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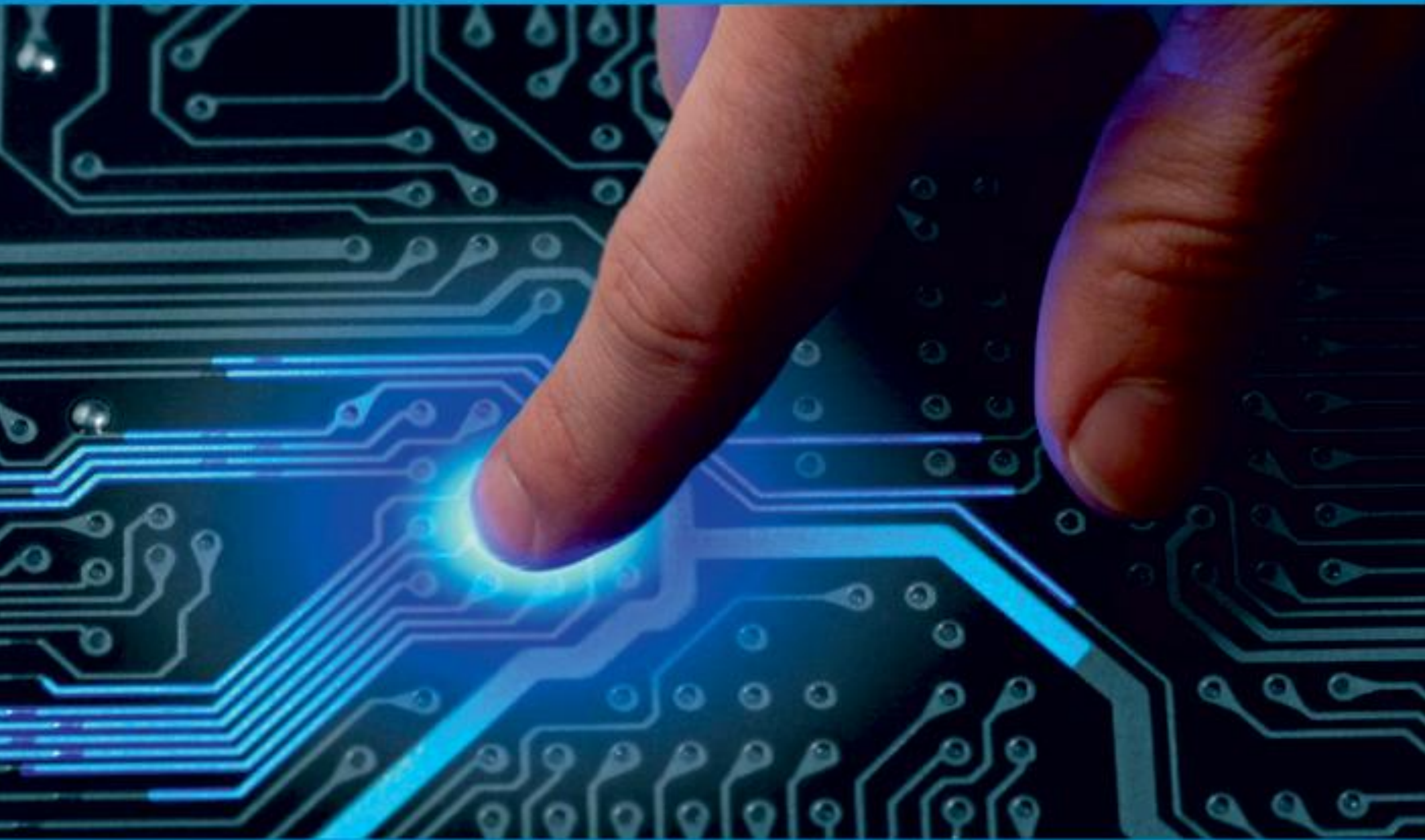

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Crop Pest Classification Using Deep Learning Techniques

Sahana Poojari[1], Shruti Nayak[2], Sushma Mirji[3], Y Pragathi[4], Dr. Gangadharappa S[5], Prof. Gowramma B H[6]

U.G. Student, Dept. CS&E, Bapuji Institute of Engineering and Technology, Davanagere, Karnataka, India[1]

U.G. Student, Dept. CS&E, Bapuji Institute of Engineering and Technology, Davanagere, Karnataka, India[2]

U.G. Student, Dept. CS&E, Bapuji Institute of Engineering and Technology, Davanagere, Karnataka, India[3]

U.G. Student, Dept. CS&E, Bapuji Institute of Engineering and Technology, Davanagere, Karnataka, India[4]

Associate Professor, Dept. CS&E, Bapuji Institute of Engineering and Technology, Davanagere, Karnataka, India[5]

Assistant Professor, Dept. CS&E, Bapuji Institute of Engineering and Technology, Davanagere, Karnataka, India[6]

ABSTRACT: This project focuses on developing a crop pest classification system using deep learning techniques. Specifically, convolutional neural network (CNN) architectures ResNet-50 and inceptionv3 are employed for accurate pest identification based on input images. Transfer learning strategies are utilized to leverage pretrained models and improve classification performance while reducing training time. The system undergoes rigorous evaluation and validation to ensure its effectiveness in automated crop pest detection, contributing to more efficient and sustainable agricultural practices.

KEYWORDS: Classification, CNN, ResNet-50, Inceptionv3, Transfer learning

I. INTRODUCTION

India is a land of Agriculture. Many peoples are directly dependent on Farming. Agriculture also plays a very important role in a nation's economy. Farmers come from rural backgrounds. They completely depend on Agricultural activity. It contributes 17% of GDP. It will help the nation by resolving unemployment problems. However, one of the most pressing challenges in agriculture is the relentless battle against pests that can devastate crops, leading to reduced yields and food shortages. Crop production always depends upon some production elements like pests, fertilizer, or water. Some pests like Bacteria, virus, fungus cause harm to the crops. This results in decrease in quality and quantity of yields of crops. Crop pests and diseases are responsible for global crop losses that can exceed 20-40% annually. In some regions, losses have been recorded at much higher levels, threatening the livelihoods of farmers and the food security of communities. Timely and accurate detection of these threats is crucial to mitigate their impact and ensure food security. Traditional methods of pest and disease identification in crops often rely on visual inspection, experience, and manual labour. These methods can be time-consuming, subjective, and prone to error. In a world where technology has revolutionized nearly every industry, it's time for agriculture to benefit from the advances in artificial intelligence, specifically deep learning techniques, to address this age-old problem. This project talks about the impact of pests on agricultural achievements. But identifying of pests is a major challenge to farmers. A manual method for analysing consumes more time. Most of the farmers are not enough educated and lack the knowledge to differentiate the different types of pests. For that purpose, it introduces the deep learning technique for identifying as well as classifying the pests. The main focus of this project is on the identifications of pest image for taking biological precautions.

II.RELATED WORK

"Faster-PestNet: A Lightweight Deep Learning Framework for Crop Pest Detection and Classification" (2023), the research conducted by Farooq Ali, Huma Qayyum, and Muhammad Javed Iqbal developed an improved Faster-RCNN approach is designed using the MobileNet as its base network and tuned on the pest samples to recognize the crop pests of various categories and given the name of Faster-PestNet.[1]. The paper "Rice pest identification based on multi-scale double-branch GAN-ResNet" proposed by Kui Hu, Yong Min Liu and Jiawei Nie in the year 2023 is a novel deep learning model for accurate and robust identification of rice pests in natural field

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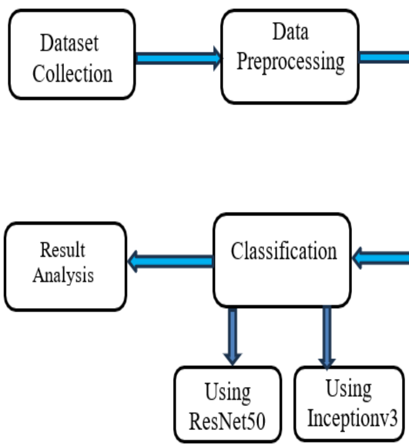
environments.[2] "Deep Learning based Pest Classification in Soybean Crop using Residual Network-50" the research conducted by authors Dhyey Shah, Rajeev Gupta, Krishna Patel, Devam Jariwala and Jeet Kanani, presents a study on soybean pest classification employing a Residual Network-50 architecture. The research utilizes deep learning techniques to automatically identify and categorize pests affecting soybean crops. [3] The paper "Paddy Pest Classification Using Deep Learning Based Features (2022)" by Ananyasreya P P and Subhija E N introduces a novel approach to identify and classify pests affecting paddy crops. Leveraging Convolutional Neural Networks (CNNs), the study employs deep learning-based features to automatically distinguish between various pests and healthy crops.[4] Mayank Mishra, Tanupriya Choudhury and Tanmay Sarkar in 2021, they proposed pest control system which use IOT and Image processing technologies. CNN based efficient image classification system for smartphone device. System use infrared sensors for detecting pest. pests detected by using sensor and ultrasonic wave equipment with the help of Image processing which keeps insects away from the field.[5]

III.METHODOLOGY

Fig. 1. System Design



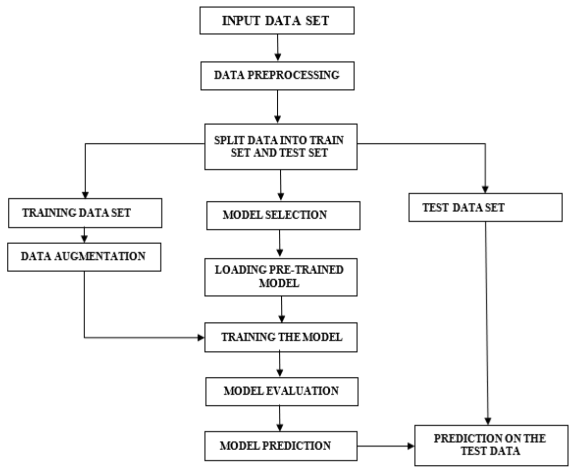


Fig. 2. Work Flow of the project

A. Image Acquisition: This step involves gathering images of pests using a camera. The sample images of the pest are collected and are used in training the system. To train and to test the system, pest images and fewer healthy images are taken. the images will be stored in some standard format.
B. Image Pre-processing: After acquiring the images, they undergo pre-processing steps. The colour space transformation from RGB to HSI (Hue, Saturation, Intensity) is performed because the HSI space aligns better with human perception of colour. Green pixel masking is employed to remove areas that represent healthy plant parts since they don't contribute to pest identification.
C. Segmentation: Image segmentation involves dividing the image into meaningful regions. Clustering techniques, particularly K-means clustering, are used for this purpose. K-means clustering is chosen for its simplicity and computational efficiency. It works by grouping similar pixels together based on their colour values.
D. Feature Extraction: Once the images are segmented, features relevant to pest identification are extracted. This step focuses on calculating the area of the segmented pest regions. By finding connected components and analysing their basic properties like area, the algorithm can isolate and describe the affected areas accurately.
E. Classification using Inspectionv3 and ResNet: A support vector machine comes under supervised learning model in machine learning. Inspectionv3 and ResNet are mainly used for classification and regression analysis. has to be associated with learning algorithms to produce an output. Inspectionv3 and ResNet has given better performance for classification and regression as compared to other processes.

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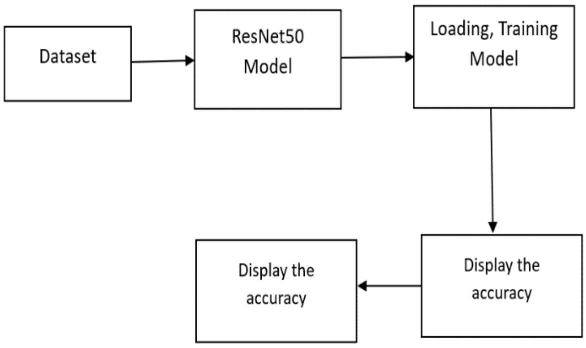

Fig. 3. Convolutional Neural Network- Resnet50

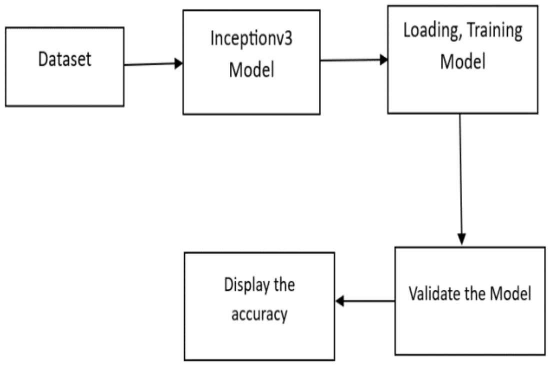

Fig. 4. Convolutional Neural Network- Inceptionv3

DATASET-This project was done to identify pests in various crops. The model is created and loaded with pre-trained weights from the pest dataset. In this analysis, there are 2,266 images of 12 separate categories of pest. Where we have taken pest like moth, beetle, grasshopper, aphids, earwig, weevil, slug, ants, earthworm, snail and bees. The scale of datasets was not the same and, therefore, not appropriate for model feeding. We had to process the dataset beforehand. Second, all the images were resized to 244 x 244 scales and placed in one NumPy series. The dataset was then split into two parts: 80% of the total images are used for the model training and the remaining 20% for testing and validating. After that apply the proposed CNN models (resnet50 and inceptionv3) to extract the features and compare the features with the trained data and classify the data.

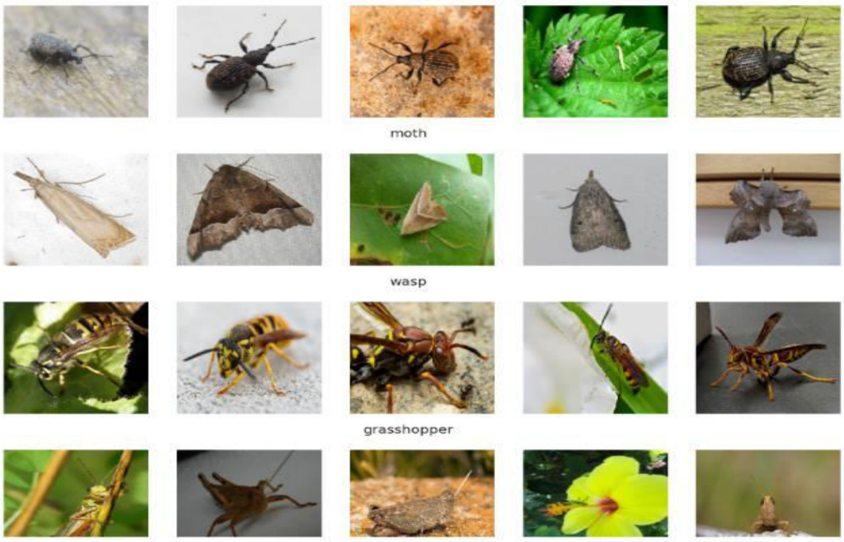

Fig. 5. Sample Pest Dataset

IV. Experimental Results

Both ResNet50 and Inceptionv3 convolutional neural network pre-trained models are implemented using python and executed with set of crop pest datasets which are publicly available. The proposed system is tested with 2266 pest images. ResNet work on the premise of building deeper networks compared to other simple networks while concurrently determining an optimal number of layers to avoid the vanishing gradient problem. InceptionV3 often achieves higher accuracy compared to ResNet50 due to its unique architecture, which includes inception modules capable of capturing features at multiple scales simultaneously. These modules perform parallel operations with different kernel sizes, allowing the model to learn diverse representations and discriminate between classes more effectively. As the model trains, the loss accuracy metrics are displayed. This model reaches an accuracy of about 72% on the training data. Whereas the Inceptionv3 model reaches an accuracy of about 85% on the training data.

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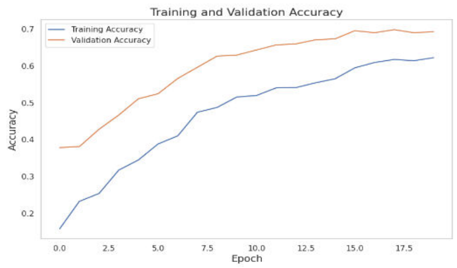
```
15/15 [==============================] - 87s 6s/step
Test Accuracy: 0.7202643171806168
Sample Predictions:
True Label: snail | Predicted Label: beetle
True Label: moth | Predicted Label: moth
True Label: catterpillar | Predicted Label: catterpillar
True Label: slug | Predicted Label: slug
True Label: moth | Predicted Label: moth
True Label: moth | Predicted Label: moth
True Label: slug | Predicted Label: slug
True Label: earthworms | Predicted Label: slug
True Label: slug | Predicted Label: slug
True Label: ants | Predicted Label: catterpillar
```

(a)

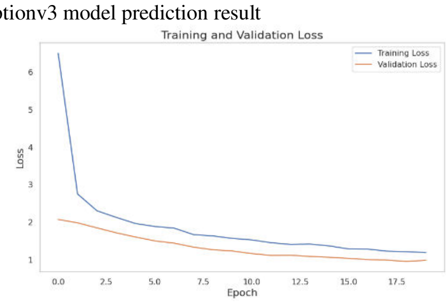
```
15/15 [==============================] - 50s 3s/step
Test Accuracy: 0.8502202643171806
Sample Predictions:
True Label: snail | Predicted Label: earthworms
True Label: moth | Predicted Label: moth
True Label: catterpillar | Predicted Label: catterpillar
True Label: slug | Predicted Label: slug
True Label: moth | Predicted Label: moth
True Label: moth | Predicted Label: moth
True Label: slug | Predicted Label: slug
True Label: earthworms | Predicted Label: earthworms
True Label: slug | Predicted Label: slug
True Label: ants | Predicted Label: catterpillar
```

(b)

Fig. 6. (a) resNet50 model prediction result (b) Inceptionv3 model prediction result



(a)



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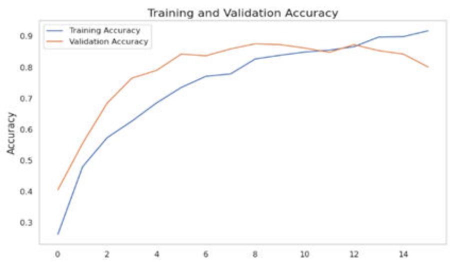
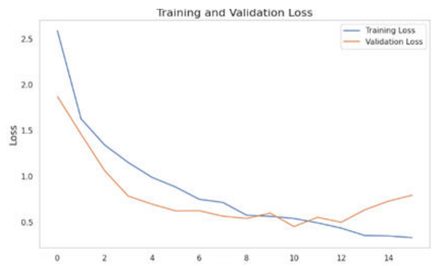


(c)



(d)

Fig. 7. (a) Training and validation Accuracy for ResNet50 model (b) Training and validation loss for ResNet50 model (c) Training and validation Accuracy for inceptionv3 model (d) Training and validation loss for inceptionv3 model

V. CONCLUSION

Crop pest classification using deep learning techniques offers a powerful solution for early and accurate pest detection, enabling farmers to take timely action and improve agricultural sustainability while reducing crop losses. User-friendly interfaces, real-time alerts, and continuous improvement are key features, ensuring practical utility and scalability. This technology holds great promise for modern agriculture.

Both ResNet50 and Inceptionv3 models for Crop Pest Classification has demonstrated notable success in accurately distinguishing between crop pest types. Despite encountering challenges such as class imbalance and potential overfitting, strategic data augmentation and fine-tuning techniques have significantly enhanced the model's generalization capabilities. The project's outcomes underscore ResNet50's efficacy in complex image classification tasks related to agriculture, paving the way for practical applications in pest management strategies and crop yield optimization. Moving forward, continued refinement and exploration of advanced techniques like transfer learning hold promise for further improving the model's accuracy and real-world applicability in agricultural sustainability efforts. Overall, this project offers a promising solution for pest identification and classification in crops, and it has the potential to be a valuable tool for farmers and researchers in the field of agriculture.

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