Fertilizers Recommendation System for Disease Prediction

1. INTRODUCTION

Agriculture is the most important sector in today's life. Most plants are affected by a wide variety of bacterial and fungal diseases. Diseases on plants placed a major constraint on the production and a major threat to food security. Hence, early and accurate identification of plant diseases is essential to ensure high quantity and best quality. In recent years, the number of diseases on plants and the degree of harm caused has increased due to the variation in pathogen varieties, changes in cultivation methods, and inadequate plant protection techniques.

Increasing consumer demand for greater food quality and sustainability has sparked a transformation in agriculture as growers strive to meet these heightened expectations while improving output. While various solutions for using data to improve profitability and yield larger harvests have been proposed, certain barriers have led growers to resist digital transformation and instead stick with traditional techniques. For example, many of these approaches place too much dependence on the grower taking manual steps to make the solution function or rely on remote internet accessibility to gather the necessary information. Consequently, tremendous amounts of agricultural data are generated, but never used.

An automated system is introduced to identify different diseases on plants by checking the symptoms shown on the leaves of the plant. Deep learning techniques are used to identify the diseases and suggest the precautions that can be taken for those diseases.

1.1 Overview

Project work involves pre-processing of digital images and extracting their feature planes, followed by classification based on the type of leaf disease. Also, the use of different pre-processing techniques focuses our analysis on the leaf disease, as this element contains all of the information regarding the leaf illness. Color feature information has also been added as an image to determine if it may aid the classification process in correctly detecting disease utilizing Convolutional Neural Network (CNN) transfer learning and more accurate feature reduction.

1.2 Purpose

Early detection of diseases in grape leaves is required as per gaps identified by the literature covered. Farmers may produce low-profit yields despite their hard work if these biotic stresses are not identified promptly. Several image processing algorithms have been developed to detect lesions, alerting farmers and allowing for early diagnosis.

The result is a suite of customized low-cost solutions that help stakeholders across roles make faster, more informed agricultural decisions to support:

• Increased profitability by yielding more bushels or tons per hectare across common crops.
• Improved sustainability with deeper insights into factors such as crop input optimization, energy consumption, land and water use, soil conservation, soil carbon content, greenhouse gas emissions.
• Higher quality such as increased protein content in barley or sugar content in beets.

2. LITERATURE SURVEY

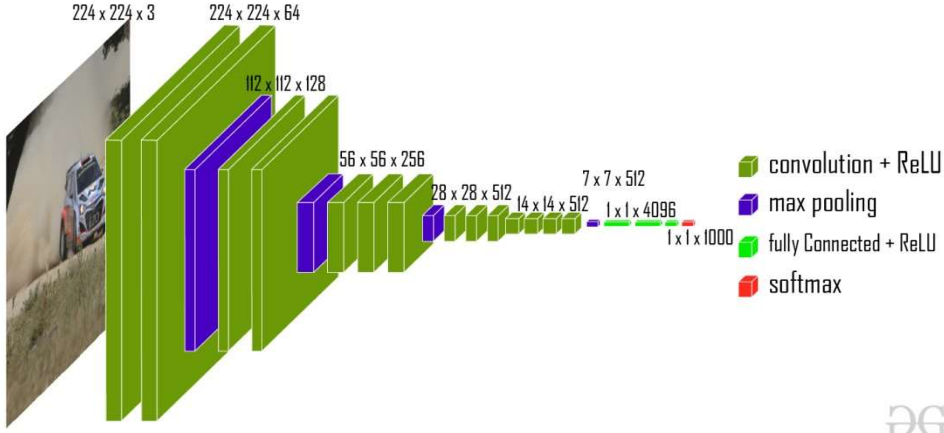
2.1 Existing problem

An automatic model for detecting and classifying an unhealthy area of plants is discussed by Atila et al. The accuracy of the Efficient Net CNN-based state-of-the-art model was compared with different models in order to detect various diseases of a plant leaf. The accuracy achieved with this model is 96.18% as compared to different architectures. The united Convolutional Neural Network for the identification of disease in grape plant is mentioned by Ji et al. United Model's representational potential is bolstered by high-level feature fusion, allowing it to outperform the competition in the grape leaf diseases identification mission. The F-CNN and S-CNN model with full image and segmented images to classify and detect disease in plant leaves. When the trained CNN model is applied to a segmented image instead of to a complete image, the accuracy achieved is more than the full image. The 23-layered deep CNN model is compared it with all other different and machine learning models in terms of accuracy is discussed by Azimi et al. As compared with other features, the nitrogen stress features are easily classified using the proposed CNN model. Disease caused various loos both in the field of crop production and economy growth. Gadekallu et al. introduce a hybrid PCA technique with optimized algorithm named whale optimization for feature extraction and evaluated the data in terms of accuracy and superiority. Rust and Cercospora are the primary two diseases that affect the quality and productivity of the coffee plant. The texture features for extraction using k-means and thresholding segmentation algorithm is done by Sinha et al. , and then the relation between infected part and healthy part is identified using texture analysis on the olive plant. Sorte et al. suggested texture-based pattern recognition algorithm to detect leaf lesions on the coffee plant. The attributes (local binary attribute and statistical attribute) are calculated and compared with the CNN identification rate. The performance of deep learning models in terms of "learning rate", "batch size", "activation function type" and "regularization rate" using tensorflow application is calculated by Kallam et al. With these terms the author finds the number of hidden layers with test and training loss. The classification of Okra's plant disease, depending on pod length, using different techniques. Different models are used to recognize wormholes, insects, and pests with AlexNet, GoogleNet, and ResNet50. The accuracy achieved using ResNet50 is better than other techniques. A CNN model with eight hidden layers that perform well than machine learning techniques is well explained by Franczyk et al.

2.2 Proposed solution:

For the detection and classification of grape leaf disease using "Deep Transfer Learning" a proposed model approach is consisting of four different steps:—data pre-processing (Resizing and normalizing the dataset), training of deep CNN model with transfer learning, feature reduction and classification technique for classify the disease data.

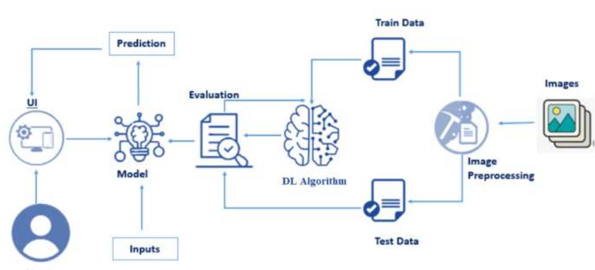
CNN is **a type of deep learning model for processing data that has a grid pattern, such as images**, which is inspired by the organization of animal visual cortex and designed to automatically and adaptively learn spatial hierarchies of features, from low- to high-level patterns



3. THEORITICAL ANALYSIS

3.1 Block diagram

The Architecture of the model



3.2 Hardware / Software designing

Anaconda Navigator is a free and open-source distribution of the Python and R programming languages for data science and machine learning-related applications.

It can be installed on Windows, Linux, and macOS.Conda is an open-source, cross-platform, package management system. Anaconda comes with so very nice tools like JupyterLab, Jupyter Notebook, QtConsole, Spyder, Glueviz, Orange, Rstudio, Visual Studio Code.

For this project, I have used Jupyter notebook and Spyder

To build Deep learning models the following Python packages are required:

- numpy
- pandas package
- tensorflow package
- keras package
- Flask package

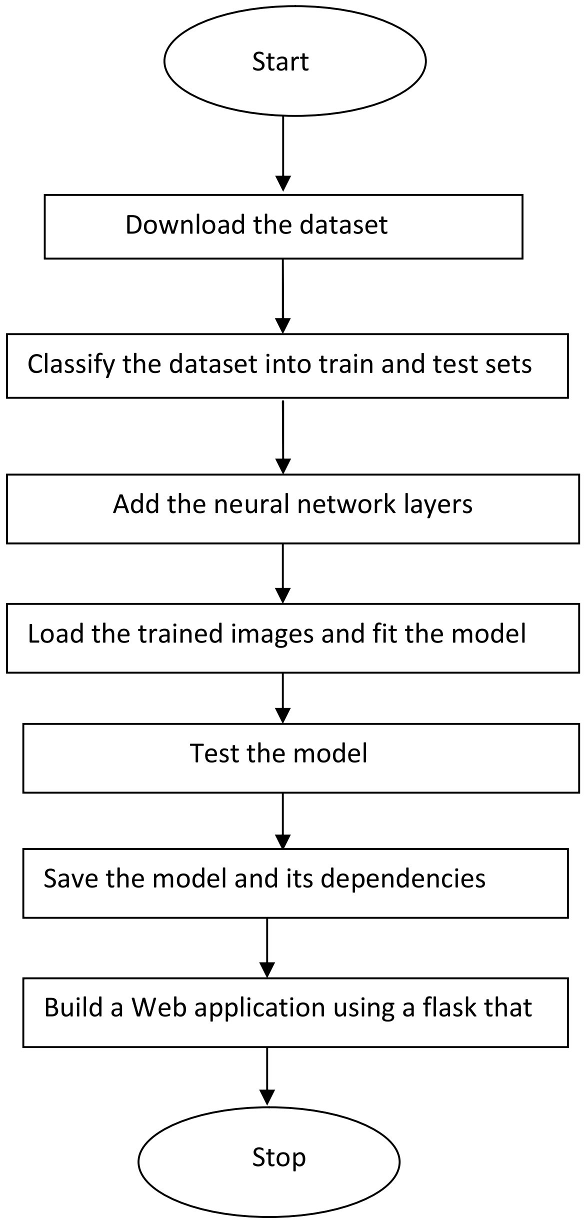
4. FLOWCHART

Project Flow

A web Application is built where the Farmers interact with the portal build

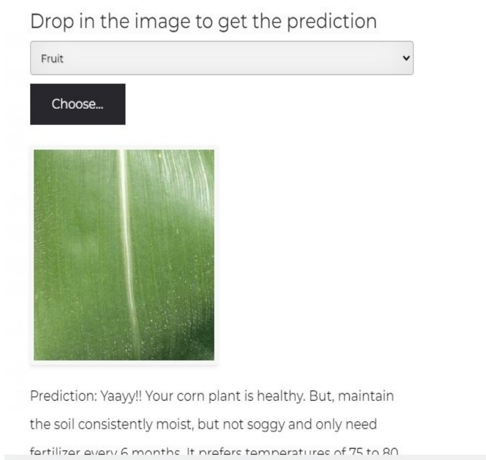
- Interacts with the user interface to upload images of diseased leaf
- Model built analyzes the Disease and suggests the farmer with fertilizers are to be used

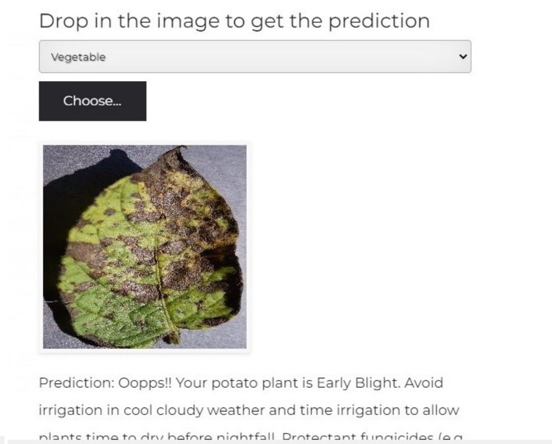
The tasks flow is as follows:



5. RESULT

The proposed method is implemented using Python The code existing CNN method was written in Python was downloaded from the web [https://github.com/cs-chan/Deep-Plant]. Output images are shown below:





6. ADVANTAGES & DISADVANTAGES

The main advantage of CNN compared to its predecessors is that it automatically detects the important features without any human supervision.

Below mentioned are the other advantages and disadvantages of applying CNN model.

Advantages:

- Very High accuracy in image recognition problems.
- Automatically detects the important features without any human supervision.
- Weight sharing.

Disadvantages:

- CNN do not encode the position and orientation of object.
- It lacks the ability to be spatially invariant to the input data.
- Lots of training data is required.

7. APPLICATIONS

It can be widely used by the agricultural industry and farming society.

8. CONCLUSION

The proposed method uses CNN to classify tree leaves, identify the disease and suggest the fertilizer. The proposed method gives accuracy for fruit dataset 96% and for veg-dataset an accuracy of 93%.

9. FUTURE SCOPE

Further research is implementing the proposed algorithm with the existing public datasets. Also, various segmentation algorithms can be implemented to improve accuracy. The proposed algorithm can be modified further to identify the disease that affects the various plant organs such as stems and fruits.

10. BIBILOGRAPHY

1. Maddikunta P.K.R., Hakak S., Alazab M., Bhattacharya S., Gadekallu T.R., Khan W.Z., Pham Q.-V. Unmanned Aerial Vehicles in Smart Agriculture: Applications, Requirements, and Challenges. *IEEE Sens. J.* 2021;21:17608–17619. doi: 10.1109/JSEN.2021.3049471. [CrossRef] [Google Scholar]
2. Hang J., Zhang D., Chen P., Zhang J., Wang B. Classification of Plant Leaf Diseases Based on Improved Convolutional Neural Network. *Sensors.* 2019;**19**:4161. doi: 10.3390/s19194161. [PMC free article] [PubMed] [CrossRef] [Google Scholar]

3. Nagaraju M., Chawla P., Upadhyay S., Tiwari R. Convolution network model based leaf disease detection using augmentation techniques. *Expert Syst.* 2021:e12885. doi: 10.1111/exsy.12885. [CrossRef] [Google Scholar]

4. Nagaraju M., Chawla P., Upadhyay S., Tiwari R. Convolution network model based leaf disease detection using augmentation techniques. *Expert Syst.* 2021:e12885. doi: 10.1111/exsy.12885. [CrossRef] [Google Scholar]

5. Salih T.A., Ali A.J., Ahmed M.N. Deep Learning Convolution Neural Network to Detect and Classify Tomato Plant Leaf Diseases. *OALib.* 2020;**7**:1–12. doi: 10.4236/oalib.1106296. [CrossRef] [Google Scholar]

6. Wspanialy P., Moussa M. A detection and severity estimation system for generic diseases of tomato greenhouse plants. *Comput. Electron. Agric.* 2020;**178**:105701. doi: 10.1016/j.compag.2020.105701. [CrossRef] [Google Scholar]

7. Almadhor A., Rauf H., Lali M., Damaševičius R., Alouffi B., Alharbi A. AI-Driven Framework for Recognition of Guava Plant Diseases through Machine Learning from DSLR Camera Sensor Based High Resolution Imagery. *Sensors.* 2021;**21**:3830. doi: 10.3390/s21113830. [PMC free article] [PubMed] [CrossRef] [Google Scholar]

8. Kundu N., Rani G., Dhaka V., Gupta K., Nayak S., Verma S., Ijaz M., Woźniak M. IoT and Interpretable Machine Learning Based Framework for Disease Prediction in Pearl Millet. *Sensors.* 2021;**21**:5386. doi: 10.3390/s21165386. [PMC free article] [PubMed] [CrossRef] [Google Scholar]