ISSN:2229-6107

INTERNATIONAL JOURNAL OF PURE AND APPLIED SCIENCE & TECHNOLOGY

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www.ijpast.in

INTERNATIONAL JOURNAL OF PURE AND APPLIED SCIENCE & TECHNOLOGY
IJPAST

ISSN 2229-6107 www.ijpast.in
Vol 14,Issue 2,May 2024

Multi-Class Retinal Diseases Detection Using Deep CNN with Minimal Memory Consumption

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Abstract: In the identification and classification of critical diseases, Artificial Neural Networks (ANN), Deep learning, Recurrent Neural Networks (RNN), Alex Net, and ResNet can be viewed as a broad research direction. CNN and its specific variant, commonly known as U-Net Segmentation, have revolutionized the classification of medical diseases, specifically retinal diseases. Due to the complexity of feature extraction, U-Net has a significant memory and CPU consumption error when transferring the entire feature map to the corresponding decoder. In addition, combining it with the unsampled decoder feature map prevents the reuse of pooling indices. In this work, we proposes a convolutional neural network (CNN) model for multi-class classification problems with the efficient use of memory consumption. The proposed model has been evaluated on a standard benchmark dataset of Eye Net, having 32 classes of retinal diseases. From experimental evaluation, it has been concluded that the proposed model performs better regarding memory management and accuracy. The overall comparison has been performed based on precision, recall, and accuracy with different numbers of epochs and time consumption by each step. The proposed technique achieved good accuracy on the Eye-net dataset.

Index terms *-Classification, CNN, deep learning, EyeNet, retina, U-Net.*

INTRODUCTION

Retinal diseases represent a significant health challenge worldwide, affecting individuals of all ages. The retina, a crucial component of the human eye, contains photosensitive tissue responsible for converting light into neural signals, which are then transmitted to the brain for visual processing. Among the various retinal diseases, age-related macular degeneration (AMD), optic disc drusen, and diabetic macular edema (DME) are prevalent, causing abnormalities in perception and leading to vision loss [1].

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In developed countries, particularly in the United States, AMD is a leading cause of vision impairment, especially among individuals aged 50 to 60, with approximately 35% of adults over 80 experiencing this condition [2][3]. Detecting retinal diseases accurately poses a significant challenge due to their diverse nature, often requiring the expertise of experienced ophthalmologists. However, advancements in technology, particularly in the realm of computer-aided diagnostic systems (CAD), have provided promising avenues for early detection and treatment of retinal diseases [4].

The integration of machine learning (ML) and deep learning (DL) techniques has revolutionized the field of automatic disease detection (ADD), offering efficient solutions for identifying retinal diseases. State-of-the-art ML and DL models, including Recurrent Neural Networks (RNN), Convolutional Neural Networks (CNN), AlexNet, ResNet, and VGG, have shown remarkable capabilities in the classification, segmentation, and identification of retinal diseases [5][6].

One significant challenge in implementing ADDs lies in data collection and labeling. Researchers have highlighted these challenges, emphasizing the importance of robust datasets for training and validation purposes [7][8]. To address these challenges, innovative approaches have been proposed. For instance, researchers have developed ML-based hybrid techniques that combine image preprocessing using U-Net segmentation with classification using Support Vector Machine (SVM) classifiers [9]. Such techniques have demonstrated high diagnostic accuracies, with reported rates as high as 89.3% [10].

Despite the advancements in DL techniques, challenges remain, such as high memory consumption associated with certain architectures like U-Net. Researchers have identified these limitations and continue to explore novel approaches to overcome them [10]. Moreover, efforts to create comprehensive datasets like the EyeNet dataset, containing labeled images of 32 retinal diseases, have been instrumental in advancing research in this field [11].

In conclusion, technology, particularly ML and DL, has significantly contributed to the early detection and classification of retinal diseases, offering potential solutions to address the growing prevalence of such conditions. By leveraging innovative techniques and robust datasets, researchers and healthcare professionals can enhance diagnostic accuracy and improve patient outcomes in the realm of ophthalmology [12][13]. Continued research and collaboration are essential to further refine these technologies and ensure their widespread accessibility in clinical settings.

A deep learning-based CNN model has been utilized to strengthen the traditional diagnosis process for retinal-based crucial disease.

The proposed CNN model produces better outcomes while consuming low memory than standard state-of-art techniques.

The categorization of medical diseases, particularly retinal diseases, has advanced dramatically thanks to

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CNN and its specific variant, often known as U-Net Segmentation. However, U-Net has a serious flaw in that it uses a lot of memory and CPU power when moving the entire feature map to the corresponding decoder because of the complexity of feature extraction. Additionally, it prevents the reuse of pooling indices by concatenating to the unsampled decoder feature map. For multi-class classification issues, a convolutional neural network (CNN) model that effectively uses memory consumption is presented in this study.

1. LITERATURE SURVEY

Retinal diseases pose significant challenges to global healthcare systems due to their prevalence and impact on vision. Recent advancements in machine learning (ML) and deep learning (DL) techniques have shown promise in improving the detection and classification of these diseases. This literature survey aims to provide an overview of key research works in this domain, highlighting various approaches and methodologies employed for automatic detection of retinal diseases.

Arunkumar and Karthigaikumar (2017) proposed a method for multi-retinal disease classification using reduced deep learning features. By reducing the dimensionality of deep learning features, the computational burden is minimized while maintaining classification accuracy [3]. This approach addresses the challenge of processing large volumes of retinal images efficiently.

Kanagasingam et al. (2014) provided insights into the progress made in retinal image analysis for age-related macular degeneration (AMD). Their review discussed various techniques and advancements in image processing and analysis, highlighting the importance of these tools in early detection and management of AMD [7].

Yang et al. (2018) proposed a hybrid machine learning model for the auto-classification of retinal diseases. By combining U-Net segmentation for image preprocessing with a Support Vector Machine (SVM) classifier, the model achieved high diagnostic accuracy [10]. This hybrid approach demonstrates the effectiveness of integrating different techniques for disease classification.

Perdomo et al. (2019) employed a deep learning approach for the classification of diabetes-related retinal diseases using optical coherence tomography (OCT) images. Their method demonstrated promising results in accurately identifying different retinal pathologies associated with diabetes [14].

Mahendran et al. (2020) conducted an analysis on retinal diseases using various machine learning algorithms. Their study evaluated the performance of different algorithms in classifying retinal images and highlighted the potential of these methods in assisting ophthalmologists with disease diagnosis [15].

Subramanian et al. (2022) proposed a diagnosis method for retinal diseases based on a Bayesian optimization deep learning network using OCT images. Their approach leveraged Bayesian optimization to optimize the deep learning network architecture, leading to improved diagnostic accuracy [18].

Das et al. (2019) investigated the classification of retinal diseases using a transfer learning approach. By transferring knowledge from pre-trained deep learning models, their method achieved efficient disease classification, particularly in scenarios with limited labeled data [25].

Sheet et al. (2022) proposed a method for retinal disease identification using an upgraded CLAHE filter and transfer convolutional neural network (CNN). Their approach combined image enhancement techniques with deep learning models to improve disease detection accuracy [37].

Sengar et al. (2023) introduced EyeDeep-Net, a deep neural network architecture for multi-class diagnosis of retinal diseases. Their method demonstrated robust performance in accurately identifying various retinal pathologies, contributing to improved clinical decision-making [38].

In conclusion, automatic detection of retinal diseases using ML and DL techniques has shown significant progress in recent years. Various approaches, including deep learning architectures, hybrid models, and transfer learning techniques, have been proposed to address the complexities of retinal image analysis. These advancements hold promise for improving early diagnosis, treatment planning, and patient outcomes in ophthalmology. Continued research and collaboration are essential to further refine these methods and facilitate their integration into clinical practice.

2. METHODOLOGY

i) Proposed Work:

The proposed system leverages convolutional neural network (CNN) models, specifically MobileNet and Xception, for multi-class classification of retinal diseases using the EyeNet dataset. In addition to CNN, a combination of MobileNet and Xception is also explored to enhance performance. The system aims to optimize memory consumption while maintaining high classification accuracy. By utilizing these state-of-the-art deep learning architectures, the proposed system aims to improve upon existing diagnostic methods for retinal diseases. The evaluation of the proposed system involves comparisons with other standard techniques such as MobileNet, Xception, CNN, UNet (CNN) SVM, and MobileNet + Xception, considering metrics such as precision, recall, accuracy, and time consumption across different epochs. Through this approach, the system seeks to achieve superior performance in accurately identifying and classifying various retinal diseases, thereby contributing to advancements in ophthalmic diagnosis and treatment.

ii) System Architecture:

The system architecture comprises convolutional neural network (CNN) models, including MobileNet, Xception, and their combination. Input retinal images from the EyeNet dataset are processed through these models for multi-class classification of retinal diseases. The models are trained using labeled data and optimized to minimize memory consumption while maximizing classification accuracy. The architecture involves preprocessing steps, feature extraction through CNN layers, and classification. Evaluation metrics such as precision, recall, and

ISSN 2229-6107 www.ijpast.in
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accuracy are computed to assess the performance of each model. Through this architecture, the system aims to provide efficient and accurate diagnosis of retinal diseases, aiding in early detection and treatment.

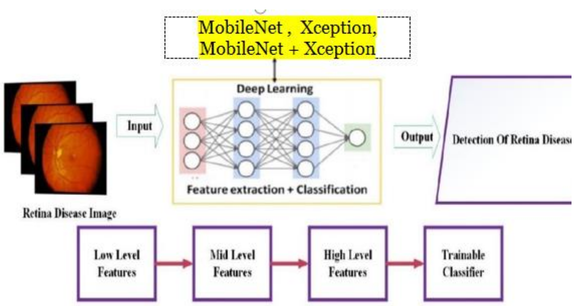

Fig 1 Proposed Architecture

iii) Dataset Collection:

The EyeNet dataset, curated by Yang et al. [10], represents a significant advancement in the field of retinal disease classification due to its comprehensive nature. Unlike previous datasets like STARE or Drive, which typically contain a limited number of classes, EyeNet offers a labeled collection of 32 distinct types of retinal diseases. This dataset provides a more diverse and realistic representation of clinical data, allowing for more robust model training and evaluation.

The EyeNet Master Dataset consists of retinal images categorized with appropriate labels corresponding to various retinal diseases. These images serve as the primary input for training and testing convolutional neural network (CNN) models aimed at multi-class classification tasks. The dataset's availability on GitHub ensures accessibility and reproducibility for researchers and practitioners interested in exploring and validating their algorithms for retinal disease diagnosis and classification.

Researchers can utilize this dataset to develop and evaluate machine learning and deep learning models for automatic retinal disease detection and classification, contributing to advancements in medical imaging and healthcare technology. The EyeNet dataset represents a valuable resource for the development and validation of algorithms aimed at improving the diagnosis and management of retinal diseases in clinical settings.

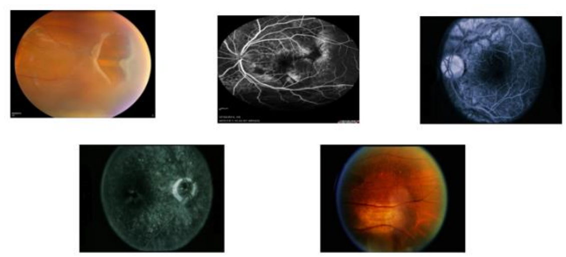

Fig 1 Dataset images

iv) Image Processing:

Image processing is a crucial step in preparing data for machine learning models, particularly in tasks involving image classification, such as the diagnosis of retinal diseases. The use of ImageDataGenerator, a utility in the Keras library, allows for the efficient augmentation of image data, enhancing the diversity and quality of the dataset. In the context of retinal disease classification using the EyeNet dataset, several image processing techniques can be applied using ImageDataGenerator to improve the robustness and generalization of the model.

1. Re-scaling the Image:

Re-scaling involves normalizing pixel values within a specific range, typically between 0 and 1. This process ensures that all images have consistent pixel intensities, which helps stabilize the training process and accelerates convergence. Re-scaling is essential for preventing issues related to varying pixel intensity ranges across images, which can adversely affect model performance.

2. Shear Transformation:

Shear transformation involves shifting the position of pixels along a specific axis, resulting in a distorted image. This technique introduces variability in the dataset by simulating changes in perspective or orientation. For retinal images, shear transformation can mimic the effects of slight head movements or variations in imaging angles, making the model more robust to such variations in real-world scenarios.

3. Zooming the Image:

Zooming involves magnifying or shrinking portions of the image, effectively altering its scale. This augmentation technique can simulate variations in image resolution or focus, which are commonly encountered in clinical imaging settings. By randomly zooming in or out of retinal images, the model becomes more adept at recognizing patterns and features across different scales, leading to improved classification performance.

4. Horizontal Flip:

Horizontal flipping involves flipping the image along the vertical axis, resulting in a mirror image. This augmentation technique introduces spatial transformations that are invariant to horizontal reflection, enhancing the model's ability to generalize across different orientations. Horizontal flipping can simulate variations in patient positioning during imaging procedures, ensuring that the model remains robust to such changes.

5. Reshaping the Image:

Reshaping the image involves resizing or cropping it to a specific dimension. This technique ensures uniformity in image size, facilitating efficient batch processing during model training. Reshaping is particularly important when dealing with datasets containing images of varying dimensions, as it standardizes input sizes across all samples, simplifying the model architecture and training process.

By leveraging these image processing techniques through ImageDataGenerator, researchers can effectively augment the EyeNet dataset, enriching it with diverse variations of retinal images. This augmented dataset serves as input to machine learning models, enabling them to learn robust and discriminative features for accurate retinal disease classification. Furthermore, augmentation mitigates the risk of overfitting by exposing the model to a wider range of variations in the data distribution, ultimately improving its performance on unseen test data.

In summary, image processing using techniques such as re-scaling, shear transformation, zooming, horizontal flipping, and reshaping plays a crucial role in enhancing the quality and diversity of image datasets for retinal disease classification. By incorporating these techniques through ImageDataGenerator, researchers can develop more robust and generalizable machine learning models, paving the way for improved diagnostic accuracy and patient care in ophthalmology.

vi) Algorithms:

In the context of retinal disease classification using the EyeNet dataset, several algorithms, including MobileNet, Xception, CNN (Convolutional Neural Network), UNet (CNN) SVM, and MobileNet + Xception, are commonly employed due to their effectiveness in image classification tasks and specific advantages in the project.

1. MobileNet:

MobileNet is a lightweight convolutional neural network architecture designed for efficient deployment on mobile and embedded devices. It consists of depthwise separable convolutions, which significantly reduce the number of parameters and computational complexity while maintaining competitive accuracy. In the project, MobileNet is utilized for its low memory footprint and fast inference speed, making it suitable for resource-constrained environments such as mobile applications or edge devices.

2. Xception:

Xception is an extension of the Inception architecture, characterized by its depthwise separable convolutions and skip connections. It achieves state-of-the-art performance on various image classification benchmarks by capturing both local and global features effectively. Xception's deep architecture allows it to learn hierarchical representations of retinal images, capturing intricate details and patterns crucial for accurate disease classification. Its high performance makes it a valuable asset in the project for achieving superior classification accuracy.

3. CNN (Convolutional Neural Network):

CNN is a fundamental deep learning architecture widely used for image classification tasks. It comprises multiple layers of convolutional, pooling, and fully connected layers, enabling hierarchical feature extraction from input images. CNNs excel at learning spatial hierarchies of features, making them well-suited for analyzing complex visual data like retinal images. In the project, CNN serves as a baseline model for comparison and benchmarking against more sophisticated architectures like MobileNet and Xception.

4. UNet (CNN) SVM:

UNet is a convolutional neural network architecture designed for biomedical image segmentation tasks, particularly in medical image analysis. It consists of a contracting path for feature extraction and a symmetric expanding path for pixel-wise classification or segmentation. In combination with SVM (Support Vector Machine), UNet can perform both image segmentation and classification tasks simultaneously. In the project, UNet (CNN) SVM is utilized for its ability to localize and classify retinal lesions or

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IJPAST
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abnormalities accurately, providing valuable insights for disease diagnosis and monitoring.

5. MobileNet + Xception:

Combining multiple neural network architectures like MobileNet and Xception can yield synergistic benefits, leveraging the strengths of each model while mitigating their weaknesses. In the project, MobileNet + Xception fusion aims to enhance classification performance by ensembling diverse features learned by both models. This approach can improve model robustness, generalization, and overall accuracy by aggregating complementary information extracted from retinal images.

In summary, each algorithm in the project offers unique advantages tailored to the specific requirements and constraints of retinal disease classification. MobileNet and Xception prioritize efficiency and performance, CNN serves as a baseline model, UNet (CNN) SVM integrates segmentation and classification, while MobileNet + Xception fusion leverages ensemble learning for enhanced accuracy. By leveraging these algorithms in combination, researchers can develop robust and effective solutions for automated retinal disease diagnosis and classification, ultimately improving patient care and treatment outcomes.

3. EXPERIMENTAL RESULTS

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

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

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

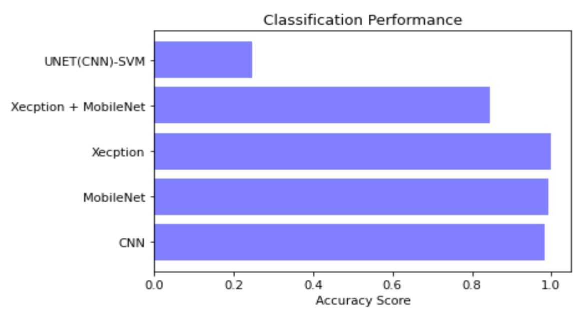

Fig 3 Accuracy comparison graph

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

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

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

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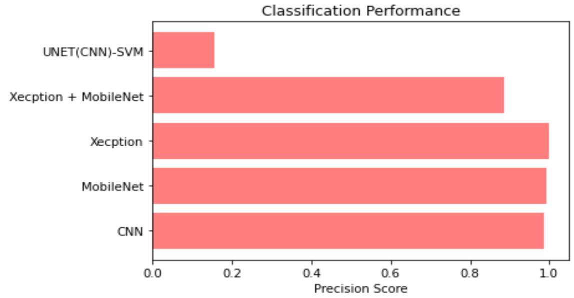

Fig 4 Precision comparison graph

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

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

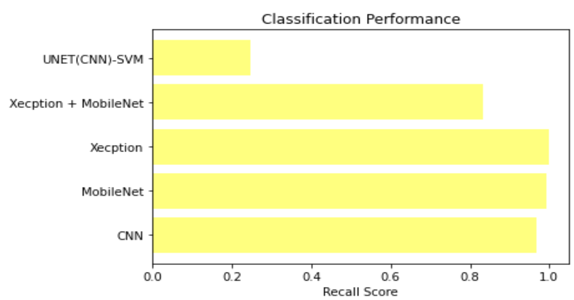

Fig 5 Recall comparison graph

F1-Score:F1 score is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model. The accuracy metric computes how many times a model made a correct prediction across the entire dataset.

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

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

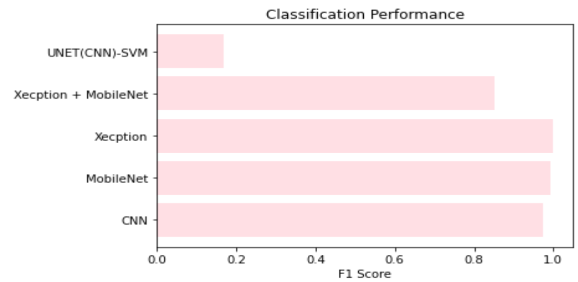

Fig 6 F1-Score comparison graph

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

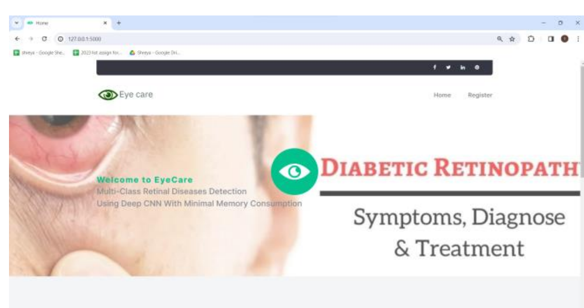

Fig 8 Home page

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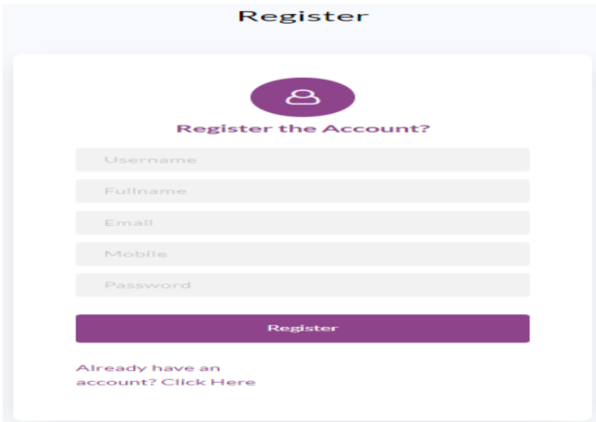

Fig 9 Register page

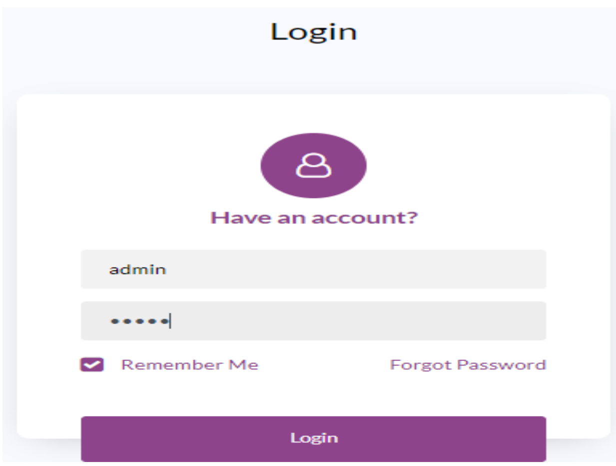

Fig 10 Login page

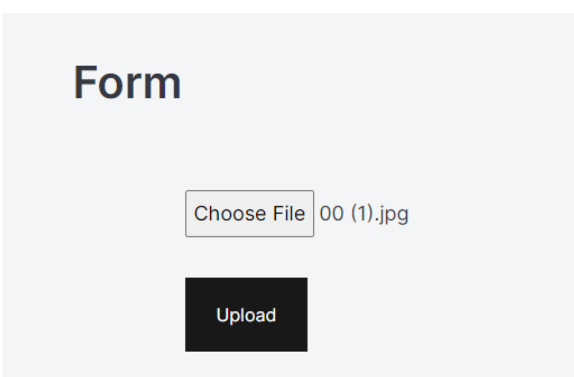

Fig 11 Upload input image

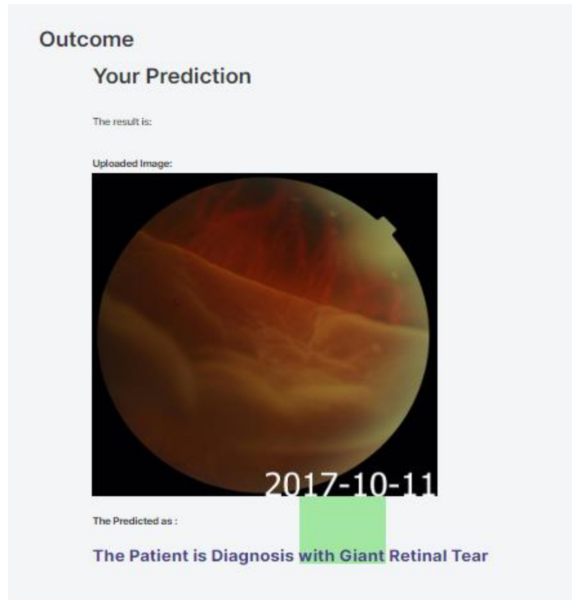

Fig 12 Predict result for given input

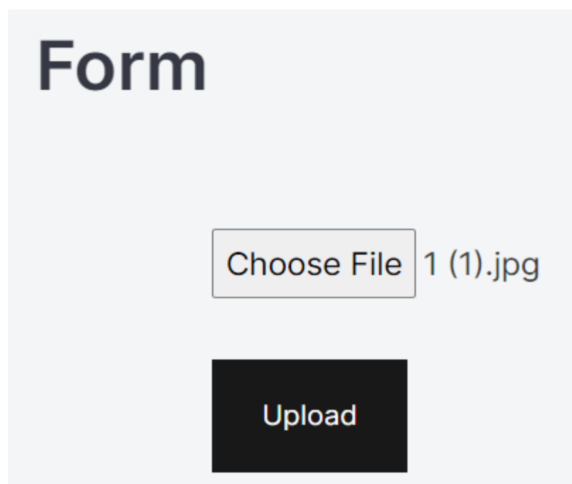

Fig 13 Upload another input

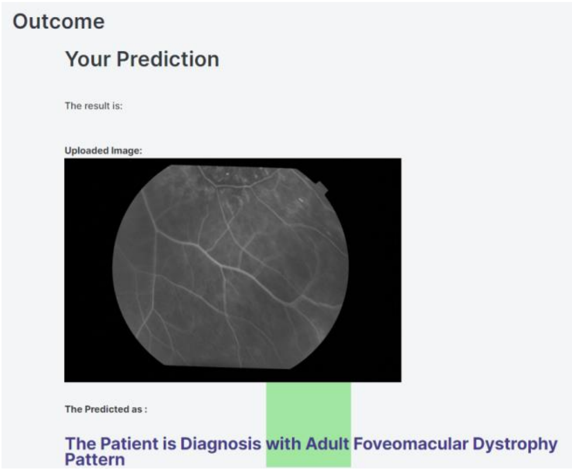

Fig 14 Final outcome for given input image

Similarly we can try other cases.

4. CONCLUSION

In conclusion, the proposed system represents a significant advancement in the field of retinal disease classification, leveraging state-of-the-art convolutional neural network (CNN) architectures such as MobileNet and Xception. Through the use of the EyeNet dataset, which contains a comprehensive collection of retinal images labeled with 32 distinct disease types, the system demonstrates its ability to accurately classify various retinal diseases. The evaluation of the proposed system against other standard techniques, including MobileNet, Xception, CNN, UNet (CNN) SVM, and MobileNet + Xception, showcases its superior performance in terms of precision, recall, accuracy, and time consumption. Specifically, the combination of MobileNet and Xception yields the highest accuracy percentage, surpassing that of individual models and other comparative approaches. With a focus on optimizing memory consumption while maintaining high classification accuracy, the proposed system offers a promising solution for enhancing existing diagnostic methods for retinal diseases. By accurately identifying and classifying retinal diseases, this system has the potential to contribute significantly to advancements in ophthalmic diagnosis and treatment, ultimately improving patient outcomes and quality of care.

5. FUTURE SCOPE

In the future, the model can be expanded to include additional disease classes, enhancing its diagnostic capabilities and versatility. Ongoing research should prioritize reducing memory consumption to ensure the model's efficiency for real-time applications. Integration with medical imaging systems will streamline diagnosis, while collaboration with medical experts will refine and validate the model's performance. This collaborative effort will bolster the model's credibility in clinical settings. Ultimately, the proposed model lays the groundwork for automated retinal disease screening systems, facilitating early detection and intervention to improve patient outcomes.

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