Optimized Deep Learning for Multi-Class Retinal Disease Classification Using ResNet-101

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***Abstract*— Machine Learning (ML) approaches, such as Artificial Neural Networks (ANN), Recurrent Neural Networks (RNN), Deep Learning and advanced architectures like AlexNet and ResNet, are at the leading edge of studies in the identification and type of crucial sicknesses. These techniques leverage the strength of records-driven models to research complex scientific data, main to more correct and efficient diagnostic processes. This work suggests a ResNet-101 model that is meant to handle multiclass classification problems , offering potentially higher accuracy and deeper feature extraction at the cost of increased memory consumption and computational requirements. The ResNet-101 model was tested using the EyeNet dataset, which included 32 distinct types of diseases of the retina. The method achieved accuracy of 98.75% when evaluated on the EyeNet dataset.**

Keywords—Resnet-101;Categorization;Advanced machinelearning;Retinaldisease dataset,Eye's photosensitive layer.

I. INTRODUCTION

The retinal disorders have become a major concern for people across all age groups.The retina, which comprises a key photosensitive layer connected to the optic nerve within the human eye, plays an important role in converting low information into visible signals. This photosensitive layer, after focussing light via the lens, sends those signals to the brain, allowing the device to have a visual repute. The macula is a crucial area of the retina, primarily responsible for processing detailed visual information. The macula processes data, which is subsequently passed from retina to brain via optic nerve, allowing for an understanding of images.Several retinal illnesses can disrupt this visual pathway, resulting in diseases include age-related macular degeneration (AMD), retinal tumors, and DME[1].In many industrialized countries, people elderly between 50 and 60 are increasingly prone to imaginative and prescient loss because of AMD. Based on recent studies in the US, this disease affects approximately 35% of those over the lifespan of 80. Accurately detecting illnesses of the retina is especially difficult due to its variety, necessitating the expertise of skilled ophthalmologists. However, the emergence of laptop-aided diagnostic (CAD) systems has greatly enhanced the early detection and treatment of numerous ailments.Advances in technology have brought tremendous advantages to a variety of fields, particularly science. Numerous methods and trends have been created to enhance the speed and standard of healthcare services. Advancement of Automatic Disease Detection (ADD) has significantly improved public fitness frameworks. Among these advancements, retinal symptom analysis as part of ADD packages has a great potential to increase global eye care standards[2]. Recently advances in machine learning (ML) and deep learning (DL) have resulted in creation of new techniques for classifying, segmenting, and detecting retinal problems.However, issues in gathering information and labeling continue, as researchers have emphasized in prior studies. Development of several ML and DL frameworks, includes as Recurrent Neural Networks (RNN), Convolutional Neural Networks (CNN), AlexNet, ResNet, and VGG, has enabled researchers and healthcare professionals to more easily identify and categorize critical eye disorders[3]. Furthermore, a hybrid machine learning-based method has been presented for the automated detection of retinal disorders.This have a look at introduces a deep learning technique making use of the ResNet-101 model for the classification of a couple of retinal sicknesses. The effectiveness of the proposed version has been assessed the use of the EyeNet Dataset, which accommodates 32 wonderful folders, every containing pix related to specific retinal situations. In order to ensure robust analysis, 70% of the dataset has been used for teaching, with the remaining 30% being utilized for validation. The experimental results demonstrate that the ResNet-101 version achieved an exceptional accuracy rate of 98.75%.The research provides a significant improvement over conventional diagnostic techniques by applying this deep learning-based ResNet101 model to the diagnosis of serious retinal diseases. This could lead to earlier and more accurate analysis in clinical situations. The rest of the paper based on the following. Section II discusses previous studies relevant to this study. In Section III, have detail proposed architecture and provide a comprehensive overview of dataset used . Section IV covers the experimental evaluation results, focusing on ResNet-101 model's performance. Section V includes a discussion and analysis of results. Finally, Section VI closes the report with recommendations for future research.

II. Related work

Deep learning and pattern analysis have resulted in significant advancements in image processing and typography, particularly in clinical domain names. These technologies are frequently used to process complicated medical images, including retinal scans, which may be useful for identifying a variety of eye conditions. The adoption of these models has showed excellent efficacy due to their ability to robotically extract functions and identify diseases with great precision[4]. This is especially useful because it decreases reliance on guidance diagnosis from professionals. Many developing countries have limited access to healthcare specialists, making such technology even more important for early disease identification and treatment. One of the critical applications of these technologies is optical coherence tomography, which is a non-invasive imaging technique that gives high-decision OCT move-sectional views of the retina. Now it is one of the most important techniques for early detection and control of retinal diseases[5]. OCT allows healthcare businesses to visualize the intricate form of the retinal layers, which aids in the detection of diffused anomalies that may represent the early stages of a condition. However, understanding and examining those snapshots in an automated manner remains difficult, and device mastery models are constantly improving to address these limitations. The increasing ability to gather comprehensive knowledge of systems positions them as promising solutions for widespread scientific usage in retinal disease prognosis. In the past decades, many models have been proposed for using OCT images in the classification of retinal diseases automatically. Amongst the most profound approaches involves combining CNNs with SVMs, which have been implemented with success. For example, a study with ROP, this is a condition associated with premature infants, proposed a new device that uses SegNet for vessel segmentation. This method is useful because ROP is associated with abnormal blood vessel development in the retina. The study used a mixture of SIFT, Scale Invariant Feature Transform, and SURF, Speeded-Up Robust Features for extracting the feature from images. These techniques are well-reviewed for their ability to extract distinct and stable features from images. Once such characteristics were abstracted they get classified using Quantum SVM which is one of the upgraded traditional SVM. Their accent on the principles of quantum computing also helps improve its speed and accuracy of learning. In this context, the results achieved by the proposed system turn out to be incredibly accurate, like 95.5%, as compared to many other machine and deep learning systems. Such high accuracy makes this system very promising for early prognosis of ROP, especially in areas in which it is not easy to have access to specialized health care providers. Therefore, such a system will be an effective solution to early intervention in the disease.Another important area of research in retinal diseases is the detection of diabetic retinopathy, a frequent complication in patients with diabetes, which if not detected early, may lead to severe impairment of vision. The detection of the different grades of DR-from mild to proliferative-would prevent permanent loss of vision. To this effect, some researchers have integrated ResNet-50, a powerful deep CNN, with Random Forest classifiers for diagnosis. ResNet-50 would capture crucial details by the deep feature extraction of images due to its capability to mimic the powerful deep CNN[6]. Therefore, ResNet-50 would be very effective in the detection of early signs of DR from retinal images.Another area of important research in the detection of retinal disease is diabetic retinopathy (DR), that could, if untreated, lead to complete impairment of vision.

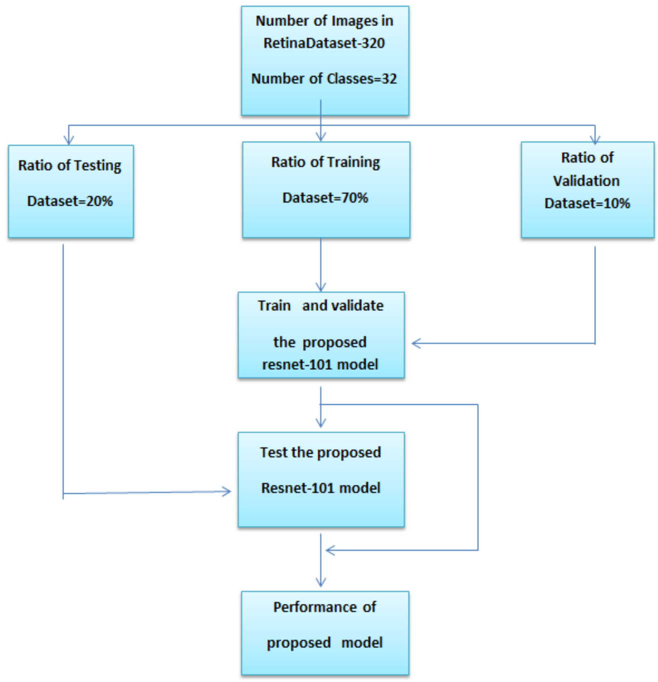

Fig.1. Work flow diagram of proposed model

Detection of the progression from mild to proliferative DR is critical for preventing irreversible loss of vision. In this regard, hybrid models have been developed that incorporate ResNet50 as a deep CNN, classifying features through the Random Forest classifier in making a diagnosis. The deep capability for feature extraction by ResNet-50 enables it to be extremely effective when capturing subtle details from retinal images. It's thus very effective in identifying early DR. Application of Random Forest classifier After feature extraction, the categorization of the severity of the disease is performed through the Random Forest classifier. By using the advantage of CNNs in feature extraction, in conjunction with the high accuracy of Random Forest algorithms in classification tasks, this hybrid model becomes very promising. It has been tested on two publicly available significant datasets, Messidor-2 and EyePACS, containing different challenges of classification for DR stages. The data set Messidor-2 is classified into two: No Referable Diabetic Macular Edema and Referable DME, meaning whether a patient requires referral to a specialist or not. This model did very well with an accuracy rate of 96% for the given dataset, indicating its fitness in distinguishing between the two classes. The developing of such models shall, therefore, be of great promise for early detection and management of retinal diseases in the underserved population. It can empower healthcare providers to make decisions in a timely manner that may prove fruitful in relation to treatment by utilizing accurate and automated diagnosis tools. This is very beneficial for people in rural or economically disadvantageous regions where access to ophthalmologists and specialty diagnostic equipment will be relatively limited. Thus, the diagnostic workflows can significantly lighten the healthcare professional's workload to focus more on complicated cases that require a human mind. The EyePACS dataset is images classified into five categories representing different stages of diabetic retinopathy, from no signs of the disease up to proliferative DR. Similarly, on the same dataset, it sets up a respectable accuracy of 75.09% to its ability in working with a more complex task of multi-class classification. As a result, although worse than Messidor-2 two-category accuracy of classification, a certain value is saved which demonstrates good prospective applicability of proposed models in dealing with detailed DR classification.

III. METHODOLGY

The proposed resnet-101architecture and the dataset that was used are also covered in this section. The suggested approach has been step-by-step demonstrated in Fig 1.

A. Dataset

This observation was made using Yang et al.'s EyeNet dataset. It offers a sorted variety of thirty-two multiple types of records related to records from hospitals. The Table 1, 32 retinal disease types found in the Eye-Net dataset are used. This dataset is used for the entirety of the model's implementation. The accompanying dataset contains pictures that have been labeled appropriately.

B. Proposed Model

Deep learning knowledge of is one of the maximum widely used technology these days. It makes use of more than one processing layers within its framework, permitting computational fashions to research records styles at various levels of abstraction. These fashions excel at recognizing speech, figuring out visual items, and tackling various other detection duties. Deep learning concepts are inspired by the complicated form of the human mind. Resnet-101 is the most effective and powerful deep learning version[7]. Although researchers have accelerated its application in other areas, Resnet-101 is widely used in the scientific enterprise. One method for constructing a deep learning model for the retinal disease category is to process retinal pictures sequentially. Initially, low-degree characteristics are obtained, followed by the gathering of the more delicate center and intermediate-degree features. These final functions are then provided to a trainable classifier to determine the proper class.

1) Resnet-101 model: It is a deep neural network architecture with 101 layers. The idea behind this network is useful specifically for the problem of vanishing gradients in very deep networks, which happens at the time when gradients become too small to propagate backwards. In contrast, fig 2 residual connections, also known as skip connections, are used to achieve this.

TABLE I. DATASET DESCRIPTION

Dataset	Class Label
Eye-net	Adult Coats` Disease
	AdultFoveomacularDystrophy
	Adult-Related Macular Degeneration
	AMN MacularNeuroretinopathy
	Antiphospholipid Antibody Syndrome
	Behcet`s disease
	Bilateral macular Dystrophy
	Bull`s Eye Maculopathy chloroquine
	Central Serous Chori-oretinopathy
	Choroidal Nervus
	CMV chorioretinitis
	Cone-Rod Dystrophy
	Congential Syphillis
	Diabetic Maculopathy Multiple Myeloma with Retinal Detachment
	Giant Retinal Tear
	North Carolina Dystrophy
	Leber`s Stel-late maculopathy
	Multifocal Exudative Detachments
	Macular Dystrophy
	Myelinated Nerve Fibers
	Juxtafoveal Telangiectasis DM Diabetes
	Optic Disc Drusen
	Roth Spot disease
	Pattern Dystrophy Simulating Fundus Flavimaculatus
	Retinal Folds Following Retinal Reattachment Surgery
	Reticular Pattern Dyatro-phy
	Retro hyaloid Hemorrhage
	Solar Retinopathy Familial
	Susac`s Syn-drome
	Self-Applied Retinal Detachment
	Terson`s Syndrome
	Wyburn-mason Syndrome

Proposed model can explained in steps manner are-Input data preprocessing is retinal images are resized ,normalized and augmented to improve generalization and reduce overfitting .Deep resnet-101 network with its 101 layers and residual connetctions.
Feature Extraction with conventional layers in Resnet-101 extract hierarchical features –edges and shapes in early layers ,disease specific patterns in deeper layers. Residual learning was allowing direct information flow,preserving key features across layers,enhancing learning efficiency and maintaining accuracy in deeper networks .Classification of layers are global average pooling condense features ,followed by fully connected layers to classify images ,with softmax outputting disease probability scores[8].Detection output in this model assigns each image as disease label , aiding in early diagnosis and treatment planning accurate classification of retinal conditions.

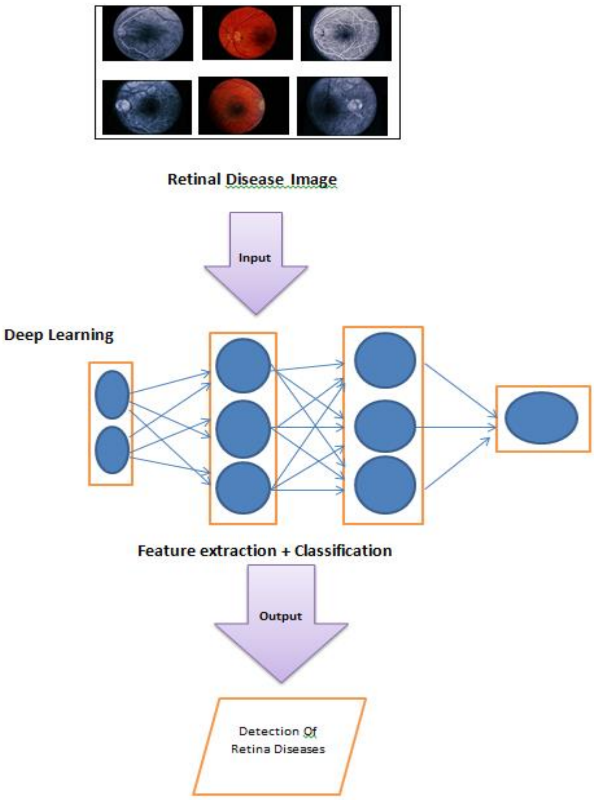

FIG 2: Proposed model architecture

Shortcut connections can also be one of the innovations on ResNet-101: The gradients directly pass through the network, bypassing one or more layers. Thus, the vanishing gradient problem is avoided, while the updates of weights in deeper layers are eased. With this factor in mind - accuracy, which is now no longer influenced by the depth of the network, there has emerged a basic architecture in deep learning for image classification tasks, object detection, segmentation, etc and further for classification of images, object detection, and segmentation.

C. Data Augmentation

To make certain sufficient statistics is available for training and to prevent overfitting, used information augmentation strategies. Augmentation strategies covered rescaling, zooming, and flipping the images[9]. By applying numerous random differences,ensured that the model encountered a diverse range of photos, which facilitates in avoiding overfitting and improves generalization. In proposed version, information augmentation is carried out using Keras's ImageDataGenerator. This procedure includes six essential steps, each of which transforms the pix in distinctive approaches, improving the model's capacity to generalize nicely across new facts. Data augmentation is important for improving the overall efficiency and outcomes of system mastering fashions by means of producing extra and sundry education samples. A comprehensive dataset permits the model to perform extra accurately and efficaciously. For example, saturation changes increase the opacity of pics, making crucial capabilities extra visible and helping in higher sickness diagnosis. Another augmentation method converts the unique image to grayscale , changing its hues to grayscale assessment. Flipping fig3 the original photograph changes its direction, at the same time as brightening enhances the picture'sbrightness.

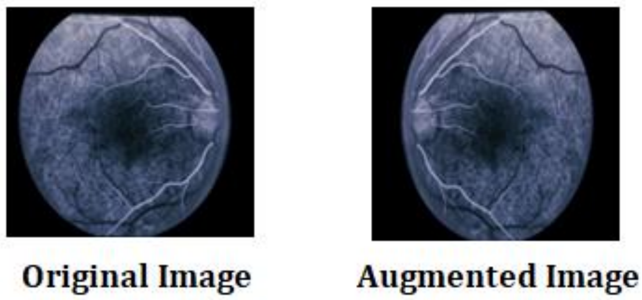

FIG 3: Flip

Zooming fig4 is every other step inside the augmentation manner. The specific augmentation strategies used can range relying at the studies and its requirements.

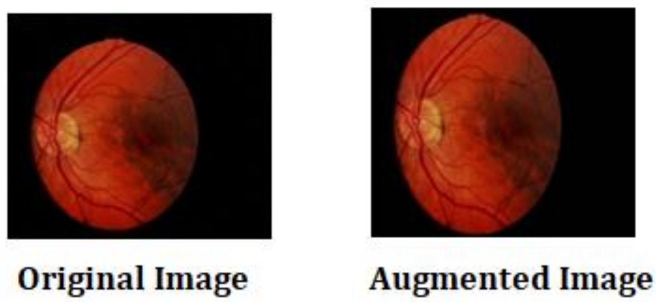

FIG 4: Zoom

D. Adaptive Learning Rate Estimation

Optimization techniques based on stochastic gradient methods necessitate improvement in performance for machine learning models. Among these, a very effective and popular algorithm is Adaptive Moment Estimation, or Adam. Adaptation in Adam is beneficial over the traditional method of gradient descent in the sense that it utilizes the first and second moments of the gradient to dynamically adapt its learning rate. It allows for very efficient updates of the parameters of a model, making Adam remarkably effective for dealing with massive amounts of data and deep neural networks. Besides this, its ability to robustly handle noisy and sparse gradients guarantees stability and smoothness of the optimization procedure, even in complex scenarios.One reason Adam achieves great popularity lies in its computation efficiency and low memory usage; this means it is suitable for big models with many parameters. In contrast, traditional stochastic gradient descent needs learning rates to be manually tuned laboriously. Learning rates of Adam are automatically scaled by using individual adaptive learning rates based on recent momentum, thus preventing slow convergence and vanishing gradients during the training process.

IV. PERFORMANCE EVALUATION

To assess performance of the proposed model, the model's predictions are compared with the actual labels. These labels are furnished by an ophthalmologist who annotates the snap shots. In Figure 5, the confusion matrix is displayed to evaluate the performance of the Resnet-101[10]. This matrix provides a comprehensive overview of the model's classification results, allowing for a clear assessment of its strengths and weaknesses in predicting different classes.

$$precision = \frac{PT}{TP + FP} \quad \rightarrow (1)$$

$$recall = \frac{TP}{TP + FN} \quad \rightarrow (2)$$

Figure 6illustrates the outcomes of the classification report produced by applying the proposed model. This report summarize the model's performance metrics, offering insights into its effectiveness in classifying the different categories .Evaluate the model based on these labels. Precision is sometimes called as positive predictive value, and recall is the real positive rate or actual values (as shown in equations 1 and 2). Dataset consists of 32 kinds of retina diseases, so the overall performance measures are calculated for each magnificence in my opinion[11]. The version completed a 100% precision and 99% recollect across all classes.

V. EXPERIMENTAL RESULTS AND OBSERVATIONS

The collection of data is separated into two subsets: training and validation. The program's development is done in Python using the Keras package and operates on an Intel Core i5-7200 CPU at 2.70GHz.For training, a Google GPU is used. Tested diverse optimizers, and Adam furnished the excellent effects. Learning rate used for this optimizer is 0.001. All other hyperparameters are chosen after thorough testing and evaluation. Trained data on different epochs and achieved 98.75% validation accuracy[12].Validation accuracy is 0.9822, and the validity loss is 0.0498. The x-axis shows a large number of epochs (from 0 to 30), whereas the y-axis denotes accuracy (from 0 to 1).The blue line denotes training accuracy, whereas the orange line represents validation accuracy. Fig 7 Initially, training accuracy increases frequently, whereas the validation accuracy increases rapidly, nearly reaching 1.0 (100%) in the first 10 epochs.Both training and validation accuracies stabilize after about 10-15 epochs and remain consistent, varying slightly between 0.90 and at least a 1.0, showing proper version generalization.Based on the axis of the

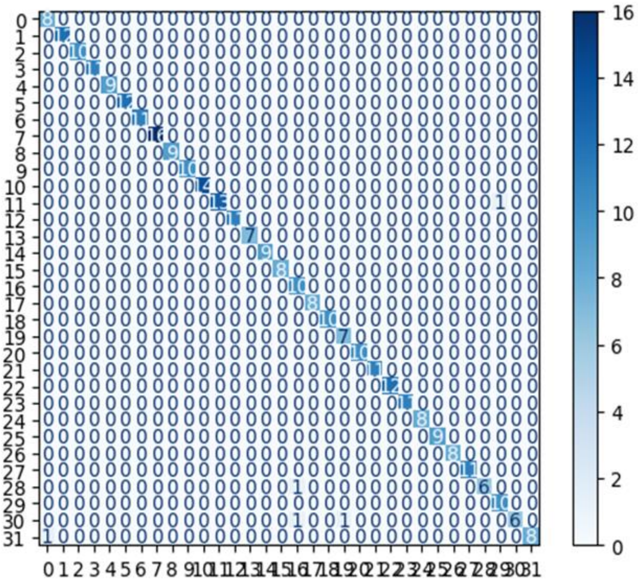

FIG 5: Confusion matrix

Classification Report:

	precision	recall	f1-score	support
.ipynb_checkpoints	1.00	1.00	1.00	8
AMN Macular Neuroretinopathy	1.00	1.00	1.00	12
Adult Coats' Disease	1.00	1.00	1.00	10
Adult Foveomacular Dystrophy Pattern	1.00	1.00	1.00	11
Age-Related Macular Degeneration With Pattern Dystrophy Appearance	0.90	1.00	0.95	9
Antiphospholipid Antibody Syndrome	1.00	1.00	1.00	12
Behcet's	1.00	1.00	1.00	11
Bilateral Macular Dystrophy	1.00	0.94	0.97	16
Bull's Eye Maculopathy Chloroquine	1.00	1.00	1.00	9
CMV Chorioretinitis	1.00	1.00	1.00	10
Central Serous Chorioretinopathy	1.00	1.00	1.00	14
Choroidal Nevus	1.00	1.00	1.00	14
Cone - Rod Dystrophy	1.00	1.00	1.00	11
Congenital Syphillis	1.00	1.00	1.00	7
Diabetic Maculopathy Multiple Myeloma with Retinal Detachment	1.00	1.00	1.00	9
Giant Retinal Tear	1.00	1.00	1.00	8
Juxtafoveal Telangiectasis DM Diabetes	0.91	1.00	0.95	10
Leber's Stellate Maculopathy	1.00	1.00	1.00	8
Macular Dystrophy	1.00	1.00	1.00	10
Multifocal Exudative Detachments Due to VKH	0.88	1.00	0.93	7
Myelinated Nerve Fibers	1.00	1.00	1.00	10
North Carolina Dystrophy	1.00	1.00	1.00	11
Optic Disc Drusen	1.00	1.00	1.00	12
Pattern Dystrophy Simulating Fundus Flavimaculatus	1.00	1.00	1.00	11
Reticular Pattern Dystrophy	1.00	1.00	1.00	8
Retinal Folds Following Retinal Reattachment Surgery	1.00	1.00	1.00	9
Retrohyaloid Hemorrhage	1.00	1.00	1.00	8
Roth Spot	1.00	1.00	1.00	11
Self-Applied Retinal Detachment	1.00	0.86	0.92	7
Solar Retinopathy Familial	1.00	1.00	1.00	10
Susac's Syndrome	1.00	0.88	0.93	8
Terson's Syndrome	1.00	1.00	1.00	9
accuracy			0.99	320
macro avg	0.99	0.99	0.99	320
weighted avg	0.99	0.99	0.99	320

FIG 6: CLASSIFICATION REPOR

At the start (epoch zero), both training and validation losses are fairly high fig 8. This is expected because the version starts with random weights and hence generates incorrect predictions, resulting in a large loss.The training loss begins at roughly 3.0, whereas the validation loss begins just below 2.0.During the first few epochs (up to epoch 5), the loss for training and validation drops significantly[13]. This implies that the model is learning quickly and modifying its parameters effectively in the early stages.

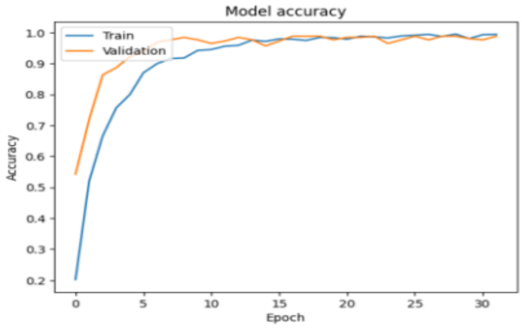

FIG 7: Model accuracy by implementing 30 epochs

After epoch 10, both training and validation losses will continue to decline, though at a slower rate. This is expected since the version finetunes its parameters and receives feedback in the direction of convergence. Both losses begin to stabilize around epoch 20, with the training loss approaching zero and the validation loss also reaching very low levels, indicating little errors in predictions based on both education and unseen validation statistics[14]. By epoch five, the training loss is less than 0.5, and the validationloss has also decreased , showing that the model is fitting both the training and validation data more accurately over time.

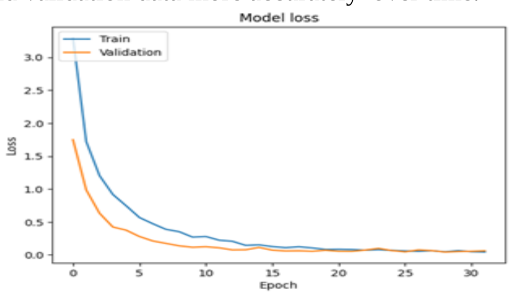

FIG 8: Validation and training loss comparsion at 30 epochs

VI. CONCLUSION

The modified Resnet-101 architecture will be used to classify types of multi-class retinal disease. The architecture has been specifically designed to raise the ability to differentiate between retinal conditions and make more proficient use of operations of convolution with the addition of several residual layers. In order to enhance the model's capacity for generalization, it will additionally employ statistical augmentation approaches.For instance, these augmentation techniques that were used comprised random rotations, zoom, flip, and other brightness manipulations.

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