International Journal of Advances in Engineering and Management (IJAEM)
Volume 4, Issue 9 Sep. 2022, pp: 716-724 www.ijaem.net ISSN: 2395-5252

Probing Deep Learning Models Efficacy for Tomato Leaf Disease Detection

Konakanchi Yashwanth, Thipparthi Sathwika Reddy
Dept. of CSE Sharda, University, Noida, India
Dept. of ECE, Guru Nanak Insitutions, Technical Campus, Hyderabad

Date of Submission: 07-09-2022 Date of Acceptance: 17-09-2022

ABSTRACT
Due to high mercantile worth and enormous production in terms of quantity, Tomato Crop turns out to be a prominent asset in Indian Market. Maladies are deleterious to the crops well-being which simultaneously influence its development. For validating negligible deprivation of the sowed crops, it's prominent to scrutinize its furtherance. There are diverse maladies encompassing the tomatoes leaf which deteriorates the cultivated plants on an escalated standard. The paper aims to provide a feasible yet effective solution for the detection of any disease encapsulating tomato crops leaf. The main motive is to deliver a prominent solution with extremely low computational complexity and higher efficiency. In this paper, we have proposed 8-Layer CNN Model as well as Pre-Trained Models such as MobileNetV2, DenseNet121, InceptionV3, and ResNet50. The architectures are subsumed encompassing various parameters with inclusion of ideation of a lightweight system amalgamated over openly available yet processed Tomato Leaf Dataset with 10 Classes available over Kaggle. The proposed model and the pre-trained models gave exceptional results providing us a substantiation. For validating our efficacy, we also corroborated models Precision, Recall, F1- Score, Area Under the Curve and also the Cohen Kappa Score.
Keywords — Convolutional Neural Network (CNN), Area Under Curve (AUC), Visual Geometry Group (VGG).

I. INTRODUCTION

Agricultural Sector is one of the most eminent sectors where preponderance of the Indian population relies upon it. In India, tomato is the most common household vegetable. Vitamin E, Vitamin C and Beta-Carotene are the three most principal antioxidants in existence in tomatoes. A very prime mineral, Potassium, is also found in it which is prominent for well-being. The cultivation area in India for tomato crop spreads out in around 3,50,00 Hectares approximately and the amount of production in terms of quantity measures around 53,00,000 Tons, as India has elucidated itself as the third largest producer of tomato around the globe. The collation of the facts such as vulnerability of crop and adverse climatic impact, leads to forming of disease on all stages of growth of the crop. 10-30% loss is instantiated due to occurrence of these maladies in crops. Thus, indagation of such diseases should be initiated to deteriorate the loss of yield of the cultivated crops and thereby impacting production forming an abstraction for the crops from diseases. Surveilling the plant through the hard way would be an extremely tedious job encountering inefficiency. As a result, a potent solution must be derived inhibiting human effort, and thereby reducing the hassle of farmers exhibiting growth of the crop. The patterns which can be visually observed are strenuous to construe, leading to misinterpretations about the disease of the crop by the farmers itself. Therefore, impediment outlook formulated by the farmers may be unproductive and also detrimental.

The farmers through their pre-existing knowledge executes certain methodologies for the prevention of crops, but due to scarcity of knowledge about the type of malady possessed by a crop, they usually misinterpret the amount of dosage of pesticide which shall be utilized. Thus, this accentuates our motivation for the creation of a potent solution for the farmers and expand their domain of perception and thereby organizing them for high yield and trivial loss.

The paper proposed, incorporates Deep Learning methodologies for the detection of a disease possessed by a crop. The Dataset consists of 10 most common maladies of a tomato crop leaf processed according to the requirement of the Deep Learning Models. We have incorporated 8-Layer CNN

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model through discernment, by removing and adding of layers. The other pre-trained models have also been induced considering the fact of feathery system for modus operandi and also elucidating the impact of layers of Deep Learning Models over a typical dataset. The obtained results constitute our aim through delivering eminent outlook with measure of

separability and the similarity agreement. To summarize the process, we collated the Tomato Leaf Disease Dataset consisting of 10 Classes with processing outlook. Further, we tried training our dataset over our model by including different number of layers in our CNN Model. Finally, we got our final valid model which gave us the best result i.e., 8-Layer CNN. Along with this, we also incorporated Transfer Learning Models such as MobileNetV2, DenseNet121, InceptionV3, and ResNet50 for comparative analysis. As a result, with varied

metrics we manifested our proposed modus operandi's cogency. The structure of the paper is as follows: Section II revolves around the related work of our problem domain.

Section III focuses upon the details of the methodology used for analysis. Furthermore, Section IV emphasizes upon implementation and tools incorporated, Section V focusing upon experimental results and its analysis, and Section VI giving the conclusion and future scope for the proposed outlook.

II. RELATED WORK

Initializing the process for sagacity, we scrutinized upon various proposed methodologies induced for Tomato Leaf Disease Detection. For Tomato Plant Leaf Disease recognition an Automated Image Capturing System has been proposed colligating confidence score of 80% stating the future scope for the inculcation of more leaf samples [1]. Incorporation of CNN and Learning Vector Quantization (LVQ) Algorithm for the Plant Leaf Disease Detection has also been elucidated with an average accuracy of 86% with future scope encompassing the utilization of different filters and different size of convolutions [2]. Convolutional Neural Network with a slight change known as LeNet has been used for the detection of Tomato Leaf Disease gaining a potency of around 94-96% with additional scope of inclusion of different learning rates and optimizers [3].

Also, Recognition of the disease using SqueezeNet model has been incorporated gaining an average accuracy of 86.92% proving a lightweight solution prospect [4]. Image Processing techniques have also been subsumed displaying an accuracy of nearly around 96.55% with 06-Classes of Tomato Leaf Disease [5]. The procurement of an efficient Tomato Leaf Disease Detection methodology has been produced analogizing a loss of 1.15% with the future scope of utilizing varied pre-trained models for better discernment [6]. Feature Extraction encompassing K-Means Clustering and Classification with Artificial Neural Network (ANN) has been used for Leaf Disease Detection gaining an average accuracy of 92.5% [7]. CNN has been further incorporated stating the efficacy of it over ANN for Plant Leaf Disease Detection with an accuracy of nearly 96.5% [8].

Early Detection of Plant Leaf Detection has been imposed with the help of Image Processing, Image Segmentation, Clustering ad Open-Source Algorithms possessing an accuracy of 98.12% [13]. Also, a specific early blight identification in Tomato Leaves has been assimilated over YOLO Framework gaining a classification accuracy of 99.952% through Xception Model [14]. ResNet50 has been incorporated for Tomato Leaf Diseases Classification gaining an output potency of 98.0% for 03-Classes [15]. Data Augmentation has also been incorporated using ResNet50 Model for Tomato Leaf Disease Detection with accuracy of 97% over 06-Classes [16].

Juxtaposition of various CNN architectures has been induced such as VGG16, GoogLeNet, DenseNet121, and ResNet101 gaining an average accuracy of 98.99% over 02-Classes [17]. Imposition of CNN over 12-Classes has been implemented procuring an accuracy of 88.80% giving an insight of inclusion of varied maladies [18]. However, a strong analogized methodology contrasting varied light-weight architectures and prowess of proposed approach with pre-trained explication hasn't been imposed yet. Moreover, the incorporation of the models over 10-Classes hasn't been brought into action yet.

As a result, our approach contrasts between the impact of classes, impact of diverse models and the impact of light-weight system over a problem domain.

III. METHODOLOGY USED FOR ANALYSIS

Scrutinizing over related work we proposed our own 8-Layer CNN model for Leaf Disease Detection. Before concluding the efficacy of our model, we initially contrasted it with different layers of CNN i.e., low and high number of layers and finally we ceased ourself to 8-Layer CNN.

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Moreover, for analogizing pre-trained models we thought of training our Dataset over the most efficient transfer learning models over 1-epoch and thereby select the model depending upon the performance. Fig.1., displays each model's performance over our 10-Class Dataset.

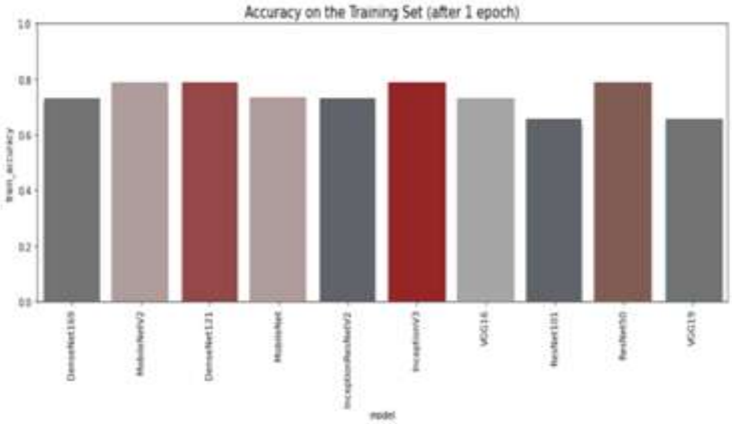

Fig.1. Different Models Efficacy of 10-Class Dataset trained over a singleEpoch.

Thus, inferring through the performance of the above models we got a potent outlook over MobileNetV2, DenseNet121, InceptionV3, and ResNet50.

Moreover, for further validation of incorporation of these models over our problem paradigm we also considered the factors affecting the model's performance. Thus, there exists certain elucidating factors inhibiting models' proficiency i.e.,

- Greater number of Parameters,
- Greater Number of Recurrent Units,
- Use of complicated Activation Functions and
- The inculcation of Deeper Networks.

As a result, the models we selected demonstrates a diverse nature of our proposed outlook.

TABLEI. COMPARISON BETWEEN PRE-TRAINED MODELS

S.No.	Model	Size (Mega-bytes)	Parameters (approx. in Millions)	Depth
1.	MobileNetV2	14MB	3.5	88
2.	DenseNet121	33MB	8	121
3.	InceptionV3	92MB	23.8	159
4.	ResNet50	99MB	25.6	168

Demonstration of the Architecture of each model:

A. 8-Layer CNN:

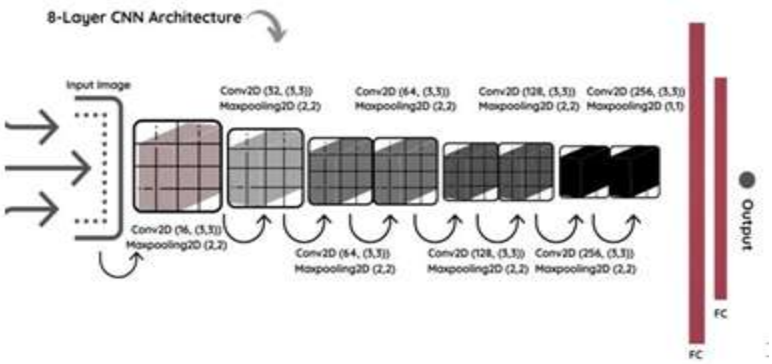

Fig.2.The8-Layered CNN Architecture (Proposed).

B. MobileNetV2:

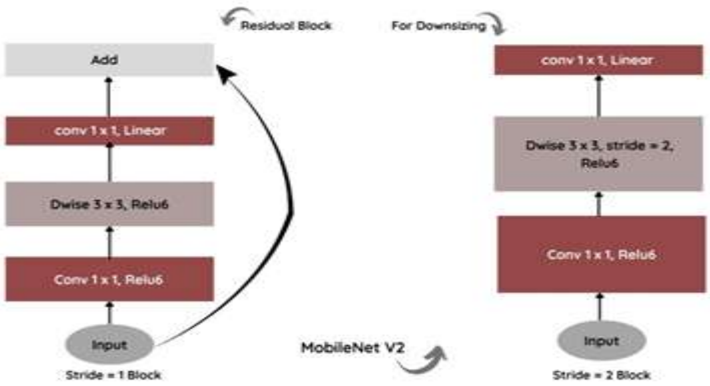

Fig.3.Mobile NetV2 Block Structure.

C.DenseNet121:

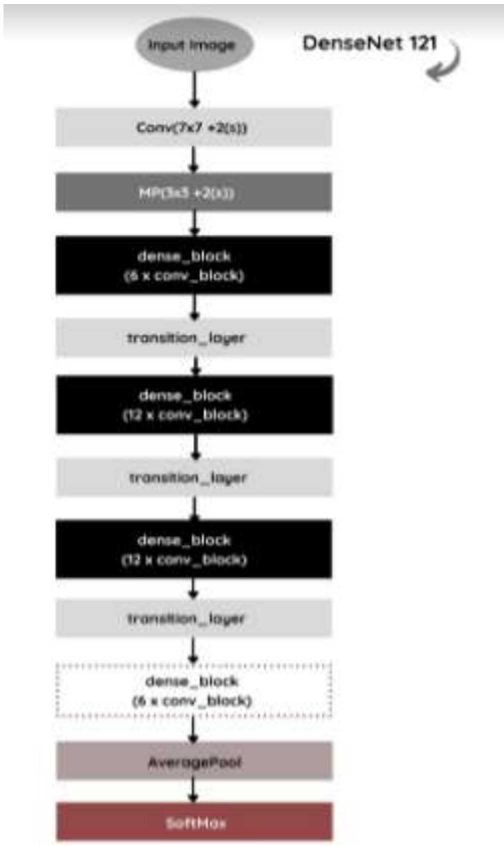

Fig.4. DenseNet121 Block Structure.

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Volume 4, Issue 9 Sep. 2022, pp: 716-724 www.ijaem.net ISSN: 2395-5252

D. InceptionV3:

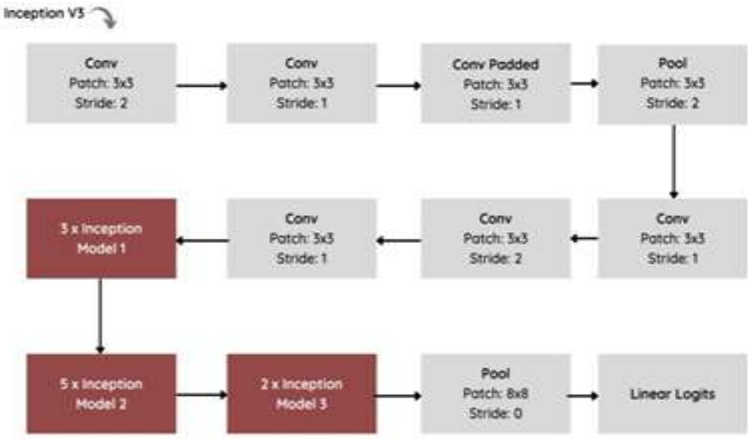

Fig.5.Inception ResNetV2 Block Structure.

E. ResNet50:

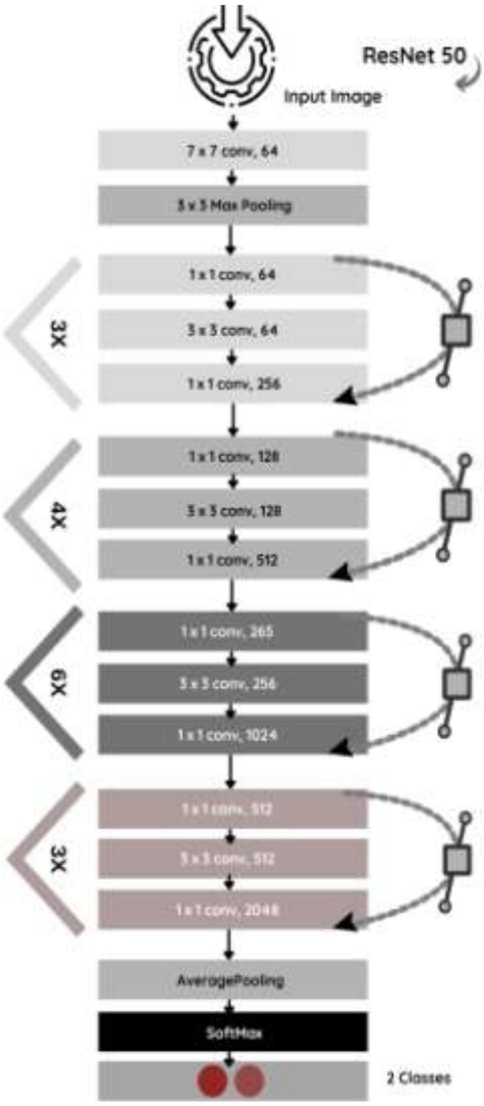

Fig.6.The Structural Diagram for ResNet50 with inclusion of Identity Mapping.

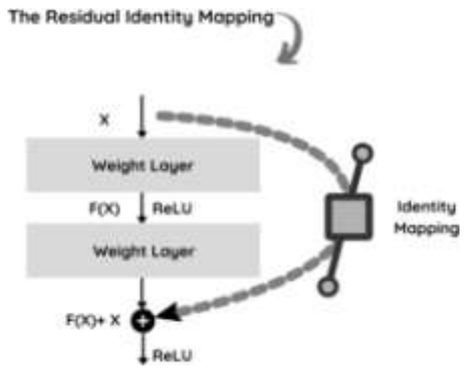

Fig.7.There presentation of Residual Identity Mapping.

An elucidated depiction of models has been subsumed through their block architectures consummating the overview of the model utilized.

IV. IMPLEMENTATION AND TOOLS

A. Dataset Utilized and Dataset Source: The Dataset consists of 10-Classes having 1000 instances each giving us a total of 10,000 samples of Tomato Leaf Diseases. The original dataset has varied dimensions which is resized to 224x224 as per the model's requirement. Data Augmentation has been applied through which our overall instances escalated to 1,20,000. The dataset has been subsumed through openly available dataset over Kaggle. The demonstration of the dataset is shown in Fig.8 and Fig. 9.

Fig.8.Dataset Visualization containing 10-Classes.

Fig.9.Clear representation of Tomato Leaf Diseases.

B. Metrics employed for ascertaining Accuracy:

The accuracy revolving around Train, Validation and Test isn't enough to analyse and impose the efficacy of a proposed methodology. Thus, to validate our result and thereby our modus operandi we induced various metrics portraying our

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potency over the problem paradigm.

We incorporated Precision, Recall and F1-Score calculated through the Confusion Matrix. Also, we inculcated Area Under the Curve (AUC) detecting the Measure of Separability to gauge the efficacy of the models utilized. Furthermore, Cohen Kappa Score which is used to gauge the agreement between the evaluators has also been imposed. Fig.11. demonstrates certain metrics gauged through Confusion Matrix.

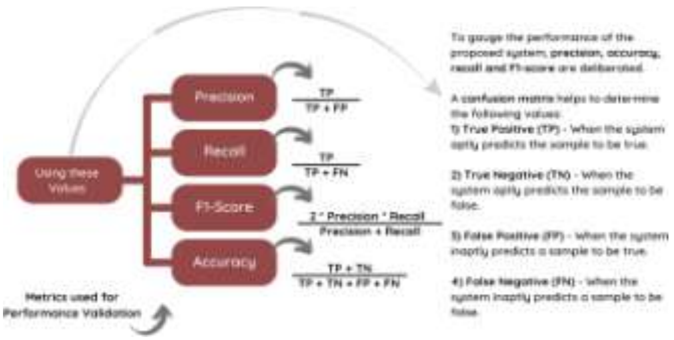

Fig .10. Metrics Evaluation Process for Precision, Recall, F1-Score, Accuracy.

C. Implementation Flow: Demonstrated in Fig.11.

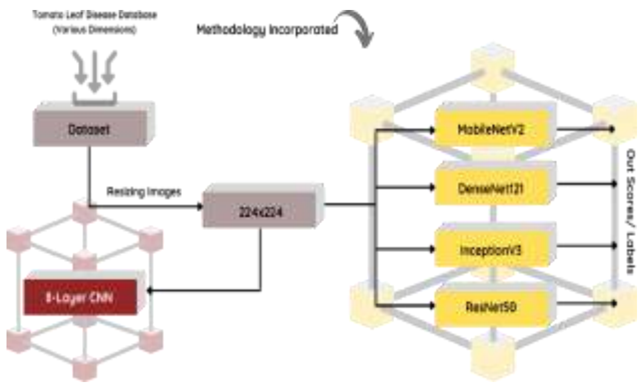

Fig.11.Implementation Structure.

V. EXPERIMENTAL RESULTS AND ANALYSIS

After the implementation of the proposed methodology, we got phenomenal results for almost every model subsumed in Fig.12 and Fig.13. The output achieved gave us an edge over the existing approaches and a formidable outlook for automating the detection Tomato Leaf Disease.

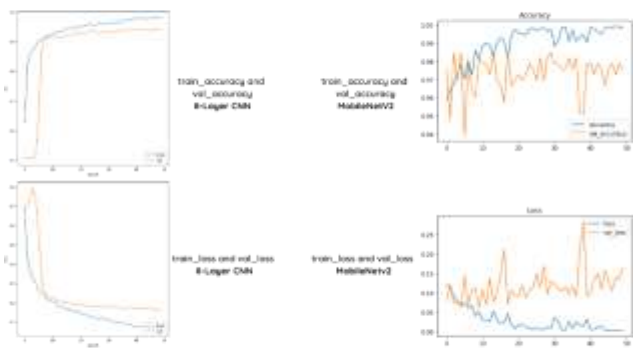

Fig.12.Graphical Results for 8-Layer CNN and MobileNetV2.

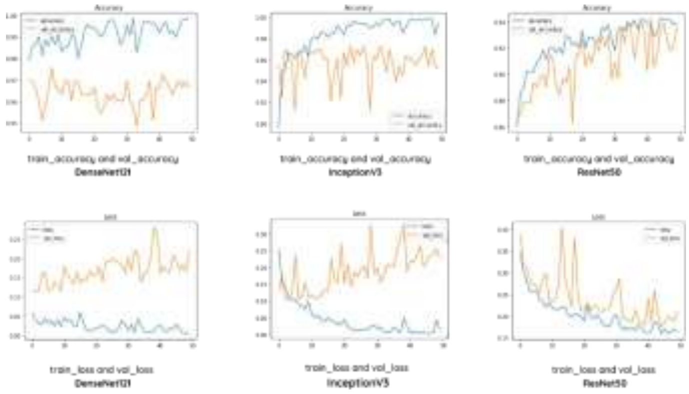

Fig.13.Graphical Results for DenseNet121, InceptionV3 and ResNet50.

TABLE II. THE DEPICTION OF TRAIN, VALIDATION AND TEST ACCURACY ENCOMPASSING INDUCED MODELS.

Model	Train-Accuracy	Validation-Accuracy	Test-Accuracy
8-Layer CNN	99.50%	96.36%	99.01%
MobileNetV2	99.87%	97.87%	98.73%
DenseNet121	99.88%	96.66%	98.51%
Inception V3	99.37%	95.14%	97.37%
ResNet50	98.19%	96.62%	97.52%

TABLE III. VARIED METRICS ACCURACIES UTILIZED TO GAUGE POTENCY OF MODELS

Model	AUC	Precision	Recall	F1-Score	Cohen Kappa Score
8-Layer CNN	1.0000	0.99012	0.99000	0.99000	0.9491
MobileNetV2	1.0000	0.98735	0.98732	0.98732	0.9345
DenseNet121	0.9999	0.98512	0.98515	0.98515	0.9311
InceptionV3	0.9990	0.97371	0.97370	0.97370	0.9295
ResNet50	0.9838	0.97523	0.97530	0.97530	0.9301

VI. CONCLUSION AND FUTURE SCOPE

From the above inference, we can analyse that all the models performed exceptionally well when juxtaposed with our related work for a 10-Class structure. 8-Layer CNN proved to be the best model portraying phenomenal efficacy giving us an elucidation for its utilization in any modus operandi related to Leaf Disease Detection. Moreover, MobileNetV2, DenseNet121, InceptionV3 and ResNet50 also proved to be a potent solution for the detection prospect. Also, we found that if any specific model has a greater number of layers, it doesn’t mean it’ll be delivering higher accuracy. The efficacy of any model depends upon the problem domain and more precisely over the dataset as we had represented in Fig.1. Through Table II, we can analyse that MobileNetV2 performs better than DenseNet121, InceptionV3, and ResNet50 even though they have greater number of layers and more complex architecture (Table-I).

Thus, our proposed outlook proved to be promising with the attained accuracy and can be used in automating the Tomato Leaf Disease Detection.

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