Disease detection for potato, tomato and pepper plants using ML algorithms

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Data Analytics

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Disease detection for potato, tomato and pepper plants using ML algorithms

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Abstract

In particular, this detailed work reviews the use of machine learning schemes for the detection of diseases of critical crops including potatoes, tomatoes, and peppers. This highly critical analysis presents the future potential of machine learning to transform conventional approaches to detecting agricultural diseases. This study points out the importance of heterogeneous and wide sets of data in successful model fitting; moreover, it discusses the difficulties of incorporating such technologies during real cultivation. These include education of farmers, infrastructure development, as well as adaptation to different weather conditions. Food security and the adoption of sustainable approaches to agricultural production is another important area reflected in this study. The paper provides perspectives on how these technologies can be integrated into current agricultural settings and stresses the need for integration between technologists, agronomists, and farmers. The study notably showcases the excellence of models such as ResNet and AlexNet, including specifically EfficientNet achieving an accuracy rating of 97.35.

1 Introduction

According to agricultural science, maintaining sustainable crop output and food security depends critically on the early identification and precise diagnosis of plant diseases. The need for effective and dependable crop health protection techniques has never been higher due to the growing worldwide population. This thesis investigates the cutting-edge topic of plant disease detection, paying special attention to techniques that make use of leaf samples. Researchers have created methods that can quickly and accurately diagnose a wide range of plant diseases by utilizing advancements in machine learning, data analysis, and imaging technologies.

1.1 Motivation and Project Background

This study's main goal is to use deep learning networks' ability to diagnose plant illnesses in pepper, tomato, and potato crops. This endeavor was sparked by the difficulties with the labor-intensive, prone to mistake, and ineffective manual method of plant disease identification that is currently in use. Although manual disease scouting necessitates a thorough understanding of pest life cycles, environmental factors, and disease signs, even seasoned farmers and agronomists are prone to making incorrect diagnoses. These errors may result in the improper application of pesticides, which might have negative impacts on the environment and human health as well as lower crop quality and the emergence of resistant diseases. To circumvent these issues, there is a pressing need to implement an accurate, automated disease detection and management system for tomato, potato, and pepper plants. Early and precise detection of plant diseases is crucial for ensuring high-quality produce and optimal crop yields. In recent years, the application of machine learning and deep learning techniques for plant disease identification has gained significant traction. Techniques such as k-nearest neighbors (KNNs), random forests, support vector machines (SVMs), and deep learning methods like artificial neural networks (ANNs) and convolutional neural networks (CNNs) have been explored extensively in agricultural contexts. Though helpful in some situations, typical machine learning classifiers lack the capacity to gradually extract high-level characteristics from complicated datasets—a skill that is essential for accurately identifying diseases in a variety of agricultural settings. Because of this restriction, deep learning techniques must be used, as they provide a more complex and nuanced analysis of plant health data. In order to create a reliable system for identifying illnesses in tomato, potato, and pepper plants, we want to use CNNs, which are sophisticated deep-learning models. As part of our strategy, we will train these models using a varied dataset that includes pictures of different illness stages in a range of environmental settings. With this approach, the shortcomings of earlier research—which depended on smaller, less diverse datasets or was hampered by problems like overfitting and negative transfer learning— are to be addressed. The suggested approach would greatly improve food security and sustainable farming practices in addition to improving disease detection accuracy by tackling these issues.

1.2 Research Question and Objective

Plant disease detection is essential to agriculture since it helps identify diseases in crops early on, improving food quality, cutting production costs, and assisting in choices to increase crop yields. Through the development of a dependable technique, this research has improved the speed and precision of diagnosis and prevention for a variety of plant diseases. Innovations of this kind are essential to global food security and sustainable farming. RQ: How efficiently can transfer learning approaches aid in precisely detecting diverse diseases in leaves of tomato, potato, and pepper plants, consequently minimizing human errors in manual disease identification?

2 Related Work

It is very crucial for scientists to identify the diseases of tomatoes, potatoes, and peppers. People who use different ways of classifying plant diseases get inspired by these efforts. In this section, the notable development in this field is reviewed with a focus on recent innovations. The study ends by stating that all these procedures work out well in disease detection among tomato, potato, and pear plants.

2.1 Progress in the Identification of Foliar Diseases: Assessing Deep Learning and Machine Learning Methodologies.

(Cai; 2023) provide a better YOLOv5 model using an upgraded Focal loss function, SimAM attention mechanism, and good multi-scale characteristic combination towards plant disease detection. When the Plant Doc dataset is tested on the model, it outperforms the original Yolov5 by being more precise and accurate in challenging cases. It will significantly contribute towards the control of diseases as well as prompt management of plant health on real time basis.

(Sharma; 2023) paper presents a machine learning approach developed to automatically detect and classify diseases of plant leaves in order to overcome shortcomings associated with conventional manned agriculture. Procedure involves image acquisition, treatment, feature selection, and disease identification. This is because, the AI and machine learning provide a more accurate and effective way of identifying insects that affect yields thus pests control. Technical development becomes more than necessary in improving agricultural practices.

There is a new approach for cotton plant disease detection proposed in the work of (Puri; 2023): Hybrid Approach of Sensors and Deep learning. It is an economical approach which blends in the sensor technology along with deep learning models to resolve such economical challenges that occur owing to these illnesses. It will involve sensor based remote sensing approach for soil analysis and applying deep learning technology in the analysis. The most effective one among many machine learning models tested was VGG16. This highlights the importance of early disease detection and areas where improvement is needed in the technology.

This study by (Mishra; 2023)shows how CNNs can be used to diagnose plant diseases. The best CNN model using 87,848 images from 25 different species attained 99.68 percentage accuracy. This demonstrates that CNNs have the capacity for use as robust diagnostic instruments for diseases in plants even without the processing of the preceding data.

They present an innovative way for precise diagnosis of plant diseases through combination of image processing and machine learning (Khirade; n.d.). For feature extraction, Support Vector Machine (SVM) is used while CNN is employed for classification resulting into a more improved accuracy for Plant Disease Dataset. Healthy or diseased plant images are categorized using this method then a suitable fertilizer is recommended depending with their disease. This research shows how Machine Learning Image Processing can enhance efficiency in detecting plant diseases.

Paper entitled, Pest Detection Utilizing Machine Learning, assesses machine learning techniques for their suitability to agricultural pest detection by (Sharma; 2023). The ability of these approaches to accurately identify pests is illustrated by the 91.8% testing dataset accuracy obtained in this study. In addition, it stresses greatly on improved system performance due to the decrease in the parameter estimation and training time. Additionally, the paper shows that such type of method can be used as an instrument to make empirical description and classification of plant leaf diseases applied in agriculture.

Plant disease diagnosis using a Random Forest algorithm employed in a machine learning study conducted by (Maniyath; n.d.) et al. A cost-efficient and effective approach suitable for different agri areas is proved by this method which generates datasets, feature extracts, and classifies plants' diseases successfully.

In this work (Mishra; n.d.) used CNNs in order to detect plant diseases via image recognition (the paper). This has an impressive precision of 0.9859 with respect to a data set composed of 54,306 pictures demonstrating that deep learning can be used for disease diagnosis of many plants. This article illustrates the use of deep learning as an innovative approach that can be used to improve global food security.

In this paper (Jouini and Sethom; 2023). a novel approach to early detection of wheat with the aid of convolutional neural networks. A study that examined several convolutional neural network (CNN) architectures on a wheat leaf image dataset consisting of healthy and diseased pixels. MobileNetV2 is proven feasible in low resource situations with over 94 testing accuracy. Also, this paper discusses the use of internet of things (IoT) with computer vision and smart sensors for effective disease control in wheat production. The evaluation of the Botani Scan system is made against some important features like precision, quickness, and time effectiveness, with reference being cited in the paper titled 'BOTANI SCAN – Revolutionising the Plant Disease Detection via Deep Learning' by (Utikar; n.d.). These factors underscore the improved system in identifying different plant diseases on a range of crops than the conventional ones. This mainly showcases how scalable and proactive Botani Scan can be considered as solution to managing diseases in agriculture making use of advanced deep learning techniques and Convolutional Neural Networks (CNN).

2.2 Progress in the Identification of Foliar Diseases: Transfer Learning Algorithms.

The treatment of the apple leave ailments through state-of-the-art multilayered NN system in response to InceptionNet by (Das; 2023). achieving an accuracy of 92.56 on the "Plant Pathology 2021: They made a great step forwards in terms of identifying diseases according to "FGVC8" data set. Furthermore, the study emphasizes on economical aspect of apple production as well as early detection of apple diseases. This indicates that it supercedes the conventional methods hence improving the contemporary approach of using diagnostic and managing strategies for diseases in agriculture. In this research paper (Thangaraj; 2023), they identify cucumber leaves disease using CNNs. It focuses on using deep-learning algorithm for image processing and points out the weaknesses inherent in manual detection methods. One of the examples where deep learning was used to make predictions is the application of Convolutional Neural Network-DenseNet121 model for the purpose of disease diagnosis and found that this technique may reach accuracy of up to 95.45

In his paper (Agarwal; 2023)proposed different CNN models based on leaf images for plant disease identification. Comparisons made on different CNN models utilized in diagnosing plant diseases and their constraints in calculating disease severity. Deep learning for plant disease diagnostics: A state of art review of this study emphasises the fact that deep learning becomes more crucial in order to deliver diagnostic results that can make sense to the stakeholders.

(Srinivas; 2023) conducted a study which showed the detection process of tomato plant diseases by means of CNN and VGG-16 models. This demonstrates the need for an effective deep learning model that can classify leaf diseases. With an accuracy of 99 percenatge, the research indicated that 11 layer model in CNN performed better than VGG-16 in predicting real-time diseases on its effectiveness in plant disease detection.

In research of (Singh; n.d.). "Strawberry Leaf Disease Detection using Transfer Learning Models" describes how MobilNetV2, EfficientNetB0, and ResNet18 transfer learning models are applied in strawberry leaf disease detection. They found out that EfficientNetB0 is the best one and it resulted in getting a high accuracy 99%. Moderate performance was obtained by MobilNetv2, 80% and Resnet18 scored 64%. This is, no doubt, an apt example of how machine learning can enable precise, accurate disease recognition in agriculture.

This work presents an overview of ML and DL approaches for plant disease detection in precision agriculture as described in this paper (Balafas; 2023). The work involves a computational study of many object detection and classification methods and provides an appropriate basis for earlier studies. It was found out which method offered the highest degree of precision in detecting objects — YOLOv5, while ResNet50 and MobileNetv2 were discovered to be more optimal in image classification.

In the research of (Beulah Christalin Latha; 2023)on "Improved YOLO X Model for Tomato Disease" is a study that employs advanced techniques in agricultural technology with regards to tomato disease diagnosis. We present a new version of the YOLO X model which is meant to improve detection precision and efficiency. The solution developed in this work is highly applicable toward identifying early diseases therefore could reduce crop loss and improve yield under precision agriculture.

The research of the application of an Inception transfer learning model for the detection of plan diseases is "Plant Disease Detection and Classification using Transfer Learning Inception Technique" presented by (Kiran; n.d.). The model has the capacity for classifying several plant diseases and shows how important machine learning is as it relates to modern methods of farming. This paper demonstrates how transfer learnings help give rapid and precise identification of plant diseases enhancing better farming. In this research of (Mishra; 2023) on "Maize plant disease prediction of UAV images for precision agriculture using multi-modal fusion", Singh and Jain address the same concern. The study relies on advanced data processing techniques using aerial photographic records for increased efficiency in disease diagnosis in precision farming.

2.3 Comparison of different papers on their key parameters.

Table 1: Summary of Machine Learning Models for Plant Disease Detection

Author(s)	**Algorithm**	**Accuracy**	**Precision**	**Recall**	**F1 score**	**Limitations/gap**
Shikha Sharma, Vinod Kumar, Shraddha Sood	CNN	85%			88.53%	in this research the limitation that was found is the Limited detection scope for specific pest types; affected by environmental factors like lighting and background which causes the low value.

3 Methodology

For the purpose of disease detection in tomato, potato, and pepper plant, this project will adopt a CRISP-DM approach. Because of its organized nature, the cross-industry standard process for data mining or short CRISP-DM are best suited for such needs.

Author(s)	Algorithm	Accuracy	Precision	Recall	F1 score	Limitations/gap
Oumayma Jounii	SVM MobileNet-v2	62.60% 94.30%	60.80% 95.40%	57.57% 93.60%	58.80% 94.50%	Lack of adaptability to different wheat varieties and growth stages; impacted by unrepresented environmental conditions in training data.
Saradindu Das, Abhilasha Sharma	Multilayer Convolutional Neural Network	92.56%	95.23%	90.29%	??	Reliance on high-quality images; difficulty in detecting diseases with subtle symptoms.
Rajasekaran Thangaraj, Mohan M, Moulik M, Logeshwari A	DenseNet 121 ResNet50 InceptionResNet Inception V3	- - - -	89% 27% 80% 89%	89% 50% 76% 89%	89% 35% 74% 88%	Potential overfitting; decreased performance in different environmental conditions or cucumber varieties.
Rahul SinghA	MobileNet-v2 EfficientNetB7 ResNet	80% 99% 64%	69% 10% 55%	66% 98% 66%	67% 99% 60%	Over-dependence on pre-trained layers; may not generalize well for rare or new strawberry leaf diseases.
Hongxia Cai, JiaYing Jiang	YOLOv5	-	57.93%	55%	-	Requires a large, diverse dataset for robustness; limited real-world applicability due to unaccounted environmental variations
Bhuvan Puri, Rameshwar Cambow	VGG 16 Resnet50 EfficientNetB7 MobileNet-v2 Resnet152v2	- - - -	98.86% 78.87% 97.14% 97.74% 98.27%			Dependency on specific sensor types; reduced accuracy in different climatic conditions or cotton cultivars.

Such an approach is important in diagnosing and analysing pattern and abnormalities related to a plant disease. I chose CRISP-DM considering its superiority over other frameworks and my initial KDK knowledge. In particular, its use for the diagnosis and treatment of illnesses in the tomato, potato, and chili plants makes it special as it gives a specific insightful study about the symptoms of afflicted disorders involving these plants. The application of CRISP-DM in a tailored fashion fits very well with the objectives and demands of our project, resulting in just being an excellent choice for the disease detection tasks that are meant to be performed in these plants.

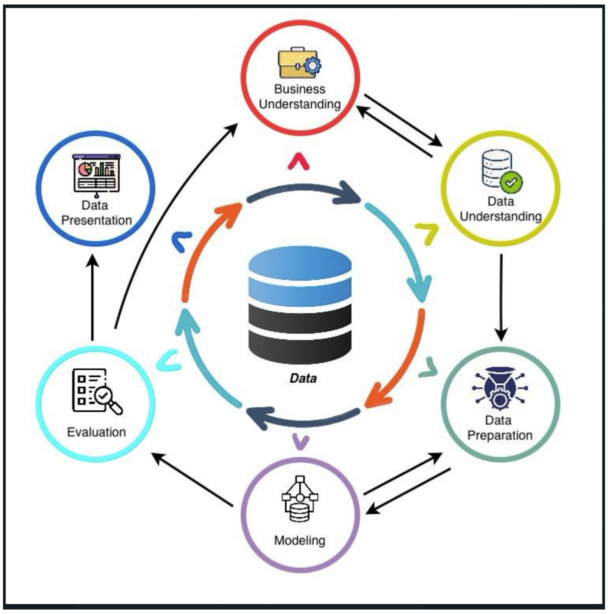


Figure 1: CRISP-DM methodology

3.1 Business Understanding

Plants disease detection business understanding involves evaluating demand, incorporating AI into agriculture, and examining the economics. Such an approach entails monitoring the ecological impact of cultivation as well as keeping up with international farming methods and legal environments. These technologies must be utilized to minimize crops losses while improving production through key stakeholder engagement, cost-effectiveness, scalability and accessibility in a wide range of farming environments.

3.2 Data Understanding

This is a huge dataset of high resolution leaf images uploaded from Kaggle that covers a variety of crops such as tomatoes, potato, and corn among others. This is a mixed set of diseased and normal leave specimens characterized against species, health condition, and other essential data; thus, it suits the application of supervised learning in AI/ML. The vast dataset plays a key role in botanic study and cultivation technologies, encouraging networking among precision farmers and environmentally friendly growers within Kaggle's platform. The dataset has around 12k train and 4k test and 4k validation images in the .JPG format.

3.3 Data Prepration

The plant village dataset is used to carry out this research, the dataset has been obtained from the Kaggle website, the dataset includes the huge variety of images of potatoes, tomatoes and pepper plant leaves which has been classified in 15 classes, the dataset has almost 12k training images and almost 4k test train images, the format of the images identified as JPEG which has been used directly in the research , the size of the images are given as height as 256 pixels and width as 256 pixels.

3.4 Data modelling and Evaluation

In evaluating the effectiveness of ResNet, AlexNet, and EfficientNet models for plant disease detection, we employed four primary metrics: these include accuracy, F1 score, recall, and precision. Accuracy is the measure of correctness of the entire prediction process. F1 score allows for balancing precision and recall, expressing how much accurate are the predictions of the models about the true values and their respective proportions among all the relevant cases. Precision measures the model's accuracy and whether its detection was in fact true or correct. Such as the extent that it can pick out all cases of diagnosed disease. In this respect, the Confusion Matrix comes in handy because it breaks down these predictions into true positives, false negatives, etc. In this project, we will explore the use of computer vision together with these classification models for the correct identification and categorization of plant diseases. These results from the evaluations are discussed in the second part of the project.

4 Design Specification

In this part of the project we have 2 sections on is for the model architecture and the second one is for the code algorithm or we can see pseudo code

4.1 model architecture

For identification of plant diseases through leaf images this specific 30-layered specialized ResNet (Residual Network) model has been created in this study. This comprises a highly sophisticated model built on deep neural networks and mainly uses the popular deep learning libraries, i.e., TensorFlow and Keras. It has both convolutional and dense layers as its architecture. The architecture of this model incorporates 2 x (3×3) convolutions with batch normalizations as well as rectified linear layers each time. These components are critical in introducing non-linearity and normalizing the inputs making the training more efficient providing for better model outcomes.

The residual connection is the structure of deep learning known as ResNET. The omitted connections are known as skip connections; they allow the network not to pass through some layers, thus correcting problems of vanishing gradient in deep networks. Once the network no longer finds anything to learn from the dataset, it may resort to learning the 'identity function' instead of the negative learning which could diminish prediction precision. ResNet can be used on different datasets and task. The new scenario feature extraction for it is not dependent on standard, pre-calibrated weights like those used by for ImageNet. In contrary, it employs a flatten layer to combine the dimension-

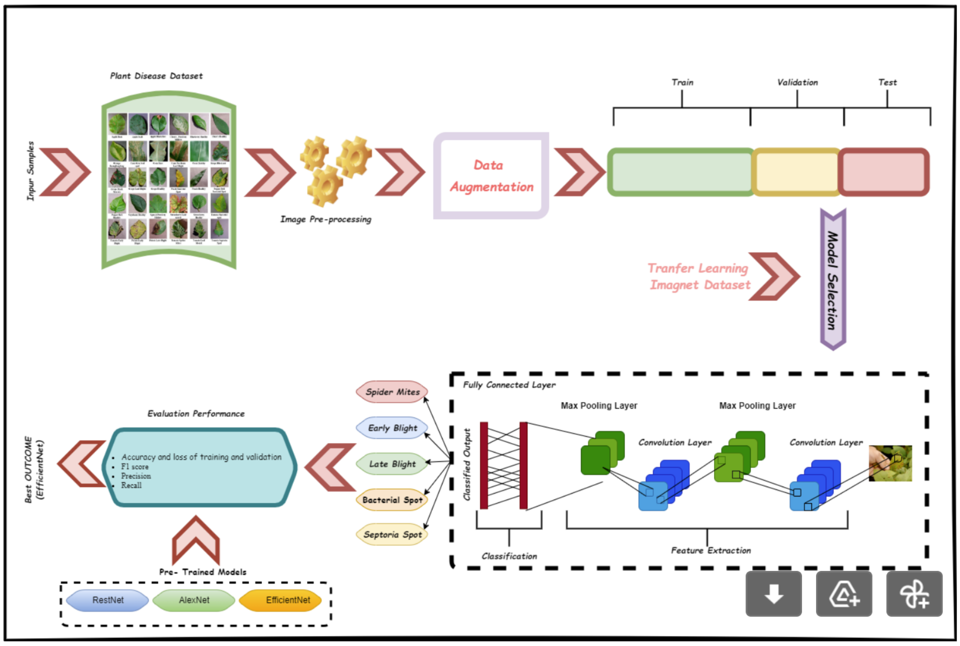


Figure 2: Model Architecture

alities of the residual blocks and the output layer. The average pooling layer is then applied before the final dense layer with a softmax activation function.

4.2 Code Algorithm

In this section we will be explaining the algorithm of codes used to find the accuracy, precision, recall and F1 score.

This proposed algorithm outlines how the model will be trained into diagnosing the diseases in plants. This involves trial-and-error adjustments of the learning rates and steps using the validation accuracy as the performance criterion. Initiation of some variables and making space for output data. Set as a loss function for training classification model is the Cross Entropy Loss. Numerous nested loops cover a fixed selection of learning rates and step sizes, creating an optimiser (SGD) with a learning rate scheduler called StepLR. The model goes through several epochs during the training process, during which it completes forward and backward passes to learn from the training data. After that, in order to measure its performance, the model conducts validations that do not alter any parameters. The algorithm intelligently adjusts the best observed validation accuracy, learning rate, as well as step size in order to avoid the preservation of all models configurations, except those that are most beneficial. After a thorough sweep across all the parameter space, it summarizes all outcomes and selects the most valid model for that particular case, depending on its accuracy. Through this methodical approach, the parameter space is explored systematically so that the model can get more power in diagnosing plant diseases well.

Algorithm 1 RestNet algorithm to determine plant disease

Input:

learning_rates = [0.1, 0.01, 0.001]: A list of learning rates to go through.
step_sizes = [5, 7, 10]: Step sizes for the learning rate scheduler.
num_epochs = 50: Number of epochs for training;
data_loaders: Datasets labeled as train and validation contained in data loaders.
device: For example, a computing device such as a CPU or GPU;

Output:

best_model: The model state with the highest verification accuracy.
best_lr: The learning rate giving the maximal validation accuracy.
best_step_size: Step size which gives the biggest validation accuracy.
best_accuracy: The highest validation accuracy obtained;
result_df: A dataframe with the output for all pairs of learning rate and step size.

Set **best_accuracy** = 0.0, **best_lr** = None, **best_step_size** = None, **best_model** = None, and **result_dfs** = {};
Define loss_function as CrossEntropyLoss;
for each lr in learning_rate_dict **do**
    for step in step_sizes) **do**
        define Optimizerwith SGD + lr_scheduler[StepLR]).
        for epoch=1 to num_epochs, **do**.
        Perform training loop over data_loaders["train"];
        - Zero gradients of optimizer;
        - Compute outputs and loss;
        - Backpropagate and update model parameters;
        - Calculate training loss and accuracy;
        end for
        Switch model to evaluation mode;
    Perform validation loop over data_loaders["validation"];
    Calculate the output and loss without tracking of the gradients.
    end for
        Calculate validation loss and accuracy;
    update best_accuracy, best_lr, best_step_size and best_model provided that the current validation accuracy is higher;
    Step the **lr_scheduler;**
    Add results as a new DataFrame to the **result_dfs**.
end for
Print current lr, step and best accuracy.
Stack all element of **result_dfs** and assign them to **result_df**.
Save **best_model**, print **best_lr**, **best step size**.
best_model, best_lr, best_step_size, best_accuracy, result_df;

Figure 3: pseudo code

5 Implementation

In the below section we will discuss how the Crisp-dm methodology is implemented.to identify the disease in plants using the different ML algorithms.

Tools and technologies used: Kaggle IDE platform is used to run the code since the dataset is very huge and it took a lot of time and we need to run on the GPU so Kaggle provides us 30hrs of free GPU unit per week which made it possible to run the code more efficiently on it, python language with numerous python pakages such as Numpy, pandas,pyTorch etc. was used to carry out this whole research

5.1 Data selection

By the way, for the Plant Village dataset, obtained from Kaggle ,We directly downloaded the dataset from Kaggle instead of executing SQL queries that identified the attributes needed in the files. It comprises a specific collection of JPEG pictures suitable for plant's disorder recognition and categorization. This dataset includes 15 classes which represent various plants under different conditions. Some of these disorders comprise such plant conditions as pepper, potato, and tomato. The class names are as follows: Pepper, Bell - Bacterial Spot, Potato – Healthy, Tomato Leaf Mold, Tomato - Yellow Leaf Curl Virus, Tomato Bacterial Spot, Tomato Septoria Leaf Spot, Tomato – Healthy, Tomato - Spider Mites/Two-spotted Spider Mite, Tomato Early Blight, Tomato - Target Spot, Pepper, Bell – Healthy, Potato - Late Blight, Tomato Late Blight, Potato - Early Blight, Tomato Mosaic Virus

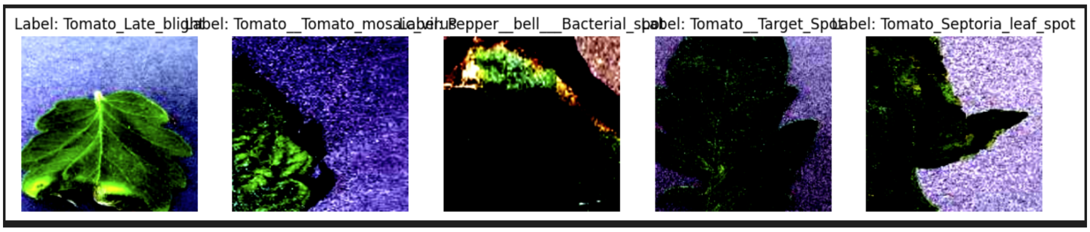


Figure 4: Sample images

5.2 Data Preprocessing

In this study the Plant Village dataset extracted from Kaggle, which was carefully partitioned for efficient training and validating. This set contains around 12K images for training, as well as about 4K of pictures each for test and validation. Sixty percent is allocated for direct training while twenty percent should be used for validation only. This provided a basis for model tuning since it ensured that the developed model would be robust enough to handle un-seen data. For this purpose, all the operations involving the uploading of the dataset into my Kaggle notebook and retrievals thereafter were done using a special platform – Kaggle integrated development environment. This research makes use of the most important libraries including matplotlib to help in data visualization, numpy for performing numerical functions and changing the data, pandas to assist in data manoeuvrability, torch to create and train the machine learning model as well as shutil library to enable the management The use of Kaggle's strong computational power, with its combined tool sets, facilitating a thorough and timely study.

5.3 Data Augementation

For Images there is one key machine learning methodology, which involves using the technique called data augmentation that makes the dataset diverse without requiring so many extra datasets. However, they are created by applying different forms of transformation such as rotation, scaling, flipping, cropping and conversion to different colours for making the new pictures look as they were captured under special circumstances outdoors. With a very large number of different scenarios included in the training set, it is most helpful during the process of "boosting" the model and substantially increases the possibility for generalization while making possible overshooting unlikely. More specific plant disease detection models could be simulated using data augmentation in PlantVillage dataset, which would include different types of plant environment and plant stages.

Image Flipping: the image is flipped horizontally or vertically, RandomHorizontalFlip() has been used to carry out the fliiping Image Rotation: In this imge is rotated on a certain angle either clockwise or anticlockwise Normalization: It is used to scale the image on same called also called as rescaling,It has been implemented by using Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225]) TorchVision Tranform: used to tranform the images using ToTensor() function Image Cropping:In this a part of image has been selected and randmoly cropped using Resize(), CenterCrop().

The above fig. 4 depicts multiple transformed versions of the same image and presents different changes. There are photos flipped top-bottom and left-right along with rotated by 90 degrees, 180 degrees and 270 degrees. It also has a version which zooms in on and out of an image, showing how much augmentation was done.

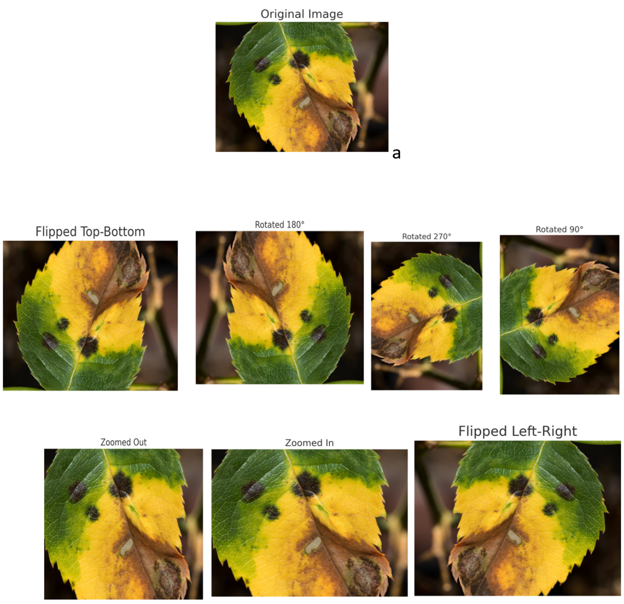


Figure 5: Augmented Images

5.4 Handling Complex images

The challenge of managing images that have complicated background, especially when high quality pictures are not available at a close distance. The key strategies include:

Background Subtraction and Segmentation: Techniques such as background subtraction can be used to separate the subject of interest from a complicated scene. More sophisticated approaches include segmentation algorithms such as U-Net or Mask R – C NN that are intended to detect and separate out particular objects in an image.

Data Augmentation: Use a data augmentation technique that artificially increases the diversity of your dataset if no high-quality images are available. This involves the use of transformations such as scaling, cropping, rotation and noise addition. This can enable the model to be more resistant against background variations.

Focus on Feature Extraction: Strong feature extraction techniques can aid the model to focus on critical aspects of an image thereby minimizing the negative effect caused by a detailed backdrop.

Use of Pretrained Models: This can be used to benefit from pretrained models on large datasets (such as ImageNet). These models already know many features and can be fine-tuned to suit your task.

Regularization Techniques: Methods like dropout, L1/L2 regularization can also be used to prevent the model from overfitting on noise or complex background in training data.

5.5 Model training

This study aims at the optimization of a deep learning application called the ResNet (Residual Network) model, which is usually used for image classification. The setup of the model operates on input images with dimensions (3×3). In order to improve the overall performance, batch size is set to 32 and the various learning rates such as 0.1, 0.01, 0.001 are experimented. Furthermore, the step size of the model was tested in the range of 5, 7 and 10 for a period of about 50 epochs.‘ The objective of this setting is to measure how these variables influence the model's ability to learn and generalize. Multiple residual blocks are used in building the ResNet architecture and help in efficient feature extraction from the dataset. Model adaptability and accuracy are improved in the training phase using data augmentation. Accuracy, both in the train as well as in the test stage, is the main measure of evaluation, one-hot encoding representing classes over in the training data. This requires ‘categorical cross entropy’ as the loss function which is appropriate for the multiclass character of the job.

Extensive experimentation on pairs of learning rates and step sizes is aimed at minimizing average training loss while maximizing validation accuracy. This goal involves finding an optimal mix with the maximum validation score as it reflects the ability of a model to correctly label an image. One of the model's configurations achieves the highest validation accuracy and is saved in dictionary (model.statedict()). The use of this systematic procedure guarantees a fit ‘bestmodel’ that exhibits outstanding fitting scores with no chance of over-fitting. Systematic testing and evaluation across all parameters demonstrate that the finalized model is indeed good and fit enough for use under the purview of the specified application.

5.6 Fine tunning of CNN models

Fine tuning is an important technique used in the specialized transfer learning application for astronomical image datasets. It entails unfrozen plus re-training the first layers of a model frozen from an initial state and then adding a particular classification layer.

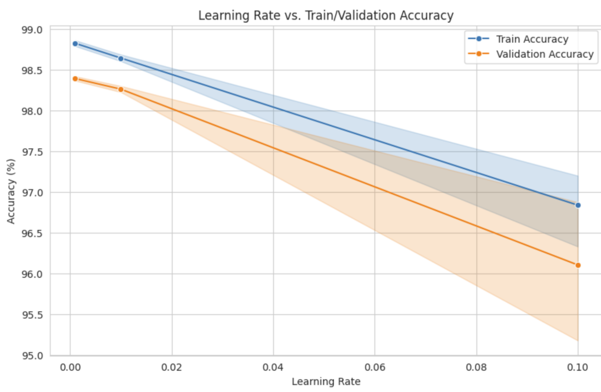
The leading layers determine this due to their ability of filtering important and detailed feature maps used for accurate classification of such datasets. As a result, the high-level feature representations of the model become specific and targeted towards the astronomy task. Nonetheless, it should be noted that this tuning may produce highly varying results despite similar hyperparameters depending on varying random seeds. However, this variability is much more pronounced in cases concerning small datasets that show clearly how transfer learning is adapting and adding value to little data. This shows how powerful transfer learning is when dealing with complicated and subtle dataset such as those prevalent in astronomy making it an asset herein.

6 Evaluation

A variety of experiments would be covered under this part as they constituted a way of producing a viable and dependable model. Model performance is evaluated using a confusion matrix, different pictorial models, the model's accuracy, and the model's loss.

6.1 RestNet

The First model was constructed which was aimed to a better accuracy and precision on a huge dataset which is plant village dataset In the fig 6 we can see that the if we increase the value of learning rate the loss is also increasing steadily for both train and validation, which shows that if we decrease the value of learning rate we will get less value of loss, which means that the loss is directly proportional to the learning rate



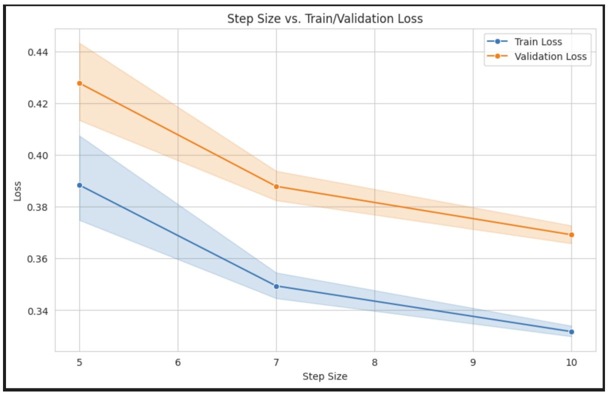


Figure 6: Train/validation accuracy on different learning rate

Figure 7: Fig.6 Train/Validation loss on different step rate

In the Fig 7 we can see that the if we increase the step size the value of loss is decreasing massively which can be beneficial for the train and validation loss estimation that shows If we increase the value of step size our train and validation loss will decrease Which means step size is inversely proportional to the train and validation loss.

In the Fig. 8 shows the line graph between the learning rate and the validation accuracy which is plotted for 3 different step size that is 5,7,10 we can see that the lowest accuracy is achieved with the smallest step size and highest learning rate whereas the highest accuracy is achieved with biggest step size that is 10 and smallest rate. Analysing through a confusion matrix in the attached fig. 8 shows that the model has varying levels of accuracy per several classes. For example, class 5 boasts 404 true positives and is thus

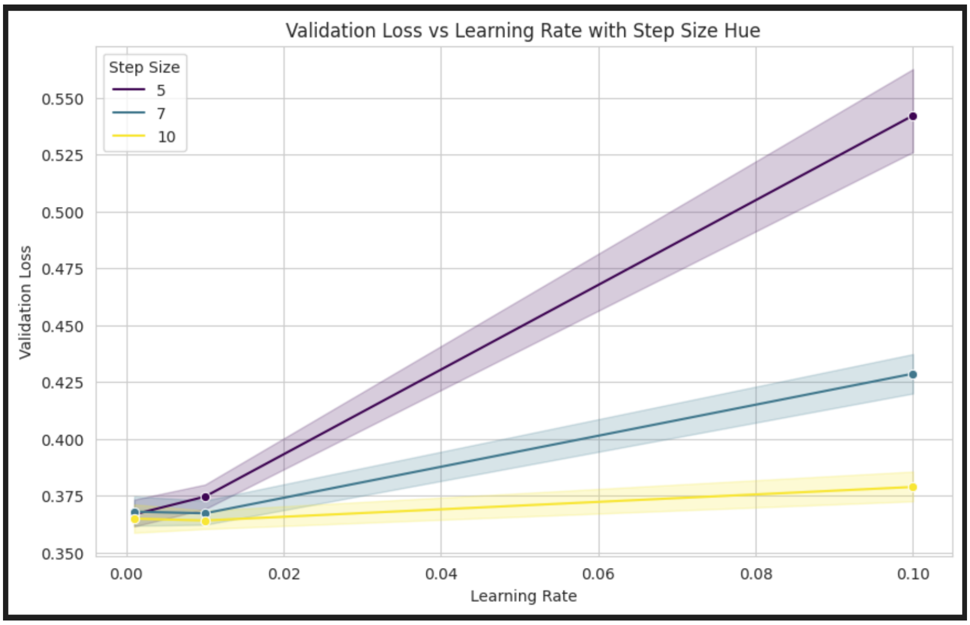


Figure 8: Validation loss with step size on different learning rate

quite accurate in its prediction. Nevertheless, several confusions are noticed in this model for example, 43 cases where a class 11 is mistakenly represented as class 10 and thus one may assume that the model has difficult distinguishing between these two categories. To calculate the precision for class 0, we divide the true positives for class 0 (190) by the sum of all the predicted items as class 0 (190+ the sum of column 0 without the first entry), while the recall is simply a number resulting All true positives are added to get a denominator, which is overall accuracy and total predictions from the model. The matrix is clear in showing the accurate and often misclassified classes and it guides on developing strategies for future improvements. Training performance of the proposed RestNet model was also noteworthy with a 88.59 accuracy value. Recalling rate of 88.60 shows that it correctly detected true positive cases whereas percent rate of precision at 89.10 affirms that it identified true positive instances. Recall, precision, and F1 were equal in this regard and delivered a decent F1 of 88.47 These indicators address reliability and strength of the model indicating its workability in actual settings mouth.

6.2 AlexNet

The second experiment was carried out on the AlexNet model to achieve a good accuracy and precision. In the Fig.10 graph shows the accuracy is increased if we change the reduce the value of learning rate train accuracy shows an steady change in whereas for validation accuracy first increases steadily and then decrease a little bit.

In the Fig. 11 shows the accuracy for train and validation data on the 3 different step sizes we can see that for the train accuracy it shows a steady line which is lowest for the smallest step and highest for the largest step size, whereas for the validation accuracy it has highest accuracy on the middle of the step step I.e 7 and lowest for the smallest step size which is 5.

In the graph (Fig.12) shows the validation loss with learning rate on all the step size we can see that maximum validation loss can be seen for the lowest value of step size on

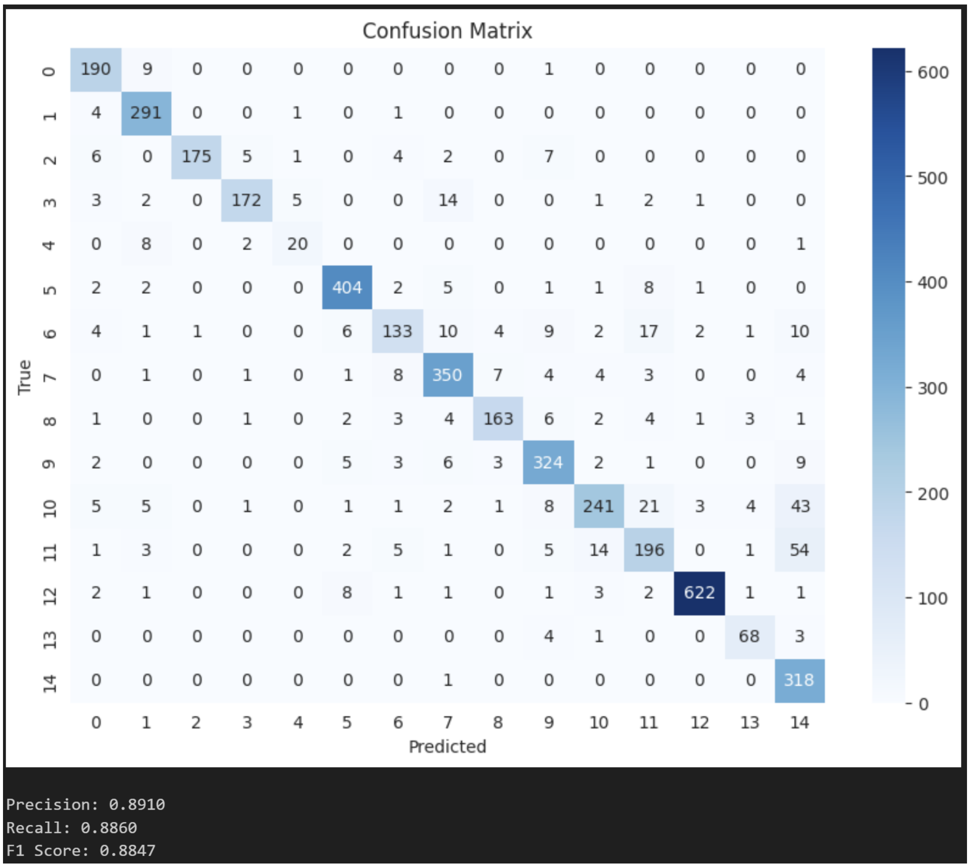


Figure 9: confusion matrix with Precision, Recall and F1 score for ResNet model

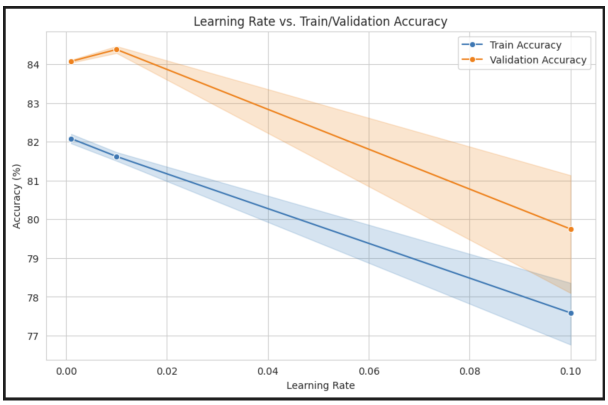


Figure 10: Train/validation accuracy on learning rate

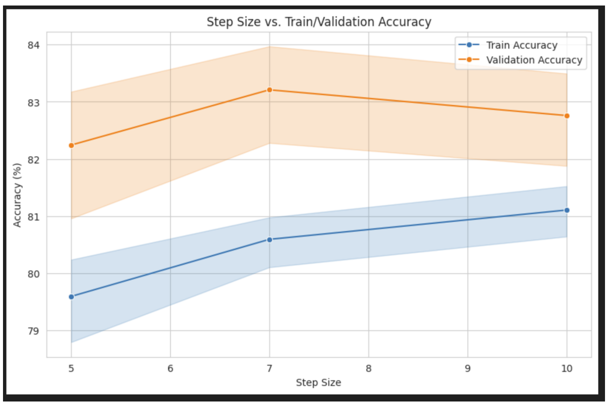


Figure 11: Train/validation accuracy on differnet step size

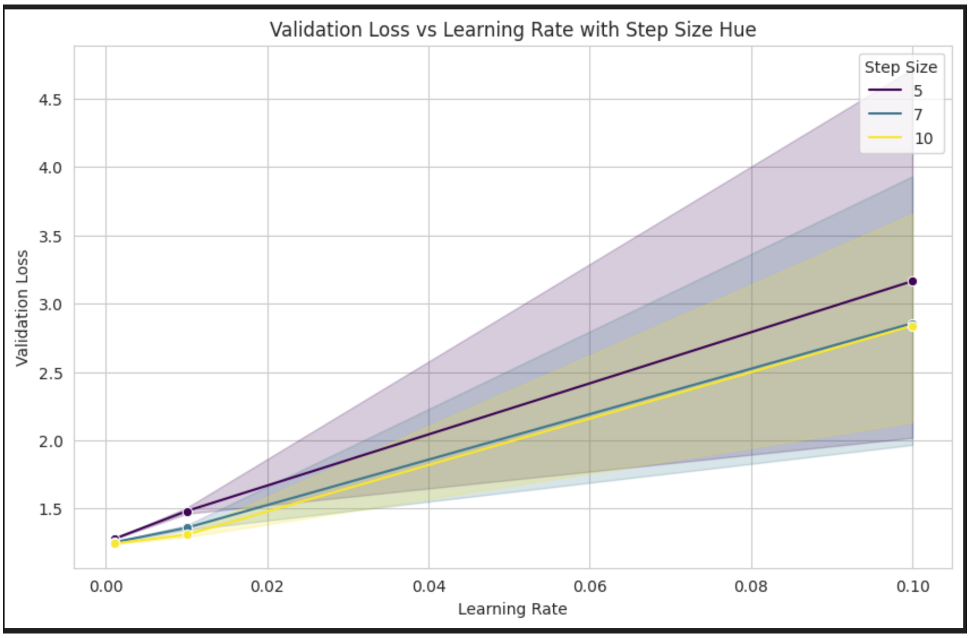


Figure 12: Validation loss with step size on different learning rate for AlexNet Model

highest value of learning rate whereas the lowest value of loss can be measures with lowest value of learning rate and highest value. The below given Fig. 12 confusion matrix shows Classification Model with 15 Labels. It assists us to comprehend how well the model has been predicting every class, as well as instances where the error might occur. Cells that follow the diagonal line from upper left corner to lower right angle reflect number of true positive examples of each category. For example, there are 37 correct predictions in class 0 and the most correct predictions at 124 are found in class 12. Non-diagonal cells indicate that the model has not correctly predicted the events (false positive and false negative). For instance, 4 occasions are in which class “0” is mistakenly predicted to be class “1”, while there are zero cases where “class 2” gets mistaken for “Class 0”. For each class the row holds its true cases in the test set, while the column shows those predictions that were made on behalf of the model concerning that particular class. To explain this, it correctly classified 14 patterns in class 14 out of 62 times predicted.

The precision of about 86.51 underlines that AlexNet achieves strong accurateness upon performing categorical jobs as its performance metrics. This means that in case the model predicts a particular class, it is right more than 86. The recall rate in this case is 85.55, meaning that the model retrieves a lot of POS. The F1 Score of 85.24 implies having achieved a reasonable balance in terms of trade-off precision and recall. The final overall accuracy of the above model is very impressive at 85.559. This goes to show that it is efficient in generalizing to new unseen data. These measures cumulatively portray the effectiveness of the model although there is room for more refinement with the aim of enhancing the precision and recall results further lowering the number of false negative and false positive cases.

6.3 EfficientNet

The third that model that has been used is efficient net. In the fig 14 graph shows the rate of change of test accuracy and validation accuracy with the learning rate as we increase

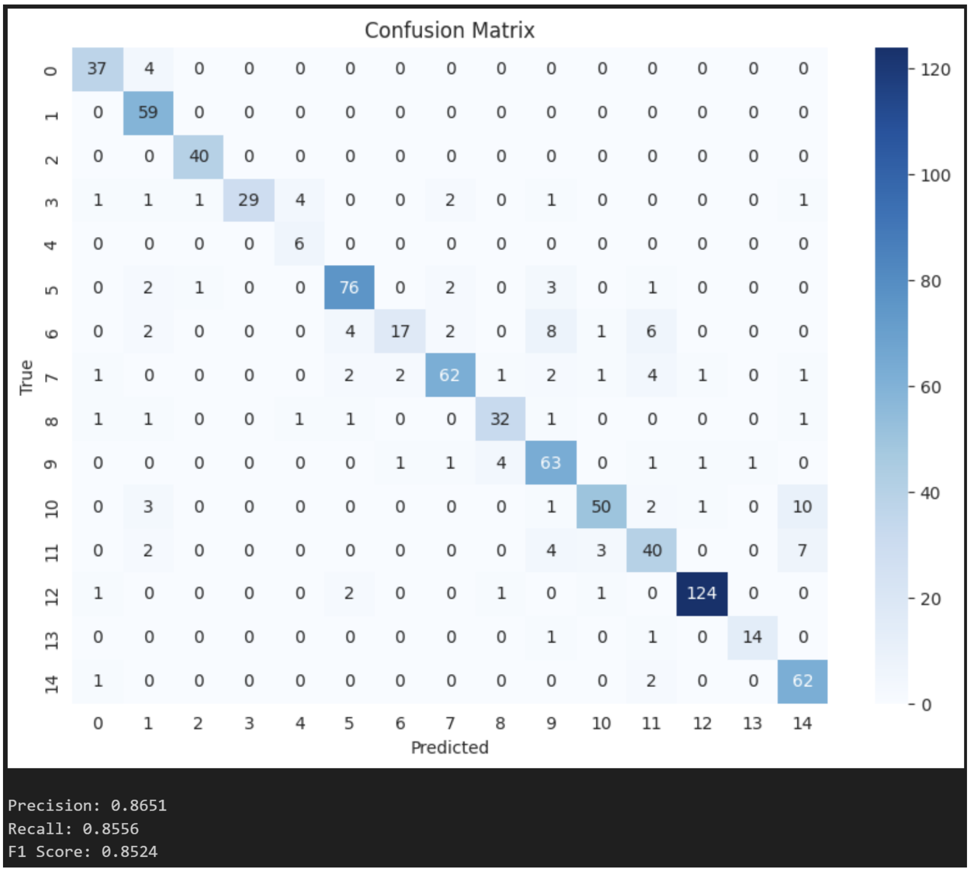
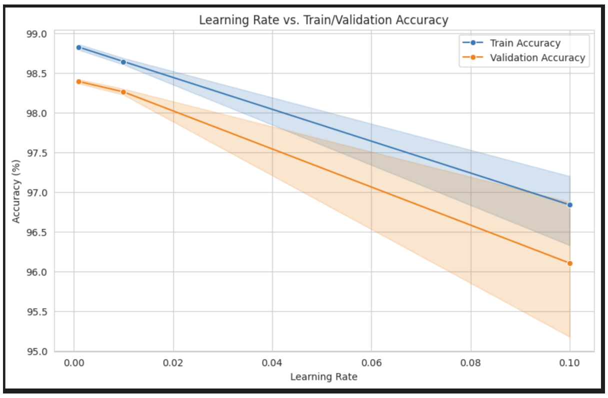


Figure 13: confusion matrix with Precision, Recall and F1 Score for AlexNet model

the learning the accuracy for both test and validation decreases.



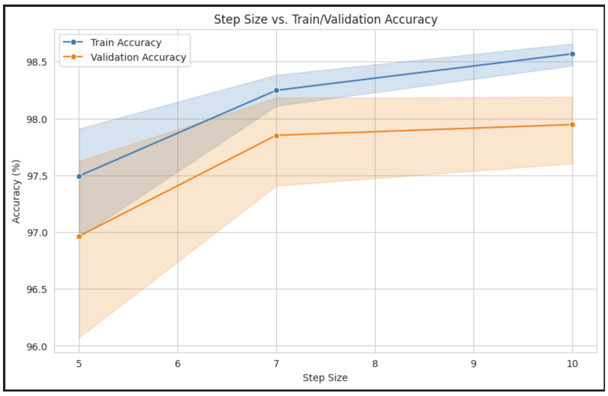


Figure 14: Train/validation accuracy on different learning rate

Figure 15: Train/validation accuracy on difefernet step size

In the Fig. 15 graph shows the rate of change of train and validation accuracy with respect to step size, the rate of change of accuracy directly proportional to the size which means that lowest accuracy can be seen with step size 5 whereas the highest can be seen with the step size 10.

In the fig 16 graph shows the validation loss vs learning rate on all the different step size we can see that, the lowest loss can be seen with the highest learning rate with smallest step size.

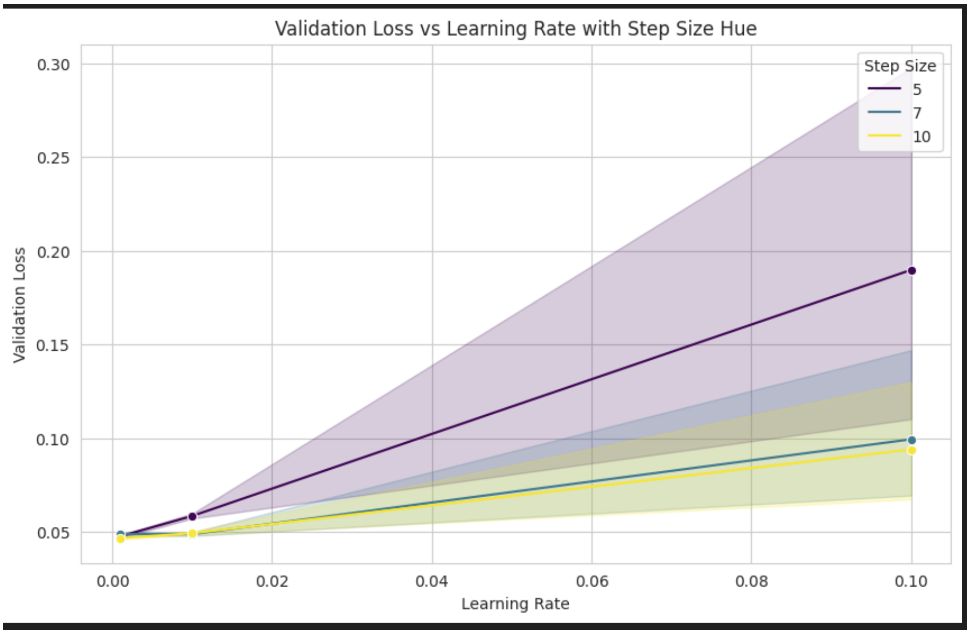


Figure 16: Validation loss with step size on different learning rate for EfficientNet Model

The below given confusion matrix (Fig. 16) shows how a 15-labels classification model performed. True positives are also represented by the diagonal numbers like 41 for class zero and 128 for class twelve. The off-diagonal numbers indicate errors: for instance, the model mixed up a 0 for a 1 while none of the 2's were mistakenly classified as 0's.O The figure below depicts the actual cases of a class in the test sets on each row, while all columns depict what the model projected. As an illustration, from 65 predictions for class 14, the model got 16 right. Thus, the model tended to predict other classes as class 14. The explained above matrix helps to understand the predictive pattern of the model and points out its strengths as well as areas that require improvements.

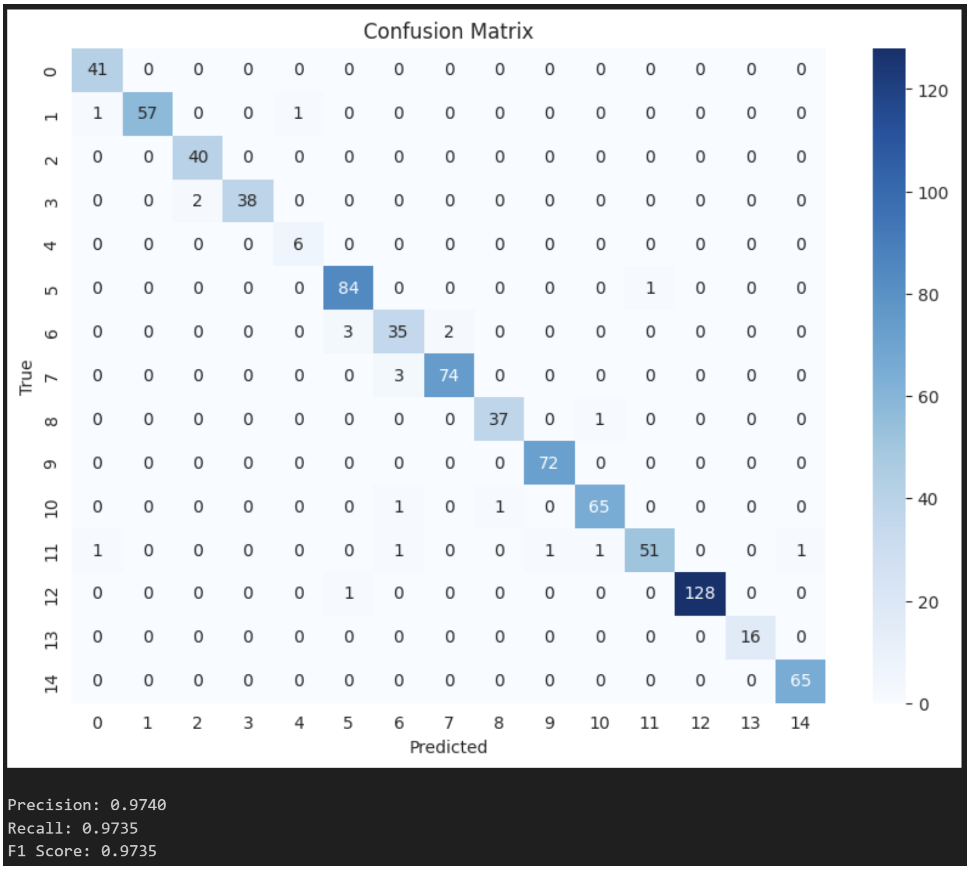


Figure 17: confusion matrix with Precision, Recall and F1 Score for AlexNet model

EfficientNet shows a high accuracy level in terms of its performance metrics, indicating that it is incredibly predictable. The model can recognize relevant cases to a great extent precision of 0.9740 equaling small rate for false positive. They recall at least 97 percent or 0.9735 which is TPR, implying that they pick up the majority of them. As such, the F1 score of 0.9735 also indicated that the model performed well with both measures of accuracy. Finally, this model achieves a test accuracy of 0.973526 and correctly classifies tests data too. Combinedly, these metrics show that EfficientNet performs its intended duties very efficiently.

6.4 specificity

In agro contexts, the specificity of machine learning models in disease detection has a significant role to play. 0 false positive rate means that the model can correctly identify healthy plants with a high degree of efficiency. Specificity that is as high as possible ensures avoiding such cases of mistaking healthy plants for being diseased ones the avoidance or wrong treatment. This has the dual effect of saving resources and operating costs, as well ensuring that a disease is efficiently managed. Limit the use of interventions like pesticide on healthy plants to promote sustainable agriculture. Sensitivity, along with specificity is yet another crucial indicator that needs validation to determine the effectiveness and reliability in detecting any disease making it an important parameter when testing performance levels for these diagnostic models. Specificity=(True negative (TN))/(True negative (TN)+False positive(FP))

This formula computes the ratio of true negatives cases that are correctly identified with disease free plants by this model. TN Cases identified as healthy, but False Positives (FP) are cases that have been wrongly indicated to be diseased. "High specificity" refers to the effectiveness of the model in differentiating individual healthy plants and thus reduces unnecessary treatments based on an erroneous diagnosis about disease. This is critical in agriculture to ensure effective resource management and sustainable practices.

6.5 Discussion

The study showed that when analyzing the three neural network models; RestNet, AlexNet, and EfficientNet when it comes to classifying using different metrics, there are unique features associated with each model. In their attempt to achieve high efficiency, EfficientNet proved to be the best-performing model, boasting an impressive precision of 0.9740, recall of 0.9735, and a robust F1 score of 0.9735, In some cases, however, RestNet failed to distinguish between different classes properly. The accuracy metric put AlexNet slightly second rate. The findings show that EfficientNet is the best of all models even though another model could be preferred in certain circumstances.

7 Conclusion and Future Work

In this research it has been comprehensively analysed as it critically examines the effectiveness of different machine learning algorithms employed in the detection of diseases in tomato, potato, and pepper plants. This detailed analysis portrays complex insights on how these models may transform agrarian practice towards eco friendly ways of farming. Amongst this, there were the remarkable achievements of the ResNet model exhibiting accuracy at 88.59%, while also, the comparable outcomes for the AlexNet model. However, EfficientNet had an amazing accuracy of 97.35%, precision of 97.40%, recall of 97.35%, and F1 of 97.35%, better than the rest of the tested models. Indeed, this shows a great improvement on precision in detection of disease, subsequently resulting into high quality decision-making process in agriculture. EfficientNet's precision translates into fewer false-positives – meaning that wrong treatment / intervention can be avoided for the sake of crop management.

In addition the summary outlines that this integration would bring about a revolution in food production. In as far as disease detection is concerned, these models are better as compared to other models, and can also be rescaled and customized for various crop types and conditions. This research could contribute towards improving precision farming in relation to crop health, higher productivity and environmental sustainability in agriculture. The enhanced disease detection will also make an impact globally on food security through yield control and resource use.

Future works comprise some adjustments and modifications in machine learning model which will be used in detection of plant diseases. Therefore, more potent algorithms must be developed and included in the automatic surveillance of diseases in agronomy toward good supervision. In addition, widening the scope of data by incorporating numerous diseases and crop categories may also lead to a higher level of applicability as well as

Author	model	key parameter
Sharma S, Kumar V, Sood . et al. (2023)	CNN	F1-score 88.53%
		accuracy 85%
Jouini O et al. (2023)	svm	accuracy 62.6% Precision 60.8% recall 57.7% F1-score 58.8%
	MobileNet-v2	accuracy 94.3% Precision 95.4% recall 93.6% F1-score 94.5%
Das S, Sharma A (2023)	Multilayer Convolutional Neural Network	accuracy 92.56%
		Precision 95.23%
		recall 90.29%
Singh R, Sharma N et al. (2023)	MobileNet-v2	accuracy 80%
		Precision 69%
		recall 66%
		F1-score 67%
	EfficientNetB7	accuracy 99%
		Precision 10%
		recall 98%
		F1-score 99%
	ResNet	accuracy 64%
		Precision 55%
		recall 66%
		F1-score 60%
Shivani	ResNet	accuracy 88.59%
		Precision 89.10%
		recall 88.60%
		F1-score 88.47%
	AlexNet	accuracy 85.55%
		Precision 86.50%
		recall 85.56%
		F1-score 85.24%
	EfficientNet	accuracy 97.35%
		Precision 97.40%
		recall 97.35%
		F1-score 97.35%

Figure 18: Result comparison with previous papers

reliability. At the same time, researchers state that there are many opportunities for commercialization of these new technologies in agricultural industries as well, including but not limited to others. Moreover, it is necessary that other innovations appear within this sphere.

In future alternative methods that can be used for the study are Exploring More Deep Learning Architectures: It is possible that different types of the neural networks such as Inception, VGGNet or DenseNet deliver better performances because of their advantageous structural design. Ensemble Methods: They include ensemble of various models which predict them to improve accuracy and robustness. The strength of each model nullifies the shortcomings in other models thus achieving even better results overall. Advanced Feature Engineering: Indeed, knowing how to isolate and choose the most pertinent features can be a real game changer for model performance. Useful methods can be t-distributed stochastic neighbour embedding (SNE) or principal component analysis (PCA). Semi-supervised Learning: The learning can be done even if the quality of labelling is low by using both types that are labelled and unlabelled data. Generative Adversarial Networks (GANs): GANs can produce pseudo training images that allow the model to 'train' using a wider dataset. Explainable AI (XAI): Tools following XAI techniques help understanding the reason of model predictions which is vital to practical applications and trust building in agricultural scenarios.

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