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Research Paper

SmartEdge PestNet: An Edge Adaptive On-Device Neural System for Real-Time Pest Recognition

G. Kiran Kumar[1*], Kodamala Vamsi[2], Bommana Pranay Kumar[2], Korivi Vijay[2], Kambala Divya Teja[2]

[1]Associate Professor, [2]UG Student, [1,2]Department of Electronics and Communication Engineering

[1,2]Geethanjali Institute of Science and Technology, Nellore-Bombay Highway, S.P.S.R, Andhra Pradesh 524137, India

*Correspondence: G. Kiran Kumar

ABSTRACT

Agriculture remains the backbone of food security, yet crop productivity is severely affected by pest infestations, leading to significant yield losses and economic damage. Traditional pest identification methods rely heavily on manual inspection by farmers or experts, which is time-consuming, subjective, and often incapable of providing early warnings. As a result, pests are frequently detected only after substantial crop damage has occurred, causing losses of up to 30–80% in major crops such as cotton, rice, and vegetables. To address these limitations, this research proposes an Edge Adaptive Neural Classifier for On-Device Pest Recognition using image processing and deep learning techniques. The proposed system utilizes an image-based pest recognition framework deployed on edge devices to enable real- time and early pest detection directly in the field. Pest images are collected through cameras or sensor-enabled devices and stored as an image dataset. Each image is preprocessed to extract pixel-level information, including RGB values and visual features essential for accurate classification. The dataset is divided into training and testing subsets, typically following an 80:20 ratio, to ensure reliable model evaluation. A neural network–based learning model is trained on the processed dataset to learn pest patterns and visual characteristics. Multiple model configurations and algorithms are evaluated to achieve optimal accuracy, and the best-performing model is selected based on performance metrics such as accuracy and prediction reliability. Once trained, the selected model is deployed on an edge device, enabling on-device inference without continuous internet connectivity. This edge- adaptive approach reduces latency, improves responsiveness, and ensures scalability in rural and remote agricultural environments. During the testing phase, the model predicts pest presence from real-time input images, allowing early alerts and timely preventive actions. compared to the existing manual pest detection system, the proposed solution offers faster prediction, higher accuracy, reduced dependency on human expertise, and proactive pest management. By enabling early pest recognition, the system supports farmers in minimizing crop damage, optimizing pesticide usage, and improving overall agricultural productivity. This research demonstrates that integrating image processing with neural networks on edge devices provides an efficient, low-cost, and practical solution for modern precision agriculture.

Keywords: Edge Computing, Deep Learning, On-Device Pest Recognition, Precision Agriculture, Real-Time Image Processing.

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1. INTRODUCTION

Modern agriculture faces diverse challenges that extend beyond traditional farming, encompassing broader social and environmental concerns. For instance, early diagnosis of crop emergencies such as pests, diseases, weeds, and water or nutrient

deficiencies is critical, as these issues can lead to severe harvest losses and economic damage, exacerbated by climate-change-induced extreme weather as shown in Fig. 1. Early detection enables targeted interventions to mitigate these impacts. Another significant example is precision farming, which involves applying treatments (e.g., pesticides, fertilizers, water) at variable rates based on field heterogeneity. Both challenges share a reliance on chemical products, posing dual drawbacks

(i) high costs for purchase and application and (ii) negative impacts on the environment and human health. Traditionally, diagnosing emergencies involves experts inspecting crops, often in rotation. However, this method is increasingly impractical. For instance, a 1-hectare crop with 2-m inter-row spacing requires inspecting 5 km of linear development. Daily monitoring is infeasible, as the average EU farm has 18 hectares per worker (2020 data, authors' calculations based on this ratio is purely indicative, as the distribution of land among farmers is highly uneven). As for precision farming, while advanced machinery supports such practices, they often remain underutilized, also due to a lack of necessary input data for onboard systems in the form of prescription maps detailing specific treatments. Traditional methods for generating such maps—using satellite images for large-scale grain crops or drones (Unmanned Aerial Vehicles, UAVs) for smaller or detail-intensive cultivation are subject to technical and practical constraints, including limited image resolution and high service costs.

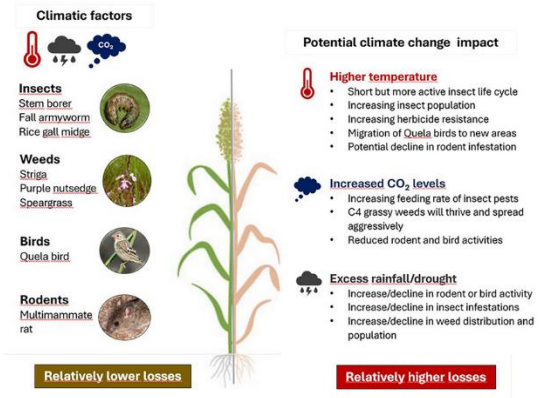


Fig. 1: Impact of climatic factors on pest dynamics and crop loss in agriculture.

AI offers a potential approach to these challenges. Deep learning (DL) models, particularly convolutional neural networks (CNNs; see), excel in automatically classifying images without human input. This theoretically enables the development of automated systems integrated into agricultural machinery and terrestrial rovers (Unmanned Ground Vehicles, UGVs) capable of autonomous operation.

2. LITERATURE SURVEY

Muhammad Hannan Akhtar et al. [1] It was stated that machine learning models deployed on mobile platforms had enabled innovative agricultural applications to support farmers in pest detection. The study explained that increasing insect threats due to climate change and evolving behavior had necessitated smart insect monitoring systems for edge and IoT environments. It was reported that model optimization techniques such as Post-Training Quantization, Quantization-Aware Training, and Data Representative Quantization had been systematically evaluated to balance model size, speed, and accuracy. The authors noted that Mobile-ViT and Efficient Net models trained with transfer learning achieved 82.6% validation and 77.8% test accuracy, while Post-Training Quantization reduced model size from 33 MB to 9.6 MB without accuracy loss. It was further stated that experiments on the IP102 dataset confirmed the generalizability of the approach with competitive performance.

Maurizio Pintus et al. [2] They studied that advances in deep learning models and next-generation edge devices had enabled real-time image classification, leading to a shift from cloud-centric IoT systems to edge-based AIoT, with cloud resources mainly used for long- term storage and analysis. It was explained that this transition had transformed agriculture by enabling autonomous monitoring, localized decision-making, early emergency detection, and precise chemical application, thereby reducing costs and environmental impact. The

review described an edge-based AIoT workflow consisting of optimal model training on high- performance systems followed by customization for deployment on edge devices. It was reported that major challenges included limited agricultural data availability due to seasonality, the need for accuracy-efficient vision algorithms suitable for constrained devices, and the optimization of models with hardware accelerators for deployment. Finally, it was noted that recent advances in image classification models, although not fully deployable, had shown strong potential for near-term improvements in agricultural AI systems.

Dennys Jhon Baez-Sanchez et al. [3] It was reported that early pest detection in edible crops had required edge-deployable sensing solutions operating under strict power, cost, and maintenance constraints. The review synthesized 178 peer-reviewed studies published between 2015 and 2025 across vision/AI, spectroscopy, and indirect sensor modalities, evaluating them using a performance–cost–implementability (PCI) rubric with validated inter-reviewer reliability. It was found that vision/AI and sensor-based systems had more frequently achieved deployment-ready PCI scores compared to spectroscopy approaches, with higher median PCI values. Pareto analysis had identified optimal trade-offs for each modality, highlighting strengths in accuracy, portability, and early-warning capability. The study concluded that the resulting decision maps had supported practical modality selection and promoted reproducible, deployment-oriented comparisons for edge-based pest detection systems.

Shida Zhang et al. [4] It was stated that the growth of the global population and the scarcity of arable land had posed significant challenges to traditional agriculture, including efficiency, precision, and sustainability. The article reported recent advances in computer vision, machine learning, and intelligent sensing, highlighting improvements in object recognition, autonomous navigation, state perception, and precision control through AI-based models. It was noted that the integration of AI with multimodal perception technologies had significantly enhanced operational efficiency, resource utilization, and environmental adaptability of agricultural equipment. The authors observed that technical challenges remained in data acquisition, adaptation to complex field conditions, and hardware–algorithm coordination. Finally, it was suggested that the convergence of digital twin technology, edge computing, and big data optimization would drive the next generation of intelligent and sustainable agricultural systems.

Chun-Chieh Wang et al. [5] It was studied that cruciferous vegetables had suffered economic losses due to damage caused by striped flea beetles and the absence of effective pest monitoring, which made infestations irregular and unpredictable. The paper stated that a solar-powered edge AI system using batteries and supercapacitors had been developed to support long-term outdoor deployment. It was explained that a Raspberry Pi had been used for IoT connectivity and image recognition, with YOLOv5 implemented for beetle detection and StyleGAN3 applied for data augmentation, achieving a recognition accuracy of 85.4%. The results were transmitted to a server via a 4G network, and experimental evaluations confirmed stable long-term operation. The study concluded that the system improved sustainability and practicality for smart pest detection in remote agricultural areas and could support future drone-based pesticide spraying.

Dachuan Xu et al. [6] It was stated that traditional methods for detecting plant diseases and pests had been time-consuming, labor-intensive, and dependent on specialized expertise, making them inadequate for modern agricultural needs. The review reported that deep learning techniques had emerged as effective solutions by significantly improving the accuracy and timeliness of disease and pest identification through advanced image processing. It was explained

that recent developments in image classification, object detection, semantic segmentation, and change detection had enhanced detection performance across diverse crops and environments, supported by transfer learning and large pre-trained models. The authors noted that challenges such as model generalization, small lesion detection, and limited high-quality datasets persisted. The study concluded that deep learning had become a key enabler of sustainable and precision agriculture by optimizing monitoring and resource utilization.

Kangshu Miao et al. [7] They researched that image recognition technology had the potential to significantly improve automation and intelligence in smart agriculture, although prior research had focused mainly on medical, industrial, and transportation domains. The study reported that a review of recent literature had been conducted to analyze applications such as plant disease and pest detection, crop species identification, yield prediction, quality assessment, and related agricultural tasks. It was noted that challenges including limited model generalization, real-time processing constraints, and insufficient dataset diversity had affected current approaches. The authors explained that transfer learning, green AI, and transformer-based models had been identified as promising solutions to reduce data and computational requirements while improving accuracy. The review concluded that these insights provided a comprehensive understanding of the status and future directions of image recognition technology in smart agriculture.

Xuehua Song et al. [8] It was stated that agricultural image processing technology had played an important role in disease detection, yield prediction, and smart agriculture, but its practical deployment had been limited by environmental interference, data scarcity, and edge- device constraints. The review reported recent advances that addressed these challenges through improvements in environmental robustness, data efficiency, and model deployment. It was explained that attention mechanisms, Transformers, multi-scale feature fusion, and domain adaptation had enhanced performance under complex conditions, while transfer learning and data augmentation had mitigated dataset limitations. The authors noted that pruning, quantization, and knowledge distillation had enabled efficient edge deployment. The study concluded that future progress would depend on multi-modal fusion, edge–cloud collaboration, hardware acceleration, and the integration of agricultural expertise with AI.

Ziye Liu et al. [9] They said that efficient recognition and management of agricultural insect pests and their predators had become critical for food security and sustainable agriculture. The study reported that a multimodal recognition framework integrating RGB images, thermal infrared data, and environmental sensor information had been proposed to overcome the limitations of single-modal models under complex field conditions. It was explained that cross-modal attention, environment-guided modality weighting, and decoupled recognition heads had significantly improved robustness, achieving superior performance with 91.5% precision, 89.2% recall, and 88.0% mAP@50, outperforming models such as YOLOv8 and DETR by over 6%. Ablation experiments had confirmed the effectiveness of key modules under challenging scenarios. The authors concluded that deployment on a Jetson Xavier device had demonstrated real-time feasibility, providing a scalable and efficient solution for precision pest management.

Xinyu Yuan et al. [10] It was started that the study had proposed an intelligent agricultural pest monitoring system combining mechanical control with deep learning to address challenges such as pest accumulation, poor image contrast, and the trade-off between accuracy and real-time performance. The authors explained that a three-axis coordinated separation device had achieved a 92.41% single-attempt separation rate, improving to

98.12% after three retries, while image preprocessing using MSRCP and bilateral filtering had enhanced illumination and reduced noise. EfficientNetv2-S with an Adaptive Feature Pyramid Network had been used for overlapping pest detection, achieving 95.72% accuracy, 94.04% mAP, and 127 FPS, and the incorporation of an SE attention module with α-CIoU loss had reached 91.30% precision for pest species recognition. Deployment on an NVIDIA Jetson Nano had demonstrated a 0.3 s detection time, 89.64% recall, and 86.78% precision, confirming the system's reliability for real-time pest monitoring in complex field conditions.

Shaohua Wang et al. [11] They said that traditional methods for detecting plant diseases and pests had been inefficient, labor-intensive, and dependent on specialized expertise, making them inadequate for modern agricultural needs. The review reported that deep learning technologies had emerged as effective solutions by significantly improving the accuracy and timeliness of disease and pest identification through advanced image processing techniques. It was explained that recent progress in image classification, object detection, semantic segmentation, and change detection, supported by transfer learning and large pre- trained models, had enhanced scalability across diverse crops and environments. The authors noted that challenges such as model generalization, small lesion detection, and limited high-quality datasets persisted. The study concluded that deep learning had become a key enabler of sustainable and precision agriculture by optimizing monitoring and resource utilization.

Shijian Huang et al. [12] It was reported that the small size of agricultural pests had posed a major challenge to detection accuracy, leading to the proposal of a Lightweight Cross-Level Feature Aggregation Network (LCFANet). The study explained that LCFANet had integrated deep feature extraction, feature fusion, and multi-scale detection using novel modules such as DTFA-C3k2, ADown-Conv, and a Cross-Level Hierarchical Feature Pyramid to enhance multi-scale and fine-grained feature representation. It was stated that a Multi-Scale Adaptive Spatial Fusion detection head and the MPDINIoU loss function had further improved bounding box regression and detection accuracy. The authors noted that the lightweight LCFANet-n model contained only 2.78 million parameters with 6.7 GFLOPs, making it suitable for edge deployment. Experimental results demonstrated state-of-the-art performance with 71.7% precision, 68.5% recall, 70.4% mAP@50, and 45.1% mAP@50–95 for small- sized pest detection.

Fuyan Sun et al. [13] It was stated that effective detection of stored-grain insect pests had been essential for preventing economic losses and ensuring food security, while existing methods had suffered from high labor demands, environmental interference, and inconsistent performance. The study reported that an improved algorithm, PDA-YOLO, based on YOLO11n had been proposed, integrating PF_C3k2, AIFI, and DMAE modules to enhance feature extraction, global context understanding, and small-target boundary detection. It was explained that training and evaluation on 6200 images of five common stored-grain pests had yielded an mAP@0.5 of 96.6%, an mAP@0.5:0.95 of 60.4%, and an F1 score of 93.5%. The authors noted that the model required only 6.9 GFLOPs and achieved a mean detection time of 9.9 ms per image. The study concluded that PDA-YOLO had effectively balanced accuracy, efficiency, and real-time performance, making it suitable for intelligent grain storage management.

Jie Xu et al. [14] It was stated that nurseries had played a vital role in modern agriculture by supporting seedling cultivation, while intelligent agricultural robots had improved efficiency through autonomous plant protection. The review reported that perception systems in such robots had relied on neural networks to process image and point cloud data for accurate feature extraction. It was explained that image-based models had been widely used for classification, segmentation,

and object detection, whereas point cloud-based approaches had been more suitable for spatial target information detection. The authors noted that these models had been applied across multiple plant protection tasks, each leveraging their respective strengths. The study concluded by identifying key challenges and future research directions to advance agricultural robotics and precision plant protection.

Kunhong Li et al. [15] It was stated that pest infestations had been a major challenge in tea production and that real-time detection using machine vision had become an important approach, despite the lack of suitable devices and open-source datasets for small-sized tea pests. The study reported that a YOLOv8-FasterTea detection algorithm based on cross-domain transfer learning had been proposed and deployed in a tea pest monitoring device. It was explained that transfer learning from the natural language character domain had enhanced small and complex feature extraction and addressed the few-shot learning problem. The authors noted that architectural modifications, including removing the P5 layer, adding a P2 small-target layer, and using lighter convolutional modules, had improved performance. Experimental results showed that mAP@0.5 increased by about 6% after transfer learning, while the final model achieved a 3.7% mAP@0.5 improvement with a 46.6% reduction in model size.

3. PROPOSED SYSTEM

The system architecture is designed to perform pest recognition through a structured processing pipeline that includes image preprocessing, multiple machine learning models for comparison, and a proposed deep learning-based classification method as shown in Fig. 2. The architecture begins with image input and processes the data through different stages such as preprocessing, feature extraction, classification, and result delivery. Traditional machine learning algorithms like KNN, LDA, and CatBoost are used as baseline models, while the proposed approach combines deep convolutional neural networks with XGBoost for improved classification accuracy. The final prediction results are delivered to users through a graphical interface and messaging platform, enabling practical usage for pest identification.

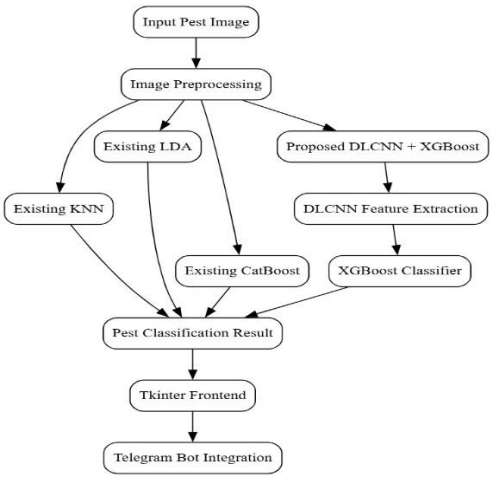


Fig. 2: System architecture for pest classification.

Image acquisition: The system starts by collecting pest images from available datasets or user inputs. These images may contain different lighting conditions, backgrounds, and orientations. The collected images act as the primary input for the pest recognition process.

Image preprocessing: The acquired images are processed to improve quality and consistency. This stage includes resizing images to a standard dimension, reducing noise, and applying normalization techniques. Preprocessing ensures that the images are suitable for feature extraction and classification while reducing the impact of unwanted variations.

Classification using existing KNN: In this stage, the pre-processed images are evaluated using the KNN algorithm as a baseline machine learning approach. The model compares the input image features with training samples and classifies the pest based on similarity with the nearest neighbours in the dataset.

Classification using existing LDA: The LDA model is applied to analysed the data by projecting features into a lower dimensional

space that maximizes class separability. This helps in identifying patterns between pest classes and provides another baseline result for comparison with other models.

Classification using existing CatBoost: The CatBoost algorithm is used as another comparative model. It is a gradient boosting based machine learning method that builds multiple decision trees and combines them to improve prediction performance and classification accuracy.

Proposed DLCNN with XGBoost: The proposed approach combines deep learning feature extraction with an advanced machine learning classifier. This hybrid model is designed to improve pest recognition accuracy while maintaining efficient processing performance.

DLCNN feature extraction: In this step, a deep learning convolutional neural network analyzes the pre-processed images and automatically extracts important visual features such as shapes, edges, textures, and patterns associated with different pest species. These extracted features provide a meaningful representation of the pest images.

XGBoost classifier: The extracted deep features are then passed to the XGBoost classifier. XGBoost processes these features using an ensemble learning strategy that combines multiple decision trees to produce accurate classification results.

Tkinter frontend: A graphical user interface built using Tkinter allows users to upload pest images and view classification results. This interface makes the system easy to use for researchers and farmers without requiring technical knowledge.

Telegram bot integration: The system also integrates a Telegram bot to enable remote access. Users can send pest images through the messaging platform, and the system processes the image and returns the predicted pest class automatically.

4. Results Analysis

The evaluation of the 10-class insect classification model, as detailed in Fig. 3, demonstrates exceptional performance and robust diagnostic capabilities. The confusion matrix heatmap reveals high overall accuracy, with most classes including Africanized Honey Bees, Brown Marmorated Stink Bugs, Cabbage Loopers, Colorado Potato Beetles, Corn Borers, and Fruit Flies achieving perfect scores of 20 correct predictions. While Citrus Canker, Spider Mites, and Thrips recorded 19 correct predictions and Corn Earworms followed closely with 18, off-diagonal misclassifications remained minimal and scattered. This indicates that the model distinguishes well between visually similar categories with negligible cross-class confusion. This precision is further validated by the ROC-AUC curves for the CatBoost classifier, where every pest species demonstrates a curve hugging the top-left corner. With AUC values essentially at 1.00 for all classes, the model exhibits near-perfect class separability and high true-positive rates, confirming its reliability and effectiveness in identifying diverse agricultural pests. The performance evaluation of the DLCNN-LDA model, as illustrated in Fig. 4, reveals exceptional classification accuracy and robust discriminative power across all ten insect categories. The confusion matrix heatmap highlights a strong concentration of correct predictions along the diagonal, with classes such as Cabbage Loopers, Colorado Potato Beetles, Corn Borers, Fruit Flies, and Spider Mites achieving perfect or near-perfect scores of 20. Other categories, including Africanized Honey Bees, Brown Marmorated Stink Bugs, Citrus Canker, and Thrips, maintain high accuracy with only single-instance misclassifications, while Corn Earworms follow closely with 18 correct predictions. These minimal off-diagonal values indicate a lack of systematic error and suggest the model distinguishes effectively between visually similar species. This high precision is further corroborated by the ROC–AUC curves, which hug the top-left corner of the plot, far above the random-guessing baseline. Achieving an AUC

value of 1.00 for every class, the DLCNN-LDA model demonstrates perfect sensitivity and an extremely low false-positive rate, confirming its reliability as a high-performance framework for multi-class pest classification.

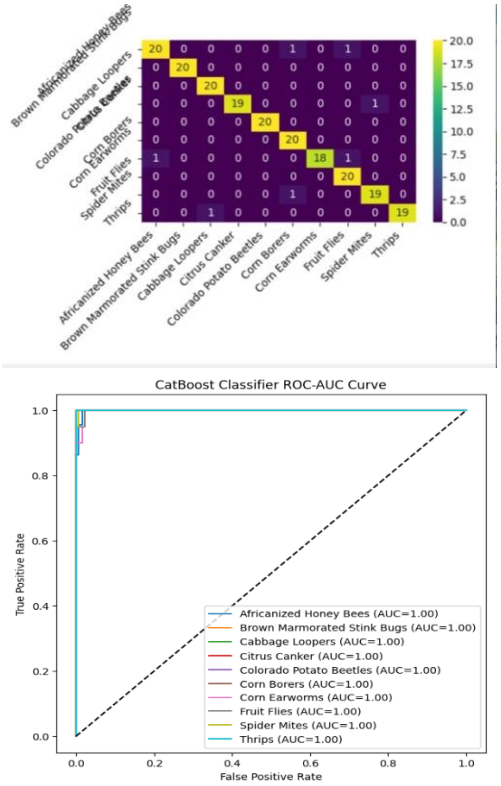


Fig. 3: Confusion matrix and ROC-AUC curve of CatBoost model

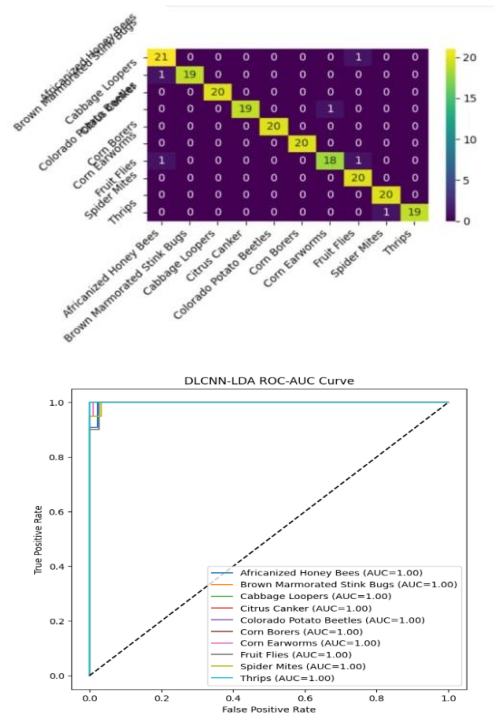


Fig. 4: Confusion matrix and ROC-AUC curve of DLCNN-LDA

Comparative Analysis

Table 1 Shows the overall comparison shows that Method-3 achieves the highest performance across all aggregate metrics, with approximately 98% accuracy and corresponding macro and micro-Precision, Recall, and F1-scores near 0.98, indicating extremely consistent classification across all insect classes. Method-1 follows closely with about 96% overall performance, demonstrating strong and stable predictions with minimal misclassification. Method-2 records the lowest overall performance at roughly 92%, reflecting a noticeable increase in classification errors compared to the other two methods. Since the dataset is balanced across classes, macro and micro averages are nearly identical for each method, confirming that performance differences are consistent across categories rather than driven by class imbalance.

Table. 1: Overall comparison evaluation.

Method	Accuracy	Precision	Recall	F1 Score
Method-1	96%	0.96	0.96	0.96
Method-2	92%	0.92	0.92	0.92
Method-3	98%	0.98	0.98	0.98

Telegram Bot Results

The Fig. 5 shows the input images Telegram-based chatbot named Agri_Pest_SAK that functions as an AI-powered agricultural pest detection system. When the user initiates the bot using the "/start" command, it prompts the user to upload a pest image and clearly states its capabilities, which include identifying the image type, assessing the severity of infestation, and providing an AI model prediction. The user then uploads images of insects on plant leaves—one showing a striped

beetle and another a red beetle with black spots—indicating practical examples of pest samples. After each image submission, the bot responds with an "Analysing…" message, suggesting that the system processes the image through a trained deep learning model for classification and severity estimation. The interface demonstrates a real-time, automated workflow where image input triggers backend AI analysis, making the bot a useful tool for farmers or agricultural professionals to quickly identify pests and evaluate crop damage. Overall, the screenshots highlight the integration of image processing and machine learning within a user-friendly messaging platform to support smart agricultural pest management.



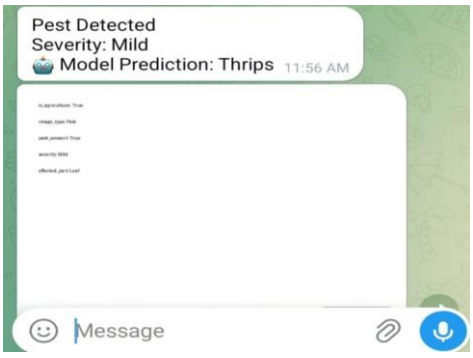




Fig. 5: Telegram Bot with Input Images.

The Fig. 6 shows a mobile chat interface displaying automated results from an AI-based agricultural pest detection system. In the first case, the system reports "Pest Detected" with a mild severity level, and the model prediction identifies the issue as Thrips, which are tiny insects that feed on plant tissues and can cause leaf discoloration and reduced growth if not managed early. In the second case, the system reports moderate severity, with the model predicting Citrus Canker, a bacterial plant disease that causes lesions on leaves, stems, and fruits, potentially affecting crop yield and quality. The interface suggests that users submit plant images, and the system analyses them to provide pest or disease identification along with an assessment of how serious the infection is, helping farmers or gardeners take timely action.

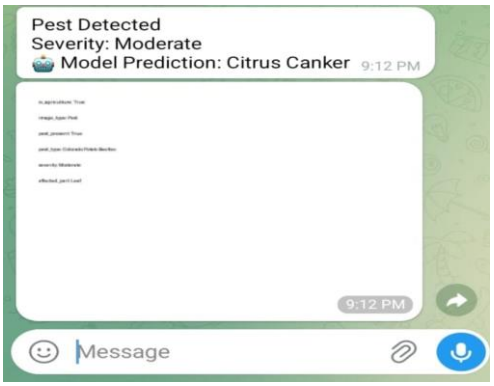


Fig. 6: Telegram bot with Output Results Analysis

5. Conclusion

This research proposed an Edge Adaptive Neural Classifier for On-Device Pest Recognition to address the challenges of manual pest detection in agriculture.

Traditional methods rely on human inspection, which is time-consuming, subjective, and often incapable of providing early warnings. The developed system overcomes these limitations by integrating image processing and deep learning techniques into an edge-based deployment framework. The proposed model captures pest images in real time, performs adaptive preprocessing to handle variations in illumination and noise, and extracts discriminative features using a lightweight neural network. The classification module predicts pest types with high accuracy, while edge optimization techniques ensure reduced model size and faster inference. By enabling on-device processing, the system eliminates dependency on continuous internet connectivity and minimizes latency, making it suitable for rural and remote agricultural environments. Experimental results demonstrate that the system achieves reliable classification performance and stable real-time operation. Early pest detection allows farmers to take timely preventive measures, reduce crop damage, and optimize pesticide usage. Overall, the integration of neural networks with edge computing provides a practical, efficient, and scalable solution for modern precision agriculture.

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