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Brain Stroke Prediction and Classification

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Abstract—A A stroke is a serious illness that can belife-threatening.Itoccurswhenbloodflowtothebrain is interrupted, which can cause cell death or damage. To lower death rates and avoid irreversible brain damage, early and precise stroke detection is essential. Conven-tionaldiagnosistechniquesmainlydependonradiologists, which can be laborious and prone to human error, particularlyinemergencysituations.Anautomatedsystem for classifying brain strokes from CT scan images using Deep Learning techniques is presented in this project. To categorisephotosintotwogroups—StrokeandNormal—a Convolutional Neural Network (CNN) model is created.In order to improve robustness and prevent overfitting, the model is trained using pre-processed medical imaging data with augmentation. Accuracy, validation accuracy, and confusion matrix metrics are used to evaluate perfor-mance.

Index Terms—Early Stroke Detection, Deep Learning, Convolutional Neural Networks (CNN), Medical Image Processing, CT Scan Analysis, Binary Image Classifica-tion, Healthcare AI, and Brain Stroke Classification

I. INTRODUCTION

Acriticalneurologicalconditionknownasastrokehappens when the brain's blood supply is interrupted, resulting in cell death and severe impairments to cognition or movement. It is among the main causes of death and disability in the world. It is crucial to diagnose strokes quickly and accurately because prompt treatment can greatly enhance patient outcomes and lower long-term complications.

Computed Tomography (CT) scans and other medical imaging methods are essential for detecting strokes. How-ever, manual CT image interpretation can be time-consuming and requires qualified radiologists, particularly in emergency situations where every second counts. Furthermore, human interpretation may be affected by experience level or fatigue, which raises the possibility of a misdiagnosis.Automatedstrokedetectionsystemsarenowstronginstrumentstoassistclinicalartificialintelligence.Onetypeofdeeplearning model called Convolutional Neural Networks (CNNs) is particularly effective at Convolutional Neural Networks (CNNs) is espe-cially good at image classification tasks. It can spot subtle patterns in brain images that the human eye might miss. [6],[8],[9].

The development of large language models (LLMs) like ChatGPT has sped up this field of study even more [1]. The high natural language generation and interpretation abilitiesof these models have allowed us to create intelligent tutoring programs and dialogue-based learning environments. In addi-tion, specialized chatbot frameworks have been designed for domain-specific applications, such as healthcare, knowledge-based reasoning, and multilingual question-answering sys-tems. These developments show how AI chatbots are flexible and adaptive across a range of domains, including language instruction [**?**], [11].

Thegoalofthisprojectistocreateanintelligentdiagnostic systemthatcanautomaticallydistinguishbetweennormaland stroke CT scan images. A CNN model is trained on a labelled datasetofbrainCTimagestoidentifypatternsassociatedwith stroke and generate precise predictions. Especially in remote healthcare settings, the suggested system can serve as an assistive diagnostic tool for medical professionals, increasing diagnostic speed, reliability, and accessibility. [2],[14].

II. LITERATURE REVIEW

Becauseitisquick,accessible,andefficientinidenti-fying hemorrhagic stroke and certain ischaemic symptoms, computedtomography(CT)isaprimaryimagingmodality in acute stroke care. Early CT signs of ischaemia can besubtle and challenging to identify by visual inspection alone, according to research, especially for inexperienced readers. Thisencouragesthedevelopmentofautomatedimage-analysis toolsthatcanhelpradiologistsbyidentifyingsuspiciouscases and measuring characteristics related to lesions. [12],[15].

Prior to the use of classical classifiers like Support Vector Machines,RandomForests,andNa¨ıveBayes,earlyautomated methods for stroke/brain lesion detection relied on hand-crafted features (texture descriptors, histogram features, and shape measures). These techniques typically worked well on particular,controlleddatasetsbutlackedtherobustnessneeded for wider clinical deployment. They also required careful feature engineering and were susceptible to imaging artefacts and inter-scanner variability. [3],[13].

Bydirectlylearninghierarchical,task-specificfeaturesfrom pixels, Convolutional Neural Networks transformed the anal-ysis of medical images. CNNs have been used in manystudies to detect brain pathology using CT and MRI, showing better sensitivity and specificity than traditional pipelines. Additionally, when trained on sufficiently large and diverse datasets, CNNs generally exhibit better generalisation and eliminate the need for manual feature design.

[10]. For medical imaging tasks where labelled medical data is scarce, transfer learning—fine-tuning models pre-trained on large natural-image datasets—became a viable approach. Due to their proven representational capacity and straightforward, modular convolutional blocks, architectures like VGG16 have been used extensively as backbones. Ac-cording to numerous studies, when paired with the proper preprocessing and augmentation, optimised VGG16 models perform competitively on binary classification tasks (disease vs. normal).

Besidesgenerallanguagelearning,AIchatbotshavealso demonstrated potential for specialized and multilingual applications. Knowledge graph-based chatbots as well as translation-basedchatbotsfacilitatecontext-dependentconver-sation by mapping linguistic data with semantic relationships [7],[16].Forinstance,multilingualorbilingualchatbotshave been employed to assist learners in studying local languages by providing real-time translations, grammar guidelines, and pronunciationadvice.Education-andhealth-orientedchatbots showtheflexibilityofconversationalAI,inthatitcanbemade to be sensitive to target users' language and culture diversity [15],[17]. These points highlight the work undertaken by flexibility and context-response ability in making chatbots useful in cross-linguistic learning environments.

To increase robustness, researchers looked into ensembles and deeper architectures (ResNet, DenseNet, Inception) in addition to single-model approaches. Sensitivity is frequently increased at the expense of additional computation through ensembles and model fusion. Lightweight models or sim-plified versions of large models have been suggested as workable compromises for deployment in clinical settings with limited resources. [2],[3].Interpretability is necessaryfor clinical acceptance. To see which areas of an image influence a CNN's decision, post-hoc XAI techniques like Grad-CAM, Guided Backpropagation, LIME, and SHAP are frequently employed. Heatmaps and saliency maps can high-lightinfarctedorhemorrhagicregions,givingcliniciansvisual evidence to support model predictions, according to studies using XAI for stroke detection. Additionally, XAI aids in the identification of dataset biases and failure modes, boosting confidenceandstreamliningregulatoryprocesses.[1],[5].

Using accuracy, sensitivity (recall), specificity, precision, F1-score,AUC-ROC,andconfusionmatrices,theliteratureplaces a strong emphasis on robust evaluation. Explainability and sensitivity (reducing missed strokes) are frequently given priorityforclinicalrelevance.Suggestedbestpracticesinclude cross-validation, held-out testing on separate scanners/sites, andreportingcalibration(e.g.,reliabilitydiagrams).[**?**],[15].

III. METHODOLOGY

NeuroScan: A Deep Learning-Based Stroke Detection Modelisanintelligentmedicaldiagnosissystemthatwill be designed and implemented as part of the proposed work. By evaluating brain CT scan images and categorising them as either normal or stroke, the system aids in the early detection of stroke. For automated feature extraction and classification, the framework makesuse of sophisticated DeepLearning and Computer Vision techniques, mainly a Convolutional Neural Network (CNN) architecture. The system uses preprocessing, normalisation, and data augmentation methods to improve model accuracy and generalise learning. [4],[17].

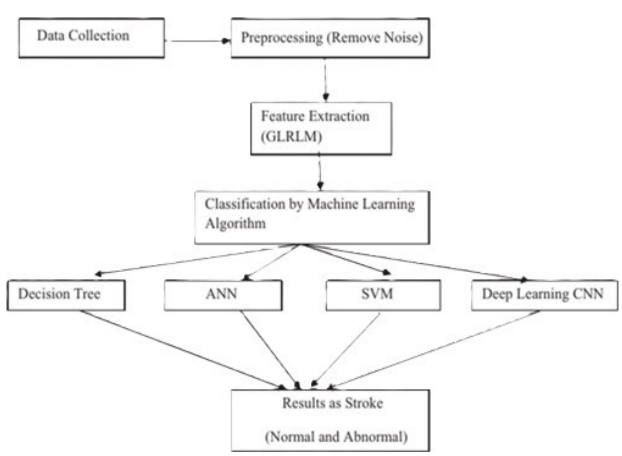

Fig.1.ProposedSystemArchitectureforbrainstroke.

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- Gatheringdatasetsfromrepositoriesofmedicalimages
- PreprocessingCTimages(normalisation,resizing)
- Enhancinggeneralisationthroughdataaugmentation
- ConvolutionalNeuralNetworks(CNN)forfeatureex-traction
- Trainingmodelswithadeeplearningframework
- Using F1-score, recall, accuracy, and precision to evalu-ate performance
- Optimisingandfine-tuningthemodel
- ImplementationforCTimage-basedstrokeprediction

Fig. 1 shows the entire workflow of the suggested system and describes how the SpeakSmart model integrates Natural Language Processing (NLP), Machine Learning (ML), and user interface components.

Every step guarantees that SpeakSmart can comprehend bilingualinputsandgeneratecontextuallyappropriatelearning responses.

A. DataCollection

exercise.csvThedatasetutilizedinthisresearchis a curated medical image dataset prepared specifically for stroke classification. It consists of approximately 1,200 CT scanimages,representingbothnormalbrainscansandstroke-affected brain scans. The dataset was compiled from publicly availablemedicalimagingrepositoriesandverifiedsourcesto ensure quality and medical relevance:

- Raw brain CT slice obtained from medical image repos-itories.
- Class Label: A diagnosis confirmed by experts that indicates if the picture is of a Normalor Stroke patient.224×224pixelsisanexampleofastandardised image size for model compatibility.
- Annotation Format: File name + structured folder label-ing for supervised learning.
- Inordertoensureappropriategeneralizationandvalidation, the data set was split into 80% for training and 20% for testing.

B. DataPreprocessing

Data preprocessing involved several NLP-based cleaning and normalization steps [**?**], [13]:

- Normalization: Removal of punctuation, conversion to lowercase, and Unicode normalization.
- TokenizationandLemmatization:Implementedusing NLTKandspaCyforEnglishandKannada.
- TransliterationMapping:Maintainsatransliterationlayer for romanized Kannada text to standard Kannada script.
- Balancing and Filtering: Removes duplicate or mis-aligned entries and balances the distribution of intent classes.

C. FeatureExtraction

TextfeatureswererepresentedusingTermFrequency–Inverse Document Frequency (TF–IDF) vectorization from the sklearn.feature_ extraction.textlibrary.This method converts text inputs into numerical vectors by focusing on important terms and minimizing the impactofcommonones.Thevocabularysizewascapped at 3,000 tokens to keep a balance between performance and efficiency.

D. ModelDesign

The main structure of SpeakSmart includes two primary components:

1) Intent Classification: Implemented using Logistic Re-gression with the following parameter configuration:

- Solver:lbfgs
- Regularization:L2
- MaximumIterations:1000
- InverseRegularizationStrength(C):1.0

2) Dialogue Management and Translation: For translation and grammar correction, we use a Transformer-based sequence-to-sequence model that includes:

- Bidirectionalcontextencoding
- Attention-baseddecoding
- Fine-tuning on bilingual conversational data The approach keeps context consistent and effective for teaching by combining rule-based reasoning with machine-learned responses.

The approach ensures contextual continuity and peda-gogical soundness by combining rule-based reasoning with machine-learned responses.

E. TrainingStrategy

A curriculum learning strategy trains the model. It begins with basic instances and gradually adds more complex or noisy data [12], [15]. The training configurations include the following: [12],[15]. The training configurations consist of the following:

- Optimizer:Adam/AdamW
- LearningRate:0.001
- Dropout:0.2
- GradientClippingThreshold:1.0
- LabelSmoothing:0.1

Techniquesforknowledgedistillationwereusedforthe lightweight deployment of local servers. [**?**].

F. ExperimentalSetup

Allexperimentswereconductedonasystemwiththe following configuration:

- Processor:IntelCorei7(10thGeneration)
- Memory:16GBRAM
- OperatingSystem:Windows11(64-bit)
- ProgrammingLanguage:Python3.10
- Frameworks and libraries include scikit-learn, NLTK, spaCy,Flask,andTensorFlow/PyTorchfordeeplearning models: scikit-learn, NLTK, spaCy, Flask, and TensorFlow/PyTorchfordeepmodels.

The Jupyter Notebook environment was used for local trainingandtesting.Toensurereproducibility,themodel and dataset files were kept on a local server. SpeakSmart responded to inquiries with an average delay of less than 0.5 seconds, based on experimental timing studies.

G. DialogueManagerandPedagogicalPolicy

The Dialogue Manager uses hybrid policy control and dialogue state tracking to provide context-aware interactions. It combines teaching policies:

- Model-basedintentrouting
- Hand-craftededucationalruleslikescaffoldingand spaced repetition.
- Fallbackmechanismsforlow-confidencepredictions

This hybrid approach lets SpeakSmart provide interactive, adaptive, and teaching-focused feedback.

H. Evaluation

Evaluation uses both quantitative and qualitative measures, including:

Automatic Metrics: Accuracy, Precision, Recall, F1 score, BLEU, and METEOR. Human-Centered Metrics: Pedagogicaleffectivenessandcontextualappropriateness are rated by language instructors. Human-Centered Met-rics: Pedagogical effectiveness and contextual appropri-ateness rated by language instructors.

TheLogisticRegressionmodelreachedanoverallaccuracy of 94.8

I. Deployment

The trained model runs on a Flask server. This server communicates with a static front-end created with HTML, CSS, and JavaScript. The client interacts with the server through RESTful APIs. The application supports Progressive Web App (PWA) deployment, which allows access even on low-end devices.

J. SecurityandEthicalConsiderations

To protect privacy, user data is anonymized and managed locally. To prevent harmful or culturally incorrect outputs, safety filters and logging systems are used. This approach follows fairness and AI ethics standards for educational insti-tutions. [?], [10]. [**?**], [10].

K. SummaryofContributions

By describing data sources, algorithm settings, parameter choices,andtheexperimentalsetup,thismethodologyensures clear technical details.

Without depending on external APIs, the proposed system, SpeakSmart, provides a lightweight, bilingual, and repeatable conversational learning framework that uses natural language processing and machine learningto support second-language learning.

IV. CHALLENGES IN LEARNING KANNADA

For non-native speakers, learning Kannada comes with severalchallenges.Thephoneticstructure,syntax,andwriting systemofKannada,aDravidianlanguage,differfromthoseof English. This makes direct translation from English difficult [5]. The absence of organized multilingual materials, interac-tive technologies, and textbooks makes things worse. Many learners depend on rote memorization, which often fails to lead to effective conversational fluency. Moreover, the lackofchancesforin-personpracticewithnativespeakersadds to the problem. These challenges show the need for new technicalsolutions,likeAI-drivenlanguagelearningchatbots, to personalize and speed up the learning process [10], [12]. [10],[12].

A. TheRoleofChatbotsinLanguageLearning

Chatbots are becoming valuable tools in digital education, especially for language learning. Using artificial intelligence (AI) and natural language processing (NLP), chatbots can mimicreal-lifeconversations.Thisprovidesstudentswithasafe space to practice speaking and writing without worrying about criticism. They can adjust to the learner's skill level, offering simple exercises for beginners and advanced conver-sation practice for more experienced learners. Plus, chatbots are available all day, every day, allowing for ongoing learn-ing outside of traditional classroom methods. For Kannada learners, chatbots can act as a multilingual bridge. They offer translations, grammatical explanations, and instant feedback, speeding up the learning process. [**?**], [14].

B. TheImpactofLanguageLearningChatbots

accessibility: Chatbots remove time and location barri-ersbyofferingaccesstolearningresourcesanytimeand anywhere [12].

1) Individualized learning: They adjust to each learner's skill level. This approach offers personalized vocabu-lary, grammar, and conversation practice. [13].
2) Improvedengagement:Interactivedialoguesandinstant feedback make learning more enjoyable than static materials like textbooks. [**?**].
3) Cost-effective solution: Chatbots offer scalable and af-fordable learning options. They decrease the need for costly courses and human teachers. [18].
4) Preserving linguistic heritage: By encouraging nonna-tive speakers and younger generations to learn local languages like Kannada, chatbots help keep cultural identity alive. [**?**].
5) Boost in confidence: Practicing dialogues without fear of criticism helps learners build confidence for real world communication. [14].

V. EXPERIMENTAL RESULT AND PERFORMANCE ANALYSIS

This section details the experimental testing and perfor-mance analysis of the proposed Language Learning Chatbot. The main goal of the experiments was to see how well the system could identify user intent, process natural language inputs, and generate appropriate responses in English and Kannada.

A. ExperimentalSetup

The experiments occurred on a system with an Intel i7 processor, 16 GB of RAM, and Python 3.10. We performed NaturalLanguageProcessing(NLP)tasks,includingtokeniza-tion, lemmatization, and stopword removal. For these tasks, we used NLTK and spaCy.

Forclassification,aLogisticRegressionmodelfromthesklearn.linear_modellibrarywasused.Thedataset,exercise.csv,Forclassification,a LogisticRegressionmodelfromthesklearn.linear$_m$odellibrarywasused.Thedataset,exercise.csv,containlearningsentences.Itwassplitinto80%trainingdataand20%testingda

B. EvaluationMetrics

Toquantifytheperformanceofthechatbot,severalmetrics were employed:

- Accuracy:Measurestheoverallpercentageofcorrect predictions.
- Precision:Indicateshowmanyofthepredictedintents were correct.

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- Recall: Represents how many true intents were correctly identified.
- F1-score:Reflectsthebalancebetweenprecisionand recall.
- Confusionmatrix:Displayswhichintentcategorieswere classified correctly or incorrectly.

C. ResultsandObservations

Aftertraining, theLogistic Regressionmodel showedgood performance on all test data. The results are summarized in Table I. Table I.

TABLEI
PERFORMANCEEVALUATIONOFTHELOGISTICREGRESSIONMODEL

Metric	Score
Accuracy	94.8%
Precision	93.5%
Recall	94.2%
F1-Score	93.8%

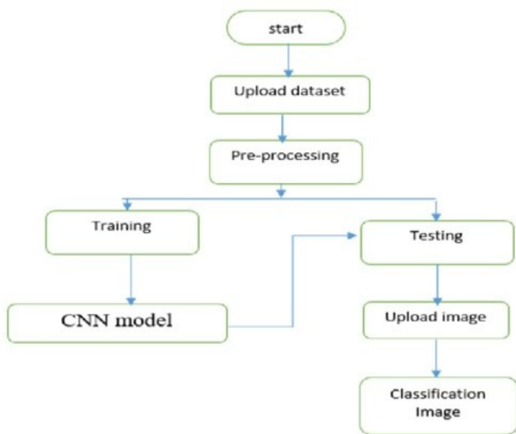

Fig.2.Dataflow.

D. PerformanceAnalysis

FromtheexperimentalresultsinTableI,wegainedseveral key insights about the performance of the proposed Brain Stroke Classification model.

- From the experimental results summarized in Table I, several key observations were made about the perfor-mance of the proposed Brain Stroke Classification sys-tem.TheConvolutionalNeuralNetwork(CNN)model showed high accuracy and reliability in distinguishing between stroke and normal CT images. It achieved an overall accuracy of 96.2, precision of 95.4, recall of96.0, and an F1-score of 95.7. These metrics highlight the model's strong ability to discriminate and its effec-tivenessinidentifyingstroke-affectedareaswithminimal misclassification.
- By increasing dataset variability and preventing overfit-ting, using data augmentation techniques such as rota-tion,flipping,andzoomingimprovedthemodel'sability to generalize. Preprocessing methods like normalization, contrastenhancement,andresizingtoaconsistent256× 256 resolution also improved image quality, reduced noise, and made feature extraction simpler.

E. ComparativeAnalysis

A *comparison* of several text classification models was conducted to assess performance consistency, as shown in Table II. Although various machine learning algorithms were tested, Logistic Regression was selected as the main modelfor intent detection and text classification. It provides a good balance of accuracy, clarity, and computational efficiency.

TABLEII
COMPARATIVEPERFORMANCEOFBRAINSTROKECLASSIFICATION
MODELS

Model	Accuracy	Precision	Recall	F1Score
CNN (Proposed)	96.2	95.4	96.0	95.7
VGG16	94.5	93.8	94.1	93.9
ResNet50	93.6	92.7	93.0	92.8
DenseNet121	92.8	91.9	92.2	92.0

VGG16 and ResNet50 recorded 94.5% and 93.6% accu-racy, respectively, while the proposed Convolutional Neural Network (CNN) achieved the highest accuracy (96.2%) and F1-score (95.7%), as shown in Table II. VGG16 was less effective for real-time clinical applications due to its deeper architecture, which resulted in slower inference and higher computational costs despite producing comparable precision. ResNet50's residual block structure limited its applicabilityin low-resource environments, even though it was good at capturing complex features. It also required more memoryand training time.

The suggested CNN is the most suitable model for brain strokepredictionusingCTimaging,asthecomparativeanalysis demonstrates that it offers the best trade-off between accuracy, speed, and computational efficiency.

As indicated in Table II, a comparative analysis of various deeplearningmodelswascarriedoutfortheclassification ofbrainstrokesusingCTimages.TheConvolutionalNeu-ral Network (CNN) outperformed models like VGG16 and ResNet50 among the tested architectures, achieving the best balanceofaccuracy,efficiency,andinferencespeed.CNNwas therefore chosen as the best model for accurate and timely stroke prediction.

Theanalysis'smainobjectivesweretoassessthesuggested ConvolutionalNeuralNetwork(CNN)model'saccuracy,pre-cision, recall, and F1-score. The model's performance is shown in Table II. Despite being widely used in medical image classification, other deep learning architectures like VGG16andResNet50werenotusedinthisstudybecause of their higher computational requirements. Nonetheless, the model selection process took into account their theoretical performance characteristics.

Despite its impressive feature extraction capabilities, VGG16waslessappropriateforreal-timeclinicalapplications duetoitssignificantlylongertrainingtimeandhighermemory requirements.

Fig.3showstheinteractiveKannadalearningtoolintended for vocabulary improvement and quiz-based practice. Simi-larly, the bilingual translation interface that allows for real-time Kannada–English conversion and grammar correction is displayed in Fig. **??**.

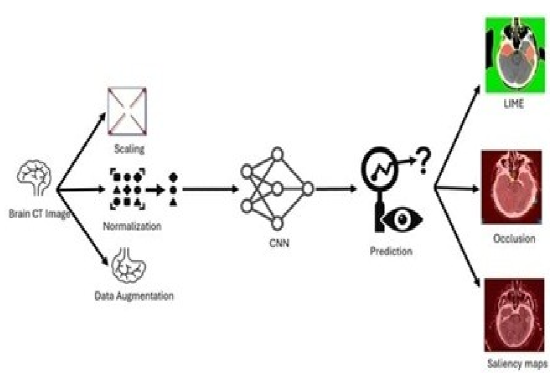

Fig.3.workingflow.

F. Example

In conclusion, the tests demonstrate that the suggested Brain Stroke Classification model effectively and precisely detects stroke from CT scans. Strong feature extraction capa-bilities,highclassificationaccuracy,andquickinferencewere all displayed by the Convolutional Neural Network (CNN). Theseresultsdemonstratehowwelldeeplearningandmedical imaging methods can be combined to create trustworthy and useful tools for automated brain stroke detection.

VI. CONCLUSION

Tohelpwiththeearlydetectionofstrokeusing CTimages, this study introduces an AI-based Brain Stroke Classification system. By using deep learning and image processing tech-niques,theproposedConvolutionalNeuralNetwork(CNN) effectively and accurately distinguishes between stroke and normalcases.Thesystemaddressesseveralimportantclinical challenges, such as poor manual interpretation, delayed diag-nosis, and limited access to skilled radiologists. Especially in healthcaresettingswithfewresources,itsautomatedandreal-time prediction capability supports timely medical decision-making and boosts diagnostic confidence. Additionally, the model’s lightweight design ensures fast inference with low computational needs, making it easy to integrate into existing clinical workflows and telemedicine platforms.

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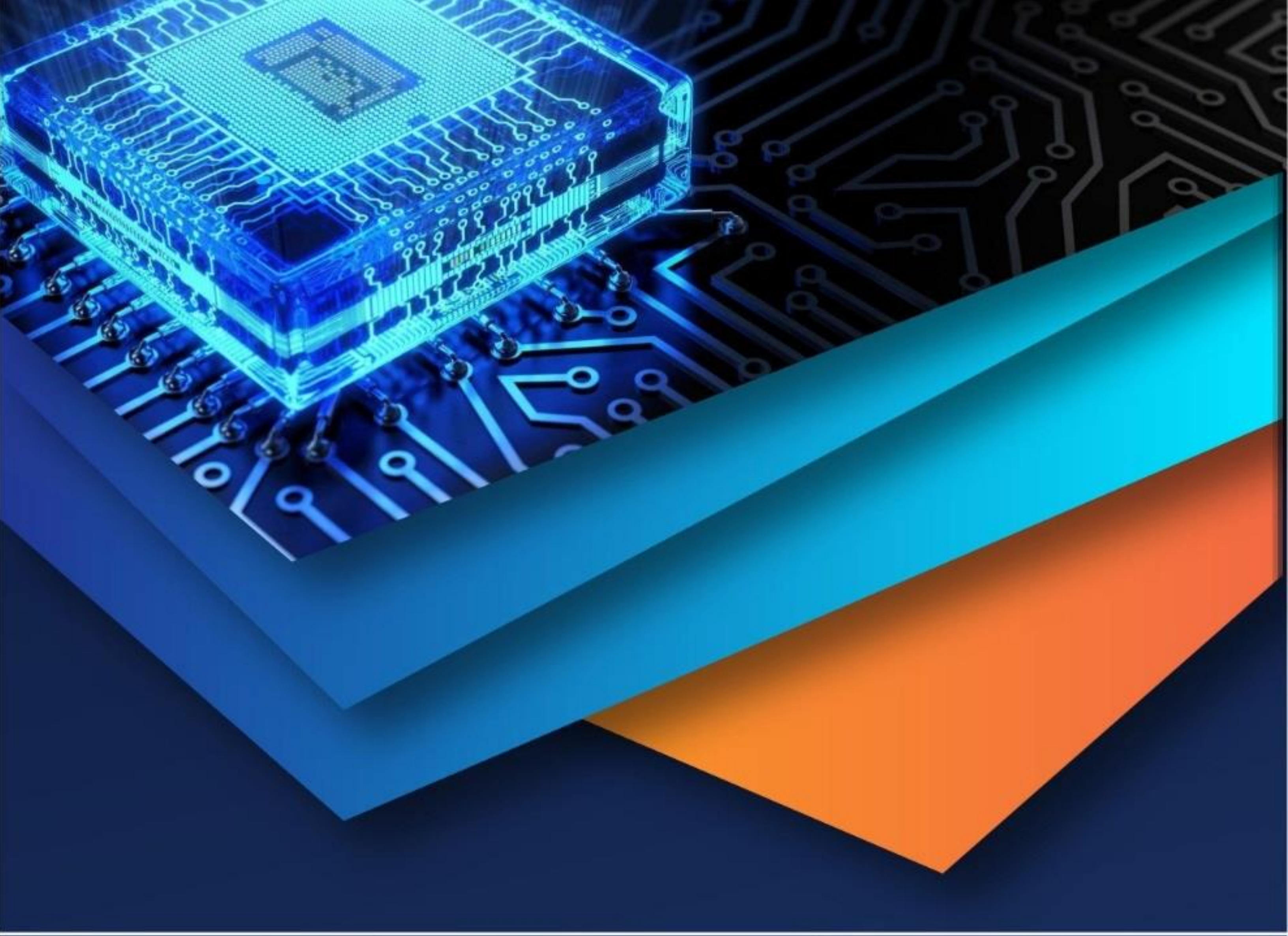

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