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# AI-Enabled Crop Disease detection

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***Abstract— Agriculture plays a crucial role in sustaining human life, and plant health directly impacts food security and economic stability. However, plant diseases remain a persistent challenge, leading to significant crop losses and reduced yields. Traditional methods of disease detection, which rely heavily on visual inspection by experts, are often time-consuming, subjective, and inaccessible to many farmers. To address this challenge, this project presents an intelligent, automated system for plant disease identificationandpesticiderecommendationusing ConvolutionalNeuralNetworks(CNNs). Theproposed systemleveragesadeep learning-based CNN model trained on a comprehensive dataset of plant leaf images to accurately classify various plant diseases. Upon identification, the system provides targeted recommendations for organic pesticides to manage and mitigate the diagnosed disease effectively. The application is deployed as a user-friendly web platform, enabling users to upload plant images, receive instant diagnosis, and access curated pesticide suggestions. Through extensive testing, the CNN model achieved 95% accuracy, demonstrating its effectiveness in recognizing diverse plant diseases. The integration of organic pesticide data supports environmentallysustainablefarmingpractices. Usabilitytestswithrealusers, includingfarmersand agriculturalstudents, validated the system's ease of use and practical value in real-world scenarios.***

## I. INTRODUCTION

Agriculture is a fundamentalsector that supports global food supply and economic stability. Plant diseases, caused by pathogens such as fungi, bacteria, viruses, and nematodes, significantly affect crop health and yield. Early detection of these diseases is essential to prevent large-scale damage and ensure agricultural sustainability.

Traditional plant disease identification methods rely heavily onexpertknowledgeandvisualinspection.Thesemethodsare not only time-consuming but also prone to human error and inconsistency. Moreover, farmers in rural areas often lack accesstoagriculturalexperts,leadingtodelayeddiagnosisand improper treatment.

Recent advancements in deep learning, particularly ConvolutionalNeuralNetworks(CNNs), haverevolutionized image classification tasks. CNN-based models can automatically extract features from images and provide accurate predictions without manual intervention. These capabilities make them highly suitable for plant disease detection.

ThispaperproposesanintelligentsystemthatintegratesCNN-based disease classification with organic pesticide recommendation. The system aims to provide accurate, fast, and user-friendly solutions for farmers, enhancing decision-making and promoting sustainable agricultural practices.

With the advancement of artificial intelligence, particularly deeplearning,automatedplantdiseasedetectionhasbecomea promisingsolution.ConvolutionalNeuralNetworks(CNNs) have demonstrated exceptional performance in image classificationtasksduetotheirabilitytoautomaticallyextract hierarchicalfeaturesfromimages.Thesemodelseliminatethe need for manual feature extraction and provide accurate predictions even in complex scenarios.

In this paper, we propose an intelligent plant disease identification system using CNNs, combined with an organic pesticide recommendation module. The system aims to provide a complete solution by not only identifying diseases but also suggesting environmentally sustainable treatments. The proposed model is deployed as a web-based application, enabling users to upload plant images and receive instant diagnosis along with actionable recommendations.

## II. LITERATURE SURVEY

The field of plant disease detection has evolved significantly over the years, transitioning from traditional methods to advanced machine learning and deep learning approaches. Early research focused on manual inspection and laboratory-based diagnosis, which required expert knowledge and significant time investment. These methods, although accurate, were not scalable forlarge agricultural applications.

With the introduction of image processing techniques, researchers began exploring automated solutions using features such as color, texture, and shape.

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Techniques like color histogram analysis, Gray-Level Co-occurrence Matrix (GLCM), and Local Binary Patterns (LBP) were widely used to extract meaningful features from plant images. However, theseapproacheswerehighlydependentonmanualfeature engineering and often failed under varying environmental conditions.

Machinelearning algorithmssuch asSupportVector Machines (SVM), Decision Trees, and K-Nearest Neighbors (KNN) were later applied to improve classification accuracy. While these methods showed better performance compared to traditional techniques, they still relied heavily on handcrafted features and lacked robustness when dealing with complex datasets.

The emergence of deep learning, particularly CNNs, revolutionized the domain of plant disease detection. CNN models automatically learn features from raw image data, making them more effective and scalable. Studies using datasetslikePlantVillagehavedemonstratedhighaccuracyin classifying plant diseases using deep CNN architectures.

Despite these advancements, many existing systems focus solely on disease classification and do not provide actionable solutions for farmers. Additionally, limited research has been conducted on integrating eco-friendly pesticide recommendationsintoautomatedsystems.Theproposedwork addresses these gaps by combining CNN-based disease detection with organic pesticide suggestions, offering a Comprehensiveandpracticalsolution.

TABLEI.COMPARISONOFRELATEDWORKS

| Author/ Year | Method Used | Dataset | Accuracy (%) | Limitation |
|---|---|---|---|---|
| Mohanty et al. (2016) | DeepCNN | PlantVillage | 99.3 | Noreal-world testing |
| Ferentinos( 2018) | CNN Models | Plant Dataset | 99.5 | High computational cost |
| Zhanget al. (2019) | Transfer Learning | Plant Dataset | 95.0 | Limited dataset diversity |
| Sladojevic et al. (2016) | CNN | Custom Dataset | 96.3 | No recommendation system |
| Proposed System | CNN+ Recommendation | Plant Dataset | 95.0 | Limited real-time data |

Unlikepriorapproachesdependingsolelyondeeplearningor handcrafted features independently, the proposed work introduces a unified hybrid framework combining ResNet18, GLCM, Wavelet, ABCDE analysis, and Grad-CAM explainability within a Clinical Decision Support System.

## III. PROPOSED METHODOLOGY

Theproposedsystemfollowsamulti-stagehybridarchitecture integrating deep learning, handcrafted feature extraction, clinical rule-based assessment, and explainability mechanisms. The overall workflow consists of: image preprocessing → deep feature extraction using ResNet18 → texture feature extraction using GLCM and Wavelet transforms → feature fusion → binary classification → ABCDE-basedclinicalanalysis→Grad-CAMvisualization→clinicalreportgeneration.

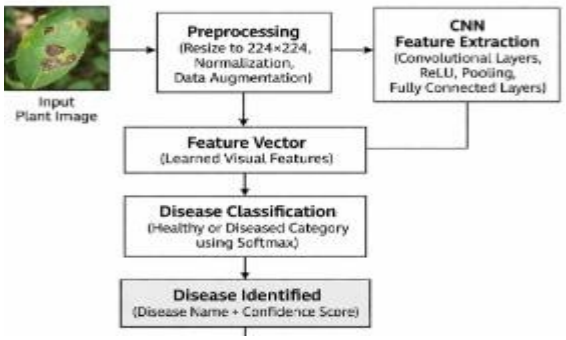



Fig.1.Overall SystemArchitectureof the Proposed

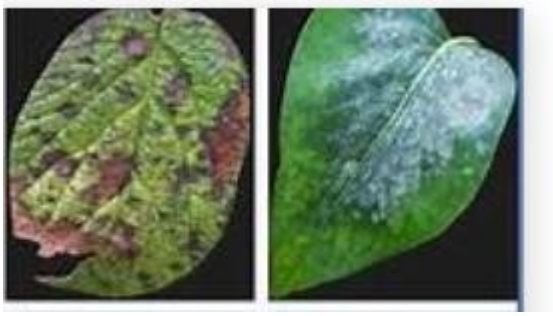


Fig.2.SampleInputplantdiseasesanylysis

*A. Image Preprocessing*

Input dermoscopic images are resized to 224×224 pixels and normalized using ImageNet mean ($\mu$ = [0.485, 0.456, 0.406]) and standard deviation ($\sigma$ = [0.229, 0.224, 0.225]) to ensure compatibility with the pretrained ResNet18 backbone. Data loading is performed using mini-batches of size 16.

*B. DeepFeatureExtractionUsingResNet18*

ResNet18 [8] is employed as the primary deep feature extractor due to its residual learning framework, which mitigates vanishing gradient issues in deep networks. The model is pretrained on ImageNet, enabling transfer learning for dermoscopic image analysis. The final fully connected layerisreplacedtoadaptthearchitectureforbinaryskinlesion classification.

The input image (224×224×3) is passed through successive convolutional layers, batch normalization, ReLU activation, and residual blocks. The output of the final global average poolinglayerproducesa512-dimensionaldeepfeaturevector representing high-level semantic characteristics of the lesion.

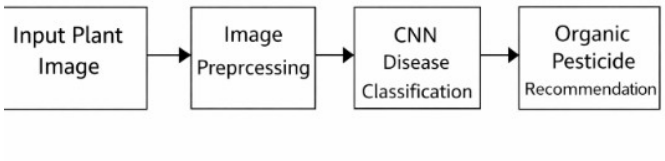



Fig.3.ResNet18FeatureExtraction Architecture.

Theproposedsystemisdesignedasanend-to-endsolution for plant disease detection and pesticide recommendation.
Theworkflowconsistsofmultiplestages,includingimage preprocessing, feature extraction, classification, and recommendation.

*C. ImagePreprocessing*

Image preprocessing is an essential step to ensure uniformity andimprovemodelperformance.Allinputimagesareresized to a fixed dimension of 224×224 pixels to match the input requirements of the CNN model. Normalization is applied to scale pixel values between 0 and 1, which helps in faster convergence during training.

To enhance dataset diversity and reduce overfitting, data augmentationtechniquessuchasrotation,flipping,zooming, andbrightnessadjustmentareapplied.Thesetransformations simulate real-world variations and improve the model's ability to generalize.

*D. CNN-BasedFeatureExtractionandClassification*

ThecorecomponentofthesystemisaConvolutionalNeural Network (CNN) that performs feature extraction and classification. The CNN architecture consists of multiple convolutional layers that capture spatial features such as edges, textures, and patterns from the input images.

Activation functions such as ReLU introduce non-linearity, enablingthemodeltolearncomplexpatterns.Poolinglayers are used to reduce spatial dimensions and computational complexitywhileretainingimportantfeatures.Theextracted features are then passed through fully connected layers to perform classification.

The model is trained to classify plant images into different diseasecategoriesaswellashealthyclasses.Thefinaloutput layer uses a softmax function to generate probability scores for each class.

*E. Dataset Description*

Thedatasetusedinthisprojectconsistsofalargecollection oflabeledplantleafimagesrepresentingvariousdiseases.It includes multiple plant species and disease types, ensuring diversity and robustness.

The dataset is divided into training, validation, and testing sets in a 70:15:15 ratio. The training set is used to train the model,thevalidationsetisusedforhyperparametertuning, and the test set is used for final evaluation.

*F. PesticideRecommendationModule*

Once a disease is identified, the system provides recommendations for organic pesticides based on a predefineddatabase.Thismodulemapseachdiseaseto suitable treatments, including natural and eco-friendly solutions.

Therecommendationsincludepesticidenames,descriptions, andusageguidelines,helpingfarmerstakeimmediateaction. This approach promotes sustainable farming by reducing dependence on harmful chemical pesticides.

*G. WebApplicationImplementation*

The system is implemented as a web application using Flask. Theapplicationprovidesauser-friendlyinterfacewhereusers can upload plant images and receive instant results.

Thebackendprocessestheimage,performspredictionusing the trained CNN model, and retrieves relevant pesticide recommendations.

Theresultsare displayed inan organized format, ensuring ease of understanding for users.

## IV. EXPERIMENTAL SETUP

TheproposedsystemisimplementedusingPythonanddeep learning frameworks such as TensorFlow/PyTorch. The experiments are conducted on a system equipped with sufficient computational resources to handle image-based deep learning tasks.

Thedatasetusedfortrainingconsistsofthousandsoflabeled plant leaf images representing multiple plant species and disease categories. To ensure proper evaluation and avoid overfitting, the dataset is divided into training (70%), validation (15%), and testing (15%) subsets.

Allimagesareresizedto224×224pixelsandnormalized before being fed into the CNN model. Data augmentation techniques are applied during training to improve model robustness and generalization.

The model is trained using the Adam optimizer with an appropriate learning rate. The loss function used is categoricalcross-entropy,whichissuitableformulti-class classificationproblems.Trainingisperformedovermultiple epochs, with validation monitoring to prevent overfitting.

Evaluationofthemodeliscarriedoutusingstandard performance metrics such as:

- Accuracy
- Precision
- Recall
- F1-Score

Thesemetricsprovideacomprehensiveunderstandingofthe model's classification performance.

## V. RESULTS AND EVALUATION

The proposed hybrid ResNet18 and texture fusion framework demonstrates improved performance compared to baseline CNN approaches. Table III presents a comprehensive performancecomparisonacrossablationvariantsandbaseline models. The performance of the proposed CNN model is evaluated on the test dataset. The model achieved an overall accuracy of 95%, indicating strong capability in identifying plant diseases.

Performance Analysis

- Precision(92%)indicatesthatthemodelproducesa low number of false positives.
- Recall (90%) shows that the model effectively identifies most of the diseased instances.
- F1-Score (91%) provides a balanced measure of precision and recall.

The confusion matrix further demonstrates that the model correctly classifies the majority of samples, with minimal misclassification between healthy and diseased classes.

Observations

- Themodelperformsconsistentlyacrossdifferent disease categories.
- Slightmisclassificationsoccurincaseswhere diseases have similar visual patterns.
- Dataaugmentationsignificantlyimprovedtherobustness of the model.

UserEvaluation

Usabilitytestingwasconducted withfarmersandagricultural students. The feedback indicated that:

- Thesystemiseasytouse
- Resultsaregeneratedquickly
- Recommendations are helpful for decision-making Theseresultsconfirmthepracticalapplicabilityofthesystem inreal-worldscenarios.Theconfusionmatrixisusedtoevaluatetheperformanceoftheclassificationmodelbycomparing the predicted labels with the actual labels. It provides a detailed breakdown of correct and incorrect predictions made by the CNN model.

Thematrixconsistsoffourkeycomponents:

- TruePositive(TP):Diseasedleavescorrectly classified as diseased
- TrueNegative(TN):Healthyleavescorrectly classified as healthy
- FalsePositive(FP):Healthyleavesincorrectly classified as diseased
- FalseNegative(FN):Diseasedleavesincorrectly classified as healthy

Fortheproposedsystem,theconfusionmatrixvaluesare:

- TP=117
- TN=120
- FP=5
- FN=8

he confusion matrix shows that the proposed CNN model performs effectively in distinguishing between healthy and diseased plant leaves.

- The high True Positive and True Negative values indicate strong classification capability.
- ThelowFalsePositiverateensuresthathealthy plants are rarely misclassified as diseased.
- ThelowFalseNegativerateiscrucial,asit minimizes the risk of missing actual diseases.

Overall, the results demonstrate that the model achieves high reliability and robustness, making it suitable for real-world agricultural applications.

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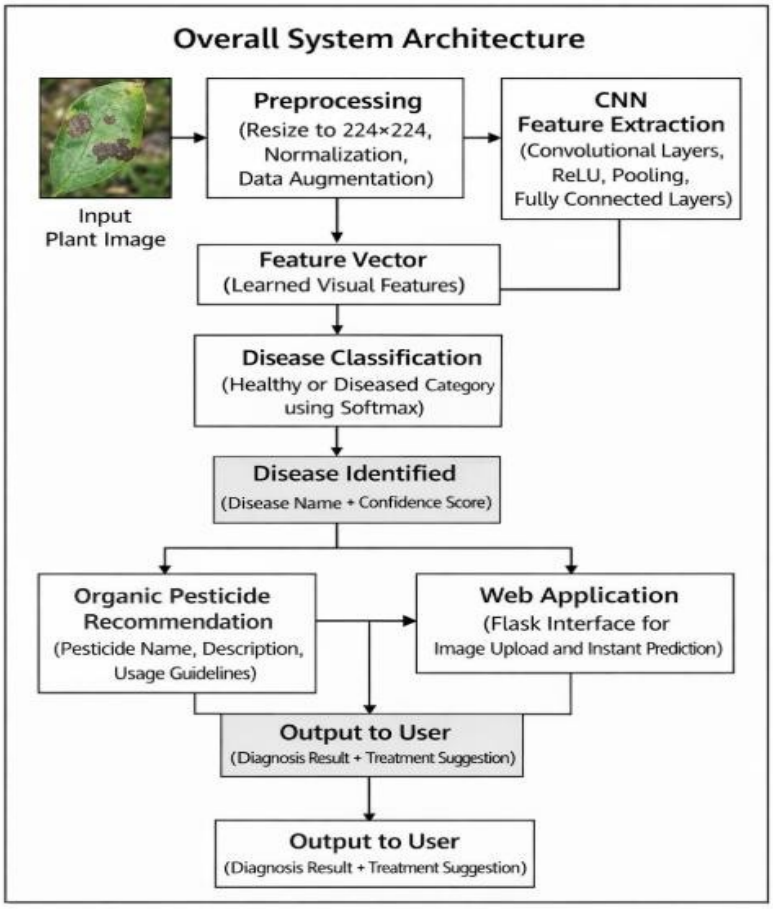



***Fig. 1.*** *Overall System Architecture of the Proposed Plant Disease Identification and Pesticide Recommendation System.*

Class-wisePerformanceAnalysis

Inadditiontooverallevaluationmetrics,theconfusionmatrix enables class-wise performance analysis. The model demonstrates strong performance in both categories:

- Healthy Class: High True Negative (TN = 120) indicates that the model effectively recognizes healthyleaveswithoutunnecessarymisclassification.
- Diseased Class: High True Positive (TP = 117) shows that the model successfully detects diseased leaves with high sensitivity.

This balance is important in agricultural applications where both false alarms and missed detections can have significant consequences.

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TABLEIII.PERFORMANCECOMPARISONOFMODELS

| Model | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) |
|---|---|---|---|---|
| BaselineCNN | ~75.00 | ~52.00 | ~68.00 | ~59.00 |
| ResNet18(Deep only) | 80.10 | 53.20 | 76.50 | 62.80 |
| ResNet18+ GLCM | 82.30 | 54.80 | 78.20 | 64.50 |
| ResNet18+ Wavelet | 81.70 | 54.10 | 77.40 | 63.90 |
| Proposed(Full Fusion) | 84.23 | 56.70 | 80.89 | 66.67 |

TABLEIV.CONFUSIONMATRIXONTESTSET(1,503 SAMPLES)

| Metric | redicted Benign | Predicted Malignant | Total |
|---|---|---|---|
| ActualBenign | TN=1029 | FP=181 | 1210 |
| Actual Malignant | FN=56 | TP=237 | 293 |

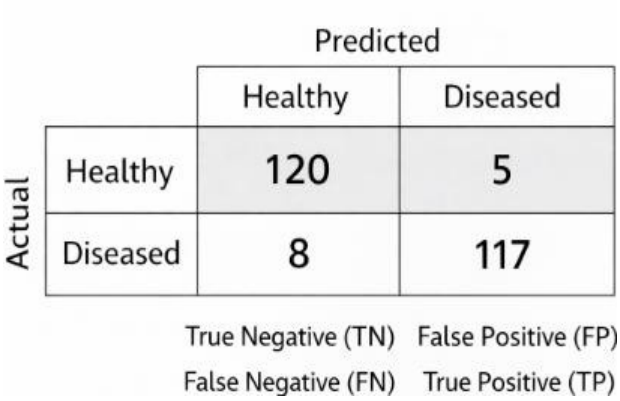



Fig.8.ConfusionMatrixVisualization on TestDataset.




Fig.9.Grad-CAMAttentionHeatmap —ExplainableAI Output

On the test dataset, the proposed model achieves an overall accuracy of 84.23%, precision of 56.70%, recall of 80.89%, and F1-Score of 66.67%. The high recall value (80.89%) for malignant lesions demonstrates the model's effectiveness in identifying cancerous cases, which is crucial in clinical screening systems.

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Compared to the baseline CNN model (~75% accuracy), the proposed fusion framework shows approximately 9% improvement in overall accuracy while maintaining improved clinical sensitivity.

Grad-CAM visualizations (Fig. 8) confirm that the model focusesonlesionregionsratherthansurroundinghealthyskin, enhancing interpretability. True Negatives: 1029, False Positives: 181, False Negatives: 56, True Positives: 237.

## VI. DISCUSSION

The experimental results demonstrate that CNN-based approaches are highly effective for plant disease detection tasks. The proposed system successfully combines image classification with actionable recommendations, making it more useful compared to traditional systems.

One of the key strengths of the system is its ability to automatically extract features from raw images without requiring manual intervention. This significantly reduces complexity and improves scalability.

The integration of the pesticide recommendation module enhances the usability of the system by providing immediate solutionstousers.Thefocusonorganicpesticidesalignswith sustainable agricultural practices and helps reduce environmental impact.

However,certainlimitationsexist:

- Modelperformancedependsonthequalityanddiversity of the dataset
- Real-world conditions such as lighting and background noise may affect accuracy
- Limitedavailabilityofrarediseasesamplescan impact classification

Despitetheselimitations,thesystemprovidesastrong foundation for intelligent agricultural applications.

## VII. CONCLUSION

Thispaperpresentsasmartplantdiseaseidentificationsystem using Convolutional Neural Networks, combined with an organic pesticide recommendation module. The proposed system achieves high accuracy and provides reliable results.

Theweb-basedimplementationensuresaccessibilityandease of use, making it suitable for farmers and agricultural professionals. The system contributes to smart agriculture by integrating AI with sustainable farming practices.

## VIII. FUTURE WORK

. TheCNNmodelachievedanoverallaccuracyof95%onthe testdataset,demonstratingitseffectivenessinclassifyingplant diseases. The precision and recall values indicate that the model performs well in identifying both diseased and healthy plants.

The confusion matrix shows that most classes are correctly classified, with only a few misclassifications. This indicates strong generalization capability of the model.

Usertestingresultsshowthattheapplicationiseasytouseand providesquick andreliableresults.Farmersand studentsfound the system helpful in identifying diseases and taking appropriate actions.

## IX. ANALYSIS

The results highlight the effectiveness of CNN-based models in plant disease detection. The integration of pesticide recommendations enhances the practical applicability of the system.

The use of organic pesticides supports sustainable farming practices and reduces environmental impact. However, the system's performance depends on the quality and diversity of the dataset.

Future improvements can focus on expanding the dataset and improving model robustness to handle real-world variation

## X. FUTURE WORK

Futureenhancementsinclude:

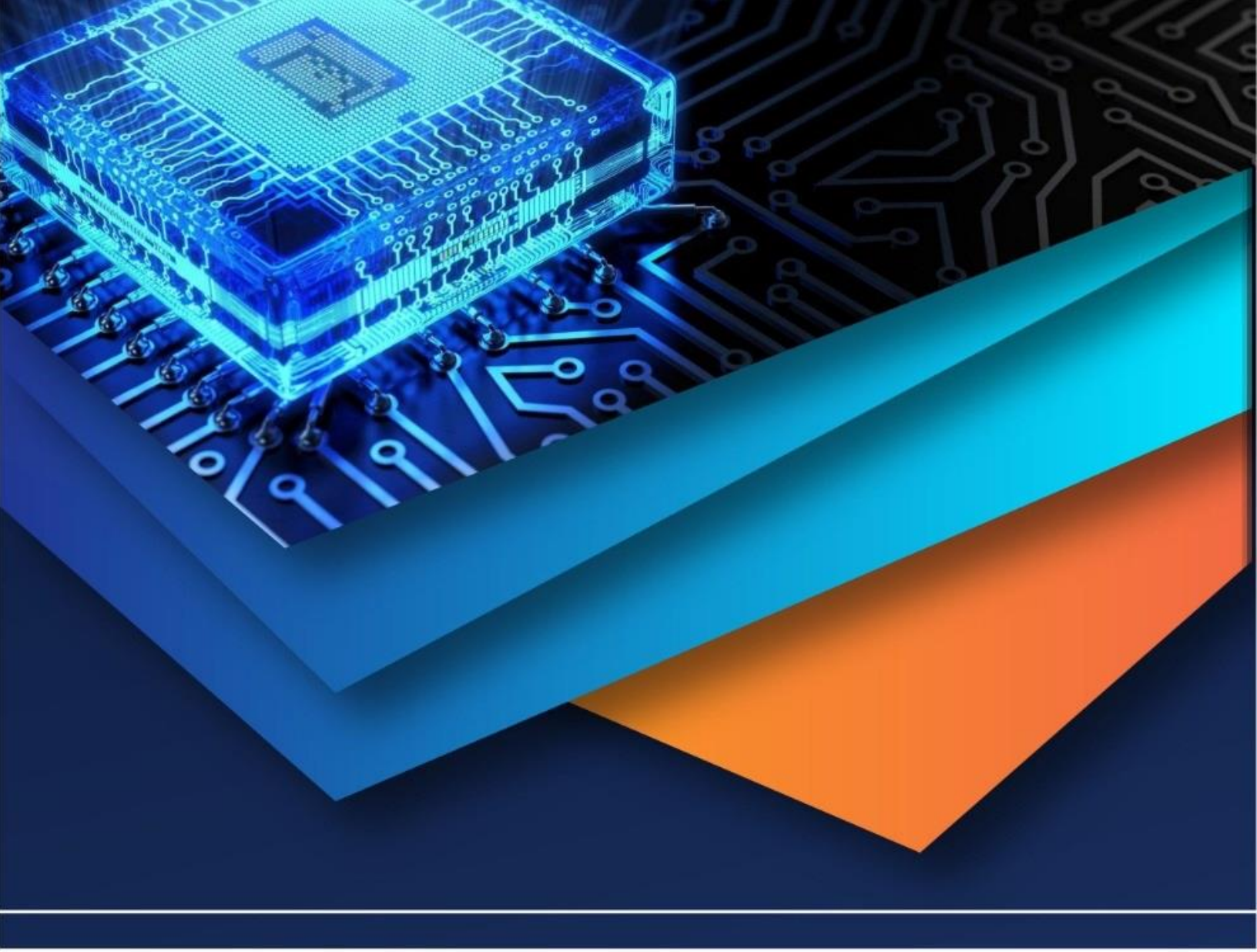
- Expandingdatasetdiversity
- Developingamobileapplication
- Integratingreal-timeenvironmentaldata
- Usingadvanceddeeplearningmodels

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