Weed Detection Using MobileNetV2

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ABSTRACT

Effective weed detection is pivotal in modern agriculture for optimizing crop yields, conserving biodiversity, and reducing reliance on herbicides. Traditional methods, such as manual inspection and chemical treatments, are labor-intensive, costly, and can negatively impact the environment. This paper presents a deep learning-based weed detection system utilizing the MobileNetV2 convolutional neural network, pre-trained on ImageNet and fine-tuned for agricultural imagery. The system classifies images into 'weed' or 'not weed' categories by extracting and analyzing visual features, enabling rapid and accurate identification of unwanted vegetation. Integrated within a user-friendly Flask web application, the solution provides real-time feedback to users and features distinct admin and user modules for streamlined management and support. Experimental results demonstrate the model's robustness and high accuracy in distinguishing weeds from crops, underscoring the potential of deep learning to revolutionize weed management practices. This approach offers a scalable, precise, and environmentally sustainable alternative to conventional weed control, contributing to the advancement of smart farming and sustainable agriculture.

Keywords: Deep learning, weed detection, MobileNetV2, image classification, smart agriculture, sustainable farming, transfer learning, web application, precision agriculture, environmental management.

I.INTRODUCTION

Agriculture is the cornerstone of global food security and economic stability, providing sustenance and livelihoods for billions of people worldwide. As the global population continues to rise, the pressure on agricultural systems to produce higher yields with fewer resources intensifies. One of the most persistent and challenging obstacles in achieving optimal crop production is the effective management of weeds. Weeds, defined as unwanted plants that grow among crops, compete for essential resources such as water, nutrients, sunlight, and space. Their unchecked proliferation can lead to significant reductions in crop yield and quality, directly impacting food supply chains and farmer incomes. Moreover, weeds can alter the ecological balance of agricultural fields, disrupt native plant communities, and act as reservoirs for pests and diseases, further exacerbating the challenges faced by farmers and environmental managers alike.

Traditional weed management strategies have primarily relied on manual labor, mechanical removal, and the widespread application of chemical herbicides. While manual inspection and removal can be effective on a small scale, these methods are labor-intensive, time-consuming, and often impractical for large-scale operations. Mechanical methods, such as tilling and hoeing, may inadvertently damage crops and degrade soil structure, leading to long-term sustainability concerns. The use of chemical herbicides, although efficient in the short term, raises significant environmental and health concerns. Overreliance on herbicides can result in soil and water contamination, harm to non-target species, and the emergence of herbicide-resistant weed populations. These limitations highlight the urgent need for innovative, sustainable, and precise weed management solutions that can enhance productivity while minimizing negative environmental impacts.

In recent years, the advent of precision agriculture has introduced a new paradigm in farm management, leveraging advanced technologies such as remote sensing, geographic information systems, and data analytics to optimize agricultural practices. Despite these advancements, accurate and timely weed detection remains a significant bottleneck in the implementation of site-specific weed management systems. Conventional image processing techniques, including thresholding, edge detection, and color segmentation, often struggle to cope with the complex and variable conditions present in agricultural fields. Variations in lighting, plant morphology, background clutter, and growth stages can significantly affect the accuracy of traditional methods, limiting their effectiveness in real-world scenarios.

The rapid progress in artificial intelligence, particularly in deep learning and computer vision, offers promising avenues for addressing these challenges. Convolutional Neural Networks (CNNs) have demonstrated remarkable success in a wide range of image classification and object detection tasks, outperforming traditional methods by learning hierarchical and discriminative features directly from raw data. In the context of agriculture, deep learning models have been applied to various tasks, including disease detection, crop type classification, yield estimation, and weed identification. The ability of CNNs to generalize across diverse and complex datasets makes them particularly well-suited for agricultural applications, where variability is inherent and data labeling can be challenging.

Among the many deep learning architectures, MobileNetV2 has emerged as a leading choice for applications requiring both accuracy and computational efficiency. MobileNetV2 is specifically designed for mobile and embedded vision tasks, utilizing depthwise separable convolutions and inverted residuals to significantly reduce model size and inference time without sacrificing performance. This makes it an ideal candidate for real-time weed detection systems that can be deployed on resource-constrained devices, such as smartphones, tablets, or edge computing platforms commonly used in agricultural settings. By leveraging transfer learning, wherein a model pre-trained on a large and diverse dataset like ImageNet is fine-tuned for a specific task, MobileNetV2 can be rapidly adapted to distinguish between crops and weeds in agricultural images with high precision.

In summary, this paper presents a novel approach to weed detection in agriculture by harnessing the strengths of deep learning and modern web technologies. The proposed system not only addresses the technical challenges associated with accurate weed identification but also emphasizes usability and accessibility for a broad range of stakeholders. Through rigorous experimentation and evaluation, the system demonstrates high accuracy and robustness, underscoring its potential to transform weed management practices and contribute to the broader goals of precision agriculture and environmental stewardship. The remainder of this paper is organized as follows: the next section reviews related work in the field of weed detection and deep learning applications in agriculture; subsequent sections detail the methodology, experimental results, and system evaluation; and the final sections discuss the implications, limitations, and future directions of the research, concluding with key contributions and recommendations for future work.

II.RELATED WORK

Detection and Classification of Plant Seedlings: Distinguishing Crop Seedlings from Weed Seedlings Using MobileNetV2 Transfer Learning Model with Fine-Tuning Layers, Authors: Rudresh Pillai.

This study presents a deep learning-based framework for accurately distinguishing between crop and weed seedlings, a critical task in precision agriculture. By leveraging the MobileNetV2 architecture and integrating fine-tuning layers, the model is trained on a dataset of over 11,000 annotated images, achieving an impressive 97% accuracy. Data augmentation techniques were employed to address class imbalance and improve generalization. The results highlight the potential of transfer learning in reducing reliance on manual labor and chemical herbicides, paving the way for more sustainable agricultural practices.[1]

Weed Detection Using AlexNet Architecture In The Farming Fields, Authors: L. Uday Kumar Reddy. This paper presents an efficient deep learning approach for weed detection in agricultural fields using the AlexNet convolutional neural network architecture. Traditional weed classification methods using SVM or ANN often fall short due to limited feature extraction capabilities. By utilizing datasets like WeedCrop, DeepWeed, and PlantSeedlings-v2, and applying image preprocessing techniques, the proposed model achieves an impressive average accuracy of 96%. The approach aims to minimize dependence on harmful herbicides, improve crop health, and automate weed management through advanced image classification techniques.[2]

Real Time Weed Detection using Computer Vision and Deep Learning, Authors: Luiz Carlos M. Junior. This research presents a real-time weed detection system for precision agriculture, integrating computer vision with deep learning techniques. By employing advanced image processing and deep neural networks, the study addresses the urgent need for accurate and efficient identification of weeds in farming fields. The proposed model enhances decision-making in agriculture by reducing manual labor and minimizing the usage of harmful herbicides. Despite existing challenges in differentiating crops, weeds, and soil under varying field conditions, the approach demonstrates the potential for deploying robust AI-driven weed management solutions across diverse agricultural environments.[3]

Deep Learning-Based Weed Detection Using UAV Images: A Comparative Study, Authors:Tej Bahadur Shahi, Sweekar Dahal, Chiranjibi Sitaula. This study presents a comparative analysis of deep learning-based semantic segmentation models for weed detection using UAV-acquired RGB images from the CoFly-WeedDB dataset. The authors evaluate several state-of-the-art AI models, including UNet, SegNet, and DeepLabV3+, paired with backbones such as VGG16, ResNet50, DenseNet121, EfficientNetB0, and MobileNetV2. Among the evaluated architectures, UNet with EfficientNetB0 emerged as the most effective model, achieving a precision of 88.20%, recall of 88.97%, and F1-score of 88.24%. The results highlight the model's strong capability for field-level weed detection, offering a viable path for precision agriculture solutions. The study supports the deployment of drone-assisted deep learning systems to enable early weed removal and reduce herbicide overuse, ultimately improving crop yield and environmental sustainability[4]

Weed Detection and Localization in Soybean Crops Using YOLOv4 Deep Learning Model, Authors:, Velpula Sekhara Babu.This study presents a deep learning-based approach for detecting and localizing weeds in soybean crops using the YOLOv4 model. It achieved high accuracy (98.42%) and strong performance compared to other models like R-CNN and SSD. The research also evaluated several pre-trained CNNs for classification, with DenseNet201 achieving the best accuracy (99.67%). By using CLAHE for image preprocessing, the system improves detection precision, helping reduce unnecessary herbicide use and supporting sustainable farming.[5]

Weeds Detection Networks, Authors:Md. Najmul Mowla, Mustafa Gök

Non-chemical weed control is vital for sustainable organic agriculture. This study investigates advanced deep learning networks for weed detection and introduces CovWNET, a novel and simple model. CovWNET is the second smallest network among those compared, having about one-third more parameters than the smallest model, MobileNetV2, but achieving 1.8% higher accuracy. Compared to DenseNet201, the top-performing model, CovWNET uses roughly five times fewer parameters and has only 2% less accuracy. This demonstrates CovWNET's efficiency and competitive performance for weed detection in organic farming.[6]

Enhanced Deep Learning Models for Real-Time Weed Classification on the Edge, Authors- K. S. Ramalakshmi, Kingshuk Karmakar, Krishna Bajaj, Kumar Abhimanyu & Gowri Srinivasa

This paper introduces a deep learning-based approach for weed detection in modern agriculture, utilizing hierarchical classification and real-time detection with advanced models. MobileNetV2 and NASNetMobile, optimized for edge devices, achieved high accuracies of 98.90% and 97.58%. Real-time detection using YOLOv7 and YOLOv8 frameworks reached precisions of 0.9860 and 0.9902. Deploying these models on edge devices enables precise, targeted weedicide application, reducing environmental impact and improving weed management efficiency for farmers.[7]

WEED DETECTION AND CLASSIFICATION USING DEEP LEARNING,Authors:Md. Najmul Mowla,

This thesis presents CovWNET, a novel and simple convolutional neural network for weed detection and classification in precision agriculture. CovWNET is the second smallest model compared, with 1.5 times more parameters but 2.8% higher accuracy than MobileNetV2, the smallest network. Compared to DenseNet, the most accurate model, CovWNET uses seven times fewer parameters and has only 1.7% less accuracy. Performance was evaluated using precision, recall, F1-score, and support, demonstrating CovWNET's efficiency and effectiveness for sustainable weed management.[8]

Weed detection and classification in sesame crops using region-based convolution neural networks, Authors- Nenavath Srinivas Naik & Harshit Kumar Chaubey,

This research uses Region-Based Convolutional Neural Networks (RCNNs) to detect and classify weeds in sesame crop images. The RCNN approach achieved a high weed detection accuracy of 96.84% and a classification accuracy of 97.79%. By identifying and categorizing weed species, the method helps farmers target specific weeds, enabling more precise and environmentally friendly weed management strategies.[9]

Weed Detection in Crops Using Lightweight EfficientNets, Authors- Atishek Kumar, Rishabh Jain & Rudresh Dwivedi,

This study proposes a deep learning-based approach for targeted weed detection and classification in crop fields to enable precise herbicide application. Using five CNN architectures—MobileNets, MobileNetV2, and EfficientNets (B0–B2)—optimized for low-powered devices, the method was tested on the Plant Seedling, Soybean, and DeepWeeds datasets. EfficientNets consistently outperformed MobileNets, achieving high accuracy rates of 98.92%, 99.97%, and 96.40% on the respective datasets, demonstrating their effectiveness for efficient and cost-effective weed management.[10]

III. METHODOLOGY

The proposed weed detection system leverages deep learning, specifically the MobileNetV2 architecture, to accurately classify images of agricultural fields as containing weeds or not. The methodology encompasses several key stages: data acquisition and preprocessing, model selection and training, system integration, and deployment via a web application. Each stage is designed to ensure robust, efficient, and user-friendly weed detection suitable for modern agricultural environments.

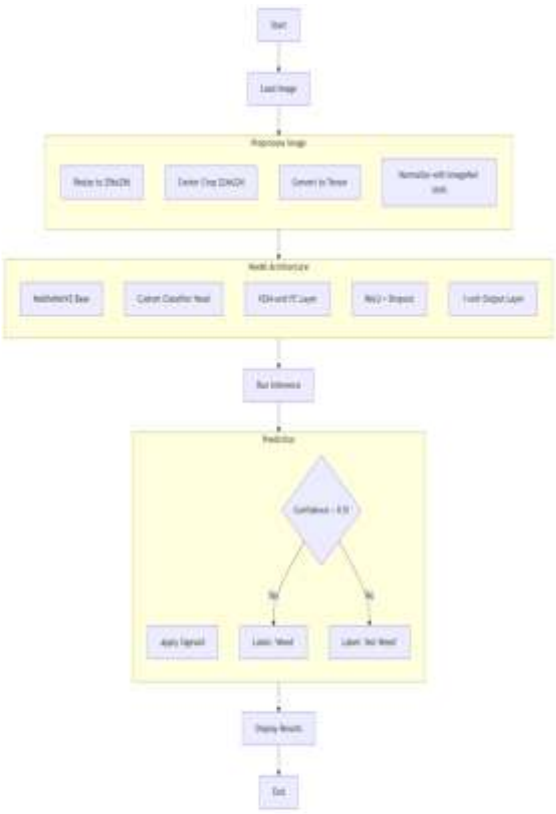


Fig 3.1: Proposed Methodology

1. Data Acquisition and Preprocessing

A diverse dataset is fundamental for training an effective weed detection model. Images containing both crops and various weed species are collected, ensuring representation across different lighting conditions, growth stages, and backgrounds. Publicly available datasets, such as those sourced from Kaggle and other agricultural research repositories, serve as the primary data sources. The dataset is divided into training (60%), validation (10%), and testing (30%) subsets to facilitate model development and unbiased evaluation. Prior to training, images undergo preprocessing steps to enhance feature extraction and model performance. Techniques such as Contrast Limited Adaptive Histogram Equalization (CLAHE) are applied to improve image contrast and normalize lighting variations, as demonstrated in related research. Images are then resized to match the input dimensions required by the MobileNetV2 model.

2. Model Architecture and Transfer Learning

The core of the system is the MobileNetV2 convolutional neural network, chosen for its balance of accuracy and computational efficiency, making it suitable for real-time applications in resource-constrained environments. MobileNetV2, originally trained on the large-scale ImageNet dataset, is adapted to the weed detection task through transfer learning. The final classification layer is replaced to output two classes: 'weed' and 'not weed.' During fine-tuning, the model learns to distinguish between crops and weeds based on visual features present in the training images. Data augmentation techniques, such as random rotations, flips, and color adjustments, are employed to increase the robustness of the model against field variability.

3. Model Training and Evaluation

The adapted MobileNetV2 model is trained using the preprocessed dataset. The training process utilizes standard supervised learning protocols, with cross-entropy loss as the objective function and the Adam optimizer for parameter updates. Early stopping and model checkpointing are implemented to prevent overfitting and ensure optimal performance. The model’s accuracy, precision, recall, and F1-score are evaluated on the validation and test sets to assess its ability to generalize to unseen data. Comparative analysis with other state-of-the-art models, such as YOLOv4, ResNet, and custom CNNs, is conducted to benchmark performance and validate the choice of architecture. MobileNetV2 has demonstrated competitive accuracy in similar agricultural image classification tasks, confirming its suitability for this application.

4. System Integration and Web Application Development

To facilitate practical deployment, the trained MobileNetV2 model is integrated into a Flask-based web application. The system is designed with two distinct modules: an admin module and a user module. The admin module allows for management of registered users, including viewing user details, deleting accounts, and maintaining a repository of frequently asked questions (FAQs) to support users. The user module enables secure registration and login, as well as the core weed detection functionality. Users can upload images of their fields, which are processed by the MobileNetV2 model. The application provides real-time classification results, indicating whether weeds are present in the uploaded image. Additionally, users can access the FAQ section for guidance and troubleshooting.

5. Deployment and Real-Time Operation

The web application is deployed on a server, making the weed detection system accessible to end-users via standard web browsers. The lightweight nature of MobileNetV2 ensures that inference is rapid, enabling real-time feedback even on devices with limited computational resources. The modular design of the application allows for future expansion, such as the integration of additional crop or pest detection features, further enhancing its utility in precision agriculture.

6. Summary

By combining deep learning with a user-friendly web interface, the proposed methodology provides a scalable, accurate, and efficient solution for weed detection in agricultural fields. The use of MobileNetV2 ensures high classification accuracy while maintaining low computational overhead, making the system suitable for widespread adoption in diverse farming contexts. This approach not only supports sustainable weed management but also exemplifies the transformative potential of artificial intelligence in agriculture

IV. TECHNOLOGIES USED

- **MobileNetV2 Architecture:**
  A lightweight and efficient convolutional neural network (CNN) model, pre-trained on ImageNet and fine-tuned for weed detection, offering a strong balance between accuracy and computational efficiency for real-time applications, especially on resource-constrained devices.
- **TensorFlow and Keras:**
  Deep learning frameworks used for building, training, and deploying the MobileNetV2 model, supporting transfer learning and rapid prototyping of neural network architectures.
- **Transfer Learning:**
  The process of adapting the pre-trained MobileNetV2 model to the specific task of weed detection, enabling high performance with limited labeled agricultural data.
- **Image Preprocessing and Augmentation:**
  Techniques such as resizing, normalization, contrast enhancement, and random

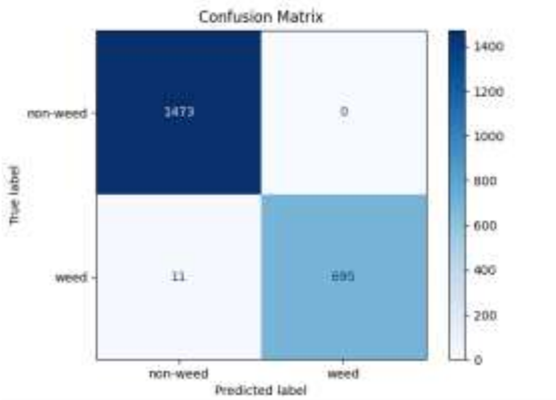
transformations (flips, rotations) to improve model robustness and generalization to diverse field conditions.

- **Flask Web Framework:**
A lightweight Python-based framework for developing the web application, enabling user registration, image upload, and real-time weed detection feedback.
- **HTML, CSS, JavaScript:**
Technologies used for designing a responsive and user-friendly front-end interface for both admin and standard users.

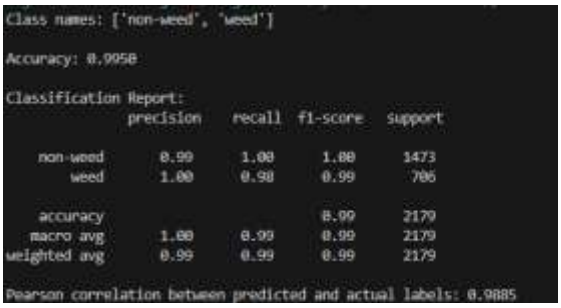
- **Database Management (SQLite/MySQL):**
Databases used to store user credentials, registration data, and frequently asked questions (FAQs) for system management.
- **REST APIs:**Facilitate communication between the web interface and the deep learning model for seamless image classification and feedback.
- **Cloud and Edge Deployment:**
The system can be deployed on cloud servers for scalability or on edge devices (e.g., NVIDIA Jetson Nano, Raspberry Pi) for real-time, in-field operation, leveraging the efficiency of MobileNetV2.
- **Docker (Optional):**
Containerization technology for packaging the application and its dependencies, ensuring portability and ease of deployment across different platforms.
- **Hyperparameter Optimization:**
Techniques such as Bayesian optimization are used to fine-tune the model for optimal accuracy and efficiency on limited hardware resources.

These technologies collectively enable the development of a robust, efficient, and scalable weed detection system suitable for modern precision agriculture.

V Result



This confusion matrix shows the model accurately classifies almost all non-weed and weed samples, with only 11 weed samples misclassified as non-weed and no non-weed samples misclassified as weed.



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Class names: ['non-weed', 'weed']

Accuracy: 0.9958

Classification Report:
              precision    recall  f1-score   support

    non-weed       0.99      1.00      1.00      1473
        weed       1.00      0.98      0.99       706

    accuracy                           0.99      2179
   macro avg       1.00      0.99      0.99      2179
weighted avg       0.99      0.99      0.99      2179

Pearson correlation between predicted and actual labels: 0.9885
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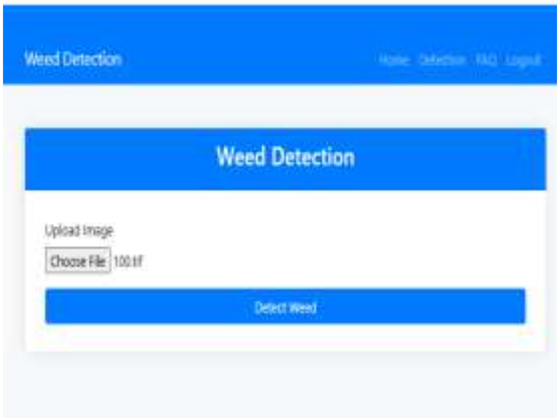
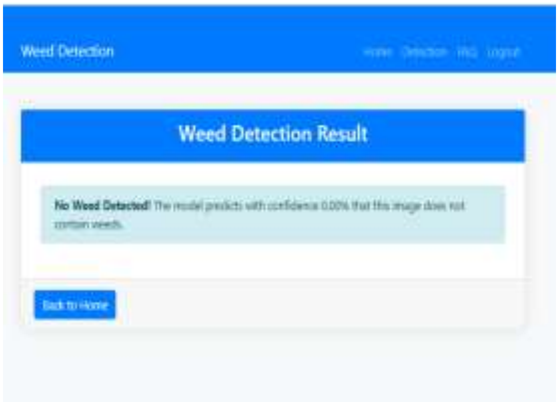
The weed detection model based on MobileNetV2 achieved a high overall accuracy of **99.5%** on a 20% subset of the validation dataset, demonstrating strong generalization performance. The classification report indicates excellent precision and recall for both classes, with an F1-score of **1.00 for non-weed** and **0.99 for weed**, showing the model's reliability in correctly identifying both categories. The confusion matrix revealed minimal misclassifications, primarily within the weed class, which had a slightly lower recall (**0.98**), suggesting a few weeds were misclassified as non-weeds. The **Pearson correlation of 0.9885** further confirms a strong linear relationship between predicted and actual labels. Overall, the model performs robustly and is well-suited for practical weed detection tasks, with minor room for improving sensitivity to weed instances.





The first snapshot illustrates the image upload interface, where users can select and submit an agricultural field image for weed detection. After uploading, the second snapshot displays the prediction result, indicating whether the image contains weed or non-weed. This user-friendly interface ensures quick and accurate feedback, making it practical for field-level decision-making.

VI. CONCLUSION

The proposed weed detection system demonstrates that deep learning, particularly the MobileNetV2 architecture, offers an effective, efficient, and scalable solution for real-time weed identification in agricultural environments. By leveraging transfer learning, image preprocessing, and lightweight model design, the system achieves high accuracy in distinguishing weeds from crops, even under diverse field conditions, while remaining suitable for deployment on resource-constrained devices. The integration of this model into a user-friendly web application further enhances accessibility, allowing both administrators and end-users to benefit from rapid, automated weed detection and streamlined management functionalities. Experimental results and comparative studies confirm that MobileNetV2 provides competitive performance with minimal computational overhead, making it an ideal choice for precision agriculture and environmental sustainability initiatives. Ultimately, this work highlights the transformative potential of artificial intelligence in agriculture, reducing reliance on manual labor and herbicides, supporting sustainable farming practices, and laying a foundation for future innovations in smart agricultural management

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