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# Automated Identification of Retinal Disorders by Deep Learning with Optical Coherence Tomography Pictures

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## ABSTRACT

A crucial problem in computer-aided diagnosis (CAD) for medical applications is the classification of retinal disorders. This paper addresses the 4-class classification problem in optical coherence tomography image analysis (OCT) to automatically identify choroidal neovascularization (CNV), diabetic macular edema (DME), DRUSEN, and NORMAL. Retinal OCT pictures were identified by the proposed classification approach using a set of four classification model instances, each based on an upgraded residual neural network (ResNet50).At the patient level, the experiment employs a 10-fold cross-validation process that is founded on the growth of the OCT retinal picture collection. According to the study's findings, multiple ResNet50 concatenation is a helpful method when the availability of pictures used in medicine is scarce. In order to better understand the decision-making process, we also ran a bottleneck test and a qualitative assessment of the model predictions.

## INTRODUCTION

These days, OCT is a potent imaging technique for the non-invasive assessment of various retinal abnormalities [1–5], helping to diagnose CNV, DME, and DRUSEN, among other conditions. However, routine manual OCT evaluation in clinical practice has become entirely impracticable due to the growing volume of imaging data supplied by modern OCT technologies.

Comparably, there is a great deal of inter-observer variability in the assessment of retinal diseases on OCT images. This variability can lead to inconsistent interpretation and less reliable diagnosis, which can waste healthcare resources and delay accurate diagnosis when performed by experienced ophthalmologists. Consequently, it will be very helpful to automatically identify retinal illnesses on retinal OCT pictures, which will enable ophthalmologists to diagnose and treat eye diseases more successfully.

Medical image detection technology has progressed in recent years thanks to machine learning approaches. The outcomes and specifics of the suggested and current Utilizing retinal characteristics from spectral domain (SD)-OCT images, techniques and a random forest algorithm were used to categorize healthy and diseased retinas, producing good accuracy results.

Average relative to 96%. suggested a technique to detect DME with high accuracy that used local binary pattern features taken from OCT images and a lexicon built using a bag of words model. 93.7% and 81.2%, respectively, were high specificity and sensitivity. Using a linear support vector machine (SVM), it was possible to categorize normal and DME retinas with 87.5% sensitivity and 87.5% specificity. and employed 4,444 SVM classifiers and histogram-oriented gradient (HOG) descriptors.

At the OCT level, the collection yielded 100%, 100%, and 86.67 accuracy for the detection of 4,444 cases of age-related macular degeneration (AMD), DME, and normal retinas, respectively. However, the generalizability of these classification algorithms is

largely dependent on criteria that are precisely established by ophthalmologists utilizing their domain expertise, protracted, difficult, or even unachievable with big datasets.
A blind cross-validation technique is used to get a result for AMD detection using a deep convolutional neural network (CNN) with an average accuracy of 91.17%, sensitivity of 92.66%, and specificity of 88.56%. Applying a 10-fold cross-validation technique yields an average accuracy of 95.45.%, sensitivity of 96.43%, and specificity of 93.75%.
employed deep learning to automatically identify DME and diabetic retinopathy in fundus pictures, obtaining a 98.1% specificity and 90.3% sensitivity on average.

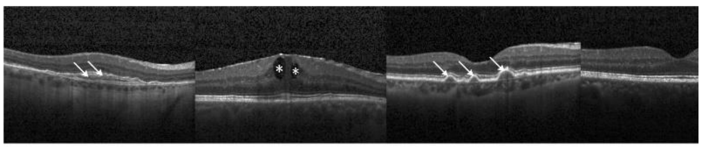



*Fig 1*

## LITERATURE REVIEW:

The literature review of a project that uses optical coherence tomography (OCT) imaging to focus on automated diagnosis of retinal illnesses based on deep learning provides a thorough analysis of all accessible papers, emphasizing significant discoveries, trends, and techniques in the area.

**1.Deep learning in OCT imaging:**

Deep learning has shown to be a game-changing method for medical imaging, yielding notable gains in precision and productivity.
For the processing of OCT images, we investigated a number of deep learning architectures, such as convolutional neural networks (CNN).
By automating the recognition and categorization of retinal disorders, these techniques lessen the need for human interpretation.

**2.Applications in the diagnosis of retinal diseases:**

Age-related macular degeneration, diabetic retinopathy, and glaucoma, which are the main causes of blindness, are highlighted in the literature.
shown how well deep learning models work to identify these disorders from OCT pictures, showing how they might transform the diagnosis of retinal diseases.

**3.Problems and their fixes:**

Although deep learning has showed potential, there are still issues with picture quality, tissue interpretability, and data variability. To overcome these obstacles, we created reliable preprocessing methods and enhanced model stability through ensemble learning. As was mentioned, the goal of efforts to make deep learning models more interpretable is to boost clinician trust in automated systems.

**4.Clinical integration and validation**:

Analyzing clinical trials and validation studies is a crucial component of the literature review.
To guarantee the dependability and relevance of deep learning-based systems, extensive datasets and real-world clinical scenarios must be studied.
This group of academics' studies emphasize how crucial it is to do thorough testing and validation in order to show how successful automated detection is in clinical situations.

**5.Future Directions and Recommendations:**

The literature review ends by suggesting possible directions for further investigation, including investigating state-of-the-art deep learning approaches, enhancing model generalization, and integrating multimodal picture data.
In order to improve early identification and treatment results for individuals with retinal illnesses, these researchers' efforts provide a strong platform for continued work in this field.

## EXISTING SYSTEM

Many methods of computer vision and machine learning techniques are used in the field of deep learning-based automated identification of retinal disorders using optical coherence tomography (OCT) pictures.

**1. DeepDR:**

This system classifies OCT pictures for retinal diseases using a convolutional neural network (CNN).
Accurate categorization is made possible by combining numerous layers to extract traits that correlate with different stages of the illness.

**2. DME-Net:**

This system uses deep learning to identify retinal swelling and fluid buildup in OCT images, with the specific goal of detecting diabetic macular edema (DME).
DME-Net locates and measures edema using sophisticated picture segmentation methods.

**3. GA-Net:**

A severe form of age-related macular degeneration, geographic atrophy is detected by this method. GA-Net detects atrophy in OCT scan regions and facilitates early diagnosis by combining picture segmentation and deep learning-based categorization.

**4. RetinaNet:**

To identify different retinal illnesses, this system employs a multi-task learning methodology. RetinaNet will be able to distinguish between several conditions, including diabetic retinopathy, age-related macular degeneration, and macular edema, by training deep learning models on a range of OCT images.

**5. VGG-16 and ResNet :**

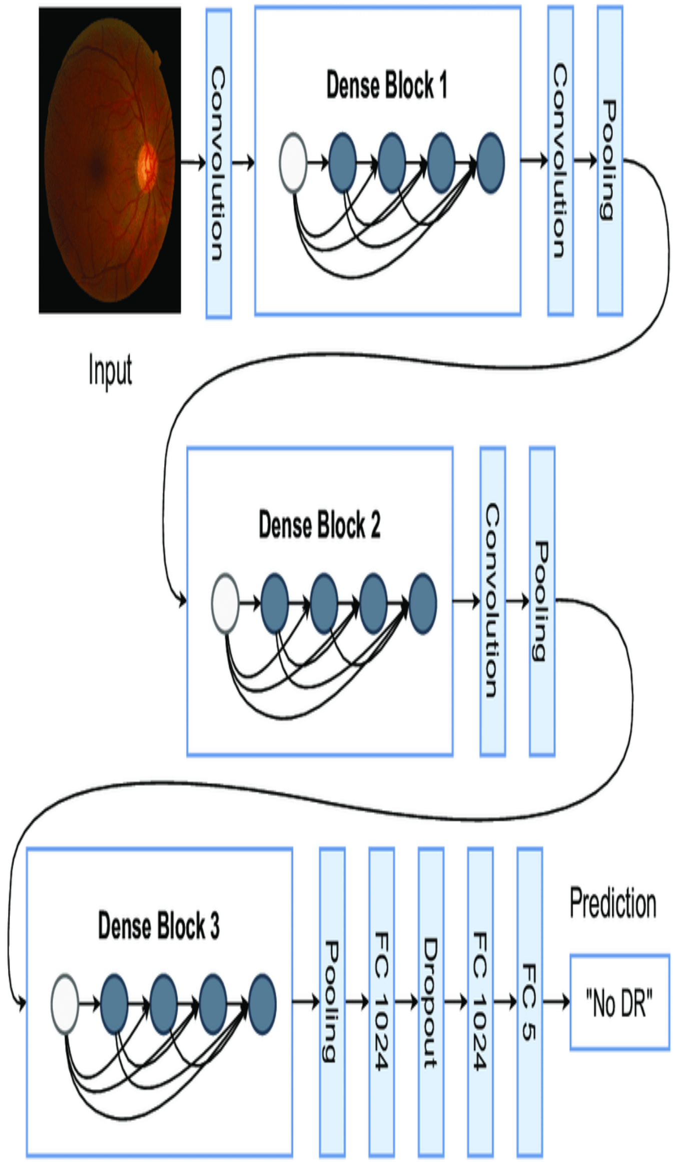
Well-known deep learning architectures ResNet and VGG-16 have been modified for the diagnosis of retinal diseases.
While VGG-16 offers a consistent and deep convolutional framework, ResNet adds residual connections to boost the model's accuracy and depth.

**6. DenseNet-based system:**

Another deep learning architecture, DenseNet has been applied to the identification of retinal disorders in OCT pictures.
Because of its extensive connectedness, it is easier to reuse features, which leads to effective training and excellent illness classification accuracy. These current systems include a broad spectrum of methodologies, ranging from general-purpose structures tailored to the identification of retinal illnesses to specialized models focused on particular diseases.

These show off the adaptability and strength of deep learning in the ophthalmology domain, giving medical professionals a useful instrument to aid in the early identification and diagnosis of retinal disorders.

PROPOSEDSYSTEM



## METHODOLOGY

**Data Collection:**

**Methodology:**

Prior to sending any photograph to researchers, all of the 4,444 patients' health information was anonymised to ensure privacy and security.
Using these OCT pictures, a better Densenet-121 based deep learning method was developed and assessed. The Heidelberg SD-OCT imaging equipment was used to get these OCT pictures. The fundamental scanning procedure includes: (15° × 5°) is the volume scan's scan range.Seven parts; scan section = B-scan. OCT real-time automatic averaging (ART).Because ART was set to 20, 20 SD-OCT photos were averaged. With this technique, we were able to get 4,444 high-resolution non-contact retinal cross-sectional pictures. Furthermore, we retrospectively documented the patient's brief medical history, encompassing personal details on retinal illness and associated therapy.

**Image labeling and data augmentation:**

**Methodology:**

An ophthalmologist examined and assessed each OCT picture to determine CNV, DME, DRUSEN, and NORMAL prior to training the deep learning model.Every picture was examined to conceal the identity of the other ophthalmologist, who made the diagnosis on their own.
An expert panel of seasoned ophthalmologists made the determination since there was debate about the picture label.

Lastly, 3,786 of the 15,573 pictures in the experimental retinal OCT dataset had the appearance of DME and were impacted by CNV. Of the cases assigned to the pictures, 2,113 were DRUSEN instances connected to CNV, while the other cases were healthy cases. As the model's performance was assessed on the test data set, its parameters were adjusted and optimized on the training and validation data sets, respectively.

To better represent clinical care, enhance the variability of OCT images in the training dataset, and lessen the likelihood of overfitting, a data augmentation process was used. To simulate the two orientations that each picture contains—Oculus Dexter (OD) and Oculus Sinister (OS), all photos were turned horizontally. Next, we randomly cropped every image—original and mirror included—and carefully examined every cropped picture to make sure every diseased area was retained. This is because to the fact that in clinical medicine, these His areas' positions may differ from those in OCT pictures.
140,370 OCT pictures in total were acquired by multiplying 14,037 photos by 2 directions and 5 random cropping. Every enhanced image was given the same label as its matching original input (CNV, DME, DRUSEN, and NORMAL).

**Densenet-121 ensembling for image recognition:**

**Methodology:**

Four classification model instances, each based on an enhanced ResNet50, were employed in our method.Fully connected, pooling, and convolutional layers make up the majority of the redesigned ResNet50.

The input picture was converted into a hierarchical feature map by the convolutional layer, which also extracted features. The retrieved features' dimensionality was decreased by conceptually merging related features into a single feature using the pooling layer, which included max-pooling and average-pooling. Fully linked layers merged these features to provide an image-level categorization.

Since training each enhanced ResNet50 from scratch would need a significant amount of data and computing time, we also apply deep transfer learning techniques that may be applied to perform tasks for other tasks. The upgraded ResNet50 incorporates sophisticated convolutions in the convolutional layers. Since training each improved ResNet50 from scratch would require a significant amount of data and computation time, we also use deep transfer learning techniques that can be applied to perform tasks for other tasks. The improved ResNet50 introduces advanced convolutions in the convolutional layers.
The enhanced ResNet50 employed in this investigation is pre-trained on the ImageNet database, which comprises tens of thousands of distinct objects and scenarios. The universal features acquired during pre-training are predicated on retinal OCT images (CNV, DME, DRUSEN) and can be applied via transfer learning. As a result, transfer learning not only greatly accelerated the training of the upgraded ResNet50, but it also made it possible to create a high-accuracy model with a modest amount of training data.

**Model training:**

**Methodology:**

Now that the picture dataset for the model training has been randomly divided into many folds, you may estimate and tune the model using 10-fold cross-validation. The dataset was divided into separate training and validation datasets within each fold at a ratio of 17:1, and these were conducted at the person (rather than picture) level. This indicates that every participant's image—including training and validation—is in the same region. On the matching training or validation datasets, the model's parameters were modified and improved. Since the performance on the validation dataset has not improved further, 10,000 steps total with a batch size of 200 photos per step and a learning rate of 10-5 were carried out for training.

**Visualizing model decisions:**

**Methodology:**

Along with model prediction and occlusion testing on the whole set of test photos, we conducted a qualitative assessment of sample CNV, DME, DRUSEN, and NORMAL images. ophthalmologist to examine her 4,444 test dataset photographs in order to provide a qualitative assessment.A very dependable correct forecast, 4,444 somewhat dependable false predictions, and a somewhat erratic prediction were all generated by the model.

Determining whether judgments are founded on significant clinical variables is made easier by the interpretability of the predicted impacts of the features in our model.

**Statistical evaluation:**

**Methodology:**

AUC metrics of overall accuracy, sensitivity, specificity, and 95% CI were implemented to evaluate model performance and the performance of the best model was compared with the results acquired by eye specialists. By dividing the total number of test photographs by the number of successfully categorized shots, the accuracy was calculated.

The total number of properly classified abnormal photos and correctly labeled normal images were divided by the total number of test images to calculate the sensitivity and specificity, respectively.

Using retinal OCT images, receiver operating characteristic (ROC) curves collected with different operating thresholds were utilized to assess how well the model could identify abnormal from normal.This offered a balance between a specificity of 1 and sensitivity of 1.The diagnostic accuracy of each parameter was summed up using the AUC.Effective models with an AUC between 0.5 and 1 performed better and had higher AUCs.

Statistical analyzes were performed using STATA version 14 and the Python package SciPy.

**MODEL ARCHITECTURE**

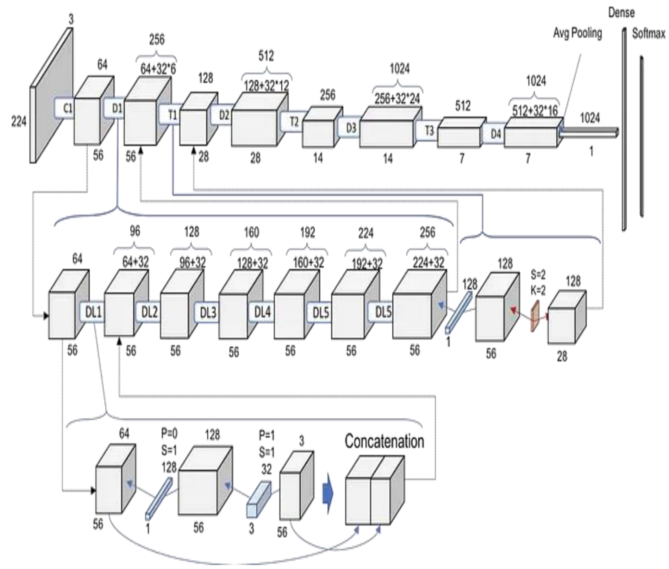


*Fig 3*

DenseNet is a network composed of pooling layers and dense blocks. DenseNet21 has 121 layers, although the topology is easily extensible to accommodate more than 200 layers. Each phase's output channels from the DenseNet are concatenated with the set of outputs that were generated before. Each phase adds K channels to the data by using a pair of 1x1 and 3x3 convolutions. As a result, the number of convolutional steps in the dense block causes the number of channels to increase linearly. DenseNet operates well with K values ranging from 12 to 40, and the network's growth rate stays constant.

A Dense Convolutional Network (DenseNet) was utilized in this paper. A novel kind of CNN called DenseNet was initially proposed by Huang et al. On several image classification datasets, including Cifar-10 and SVHN, it achieved state-of-the-art performance. DenseNet architecture uses dense blocks to link layers. Every layer creates a feature map that transfers data to levels below it using inputs from earlier levels.

**Model Limitations:**

**Overall model limitations:**

Interpretability is lower for a deep learning model than it is for certain other methods.depends on how well and consistently the picture capture and training data labeling processes are carried out.

## RESULT AND ANALYSIS :

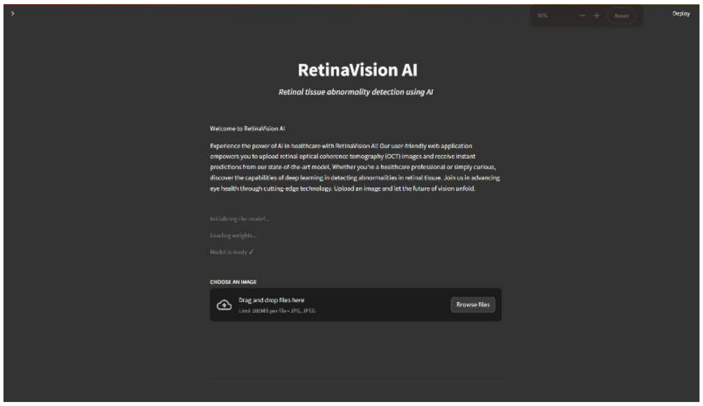



*Fig 4 : Home Page*

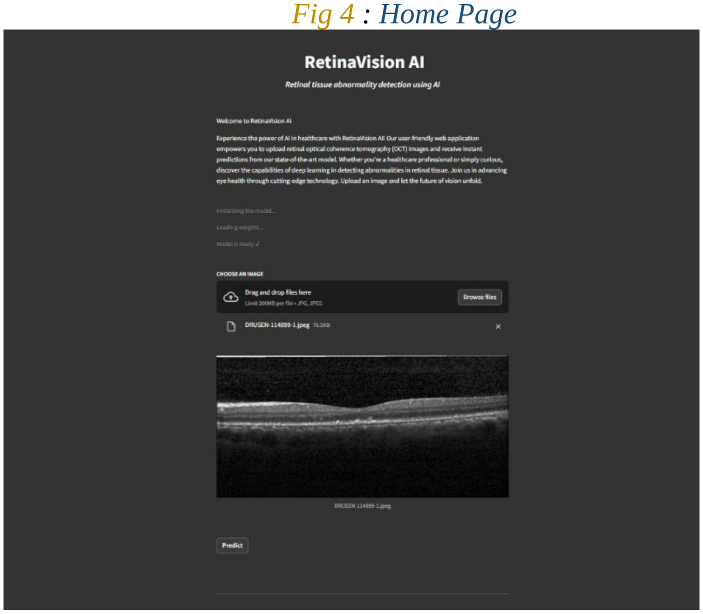



*Fig 5: Inserting OCT Image*

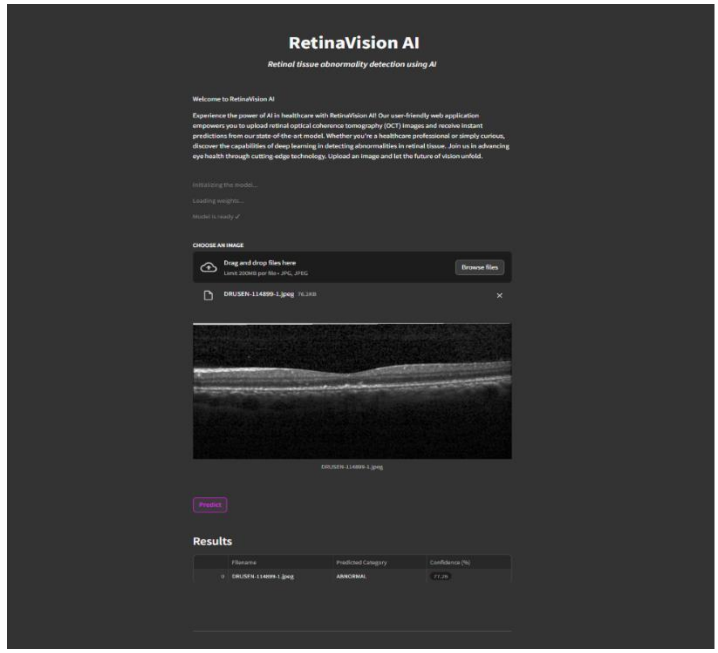



*Fig 6* : Prediction

by inserting the OCT picture from the home page into the model, as seen in fig. 4 above. Utilizing the Browse files displayed in Figure 5, one may upload an image.Just clicking the "predict" button will provide the precise findings shown in Figure 6. The model makes predictions about whether an OCT image is normal or abnormal (DME, CNV, or DRUSEN).

## MODEL PERFORMANCE & PERFORMANCE METRICS:

| Metric | Training Set | Validation Set | Test Set |
|---|---|---|---|
| **Accuracy** | 94.63% | 95.53% | 95.37% |
| **Recall** | 95.59% | 97.01% | 96.67% |
| **Precision** | 93.25% | 93.64% | 93.67% |
| **F1** | 94.35% | 95.28% | 95.12% |
| **ROC- AUC** | 98.77% | 98.92% | 98.75% |

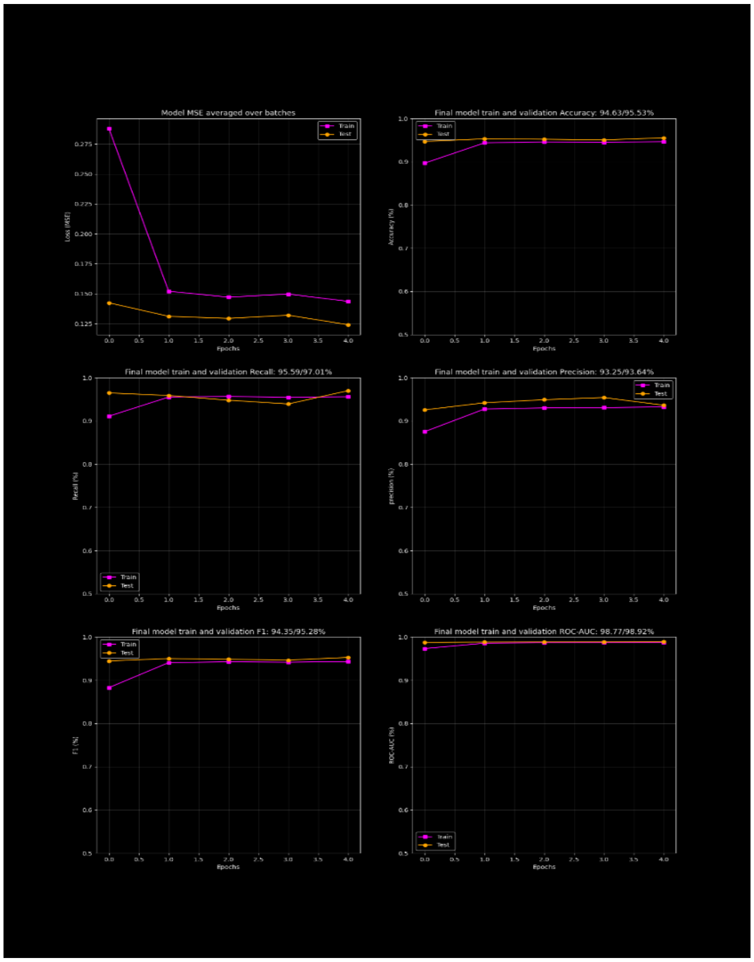



*Fig : 7*

## CONCLUSION AND FUTURE HOPE:

The OCT scanned pictures of the retina are classified into four groups of retinal disorders using a deep learning based model in this work. DenseNet121 (Resnet) network architecture serves as the foundation for the suggested paradigm. The increasing application of OCT imaging techniques and computer-aided diagnosis (CAD) in the diagnosis of medical illnesses served as the impetus for the study. We used the previous work as guidance to create a VGG-19 architecture-based transfer learning model for the detection of retinal diseases. Using transfer learning techniques (using pre-learned weights from the ImageNet dataset), this model is being trained, validated, and evaluated on the Mendeley retinal OCT image dataset.

We evaluate the performance of the proposed model on both the development and foreign datasets. Modern models for identifying retinal disorders were contrasted with the findings. A thorough statistical analysis was conducted, taking intoaccount performance, accuracy, recall, precision, F-1 score, and other factors. According to the results, the recommended transfer learning model works better at automatically identifying retinal diseases than the most advanced method. The suggested investigation may be expanded in the future to include the identification of various retinal conditions, including retinitis pigmentosa, retinal tears, and retinal detachments. An OCT angiography and fundus image database may also be used to evaluate the model.

## REFERENCES:

Kermany, Daniel; Zhang, Kang; Goldbaum, Michael (2018), “Large Dataset of Labeled Optical Coherence Tomography (OCT) and Chest X-Ray Images”.