Crop Pest Recognition Using Image Processing

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Declaration

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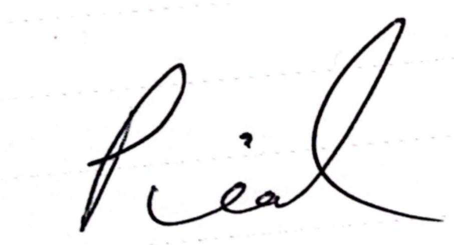

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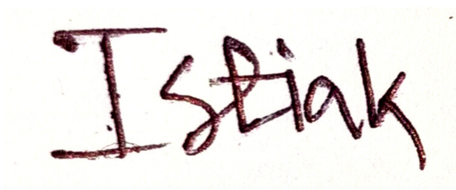

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Abstract

One of the most vital aspects of a human's existence is food [15]. Each food contains several nutrients which help in growth and development of the human body. It also prevents our body from various diseases. Most of the food we consume comes from crops, trees and plants. Pests infestation is the biggest threat for the agriculture sector.It can cause various types of diseases in crops and reduce crop production. As a result, it is necessary to detect pests early and take necessary steps to stop the infestation. For decades, humans used traditional manual techniques to detect pests. However, this technique is very time consuming, laborious and less accurate. With the development of deep learning , pest detection has become easier than the traditional techniques. Although these deep learning techniques can achieve high accuracy, the techniques can be time consuming and need high computational power. These drawbacks might cause problems in real world application. The aim of this study is to propose an approach that will be lightweight so that it consumes less time to train and needs less computational power. So, the farmer implements this model and detects pests quickly and takes necessary actions. This will increase the production of crops rapidly.

Keywords: Computational power; Human body; food; Pests; Crops; Infestation; Production; Development; Disease

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Chapter 1

Introduction

The population of the world is predicted to increase to 9.7 billion in 2050 and may peak at over 11 billion in 2100. This means that in order to feed the growing population, there has to be a sufficient supply of food while minimizing crop damage[4]. In agriculture, pests have always been a big issue for decades. Because it causes a lot of harm to the crops. As a result, the monitoring of the pest has become very important. There are numerous species in the world, making identification challenging. This presents a significant obstacle for pest control. Previously, people relied on manual classification to identify pests in crop fields, which is extremely laborious,time-consuming, expensive, and error-prone [2][3]. Early detection of insect attacks allows farmers to reduce crop damage, increase crop production, and use fewer pesticides [6].

However, with the development of modern science and technology and digital cameras, computer vision and machine learning has become a popular approach in the agriculture field [6][4]. This technique gives accurate information about the characteristics of pests and saves time and reduces intensive labor which were the biggest drawbacks of manual classification [3].

1.1 Problem Statement

Pest infestations are one of the most significant threats for the agriculture sector. Pest infestations can cause various diseases to crops and harm productivity [10]. While there are many deep learning techniques that exist for pest recognition, there is a need for more research to address the challenges in existing techniques.

There is a lack of diverse and large data to train pest recognition models.As a result, many existing models rely on small datasets, hindering their ability to identify the pest in the environment properly.

Another issue is the efficiency of the existing models.This existing model can acquire higher efficiency but it needs high computational power and memory. This can create challenges for real life applications.

1.2 Research objectives

Rice,sugarcane, cotton and jute are the important crops of Bangladesh. Every year many pests such as - Rice yellow stem borer, Dark headed stem borer, green leaf hopper, pink borer, jute white mite, spotted bollworm etc. attack the fields of the mentioned crops. As a result, the production of the crop is hampered and farmers have to face a huge loss. The main purpose of this paper is to enhance the pest recognition model in the agricultural sector to reduce pest infestation. So, crop production increases. The key points of our research are as follows :

- To collect images of harmful pests of rice,sugarcane, cotton and jute.
- To select a lightweight algorithm for real time processing of pest images.
- To implement state of the art algorithms in pest recognition.
- To compare the accuracy of state of the art algorithms with each other.

Chapter 2

Related Work

Recently, deep learning has gained a lot of attention and is used in various fields, including agriculture. There are a lot of techniques that are developed and applied in agriculture for pest recognition.

The authors [2] used images of 24 pests in crop fields. They added more images which were collected from the internet and used data augmentation techniques to improve the generalization of the proposed technique. They used 660 images for the work. An improved network architecture based on VGG-19 was implemented here. The first 16 convolutional layers of this network were used to extract features from the images. Finally, FC6 and FC7 full connection layers were used to extract feature information. The proposed model performed better than other models such as SSD and Fast RCNN. The proposed model achieved a higher accuracy against SSD and Fast RCNN. The inference time (0.083 s) of the proposed method was low against other models. Moreover, the training time of the SSD (38 hours) and Fast RCNN (70 hours) took more time than the proposed method.

Liu et al. proposed [3] a model named PestNet. This is a convolutional neural network-based pest detection architecture that was made for pest detection.They build their own dataset for the large-scale multi-class pest detection task named Multi-Class Pests Dataset 2018 (MPD2018). PestNet has achieved 75.46% mAP, which is higher than other state-of-the-art methods.

The authors [6][7] used computer vision for the insect's recognition in various crop fields. They used 3 datasets for recognition. 92.1, 96.5 and 92.3% were achieved from this three dataset using the technique by combining the features of texture, color, shape, HOG-PCA and GIST-PCA.

Paper [4] [1] proposed Atten-Mobnet uses MobileNet-V2 and an attention module for pest recognition. This model focuses on less computation, memory efficiency and better accuracy. The author used this proposed approach and state-of-the-art methods on an open dataset and a local dataset. The proposed approach achieved higher accuracy in both training accuracy (99.07%) and test accuracy (93.55%) compared to other state-of-the-art methods with less computation power and memory.

In paper [11] [17]Crop pest recognition in the field introduces a pioneering method,MCapsNet which is aiming to overcome the challenges posed by traditional methods and enhance crop protection. By incorporating a modified Capsule Network and an attention mechanism, the proposed approach demonstrates superior performance compared to traditional convolutional neural networks(CNNs) and CapsNet. The attention mechanism proves effective in capturing crucial classification features and MCapsNet exhibits success in classifying diverse insect types in field crops.By applying Modified Capsule Network (MCapsNet) with an attention mechanism for crop pest recognition in field images.MCapsNet leverages deep learning capabilities, specifically Capsule Networks to automatically extract invariant features from diverse pest images which points out mechanism enhances feature extraction by focusing on relevant contextual relationships and the LeakyReLU activation function accelerates model convergence. Through experiments on a dataset comprising images of common crop pests, MCapsNet demonstrates superior accuracy and recall compared to other CNN models. The key contributions lie in the effective integration of Capsule Networks, attention mechanisms and LeakyReLU activation for robust crop pest recognition which offers a promising solution for practical implementation in agriculture to enhance crop protection.

Likewise on other papers, Insect pest recognition addresses crucial points in agriculture and ecology in terms of variations in insect appearance. A CNN-based (ResNet) and attention-based (Vision Transformer, Swin Transformer) feature fusion network is suggested by the authors [14]. Grad-CAM is used for localization, and an attention-selection process is introduced to reconstruct attention areas by the integration of significant regions from various models. The study reflects conduct on the IP102 dataset, demonstrating superior performance compared to advanced CNN models[8]. To make Grad-CAM applicable to attention-based models, the study reshapes their output tensors. An attention-selection mechanism which is based on the Image Fusion Convolutional Neural Network (IFCNN)and it is introduced to reconstruct attention areas and synthesize features from different models. The approach is applied to the challenging IP102 dataset which demonstrates superior classification performance compared to single-attention features and other CNN-based models.

The paper [9] investigates advanced image recognition technology for the identification of crop diseases and insect pests which focuses on three-dimensional image recognition and image quality classification.The approach of this paper involves enhanced three-dimensional panoramic image synthesis. This method combines object detection, coordinate ascending and inverse mapping to render a pre-prepared three-dimensional model onto estimated positions.The synthesis is facilitated by a deep convolutional neural network (DCNN) which design to address limitations of prior techniquesAcknowledging data imbalance in crop disease and insect pest images.The author introduce a quality classification model and train the DCNN-G model using Google data analysis to incorporating strategies like data enhancement and transfer learning.YOLO-V4 is also employed for testing and demonstrating effective image classification.

The author [13] proposed a model for pests detection.They have used MobileNet as the base network. This efficient CNN approach is designed for mobile devices with a smaller footprint than conventional CNNs. They used this approach on the IP102 dataset, which contains the images of pests of 102 classes and contains more than 75,000 photos. They compared the proposed model with other deep feature extraction frameworks.The proposed model got higher accuracy (82.43%) than other frameworks.Also, the proposed model had less parameters than other models which means less model complexity than others.

N. Ullah et al. [10] introduced the DeepPestNet model for improving insect classification performance by identifying insect species in field crops at an early stage. This model will be beneficial for improved crop quality and production. This model extracts features automatically. They used augmentation and image rotation methods for the generalization of the model. They achieved a groundbreaking accuracy(100%) from other state-of-the-art models(googlenet,squeezenet).

The paper [10] provides research on organic farming, sustainable agriculture, and current methods for managing pests and diseases. It discusses current information and communication technology (ICT) strategies for resolving issues in agriculture and examines earlier research on semantic technologies and plant pest diagnosis systems. In the method of system development, data collecting, diagram, and research. It explains the development of the knowledge base population tool (KB Instantiator) and the pests and disease management ontology (CropPestO). There is also a full explanation of how the system is evaluated in a simulated environment.The system's performance in a simulated environment is evaluated. Metrics including precision, recall, accuracy, and F-measure are used to evaluate how well the system works to identify illnesses and pests based on entered symptoms.

This thesis [12] addresses the global agricultural challenge of crop pest detection by proposing an advanced deep learning model. The proposed ResNet50 PCSA model combines a parallel attention mechanism with residual blocks to enhance accuracy and real-time performance. Expensive experiments showcase its effectiveness ,achieving a remarkable accuracy of 98.17% on crop pest image and demonstrating adaptability to rice leaf diseases. ResNet-50 is chosen for feature extraction and data augmentation techniques are employed for robust training. The ResNet-50-PCSA model utilizes a bottleneck-PCSA model within ResNet-50 to refine features which a carefully curated dataset comprises 10 common crop pests and contributes to the model and its accuracy is 98.17%. Comparative experiments with SENet and CBAM highlight the efficacy of the parallel attention mechanism. The model's adaptability is tested on a public dataset of rice leaf diseases, achieving a high accuracy of 99.35%.Comparative experiments with other CNN models showcase the ResNet-50-PCSA model's versatility beyond pest recognition.

This paper[16] proposed a fast and light weight model YOLO_MRC for counting and real time recognition of Tephritidae pests. As the model is lightweight , it can be easily used in real world applications. After comparing with other improved models of YOLO , they found their model not only was highly accurate but also light and time efficient than other models.

This paper [5] explains about a smartphone application that uses artificial intelligence, namely the faster region-based convolutional neural network, integrated with cloud computing, to address the difficulties of agriculture pest identification through deep learning.This application aims to automatically classify five major crop pests. The study validates the proposed model ,achieving an impressive recognition accuracy of 99.0% for all the tests.The datasets comprises 500 images from the public IP102 dataset which divided into 80-20% from training and testing.The application is developed using python,Apache Cordova framework for cross-platform compatibility,Flask web for handling HtTTP requests,MySQL for database management and Python Anywhere for cloud hosting.

Unlike other papers, this paper [15] explains crop pest and disease detection in the agriculture sector,specially sourced from local farms in Ghana. The dataset includes both raw and augmented images with a total of 22 classes covering Cashew , Cassava,Maize and Tomato crops.this paper outlines the experimental design,emphasizing the image data acquisition process and it is annotated by expert plant virologists and the subsequent verification of labels.The dataset images vary in size, providing diverse conditions for training computer vision algorithm.

Chapter 3

WorkPlan

3.1 Proposed work plan

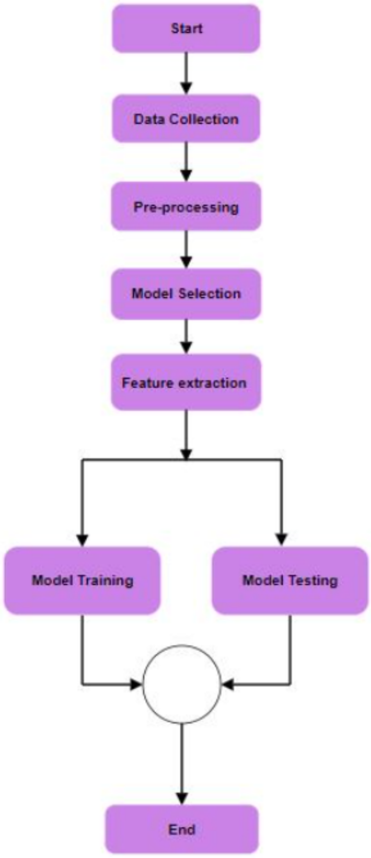

Figure 3.1: Workflow

3.1.1 Data collection and preprocessing

We will collect a dataset of pictures of pests from the internet, farmers, insect experts and click photos by ourselves. Preprocessing the pictures to remove useless information and noise.

3.1.2 Model Selection

We will select the best model which will be highly capable for pest identification. E.g. CNN,VGG16,Resnet50 etc. Feature extraction: Extract relevant features from the image. The features can be color, texture, shape etc.

3.1.3 Model Training

We will split the dataset into a training and testing set. We will train the model with a train set and test the model with a testing set. We are planning to use CNN model for pest recognition. Because CNNs are very beneficial to reduce the number of parameters without losing the quality of Data(image). We know the image has a large number of features (each pixel is counted as features). The Convolutional layer will extract relevant features from the image. The Pooling layer is there to reduce the number of parameters which reduces the computation and speeds up the process of learning and reduces the chance of overfitting. In the fully connected layer those images got processed and detected thoroughly and in the output we got the result that we needed and then we could detect the pest and its kind. In the fully connected layer those images got processed and detected thoroughly and in the output we got the result that we needed and then we could detect the pest and its kind.

Chapter 4

Conclusion

According to FAO, every year pests cause a lot of damage to crops [13]. Therefore, smart agriculture presents the best option to farmers to reduce their losses. In our paper we are going to recognize the crop pest which will be going to detect the pest and inform it to use as an output.In this case, we are going to use 3 GB image data for research and we will use CNN Algorithm to train data and get our required output.The main prospect of this research work is adding new agricultural pest classification model with recommended pesticides for different crops.

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