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Deep CNN-Based Multi-Class Retinal Disease Detection with Reduced Memory Overhead

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Abstract:

Extensive research directions for important disease diagnosis and classification includes ANN, Deep learning, RNN, Alex Net, and ResNet. Retinal disease classification has been transformed by CNN and U-Net Segmentation. The intricacy of feature extraction causes U-Net to pass the entire feature map to the decoder, which causes errors related to memory and CPU. It stops pooling index reuse when combined with the unsampled decoder feature map. For problems involving multiple classes of data, this study presents a convolutional neural network (CNN) model that makes optimal use of memory. The suggested model was evaluated using an Eye Net benchmark dataset that contained 32 different forms of retinal illnesses. The proposed model enhances memory management and precision, according to the experimental results. In order to compare accuracy, precision, and recall, various epochs and step timings were utilized. The suggested approach performed well on Eye-net.

Keywords: Classification, CNN, deep learning, EyeNet, retina, U-Net

1. Introduction:

Retinal diseases affect individuals of all ages around the globe. Retinal photoreceptors transform light into visual neural impulses that the brain interprets. Common retinal disorders that cause vision loss and sensory deficits include AMD, optic disc drusen, and DME. Among people aged 50–60 and 35% of persons aged 80 and more, AMD is the leading cause of visual impairment in industrialised nations, notably the United States. The variety of retinal diseases makes accurate diagnosis challenging. Ophthalmologists with experience are required. New avenues for the detection and treatment of retinal diseases have opened up thanks to technological advancements, particularly computer-aided diagnostic systems (CAD).Automated disease detection (ADD) has been greatly improved by combining ML and DL, which has led to more accurate techniques of diagnosing retinal diseases. Retinal diseases can be classified, segmented, and identified using modern ML and DL models such as RNN, CNN, AlexNet, ResNet, and VGG. Significant difficulties in implementing ADD arise from the need to collect and label data. Strong datasets are essential for training and validation, according to researchers. To get over these problems, other approaches have been proposed. To develop ML-based hybrid approaches for image preprocessing and classification, researchers have integrated SVM classifiers with U-Net segmentation. Such approaches have achieved an impressive diagnosis accuracy rate of 89.3%. U-Net topologies use a lot of RAM, but DL methods have gotten better. Attention has been drawn to these limitations, and scientists are looking at potential remedies. Research has also been assisted by the creation of large databases such as EyeNet, which has tagged pictures of 32 retinal illnesses. There may be solutions to the increasing frequency of retinal diseases thanks to technological advancements, particularly in ML and DL, which have aided in the early detection and classification of these problems. Researchers and practitioners in the field of ophthalmology can enhance diagnostic precision and patient results by utilising cutting-edge methodologies and massive datasets. To enhance these technologies and increase their accessibility in therapeutic settings, additional research and cooperation are required. An enhanced CNN model based on deep learning has been developed for the diagnosis of serious illnesses utilising retinal imaging. Even though it uses less memory, the CNN model achieves better results than state-of-the-art approaches. In particular, medical condition classification using CNN and U-Net Segmentation has been substantially enhanced, especially for retinal illnesses. Due to the difficulties of feature extraction, U-Net uses a lot of memory and CPU resources while transferring the entire feature map to the decoder. To prevent the reuse of pooling indices, concatenating to the unsampled decoder feature map is necessary. In order to facilitate multi-class classification, this study introduces a CNN model that is memory efficient.

2. Literature Overview:

The incidence and severity of retinal illnesses on eyesight pose challenges to healthcare systems worldwide. The diagnosis and categorisation of diseases might be enhanced by newly created deep learning (DL) and machine learning (ML) techniques. This literature review summarises the most important studies on approaches for automatic identification of retinal diseases. Arunkumar and Karthigaikumar (2017) employed reduced deep learning features for the classification of multi-retinal disorders. Computing overhead is reduced while classification accuracy is maintained by deep learning feature dimensionality reduction [3]. This approach efficiently processes large retinal pictures. Advances in AMD retinal image analysis were described by Kanagasingam et al. (2014). Image processing and analysis approaches were reviewed for their potential utility in identifying and managing AMD [7]. For the purpose of auto-classifying retinal illnesses, Yang et al. (2018) proposed a machine learning/hybrid strategy. Utilising U-Net segmentation for image preprocessing and an SVM classifier, the model demonstrated exceptional diagnosis accuracy [10]. Methods for disease classification can complement one another, as demonstrated by this hybrid approach. In their 2019 study, Perdomo et al. used optical coherence tomography (OCT) pictures and deep learning to categorise diabetic eye diseases. There was hope in their method for detecting diabetic retinal disease [14]. In their analysis of retinal problems, Mahendran et al. (2020) utilised machine learning approaches. By comparing several algorithms for retinal image classification, they demonstrated how these algorithms could aid ophthalmologists in disease diagnosis [15]. Using optical coherence tomography (OCT) images and a Bayesian optimisation deep learning network, Subramanian et al. (2022) were able to diagnose retinal diseases. In order to make better diagnoses, they used Bayesian optimisation to enhance the design of the deep learning network [18]. Classifying retinal illnesses was done using transfer learning by Das et al. (2019). By using information from previously trained deep learning models, their method was able to efficiently classify diseases, even when only little labelled data was available [25]. When it comes to diagnosing retinal illnesses, Sheet et al. (2022) suggested an improved CLAHE filter and transfer CNN. To make disease identification better, they applied deep learning algorithms and image augmentation [37]. The EyeDeep-Net architecture for multi-class retinal ailment diagnosis was created by Sengar et al. in 2023. Their method enhanced clinical decision-making by consistently identifying retinal disorders [38]. Detection of retinal diseases has been greatly improved in recent years because to ML and DL. Due to the complexity of retinal image processing, new architectures based on deep learning, hybrid models, and transfer learning have been created. These advancements could be useful for ophthalmology in terms of early diagnosis, treatment planning, and success rates. To refine these techniques and incorporate them into clinical practice, additional research and teamwork are required.

3. Methodologies and Approaches:

3.1 Proposed System:

Issues with the prevalence and severity of retinal illnesses are a concern for healthcare systems worldwide. Modern approaches to ML and DL have the potential to enhance illness categorisation and diagnosis. This overview of the literature summarises the key works on automatic identification of retinal diseases. With the help of limited deep learning, Arunkumar and Karthigaikumar (2017) were able to categorise disorders affecting several retinas. Computing expenses are reduced while classification accuracy is maintained by deep learning feature dimensionality reduction. [3]. Large retinal pictures are effectively processed by this technology. Latest developments in AMD retinal image analysis were detailed by Kanagasingam et al. (2014). Image processing and analysis approaches were used to investigate AMD identification and management. [7].In order to classify retinal diseases, Yang et al. (2018) suggested a hybrid approach that uses machine learning. An SVM classifier and U-Net segmentation performed well as image preprocessors, leading to accurate diagnoses [10]. Methods for disease classification can complement one another, as demonstrated by this hybrid approach. Using optical coherence tomography (OCT) and deep learning, Perdomo et al. 2019 diagnosed diabetic ocular complications. It appeared like their method for detecting diabetic eye problems was promising [14]. Retinal problems were examined by Mahendran et al. (2020) using machine learning. This study examined various retinal image classification algorithms to demonstrate how they could aid ophthalmologists in disease diagnosis [15]. Bayesian optimisation deep learning networks and optical coherence tomography (OCT) images were used to identify retinal diseases by Subramanian et al. (2022). To enhance diagnosis, the design of the deep learning network was optimised using Bayesian methods [18]. Retinal disorders were categorised using transfer learning by Das et al. (2019). Their approach was able to effectively classify diseases using deep learning models that had been trained earlier, even when labelled data was scarce [25]. In order to better diagnose retinal diseases, Sheet et al. (2022) proposed enhancing the CLAHE filter and transferring CNN. To make disease detection better, they employed deep learning in conjunction with image augmentation [37]. In 2023, Sengar et al. created EyeDeep-Net for the purpose of diagnosing retinal diseases across multiple classes. Clinical decision-making was enhanced by their method, which reliably detected retinal disorders [38]. Nearly all retinal diseases may now be more accurately detected with the help of ML and DL. The development of deep learning, hybrid models, and transfer learning architectures was prompted by the complexity of retinal image processing. Ophthalmology might benefit from these developments in terms of early diagnosis, treatment planning, and outcomes. Improving and clinically applying these strategies requires research and collaboration.

3.2 System Architecture:

The system architecture incorporates CNN models such as MobileNet and Xception, as well as combinations of the two. These algorithms analyse retinal images from EyeNet in order to classify retinal diseases into multiple categories. Train models with labelled data to get the best possible classification accuracy with the least amount of memory usage. Preprocessing, feature extraction from CNN layers, and classification are all part of the design. We test each model using three metrics: accuracy, recall, and precision. Optimal early detection and treatment of retinal diseases is the goal of the system's design.

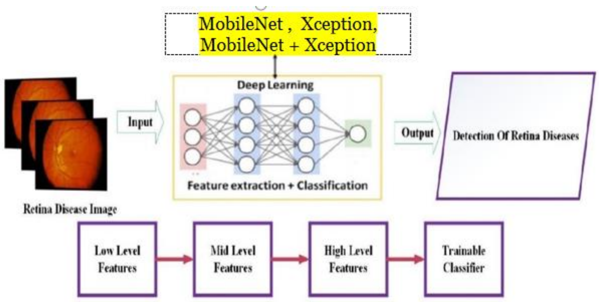

Fig.1. Proposed Architecture

3.3 Dataset Collection:

The EyeNet dataset by Yang et al. [10] improves retinal disease categorisation since it is comprehensive. While STARE and Drive only have a handful of classifications, EyeNet has 32 different retinal disorders that have been classified. Model training and evaluation are both enhanced by this dataset's more diversified and realistic representation of clinical data. Images of the retina annotated with the names of retinal diseases are part of the EyeNet Master Dataset. In order to train and evaluate CNN models for multi-class classification, these images are utilised. Researchers and practitioners can access and replicate the dataset on GitHub to test algorithms for eye illness detection and categorisation. To improve medical imaging and healthcare technology, researchers can use this dataset to build and test deep learning and machine learning models for autonomous retinal disease diagnosis and categorisation. To enhance clinical identification and treatment of retinal diseases, the EyeNet dataset is helpful for algorithm development and validation.

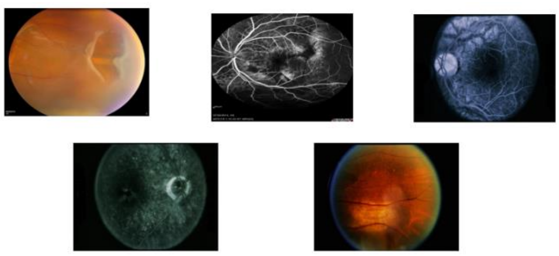

Fig.2. Dataset images

3.4 Image Processing:

Image processing is essential for data preparation for ML models, particularly for image classification tasks such as diagnosing retinal diseases. The ImageDataGenerator module in the Keras package effectively enhances the variety and quality of image data through augmentation. To make the model more generalisable and robust, ImageDataGenerator may use EyeNet to classify retinal illnesses using a variety of image processing techniques.

Re-scaling the Image: The process of rescaling involves normalising the pixel values to a range of 0 to 1. This method guarantees consistent pixel intensities across images, which stabilises training and accelerates convergence. Rescaling is required because modifying the intensity ranges of individual pixels across photos could degrade the performance of the model.

Shear Transformation: By moving pixels along an axis, shear transformation warps images. This technique mimics changes in perspective or orientation to increase the dataset's inherent variability. To make the model more robust against real-world variations, shear transformation can mimic small head movements or changes in imaging angle in retinal photographs.

Zooming the Image: You can adjust the scale of an image by magnifying or reducing its components with zooming. Image quality or focus changes are common in clinical imaging, and this augmentation technique can simulate those. To improve classification performance, the model is trained to detect patterns and features at numerous scales by arbitrarily zooming in and out of retinal pictures.

Horizontal Flip: By horizontally flipping along the vertical axis, mirror images are formed. This method of augmentation enhances the model's generalisability across orientations by adding horizontal reflection-invariant spatial changes. The model's robustness is enhanced by the ability to replicate changes in patient position during imaging by horizontal flipping.

Reshaping the Image: A specific size is achieved by cropping or resizing the image. For efficient model training batch processing, this strategy keeps image sizes uniform. To simplify model building and training, reshaping is essential for datasets with images of varying sizes since it standardises input sizes across all samples. Researchers can use ImageDataGenerator and other image processing technologies to add retinal images to EyeNet. To better classify retinal illnesses, machine learning models train on this enhanced dataset to discover robust and discriminative features. In addition to improving the model's performance on unknown test data, augmentation helps decrease overfitting by exposing it to more variations in the data distribution. The quality and variety of the retinal illness classification picture dataset are enhanced by image processing techniques such as re-scaling, shear transformation, zooming, horizontal flipping, and reshaping. Researchers can improve diagnosis accuracy and patient care by using ImageDataGenerator to develop ophthalmology-specific machine learning models that are more robust and generalisable.

3.5 Algorithms:

Many popular methods for retinal illness classification utilising the EyeNet dataset include MobileNet, Xception, CNN, UNet, SVM, and MobileNet + Xception. These methods are chosen for their picture classification performance and project benefits.

MobileNet:
Designed specifically for use on embedded and mobile devices, MobileNet is a lightweight convolutional neural network architecture. Minimising parameters and computational complexity without sacrificing accuracy is achieved using depthwise separable convolutions. Because of its fast inference speed and small memory footprint, MobileNet is ideal for resource-constrained environments such as edge devices and mobile apps, which is why it is used in this project.

Xception:
An Inception variant, Xception, stands out with its depthwise separable convolutions and skip connections. It has excellent picture classification performance because it captures both local and global features well. To accurately classify diseases, Xception's deep architecture develops hierarchical retinal image representations, which allow it to pick up on fine details and patterns. The project is able to attain higher categorisation accuracy thanks to its good performance.

CNN (Convolutional Neural Network):
For picture categorisation, CNN is a well-liked deep learning architecture. Its fully linked, convolutional, and pooling layers allow for hierarchical feature extraction from input images. When it comes to analysing images of the retina, CNNs are the way to go because of how well they learn spatial feature hierarchies. The project's MobileNet and Xception architectures are evaluated using CNN.

UNet (CNN) SVM
UNet is a medical image segmentation and analysis architecture based on convolutional neural networks. For feature extraction, it uses contracting routes, while for pixel-wise classification or segmentation, it uses symmetric expanding paths. Image segmentation and classification can be done concurrently using UNet and SVM. For the purpose of disease diagnosis and monitoring, the project employs the application of UNet (CNN) SVM to accurately localise and categorise retinal lesions or anomalies.

MobileNet + Xception
Combining several neural network topologies, such as MobileNet and Xception, allows for the optimisation of strengths while minimising weaknesses. To enhance classification, MobileNet + Xception fusion merges features from both models. In order to make the model more accurate, resilient, and generalisable, this technique compiles supplementary retinal image data.
In general, the study's algorithms all have their own set of benefits when it comes to the criteria and limitations for retinal illness classification. UNet (CNN) SVM features segmentation and classification, CNN serves as a baseline model, and MobileNet + Xception fusion use ensemble learning to achieve accuracy. In order to improve patient care and treatment outcomes, researchers can use these algorithms to build robust and effective automated systems for diagnosing and classifying retinal diseases.

4.Findings and Trends:

Accuracy: The ability of a test to differentiate between healthy and sick instances is a measure of its accuracy. Find the proportion of analysed cases with true positives and true negatives to get a sense of the test's accuracy. Based on the calculations:

Accuracy = TP + TN TP + TN + FP + FN

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

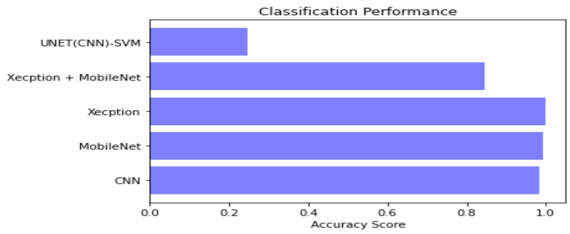

Fig.3. Accuracy comparison graph

Precision: The accuracy rate of a classification or number of positive cases is known as precision. Accuracy is determined by applying the following formula:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

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

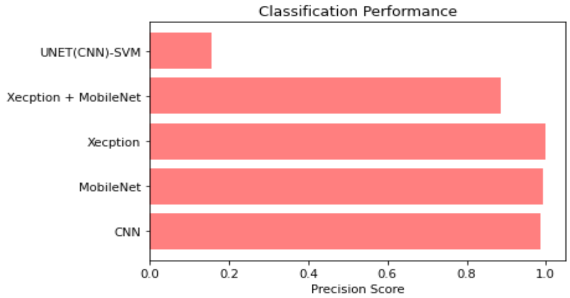

Fig.4. Precision comparison graph

Recall: Recall is a measure of a model's ability to identify all instances of a class that are relevant in machine learning. By comparing the number of correctly predicted positive observations to the total number of positives, it reveals how well a model captures examples of a class.

$$Recall = \frac{TP}{TP + FN}$$

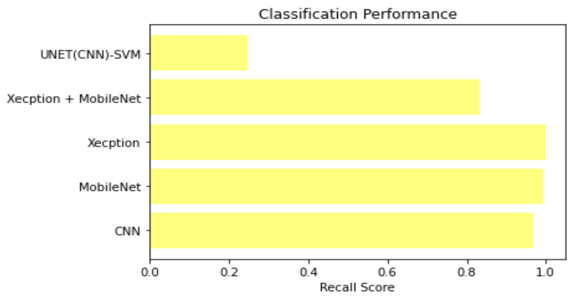

Fig 5 Recall comparison graph

F1-Score: A high F1 score indicates that a machine learning model is accurate. Improving model accuracy by integrating recall and precision. How often a model gets a dataset prediction right is measured by the accuracy statistic.

$$\textbf{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\textbf{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

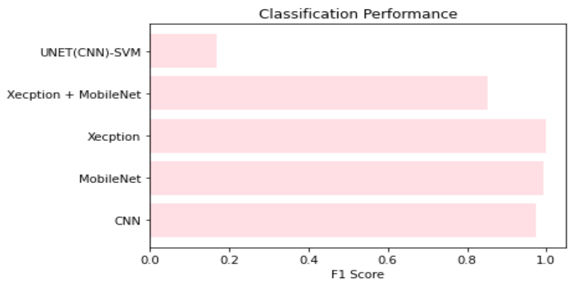

Fig.6. F1-Score comparison graph

ML Model	Accuracy	Precision	Recall	F1_Score
CNN	0.984	0.988	0.969	0.975
Extension Mobile Net	0.992	0.992	0.992	0.992
Extension Xception	1.000	1.000	1.000	1.000
Extension Xception + MobileNet	0.844	0.885	0.833	0.851
UNET (CNN) + SVM	0.245	0.155	0.885	0.167

Fig.7. Comparison table of performance evaluation metrics of all algorithms

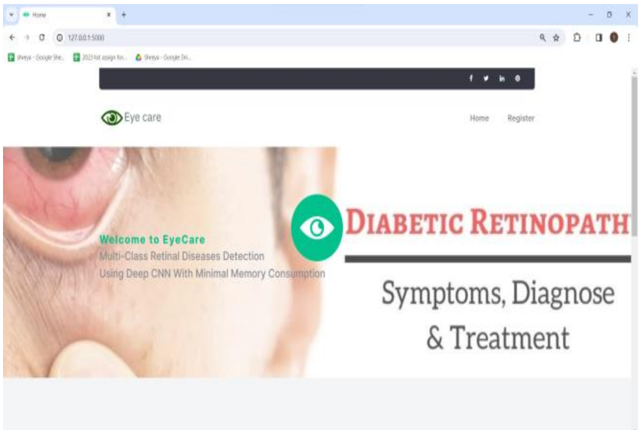

Fig.8. Home page

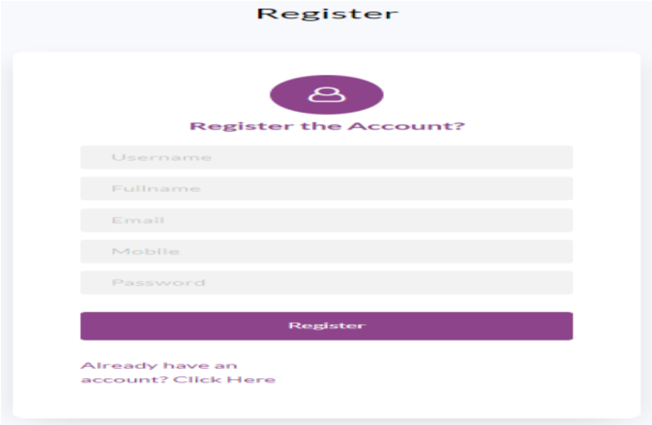

Fig.9. Register page

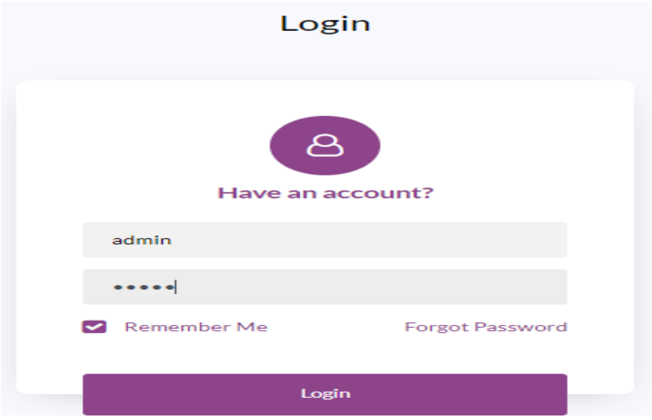

Fig.10. Login page

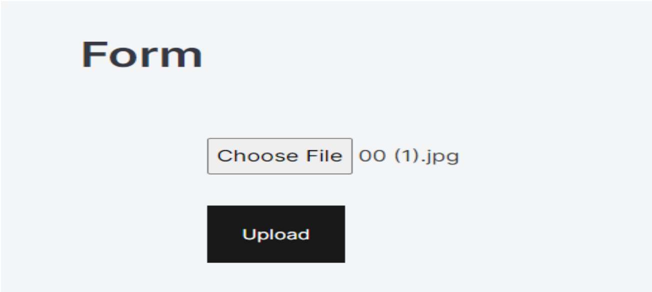

Fig.11. Upload input image

Fig.12. Predict result for given input

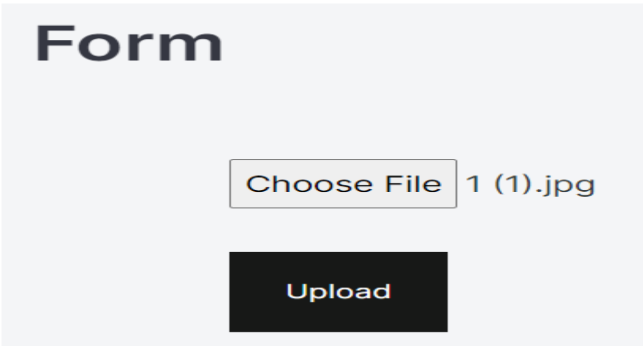

Fig.13. Upload another input

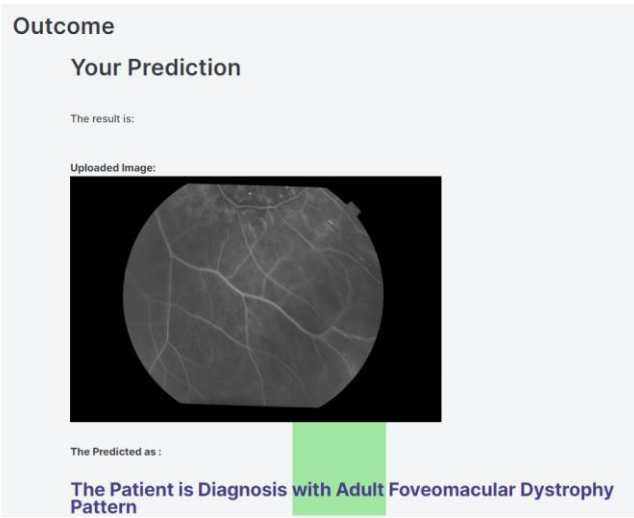

Fig.14. Final outcome for given input image

Similarly, we can try other cases.

5.Conclusion:

In general, the suggested method improves retinal disease categorisation by utilising state-of-the-art convolutional neural network (CNN) architectures such as MobileNet and Xception. Using the EyeNet dataset—which includes retinal images tagged with 32 disease kinds—the approach correctly identifies retinal illnesses. With respect to accuracy, precision, recall, and time consumption, the proposed system surpasses MobileNet, Xception, CNN, UNet (CNN) SVM, and MobileNet + Xception. When compared to other approaches and individual models, MobileNet and Xception both have the highest accuracy rate. The proposed technique for detecting retinal diseases promises an improvement over existing methods by optimising memory usage without sacrificing classification accuracy. By accurately identifying and categorising retinal diseases, this method has the potential to enhance ocular diagnosis and treatment, leading to better patient outcomes and care.

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