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Classification of Uncertain ImageNet Retinal Diseases using ResNet Model

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Abstract: An automated method is required to detect retinal diseases. The goal of this study is to build automated screening methods for retinopathy (DR) and other eye diseases using deep learning. In this study present an approach for detecting retinal illness using a CNN. In order to find these patterns, CNN may be employed by extracting features from the data. A color Fundus image-based technique is proposed by the authors of this study to detect retinal disorders. Without prompt diagnosis and treatment, retinal disorders may cause permanent vision loss. The condition must be diagnosed at an early stage in order to get the right therapy and cure it. Deep learning models may be used to train and test the data in order to classify different retinal disorders, where several common retinal diseases and conditions are classified and normalized. This study looked at how retinal pictures may be used to classify eye illnesses using CNN. Over eight different retinal illnesses are included in this dataset, which applied a CNN model to Pretrained on Classification of uncertain ImageNet Retinal Diseases using ResNet Model has been implemented, CNN is built for retina pictures with varying task functions and depths. Various filtering and pooling strategies are tried and shown to have a significant impact on network performance. This is possible because employing a convolutional neural network to process the retinal pictures. It has been discovered that this suggested method has an accuracy rate of more than 80%.

Keywords — *Convolutional Neural Networks (CNN), Image Processing, uncertain ImageNet dataset, pretrained model,*

1. Introduction

More than 2 million individuals worldwide are affected with inherited retinal disorders (IRDs), which are a big, clinically and genetically diverse cluster of illnesses. Given that IRDs account for the most common hereditary types of human vision impairment, the disease's effect on both individuals and society cannot be overstated. These images are critical in the diagnosis of a wide range of eye illnesses. Ocular illnesses can be effectively managed if detected and diagnosed in the early stages, which is why early detection and diagnosis are so important. Rather than using handmade algorithms, deep learning models that automatically learn key characteristics for particular tasks have progressively improved the performance of medical image analysis.

Retinal fundus picture deterioration is a common occurrence while photographing the retina. It is difficult for ophthalmologists and automated systems to establish medical diagnoses because of artifacts such as inadequacy of light or blurry images. The quality of the fundus photographs is thus critical. In the past, ophthalmologists would manually examine the quality of their work, which is time-consuming. Consequently, professionals or an automated system will require automated assessment approaches to aid them.

The quality of retinal fundus images may be assessed automatically in a number of ways. They fall into three basic categories: structural, generic, and feature-based. Using approaches based on structural features, retinal images' quality may be evaluated by segmenting blood vessel structures. Simple image characteristics are derived from the retinal picture without segmenting the structures in generic techniques for assessing the quality of the retinal image; whereas combination based approaches incorporate both generic and structural features for quality evaluation.

To identify Retinal Diseases, an automated approach is needed. Deep learning-based automated screening systems for diabetes-related retinopathy (DR), glaucoma, and other eye illnesses are intended to be developed via this research effort. This model for employing a CNN to detect retinal disease has been given here. CNN may be used to identify these complex patterns by extracting features from the data. The goal is to diagnose retinal illness at an early stage, which will allow us to avoid serious complications. These measures help us to minimize the harm caused by delayed diagnosis, as well as giving us more time to cure the underlying problem. The authors of this research suggest a colour fundus image-based approach for identifying retinal diseases in detailed by following sections.

2. Motivation

The aim for expanding this approach is to detect retinal diseases in earlier stage, which helps us to prevent major damage. This allows us to reduce the damage caused by late diagnosis, as well as gives time to treat the cause with more efficient medicine. This paper proposes a generic retinal disease classification system for color fundus images.

3. Literature Survey

In this section, a brief description about Classification of Retinal Diseases & their methods to employ has been discussed. The

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following survey hasn't tolerated the Classification of uncertain ImageNet Retinal Diseases, which built for retina pictures with varying task functions and depths. Hence proposed a novel Classification of uncertain ImageNet Retinal Diseases using ResNet Model, which is possible because employing a convolutional neural network to process retinal pictures & outperforms the existing methods.

The topic of [1] is OCT-based Transfer Learning for Automated Categorization of Retinal Eye Disorders. SVM instances using two transfer learning structures and categories losses were employed in the proposed DL classification models for retinal ailment categorizations. To classify [2], a convolutional neural network is utilized. Deep learning and transfer learning are used in [3]by Berrimi, M., & Moussaoui, A. (2020, October) to develop a new classification model for retinal disorders based on OCT images, which can be used to automatically identify various retinal diseases. To categorize the normal and abnormal situations in [4], a Convolutional Neural Network (CNN) is employed Ophthalmologists may diagnose diabetic maculopathy more quickly and readily with the aid of this paper's goal of developing an effective Computer Assisted Diagnosis (CAD) system. For the categorization of retinal OCT images into diagnostically important classifications, including healthy, AMD, diabetic macular edoema (DME), and choroidal neovascularization (CN), researchers presented the Deep Recurrent Residual Inception Network (RRI-net) in [5]. (CNV). Classifying retinal disorders using a transfer learning technique has been discussed in [6]. The VGG19 model was used by the authors to fine-tune the network in order to extract information. A copy of the data can be seen for free at [7]. In [8], the symptoms of hypertensive retinopathy are described in detail. According to [9], non-proliferative retinopathy is the initial stage of diabetic retinopathy. Networks trained using Residual Neural Networks are thought to be more accurate and easier to construct [10]. According to [11], it is a widely held belief that larger datasets lead to stronger deep learning models. Diabetic retinopathy can be detected via an automated technique [12].

Maryada, S. K. R [2022] Artificial intelligence (AI) applications in medical imaging informatics have sparked a lot of interest in the scientific community. Automated analysis of retinal fundus photography, for example, aids in the diagnosis and monitoring of diseases such as glaucoma, diabetic retinopathy, hypertensive retinopathy, and cancer in the field of ophthalmology. However, a vast and varied dataset is required for training and validation of a viable AI model. While there are a great number of fundus pictures accessible online, compiling them into a clean, well-structured dataset is a time-consuming and labor-intensive procedure. In this paper, present a two-stage deep-learning approach for identifying clean retinal fundus pictures and deleting photos with severe artefacts automatically. Two transfer-learning models based on the ResNet-50 architecture that have been pre-trained using ImageNet data are created in two phases, with increased SoftMax threshold settings to minimise false positives. The first stage classifier recognises the "easy" pictures, whereas the second stage classifier identifies the "tough" (or undecided) images. In this research first find 1,227 retinal fundus photos using Google's search engine. When compared to a single-stage model with a PPV of 95.74 percent, Proposed two-stage deep-learning model produces a positive predictive value (PPV) of 98.56 percent for the target class. False positives for the retinal fundus picture class are reduced by two-thirds using the two-stage methodology. Without reducing the number of photos categorised by the model, the PPV across all classes rises from 91.9 percent to 96.6 percent. This two-stage model's greater performance suggests that constructing an ideal training dataset might help deep-learning models perform better. [13]

Subramanian, M [2022] Since they may appear gradually and without warning, retinal abnormalities have become a major public health issue in recent years. In the most severe situations, these disorders might result in total blindness since they can damage any portion of the retina. In order to diagnose retinal illnesses more accurately and, if possible, early, automated methods must be developed. Retrained convolutional neural networks (CNNs) may be used to identify retinal abnormalities in OCT pictures, and this is the focus of this article. CNN models, such as VGG16, DenseNet201, InceptionV3, and Xception, are utilized to classify seven distinct retinal disorders from a dataset of photos with and without retinal diseases in this work. A number of other techniques are used to improve the generalizability of generated models, including Bayesian optimization and picture augmentation. In addition, this study compares and analyses the offered models, as well. More than 99 percent of retinal disorders can be detected using DenseNet201 on the Retinal OCT Image dataset, whereas other techniques only identify a limited number of retinal diseases. [14]

Sunija, A. P [2021] in the suggested study, down sampling and weight sharing were used to increase training efficiency and were shown to drastically decrease trainable parameters. Color OCT pictures of the retina were also used as a reference for class activation mapping. Even though the suggested network only utilized 6.9 percent of learnable parameters, it surpassed its predecessor ResNet-50 in classification. Because it is simpler and has fewer learnable parameters than previous models, the presented approach has the potential to be used in real-time applications. [15]

Elsharif, A. A. E. F [2022] among the various eye disorders, Age-Related Macular Degeneration (AMD), which affects central vision and is a primary cause of blindness in those over 50, is the most prevalent. AMD may take one of two forms: wet or dry. DRUSEN and AMD. This is a consequence of diabetes called Diabetic Macular Edema (DME), which is characterized by fluid buildup in the macula and consequent damage to the fovea. The longer it goes untreated, the more likely it is to cause visual loss. Consequently, the significance of early illness identification cannot be overstated. The primary objective is to aid physicians in the early detection of these illnesses before they progress to an advanced state. For the diagnosis of retinal diseases, optical coherence tomography (OCT) is essential. OCT is a kind of imaging procedure used to get detailed images of the retina. In this study, look at several methods and methodologies for classifying OCT pictures of retinal disorders using deep learning. VGG-16, ResNet-50, Inception V3, and Exception are the models used to enhance patient care because they lower expenses and enable rapid and accurate analysis of huge research. Because of the high accuracy of ResNet-50's testing, clinicians will have an easier time diagnosing retinal illnesses as a consequence of these findings. [16]

Kabir, H. D [2022] Different random initialization, model selection and augmentation parameters have been used to train many deep neural networks (DNNs) in order to represent the epistemic uncertainty. First, extract characteristics from the pre-trained neural network. The distribution of opacity score throughout the test is obtained by applying features to the ensemble of completely linked layers. ResNet and DenseNet DNNs are also trained so that system can see how model selection affects prediction and uncertainty. The suggested uncertainty quantification approach is also shown in the study. The suggested method's scripts may be found at GitHub.[17]

Ke, A [2021] Pretrained models created for ImageNet are often used in deep learning approaches for interpreting chest X-rays. ImageNet-pretrained weights outperform random initialization in this paradigm, which posits that stronger ImageNet architectures are better in chest X-ray tasks. A large chest X-ray dataset (CheXpert) is used to test these assumptions in this study. This study compare transfer and parameter performance for sixteen convolutional models. First, discover no correlation between ImageNet and CheXpert performance for models without and with pretraining. Proposed system results show that the selection of a model family has a greater impact on performance than the size of a family on medical imaging tasks. A statistically significant gain in performance is seen across all designs, with the greatest boost in performance for smaller architectures. As for the fourth step, look at whether ImageNet architectures are too huge for CheXpert by removing final blocks from pretrained models, and discover that increase parameter-efficiency by an average of 3.25% without suffering a statistically significant loss in performance. ImageNet and chest x-ray interpretation performance are now linked experimentally for the first time by the findings of this study.[18]. Gelman, R [2022] Transfer learning increased DR classification performance, as evaluated by Kappa, for all networks, but the impact varied from minimal to considerable. For SD-OCT–based categorization, transfer learning had no influence on accuracy in eight of the nine networks examined. According to these findings, transfer learning may significantly improve DR classification performance, while it may have only a minor impact on SD-OCT classification performance.[19]

Ge, Z [2021] On the "closed-set" picture recognition, the current generation of deep neural networks has reached close-to-human results. "Open-set" recognition algorithms, which strive to reject new classes while maintaining high identification accuracy on known classes have been more popular in recent years [20]. ImageNet's generic domain-trained open-set algorithms have not been tested in a more particular domain, such as medicine; hence their performance in that domain is unknown [21][22]. A lack of principled and formal assessments for these generic open-set approaches will lead to ineffective adoption of AI-based medical diagnostics and increased risks of poor decision making. Using a variety of general and medical datasets, rigorously compare and contrast current state-of-the-art open-set approaches, examining both "similar-domain" and "different-domain" open-set situations. Results and concepts are summarized and explained in terms of how the models respond to different levels of openness as well as varied distributions of open courses [23]. To demonstrate the primary difference between open-set models trained in general domains and those trained in medical domains by analyzing the findings quantitatively and qualitatively [24]. Confidence calibration and inference efficiency are also used to assess characteristics of model resilience in healthcare workflows.[25]

4. Proposed System

In this section a brief discussion on Classification of uncertain ImageNet Retinal Diseases using ResNet Model has been implemented. Figure 1 represents workflow of proposed system for retinal disease classification.

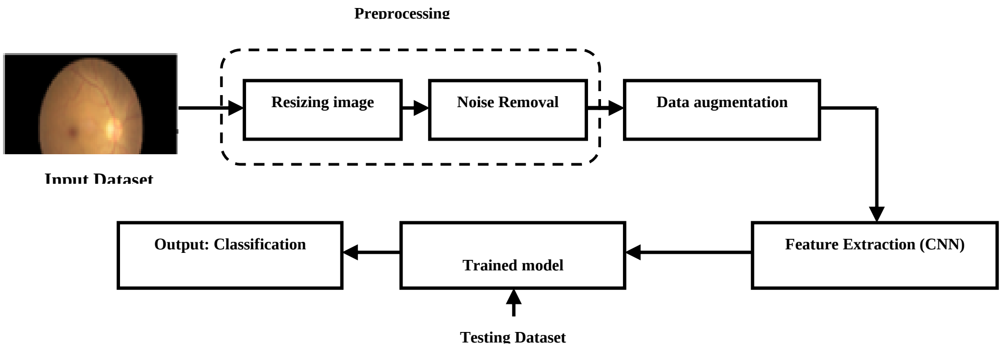

Figure 1: The Block Diagram

1.1 Pre-Processing

Pre-processing a picture is a dangerous stage in the whole process. It removes any inconsistencies that might jeopardize the model's performance. To meet the demands of the model, resize the photographs. Those characteristics that have a greater impact on the decision-making process have been improved so that the model can more readily discover and use them.

The main steps involved in Pre-processing are:

- Resizing/Cropping image
- Noise Removal

A. Resizing/Cropping image

Resizing/Cropping of images involve modifying the image in such a way that it is useful for the model. In the proposed model, the images are reduced to a consistent 16*16 resolution, because if they are reduced any smaller, then there might be risk losing some of the image's important features. So, the resizing resolution should be in such a way that the image should be fit in the model as well as no important features are lost. If the image is less than the needed size, it will be enlarged it to the appropriate size. Pre-processing achieves the resizing of image, suited for the model.

B. Noise Removal

In general, the image sensor and electronics of a scanner or digital camera can create noise in pictures. Image noise can also come from film grain or a photon detector's shot noise. Gaussian noise, salt-and-pepper noise, quantization noise, anisotropic noise, and other sounds can also be generated. To eliminate various sorts of sounds from pictures, in this syudy utilize computer vision Image Denoising and other appropriate filters such as Linear filter, Non-linear filters, and Adaptive filters.

1.2 Data Augmentation

Most people are familiar with picture data augmentation [11], which involves producing new photos in the training dataset that are identical to the originals but have been altered in some way. Using the next improved approach, Rotation Augmentation, raw images are rotated clockwise by a predefined degree, which may range from 0 to 360 °. In this study rotated the image in the dataset at four distinct angles in proposed experiment (45°, 90°, 135°, & 180°). The Keras deep learning neural network toolkit's "Image Data Generator" class enables you to fit models using picture data mining algorithms.

A variety of techniques, including pixel-scaling approaches, are supported. Data pre-processing strategies for picture data include the following:

- The image is shifted using the width shift range and height shift range parameters.
- Images are flipped using the horizontal and vertical flip variables.
- Rotation of images using the rotation range parameter
- Image brightness may be controlled using the brightness range option.
- The zoom range option allows you to zoom in on an image.

Feature Extraction

To minimize the amount of features in a dataset, new features can be created from the current ones using feature extraction (and then discarding the original features). They can then summarize the majority of the information that was previously available in their original form. For extracting characteristics from photos, Convolutional Neural Networks (CNNs) are a powerful tool. Color, Shape, Texture, and other features are included. The initial training of a CNN is computationally intensive. Consequently, the Transfer Learning method is used. Feature extraction is done using pre-trained CNNs, which can then be used to train any classifier. In the proposed model, ResNet is used as feature extractor. These features can now be fed into any classifier of proposed choice for classification.

1.3 Training

In this phase, a ResNet [10] model is trained to conduct semantic segmentation. Residual networks are well-known for making the training of much deeper networks easier. A model is trained by feeding datasets into it at this stage. And it is at this step that a deep learning algorithm is learned. Deep learning algorithms come in a variety of flavors, the most prevalent of which being supervised and unsupervised learning algorithms.

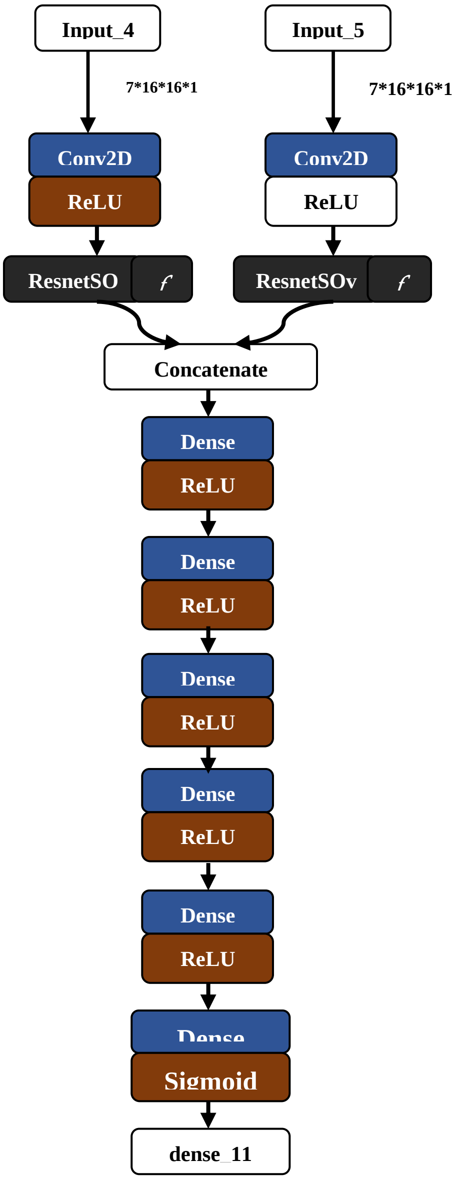

Figure 2: ResNet50 Neural Network [10]

This proposed model is a supervised one, since this employed training the model using class labels. The model's weights must be initialized at random. As a result, the algorithm learns to modify the weights as needed. In the proposed model, a completely conventional ResNet50 is trained to conduct semantic segmentation and subsequently produce an output of disease identified in a picture. Due to computational restrictions, pictures have been cropped to a size of 16*16, using pre-processing, and the size of all 4474 images has been uniformed. The model accepts an R RGB picture of dimension 16*16 as an input produces the disease name if the retina is affected by it.

Figure 2 represents the ResNet50 neural network of the proposed system with two input layers, two convolutional layers with ReLU as an activation function, five dense layers with ReLU activation function & one dense layer with sigmoid fuction and an output dense layer.

The quality of training data, accurate specification of success criteria, and the complexity of model selection might all influence the length of training. Factors such as the training technique, weight distribution, and model complexity all have an impact.

Other variables unrelated to the data or models, such as computational capacity and expert resources, might influence the training time. In this proposed system, the ResNet model is trained with 180 iterations or epochs, to achieve better accuracy, which is over 80%.

1.4 Classification

The proposed system's aim is to detect retinal diseases from a representation. This can be defined as categorization problem, since the model is dealing with eight classes: ['N', 'D', 'G', 'C', 'A', 'H', 'M', 'O'] i.e., 'N': 'Normal Fundus', 'D': 'Moderate nonroliferative retinopathy', 'G': 'Glaucoma', 'C': 'Cataract', 'A': 'Agerelated macular degeneration', 'H': 'Hypertensive retinopathy', 'M': 'Pathological Myopia', 'O': 'Macular epiretinal membrane'.

A. Normal Fundus

Normal fundus pictures of the right (left) and left (right) eyes, taken from the front, with left to the person's right in each image. There are no signs of illness or pathology in any of the funduses. Figure 3 shows normal fundus images.

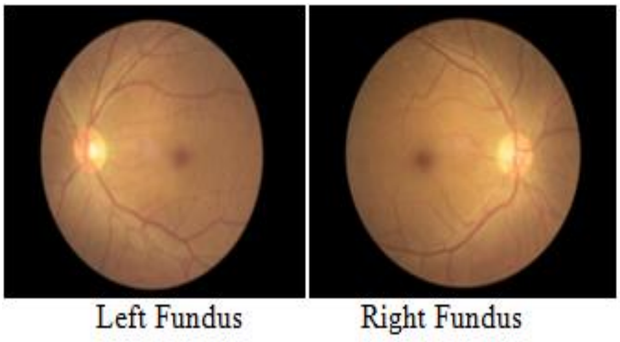

Figure 3: Normal fundus [7]

B. Non-proliferative retinopathy (NPDR) of the moderate to severe kind

NPDR [9] is a kind of non-proliferative diabetic retinopathy with few to no symptoms. When you have NPDR, your retina's blood vessels have been permanently destroyed. Fluid may leak into the retinal due to microaneurysms, which are small blood vessel bulges. Images of moderate no proliferative retinopathy are shown in Figure 4.

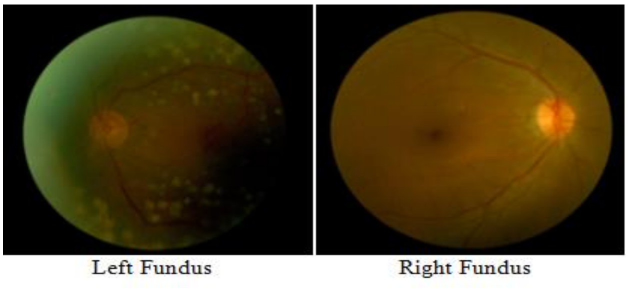

Figure 4: Moderate non-proliferative retinopathy [7]

C. Glaucoma

A series of eye diseases known as glaucoma affect the visual cortex, which is essential for normal eyesight. An unusually high ocular pressure might lead to this kind of injury. In those over 060, glaucoma is a primary cause of blindness. Images of glaucoma are shown in Figure 5.

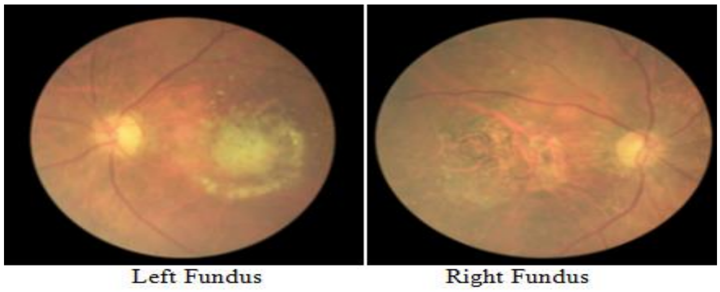

Figure 5: Glaucoma [7]

D. Cataract

A cataract is the clouding of the eye's typically clear lenses. Cataract sufferers describe the experience of gazing through hazy lenses as being similar to viewing throughout a fogged-up windows. There is no natural cure for cataracts. According to the Mayo Clinic, no research has shown how to prevent or halt the growth of cataracts. However, there are several healthy lifestyle behaviours that may be beneficial: Have your eyes examined on a regular basis. Figure 6 shows Cataract images.

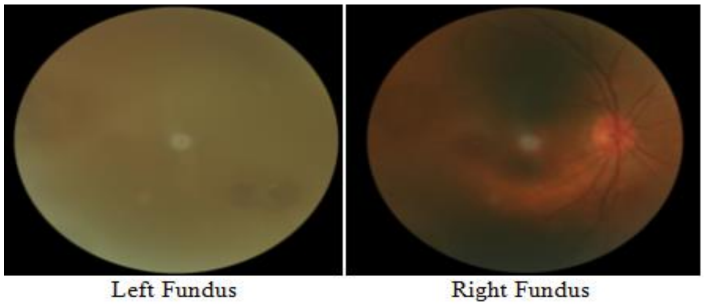

Figure 6: Cataract [7]

E. Age-related macular degeneration

Age-related macular degeneration (AMD) is a degenerative eye condition that may cause blindness. Among those over 60, it is the most common cause of severe, long-term vision loss. It occurs when the macula, the retina's small centre portion, degenerates. The disease is known as age-related macular degeneration because it affects individuals as they become older. It seldom causes blindness, but it can cause major vision problems. Figure 7 depicts pictures with defects caused by age-related macular degeneration.

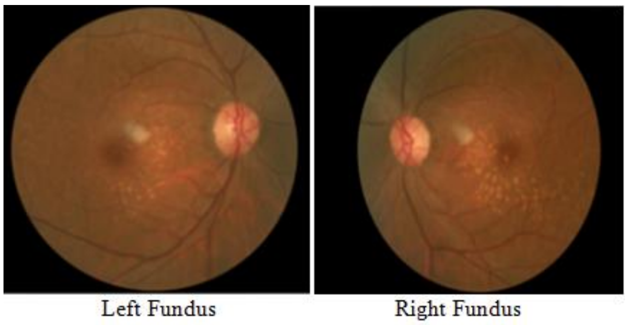

Figure 7: Representation of AMD [7]

F. Hypertensive retinopathy

Hypertensive retinopathy [8] is vascular injury to the retina induced by high blood pressure. Symptoms frequently appear later in the course of the illness. Arteriolar constricting, arterio - venous nicking, vascular wall changes, flame-shaped hemorrhages, cotton-wool patches, yellow hard exudates, and optic disc edema may all be detected on funduscopic examinations. Figure 8 shows Hypertensive retinopathy images.

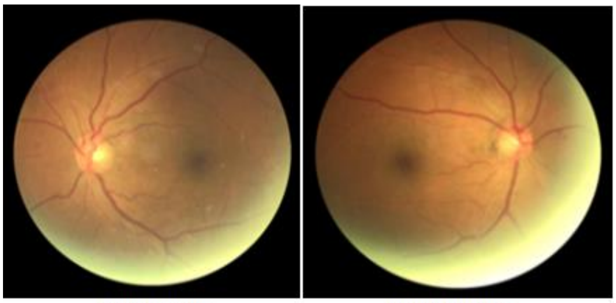

Figure 8: Hypertensive retinopathy [7]

G. Pathological Myopia

Pathological myopia refers to extreme nearsightedness that has resulted in degenerative changes in the rear of the eye. Pathological myopia is a condition that causes vision loss that can't be cured with normal eye glasses and eye lances. The main factors proposed for driving the development of pathological myopia are elongation of the axial length and posterior staphyloma. Figure 9 shows Pathological myopia infected images.

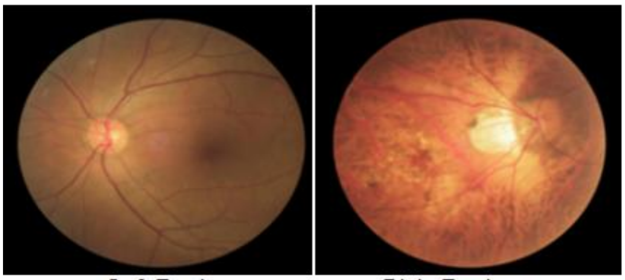

Figure 9: Pathological Myopia [7]

H. Macular epiretinal membrane

A thin layer of fibrous tissue called an epiretinal membrane may grow on the surface of the retina's macular area, causing vision issues. Macular pucker, macular fibrosis, surface wrinkling retinopathy, and cellophane maculopathy are all terms used to describe an epiretinal membrane. Treatment isn't required for all epiretinal membranes. Early epiretinal membranes without any visual disturbances can be observed. In severe cases that effect vision, surgery is needed. Figure 10 shows the macular epiretinal membrane infected images.

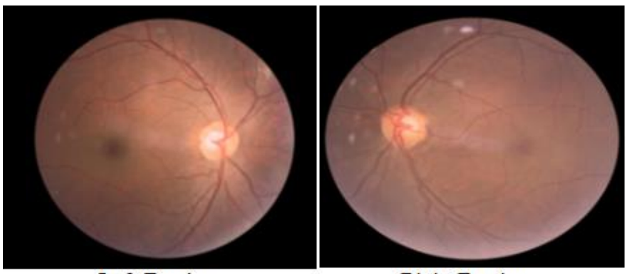

Figure 10: Macular epiretinal membrane [7]

1.5 Dataset

The retinal colour fundus images are included in the Dataset. This Dataset is accessible for free on uncertain ImageNet Kaggle [7]. The data collected for training needs to be split into three different sets: Training, Validation & Test. Table I gives the details and statistics about the dataset.

Table 1 shows the statistics of dataset that is used for classification. The dataset has been split into 70.00% for training dataset, 20.00% for testing dataset & 10.00% for validation dataset. Out of all #6392 images, #4474 images are used for training, #1278 images for testing and 639 for evaluation purpose.

TABLE: 1 STATISTICS OF DATASET [7]

Subset	Dataset
Training	4474
Testing	1278
Validation	639
Total	6392

1.6 Performance Evaluation Measures

In this section the suggested system's performance is determined by a number of factors, as detailed below:

(i) **Confusion matrix:** As indicated in Table 2, it is used to evaluate the classification algorithm's performance.

TABLE: 2 2X2 CONFUSION MATRIX

	Actual a=00	Actual b=01
Predicted a = 00	#TP	#FP
Predicted b = 01	#FN	#TN

(ii) **Classification:** The Classification Accuracy Rate (CAR) is calculated using formula (1), where TP denotes True Positives, FP denotes False Positives, FN denotes False Negatives, and TN denotes True Negatives.

$$\text{Accuracy} = (T_P + T_N) / (T_P + T_N + F_P + F_N) \quad (1)$$

(iii) **Precision***:* It is determined using formula (2), which assesses the result's relevance.

$$\text{Precision} = T_P / (T_P + F_P) \quad (2)$$

(iv) **Recall:** Equation (3) is used to determine the relevance of the produced result.

$$\text{Recall} = T_P / (T_P + F_N) \quad (3)$$

(v) As demonstrated in Equation, F-Measure is utilised to find the optimum balance of accuracy and recall (4).

$$F1 = 2 * (\text{precision} * \text{recall}) / (\text{precision} + \text{recall}) \quad (4)$$

1.7 Metrics And Statistics

TP, FP, TN, and FN are the statistical measurements used to analyze the performance of the suggested system (FN). The proposed system's trained accuracy is calculated from the metrics shown below:

Accuracy = (5414+40682)/(5414+866+40682+1582) = 0.949571

Precision = 5414/(5414+866) = 0.862101

Recall = 5414/(5414+1582) = 0.773870

The proposed system's validation statistics are calculated from the metrics shown below:
Accuracy = (856+6493)/(856+146+6493+273) = 0.946060
Precision = 856/(856+146) = 0.854291
Recall = 1103/(856+273) = 0.758193

The proposed validation model's statistics are calculated from the metrics shown below:
Accuracy = (1103+8158)/(1103+161+8158+290) = 0.95356
Precision = 1103/(1103+161) = 0.872626
Recall = 1103/(1103+290) = 0.791816

5. Results And Analysis

In this section the proposed system's performance has been discussed & analyzed. The major objective of this approach is to help people who are suffering from retinal diseases. This proposed system successfully detected the retinal disease of a person from a picture which is obtained from color fundus with an accuracy of over 85 percent. The input picture is used to generate the disease name of the retinal image, if it is suffering from one of the diseases provided in the dataset.
Figure 11 shows the classification report of the proposed system, which includes precision, recall, F1-score and support values of all classes, micro average, macro average, weighted average and samples average.

	precision	recall	f1-score	support
N	0.804574	0.957921	0.874576	404.0
D	0.914835	0.798561	0.852753	417.0
G	1.000000	0.782609	0.878049	69.0
C	0.955882	0.878378	0.915493	74.0
A	0.911111	0.539474	0.677686	76.0
H	1.000000	0.272727	0.428571	33.0
M	1.000000	0.730769	0.844444	52.0
O	0.858537	0.656716	0.744186	268.0
micro avg	0.872627	0.791816	0.830260	1393.0
macro avg	0.930617	0.702144	0.776970	1393.0
weighted avg	0.883418	0.791816	0.822870	1393.0
samples avg	0.848023	0.819467	0.826798	1393.0

Figure 11: Classification Report

Figure 12 shows the prediction result of the model when given left fundus and right fundus into the model for testing.

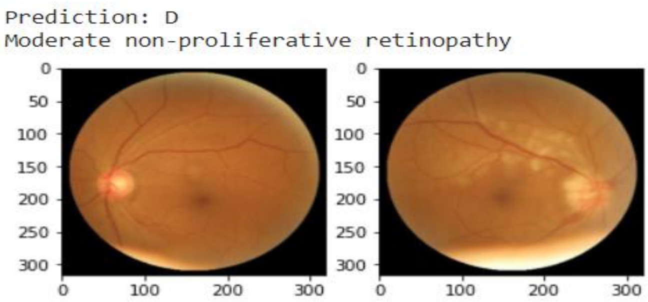

Figure 12: Proposed system's output

The Table 3 shows the analysis and comparison between two models: ResNet50 and EfficientNet-b7 when trained with ODIR-5K (Ocular Disease Intelligent Recognition) [7] dataset.

TABLE:3 ANALYSIS OF TRAINED MODELS

Model	ResNet50	EfficientNet-b7
Accuracy	0.7748	0.8823
Loss	0.1449	0.6652
No. of Classifications	8	8
Epochs	100	100
Training Size	70	70
Validation Size	10	10
Testing Size	20	20

When trained with the dataset that has been splinted into 70% for training dataset and 30% for testing and validating dataset, the ResNet50 model provided an accuracy of 0.7748 with 0.1449 loss in 100 epochs. Whereas the EfficientNet-b7 provided an accuracy of 0.8823 with 0.6652 loss in the same 100 epochs when evaluated against 8 different conditions.

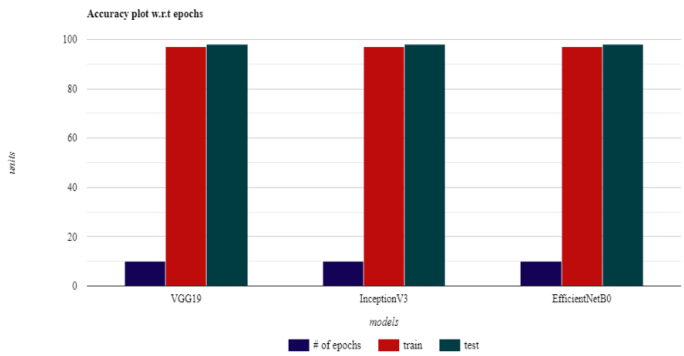

Figure 13: Accuracy Plot w.r.t Epochs

Figure 13 shows the plot of accuracies w.r.t epochs of different deep learning pre-trained models like VGG19, InceptionV3 and EfficientNetB0 provided when training with Retinal Fundus Multi-disease Image Dataset (RFMiD) [13] dataset. Unlike ODIR-5K dataset, RFMiD contains 3200 color fundus retinal images with 45 different eye conditions like diabetic retinopathy, age-related macular degeneration, etc.

6. Conclusion

In order to detect retinal illness, an automated technique is needed. This research project aims to develop automated screening methods for diabetes-related retinopathy (DR), glaucoma, and other eye diseases using deep learning. In this study, the use of a CNN to identify retinal disease was discussed. Extracting features from the data collection may help discover these trends. The fundamental goal of this research is to avoid serious problems by recognising retinal disorders as soon as possible. The benefits of early detection are lessened, and more time is given to deal with the basis of the problem. They recommend that colour fundus images be utilised to diagnose retinal diseases.
In this study, models for detecting retinal diseases in photographs provided by the user were built. As soon as an image is selected, an algorithm begins to evaluate it. No matter how successful different deep learning algorithms are in classifying eye problems, the time necessary to collect and annotate data is sometimes overlooked. As a consequence, CNNs with no solid ImageNet dataset suffer a considerable decrease in performance. Our goal is to increase the model's performance while also

generating a better model using real-time pictures taken from actual patients.

References

[1] Adel, A., Soliman, M. M., Khalifa, N. E. M., & Mostafa, K. (2020, December). Automatic Classification of Retinal Eye Diseases from Optical Coherence Tomography using Transfer Learning. In 2020 16th International Computer Engineering Conference (ICENCO) (pp. 37-42). IEEE.

[2] Bhadra, R., & Kar, S. (2020, October). Retinal Disease Classification from Optical Coherence Tomographical Scans using Multilayered Convolution Neural Network. In 2020 IEEE Applied Signal Processing Conference (ASPCON) (pp. 212-216). IEEE..

[3] Berrimi, M., & Moussaoui, A. (2020, October). Deep learning for identifying and classifying retinal diseases. In 2020 2nd International Conference on Computer and Information Sciences (ICCIS) (pp. 1-6). IEEE..

[4] El-Hag, N. A., Sedik, A., El-Shafai, W., El-Hoseny, H. M., Khalaf, A. A., El-Fishawy, A. S., ... & El-Banby, G. M. (2021). Classification of retinal images based on convolutional neural network. Microscopy Research and Technique, 84(3), 394-414..

[5] Hassan, B., Qin, S., & Ahmed, R. (2020, December). RRI-Net: classification of multi-class retinal diseases with deep recurrent residual inception network using OCT scans. In 2020 IEEE International Symposium on Signal Processing and Information Technology (ISSPIT) (pp. 1-6). IEEE..

[6] Das, A., Giri, R., Chourasia, G., & Bala, A. A. (2019, July). Classification of retinal diseases using transfer learning approach. In 2019 International Conference on Communication and Electronics Systems (ICCES) (pp. 2080-2084). IEEE..

[7] Hasan, M. K., Tanha, T., Amin, M. R., Faruk, O., Khan, M. M., Aljahdali, S., & Masud, M. (2021). Cataract Disease Detection by Using Transfer Learning-Based Intelligent Methods. Computational and Mathematical Methods in Medicine, 2021..

[8] Noronha, K., Navya, K. T., & Nayak, K. P. (2012, December). Support system for the automated detection of hypertensive retinopathy using fundus images. In International Conference on Electronic Design and Signal Processing (ICEDSP) (pp. 7-11)..

[9] Xiao, Z., Zhang, X., Geng, L., Zhang, F., Wu, J., Tong, J., ... & Shan, C. (2017). Automatic non-proliferative diabetic retinopathy screening system based on color fundus image. Biomedical engineering online, 16(1), 1-19..

[10] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778)..

[11] Shorten, C., & Khoshgoftaar, T. M. (2019). A survey on image data augmentation for deep learning. Journal of big data, 6(1), 1-48..

[12] Priyanka Konatham, Mounika Venigalla, Lakshmi Pooja Amaraneni, K. Suvarna Vani, " Automatic Detection of Optic Disc for Diabetic Retinopathy", IJITEEE,May 2020.

[13] Maryada, S. K. R., Booker, W. L., Danala, G., Ha, C. A., Mudduluru, S., Hougen, D. F., & Zheng, B. (2022, April). Applying a novel two-stage deep-learning model to improve accuracy in detecting retinal fundus images. In Medical Imaging 2022: Computer-Aided Diagnosis (Vol. 12033, pp. 135-142). SPIE.

[14] Subramanian, M., Kumar, M. S., Sathishkumar, V. E., Prabhu, J., Karthick, A., Ganesh, S. S., & Meem, M. A. (2022). Diagnosis of retinal diseases based on Bayesian optimization deep learning network using optical coherence tomography images. Computational Intelligence and Neuroscience, 2022.

[15] Sunija, A. P., Kar, S., Gayathri, S., Gopi, V. P., & Palanisamy, P. (2021). Octnet: A lightweight cnn for retinal disease classification from optical coherence tomography images. Computer methods and programs in biomedicine, 200, 105877.

[16] Elsharif, A. A. E. F., & Abu-Naser, S. S. (2022). Retina Diseases Diagnosis Using Deep Learning. International Journal of Academic Engineering Research (IJAER), 6(2).

[17] Saikumar, K., Rajesh, V. A machine intelligence technique for predicting cardiovascular disease (CVD) using Radiology Dataset. Int J Syst Assur Eng Manag (2022). https://doi.org/10.1007/s13198-022-01681-7

[18] Ke, A., Ellsworth, W., Banerjee, O., Ng, A. Y., & Rajpurkar, P. (2021, April). CheXtransfer: performance and parameter efficiency of ImageNet models for chest X-Ray interpretation. In Proceedings of the Conference on Health, Inference, and Learning (pp. 116-124).

[19] Gelman, R., & Fernandez-Granda, C. (2022). Analysis of Transfer Learning for Select Retinal Disease Classification. Retina, 42(1), 174-183.

[20] Ge, Z., & Wang, X. (2021). Evaluation of Various Open-Set Medical Imaging Tasks with Deep Neural Networks. arXiv preprint arXiv:2110.10888.

[21] Mythreya, S., Murthy, A. S. D., Saikumar, K., & Rajesh, V. (2022). Prediction and Prevention of Malicious URL Using ML and LR Techniques for Network Security: Machine Learning. In Handbook of Research on Technologies and Systems for E-Collaboration During Global Crises (pp. 302-315). IGI Global.

[22] Saikumar, K., Rajesh, V., Babu, B.S. (2022). Heart disease detection based on feature fusion technique with augmented classification using deep learning technology. Traitement du Signal, Vol. 39, No. 1, pp. 31-42. https://doi.org/10.18280/ts.390104

[23] Kailasam, S., Achanta, S.D.M., Rama Koteswara Rao, P., Vatambeti, R., Kayam, S. (2022). An IoT-based agriculture maintenance using pervasive computing with machine learning technique. International Journal of Intelligent Computing and Cybernetics, 15(2), pp. 184–197

[24] Nagendram, S., Nag, M. S. R. K., Ahammad, S. H., Satish, K., & Saikumar, K. (2022, January). Analysis For The System Recommended Books That Are Fetched From The Available Dataset. In 2022 4th International Conference on Smart Systems and Inventive Technology (ICSSIT) (pp. 1801-1804). IEEE.

[25] Jothsna, V., Patel, I., Raghu, K., Jahnavi, P., Reddy, K. N., & Saikumar, K. (2021, March). A Fuzzy Expert System for The Drowsiness Detection from Blink Characteristics. In 2021 7th International Conference on Advanced Computing and Communication Systems (ICACCS) (Vol. 1, pp. 1976-1981). IEEE.