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Crop Pest Detection using Convolutional Neural Network

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Abstract

Pests in plants can cause significant losses in agricultural production. As a result, various technologies are used nowadays to improve agriculture's efficiency and make it more sustainable. This research highlights the contribution of machine learning algorithms and image recognition technologies for pest identification. Farmers can use the system to recognize pests and take the necessary actions to reduce them. Convolutional Neural Networks (CNN) is used in this study for image recognition tasks, including pest identification in agricultural fields. The algorithm is trained using the Agricultural Pests Dataset acquired from Kaggle. The experiment results showed that the CNN performed better than the other state-of-the-art machine learning models, with a much lower false rejection rate of 0.12% and an accuracy of 99%.

Keywords: Machine learning algorithm, Crop Growth, Pest Detection, CNN, Image processing

1. Introduction

Agriculture is the practice of cultivating the natural resources to sustain the human life and provide economic gain. It combines creativity, imagination, and skill integrated into planting crops, raising animals, etc, along with new technologies and modern production methods [6]. It is also the backbone of the economy and plays a vital role in every nation as it supports livelihood through food, provides raw materials, and builds a strong economy through trade. Present-day agriculture especially in developing nations is facing numerous issues due to soil erosion, irrigation problems, increased demand for water, inadequate drainage, pest and

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disease attacks, etc. But as the world's population continues to grow rapidly, the demand for food rises accordingly. so, it is becoming increasingly difficult for the agriculture sector to find methods and strategies that will enable them to completely meet the increasing demands for food and adapt to the changing preferences of consumers.

Though the government has taken necessary actions and has come up with solutions for the majority of the issues faced in agriculture managing the pests remains a great challenge. Pests and crop diseases cause the loss of up to 40% of the world's agricultural production annually [1]. Crop pests increase the cost of production in addition to significantly lowering crop yield and quality. Pesticide spraying is currently the primary method of controlling agricultural pests; while very successful, it has severely damaged the natural environment and are toxic to its host. For pest treatment to be effective, agricultural pests must be promptly and accurately identified. The proposed study has come up with a pest identification system using a convolutional neural network trained on the Agricultural Pests Dataset acquired from Kaggle. The system's primary objective is to reduce agricultural pest damage and increase crop yields.

2. Related Work

Jayaraj et al. [1], proposed a system for an automated irrigation that is cost-effective and a fertigation system integrated with MATLAB-based image processing for detecting nutrient deficiencies and diseases in rice, specifically targeting nitrogen and magnesium deficiencies. The prototype included a Raspberry Pi, temperature solenoid valves, and DHT11. The suggested framework allows farmers to monitor weather conditions through a mobile application. Additionally, farmers have the option to control the system according to their needs. This integrated technique offers a complete remedy for effective crop management., ensuring optimal nutrient levels and disease prevention in rice cultivation.

Najmul Mowla MD et al. [2] proposed an early-stage pest and crop disease management, and energy conservation that is essential for satisfying the rising demand with specific suggestions for the future, highlighting the incorporation of cutting-edge technology to support the advancement of smart agriculture systems in the future.

Rubina Rashid, Waqar Aslam, et al. [3] proposed a system using Convolutional Neural Networks (CNNs) to diagnose corn leaf diseases in Precision Agriculture (PA). MMF-Net, a CNN-based architecture, achieved 99.23% accuracy in experiments using RL-block and PLblocks, real-life environmental parameters, and multiple classifiers, presenting a promising solution for identifying plant leaf diseases.

Saeed Azfar, Adnan Nadeem et al. [4] proposes a drone-based system for crop health maintenance and pest identification, enhancing field surveillance. It uses a predictive algorithm and decision-making theory, aiming to modernize pest management techniques, increase crop yield, and generate revenue.

Yogesh Kumar et al. [5] proposed a novel and fast methodology to detect and enumerate the pests present in an image using a rapid feature detection algorithm. The amount of Agriculture-related pesticide use pollutes the environment, and this algorithm is implemented by advanced machine vision systems [6]. The review on the computer vision approaches for plant species identification in [7] describes the capability of computer vision in plant species identification for future researchers. The research [8] explains that the CNNs could learn useful feature extracts directly from the raw data. The authors Kasinathan and team [9] used several base classifiers such as K-nearest neighbor, Random Forest, XG Boost, etc, and evaluated the results using the majority classifier. The research results demonstrated that the employment of majority voting with ensemble classifiers showed improvement in classification accuracy. The research on crop pest identification using transfer learning [10] suggested that the use of a multilayer network model could overcome the poor identification effects in existing and afford a reliable sample dataset for recognition by applying image data enhancement. The comprehensive report on the seminal works in pest detection and classification in [11] suggests the potential of artificial intelligence algorithms to reduce pest infestations. The use of support vector machine (SVM) classifier in calculating the infected area in [12] along with the K-means for clustering the accurate location of the pests in the leaves improved the accuracy of the model in pest identification. The application of machine vision in crop management and plant protection [13] with the software prototype system enabled the farmers to identify the infected parts of specific plants automatically. The use of a random forest (RF) classifier for the identification of rapeseed species showed 96% recognition rate on the five kinds of rapeseed species a cabbage caterpillar, flea beetle, erythema,colaphellus bowringii baly, and aphid [14]. The ANN (Artificial Neural Network)-based classification and identification system presented in [15] demonstrated accurate and fast pest identification across five different plants after proper training.

Although existing research has employed advanced artificial intelligence algorithms, the work has been too narrowly focused on pest identification for specific plants or crops, The proposed system aims to develop a pest identification model that can be used on all types of crops by training on the Agricultural Pests Dataset acquired from Kaggle. The system uses convolutional neural networks for the identification of the pests and compares the results of the CNN with other state-of-the-art machine learning models trained on the same dataset.

3. Methodology

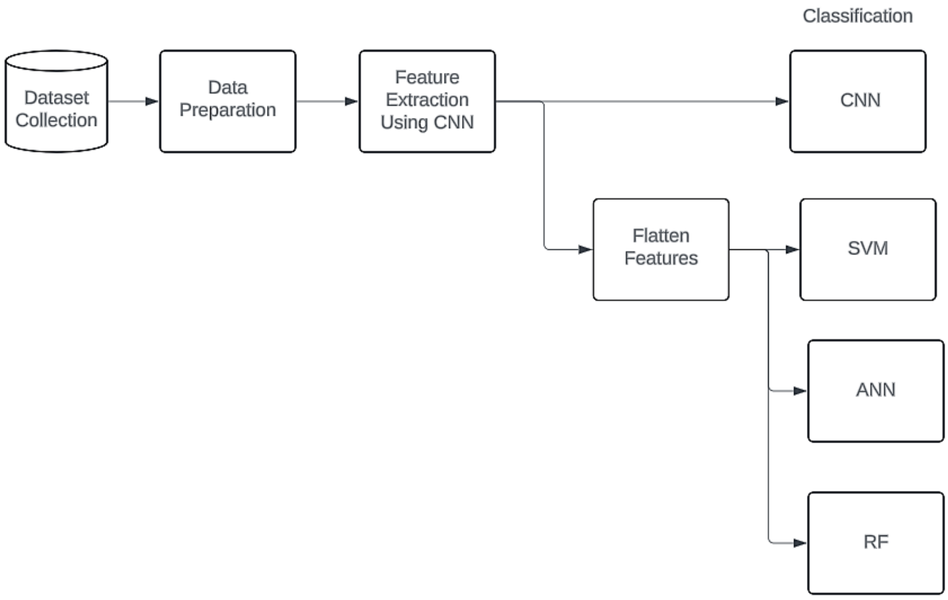

Figure 1. Block Diagram for Pest Identification

The "Agricultural Pest Image Dataset" [16] is a collection of images of 12 agricultural pests, including Slugs, Wasps, Earwigs, Ants, Weevils, Beetles, Earthworms, Grasshoppers, Caterpillars, Moths, Snails, and Bees, It was obtained from Flickr using the API and resized accordingly. The dataset was preferred as it helps researchers develop machine-learning and deep-learning models for pest identification and classification in agricultural settings. The dataset has a total of 5496 samples Figure 2 below shows the distribution of the dataset on 12 agricultural pests.

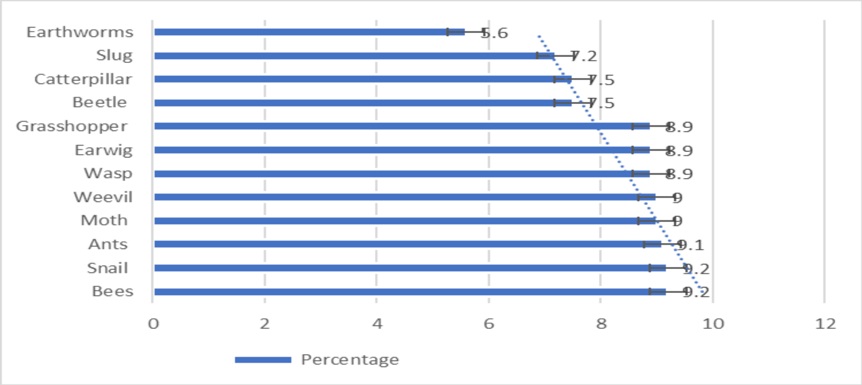

Figure 2. Dataset Distribution

To ensure uniform inputs for models, the dataset was resized to 224x224 pixels using TensorFlow, and the pixel values were normalized to a range of [0,1] using NumPy. Further, the dataset was split in a ratio of 80:20 for training and testing. The labels "pest' and 'not a pest' were labeled using the 'LabelEncoder' in Scikit-learn. The features were extracted using the pre-trained VGG16. The extracted features flattened before training for SVM, RF, and ANN. After training the models were evaluated using the testing dataset. The hyperparameters used are listed in the Table.1 below.

Table 1. Hyperparameter Used

Hyperparameter	Configuration
Batch Size	32
Learning Rate	0.001
Optimizer	Adam
Number of Epochs	50

4. Results

The research was developed in MATLAB including the essential Toolbox of MATLAB and libraries such as TensorFlow, Scikit learn, NumPy, and Pandas. The model was evaluated using metrics like accuracy, F1-score, specificity, and sensitivity, The input image and the output obtained are depicted in Figures 3 as well as 4.

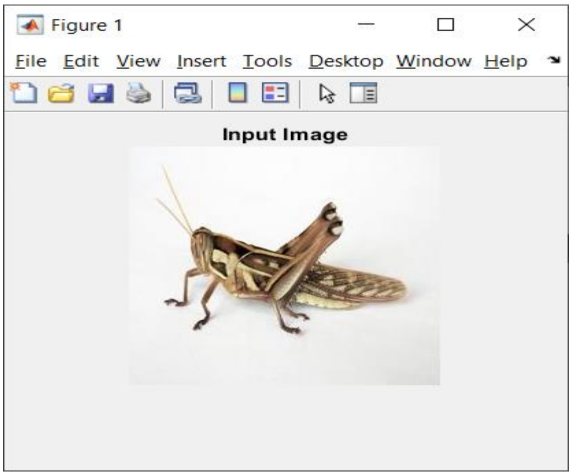

Figure 3. Input Image

```
Loading Data...
Pest Name:  Grasshopper


Parameter Analysis
Status           :  Pest
Accuracy         : 99.5726
Sensitivity      : 0.5
Specificity      : 0.5
F1-Score         : 0.46088
```

Figure 4. MATLAB Output for CNN

Table 2 below compares the performance of the RF, SVM, ANN, and CNN

Table 2. Performance Score Comparison

Performance Metrics	RF	SVM	ANN	CNN
Accuracy	0.92	0.918	0.934	0.99
Sensitivity	.46	.45	.48	.5

Specificity	.455	.446	.479	.5
F1 score	.445	.44	.45	.046

The performance scores of the models illustrated in the table above show that CNN performs better with an accuracy of 99% compared to the other machine learning model's SVM which shows 91.8% accuracy, Random Forest which shows 92% accuracy, and ANN which shows 93% accuracy.

The probability that a pest predictor will mistakenly reject an access attempt by the proper diseases is measured by the false rejection rate. A system's false rejection ratio (FRR) is typically calculated by multiplying the total number of incorrect rejections by the total number of disease forecasts.

$$FALSE\ REJECT\ RATE\ =\ FN\ /\ (TP + FN)$$

$$FN\ =\ Actual\ Scores\ exceeding\ Threshold$$

$$TP + FN\ =\ All\ Actual\ Scores$$

CNN has a lower rejection rate than the other state-of-the-art models that include, Random Forest, Support Vector Machine, and Artificial Neural Network. Table 3 below illustrates the FRR observed for the algorithms.

Table 3. False Rejection Ratio

Algorithms	**FRR**
Convolutional neural network	0.12
Artificial neural network	0.18
Support Vector Machine	0.25
Random Forest	0.40

4.1 Limitations

The research compares various cutting-edge methods for pest management in agriculture using the agricultural pest dataset. The results indicate high accuracy, demonstrating good model performance. However, due to the imbalance in the dataset, the model performs well on the majority class with high accuracy and ends up with a poor performance on the minority class. So, in the future, the research will focus on employing a balanced dataset along with resampling techniques and other deep learning algorithms that would better suit pest management.

5. Conclusion

This study presents a comparison of the various machine learning models on pest management using the agricultural pest dataset. The research compared four models, RF, SVM, ANN, and CNN. The results demonstrated that the CNN performed better with a higher accuracy of 99%. However, the models were biased with high performance on the majority class and low performance on the minority class. To overcome this future work will focus on using a balanced image dataset and resampling techniques to improve its performance while also improving the accuracy and reliability of pest detection.

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