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Harnessing Deep Learning Methods for Detecting Different Retinal Diseases: A Multi-Categorical Classification Methodology

Dr. P. Manikandaprabhu[1]; S.S.Subaash[2]
Assistant Professor[1]; PG Student[2]
PG & Research Department of Computer Science,
Sri Ramakrishna College of Arts & Science, Coimbatore, India

Abstract:- Medical image classification plays a vital part in identifying and detecting diseases. Vision impairment affects 2.2 billion individuals globally, with cataracts, glaucoma, and diabetic retinopathy as major contributors. Timely diagnosis, crucial for effective treatment, often relies on imaging like color fundus photography. This study tackles multi-class classification challenges in retinal diseases using MobileNetV2. Traditional CNN models struggle with accuracy and efficiency, prompting the exploration of lightweight architectures. Leveraging MobileNetV2's efficiency, the aim is to improve diagnosis using a comprehensive ocular disease dataset. By integrating deep learning with conventional methods, growing challenges in ophthalmological analysis are addressed. The research underscores the importance of collaborative efforts in dataset curation, architecture design, and model interpretability to advance the multi-class classification of retinal diseases.

***Keywords**:- Color Fundus Photography, Classification, Deep Learning, Diabetic Retinopathy, Medical Image Processing, Multi-Class Classification.*

I. INTRODUCTION

As per the World Health Organization (WHO), more than 2 billion people around the world are affected by various types of visual impairment [1]. This includes several eye diseases that can lead to blindness. Currently, major causes of visual disability are chronic diseases such as cataracts, diabetic retinopathy and glaucoma [2]. However, early diagnosis creates an opportunity for effective treatment of eye diseases. Color fundus photography (CFP), which captures images inside the eye, is primarily used to detect various eye diseases. Recently, neural network models [3, 4] models based on DL demonstrate promising results in the classification of the healthcare images and the detection of objects. This has led to extensive research on models based on convolutional neural networks for eye disease detection [5].

Analysis of retinal tissue using diverse imaging methods such as OCT (optical coherence tomography), fundus imaging, and fluorescein angiography is often done when evaluating someone's overall health. Fundus imaging is a less expensive, less invasive form of OCT imaging used to diagnose several eye diseases. Such conditions that ophthalmologists frequently diagnose using fundus imaging include diseases such as glaucoma, diabetic retinopathy and cataract [6]. Cataracts occur when the lens in the eye, which is normally clear, becomes cloudy, resulting in impaired vision similar to looking through frosted or fogged glass [7]. It is the top problem linked to diabetes and the main reason why adults lose their sight. This disease damages the blood vessels in the retina and causes vision loss. Early detection and early intervention can help minimize cases of blindness[8]. Glaucoma is a condition that affects the optic nerve and leads to the loss of side vision. [9]. In this study, I have a dataset containing normal images, diabetic retinopathy images as well as cataract and glaucoma involvement. There are about a thousand images per class collected from various image repositories.

Some approaches where deep learning (DL) techniques have been used involve massive medical data to help diagnose ophthalmologists. In addition, the interpretation of DL models for multi-class classification proves to be challenging. Furthermore, it is not easy to interpret DL models regarding multi-class classification. However, these difficulties can only be resolved if complex datasets are managed efficiently, robust DL architectures are designed, and model interpretability is improved. Previous research using traditional CNN models such as ResNet-50 or DenseNet121 showed that CNN-based methods had limitations in classifying eye disorders [9]. These algorithms present weaknesses in terms of accuracy, storage requirements, and processing speed because their mathematical operations are too complex.

In this research paper, an attempt has been made to address these issues using a lightweight model (MobileNet V2). In this case study, this model outperforms previous works in terms of both performance and accuracy. Three classifications have also been made for diseases that are potentially blinding. It is an efficient CNN architecture created by Google researchers [10]. It was introduced in 2018 as an upgrade to the original MobileNet, which offered higher speed and accuracy [11]. Figure 1 presents an instance of the pool image from the dataset used for this classification task.

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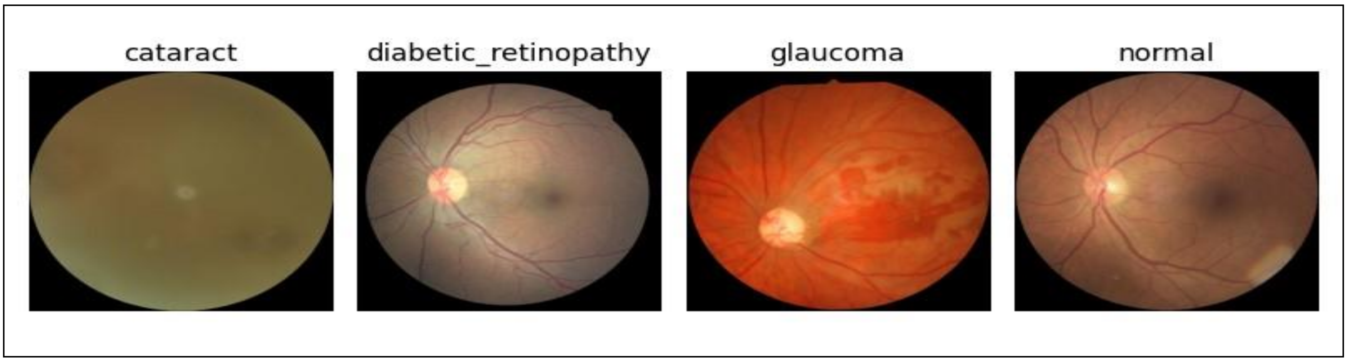

Fig 1: Fundus Image from Ocular Disease Dataset

II. RELATED WORK

Numerous studies have explored the classification of eye diseases, particularly focusing on stages crucial for diagnosing conditions that pose a risk of blindness. Researchers have introduced diverse models to address this classification task, with several authors contributing valuable insights and achieving promising outcomes.

E. Abitbol et al. [14] , this research aimed to assess the effectiveness of a Deep Learning (DL) model, specifically the DenseNet121 network, in distinguishing between SCR(sickle cell retinopathy), RVOs (retinal vein occlusions), diabetic retinopathy (DR) and normal eyes using UWFCFP (ultra-wide field color fundus photography). Utilizing a dataset from Creteil University Hospital comprising 224 images for each disease category, this model was trained for 10 epochs. Results revealed an overall accuracy of 88.40%, with an AUC of 88.50%.

Kangrok et al. [15] proposed a technique to detect diabetic retinopathy (DR) by automatically segmenting the ETDRS (Early Treatment Diabetic Retinopathy Study) 7 standard fields (7SF) to remove unwanted components from fundus images. Afterwards, these processed images were fed into a ResNet-34 model for disease classification, achieving an accuracy of 83.38%.

W. Xu et al. [16], focused on developing a deep learning-based intelligent system for classifying and diagnosing RVO (retinal vein occlusion) using fundus images. They utilized 501 fundus images from RVO patients and healthy individuals, training and testing their model on this dataset. Employing the ResNet18 framework, the images were divided into four groups for analysis. After training over fifty epochs, one of three attention mechanisms—SENet, CA, or CBAM—achieved impressive accuracy levels exceeding 94% in each of the four groups.

Ghoushchi, Saeid Jafarzadeh, et al. [17], introduced a combined method using genetic algorithms and fuzzy C-means to predict diabetic retinopathy (DR) from angiographic images of diabetic patients. This technique yielded a accuracy of 78%.

Sarki et al. [18], introduced a novel CNN model designed for classifying Diabetic Eye Disease (DED) into various categories. They utilized 1,748 data points from the Messidor, DRISHTI-GS, Messidor-2, and Kaggle cataract databases, enhancing retinal fundus images with contrast using mathematical morphology. Through optimization of model parameters and image quality enhancement, particularly with the RMSprop optimizer, this proposed model achieved an accuracy of 81% from the test dataset.

Zhuang et al. [19], proposed a WVA (weighted voting algorithm) for the classification of Diabetic Retinopathy (DR) disease. They developed and trained a network model to implement this algorithm, which was subsequently applied to hospital data for evaluation. The results demonstrated a high accuracy rate of 92%, indicating the effectiveness of their approach in accurately categorizing DR disease cases..

T. Babaqi et al. [20], aimed to differentiate between normal eyes and those affected by diabetic retinopathy, cataracts, or glaucoma. They utilized transfer learning and convolutional neural networks (CNN) for multi-class classification. Their dataset comprised approximately 4200 color photographs representing normal eyes, cataracts, diabetic retinopathy, and glaucoma. The images were resized from 512×512 to 224×224 pixels. The proposed approach utilized transfer learning with a pre-trained EfficientNet CNN architecture model, achieving an accuracy of 84% in classifying the eye conditions.

Azhar et. al. [21] utilized a combination of CNN for feature extraction and SVM for predicting cataract [21]. This hybrid system architecture was designed to effectively classify cataracts based on extracted features. By utilizing CNN for feature representation and SVM for classification, this model attained an impressive accuracy rate of 95.65%. This approach demonstrates the effectiveness of integrating deep learning techniques with traditional machine learning algorithms for accurate disease prediction and classification tasks.

While many studies have demonstrated promising outcomes in ocular disease classification from fundus images, only a limited number have tackled the challenge of simultaneously classifying multiple ocular diseases. Moreover, the development of an automated eye disease

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diagnostic tool requires a robust model trained comprehensively on various ocular diseases to accurately detect them from dataset with fundus images.

The models that have been discussed up to this point excel at specific classification or segmentation tasks. However, it lacked the versatility needed for a generalized ocular disease detection system. The aim of this proposed method is to classify eye diseases from color fundus photos with maximum efficiency. Although classification models based on Convolutional Neural Networks (CNNs) have been utilized in eye disease classification before, the most advanced models like MobileNetV2 and ResNet-50 have not been extensively explored in this context. These models have shown exceptional performance in classification tasks across diverse medical imaging datasets. Therefore, we chose to evaluate their performance on this dataset to determine their suitability for constructing an autonomous ocular disease detection system.

III. PROPOSED MULTI-CLASS RETINAL DISEASE CLASSIFICATION MODEL

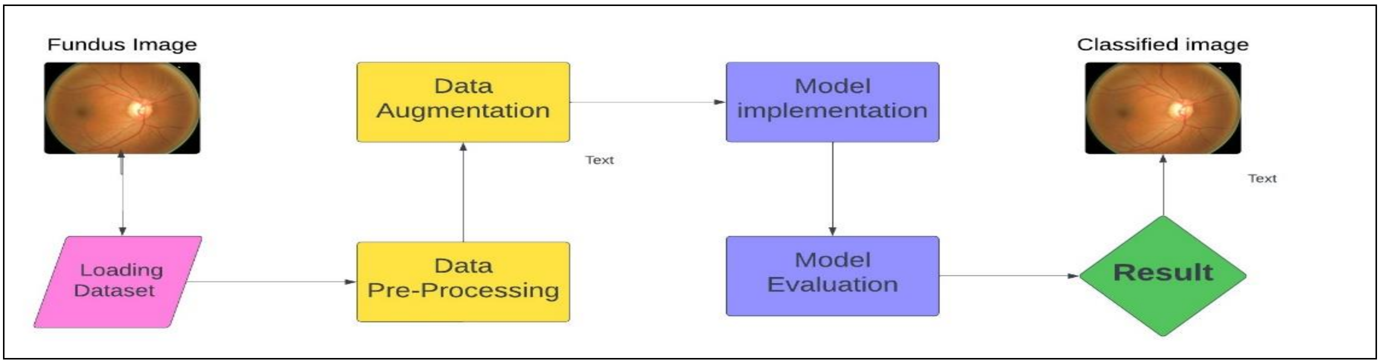

Fig 2: Work Flow of the Proposed Classification Model

A. Dataset Description

Fundus images were obtained from various databases including ODIR, DRISTI GS and ORIGA, and a total of 4136 images were selected for analysis in this study. These fundus images are classified according to four different eye diseases: cataract (C), glaucoma (G), diabetic retinopathy (DR), and normal (N). Table 1 shows the classification of the data.

Fundus imaging is an important technique in ophthalmology that provides detailed information the inner parts of the eye, such as blood vessels, retina and optic disc. These data are from multiple sources and represent a representative sample of the most common eye diseases such as glaucoma, diabetic retinopathy and cataract.

Table 1: Presenting the Distribution of Images in the Dataset

S.no	Number of Images	Class Name
1	935	Cataract
2	1163	Diabetic Retinopathy
3	876	Glaucoma
4	1062	Normal

B. Pre-Processing

It is an important preparatory step for dataset images in deep learning models[20]. This part highlights the importance of pre-processing in ensuring that data are uniform and fit with model architectures. It presents brief descriptions of some commonly used techniques which are covered in detail in the following sections.

- Resizing Images: Inconsistent dimensions of images may pose challenges to the training of the model. Dimensioning the images into say 224x224 pixels, helps make them uniform and compatible with deep learning models. This process simplifies computations and improves accuracy.
- Converting Color Space: Different frameworks deploy specific color spaces for their images. Conversion from BGR to RGB, a common representation, is vital since different color spaces must be aligned before they can be suitable for use in deep learning frameworks that enable accurate predictions by models.
- Normalizing Pixel Values: Pixel values usually range between 0-255 per channel for each color image. Normalizing these values between 0-1 helps to reduce redundancy and accelerate the training process of a model This ensures that there is similarity across input data thus better convergence as well as performance from a model.
- Appending Images and Labels: Ensuring consistency between images and labels is important for supervised learning purposes Storing pre-processed images with their corresponding labels.

C. Augmentation

To enlarge variety of datasets, augmentation is done by creating synthetic alterations in the original images. For example, rotation, shifting and flipping are processes that

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bring in variations thereby making the models to be more reliable in real world situations. Augmentation deals with over fitting, improves generalization and enhances model performance especially when there is little data for training.

After augmentation, the dataset is divided into training, testing, and validation set. The distribution of dataset following its splitting is shown in Table II. It uses training data for model training while validation data helps in hyper parameter tuning as well as performance monitoring. In addition to that, testing measures if a model can generalize on unseen items thus ensuring that it performs reliably.

Table 2: Distribution of the Images after Splitting the Dataset

Dataset	Number of Images	Image Shape	Number of Classes
Total	4036	(224, 224, 3)	4
Training	3228	(224, 224, 3)	4
Testing	808	(224, 224, 3)	4

D. Class Balancing

An unequal number of classes in the data sample leads to a situation when some categories have a very low number of instances relative to others. This makes this model biased towards the class which has more instances and it performs poorly on the few minority classes. To avoid this problem, class weights are determined based on individual counts for each class that is present. Consequently, the models give higher weightings to fewer examples while giving lesser weightings to more instances. These weights are then employed during training to adjust the loss function to favor minority classes and guarantee equal learning from any class regardless of its number. The introduction of class weights in the training process makes the model more sensitive about minor classes leading to better overall performance and an increased ability to generalize on unseen data.

E. Model

After preprocessing and data augmentation, the dataset undergoes division into training and testing subsets. These subsets are then utilized to calculate the performance of various pre-trained models and decide which model is suitable for this research based on its accuracy.

➢ *Classification Using MobileNetV2*

In this study, first, the MobileNetV2 model is used, a lightweight convolutional neural network architecture designed for efficient deep learning tasks. This image classification framework has an inverted residual structure, whereas the residual blocks incorporate thin bottleneck layers at both the input and output stages. Additionally, the convolutions employed in this model are especially lightweight, and its narrow layers lack non-linearity. During training, the Adam optimizer was used with specific parameters. Training the model extended over 30 epochs, allowing it to learn effectively to extract features and classify images. MobileNetV2 offers a range of alternates optimized for different needs, such as model size, speed, and performance. For this study, the standard MobileNetV2 architecture was selected due to its balance between compactness, computational efficiency, and accuracy. The structure of the MobileNetV2 model is shown in Figure 3.

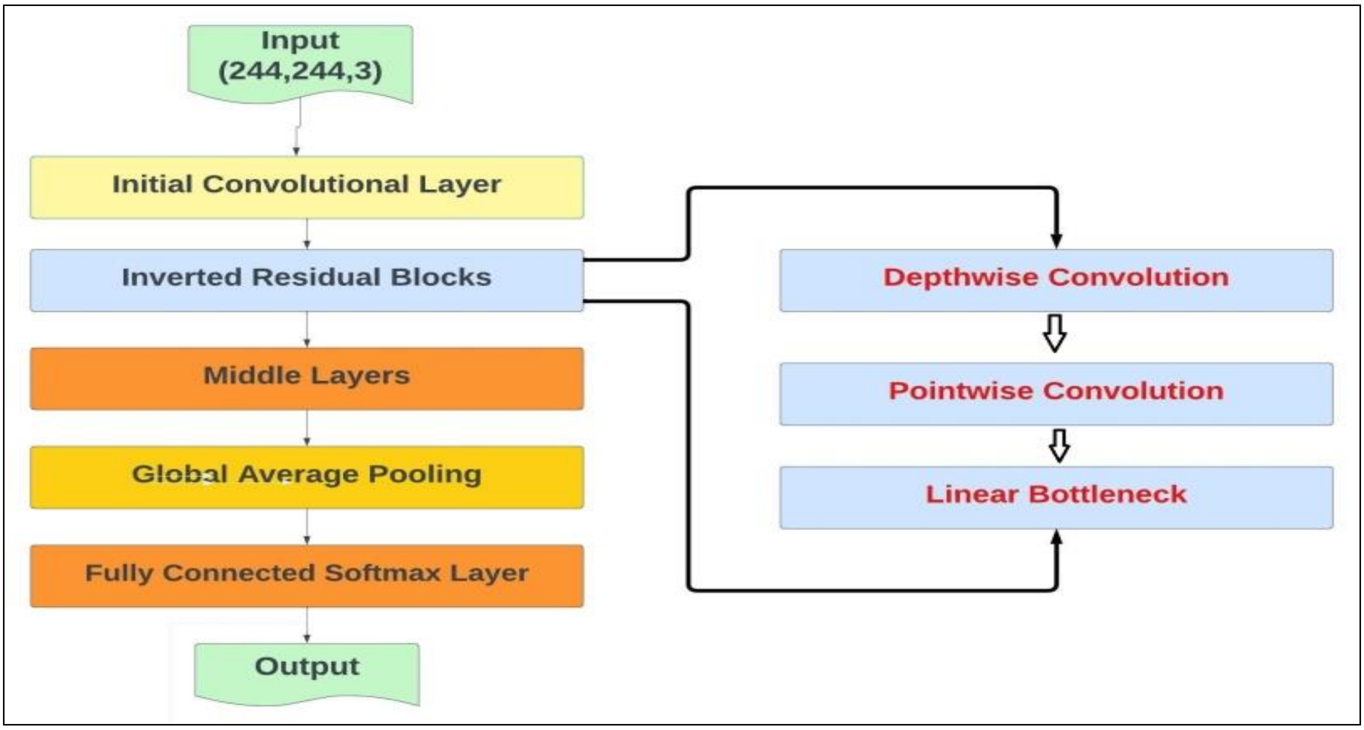

Fig 3: Mobile NetV2 Architecture

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To perform MobileNetV2 model for this provided data, first the dataset is imported into PyCharm environment. Following that, we imported the MobileNetV2 classification model, utilizing its pre-trained weights and architecture. The classification layers were added to the model and it is depended on the features extracted by the layers of MobileNetV2 up to the point before the flatten operation. Following that, the model is set up and configured with a loss function (Categorical Cross-Entropy). These allowed us to effectively train and evaluate the performance of the model using the provided data. Finally, to assess the efficiency of our model, we generated graphs depicting the accuracy and cross-entropy metrics across different epochs. Figure 3shows the structure of the MobileNetV2 model.

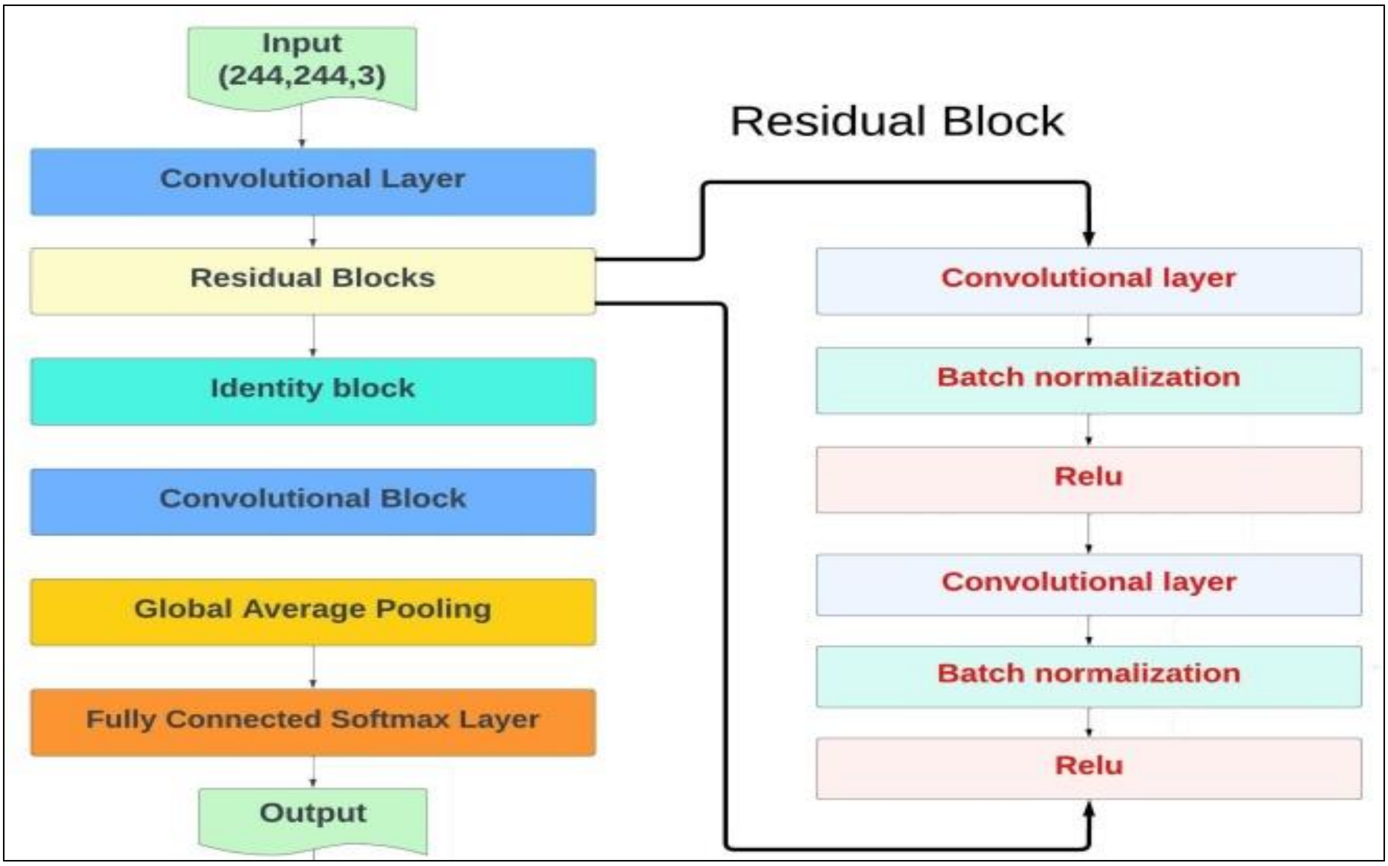

Fig 4: ResNet-50 Architecture

➢ *Classification Using ResNet-50*

ResNet-50 model, a deep CNN architecture mostly used for image classification tasks. This model is pre-trained on a huge classification dataset with 14 million images (Imagenet) containing 1000 classes. To enable ResNet-50 to classify eye diseases, it is trained further using transfer learning techniques from this dataset. This involves freezing all layers but the last one through fine-tuning. Training goes through different epochs with an early stopping method that is implemented to avoid overfitting of training data.. After fine-tuning, the parameters of the model are unfrozen and an optimal learning rate is chosen for subsequent learning steps. By iterative training and evaluation processes, code aims at maximizing performance. Figure 4 displays the structural design for ResNet-50 model.

➢ *Classification Using DenseNet-121*

DenseNet-121 is a neural network that has dense connections between layers. It shares all the feature maps from the previous layers thereby enhancing information flow and gradient propagation. The model uses ImageNet pre-training, which includes bottleneck layers for computational efficiency. With 121 layers, it effectively balances depth and efficiency thereby making it suitable for various image tasks such as classification, detection, and segmentation. Figure 5 below shows the structure of DenseNet-121 model.

Those added category layers are composed of global average pooling, dense ReLU units as well and dropout layers to avoid overfitting. The base model's layers remain frozen to maintain their learned functions throughout the training whereas only its custom-type layers are adjusted using the dataset. During compilation with the Adam optimizer, training involves utilizing the sparse categorical cross-entropy loss function, while testing involves utilizing educational and evaluation metrics, respectively.

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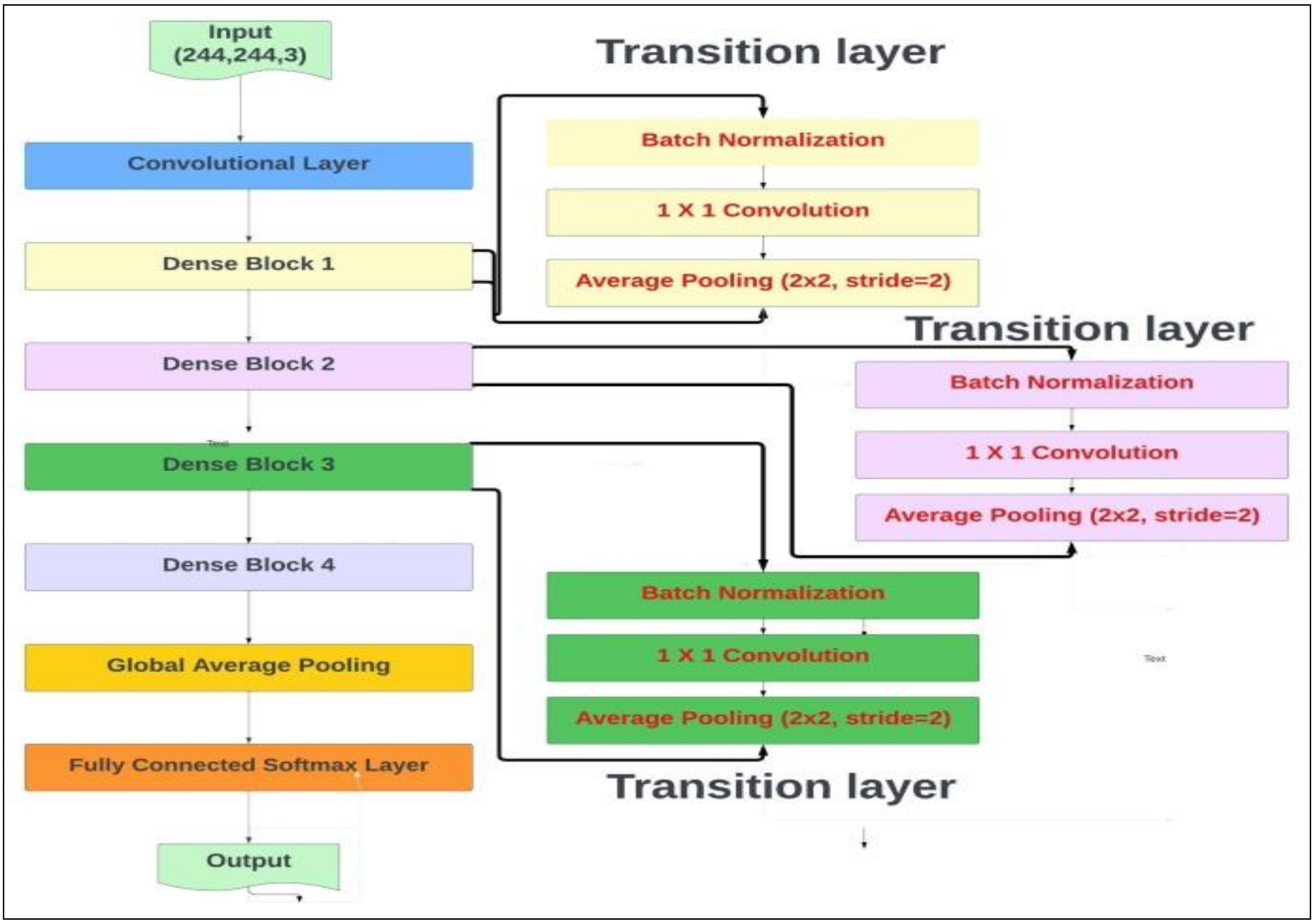

Fig 5: DenseNet-121 Architecture

F. Model Evaluation

The precision, recall, and F1 scores were used for analysis metrics in this model. These scores are also known as performance measures to evaluate how well a model has performed on the test dataset.

➢ *Precision*

Precision is a measure of the number of true positives, correctly predicted positive cases by the model, and overall cases detected as positive.

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

➢ *Recall*

Recall, also known as the true positive rate, measures the accuracy of positive predictions among all positive instances in the dataset. It's calculated as the ratio of true positives to the sum of true positives and false negatives (missed positives).

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

➢ *F1 Score:*

The harmonic mean between precision and recall produces an F1 score which provides a balanced measure that considers both false negatives and false positives.

$$\text{F1 score} = \frac{2*(\text{Precision} * \text{Recall})}{2*(\text{Precision} + \text{Recall})}$$

➢ *In These Terms:*

- True Positives (TP) amounts to cases where the model accurately identifies a positive outcome when it is truly positive.
- False Negatives (FN) are occurrences where the model fails to recognize a positive outcome that is positive.
- False Positives (FP) are the states where the model incorrectly identifies a negative outcome as positive.
- True Negatives (TN) represents cases where the model correctly identifies a negative outcome that is truly negative.
- These metrics are calculated test dataset. The average='weighted' parameter in these metrics score functions indicates that the calculation should be weighted by the number of instances for each class, providing an overall score across all classes.

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IV. EXPERIMENTAL RESULTS

In total, three different experiments were conducted to measure the effectiveness of these models (MobileNetV2, Resnet-34 and DenseNet-121).

A. Resnet-50 Classification Model

This model underwent training for 30 epochs to classify ocular diseases. During training, it exhibited significant performance, achieving an accuracy of 91.47% on the data used for training. Subsequently, when tested on previously unseen images constituting the test set, the model achieved an accuracy of 90.85%. In Figure 6, accuracy of both training and testing shows a steep increase as the number of epochs progresses. Simultaneously in figure 7, the training and validation loss (cross entropy) steadily decrease over epochs.

This trend indicates the model's improving capability to differentiate between various image classes with extended training, ultimately resulting in enhanced accuracy.
The ResNet-50 model showed a precision of 89.75%, recall of 91.25% and 86.27% in F1 score. Detailed evaluation metrics are presented in Table III.

Table 3: The Performance Evaluation Measures For Resnet-50

Class	**Precision**	**Recall**	**F1-Score**
Normal	0.80	0.88	0.78
Glaucoma	0.81	0.79	0.69
Diabetic Retinopathy	0.99	0.99	0.99
Cataract	0.99	0.99	0.99

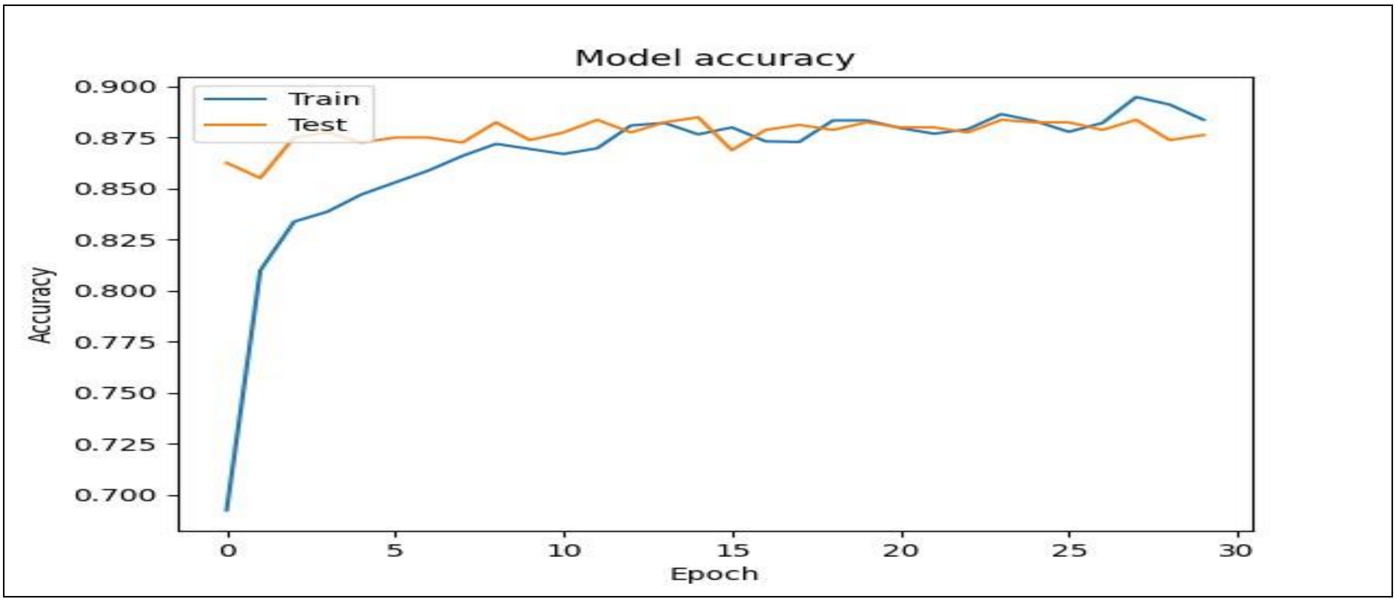

Fig 6: Chart Displaying Accuracy during Training and Validation of ResNet-50 Model

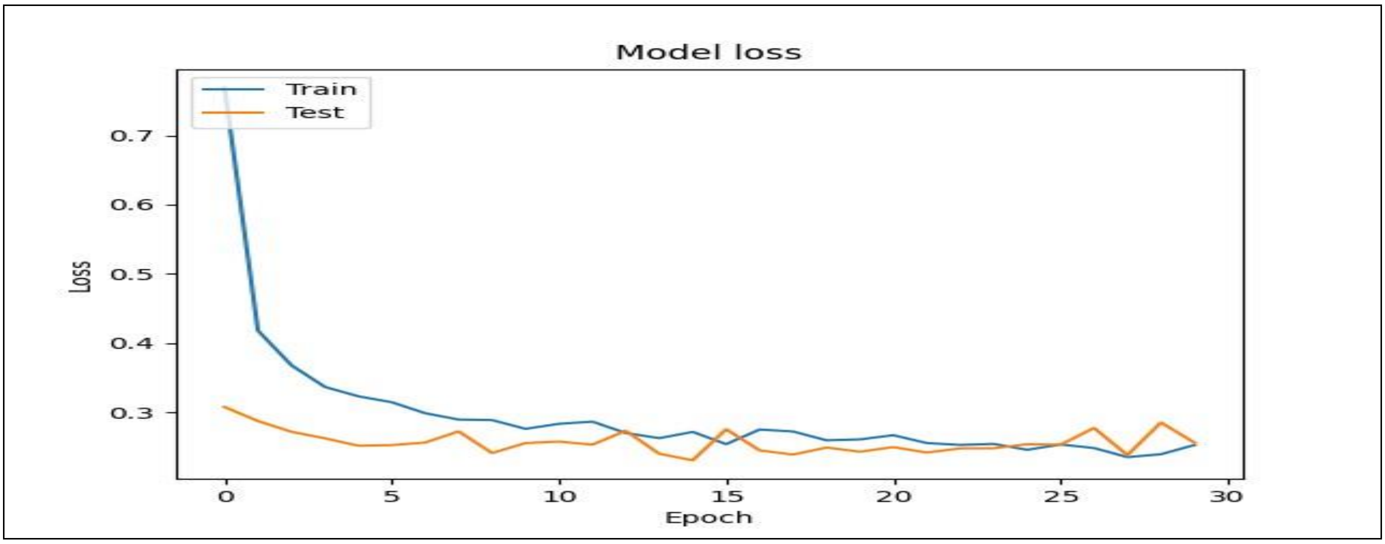

Fig 7: Chart Displaying Loss during Training and Validation of ResNet-50 Model

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B. Dense Net-121 Classification Model

Similarly, DenseNet-121 model is also trained for 30 epochs. It demonstrated remarkable performance on both training and test sets, achieving an accuracy of 81.97% and 88.82%, respectively.

The DenseNet-121 model exhibited an overall precision of 87.73% and a recall of 87.75%, achieving 84.54% of F1score. Detailed class-wise performance metrics of the DenseNet-121 model are presented in Table IV. Similar to the Resnet-50 model, DenseNet-121 model utilized the cross entropy function as its loss function. Figure 8 explains the training and validation accuracy of this model. It is evident from the figure 9 that the accuracy of the training data consistently improves with the epochs increased, while the training and validation loss steadily decreased over epochs.

Table 4: Performance of the Densenet-121 Model

Class	Precision	Recall	F1-Score
Normal	0.64	0.97	0.80
Glaucoma	0.95	0.64	0.71
Cataract	0.98	0.94	0.96
Diabetic Retinopathy	0.94	0.96	0.95

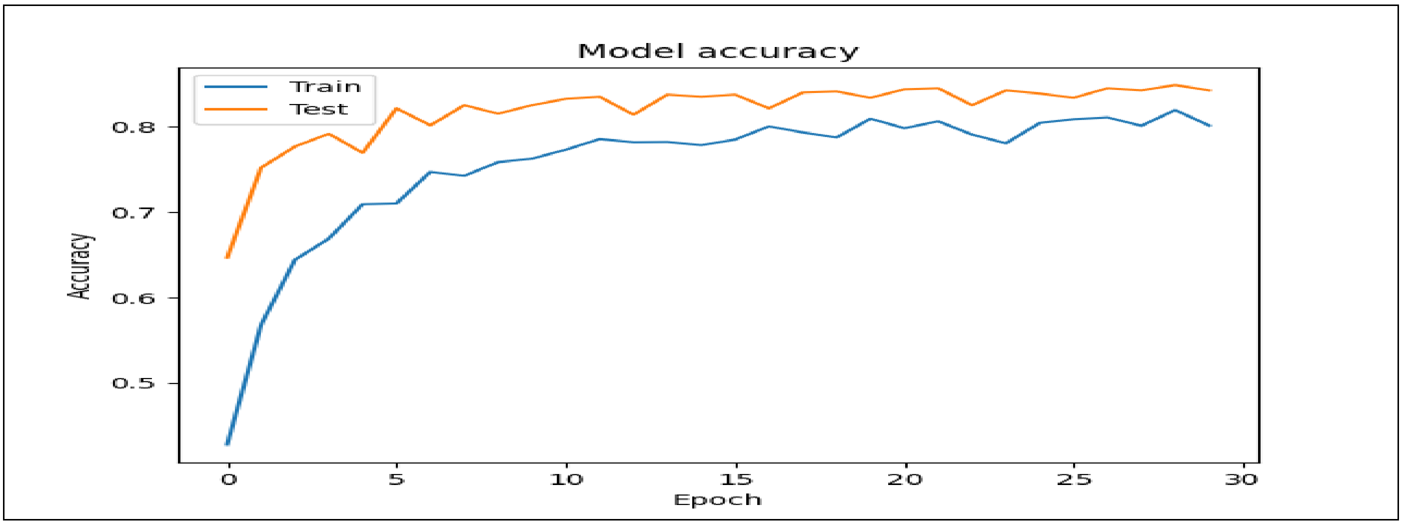

Fig 8: Accuracy Graph of Training and Testing set in DenseNet-121model

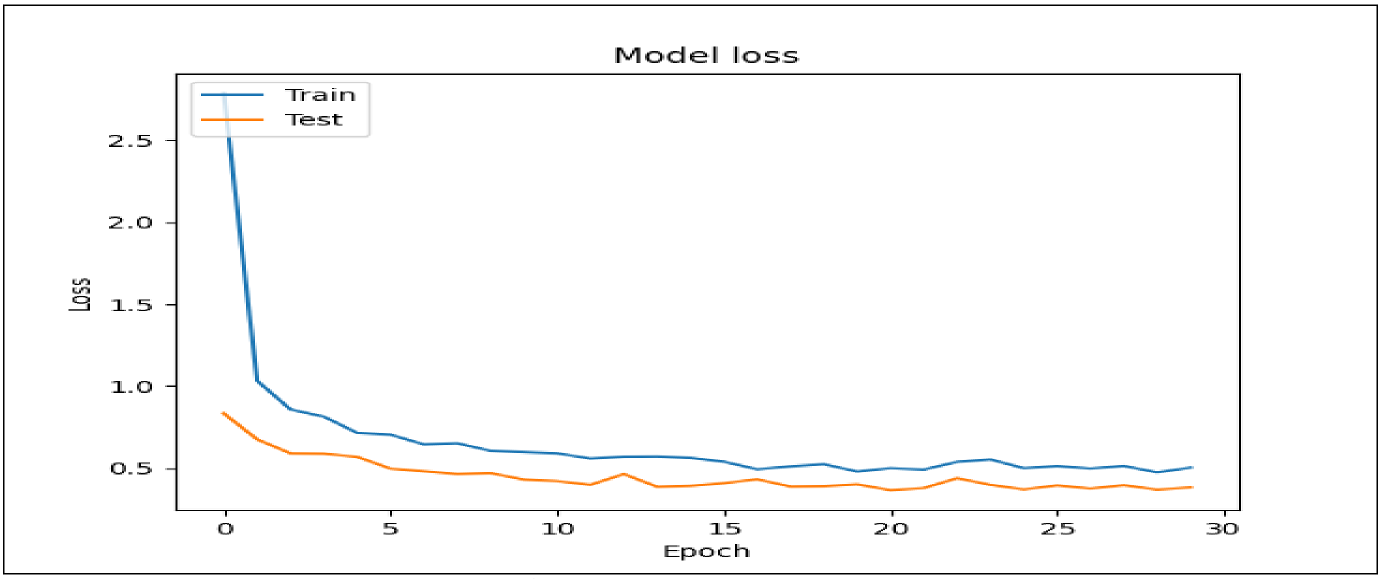

Fig 9: Loss Graph of Training and Testing set in DenseNet-121 Model

C. MobileNetV2 Classification Model

MobileNetV2 model attained an accuracy of 95.65% on the training set, while got a slight lower accuracy of 94.23% on the test set. This is attained by training the model for more epochs and fine-tuning it to improve accuracy. Detailed class-wise performance metrics for this model can be found in Table V.

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Table 5: Evaluation Metrics of Mobilenetv2 Model

Class	Precision	Recall	F1-Score
Normal	0.95	0.94	0.88
Glaucoma	0.94	0.89	0.84
Cataract	0.99	0.98	0.99
Diabetic Retinopathy	0.98	0.97	0.99

In Figure 10, both training and validation accuracy show extensive growth with increasing epochs. Simultaneously in Figure 11, the loss of training and validation reduced as the epochs increased. This occurs as the model continuously learns more about the image features over epochs, improving its capacity to differentiate between images of different classes by increasing the accuracy. This classification model gained a precision score of 96.51%, recall of 94.36%, and F1 score of 93.52%.

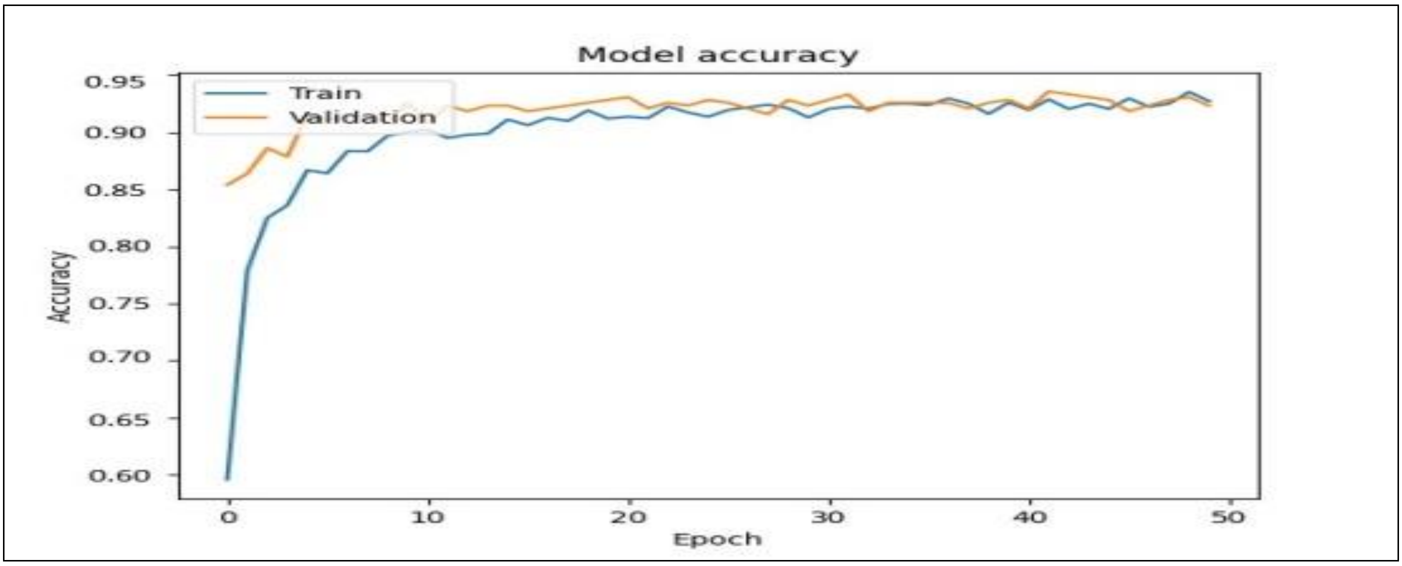

Fig 10: Graph Explaining the Accuracy of MobileNetV2 Model during Training and Testing

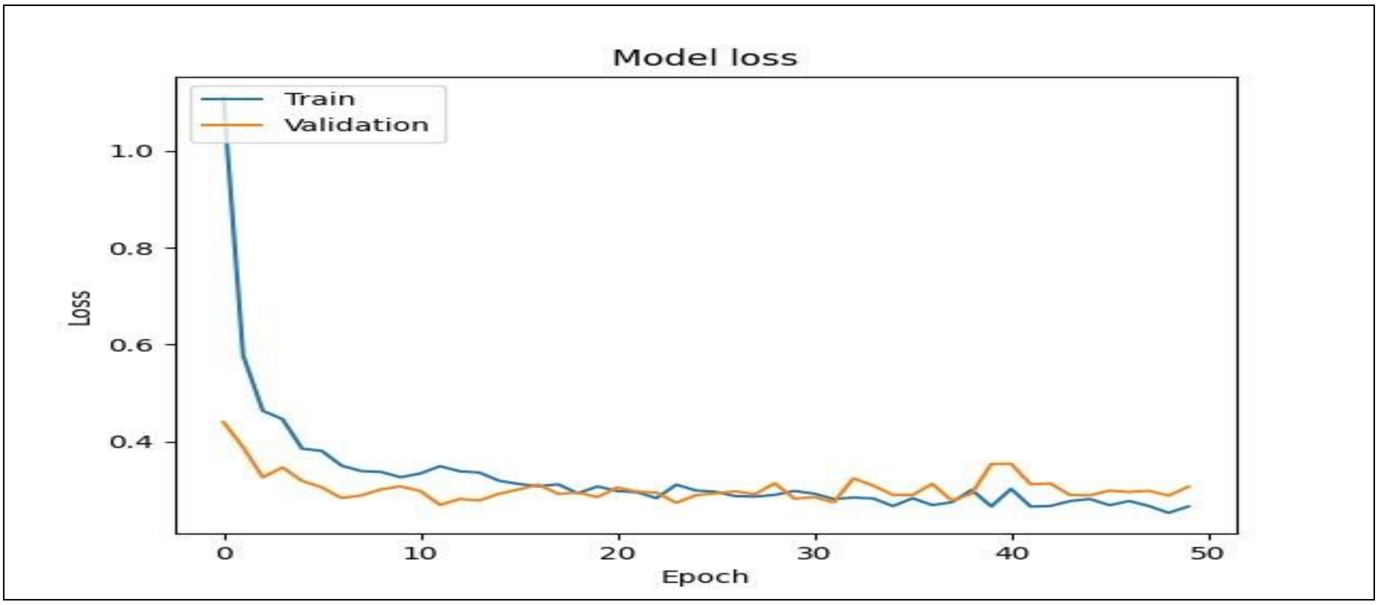

Fig 11: Graph Explaining the Loss of MobileNetV2 Model during Training and Testing

D. Comparison of models

Table 6: Overall Performance of Three Models

Model	Precision	Recall	F1-Score
ResNet-50	89.75%	91.25%	86.27%
DenseNet-121	87.73%	87.75%	84.54%
MobilenetV2	96.51%	94.36%	93.52%

Detailed model-wise performance metrics is presented Table VI. Among these three models, MobileNetV2 attained the maximum accuracy of 94.23%, with a 0.96, recall of 0.94, and an F1-score of 0.93. In contrast, ResNet-50 and DenseNet-121 exhibited slightly lower in evaluation metrics. The overall performance metrics are visualized in Figure 12.

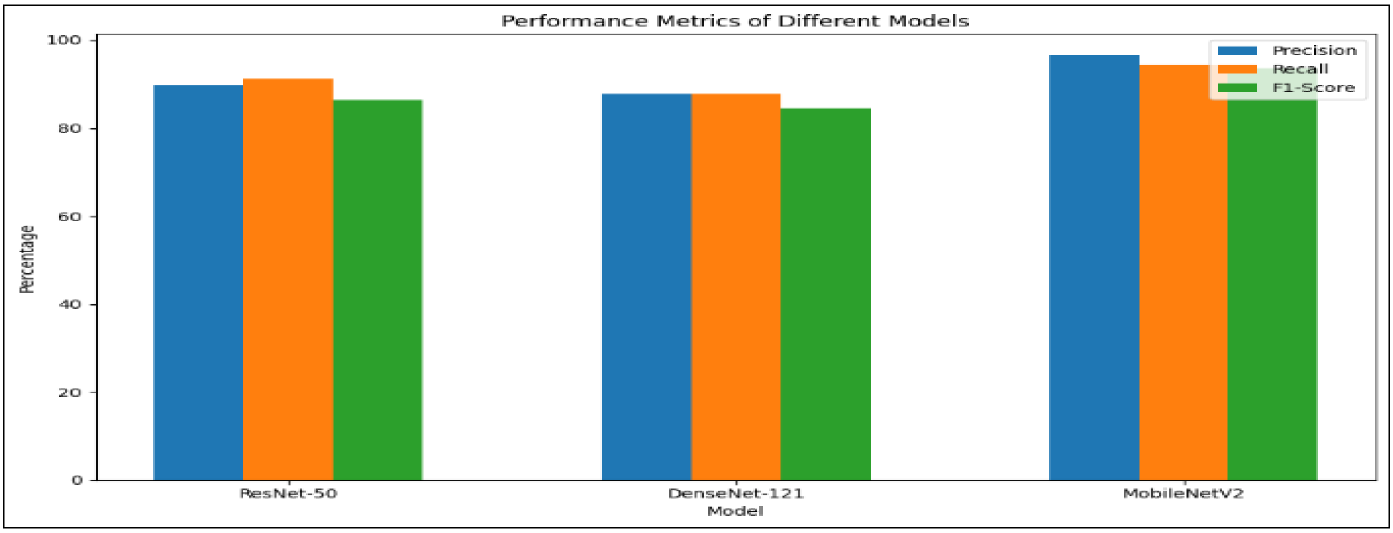

Fig 12: Comparison Chart of Models Performance

The lightweight architecture of MobileNetV2 allows for the optimal use of computational resources while maintaining high accuracy, which may be the reason for its higher overall performance. However, while being widely used and well-configured CNN designs, ResNet-50 and DenseNet-121 may also experience computational inefficiencies as a result of their more intricate topologies. From the results, performance of MobileNetV2 model better than the other algorithm in this particular task of classification, even if they still attained excellent overall performance in terms of the metrics that are calculated for this task.

V. CONCLUSION

In this research, three neural network-based models were developed for classifying eye diseases: ResNet-50, DenseNet-121, and MobileNetV2. Among these three models MobileNetV2 attained the highest accuracy at 94.23% in classifying the eye diseases from fundus photographs. The remaining model achieved a satisfactory level of accuracy in its performance. After conducting immense investigation on this open-source dataset, the efficiency of this suggested approach is confirmed.. It outperforms existing CNN-based eye disease classification models while maintaining lower computational requirements. A notable aspect of this proposed method is its adaptability to classify diseases based on various types of medical images. Additionally, the models introduced in this research have the potential to contribute to the development of a easily accessible and real time eye disease classification system. Such a system shows great potential in assisting healthcare professionals and can potentially revolutionize the field in diagnosing the disease in eye.

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