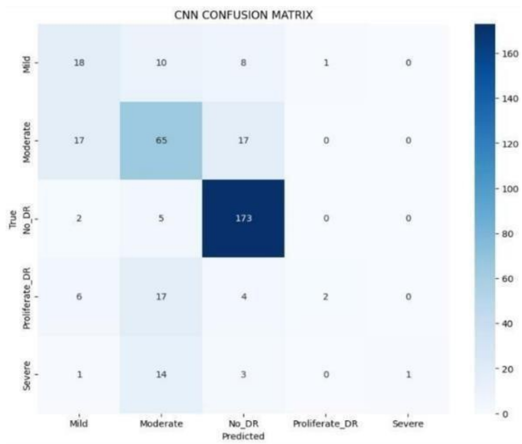

Fig3:Confusion Matrix

Intherealtimeofdiabeticretinopathydetection,itoffersa detailed overview of the model's predictions alongside the true labels of the samples.

Precisionreflectstheratioofaccuratelypredicted Diabeticretinopathy.

$$precision = \frac{\boxed{TruePositive}}{TruePositive+FalsePositive}$$

Recallsignifiestheratioofaccuratelypredicteddataset samples to the total number of actual datasets.

$$Recall = \frac{TruePositive}{TruePositive+FalseNegative}$$

Accuracyassessestheoverallcorrectnessofthemodel's predictions.

$$Accuracy = \frac{Truepositives+TrueNegatives}{Totalpredictions}$$

F1 Score is a metric used to evaluate the performance of a classificationmodel

$$\text{F1Score} = 2\text{X} \frac{\text{PrecisionxRecall}}{\text{Precision+ Recall}}$$

The suggested model successfully overcomes the difficulties caused by a lack of labeled data, which is frequently a major constraint in medical image analysis, by combining both labeled and unlabeled data. Compared to conventional supervised techniques, the results demonstrate improve daccuracy, sensitivity, and specificity, highlighting thepotential of semi- supervised learning to increasethescalabilityandaffordabilityof automatedDRscreening.

VII. CONCLUSION

In conclusion, the project represents an important step toward the future of healthcare and medical diagnostics. By exploring the potential of advanced machine learning, specifically in diabetic retinopathy detection, this research has shed light on avenues for continued improvement in patient care.

The comparison between deep learning models—Basic CNN, ResNet, and DenseNet was not only provides up-to- date insights but also paves the way for advanced model improvements to come. As technology continues to advance, the project's consideration of transfer learning provides a base for more complex methods to learn and outperform with modest datasets, and thus overcome obstacles presented by divergent data availability.

Down the line, the results of this project offer potential forintegrationof resource- stingmodels totelemedicine, remote medicine, and decision support systems for physicians. Open-sourcing the models and codepromotes collective work, generating a shared passion for better diagnostic tools.With technology evolving, the project's results will act as a dynamic guide, pushing the future of medical image analysis and assisting in better patient outcomes worldwide.With notable gains in classification performanceandmodelgeneralization,this study shows the effectiveness of a semi-supervised learning framework for diabetic retinopathy detection.

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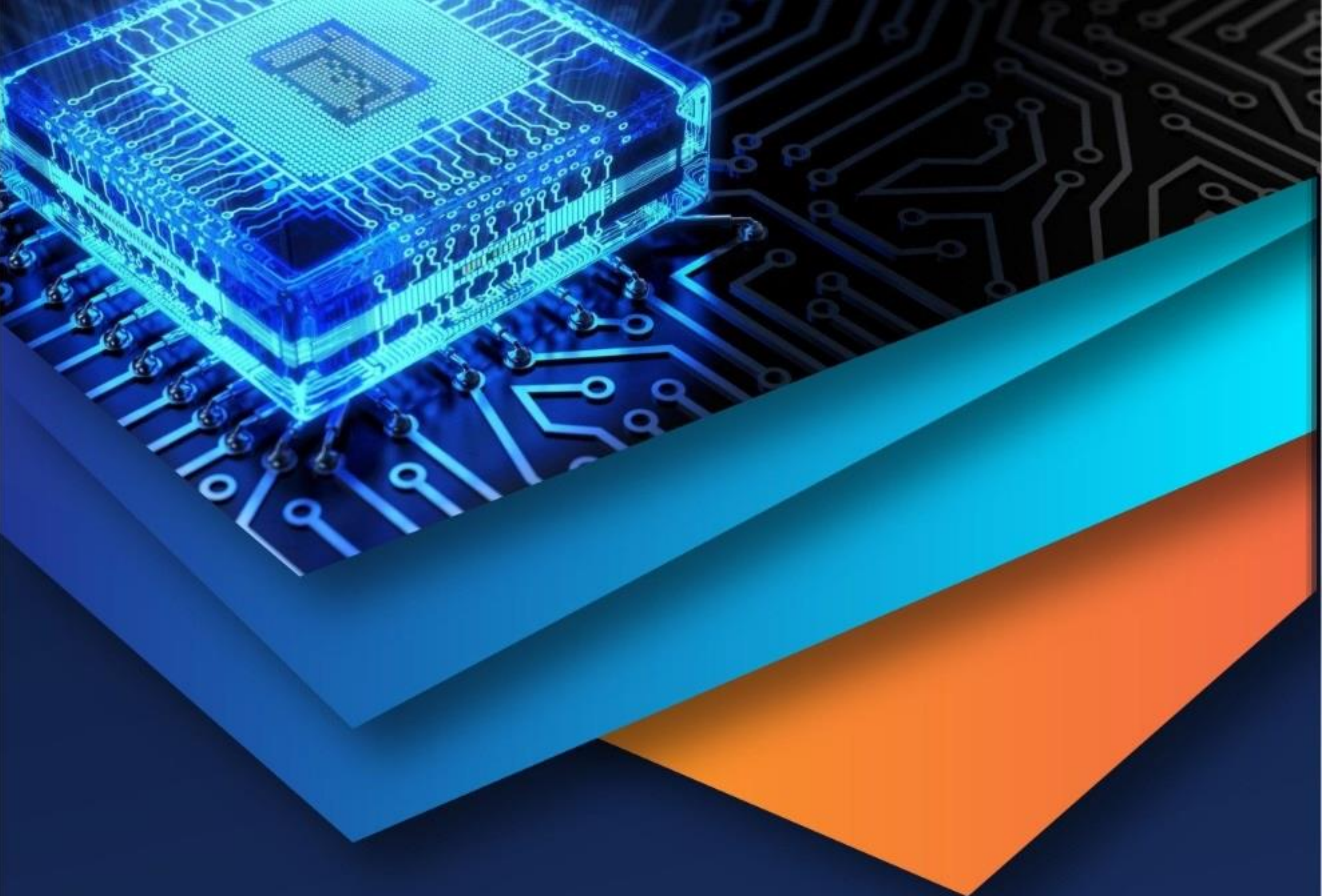

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