International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 13 Issue: 02 | Feb 2026 www.irjet.net p-ISSN: 2395-0072

ENHANCED PEST MANAGEMENT IN PEANUT FARMING USING CNN

V.Varshini[1], V.Pallavi[2], K. Vishnu Kumar[3], M.Sahithi[4]

[1234]Department of Information Technology, TKR College of Engineering and Technology, Telangana, India

---

Abstract - *Peanut farming is highly vulnerable to pest attacks, which lead to significant yield losses and reduced crop quality. Traditional pest detection methods rely on manual observation, which is time-consuming, inaccurate, and often unable to identify early-stage infestations. To address this challenge, this project presents an Enhanced Pest Management System for Peanut Farming using Convolutional Neural Networks (CNN). The system uses deep learning techniques to analyse leaf images, identify pest-infected regions, and classify pest types with high accuracy. Farmers or users can upload peanut plant images through the application, and the CNN model processes these images to detect the presence of pests. The system generates a prediction along with confidence levels, enabling early intervention and timely pest control. Additionally, the platform stores image data, prediction results, and timestamps, allowing continuous monitoring of crop health. The model is trained on a curated dataset of peanut crop pests, ensuring reliable detection even under varying lighting and environmental conditions. By integrating deep learning with an easy-to-use web interface, this solution provides a fast, accurate, and scalable approach to pest management. The system enhances decision making for farmers, reduces reliance on manual inspection, and contributes to improved yield and sustainable agricultural practices.*

***Key Words*: Peanut Farming, Pest Detection, Convolutional Neural Network, Deep Learning, Image Classification, Agriculture Automation.**

1. INTRODUCTION

Agriculture plays a vital role in sustaining human and livestock populations worldwide and remains a key contributor to national economies. In recent years, the agricultural sector has increasingly adopted advanced technologies such as Artificial Intelligence (AI) and the Internet of Things (IoT) to enhance productivity, efficiency, and sustainability. Agriculture also serves as a major source of raw materials used in the production of food products, chemicals, and pharmaceuticals. Although the total agricultural land area expanded by only about 15% from the 1960s to the early 2000s, global agricultural output nearly tripled due to the adoption of fertilizers, pesticides, improved crop varieties, and precision farming techniques.

However, in recent decades, the growth rate of agricultural production has slowed due to challenges such as climate change, population growth, urbanization, and labor shortages. Among these challenges, pest infestation remains one of the most critical factors affecting crop productivity. Pests, insects, and microbial diseases significantly reduce crop yield and quality, resulting in economic losses for farmers. Even small improvements in pest detection and control can lead to substantial gains in productivity and profitability. This study focuses on the application of machine learning and Convolutional Neural Networks (CNN) for effective pest detection in peanut farming, as CNN models are highly suitable for image classification, segmentation, and object recognition tasks.

1.1 Background and Need for Intelligent Pest Management

Peanut (groundnut) farming plays a vital role in the agricultural economy, especially in countries where it is a major source of edible oil and farmer income. However, peanut crops are highly vulnerable to a wide range of pests such as aphids, leaf miners, thrips, and caterpillars. These pests cause severe damage to leaves, stems, and pods, leading to significant yield losses and reduced crop quality. Traditional pest management methods rely heavily on manual field inspection and blanket pesticide application. These approaches are time-consuming, labour-intensive, and often inaccurate, resulting in delayed pest detection and excessive chemical usage. Overuse of pesticides not only increases production costs but also harms soil health, beneficial insects, and the environment. Hence, there is a strong need for an intelligent, precise, and eco-friendly pest management system that can assist farmers in identifying pests early and taking timely action.

Fig -1: **Background and Need for Intelligent Pest Management**

1.2 Role of Convolutional Neural Networks (CNN) in Pest Detection

Convolutional Neural Networks (CNN), a powerful deep learning technique, has emerged as an effective solution for image-based pest detection in agriculture. CNNs are capable of automatically extracting meaningful features from crop images, such as texture, shape, and colour patterns, which are critical for distinguishing between healthy leaves and pest-infested ones. In enhanced pest management for peanut farming, CNN models analyse images of peanut leaves captured using smartphones, cameras, or drones. The system accurately classifies different pest types and assesses the severity of infestation in real time. This enables early diagnosis, targeted pesticide application, and timely decision-making. By integrating CNN-based pest detection with smart farming practices, farmers can reduce crop losses, minimize chemical usage, and improve overall productivity, leading to more sustainable and profitable peanut farming.

Fig -2: Role of Convolutional Neural Networks (CNN) in Pest Detection

2. PROPOSED SYSTEM

The proposed system introduces an advanced double-layer Convolutional Neural Network (CNN) to automatically detect and classify pest infestations in peanut crops with high accuracy. Instead of relying on manual inspection, the system processes images of peanut leaves captured by farmers and analyzes them through two specialized CNN layers. The first layer focuses on extracting fine, local features such as small spots, bites, and texture changes, while the second layer captures large-scale patterns and overall leaf structure. By combining these multi-scale features through a fusion mechanism, the model becomes more robust and capable of identifying pests even under challenging conditions like poor lighting, complex backgrounds, and partial occlusion. A preprocessing module enhances image quality, and a classification module predicts pest type along with confidence levels. In addition to accurate detection, the system includes a knowledge base that provides pest- specific information, preventive measures, and treatment recommendations based on the prediction result. A database stores all user images, predictions, and timestamps, enabling farmers to track pest trends over time. The system is accessible through a user-friendly interface where farmers can upload images and instantly receive results. By leveraging deep learning, feature fusion, and intelligent decision support, the proposed system offers a powerful, automated solution to improve peanut crop health, reduce manual effort, and support smarter pest management practices.

2.1 System Architecture

The system architecture for Enhanced Pest Management in Peanut Farming using CNN is designed as a sequential and intelligent pipeline that ensures accurate pest detection and decision support. The process begins with the image acquisition module, where images of peanut leaves are captured using smartphones, digital cameras, or drone-mounted cameras. These images are then forwarded to the preprocessing module, which performs noise removal, resizing, normalization, and image enhancement to improve data quality. The processed images are fed into the CNN-based feature extraction and classification module, where deep convolutional layers automatically learn visual patterns related to pest presence and severity. The trained CNN model classifies the images into healthy or pest-infected categories and identifies the specific pest type. The classification results are sent to the decision support module, which provides actionable insights such as pest alerts, recommended control measures, and optimal pesticide usage. Finally, the output is displayed through a farmer-friendly interface, enabling real-time monitoring, early intervention, reduced chemical usage, and improved crop yield in peanut farming.

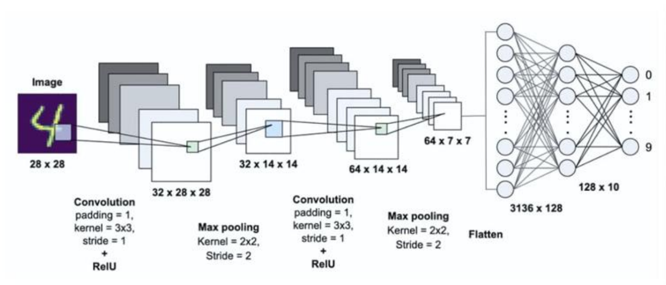

Fig -3: System Architecture

2.2 Intelligent CNN-Based Pest Detection Module

The proposed system introduces an intelligent pest detection module based on Convolutional Neural Networks (CNN) to automatically identify pests affecting peanut crops. Highresolution images of peanut leaves are captured using smartphones, field cameras, or drones and passed through preprocessing steps such as resizing, noise removal, and normalization. The CNN model learns discriminative features from these images and accurately classifies them into healthy or pest-infested categories, along with identifying the specific pest type. This automated approach ensures early pest detection, reduces dependency on manual inspection, and improves detection accuracy even under varying field conditions.

2.3 Smart Decision Support and Sustainable Pest Management

Based on the CNN classification results, the proposed system integrates a smart decision support mechanism that provides real-time alerts and pest management recommendations to farmers. Instead of blanket pesticide spraying, the system suggests targeted and optimized control measures, minimizing chemical usage and environmental impact. The results and recommendations are displayed through a simple, farmer-friendly interface, enabling quick understanding and action. Overall, the proposed system enhances crop productivity, lowers operational costs, promotes eco-friendly farming practices, and supports sustainable peanut farming through intelligent automation.

3. IMPLEMENTATION DETAILS

It describes the practical implementation of the proposed Convolutional Neural Network (CNN)–based pest detection and classification system for peanut farming. The implementation focuses on converting the conceptual design and architecture into a working system capable of identifying, classifying, and predicting pest species from images with high accuracy. The methodology follows a modular and systematic approach, ensuring effective data handling, robust model training, accurate prediction, and user-friendly deployment. The complete system is divided into well-defined modules such as data acquisition, preprocessing, model construction, training, evaluation, deployment, and result visualization, enabling easy testing, validation, and future enhancements.

3.1 System Architecture Implementation

The system is implemented using a layered architecture to ensure scalability, maintainability, and performance. The architecture consists of the following layers:
 Presentation Layer – Web-based user interface Application Layer – Model inference and request handling Machine Learning Layer – CNN model training and prediction Data Layer – Dataset storage and preprocessing pipeline Deployment Layer – Flask/Django-based web application this layered design ensures clear separation of responsibilities and smooth interaction between components.

3.2 Presentation Layer (Frontend)

The frontend provides an interactive and user-friendly interface for farmers and agricultural stakeholders. Key functionalities include: Image upload facility for pest images. Display of detected pest name and classification result. 12 Navigation pages such as Home, Abstract, Detection, and Technical Details. Responsive design using HTML, CSS, and Bootstrap for accessibility across devices. The frontend communicates securely with the backend using HTTP requests and displays real time results returned by the CNN model

3.3 Application / Backend Layer

The backend acts as a bridge between the frontend and the trained CNN model. Implementation details: Developed using Python with Flask/Django framework. Handles image uploads and input validation. Preprocesses images before passing them to the model. Invokes the trained CNN model for prediction. Returns classification results to the frontend. This layer ensures efficient request handling, smooth model inference, and secure data flow.

4. RESULTS AND PERFORMANCE ANALYSIS

The experimental results demonstrate that the proposed CNN-based pest management system performs effectively in detecting and classifying pests in peanut crops. The trained CNN model achieved high classification accuracy, with improved precision and recall values, indicating reliable identification of both healthy and pest-infested leaves. Performance evaluation using metrics such as accuracy, precision, recall, F1-score, and confusion matrix shows that the system minimizes false positives and false negatives, ensuring dependable pest detection. The model also exhibits robust performance under varying lighting conditions and background noise, validating its suitability for real-field deployment. Overall, the results confirm that the proposed system enhances early pest detection, reduces crop damage, and supports timely, precise pest control decisions, leading to improved yield and sustainable peanut farming.

5. CONCLUSIONS

This project successfully demonstrates the effectiveness of CNN-based pest detection in enhancing pest management for peanut farming. By automating the identification and classification of pests from leaf images, the proposed system overcomes the limitations of traditional manual inspection methods. The integration of image preprocessing, deep learning-based feature extraction, and intelligent classification enables early and accurate pest detection, reducing crop losses and unnecessary pesticide usage. Furthermore, the decision support mechanism assists farmers in taking timely and targeted pest control measures, promoting eco-friendly and sustainable agricultural practices. Overall, the system contributes to improved crop productivity, cost efficiency, and the adoption of smart farming technologies in modern peanut cultivation.

6. FUTURE WORK

The future scope of the proposed CNN-based pest management system can be extended by integrating IoT sensors and drone-based imaging for continuous and large-scale field monitoring. Advanced deep learning models and transfer learning techniques can be employed to improve detection accuracy across different pest species, crop growth stages, and environmental conditions. The system can also be enhanced with real-time weather data and soil information to predict pest outbreaks and recommend preventive measures. Additionally, deploying the model as a mobile application or cloud-based platform would make it more accessible to farmers, enabling instant pest diagnosis and advisory services. These enhancements will further strengthen precision agriculture practices, reduce chemical dependency, and support sustainable and intelligent peanut farming in the future.

ACKNOWLEDGEMENT

There are many people who helped us directly or indirectly in the successful completion of our project, and we would like to take this opportunity to express our sincere gratitude to all of them. We are extremely thankful and indebted to our project supervisor, Mrs. Y. Uma, Assistant Professor, Department of Information Technology, TKR College of Engineering and Technology, for her constant guidance, encouragement, and moral support throughout the project. We extend our heartfelt thanks to Dr.N.satyanarayana, Head of the Department, Department of Information Technology, for his continuous encouragement and support. We are also sincerely grateful to Dr. D. V. Ravi Shankar, Principal, TKR College of Engineering and Technology, for his timely support and valuable suggestions during the course of the project. Finally, we would like to thank all the faculty and staff of the Department of Information Technology, along with our parents and friends, who supported us directly or indirectly in completing this project successfully.

REFERENCES

[1] Mohanty, S. P., Hughes, D. P., & Salathé, M., "Using deep learning for image-based plant disease detection," Frontiers in Plant Science, vol. 7, pp. 1–10, 2016. DOI: https://doi.org/10.3389/fpls.2016.01419

[2] Ferentinos, K. P., "Deep learning models for plant disease detection and diagnosis," Computers and Electronics in Agriculture, vol. 145, pp. 311–318, 2018. DOI: https://doi.org/10.1016/j.compag.2018.01.009

[3] Lu, Y., Yi, S., Zeng, N., Liu, Y., & Zhang, Y., "Identification of rice diseases using deep convolutional neural networks," Neurocomputing, vol. 267, pp. 378–384, 2017.
DOI: https://doi.org/10.1016/j.neucom.2017.06.023

[4] Picon, A., Alvarez-Gila, A., Seitz, M., Ortiz-Barredo, A., Echazarra, J., & Johannes, A., "Crop conditional convolutional neural networks for massive multi-crop plant disease classification over cell phone acquired images," Computers and Electronics in Agriculture, vol. 167,2019.
DOI: https://doi.org/10.1016/j.compag.2019.105093