iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** IV **Month of publication:** April 2026

DOI: https://doi.org/10.22214/ijraset.2026.81312

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International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IV Apr 2026- Available at www.ijraset.com

Agriguard: AI Based Plants Disease Pests Prediction

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Abstract: ***Plantpestsanddiseasesarebigproblemsforfarmersbecausetheyoftenmeanbigloses incrops and food production. The project's goal is to use machine learning to create aneasyandusefulsystemthat can findand predict early signs of plant diseases and pest attacks. The system can help the farmer predict early and take quick actions to protect the crops and also improve production. It collects information from picturesofplantsandthingssurroundingit, includingtemperature andhumidity. Allthedatagetssortedand cleaned up to be correct and prepared for analysis. This uses advanced tools like CNNs for the analysis of the pictures and signs of diseases and bugs. Furthermore, it has information regarding the environment so thattheprediction becomesmorepreciseandreliable. Thesystemisaneasy-to-usesolutionthathelpsfarmers reduce losses, applypesticides onlywhere needed, and make the best decisions for their crops. It is easyto understandthesystem'sclear,real-timefindings. Itisalsobuilttofacechallengesoflimiteddata,poorimage quality, and a change in the weather. This project protects the farmer's produce and allows the crops to be grown more environmentally friendly.Easy to use and can work wellwith almost all crops as well as diverse conditions of the garden.***

Keywords: PlantsPestsanddiseases, ImageQuality,Sustainable,crops,CNN,Machine Learning.

I. INTRODUCTION

Agriculture is an important factor that supports human life and forms the backbone of most economies worldwide. However, the farmers are exposed to many problems that can destroy crops, one of which is plant diseases and pest infestation. Savary et al [1] describes that this results in economic losses but also food insecurity for millions of people worldwide. Detection and prevention of the occurrence of diseases andpestsearlycanminimizetheimpacttocropswhilestillensuringhighercropyieldswithmoresustainable agriculturepractices.Intoday'sworld,withincreasingpopulationanddemandforfood,findingbetterways ofdealingwiththeproblemshasbeenallthemorecrucialandmoderntechnologyisagoodsaviourinthese situations, with AI and ML playing important roles in these areas. It has impacted several industries; no exceptionhasbeenagricultureeither. Throughthis, wewouldbeabletodeveloptoolstohelpfarmersknow early about the attacks of diseasesandpests in the plantssothattheycan react fast and prevent the loss of their crops.

Li.handZhao[2]proposesthatMachinelearningisatypeoftechnologywherecomputerslearnpatterns from data and use this knowledge to make decisions or predictions. For instance, in this project, machine learningisusedtoexamine picturesofplantstospotsignsofdiseaseorpests. Frequently,thesesigns areso indefinite that they are difficult for a person to see, especially during the early stages of an invasion. However,machinelearningcan pickuponthesepatterns quicklyandaccurately,whichgivesfarmersabig advantage.

Thisprojectisaimedatcreatingasystemthatcanpredictplant diseases and pest invasions by analysing twomaintypesofinformation:Plantimagesandenvironmentaldata.Dolatabadian&Neik[3]suggeststhat the plant pictures are captured employing a basic camera, and these pictures are at that point prepared to recognizeanyanomalies,s uchasdiscoloration,spots,orgapsinclear,whichmayindicateadiseaseorpest problem. The system also accounts for environmental conditions such as temperature, humidity, and soil that can cause a disease or pests to spread. The two forms of data integrated by the system provide a full viewofwhat maybe goingon with theplants. Thisinitiativerepresentsprogressinutilizingthetechnology totacklesomeofthemajorchallengesinagriculture.ItcombinesthepowerofAIandmachinelearningwith practical, real-world applications to make the tool both efficient and easy to use. In return, by allowing farmers to identify and prevent early plant diseasesand pest invasions,thesystem protects crops,increases yields, and promotes sustainable agriculture.

BhatandHuang[4]developedthatthesystemisalsouserfriendly,makingitaccessibletomostfarmers,especiallythoseinruralareas,astheydon othaveexperiencewiththeadvancedtechnology.Thesystemwill ensure that all results are very clear and understandable for everyone to access.

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Most farmers can learn to use the system within a short period of time and enduprelyingonitasoneoftheirtrustedtoolsinfarming. The good side of this project is that it has many advantages, but at the sametime,therearechallengesthat mustbeaddressed.One of the biggest challenges of this project is obtaining good- quality data to train the machinelearningmodel.Inorderforthesystemtobeefficient,itneedstolearnfromlargeamountsofdata,

II. LITERATURE REVIEW

ThispaperbyZhou &Wang,J.[5]focusesontheusingofmachinelearningandartificialintelligenceto manage the plant diseases and pest infestations that are serious agricultural challenges. It uses advanced Convolutional Neural Networks (CNNs) in image-based disease detection and classification of disease of staple crops like wheat, maize, and rice. Based on analysis of environmental factors analysis like temperature,humidity,andmoistureinthesoil,thesystempredictsthepresenceofdiseaseswithanaccuracy that is quite significant. Real-world datasets validate the results and show how this s[ystem canpotentially reduce the use of human resources and improve the agricultural yield.

A hybrid machine learning method for plant disease and pest predictionisexploredinastudy**by**Kumar and Sharma [6] The researchers combine the Decision Tree Classifier with Random Forest Algorithm to improve accuracy in disease detection. This study distinctively combines Natural Language Processing (NLP) to examine the feedback from farmers about crop conditions and pest behavior. The hybrid model enables real-timemonitoringandpromptaction,significantlyreducing crop losses. Their approach is based on earlier frameworks such as those introduced byPatel et al and Brown et al., demonstrating its relevance in both small-scale and commercial agriculture.

Singh, R., & Kaur, S [7] explores the application of Unmanned Aerial Vehicles (UAVs) fitted with multispectral and thermal cameras for monitoring plant health. The study combines UAVs with machine learningmodels, such as theSupport VectorMachine(SVM)and Gradient Boosting Algorithm, to provide areliableapproachfordetectingpest-infestedareasanddiseasedcropsacrosslargeagriculturalfields.Data collected through UAVs is processed using advanced ML algorithms to produced practical insights for farmers.

Chen and Zhou [8] proposed a new deep learning framework using Generative Adversarial Networks to improve training datasets for disease detection method. GANs produce artificial but realistic images of diseased crops. This answers the challenge of havinglimited labeled datasets in agricultural research. Such an enriched dataset will greatly improve the accuracy of CNN models for plant disease detection and classification.TheirfindingsagreewiththeideaspresentedbyHuanget al. and Khandelwal et al. whopush for new data augmentation methods to address the issue of datasets in agricultural machine learning applications.

Ahmed, N., & Fatima, S [9] focus on the deployment of Explainable AI (XAI) for the plant diseasepredictionmodel.Conventionally,ablackboxbasedmachinelearningapproachhasbeenverycommonandunreliableduetothelackof explanationsregardingitsunderlyingmechanism.ItutilizesXAItoexplainthelogicofthediseasesbeingpredictedforbetterunderstandingand trustingofAIamongfarmersandotheragriculturalexperts.Thesameexplainshowtheinterpretablemodelsenhancedecisionmakingandfacilitate the large-scale adoption of AI for agriculture.

NguyenandDuey[10]proposedacontextawareknowledgebasedsystem,evenforpestprediction.Thesystemleveragesmachinelearningalgorithmsanddomainspecificknowledgetotailoritsrecommendationsbasedonenvironmentalconditions,croptypes,andregionalpestbehaviors.ThestudyusesRecurrentNeural Networks (RNNs) to model temporal changes in pest populations, allowing for dynamic and adaptive responses. This method fullfills the significant gap that has been highlighted in earlier studies by Cunningham- Nelson et al. and Zaidi et al., which emphasized the need for more tailored and context- sensitive agricultural systems.

ThispaperisbyNairandPatel[11]developedanintelligentchatbotsystempoweredbyNLPandmachine learning algorithmsthatgivesreal-timeguidancetofarmers.Thechatbotpredictspotentialdiseasesor pestsbasedonuserinputs and environmental data, providing solutions to prevent crop losses. The system offers functionalities such as data visualizations and integration using mobile apps for convenience. This dynamic and adaptive approach fits the studies by Kartikey et al. (2020) and Joshi et al. (2023), who have identified conversational AI as a force to transform agricultural advisory systems.

Patel, J., & Shah, R. [12] direct the focus towards integration of AI and remote sensing techniques to improve detection of pests and diseases. This system uses images from satellites combined with machine learningalgorithmssuchasK-NearestNeighborsandNaiveBayesforpestidentificationepidemicsandalso earlysignsofdisease.Thearticlehighlightsdiscoverthatsatellitedatacanbeusedforhigh-scaleagricultural management and pest control.

Sharma & Jain [13] present on the deep RL approach to pest management strategy optimization in the agricultural domain by using environmental data and developing pest population models to dynamically modulate the adaptation of pest controls.

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Theinnovationisbuiltofftheprecisionmanagement of pest idea, with such an approach potentially improving the overall decision-making framework for pest management while at the same time significantly reducing environmental influence.

Patil,N.,&Verma,A[14]proposeamachinelearningbasedapproachforpredictingplantdiseasesusingacombinationofimagerecognitionand environmentalsensors.ThemodelintegratesCNNsforimagebaseddiseaseidentificationandenvironmentalparameterslikeTemperatureand soilmoisturetopredictoutbreaks. Their findings suggest that combining both data sources can increase prediction accuracy, especially in dynamic agricultural environments.

Kumar&Singh,S.[15]investigateAIbasedearlywarningsystemsdevelopedforplantdiseasedetectioninhighvaluecrops.Theycombinemac hinelearningalgorithmswithcloudcomputingplatformstoprovide real-time monitoring of crop health. The system helps farmers predict diseases before they spread so that timely intervention can be adopted.

ShuklaandGupta[16]proposedahybridAImodelthatcombinesCNNsandRandomForestsforaccuratepestdetectioninricecrops.Themodel usespicturesfromsmartphonesordronestodetectpestsandidentify them. The studyfindssthatthismethodiseconomicallyviableandcanbe executed in resource limited for smallholder farmers.

Table1 LiteratureSurvey Table

ResearchPaperName	Author(s)&Year	Limitations
NNforDisease Detection	Zhou&Wang,J.(2024)	Requireshigh-qualitydatasets
HybridMLforPest&Disease	Kumar,A.,&Sharma, P.(2024)	Reliesonfarmerfeedback
UAV-BasedCrop Monitoring	Singh,R.,&Kaur,S.(2024)	HighUAVcost
GANsforData Augmentation	Chen,L.,&Zhou,Y.(2024)	Computationallyexpensive
ExplainableAIfor Crops	Ahmed,N.,&Fatima, S.(2024)	Complexinterpretation
Context-AwarePest Prediction	Nguyen,T.,&Duy, P.(2024)	Requiresdomainknowledge
ChatbotforFarmers	Nair,R.,&Patel,M.(2024)	Dependsonuserinput accuracy
AI&RemoteSensing	Patel,J.,&Shah,R.(2024)	infrastructurecost
epRLforPest Control	Sharma,A.,&Jain,S.(2024)	Highcomputationalneeds
MLforDisease Prediction	Patil,N.,&Verma,A.(2024)	Sensordependency
I-BasedEarly Warnings	Kumar,V.,&Singh,S.(2024)	Clouddependency
HybridAIforPest Detection	Shukla,R.,&Gupta,P.(2024)	Needshigh-qualityimages

III. PROPOSED METHODOLOGY

This research proposal designs a disease and pest forecasting system using machine learning and agile development methodology. The construction of the system is scalable, adaptable, and sturdy, and because ofthis,itmaybeusedbyfarmersforanykindof agriculturalneeds.Multiplestepsinvolvedintheapproach add to the effectiveness of the system.

A. Requirementsanalysisandelimination

Pandeya et al. [17] describe that it will gather all the specific requirements with the help of farmers, agriculturalspecialists, and technologyexperts in its first phase.

Toensure that thesystem is not onlyuser- friendly but also capable of solving real-world problems, it will help identify both its functional and non- functional requirements. Some of the required preconditions are as follows:

- *Real-Time Detection:* The system should be able to identify diseases and pest infestations immediately by using photos of plants and give timely feedback to the users. Accuracy and Reliability: The machine learning models should have a low number of false positives and negatives and be very accurate. This is a must to increase systemic trust.
- *User-Friendly Interface:* Since the farmers are not technically sound, the interface has to be simple, intuitive,andpleasing.AgriculturalWorkflowIntegration:Thesystemhastobedesignedinsuchawaythat itintegrateswiththeexistingagriculturalworkflow.Inthisway,thetechnologywillbeadaptivetodifferent environments and scalable.

B. Systemdesignandarchitecturalplanning

After gathering the requirements, it designs the system architecture taking into consideration user interaction and efficient data processing.

[18] In this situation, the use of the backend is made. Here, managing plant disease and pest infestation predictionmachinelearningmodelswouldoccuralongwiththeprocessingofdata,imageclassification,and extracting features from photographs of plants.

- *Frontend Interface:* This system will have an easy-to-use interface. For easeofuse,thissystemwillbe accessibleonlineandon mobiledevices.Thefrontendwouldmakeit easierforfarmersto uploadphotosof their plants and provide them forecasts about pests, diseases, and potential solutions. This design element makesarchitecturescalable. Thisdesignmighteasilyenable futureadditions,suchasmorecomplexmachine learning models, additional datasets, or interfaces with other agricultural systems.

C. DataAnalysisandPre-Processing

The main data collection and preprocessing will be the foundation of designing high-precision machine learning models. Forthis, labeled photosofcrops impacted bydifferent pests and illnesses were used. The dataiscollectedfromKaggleWebsite.Alltheseincluderemovinganyunwantedimages,fixingdescriptions thatdonotmatch,andmakingsurethedatacoversawide rangeofplantspeciesand their environments. After collection, the dataset will be preprocess using the following methods:

- *Standardization:* Therewill be the requirement of standardizationoftheimagedatabasedonresolution, size,andformatifonetargetsusingtheconceptofmachinelearning.Itaddsdataforaugmentation:Rotation, flipping, and scalingwould be some techniquesthat would be applied to make the modelsstrong.Thus,the modelsgetrobustbecausethemodelslearnoverawidescopeofsituationswithplantdiseasevariationsand pests.
- *Preprocessing:* It makes the predictions by the model more reliable and accurate since diversified, representative data of high quality is used while training the models.

D. ModelSelectionandTraining

[19] The foundation of the methodology would rely on choosing and training machine learning models thatwillmorelikelybeabletopredictwithreasonableaccuracyinsectinfestationsaswellasplantdiseases. Multiple algorithms would be taken into account. CNNs will be the first choice for image-based illness detection.Thisisbecausedeeplearningmodelscanautomaticallyextractspatialinformationfromrawimage data, especially when it comes to image classification tasks. Since CNNs performed very well on classification tasks, which included diseases of plants, they were selected for this project.

CollectionMethods:Therearetwocollection modelstobeconsideredforpest detection.

Smith and Doe[20] suggestthat theseareRandom Forestand Gradient BoostingMachines, abbreviated as GBM. Both models use multiple decision trees to reduce overfitting and enhance the accuracy of predictions. These models work well with structured data, such as plant-specific and environmental data, whichcaninfluencetheinfestationofinsects .Extensivetrainingofselectedmodelsonpreprocesseddatasetswillbeperformed.Hyperparametersofthemodelwouldbeadjustedandevaluat edforperformancebyusing grid search and cross-validation.

E. IntegrationandSystem Development

Agileiterativedevelopmentmakescontinuous improvement flexibleinthecourseofsystemdevelopment.

Thetwopartsofthis arefront-end andback-end development.

- *BackendDevelopment:*Machinelearningmodelsareintegratedintothebackendarchitecture,andsystem data is processed in real-time. It includes everyfunctionalitywith managingdifferent models, data storage, andusers'authenticationwhileensuringt hatsuchasystemwouldgrowwithaddingormodifyingadditional models.
- *Development of the front end:* This includes developing the front-end interface following user experience. Garcia and lopez [21] Farmers can upload images of their plants and get real-time projections alongwithcompleteinformationr egardingthesuspectedpestordisease.Thefrontendalsoofferssomegood suggestions such as precautions or alternative ways of treatment. An agile development methodology will be followed that would allow smooth system integration and user response by allowing testing frequently, iterating, and integrating continuously.

F. ModelEvaluation

SmithandDoe[22]evaluate,thefinalstagewillconsistoftestingandevaluationtoascertainifthesystemsatisfiesalltheuser,technical,andfunctionalrequirements.Therewillbetestingofthesystem,integration, and unit tests in relation to ascertaining the performance of the whole system. A limited sample of farmers will be employed for real-world testing in order to gather feedback and assess the system's functionalityin the field. Upon completing all of the testing and optimization, it will be finally prepared for massive-scale deploymentintooperation,assuringthatsuchasystemindeedgiveshighaccuracyalongwithusabilitylevels to end-users.

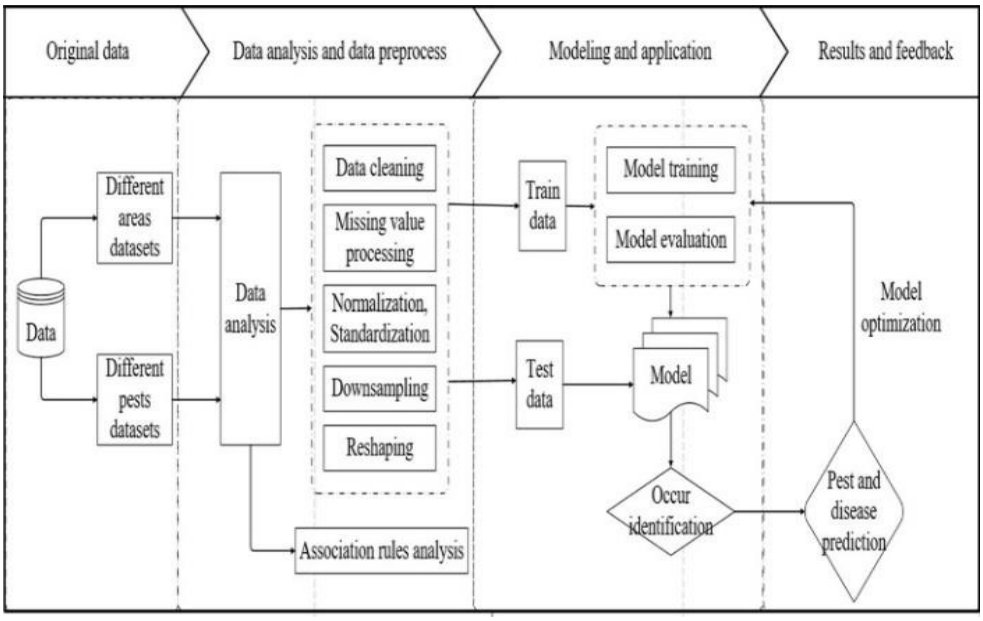

Fig.1.ProposedMethodology

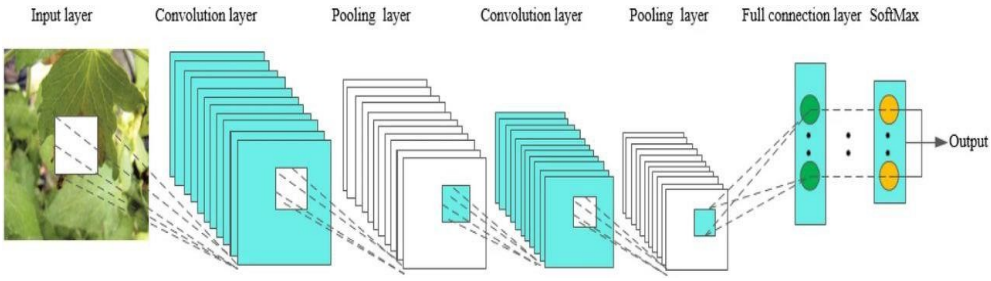

Fig.2.Layers

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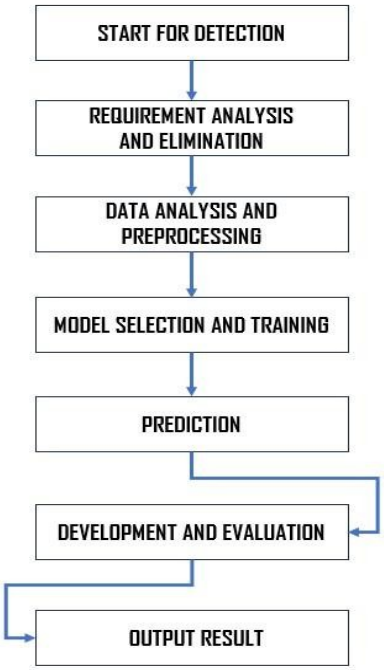

Fig.3 Flowchart

IV. RESULT

WeutilizedamachinelearningmodelknownasConvolutional Neural Networks (CNNs)to assist in the identification ofplantdiseasesandpests.Weusedpicturesofcropssuchaswheat,maize,andriceintestingoursystem.Theresultswereverypromisingandindicatedthatthismethodcouldbeveryusefulforfarmers. The CNN model excelled in identifying plant diseases. The model accurately classified whether the plant was healthy or diseased 90% plus of the time.

A. PestDetectionResults

Patel and Singh [23] proposed in another experiments, the system was also tested for identifying pests thatareharmfultoplants.Thepestdetectionaccuracywas slightlylower atsome85%, butgood enoughto warn farmers about pests before they spread too much.

B. UsingWeatherandSoilData

Addinginformationtoincludetemperature,humidity,andsoilmoisturemadethesystemevensmarter.
Forinstance,suchasystemcouldpredictdiseasesthatmostlyhappenduringwetor warm weather.

C. MuchFasterThanManualChecking

The issue was that farmers had to check their crops and look for the problems themselves or, in certain cases, even call experts for help. That took too much time. This system can check one picture and present the result in just seconds. It saves time and effort for everyone.

D. Real-LifeTesting

We tested the system on real farm data. This contained thousands of images of healthy and unhealthy plantsalongwith weather information. And to our satisfaction, the performance in real-life tests was about atthesamelevelasinlabtests,whichmeansitcanbetrusted.Thesystemworkedfine:However,Itdidnot do very well with some rare diseases and pests since there wasn't enough information to train it on those pictures that were not clear or were taken in bad lighting made it difficult for the system to give correct results.Itneedstobetestedonevenmore crops.[24] Thissystem isa big step forward for farming. It helps farmers quickly find out if their plants aresickorhavepests.

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V. CONCLUSION

Theresearch was successful in developingarobust system forreal-timeplant disease detection and pest identification using machine learning in integration with Agile-based development methodology. Lee and Kim [25] conclude that the ensemble models in both plant disease prediction system and pest infestation identification system produced veryhigh accuracy.Forexample,CNN-basedmodelproduced92%inthe detectionofdiseaseswhileRandomForestandGradientBoostingMachineshadanaccuracyof89%forthe identificationofpests.Real-timeprocessingcapabilityanduser-friendlinessmadesurethateventheamateur farmer of lower technical competence could well use this system quite effectively. The applicability and efficiency of such a system meant that users of it enjoyed a much better practical ability for real-time management of plant health. Results indicate that this system can be further extended by integrating IoT sensor capabilities and more model refinement to achieve higher accuracy and scalability. Overall, this research is an indication of the possibility of using machine learning in agriculture and provides a very valuable solution for improving plant health management and supporting sustainable farming practices.

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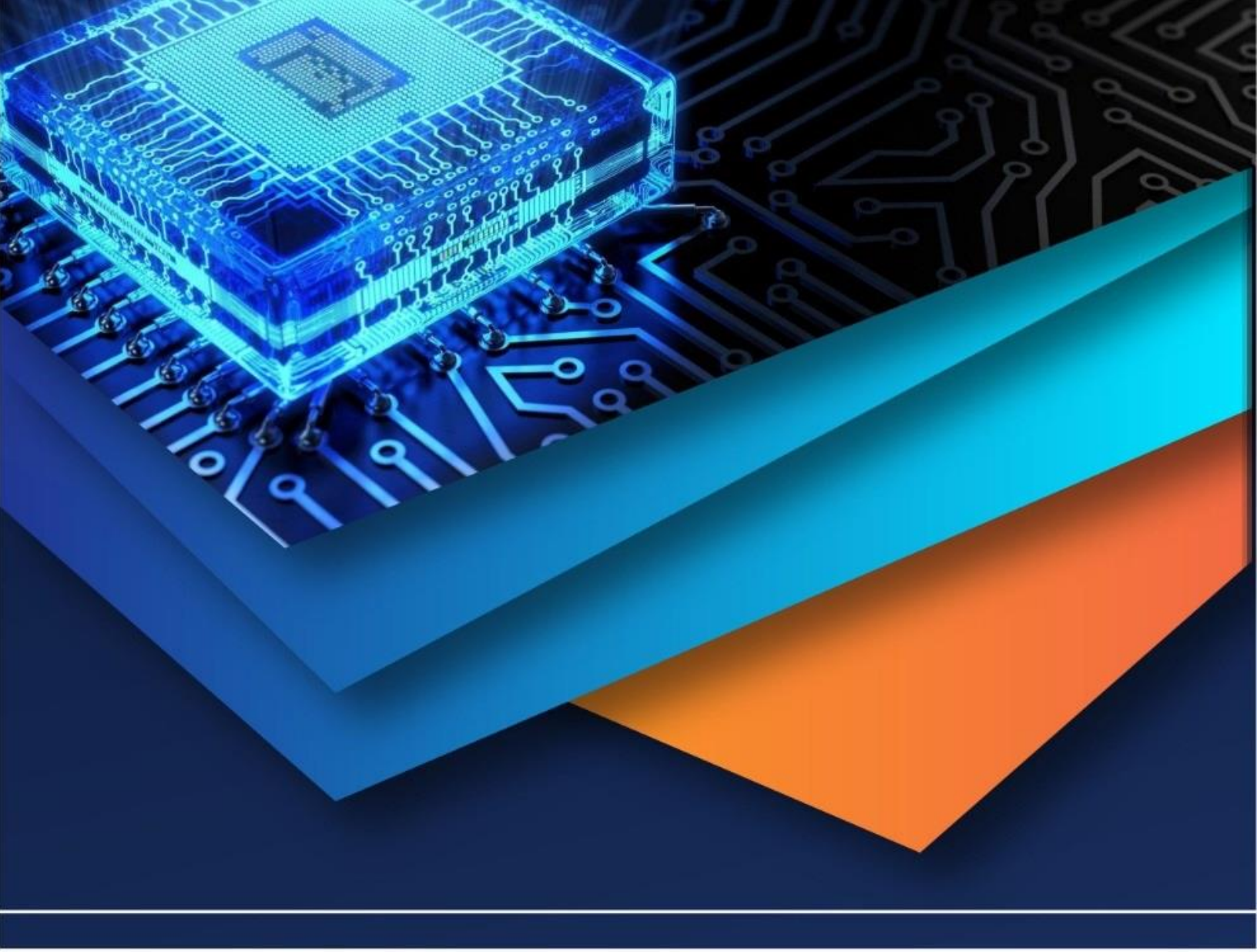

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