Affixing Ocular Disorder Detection of Diabetic Retinopathy for Ophthalmoscopy exerting Deep Learning and Transfer Learning Paradigm

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Abstract— **The reticence of ocular disorder in the community has been a major deterrent to one being visually impaired before getting diagnosed. The genesis lies deeper in the inefficiency of ophthalmologists configuring the root cause of defacement. One such predicament is Diabetic Retinopathy (caused due to changes in retinal blood vessels) which is in an upsurge causing apprehension for vision loss. Meagre research has been carried out using different learning techniques giving a vague prospect of a cogent solution. In this paper, we have subsumed potent Deep Learning (8-Layer CNN) and Transfer Learning architectures (MobilenetV2, DenseNet121, InceptionV3, ResNet50, VGG16) for deducing the potentiality of a person having Diabetic Retinopathy using a 02-Class model with collating varied dataset namely APTOS 2019 and HRF Image Database begetting pre-eminent accuracy results with metrics comprehended such as f1 Score, Area Under Curve, Cohen's Kappa Score for corroboration.**

Keywords — Convolutional Neural Network (CNN); Area Under Curve (AUC); Asia Pacific Tele-Ophthalmoscopy Society (APTOS); High-Resolution Fundus (HRF) Database; Visual Geometry Group (VGG).

I. INTRODUCTION

As claimed by the World Health Organization (WHO), 422 million people across the globe are agonized of diabetes and majorly inclined towards low-income and middle-income countries imputing 1.6 million fatalities each year and accountable for 2.6% of Global Blindness. The visual affliction caused due to diabetes is well known as Diabetic Retinopathy. Diabetic Eye Disease refers to a congregation of eye quandaries that can occur as an outcome of Diabetes. It can stimulate severe vision loss or even blindness. According to National Center for Biotechnology Information (NCBI), Diabetic Retinopathy has a consequential repercussion over Global Health Systems and this malady will leap from 126.6 million in 2010 to 191.0 million in 2030 along with Vision-Threatening Diabetic Retinopathy (VTDR) escalating from 37.3 million to 56.3 million if elicit manoeuvre is not executed. It's the most habitual diabetic eye disease and is a prominent inducement of blindness in a person with diabetes.

The retina is the light-sensitive tissue at the fundus of the eye and a healthy retina is obligatory for optimal vision. In some people with Diabetic Retinopathy, blood vessels of the retina might distend and emanate fluid or blood, while in some, abnormal new blood vessels augment on the surface of the retina. Ophthalmologists use fundus imagery for detecting a person possessing Diabetic Retinopathy but due to certain anthropoid constraints, it's difficult to determine its existence. Scanty architectures have been extrapolated for automating the process over this domain overlooking its exigency. For the frontal eyes' deformity detection, there are sundry methodologies but the contrary is not concordant. As a result, the motivation behind this paper is to put a step forward for alleviating the process of fundus detection and thereby palliating the process for Ophthalmologists as well as the person suffering from the fundus lurgy. Reckoning the effectiveness of promptly applied models, in this proposed work, we have tried to induce a stratagem encompassing best Deep Learning and Transfer Learning Approaches through varied research over this turf based on model complexity and real-time usability for actuating the process for instantaneous wield. A comparative analysis has been carried out between these models determining the best outlook for Diabetic Retinopathy Detection over the amalgamation of APTOS 2019 and HRF Image Database which consists of the affected and unaffected fundus portrayal.

II. LITERATURE SURVEY

Initiating the discernment for the impact of Diabetes over ocular phenomenon led to various researches for optimizing the process for consummating optimal results. Diabetic Retinopathy Detection and Prognosis Evaluation employing Ensemble Deep Convolutional Neural Networks have been toted out with detection accuracy of 78.88% and prognosis evaluation accuracy of 61.9%, as it lagged the data pre-processing outlook **[1]**. Furthermore, the Pilot diagnosis of Diabetic Retinopathy has been evaluated using Random Forest Algorithm achieving an accuracy of 94.38%, but the accuracy could've been improved by editing the features of this algorithm **[3]**. Transfer Learning architecture VGG16 has been incorporated getting Area Under Curve (AUC) = 0.80 for a 05-Class Classification Model and would have done better if more training data would have been induced **[5]**. Convolutional Neural Network (CNN) has been persuaded for the presence and severity of Diabetic Retinopathy Detection with a validation accuracy of 74% which can be improved procuring different paradigms of learning **[7]**. Moreover, the Digital Image Processing technique has been evaluated for infirmity detection over the DiaretDB database with a TPR score of 0.87 which can be improved using various Machine Learning outlooks and pre-processing the database used **[8]**. Micro-Aneurysm detection which is the initial stage of Diabetic Retinopathy has been assessed over MATLAB Neural Network Pattern Recognition Tool (NPRTOOL) getting an accuracy of 56.3% due to low resolution of images and less proportion of Training Data **[11]**. Pre-Diagnosis of Diabetic Retinopathy using Blob Detection through feature extraction has also been inferred with an accuracy of 83% lagging with effective classification prospects **[14]**. Intensity-based optic disc detection for automating diabetic retinopathy through various anomalies in an affected person **[15]**. However, an impactful elucidation hasn't been imposed, and yet our approach explicitly retaliates the prowess of the Deep Learning and Transfer Learning Techniques (8-Layered CNN, MobileNetv2, DenseNet121, InceptionV3, ResNet50, VGG16) over an effectively blended two gilt-edged dataset of APTOS 2019 and HRF Image Database.

III. METHODOLOGY USED FOR ANALYSIS

As referring to the literature survey, we solicited a 02-Class Model instead of a 05-class model. This is because the 05-Class model seemed to be a palaver as it didn't give optimum results. After all, the severity of the disease is subjective and can be adjudicated by the Ophthalmologists themselves. Certainly, it's salient to gauge the existence of disease at the embryonic stage rather than its extremity. So expediting the process we engulfed the 05-Class Dataset of APTOS 2019 as in Fig.1 to a 02-Class Dataset as in Fig.2.

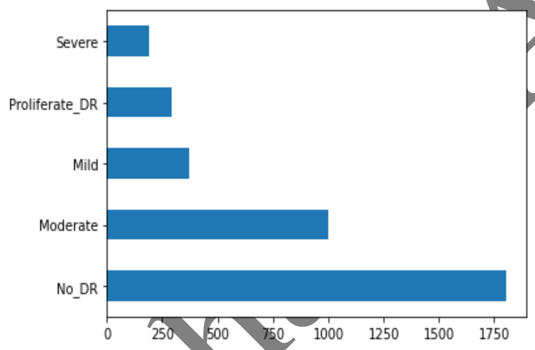

Fig.1. 05-Class Image Data with the denomination of Severity of Diabetic Retinopathy.

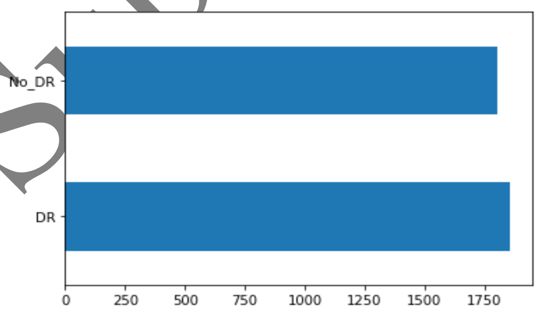

Fig.2. 02-Class Image Data with the denomination of the absence/presence of Diabetic Retinopathy.

Further, we assimilated different models for analysis from Deep Learning and Transfer Learning Paradigm based on their size, several parameters and depth of models for better ensue and rapid computation.

Basic factors impacting the performance of the model:

- **More Parameters:** (i.e., Learnable Weights, Bigger Network) – Slower than a model with Fewer Parameters
- **More Recurrent Units:** Slower than a Convolutional Network, which is slower than a Fully-Connected Network
- **Complicated Activation Functions:** Slower than simple ones, such as ReLU
- **Deeper Networks:** Slower than shallow networks (with the same number of parameters)

Contemplating over above factors we constrained ourselves over certain models which are mentioned below:

- **Deep Learning Proposed Model:** 8-Layer Convolutional Neural Network.
- **Transfer Learning (Pre-trained) Models:** Transfer Learning is a Machine Learning approach where a model marshalled for a particular task is reutilized as the initial point for a model on another task. These models are pre-trained over 1000 Classes of ImageNet Database of 224x224 Image Dimension which can be further used for different Classification Problems. When using these models, one should not change the domain of the problem i.e., these models are optimal for Classification Problems only.

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
5.	VGG 16	528MB	138	23

Table.1. Comparison between Pretrained Models over different Criteria.

Let's see the architecture of each model:

1. 8-Layer CNN: The Deep Learning architecture is 8-Layer Convolutional Neural Network with 8 convolutional layers abridged with different filter sizes for feature extraction, Max Pooling (for preserving features), Flattening, and margining with two fully-connected layers emanating the output as shown in Fig.3.

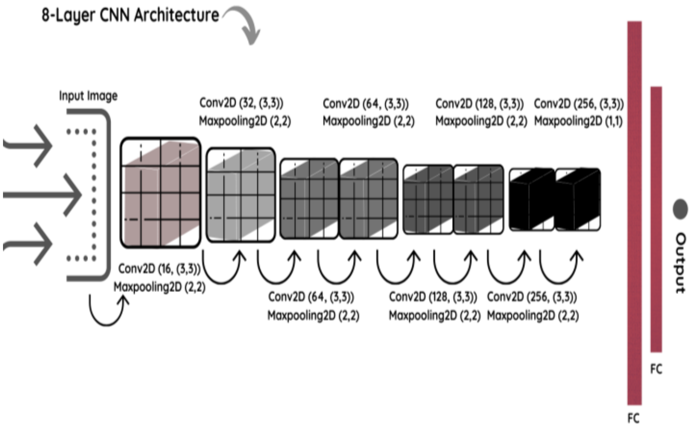

Fig.3.Proposed 8-Layer CNN Architecture.

2. MobileNetV2: The architecture consists of 02-Types of Blocks namely: a] Residual Block with Stride = 1, b] Downsizing Block with Stride = 2. The Initial Layer comprises of 1x1 Convolution collating ReLU6 and the Second Layer is the Depth-wise Convolution as shown in Fig.4. The Third Layer is another 1x1 convolution excluding any non-linearity.

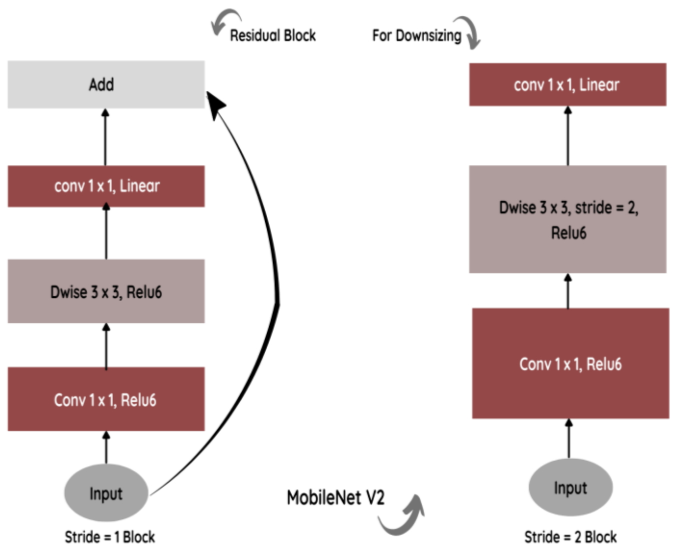

Fig.4. MobileNetV2 Architecture with 02-Blocks of Stride=1 and Stride =2 known as Residual Block and Downsizing Block Respectively.

3. DenseNet121: DenseNet initiates with, a] Basic convolution and pooling layer, b] A Dense Block escorted by Transition Layer, c] Dense Block followed by a Transition Layer (*2) and, d] Ultimately a Dense Block followed by a Classification Layer as shown in Fig.5. Here 121 denotes the depth of the model as mentioned in Table.1. as a result, entitled DenseNet121.

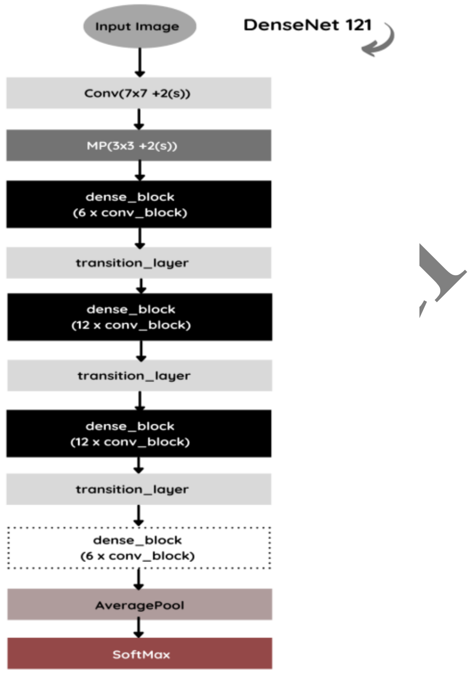

Fig.5. DenseNet121 Architecture with multiple dense blocks followed by multiple transition layers and a Classification Block

4. InceptionV3: The architecture is a Convolutional Neural Network from the Inception Domain making assorted furtherance inducing Label Smoothing, Factorized 7x7 Convolutions, and the use of Auxiliary Classifier to disseminate label particulars, as sliding down the network (Incorporating Batch Normalization for the layers along with the side head) as shown in Fig.6.

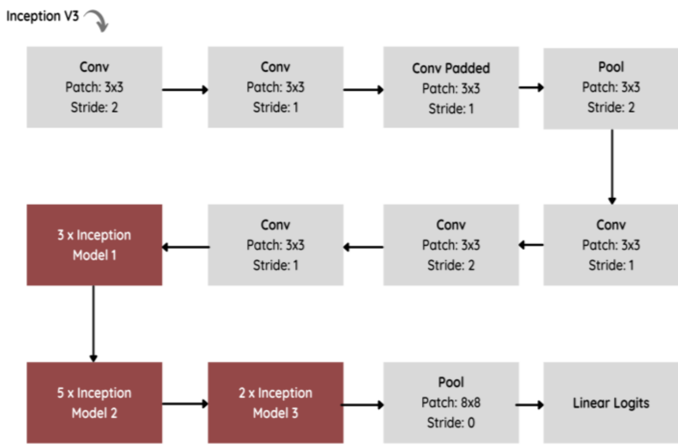

Fig.6. InceptionV3 Architecture with Batch Normalization and ReLU used after Conv Layer.

5. ResNet50: ResNet can restructure network layers in terms of residual learning functions with a mapping reference to the input layer. In ResNet50, as shown in Fig.7, the layers which are stacked, instantaneously fit the desired mapping i.e., Residual Mapping. ResNet50 subsides the Vanishing Gradient effect by incorporating a substitute shortcut path to bypass. The Identity Mapping in Fig.8, permits the model to flow through discretionary layers. This assists the model to subjugate overfitting problems over the training set.

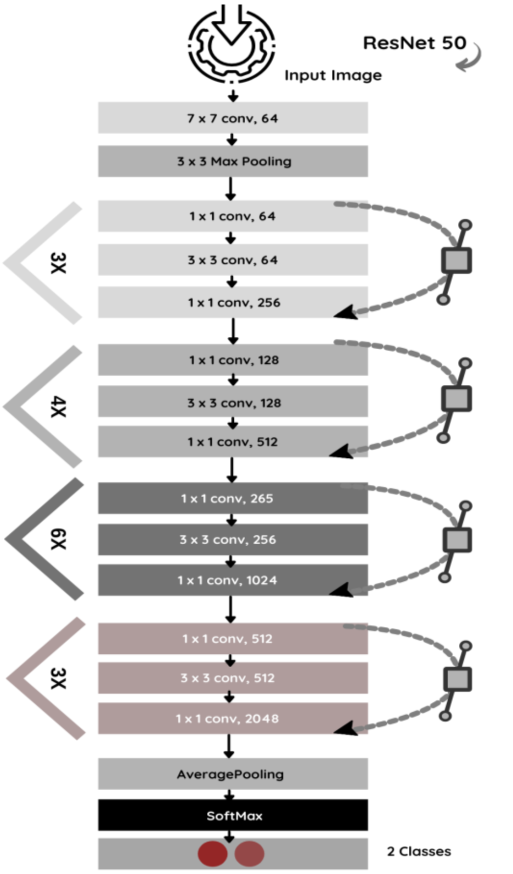

Fig .7. ResNet50 Block Diagram with Identity Mapping.

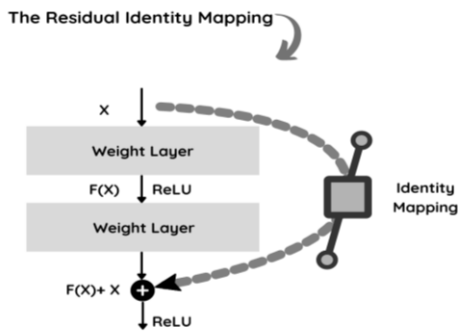

Fig .8. Residual Identity Mapping in ResNet50 Network.

6. VGG16: In this architecture, we have initiated two layers possessing 64 Channels of 3x3 filter size with the same padding and the process is continued by altering the channel size and inculcating Max-Pooling and Flattening. Further, there are 3 fully connected layers with an output of (1,4096) vectors in which the 3rd layer is passed to the SoftMax layer for normalization of classification vectors as shown in Fig.9.

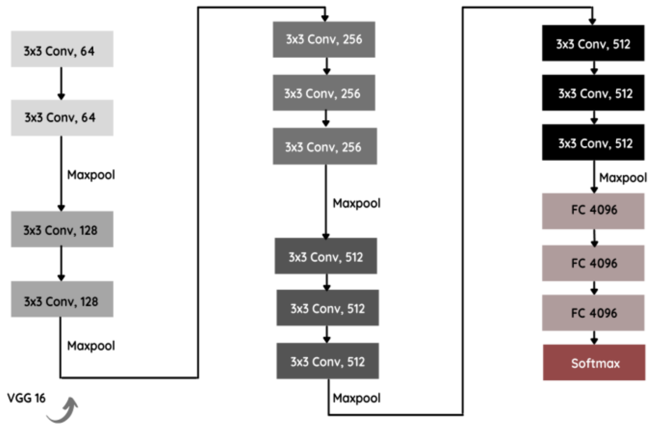

Fig .9. VGG16 Block Architecture.

These architectures are best in terms of computation and feasibility with different depth and parameters engulfed. The diagrammatic outlook is manifested for each model in terms of modus operandi.

IV. IMPLEMENTATION AND TOOLS

a. Dataset Utilized and Dataset Source: The dataset has been speculated from the open dataset of APTOS 2019 and HRF Image Database which consists of various high-resolution imagery of 4000 instances and has been aggregated for ideal results. As we're training over pre-trained models, we revamped our dataset by resizing it into 224x224 and applying Gaussian Filter for image smoothing and noise filtering. The demonstration of the dataset is shown in Fig.10.

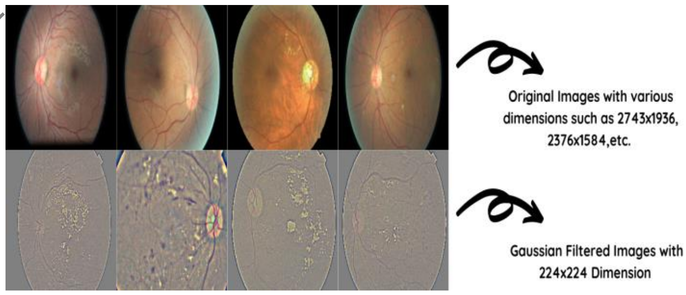

Fig .10. Dataset Visualization containing Images from APTOS2019 and HRF Image Database along with Gaussian Filtered Images.

b. Frameworks Used: TensorFlow and Keras have been used to instantiate the training process of the models. All the models have been trained over 100 epochs utilizing these frameworks with CPU processing itself.

c. Metrics Implemented for Gauging Accuracy: The training and validation accuracy won't be enough to gauge the efficiency of the models. So, we consolidated various metrics such as Precision, Recall, F1-Score, and Accuracy using Confusion Matrix for every pre-trained model used as shown in Fig.11. We also encapsulated Cohen's Kappa Score for the estimation which measures the agreement between two evaluators rating the same thing, corrected for the probability that the evaluators may agree by chance. A score of 0 means dissimilar agreements and a score of 1 means that there is a complete agreement between the evaluators.

Cohen's Kappa coefficient formula: $\mathbf{K = P_0 - P_e / 1 - P_e}$
Where, K= Cohen's Kappa Coefficient, P_0 = Probability of Agreement, P_e = Probability of Random Agreement

Also, Area Under Curve (AUC) has been speculated for analysing the efficacy of the model which represents the Degree or Measure of Separability. An excellent model has AUC near to 1 pointing towards a good separability and a poor model has an AUC near 0 which intimates the awful Measure of Separability.

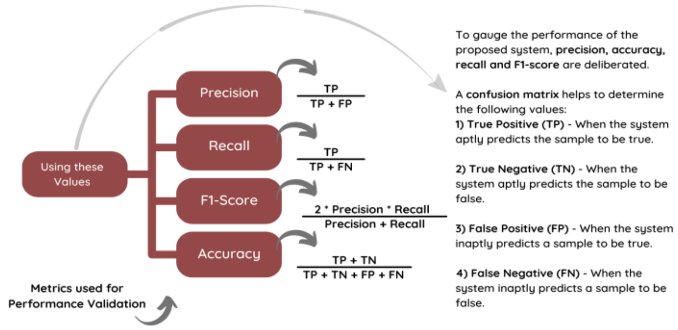

Fig .11. Metrics Evaluation Process for Precision, Recall, F1-Score, Accuracy.

d. Implementation Flow: Demonstrated in Fig.12.

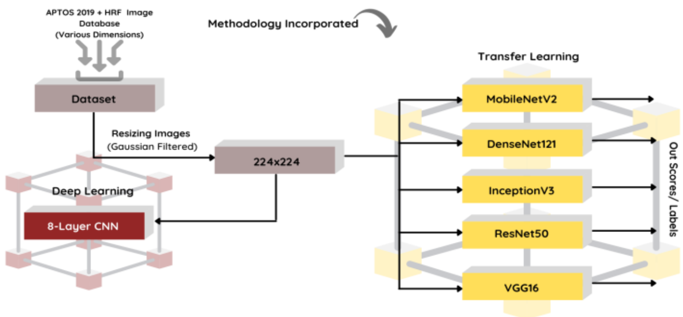

Fig .12. Implementation Structure.

V. EXPERIMENTAL RESULTS AND ANALYSIS

Post-implementation we got overwhelming and ideal results as shown in Fig.13, Fig.14, and Fig.15. The Graphs show the embracing demonstration obtained and a great vista in action giving an upper hand in automating the Diabetic Retinopathy Detection for Ophthalmologists.

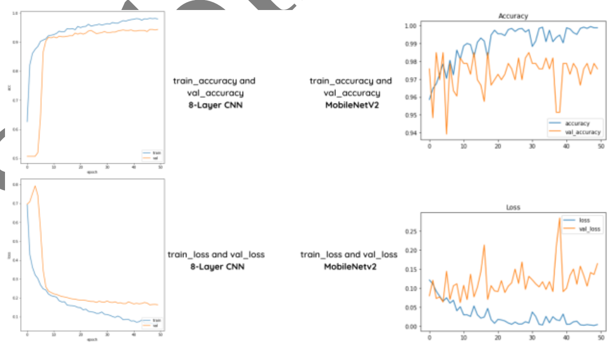

Fig .13. Graphical Results for 8-Layer CNN and MobileNetV2.

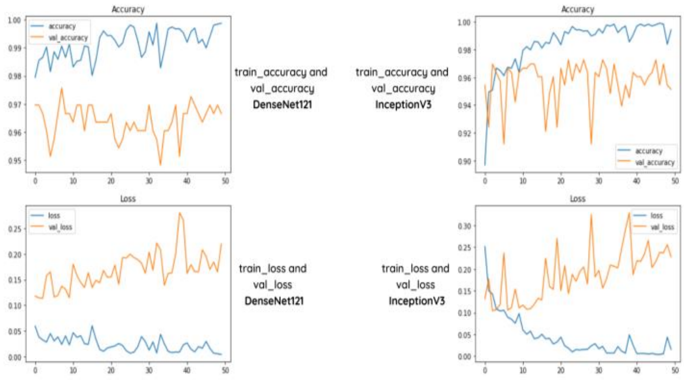

Fig .14. Graphical Results for DenseNet121 and InceptionV3.

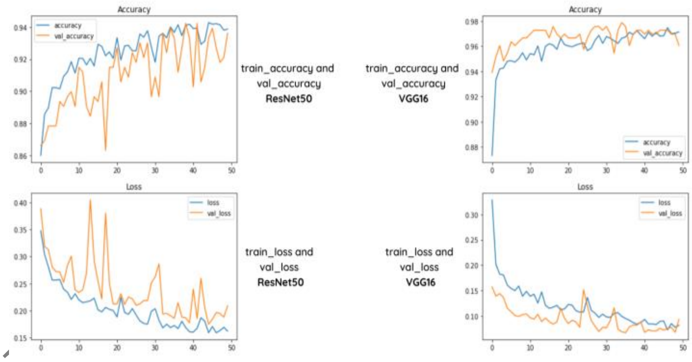

Fig .15. Graphical Results for ResNet50 and VGG16.

Model	Train-Accuracy	Validation-Accuracy	Test-Accuracy
8-Layer CNN	98.28%	94.36%	95.45%
MobileNetV2	99.87%	97.87%	96.73%
DenseNet121	99.88%	96.66%	95.91%
Inception V3	99.37%	95.14%	95.37%
ResNet50	94.19%	93.62%	92.92%
VGG16	95.45%	96.66%	95.37%

Table.2. Comparative Analysis of Different Models based on Train, Validation, and Test Accuracy.

Model	AUC	Precision	Recall	F1-Score	Cohen Kappa Score
8-Layer CNN	0.9718	0.95456	0.9545	0.9545	0.9091
MobileNetV2	1.0000	0.96739	0.9673	0.9673	0.93425
DenseNet121	0.9999	0.95948	0.95913	0.95913	0.91827
InceptionV3	0.9990	0.95485	0.95368	0.95369	0.9074
ResNet50	0.9838	0.92946	0.92916	0.9292	0.85795
VGG16	0.9956	0.9544	0.95368	0.95369	0.90737

Table.3. Comparative Analysis of Different Models based on Confusion Matrix.

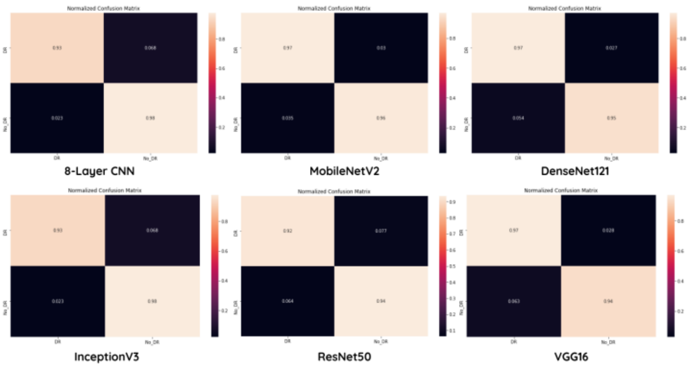

Fig .16. Confusion Matrix for 8-Layer CNN, MobileNetV2, DenseNet121, InceptionV3, ResNet50, VGG16.

VI. CONCLUSION AND FUTURE SCOPE

From the above elucidation, we can infer that all the models performed exceptionally well when juxtaposed with the models in our Literature Survey. MobileNetV2 being lightweight and containing fewer parameters performed phenomenally and gave us an insight into a computationally feasible panorama. Furthermore, 8-Layer CNN, DenseNet121, and Inception V3 proposed a proximate vista in terms of Accuracy. The analysis got us to a model which we would incorporate for real-time malady detection i.e., MobileNetV2 due to its nonpareil output. Although, ResNet50 and VGG16 did well, due to increased depth they would be a computationally tedious option.

The real-time fundus imagery system homogenized with this architecture forming a one-shot system for Diabetic Retinopathy Detection would be a great future scope and would benefit Ophthalmologists and thereby people suffering from Diabetes for its early discernment.

More data can be assimilated for more accurate results as data remains the biggest constraint in creating a medical automation system.

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