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PERFORMANCE EVALUATION OF VARIOUS CNN ARCHITECTURES FOR PLANT IMAGE CLASSIFICATION WITH DEEP LEARNING

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Abstract

The purpose of the study is to analyze and compare the classification and identification results taken from various deep learning models and techniques used for computer vision 2D object classification tasks. Here for this study 6 different plant datasets were taken. Firstly, the work starts with CNN architecture from scratch with an accuracy result 73.1%. Again when it is trained with the augmented datas, the performance of the work gets increased as 82.88%. The aim of the current paper is to check the performance when pre-trained Networks were applied. For that, using the same dataset one of the CNN model, ResNet50 were taken and after that this paper will check the performance and finally compares with other CNN model to classify the datasets and conclude the comparison results.

Keywords: Classification, Augmented Dataset, CNN Model, ResNet Model.

1. INTRODUCTION

After initially implementing a basic CNN model with 3 convolutional layers and 3 max pooling for auto-feature extraction from the images, the accuracy achieved was 73.1%. However, upon incorporating dropout into the model, the accuracy significantly improved to 77.05%. To decrease the risk of overfitting and finishing with dense fully connected layer, dropouts were used. When there is no improvement in the model, the training process is stopped. When CNN were used for training, the basic configuration parameters were initialized with a batch size of 20 and 2000 sample pictures, indicating that each epoch will have 100 iterations, the model were trained with a total of 30 epochs with a validation set of 1000 images to test. Model overfitting occurs when we have a limited amount of training data. To avoid overfitting and to improve the performance the current datasets were augmented. When it is augmented, the dataset gets increased and when the performance is evaluated, this model achieves 82.88% accuracy. To further measure the performance level, one of the pre-trained model ResNet50 were applied for the dataset and evaluated the performance and while finally comparing with other networks, the final performance were evaluated in this study.

2 PROPOSED METHODOLOGY: APPLYING PRE-TRAINED RESNET50 ARCHITECTURE WITH DATA AUGMENTATION BY COMPARING OTHER CNN ARCHITECTURE.

2.1 Introduction

Initially, the model begins training on a dataset consisting of 2000 samples. However, after approximately 2-3 epochs, overfitting becomes evident on the training data when utilizing Model 1, which includes 3 convolutional layers for feature extraction and a flatten

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layer to process the output feature maps. Despite achieving an average accuracy of 77.05%, the overfitting issue hinders further improvement on unseen data.

After a few epochs, the previous model stops overfitting because it was trained on limited data samples. As a result, Data Augmentation with CNN architecture (Model 2) was used to increase performance. The images were increased from the current images by using image transformation. This model's average accuracy is 82.05%. When CNN with image augmentation is used, the validation accuracy improves to roughly 80%, which is better than the previous model. This model is no longer overfit, as validation and training accuracy are virtually identical.

Pre-trained CNN architecture with data augmentation were used to boost performance in Model 3. The images were enhanced with a total of 3600 samples after image augmentation. ResNet50 is the pre-trained CNN architecture used in this model and its performance is compared to that ofother CNN architectures using performance metrics. Finally, the result indicates that ResNet50 is the best pre-trained model, with an accuracy of 89.70%.

2.2 Applying Pre-trained ResNet50 architecture with data augmentation by comparing other CNN architecture.

Pre-trained models are frequently used in the following two popular ways when creating new models or reusing existing ones:

- Performing feature extraction using a pre-trained model
- Conducting fine-tuning of the pre-trained

Table 1.1: Performance Metrics with ResNet50()

Class	Truth overall	Classification overall	ACC	PREC	REC	F1	TP	TN	FP	FN	ERR	TNR
1	91	98	**97.38**	0.89	0.96	0.92	87.6	480	12.3	4.8	0.03	0.98
2	84	84	**98.25**	0.94	0.94	0.94	79	493	6.5	6.1	0.02	0.99
3	85	98	**96.34**	0.83	0.95	0.89	81.4	480	18.5	4.8	0.04	0.96
4	95	98	**96.34**	0.88	0.91	0.89	86.4	475	13.5	9.8	0.04	0.97
5	110	98	**96.16**	0.95	0.85	0.89	93.8	465	6	19.8	0.04	0.99
6	108	97	**94.94**	0.91	0.81	0.86	88.8	463	11	22.5	0.06	0.98

From the above table, Accuracy of class 2 is high when compared with the other classes. And the overall accuracy is 89.7 when ResNet50 architecture is used.

Table 1.2: Result-1 Training and Validation accuracy metrics after augmentation with ResNet50 Model

Epoch	Time in sec	Loss	Accuracy	Val_Loss	Val_Accuracy
1/30	1s 373us/step	0.4325	0.7657	0.2958	0.8530
2/30	1s 286us/step	0.2857	0.7955	0.3294	0.8643
3/30	1s 289us/step	0.2353	0.8243	0.2708	0.8500
29/30	1s 287us/step	0.0121	0.9943	0.7760	0.8730
30/30	1s 287us/step	0.0102	0.9187	0.8344	0.8720

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We achieve a remarkable validation accuracy of about 87% using a pre-trained CNN as a feature extractor, which is a notable 6% improvement over our standard CNN model with picture augmentation. However, a significant difference between the training and validation accuracy after the fifth epoch makes it clear that the model is overfitting. Despite this, it remains the most successful model we have experimented with thus far. To further enhance its performance, let's proceed to apply our image augmentation technique to this model.

2.3 Pre-trained CNN model with Image Augmentation

We'll utilise the same data generators we did earlier for our train and validation datasets. In this phase, we will construct and train our deep learning model without extracting bottleneck features as

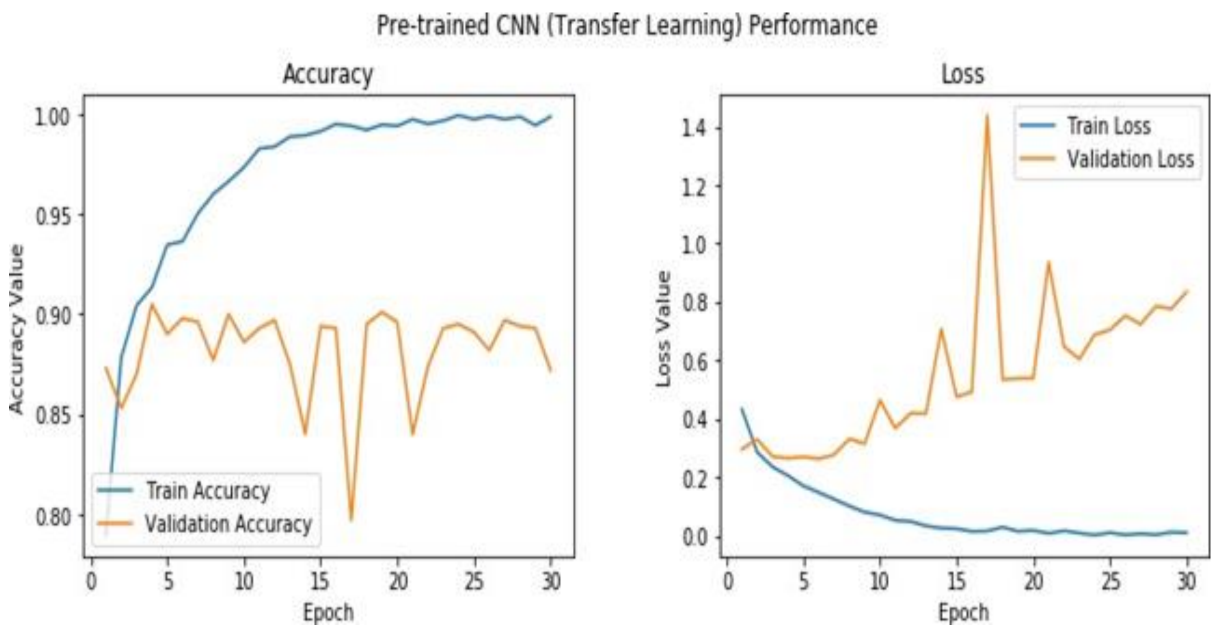

Fig. 1.1: ResNet50 (feature extractor) Performance

we did previously. Instead, we will leverage data generators, allowing us to pass the ResNet50() model object directly into our custom model. As we plan to train for 100 epochs and aim to avoid abrupt changes to our model layers' weights, we will slightly reduce the learning rate. It is important to note that we are still treating the ResNet50() model solely as a feature extractor, and its layers remain frozen during this process.

Table 1.3: Result-2 Training and Validation accuracy metrics after augmentation with ResNet50 Model with 100 epochs

Epoch	Time in sec	Loss	Accuracy	Val_Loss	Val_Accuracy
1/100	45s 449ms/step	0.6511	0.6153	0.5147	0.7840
2/100	41s 414ms/step	0.5651	0.7510	0.4249	0.7980
3/100	41s 415ms/step	0.5069	0.7827	0.3790	0.8030
99/100	42s 417ms/step	0.2656	0.8907	0.2757	0.8850
100/100	42s 418ms/step	0.2876	0.8733	0.2665	0.8970

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Our study shows a significant improvement over our previous model, with an amazing overall validation accuracy of 90%. Additionally, the low validation accuracy and close proximity to the train suggest that the model is not overfitting, which is a good indicator. So that we can subsequently assess this model's performance using test data, let's move on to saving it to disc.

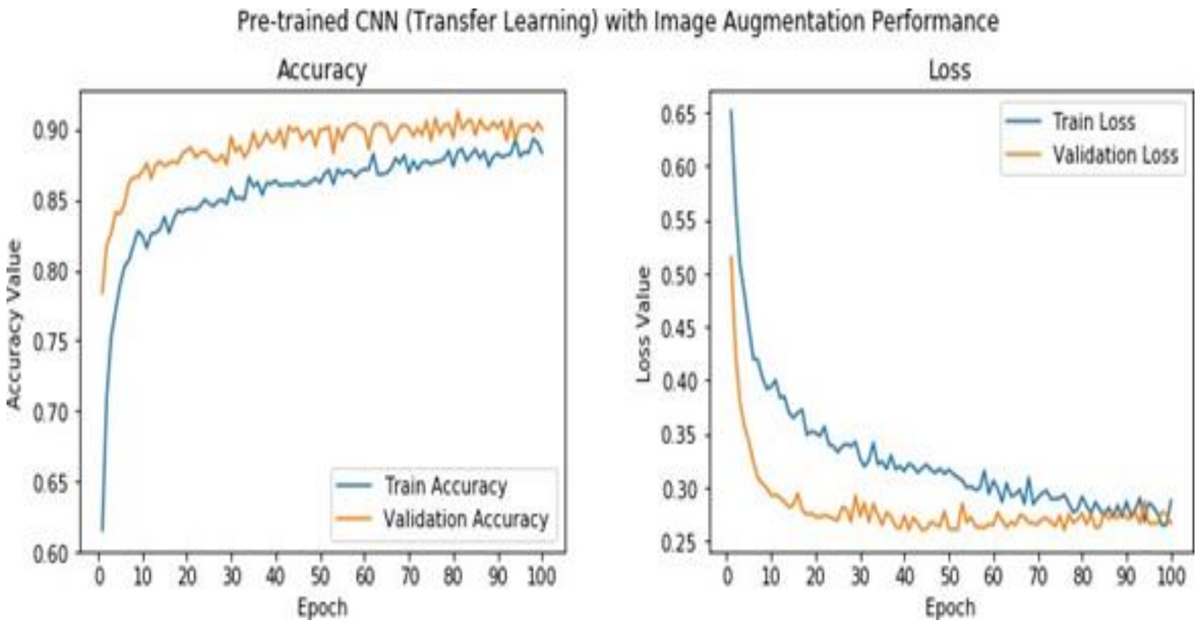

Fig. 1.2: Pre-trained CNN (feature extractor) with Image Augmentation Performance

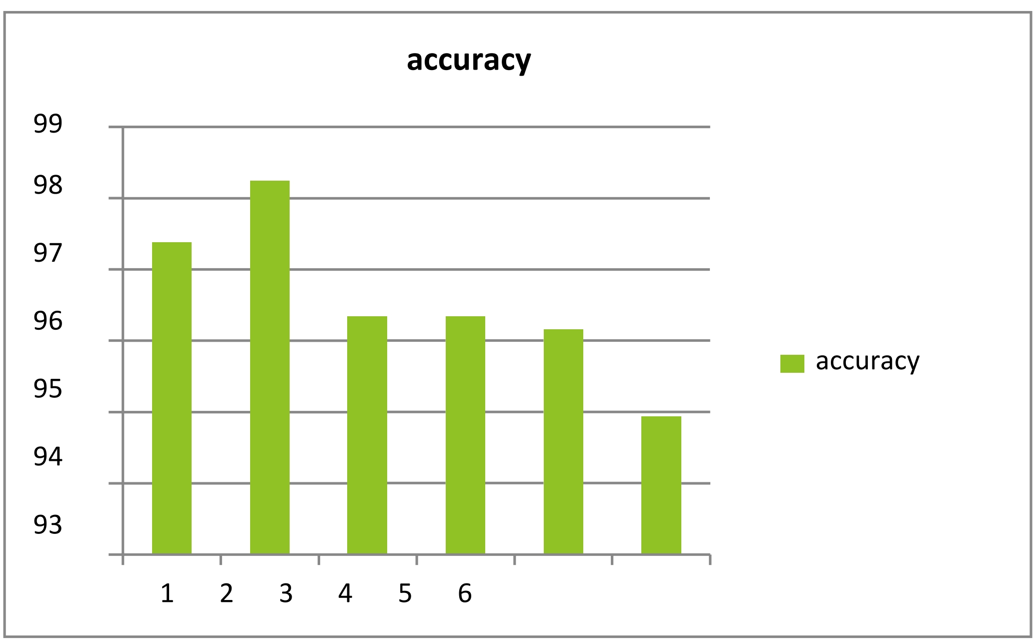

Fig. 1.3: Performance Evaluation chart – Accuracy – ResNet50

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In Fig. 1.3, Accuracy level is plotted using the Table 1.1 and finally measures that FENUGREEK (category 2) is having high accuracy level when compared with all the other categories.

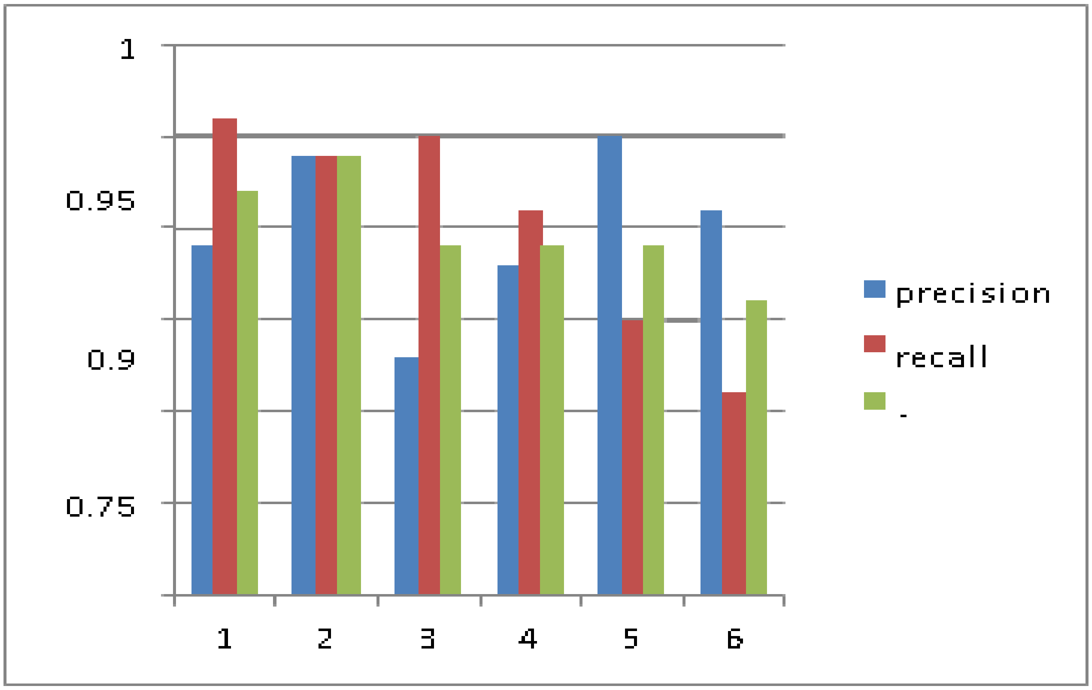

Fig. 1.4: Performance Evaluation chart – (Precision, Recall, F1-score) – ResNet50

In Fig. 1.4: Precision, Recall and F1-Score is plotted in the chart.

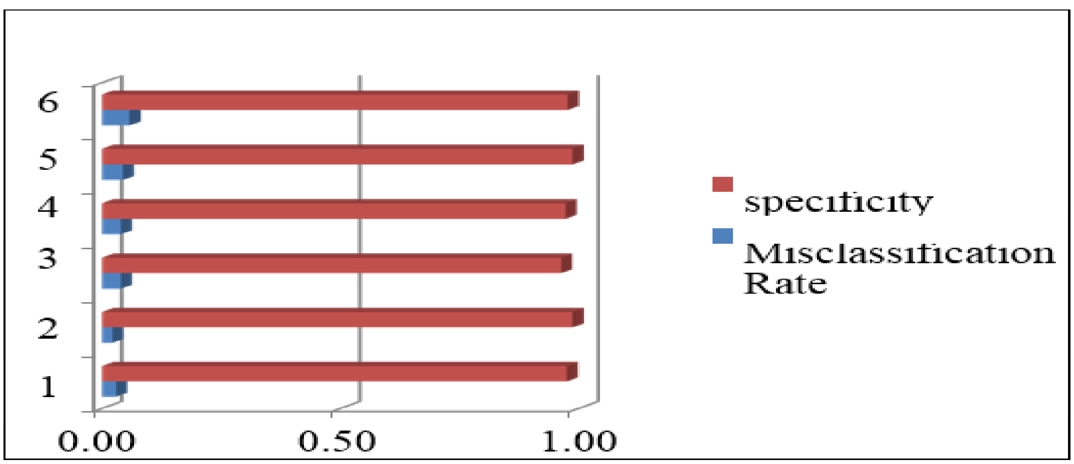

Fig. 1.5: Performance Evaluation chart - (Specificity, Misclassification Rate) – ResNet50

In Fig. 1.5 Specificity (TNR), Misclassification Rate is plotted. Using the same Plant dataset, the Resnet50 is compared with AlexNet, GoogLeNet, ResNet18(), ResNet34(),

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ResNet101, ResNet152 with the following measures-ACCURACY, PRECISION, RECALL, F1 SCORE, ERROR, SPECIFICITY for each category.

Table 1.4 Comparison Results with AlexNet, GoogleNet, ResNet18,ResNet34, ResNet50, ResNet101, ResNet152

Network	Accuracy
ALEXNET	82.20
GOOGLENET	84.56
RESNET18	87.09
RESNET34	87.71
RESNET50	89.70
RESNET101	88.20
RESNET152	88.50

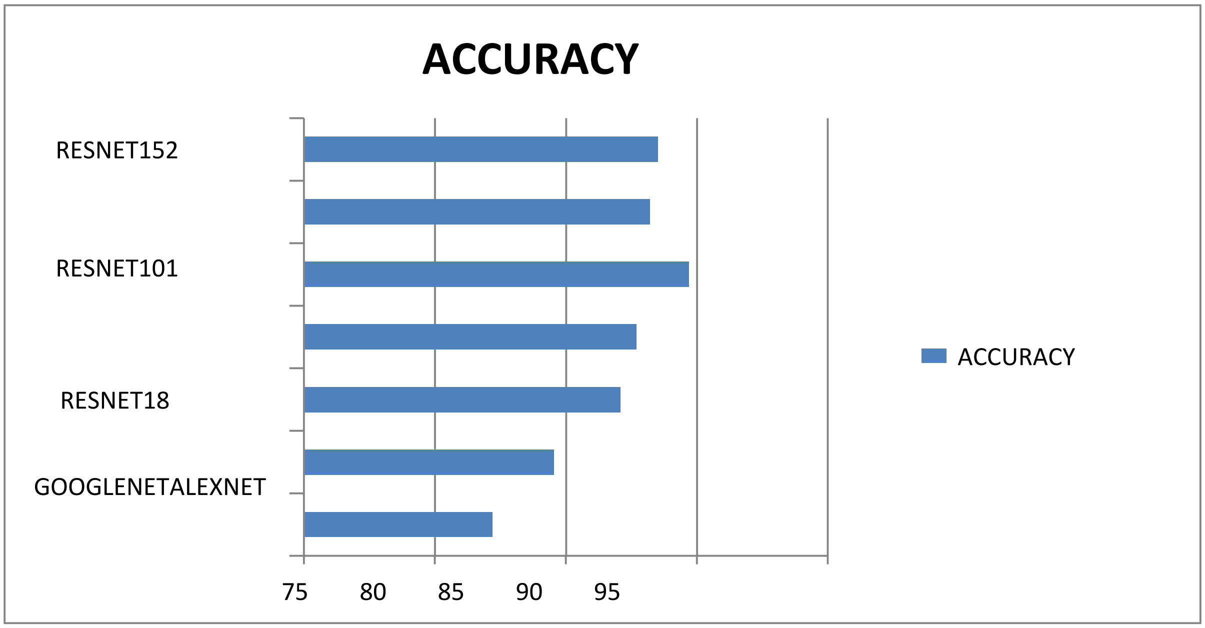

Fig. 1.6 Comparison Result

Fig. 1.6 shows the comparison result chart in which the accuracy of ResNet50() is higher than other network.

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Table 1.5: Comparative Measures with various network architecture withrespect to Accuracy, Precision, Recall, F1 Score

Network	Category	Accuracy	Precision	Recall	F1 Score
ALEXNET	AVARAI	96.58	0.85	0.94	0.89
	FENUGREEK	94.01	0.85	0.8	0.82
	GUAVA	94.69	0.82	0.86	0.84
	NAVAL	94.01	0.81	0.83	0.82
	NEEM	92.81	0.81	0.77	0.79
	TULSI	93.66	0.85	0.79	0.82
GOOGLENET	AVARAI	97.43	0.9	0.95	0.92
	FENUGREEK	94.17	0.83	0.83	0.83
	GUAVA	95.03	0.81	0.88	0.84
	NAVAL	95.71	0.82	0.91	0.86
	NEEM	93.65	0.86	0.78	0.82
	TULSI	93.14	0.86	0.76	0.81
RESNET18()	AVARAI	97.62	0.97	0.9	0.93
	FENUGREEK	95.25	0.83	0.88	0.85
	GUAVA	96.43	0.83	0.95	0.89
	NAVAL	96.1	0.96	0.83	0.89
	NEEM	94.57	0.88	0.81	0.84
	TULSI	94.23	0.77	0.87	0.82
RESNET34()	AVARAI	97.95	0.92	0.96	0.94
	FENUGREEK	95.73	0.81	0.92	0.86
	GUAVA	96.08	0.88	0.89	0.88
	NAVAL	95.9	0.96	0.83	0.89
	NEEM	95.9	0.91	0.85	0.88
	TULSI	93.86	0.78	0.84	0.81
RESNET50()	AVARAI	97.38	0.89	0.96	0.92
	FENUGREEK	98.25	0.94	0.94	0.94
	GUAVA	96.34	0.83	0.95	0.89
	NAVAL	96.34	0.88	0.91	0.89
	NEEM	96.16	0.95	0.85	0.89
	TULSI	94.94	0.91	0.81	0.86
RESNET101()	AVARAI	97.95	0.92	0.96	0.94
	FENUGREEK	95.72	0.81	0.91	0.86
	GUAVA	96.06	0.88	0.89	0.88
	NAVAL	95.89	0.96	0.82	0.89
	NEEM	95.89	0.91	0.85	0.88
	TULSI	93.84	0.79	0.84	0.81
RESNET152()	AVARAI	97.79	0.92	0.95	0.93
	FENUGREEK	96.26	0.93	0.86	0.89
	GUAVA	97.45	0.91	0.94	0.92
	NAVAL	95.93	0.95	0.83	0.89
	NEEM	95.42	0.81	0.91	0.85
	TULSI	94.06	0.79	0.84	0.81

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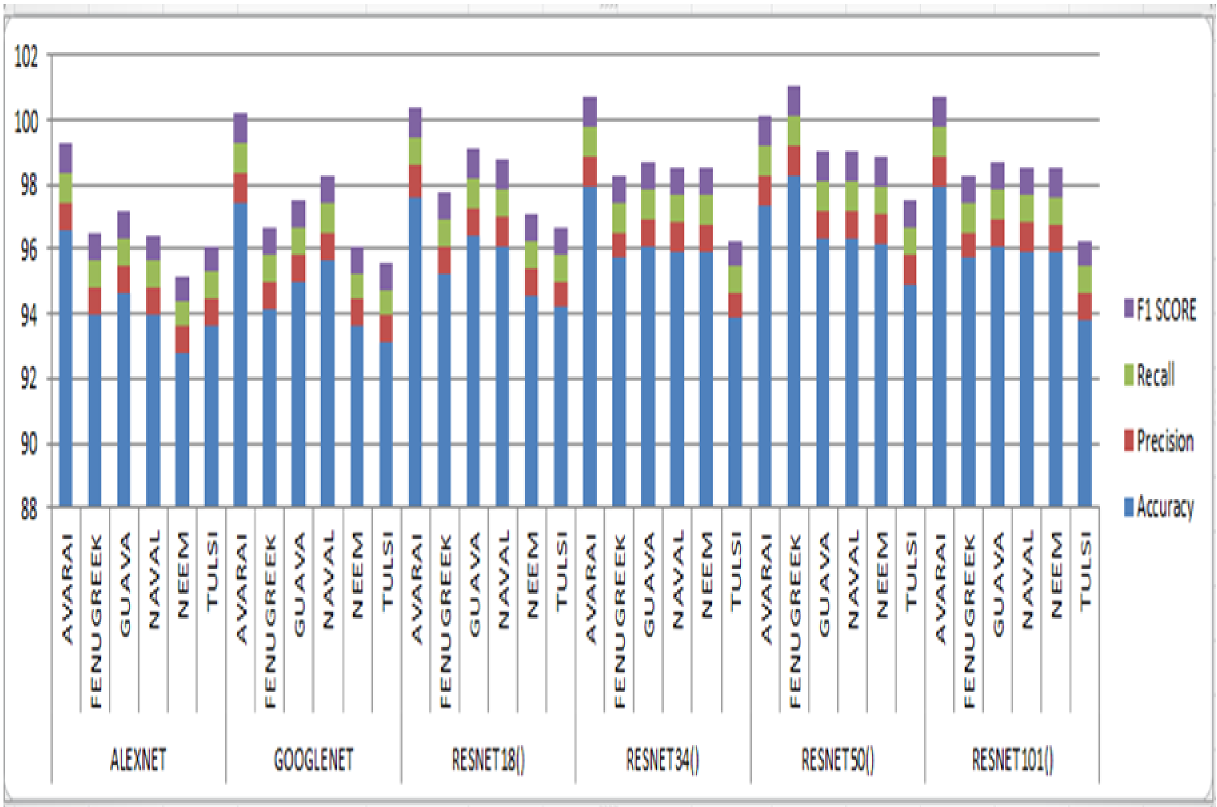

Fig. 1.7: Comparison Chart according to the performance metrics

From Fig. 1.7 Comparison chart according to the performance metrics (Accuracy, Precision, Recall and F1 score) is plotted. Deep Learning CNN-based algorithms have been used for this purpose and have demonstrated to be the most accurate. The network's classification accuracy 89.50%, with the highest result coming from pre-trained ResNet50 combined with SVM. Only using CNN for classification can take a long time to train but only a short time to identify, however the testing time for the ResNet50() based technique is fairly long.

3. CONCLUSION AND FUTURE WORK

Based on the results, it can be seen that our suggested model ie applying Pre-trained ResNet50 architecture with data augmentation by comparing other CNN architecture outperforms all other methods in terms of training and testing accuracy and with a validation accuracy of 89.5%. When compared with our basic CNN model, our best model is our pre-trained ResNet50 architecture. Finally, the result indicates that ResNet50 is the best pre-trained model, with an accuracy of 89.70% when compared with AlexNet (82.20), GoogLeNet (84.56), ResNet18 (87.09), ResNet34 (87.71), ResNet101(88.20) and ResNet152 (88.50).

The neural networks are also distributed over numerous CPUs, consuming significantly more resources. Overall, the best performance comes from utilising pre- trained

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ResNet50 with SVM. The future work of this study is again to improve the performance, we will fine-tune the ResNet50() model by applying transfer learning to solve vanishing gradient problem.

The primary focus of this research is to train a CNN system and successfully classify various objects into distinct classes. Throughout this study, it is important to note that each image within the dataset exclusively comprises a single object. All these implementation work were implemented using MATLAB and Python. The extended scope of this work will be identification of plant diseases through Deep Learning method by extracting the characteristics of diseased parts and to classify the target diseases areas which would contribute to a better accuracy.

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