Precision Weed Identification In Groundnut Crops Using Imageprocessing Techniques

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Abstract- *Weed infestation is one of the major problems affecting crop growth and reducing agricultural productivity in groundnut cultivation. Early identification and management of weeds are essential to improve crop yield. In this study, an image-based system was developed to identify weeds in groundnut fields. Images of groundnut crops and weeds were collected using a mobile camera under natural field conditions. The collected images were pre-processed using resizing and enhancement techniques to improve image quality.*

A web-based application was developed to make the system easy to use. The application allows users to upload field images and automatically analyzes them to identify whether the image contains crop plants or weeds. A Convolutional Neural Network (CNN) model was used to classify crop and weed images accurately. Based on the detection results, the system also provides suitable herbicide recommendations to control the identified weeds effectively.

The results are displayed through a simple and user-friendly interface. This developed web system helps farmers quickly detect weeds and select appropriate herbicides, thereby supporting better decision-making, reducing manual labor, minimizing excessive herbicide usage, and improving weed management practices in groundnut cultivation.

Keywords: Groundnut Crop, Weed Detection, Image Processing, Convolutional Neural Network (CNN), Deep Learning, Herbicide Recommendation, Web Application.

I. INTRODUCTION

Agriculture plays a major role in the economy of India, and groundnut (Arachis hypogaea L.) is one of the important oilseed crops cultivated widely in Tamil Nadu and other states. It is valued for its high oil and protein content and contributes significantly to farmers' income. However, groundnut productivity is highly affected by weed infestation, especially during the early growth stages of crop development.

Weeds compete with crops for nutrients, water, sunlight, and space, resulting in significant yield reduction. If weeds are not controlled during the critical growth period, yield loss may reach nearly 30–50%. Traditional weed management practices such as manual weeding require more labor and increase production cost. Similarly, excessive herbicide application may cause environmental pollution and affect soil health.

Recent advancements in image processing, artificial intelligence, and deep learning provide efficient solutions for automated weed detection. Digital images captured using RGB cameras can be analyzed to identify weeds based on color, shape, texture, and plant characteristics. Convolutional Neural Networks (CNNs) have shown high performance in image classification tasks by automatically extracting important features from images.

In this study, a CNN-based weed detection system was developed for identifying weeds in groundnut fields using images collected from Kurinjipadi Taluk, Cuddalore District, Tamil Nadu, India. A web application was also developed to provide real-time weed detection and herbicide recommendations for farmers. This system supports precision agriculture by reducing manual labor, minimizing unnecessary herbicide usage, and improving crop productivity.

Furthermore, the adoption of precision agriculture technologies has increased the demand for smart and automated farming solutions. Image-based weed detection systems help farmers monitor large agricultural fields efficiently and enable early identification of weed growth before severe crop damage occurs. By integrating deep learning models with user-friendly web applications, farmers can easily upload field images and obtain instant results without requiring technical expertise. This approach improves decision-making, reduces operational costs, and promotes sustainable agricultural practices by enabling selective herbicide application only where weeds are detected.

II. LITERATURE REVIEW

Several researchers have applied image processing and deep learning techniques for automated weed detection in agriculture. Burgos-Artizzu et al. (2011) developed an automatic crop–weed discrimination system using computer vision techniques and Support Vector Machine (SVM) classification, achieving good accuracy under controlled conditions. However, their model performance was affected by overlapping plants and complex backgrounds.

Lottes et al. (2017) proposed a Convolutional Neural Network (CNN)-based crop and weed classification system using RGB images collected from agricultural fields. Their study proved that deep learning models perform better than traditional machine learning methods in identifying weeds.

Dos Santos Ferreira et al. (2017) applied deep CNN models for weed detection in soybean crops and achieved more than 90% classification accuracy. Their research highlighted the effectiveness of deep learning in handling variations in plant size and field conditions.

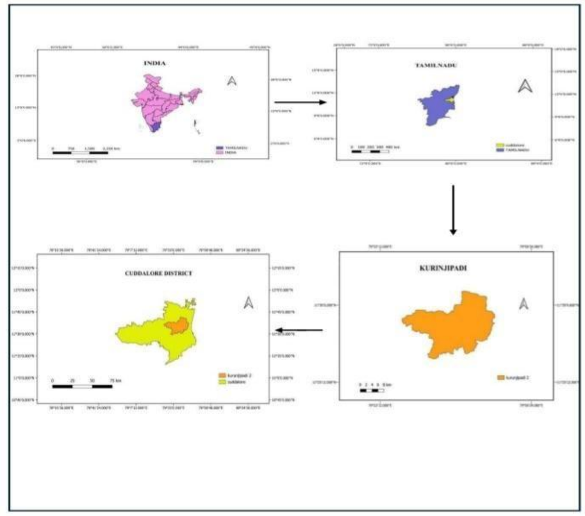
Olsen et al. (2019) introduced the DeepWeeds dataset for large-scale weed classification and demonstrated that deep learning models such as ResNet achieved high accuracy in weed identification.

Based on previous studies, it is observed that CNN-based image processing techniques provide efficient solutions for automated weed detection. Therefore, this study focuses on developing a CNN-based weed identification system for groundnut crops along with herbicide recommendation through a web application.

III. MATERIALS AND METHODS

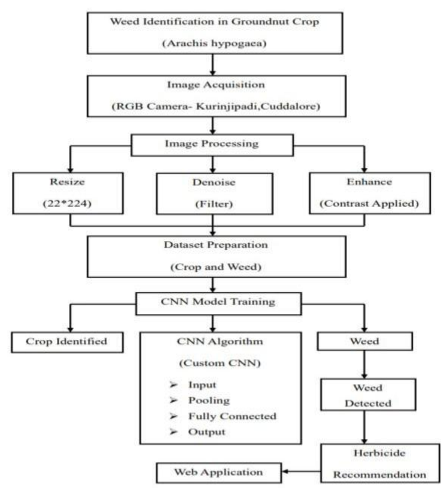
Study Area

The study was conducted in Kurinjipadi Taluk, Cuddalore District, Tamil Nadu, India, which is an important agricultural region known for groundnut cultivation. The study area lies between 11.50°N to 11.75°N latitude and 79.50°E to 79.75°E longitude. The region experiences a tropical climate with moderate temperature and seasonal rainfall, making it suitable for groundnut cultivation. Weed infestation is commonly observed in this area, affecting crop productivity. Therefore, this region was selected for implementing the proposed weed detection system.



Data Collection

Groundnut crop images and weed images were collected from agricultural fields using a mobile RGB camera under natural field conditions. Images were captured at different angles, lighting conditions, and weed densities to ensure dataset diversity. Both crop images and weed images were included to improve the



model's classification performance. The collected dataset served as the primary input for training and testing the CNN model.

Image Preprocessing

The collected images were pre-processed to improve image quality and ensure uniformity before model training. Preprocessing techniques included:

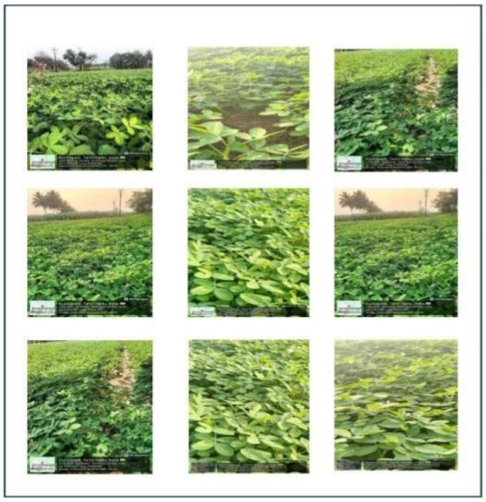
- Resizing imagestostandard dimensions (224 × 224)
- Noise removal using filters
- Color enhancement for better feature visibility.

These steps improved image clarity and helped the model identify important features such as leaf shape, texture, and color differences between crops and weeds.

Dataset Preparation

After preprocessing, the images were organized into two categories:

- Groundnut crop images
- Weed images

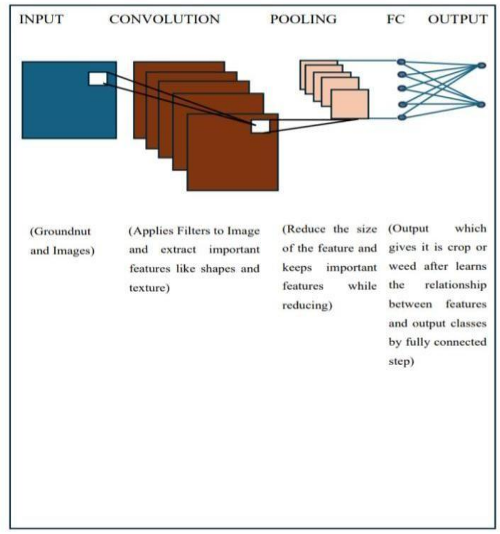


The labeled dataset was divided into training and testing datasets. This dataset was used to train the deep learning model for classification tasks.

CNN Model Development

A Convolutional Neural Network (CNN) model was developed using TensorFlow to classify crop and weed images. The CNN architecture consists of:

- Input layer
- Convolution layer
- Pooling layer
- Fully connected layer
- Output layer



The model automatically extracts image features and classifies the uploaded image as either crop or weed.

Weed Detection

After training, the CNN model was tested with new field images. The system analyzed uploaded images and detected whether weeds were present in the field. This automated detection reduces manual labor and improves weed management efficiency.

Herbicide Recommendation System

When weeds were detected, the system provided suitable herbicide recommendations. In this study, the application suggested Pendimethalin with appropriate dosage based on weed intensity for effective weed control.

Web Application Development

A web application was developed using Flask to make the system user-friendly. Farmers can upload field images through the application and receive instant weed detection results along with herbicide recommendations. This improves accessibility and practical implementation in precision agriculture.

IV. RESULTS AND DISCUSSION

The proposed weed detection system was successfully implemented using image processing and deep learning techniques. Groundnut crop and weed images collected from Kurinjipadi Taluk, Cuddalore District, Tamil Nadu, India were used for model development. The collected images represented different field conditions such as varying backgrounds, lighting conditions, and weed densities.

During image preprocessing, resizing, noise removal, and color enhancement techniques improved image quality and made important features more visible. These processed images provided better input for CNN model training.

The Convolutional Neural Network (CNN) model successfully learned important visual features such as leaf shape, texture, and color differences between crop plants and weeds. The trained model effectively classified uploaded images into crop and weed categories.A web-based application developed using Flask successfully allowed users to upload field images and receive real-time detection results. When weeds were identified, the system recommended Pendimethalin herbicide with appropriate dosage for effective weed management.

The developed system reduces manual labor, saves time, minimizes excessive herbicide usage, and supports precision agriculture practices by providing faster and more accurate weed identification. The results demonstrate that image processing combined with deep learning can be effectively used for smart agricultural applications.

V. CONCLUSION AND FUTURE SCOPE

This study successfully demonstrated the application of image processing and deep learning techniques for precision weed identification in groundnut crops. Images of groundnut crops and weeds were collected from Kurinjipadi Taluk, Cuddalore District, Tamil Nadu, India under natural field conditions and were preprocessed using resizing, noise removal, and color enhancement techniques to improve image quality.

A Convolutional Neural Network (CNN) model was developed using TensorFlow to classify crop and weed images based on visual characteristics such as shape, texture, and color. The trained model successfully identified weeds in uploaded images and provided reliable classification results.

A web application developed using Flask made the system easy to use by allowing users to upload images and receive instant weed detection results. The application also recommended suitable herbicides such as Pendimethalin for effective weed control.

The developed system reduces manual labor, saves time, minimizes excessive herbicide usage, and supports precision agriculture practices. Overall, this study proves that deep learning-based weed detection systems can provide practical solutions for improving crop management and agricultural productivity.

Future Scope

In future, the system can be improved by increasing the image dataset with different weed species and field conditions to improve model accuracy. Drone-based image collection and real-time monitoring systems can also be integrated for large-scale agricultural applications.

The system can be further developed as a mobile application to provide easier access for farmers. Multi-class weed identification and advanced deep learning models can also be implemented for better precision farming applications.

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