ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24JUN654

Classifying Crop Leaf Diseases using Different Deep Learning Models with Transfer Learning

[1]Lakshin Pathak
Institute of Technology
Nirma University Ahmedabad,India

[2]Mili Virani
Institute of Technology
Nirma University Ahmedabad, India

[3]Drashti Kansara
Institute of Technology
Nirma University Ahmedabad, India

Abstract:- Within the scope of the research, we put forward a technique of exactly confirming the distinctiveness of agricultural leaf pathologies with the assist of deep mastering algorithms and switch getting to know generation. We have pre-skilled models like VGG19, MobileNet, InceptionV3, EfficientNetB0, Simple CNN where we are seeking to increase the utility for the crop disorder type. Through searching at some metrics as cited Accuracy, Precision, Recall and F1 score for a better knowledge of a crop leaf photo category, we observe how each version performs. Our paper shows that artificial intelligence is fairly useful for the obligations of the automatic disease detection and switch mastering (as a method for reusing the existing understanding in the new software) is also beneficial. The contribution of this work to the development of reliable systems of save you sicknesses in production touches upon the rural exercise to achieve superiority fits into precision agriculture and sustainable farming. Future research ought to possibly include centered regions concerning a stability of datasets and stepped forward model interpretability which in turn will improve the fulfillment of these strategies in agricultural contexts.

Keywords:- *Crop Diseases, Leaf Diseases, Deep Learning, Transfer Learning, Classification.*

I. INTRODUCTION

Crop illnesses pose a full-size threat to the arena's meals protection due to the fact they reduce crop yields and great. Early detection and accurate classification of those ailments are essential for well timed intervention and powerful disordercontrol. Standard techniques of diagnosing sicknesses often require a variety of time and exertions. In recent years, deep mastering strategies consisting of convolutional neural net- works (CNNs) have proven promising outcomes in automated sickness detection and class responsibilities. Transfer studying, which leverages the expertise of pre-educated models, has beenshown to improve the overall performance of deep learning fashions even more, mainly in domain names where education records is scarce.

In this paintings, we gift a comprehensive observe on the type of agricultural leaf illnesses the use of several deep studying models and switch learning. By adjusting pre-trainedfashions, we take a look at how well transfer getting to know fits the assignment of agricultural disease type. We analyze and evaluate the overall performance of various deep mastering architectures, together with VGG19, MobileNet, InceptionV3, EfficientNetB0, and a simple CNN, using a dataset of cropleaf pictures.

The balance of the document is organized as follows. In Section II, knowledge is provided on agricultural illnesses, advanced learning, and transferable learning. Section III covers the pertinent studies on crop disease categorization. In Part IV, the issue is stated and the mathematical framework for transfer learning in deep learning models is explained. Section V illus- trates the recommended architecture for the categorization of crop leaf diseases. Experimental information and performance comparisons between various kinds are discussed in Section VI, The work is concluded in Section VII, which also offers recommendations for further research.

A. Motivation

The necessity for automated and particular methods for crop ailment diagnostics is what drove this research. Conventional illness detection strategies are often exertions-in depth, sub- jective, and vulnerable to human blunders. Our purpose is to create a dependable and powerful approach for categorizing crop leaf illnesses with a view to help farmers and agricultural professionals become aware of and deal with diseases early on. We will achieve this with the aid of utilizing deep gaining knowledge of techniques and switch studying.

B. Research Contribution

This take a look at affords a thorough evaluation of 5 wonderful deep getting to know fashions employing trans-ferred mastering for the category of agricultural leaf diseases. Of the algorithms analyzed had been VGG19, MobileNet, InceptionV3, EfficientNetB0, and a easy CNN. By employing switch gaining knowledge of, fashions that have been educatedare changed to the awesome field of crop disorder type, improving their potential to extract appropriate characteristics from constrained units of training data. By comparing those models' performance, essential information on the manner wherein they paintings for automation contamination progno- sis may be acquired.It is possible to decide how suitable everyversion is for usage in actual agricultural contexts via looking at its advantages and drawbacks. With the guidelines it makes for deep mastering architectures suitable for sure agricultural contexts, this comprehensive assessment contributes to the place of crop sickness manage. Furthermore, which will in addition boom

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24JUN654

accuracy in classification and resilience, this paintings makes recommendations for extra research, includ- ing optimizing model hyperparameters and exploring different transfer gaining knowledge of techniques.

C. Organization

The the rest of the record is dependent as follows: Back- ground facts on crop diseases, transfer learning, and deep getting to know is given in Section II. A survey of associated work in the situation of agricultural sickness category is provided in Section III. The trouble is formulated in Section IV, at the side of a description of the mathematical framework for transfer learning in deep getting to know models. The suggested structure for categorizing crop leaf sicknesses is proven in Section V. In Section VI, the overall performance ofnumerous fashions is in comparison and experimental effects are mentioned. The paper is ultimately concluded in Section VII, which also indicates options for destiny studies.

II. BACKGROUND

In this phase, we explore the historic heritage relevant toour observe placing, emphasizing crop illnesses, deep getting to know, and switch studying. We describe the significance of automated disorder analysis in agriculture and highlight the ideas of switch learning and deep mastering and the way they apply to our objective of crop leaf ailment type.

A. Crop Diseases

Since a extensive range of pathogens, along with micro organism, viruses, nematodes, and fungi, might also reason crop diseases, they pose a main threat to agricultural produc- tiveness and meals protection. Lesions, wilting, discoloration, anomalies, and different symptoms are some of the signs that those issues gift with, affecting the plant's leaves, stems, roots, and end result. Common times encompass powderymould, rust, blight, and leaf spots. It is critical to successfully categorize agricultural sicknesses and pick out them early so one can minimize output losses and put into effect anappropriate manipulate actions. Intelligent ailment detection structures have the capacity to pick out diseases speedy and as it should be, which might also lead to higher crop managementpractices and informed choices for farmers.

B. Deep Learning

In order to research hierarchical representations of data, a subfield of device learning referred to as "deep studying"use multiple-layer neural networks. Convolutional neural net- works, or CNNs, are a nicely-preferred own family of deep getting to know models which might be talented in photo reputation and categorization. Layers for pooling and con- volutional operations come after completely connected layers for category in CNN architectures. Given their capability to robotically extract relevant traits from uncooked enter records,those models are distinctly valuable for duties including object identification, segmentation, and photo categorization. When it involves crop disease type, deep gaining knowledge of models may additionally utilize these innate competencies to scan crop leaf pix and notice styles that might suggest a selected illness.

C. Transfer Learning

Using knowledge from one assignment to tackle a similar but unrelated activity is known as transfer learning. Ap- plying previously developed models—trained on enormous datasets—to novel problems with limited training data is known as transfer learning in the context of deep learning. In domains like crop disease classification, where access to labeled training data may be limited or unaffordable, this approach might prove to be very beneficial. By modifying the parameters of previously trained models or employing them as feature extractors, transfer learning accelerates convergence and enhances generalization on novel tasks. Transfer learning, which allows us to access the information stored in pre-trained models and adapt it for the specific domain of crop leaf diseaseclassification, is how our study enhances the efficacy as well as effectiveness of our classification models.

III. RELATED WORK

This section summarizes the latest developments in the field of deep learning-based agricultural disease categorization. Keyresearch studies are compiled in Table I, which also highlightsthe techniques used and how well they work with benchmark datasets.

IV. PROBLEM FORMULATION

When addressing the categorization of crop illnesses the usage of deep gaining knowledge of with transfer studying, the manner includes several critical steps: Describing Input Data consists broadly speaking of preprocessing a dataset of crop leaf images, which generally entails resizing the pics to match the input requirements of the pre-educated model, normalizing pixel values, and augmenting the dataset to enhance model robustness.

Computing Model Predictions involves leveraging a pre- educated neural community, enhancing its architecture barely to fit the unique assignment of ailment detection, and then passing the preprocessed pix through the network to generate predictions.

Optimizing Model Parameters is finished via nice- tuning, wherein the mastering charge is adjusted, and the version is educated at the crop disorder dataset the usage of techniques like stochastic gradient descent to reduce the loss charac- teristic, efficiently improving the accuracy of contamination categorization.

This comprehensive technique ensures that the version not only learns standard functions from big, numerous picture datasets however additionally adapts to the nuances of par- ticular crop diseases, main to greater dependable and specific diagnostics.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24JUN654

Table 1 Plant Disease Detection Studies

Plant	Year	Title	Model used	Plant disease	Pros	Cons	Accuracy
Lemon	2024	[1]	SVM,KNN, CNN	Citrus canker disease, Lemon leaf diseases	Utilization of various image processing techniques, The use of visual analysis and learning procedures inagriculture, particularly in identifying and classifyingplant pathogens	Severe purity reductions and harvestissues in lemon cultivation, Decreasedagriculture income and manufacturing due to leaf diseases affecting food resource vulnerability	Confusion matrix evaluation
Apple	2023	[2]	EfficientNet V2S	Apple Scab, Black Rot, Cedar AppleRust, and Healthy	Efficient Transfer Learning, Class ImbalanceHandling, High Accuracy, Generalization, Careful Hyperparameter Selection	Limited Exploration, Domain-specific Knowledge, Real-life Adaptation, Feature Extraction Limitations, Model Interpretability	99.21%
Apple, Grape	2022	[3]	VGGNet-19	Apple: apple scab, blackrot, canker, powdery mildew, Grape: black rot, leaf blight, esca, blackmeasle	Early Disease Detection, Efficient Model Training	Limited Dataset Informa- tion, Lack of ComparativeAnalysis, Limited Valida-tion Results	Apple:97.52%, Grape: 95.75%
Cucumber	2021	[4]	CNN	Cucumber Disease	Novel approach involving feature fusion and PCAfor enhanced accuracy	Lack of comparative anal- ysis of classification algo-rithms	94.30%
Tomato	2018	[5]	LeNet	Bacterial leaf spot, Septorial leaf spot, Yellow Leaf Curl	Simple Implementation, Effective Classification	Validation Accuracy, Dataset Dependency, Limited Scope	94.8%
Maize	2018	[6]	SVM	Cercospora leaf spot, common rust, leafblight	Sophisticated approach to disease classificationus- ing Bag of Features andSVM	Lack of detailed methodology information for re-producibility	80-84%
Potato	2017	[7]	SVM, RF, ANN	Early blight, Late blight	Robust system performance indicating practical applicationpotential	Abstract could be more concise and focused	SVM:84%, RF:79%, ANN:92%

A. Mathematical Framework

The crop pics of leaves which can be enter are first repre- sented as multi-dimensional arrays of pixel values. A variety of probabilities for every of the several sickness categories is generated the use of a deep studying model that examines each picture. Before the likelihood of each contamination magnificence is anticipated, the supply photo is surpassed via the layers of the neural community's structure and subjectedto a whole lot of modifications and computations.

B. Optimization Objective

The primary goals of optimization are to lower the loss fee and maximize the version's accuracy on a validation set. To trythis, optimization techniques together with Adam or stochastic gradient descent (SGD) are hired. In order to continually adjust the model factors, the ones approaches compute slopes from smaller batches of education records. In order to save you overfitting and decorate model generalization, normalization techniques like decay of weights and dropouts also are done. These techniques guarantee sturdy overall performance on unidentified records and inhibit reminiscence, allowing the version to accumulate records from the initial statistics set.

C. Evaluation Metrics

Common metrics like the F1-s recollect, accuracy, and particular are used to evaluate the efficacy of a model. Whereas accuracy measures the share of correctly classified samples, unique measures the proportion of true favorable forecasts amongst every one of the favorable judgments. Similar to sensibility, keep in mind measures the percentage of real samples with effective outcomes that correspond to actual constructive expectations. As a harmonic average of preciseness and recollect, the F1-rating offers an affordable assessment of the model's efficiency. Additional techniques used to evaluate the version's robustness and become aware of areas in need of improvement include verification by means of cross-legitimate and confusion matrix evaluation. The process of pass- guarantees that the algorithm operates reliably across numerous records subsets, while uncertainty matrix analysis clarifies the blessings and disadvantages of thealgorithm in regards to classifying extraordinary contamination classifications. Collectively, those assessment metrics provide an extensive examination of the model's efficacy in crop leaf illness categorization.

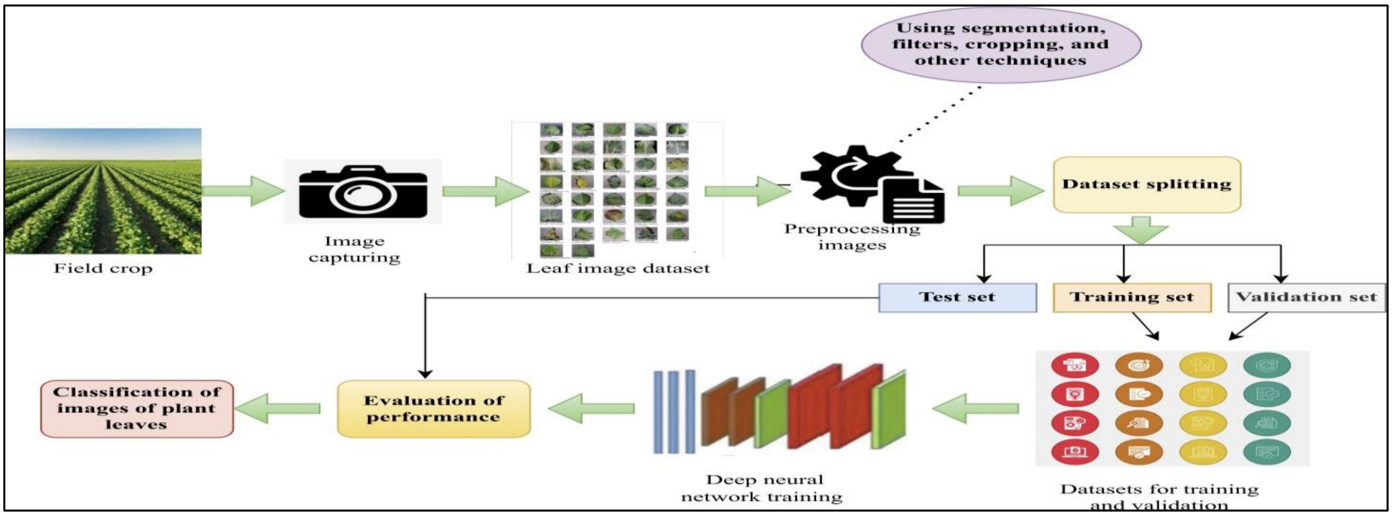

Fig 1 System Model Diagram

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24JUN654

V. PROPOSED ARCHITECTURE

A. Dataset

20,600 images in all, arranged into 15 groupings representing various crop leaf diseases. Photographs from Kaggle were used to organize these images into folders corresponding to various illness categories.Using Kaggle, an online venue for both machine learning and data science contests, this set of data was obtained. It is frequently utilized for study and evaluation in the domains of visual analysis and the fields of agriculture. For the purpose of creating and evaluating neural network models for the classification of agricultural illnesses, the information's methodical arrangement facilitates acquisition and usage.

B. Models Used

The subsequent deep learning models are used by us to classify agricultural diseases:

- *VGG19:*

VGG19 is a convolutional neural network architecture with 19 layers, known for its simplicity and effec-tiveness in image classification tasks. It consists of convolu- tional layers with small receptive fields of 3x3 pixels, followed by max-pooling layers. VGG19 achieves high accuracy by stacking multiple convolutional layers, enabling the networkto learn complex features from input images.

- *MobileNet:*

Convolutional neural networks like Mobile Net are compact and optimized for integrated as well as portable visual systems. It keeps high precision while reducing the model's footprint alongside computing cost by using depthwise differentiated convolutions. Mobile Networking is appropriate for contexts with limited resources because it strikes a reasonable mix among design effectiveness and performance.

- *InceptionV3:*

An effective way to combine information from various receptive zones is to use InceptionV3, the design of deep convolutional neural networks that presents the idea of revelation components. Enhanced efficiency and more efficient use of computing power are made possible by this design. Because of its capacity to collect extensive topological infor- mation, InceptionV3, which obtains cutting-edge scores on a variety of visual categorization criteria.

- *EfficientNetB0:*

Optimizing fashions dimension, length, and great to offer the present day in overall performance is the inspiration of EfficientNetB0, an adaptable convolutional neural community (CNN) layout. Complex scale is used to maximise the network's efficiency beneath diverse limits on resources. When it comes to gaining knowledge of as well installation, EfficientNetB0 is cost-effective since it attains high precision the usage of fewer variables than fashionable fashions.

C. Mathematical Representations

We're going to express the mathematical formulas for each tier of our suggested design before moving on to its information layer:

- *Data Layer:*

Utilizing arrays with multiple dimensions of pixel counts, the information tier prepares incoming crop leaf pictures. Prior to being sent into the cognitive level, each picture x is subject to processes including scaling, standardization, and enhancement.

- *Intelligence Layer:*

Previously trained neural networks, such as VGG19, MobileNet, InceptionV3, and EfficientNetB0,are included in the cognitive level. By optimizing the models' predictive characteristics using the data we provide, transfer- able information is applied to modify the algorithms for the purpose of classifying agricultural diseases. Through transfer- ring the information gained from an initial task—typically an enormous dataset—to a goal task—crop illness classifi- cation—this technique minimizes the requirement for a lot of practice information as well as computer power. Transfer learning has the following algebraic representation:

$$\vartheta_{new} = \arg\min_{\vartheta_{new}} L\left(f_{\vartheta_{new}}(x), y\right) + \lambda R\left(\vartheta_{new}\right)$$

Where θ_{new} represents the parameters of the adapted model, L is the loss function, $f_{\theta new}(x)$ is the output of the adapted model given input x, y is the ground truth label, R is the regularization term, and λ controls the regularization strength.

- *Application Layer:*

To forecast illness classifications consistent with traits retrieved via the reasoning level, theprogram's degree consists of absolutely interconnected stages together with softmax classifications. A softmax activationcoefficient is used for the logarithms produced with the aidof the layers that are completely related which will determine the cease end result $\hat{y}$.

VI. RESULTS AND DISCUSSIONS

In this segment, we present the experimental effects and discuss the overall performance of numerous deep studying models for classifying crop leaf illnesses. We examine the accuracy, precision, don't forget, and F1-rating of each model and analyze their strengths and weaknesses.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24JUN654

Table 2 Performance Metrics of Deep Learning Models

Model Name	Accuracy (%)	Precision	Recall	F1-Score
VGG19	81	0.81	0.75	0.77
MobileNet	93	0.93	0.94	0.93
InceptionV3	83	0.85	0.85	0.85
EfficientNetB0	88	0.92	0.88	0.89
5 layer CNN	80	0.77	0.76	0.78

A. Experiment Setup and Roles

We ran our research on a dataset that protected photos of crop leaves that have been amassed from net data and agricultural studies facilities. The dataset changed into pro- portionately cut up into test, validation, and training sets. To construct and train our fashions, we used popular deep learning frameworks like PyTorch and TensorFlow. Hyperparameters, optimization strategies, model topologies, and other experi- mental roles and settings were all precisely particular andrecorded.

B. Evaluation Metrics

We assess each model's performance using industry-standard metrics like as F1-score, recall, accuracy, and preci- sion. These metrics shed light on the model's general efficacy in identifying the underlying patterns in the data as well as its capacity to accurately categorize crop leaf diseases.Furthermore, we use confusion matrices to pinpoint frequent misclassifications and evaluate the models' resilience.

C. Training Performance

We plot training curves that illustrate the link between schooling epochs and measures like accuracy and loss to be able to compare the models' schooling overall performance. These charts assist spot viable problems like overfitting or underfitting and provide insightful information approximately the convergence conduct of the fashions. To increase typical overall performance, we are able to decide on model architec- ture, regularization strategies, and optimization strategies with the aid of carefully inspecting the schooling curves.

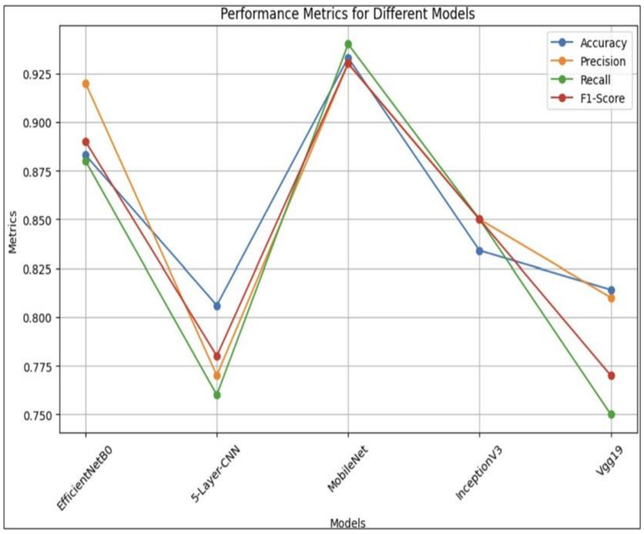

Fig 2 Performance Metrics Different Model

The schooling and validation accuracy curves (Figure 2) display the improvement of accuracy because of the reality the version trains over a couple of epochs. The education accuracy measures how properly the model plays on the training records, while the validation accuracy measures its general ordinary typical performance on unseen validation statistics. Ideally, every schooling and validation accuracy need to growth through the years, indicating that the version is studying applicable patterns from the records. If there maybe a large gap amongst education and validation accuracy, it may advise overfitting.

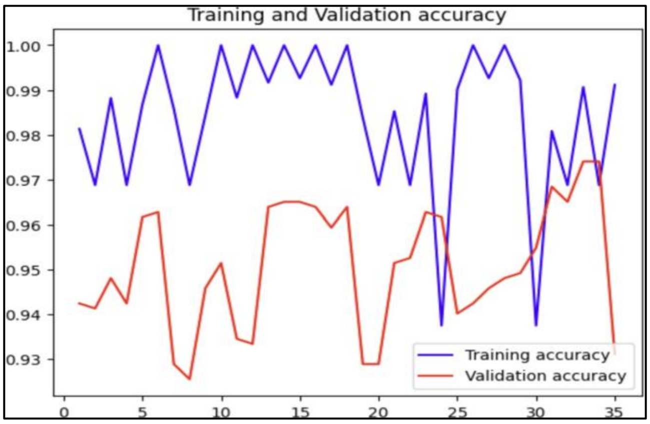

Fig 3 Training and Validation Accuracy Augmented Dataset using Effe- cientNet B0

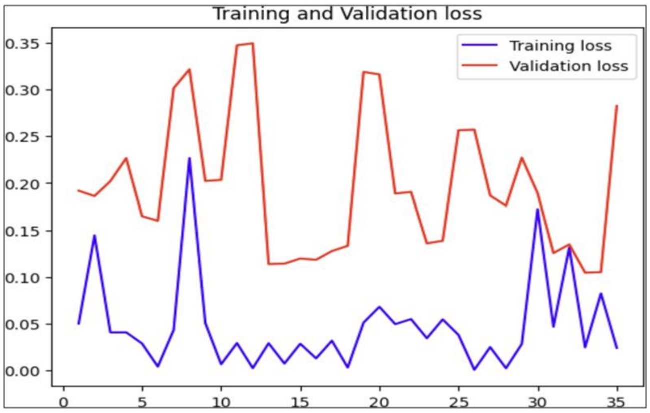

Fig 4 Training and Validation Loss Augmented Dataset using EffecientNet B0

The schooling and validation loss curves (Figure three) display how the dearth of the version modifications over education epochs. Loss is a degree of the manner nicely the version is acting, with lower values indicating better overall performance. Similar to accuracy, each training and validation loss must decrease through the years. If the training loss continues to decrease even as the validation loss starts togrowth, it is able to imply overfitting.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24JUN654

VII. CONCLUSION AND FUTURE SCOPE

In this studies, we proposed a method that combines switch getting to know and other deep studying fashions to categorise crop leaf diseases. With each model, we have been able to attain encouraging findings thru our studies, demonstrating their ability for computerized disorder diagnosis. In particular,

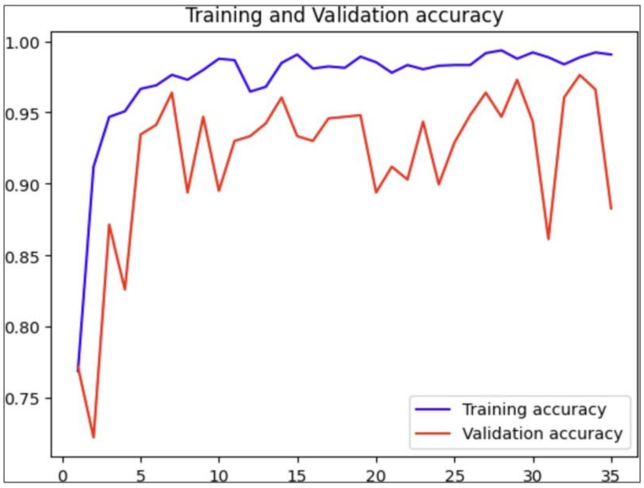

Fig 5 Training and Validation Accuracy Original Dataset

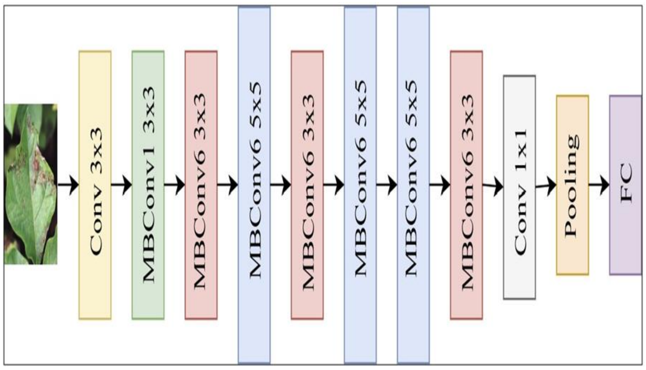

Fig 6 Model Architecture

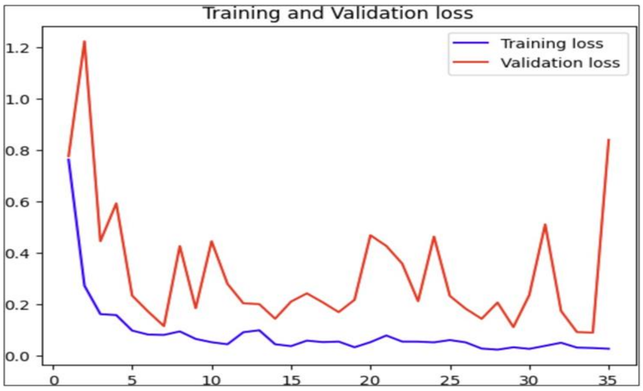

Fig 7 Training and Validation Loss Original Dataset

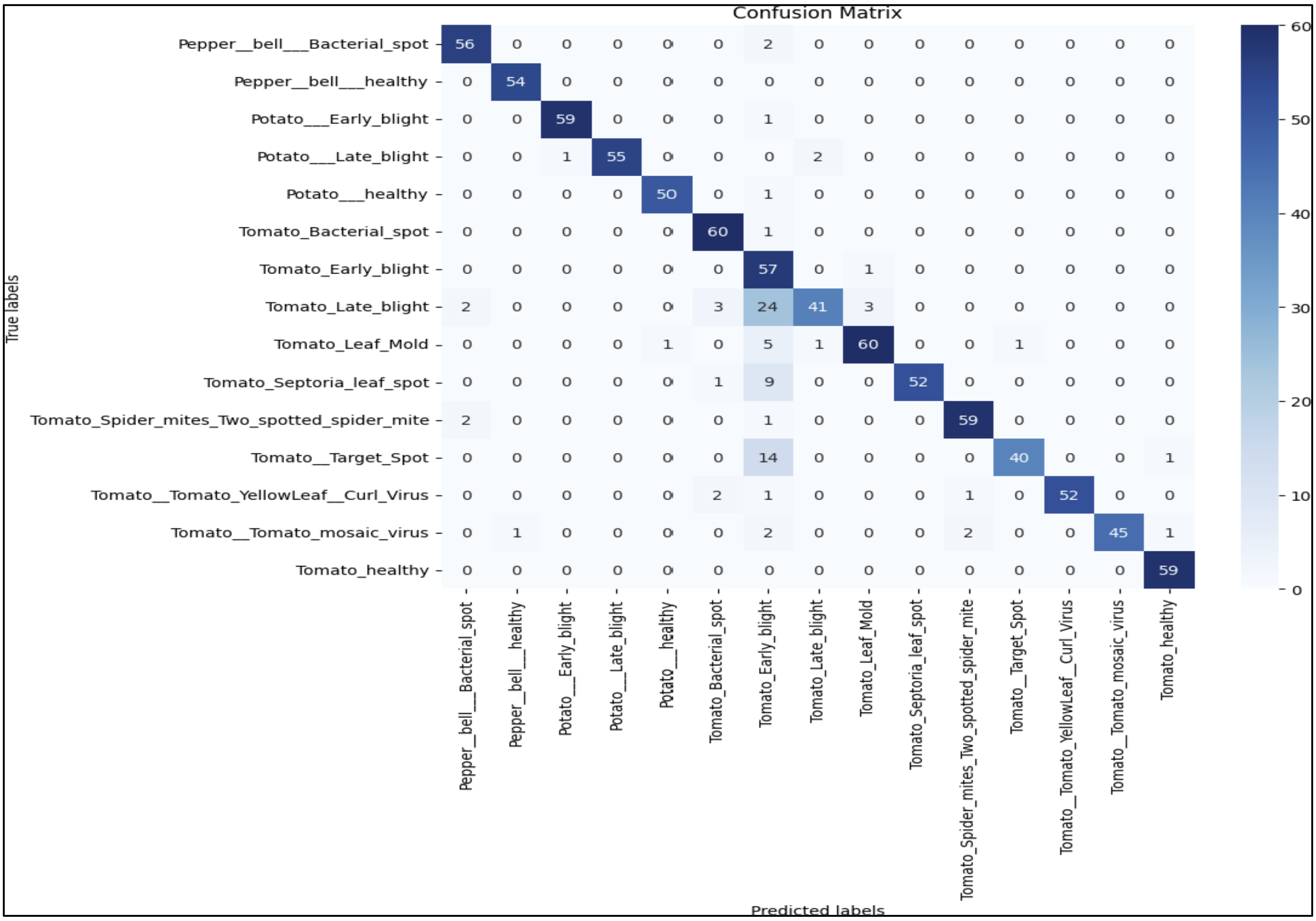

Fig 8 Confusion Matrix Original Dataset Efficient Net B0 Model

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24JUN654

Table 3 Experimental Setup

Parameter	Value
Optimizer	Adam
Learning Rate	0.001
Number of Epochs	35
Image Dimension	224x224
Batch Size	32
Train-Test Split Ratio	70-30
Loss Function	Categorical Crossentropy
Performance Metric	Accuracy
Dropout	Not Applied

MobileNet obtained the most accuracy of 93 %, accompanied by means of InceptionV3 with 85% and EfficientNetB0 with 88%. VGG19 received the bottom accuracy of 81%. These effects spotlight how nicely deep studying fashions apprehend crop illnesses, that is important for prompt intervention and crop management strategies.

In particular, when using the EfficientNetB0 model on the augmented dataset, we achieved a test accuracy of 94.35%. This demonstrates the effectiveness of utilizing data augmen- tation techniques to improve model performance.

There are a number of directions that future study could go. First and foremost, in order to guarantee the models' resilience across various illness classes, it is imperative to tackle the difficulties presented by imbalanced datasets. Furthermore, improving the interpretability of the model can offer insight- ful information about the decision-making process, helping agronomists and farmers better comprehend and believe the model's forecasts. Furthermore, determining the scalability and dependability of these models requires implementing them in actual agricultural settings and analyzing how well they work in real-world scenarios. We can help develop strong and dependable crop disease control solutions by tackling these obstacles and keeping improving our strategy, which will ultimately increase agricultural output and food security.

Table 4 Classification Report Effecient Net B0

Class	Precision	Recall	F1-score	Support
Pepper__bell__Bacterial_spot	1.00	0.98	0.99	58
Pepper__bell__healthy	1.00	0.91	0.95	54
Potato__Early_blight	1.00	0.97	0.98	60
Potato__Late_blight	0.96	0.95	0.96	58
Potato__healthy	0.89	0.80	0.85	51
Tomato_Bacterial_spot	0.98	0.89	0.93	61
Tomato_Early_blight	0.85	0.90	0.87	58
Tomato_Late_blight	0.91	0.92	0.91	73
Tomato_Leaf_Mold	1.00	0.94	0.97	68
Tomato_Septoria_leaf_spot	0.89	0.81	0.85	62
Tomato_Spider_mites_Two _spotted_spider_mite	0.90	0.56	0.69	62
Tomato__Target_Spot	0.97	0.65	0.78	55
Tomato__Tomato_Yellow Leaf__Curl_Virus	1.00	0.96	0.98	56
Tomato__Tomato_mosaic _virus	0.42	1.00	0.60	51
Tomato_healthy	1.00	1.00	1.00	59
Accuracy			0.88	886
Macro avg	0.92	0.88	0.89	886
Weighted avg	0.92	0.88	0.89	886

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24JUN654

REFERENCES

[1]. V. Sudha, U. Hemalatha, S. G. Shankar, and Thiyagarajan, "Lemon leaf disease detection using machine learning," *SSRG International Journal of Computer Science and Engineering*, vol. 11, no. 1, pp. 1–10, 2024.

[2]. M. H. Ashmafee, T. Ahmed, S. Ahmed, M. B. Hasan, M. N. Jahan, and A. A. Rahman, "An efficient transfer learning-based approach for apple leaf disease classification," in *2023 International Conference on Electrical, Computer and Communication Engineering (ECCE)*, pp. 1–6, IEEE, 2023.

[3]. M. S. Arshad, U. A. Rehman, and M. M. Fraz, "Plant disease identifica- tion using transfer learning," in *2021 International Conference on Digital Futures and Transformative Technologies (ICoDT2)*, pp. 1–5, 2021.

[4]. J. Kainat, S. Sajid Ullah, F. S. Alharithi, R. Alroobaea, S. Hussain, and S. Nazir, "Blended features classification of leaf-based cucumber disease using image processing techniques," *Complexity*, vol. 2021, pp. 1–12, 2021.

[5]. P. Tm, A. Pranathi, K. SaiAshritha, N. B. Chittaragi, and S. G. Koolagudi,"Tomato leaf disease detection using convolutional neural networks," in *2018 eleventh international conference on contemporary computing (IC3)*, pp. 1–5, IEEE, 2018.

[6]. K. Aravind, P. Raja, K. Mukesh, R. Aniirudh, R. Ashiwin, and Szczepanski, "Disease classification in maize crop using bag of fea- tures and multiclass support vector machine," in *2018 2nd international conference on inventive systems and control (ICISC)*, pp. 1191–1196, IEEE, 2018.

[7]. P. Patil, N. Yaligar, and S. Meena, "Comparision of performance of classifiers-svm, rf and ann in potato blight disease detection using leaf images," in *2017 IEEE international conference on computational intelligence and computing research (ICCIC)*, pp. 1–5, IEEE, 2017.