Pest Control with CNN Architectures

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***Abstract*—This paper delves into diverse methodologies for pest control using machine learning architectures. The states of Punjab and Bihar are among the most severely affected by pests in India, resulting in annual crop losses of nearly INR 2 lakh crore as of 2024 [1]. Research indicates that this issue is primarily attributed to a lack of farmer awareness rather than inadequate facilities. This paper explores various approaches proposed by researchers to identify the most optimal and accurate Convolutional Neural Network (CNN) models for addressing this challenge. In addition to theoretical discussions, practical applications of these models are also explored.**

Keywords—Machine Learning Models; Convolutional Neural Network (CNN); Model Training; Disease Detection; Bacterial Blight; Rice Blast.

I. Introduction

Recent analysis from a reputable news outlet has highlighted a 15% decrease in the share of the agriculture sector in India's GDP for the year 2023 **[2]**. This decline could be attributed to several factors, including advancements in the service and manufacturing sectors. However, another perspective suggests that government efforts to bolster the primary sector may not have yielded the expected results, contributing to this downward trend. It is possible that the service sector could play a role in mitigating these challenges.

As someone with a background in agriculture, the author acknowledges that many working-class families lack awareness regarding the potential risks associated with crop management. Nevertheless, the increasing access to the internet and smartphones in recent years has provided Indian farmers with a valuable advantage compared to their counterparts in other countries facing similar issues. Leveraging these technological advancements more effectively could significantly benefit the agricultural sector.

This study aims to examine various diseases affecting crops and identify the best approaches for their detection. Additionally, it will explore different machine learning techniques proposed by experts in the field. Ultimately, this paper proposes a comprehensive solution encapsulated within an infrastructure comprising a model builder server and an Android mobile application client. This solution is designed to address crop-related challenges universally, benefiting farmers and stakeholders alike.

Additionaly, This study also appends a proposal from Paddy Crop Disease Detection using Machine Learning [18] of integrating all these proposed models inside an android app.

Infrastructure is not part of the study but it will get covered optionally.

II. Crop diseases

There are quite a lot of crops and diseases throughout the world but in this study, we are considering that affects mostly the Indian Subcontinent agriculture sector like Rice, Paddy, Apple, Maze, etc.

A. *Scab*

Fig 1: Apple Scab

Scab is one of the most common disease among fruits. It iks caused by ascomycete fungus Venturia inaequalis. Apple scab can be observed on leaves, petioles, sepals, fruit and pedicels and, less frequently, on young shoots and bud scales **[3].** The most affected crops by this disease are Apple and Rose.

B. *Black Rot*

Fig 2: Apple Black Rot

Black rot is a fungal disease caused by an ascomycetous fungus, Guignardia bidwellii, that attacks grape vines and several other citrus during hot and humid weather **[4]**. The most affected crops from black rot are apple, corn and grape.

C. *Rust*

Fig 3: Apple common Rust

Rust is a bacterial disease caused by Pucciniaceae.It affects a lot of western crops like apple and corn. It creates yellowish 0.3 radian long spots on the leaves and can be detected easily **[5]**.

*D. **Gray Leaf Spot***

Fig 4: Corn Gray Leaf Spot

Gray leaf spot (GLS) is a foliar fungal disease that affects grasses. Gray leaf spot is typically the most serious foliar disease of corn in the Indian subcontinent corn belt **(6)**. It forms yellowish cluster of dots on the leaves.

E. Black Measle

Fig 5: Grapes Black Measle (Esca)

One of the common fungal diseases is Esca (Black Measles) which is found in the Grape Plants and can be easily identified as brown streaking lesions on any part of the leaf. The affected leaves can dry off completely and fall off from the plant prematurely which eventually results in death of the plant **(7)**.

F. Early and Blight

Fig 6: Tomato Early Blight

Early blight and late blight, two serious diseases of potato, are widely distributed. Both are found everywhere potatoes are grown. The terms “early” and “late” refer to the relative time of their appearance in the field, although both diseases can occur at the same time **(8)**.

I. Bacterial Spot

Fig 7: Tomato Bacterial Spot

Bacterial spot is the most destructive leaf disease of capsicum. Black rot of brassica plants often follows infection by bacterial spot. It’s caused by bacterium Xanthomonas campestris. **(9)**

C. Spider Mite

Fig 8: Tomato Spider Smite

Spider mites are pests those generally live on the undersides of leaves of plants, where they may spin protective silk webs, and can cause damage by puncturing the plant cells to feed **[10]**. This is one of the most affecting issue among horticulture sector of Indian Subcontinent.

D. Yellow Curl Virus

Fig 9: Tomato Yellow Curl Virus

As the name suggests, prior symptoms of this disease is that leaves bend circularly. It also creates light greening towards edges of the leaf. It is carried by Silverleaf whitefly [**11**].

E. Mosaic Virus

Fig 10: Tomato Mosaic Virus

It is caused by a virus that infect plant foliage to have a mottled appearance. Such viruses come from a variety of unrelated lineages and consequently there is no taxon that unites all mosaic viruses **[12]**.

III. LITERATURE SURVEY

Shruthi U, Nagaveni V, and Raghavendra B K conducted a study examining various machine learning classification techniques for plant disease detection. Their work included methods such as Artificial Neural Network (ANN), K-nearest neighbor, Convolutional Neural Network (CNN), fuzzy classifier, and Support Vector Machine (SVM). Among these, CNN demonstrated superior accuracy in detecting multiple diseases across different crops [13].

In a separate study, V.Vanitha proposed an automated disease detection system for rice using deep learning techniques. The model successfully identified three different paddy diseases and healthy leaf images, achieving an impressive accuracy of 99.53% after training on three CNN architectures [14].

Likewise, Shamim Mahbub, Md. Abu Nasim, Md. Jahid Hasan, and Md. Shahin Alom developed a system integrating Support Vector Machine with Deep Convolutional Neural Network to identify and classify rice diseases. This AI model accurately distinguished nine types of rice diseases with an accuracy of 97.5%, supporting farmers in disease management and production improvement [15].

Additionally, Anuradha Badge explored crop disease detection using Machine Learning in Indian Agriculture, focusing on the use of Canny's edge detection algorithm, particularly for wheat crops. Their research showed promise in efficiently identifying crop diseases from images [16].

IV. PROPOSED ARCHITECTURES

In this section we will go mainly through an architecture proposed by Microsoft along with An experimental CNN proposed by the author.

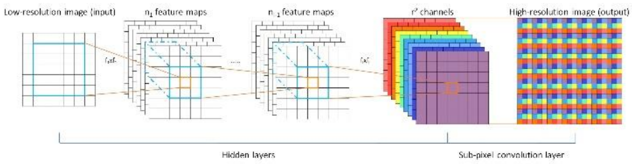

Fig 11: Infrastructure of a CNN

This infrastructure is using a dataset from Kaggle for crop diseases “new-plant-diseases-dataset” [17], that contains 70000 images along with 30000 validation images.
Using this dataset, we are accessing 30+ different diseases that affects fruit crops.

A. ResNet50

ResNet50 is a 50 layer long sequential model proposed by Microsoft. It includes 48 CNNs along with a average pool layer and a Max Pool layer.

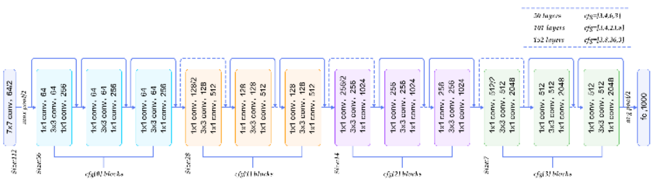

Fig 12: ResNet 50 Architecture

This model map image using overlapping cluster with the convulation algorithm along with ReLU activation function for threshold costraint.

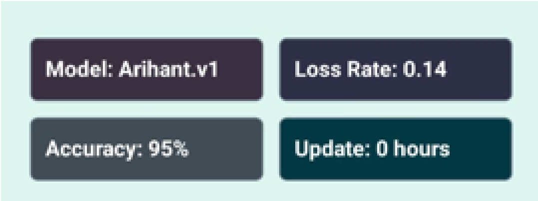

Fig 13: Snapshot of ResNet50 model details from Client App

ResNet 50 performed too well on with this dataset, achieveing 95.3% accuracy. Now, this model can be used as our base model, but, beneath the accuracy, it also costed us 1.3 hour of training time. Which is quite costly for being frequent on the host server where our model would be building to later, get integrated with the client for use of the clients i.e- farmers. So, for R&D purpose, this model may go pretty well but not for production. Hence, There comes another optimized proposal.

B. Arihant (A custom CNN)

Considering the cost consumption of the previous model, here is a proposal for a 18 layered CNN that includes 9 Convulational layer with 2D MaxPooling in between.

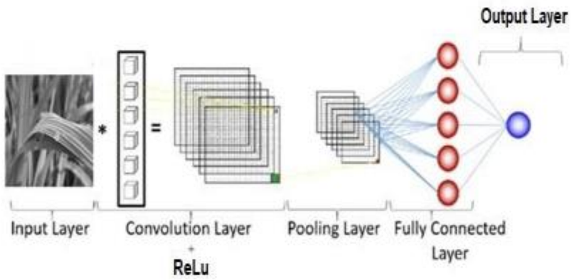

Fig 14: Arihant Model Architecture

This model performed well too, ofcourse with less accuracy in compare with ResNet50 model. But, It’s more optimal approach as well as it has training on same dataset with decrease of 50% training time, getting 89% accuracy, which is considerable as for now.

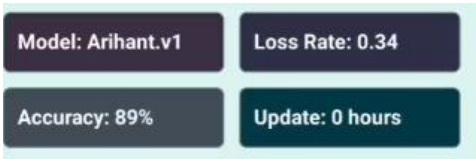

Fig 15 : Snapshot of Arihant model details from Client App

Now, this model can be considered prodcution worthy for the user application. Next task is integrating it with the client application.

Model ID	Models Performance		
	Model Names	***Accuracy***	***Loss Rate***
T0	Arihant v1 (Custom)	95.3%	0.14
T1	Arihant v1 (ResNet)	89.1%	0.34

V. ECOSYSTEM INTEGRATION [19] (Optional)

In proposed eco system, There will be a server that will consist a continous training module for model training and an API server to receive inputs for the model and later to deliver result to the client for the given input.

This server will also include a database to provide additional details for the disease class and the cure for the disease.

Now, Last but not the least, there would be a multiplatform client for the model through a the application.

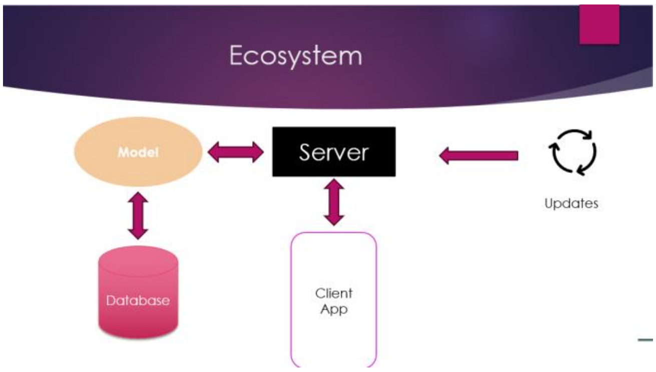

Fig 16 : Ecosystem Architecture

For server's learning module, application is integrated with both the models that can be deployed optionally. Model is trained and stored for the later use. The model gets updated authomatically every 24 hours on interaction with the API.

This gives realtime processed data to the client with any furtehr updates.

Now, as the learning module is autonomous and does not require any human intervention, There has to be a module to update dataset automatically. Here comes the public contribution part. Now when someone can use the app, and if the data is inaccurate, they can provide feedback to guide the model. The provided feedback would be appended inside the current dataset and next time when the model will retrain itself, it will automatically include the new feedback.

Then, there is a request handler module serving as a middleware between the client and the model to deliver messages between them. This request handler is written with Flask in Python.

Now, The last, The client app, is an multiplatform mobile app for client use cases made with React Native.

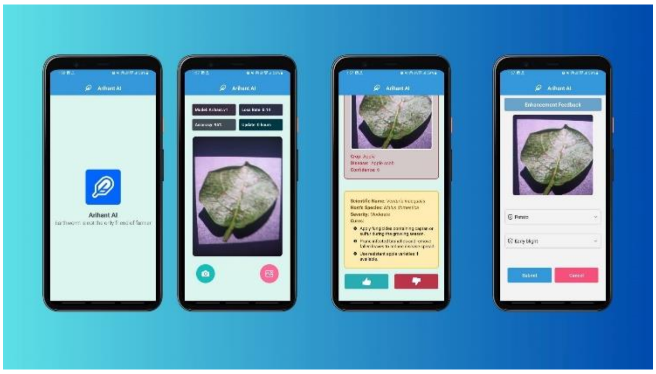

Fig 17 : The Proposed Solution Preview

- The client has an optional facility of capturing picture from camera or select one from gallery
- Client then sends captured image to the server
- Later to Receive the predicted output according to the trained model.
- There is an additional model info on the top of every pages that includes Model ID, Accuracy, Loss rate and last update duration.
- Application also suggest the cure based on the predicted disease.
- In case, the model delievered wrong output, there is a feedback page to provide the necessary details, that would be included in the next update of the model.

VI. CONCLUSION

Through out the study case, we went through different disease and pests harming rural agricultral infrastructure. Later, we glanced at previous works by different researchers and their proposed works.
Furthermore, We took inspiration from the proposals and proposed our solution for the sake of accuracy and resource consumption using 100,000 pictures to train and validate. Additonally, We implemented a solution, that inmerged machine learning and mobile application programming to provide the blended solution that can detect 30+ crop diseases and suggest cure for it.

Overall, this could be used as a solution by farmers who lack awareness in the field.

VII. ACKNOWLEDGEMENT

- The proposal for using ResNet50 as base model was inspired by an attempt from Atharva Ingle 3 years ago through a kaggle notebook with 99.2% accuracy [20]
- The idea of integarting the machine learning model inside an android app was inspired from a journal "Paddy Crop Disease Detection using Machine Learning" [18]
- The solution was completely implemented and deployed in CIC Tech-a-thon, 2023, a hackathon organised by Lovely Professional University.

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