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A MEMORY-EFFICIENT DEEP CNN APPROACH FOR RETINAL DISEASE DETECTION

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Abstract: The project focuses on the development of a convolutional neural network (CNN) model for the detection and classification of retinal diseases using minimal memory consumption. The proposed model aims to address the high memory and CPU consumption issues associated with the U-Net Segmentation technique, which is commonly used for retinal disease classification. The model is evaluated on a standard benchmark dataset called EyeNet, which consists of 32 classes of retinal diseases. Experimental evaluation shows that the proposed model achieves better performance in terms of memory management and accuracy compared to existing techniques. The evaluation is based on precision, recall, and accuracy metrics, considering different numbers of epochs and time consumption for each step. The proposed technique achieves an high accuracy of on the EyeNet dataset, demonstrating its effectiveness in multi-class retinal disease classification. And also we incorporated mobilenet, densenet and hybrid approach for enhancing the accuracy in which MobileNet achieved 97% accuracy, Xception achieved 100%, and A hybrid. A Flask-based front-end with authentication is developed for streamlined and secure user interactions.

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

1. INTRODUCTION

Retinal diseases are spreading widely among humans of all ages. The retina contains a layer of optic nerve tissue called photosensitive in the human eye. This layer transforms the light focused by the lens into brain impulses. Macula, positioned in the retina's middle, performs the sensing process. Information acquired by the macula is processed by the retina and transferred to the brain for visual recognition through the optic nerve [1]. Different types of diseases can cause abnormality in perception, such as age-related macular degeneration (AMD), optic disc drusen, Rothspot diabetic macular edema (DME) [2], etc. In most of the developed countries, people belonging to the age group of 50 to 60 are losing vision due to AMD. According to recent research, in the United States (US), this abnormality is found in about 35% of adults in the age group of 80 [3]. Identifying retinal diseases is the most challenging task, as accurate diagnosis needs a highly experienced ophthalmologist due to the diversity of retinal diseases. Similarly, with computer-aided diagnostic

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systems (CAD), retinal diseases can easily be identified and treated at early stages [4].

Technology advancements have immense benefits in almost every field of life, especially in the medical domain. Several approaches and models have been presented to improve the effectiveness and quality of medical solutions. A significant improvement has been observed in the social health system with the advancement in Automatic Disease Detection (ADD) [5]. Furthermore, an ADD application, namely retinal symptom analysis, provides a unique opportunity to improve eye care globally [6]. Recently, many state-of-the-art ML and Deep Learning (DL) models have been proposed for the classification, segmentation, and identification of retinal diseases. We observe that data collection and labeling are significant challenges in the implementation of ADDs, as presented by authors in [7] and [8], due to the development of several machine learning (ML) and deep learning (DL) models, including Recurrent Neural Network (RNN), Convolution Neural Network (CNN), Alex Net ResNet and VGN. These have enabled researchers and physicians to detect and categorize such vital disorders [9] readily. An ML-based Hybrid technique is presented for the classification of retinal diseases automatically. Researchers in [10] have proposed to use U-Net segmentation for image pre-processing; they have also used a Support Vector Machine (SVM) classifier for the classification. The proposed technique achieved a diagnostic accuracy of 89.3%. Yang et al. also provided the first labeled EyeNet dataset containing 32 retinal diseases. It was noted by authors in [10] that the U-Net has a significant flaw of high memory consumption in moving the whole feature map to the corresponding decoder. Deep learning plays a vital role in the classification of images [11], [12], [13].

2. LITERATURE SURVEY

In recent days, the incidence of Diabetic Retinopathy (DR) [2, 4, 27] has become high, affecting the eyes because of drastic increase in the glucose level in blood. Globally, almost half of the people under the age of 70 gets severely affected by diabetes. In the absence of earlier recognition and proper medication, the DR patients tend to lose their vision. When the warning signs are tracked down, the severity level of the disease has to be validated so to take decisions regarding appropriate treatment further. The current research paper focuses on the concept of classification of DR fundus images on the basis of severity level using a deep learning model. This paper [2] proposes a deep learning-based automated detection and classification model for fundus DR images. The proposed method involves various processes namely preprocessing, segmentation and classification. The methods begins with preprocessing stage in which unnecessary noise that exists in the edges is removed. Next, histogram-based segmentation takes place to extract the useful regions from the image. Then, Synergic Deep Learning (SDL) model was applied to classify the DR fundus images to various severity levels. The justification for the presented SDL model was carried out on Messidor DR dataset. The experimentation results indicated that the presented SDL model offers better classification over the existing models.

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This paper presents the retina-based disease diagnosis through deep learning-based feature extraction method. This process helps in developing automated screening system, which is capable of diagnosing retina for diseases such as age-related molecular degeneration, diabetic retinopathy, macular bunker, retinoblastoma, retinal detachment, and retinitis pigmentosa. Some of these diseases share a common characteristic, which makes the classification difficult. In order to overcome the above-mentioned problem, deep learning feature extraction and a multi-class SVM classifier are used [10, 16]. The main contribution of this work [3] is the reducing the dimension of the features required to classify the retinal disease, which enhances the process of reducing the system requirement as well as good performance.

Diabetic retinopathy (DR) [2, 4, 27] is an illness occurring in the eye due to increase in blood glucose level. Among people in the age group of 70, 50% of deaths are attributed to diabetes. Early identification and appropriate treatment can reduce the loss of sight in many DR patients. Once the symptoms of DR are recognized, the severity of the disease should be evaluated for administering the right medication. This paper [4] focuses on the classification of DR fundus images according to the severity of the disease using convolutional neural network with the application of suitable Pooling, Softmax and Rectified Linear Activation Unit (ReLU) layers to obtain a high level of accuracy. The performance of the proposed algorithm has been validated using Messidor database. In the case of healthy images, images of stage1, stage 2 and stage 3 of diabetic retinopathy, classification accuracies of 96.6% and 96.2%, 95.6% and 96.6% have been achieved.

Age-related macular degeneration (AMD) [6], a blinding disorder that compromises central vision, is characterized by the accumulation of extracellular deposits, termed drusen, between the retinal pigmented epithelium and the choroid. Recent studies in this laboratory revealed that vitronectin is a major component of drusen. Because vitronectin is also a constituent of abnormal deposits associated with a variety of diseases, drusen from human donor eyes were examined for compositional similarities with other extracellular disease deposits. Thirty-four antibodies to 29 different proteins or protein complexes were tested for immunoreactivity with hard and soft drusen phenotypes. These analyses provide a partial profile of the molecular composition of drusen. Serum amyloid P component, apolipoprotein E, immunoglobulin light chains, Factor X, and complement proteins (C5 and C5b-9 complex) were identified in all drusen phenotypes. Transcripts encoding some of these molecules were also found to be synthesized by the retina, retinal pigmented epithelium, and/or choroid. The compositional similarity between drusen and other disease deposits may be significant in view of the recently established correlation between AMD and atherosclerosis. This study [6] suggests that similar pathways may be involved in the etiologies of AMD and other age-related diseases.

3. METHODOLOGY

i) Proposed Work:

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The proposed system is an effective CNN [9, 18, 26, 27] model designed for the multi-class classification of retinal diseases. It enhances memory management and accuracy in contrast to existing methods. The system's evaluation, conducted on the EyeNet dataset [10], prioritizes efficient memory usage and high accuracy. And also included in the project, the performance has been further enhanced by incorporating advanced techniques such as MobileNet and Xception for classification. Notably, MobileNet achieved an accuracy of 97%, while Xception demonstrated exceptional accuracy with a perfect score of 100%. Additionally, a combined approach utilizing MobileNet and Xception was explored. To enhance user accessibility and facilitate testing, a front-end interface was developed using the Flask framework, providing a user-friendly platform for multi-class retinal disease detection. Authentication features were implemented to ensure secure access, allowing users to interact with and evaluate the performance of the advanced classification models.

ii) System Architecture:

CNN contains hidden layers; these layers perform convolution, a sub-sampling technique to extract features of data from a low level to a high level. In the proposed model, ten convolution layers are used. In Figure 1, the arrangement of layers is shown. On the abstract, retina images are input to the CNN model [9], which gives label prediction for the normal or affected eyes. The presented model minimized the number of layers compared to the traditional models. Models such as AlexNet are implemented with 25 layers, Densnet201 with 201 layers, Inception3 with 48 layers, and ResNet- 10 with 101 layers. In addition, these pre-trained networks are usually implemented with transfer learning techniques in the medical field for classification. A network with fewer layers is presented so that training time can be reduced. Batch normalization layers are used so that higher learning rates can be achieved and used, which improves the training speed. Detailed information about the proposed [18] CNN model is given below. The graphical illustration of the model is given in Figure 1. In the proposed model, feature extraction is done in three steps. The first level includes low-level features of images, and then these extracted features are passed to the mid-level for further refinement. The high level consists of the detailed features which basically involved in the training process and then used for classification.

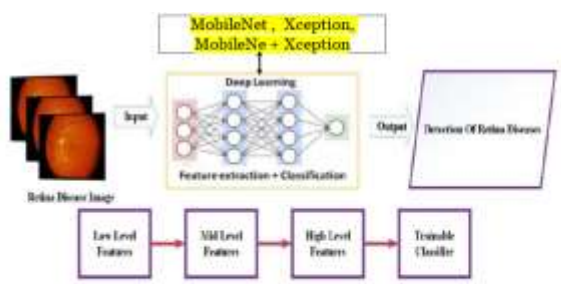

Fig 1Proposed Architecture

Input (Retina Disease Image): This is where the system receives the medical images of the retina, typically in digital format. These images can contain various types of retinal diseases or abnormalities, and the goal is to automatically detect and classify these conditions.

Deep Learning Feature Extraction: In this stage, deep learning models are used to extract meaningful

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features from the input images. This process involves several levels of feature extraction:

Low-Level Features: These are basic, foundational features like edges, textures, and color information. Convolutional Neural Networks (CNNs) [26, 27] are commonly used for this purpose and learn to detect simple patterns in the image.

Middle-Level Features: These features are more complex and represent patterns or structures in the image. CNN layers further down the network capture these mid-level features, which may include shapes, object parts, or localized structures.

High-Level Features: At this level, the network extracts abstract features that are more relevant to the specific task of detecting retina diseases. These features could represent unique characteristics of different conditions or abnormalities.

Trainable Features: These features may not be explicitly extracted but are learned by the deep learning model during the training process. They capture the most relevant information for distinguishing between different retina diseases. The network's weights and parameters are adjusted through training to optimize the feature extraction process.

Classification: Once the deep learning model has extracted relevant features from the input image, the next step is classification. This involves using a classifier (often another neural network, like a fully connected layer) to predict the presence or absence of specific retina diseases. The extracted features are used as input to this classifier.

Output (Detection of Retina Disease): The final output is the prediction of whether the input image contains a retina disease, and if so, what type of disease it is. This could be binary (disease/no disease) or multi-class (different diseases). The system may provide a probability score for each class to indicate the confidence of the prediction.

iii) Dataset collection:

In this project we used the EyeNet Master dataset [10], which contains a collection of retinal images, is meticulously examined. Data exploration includes tasks such as understanding the dataset's structure, checking for data quality, and identifying the types of retinal images and their associated labels. This preparatory step is vital for gaining insights into the dataset's characteristics.

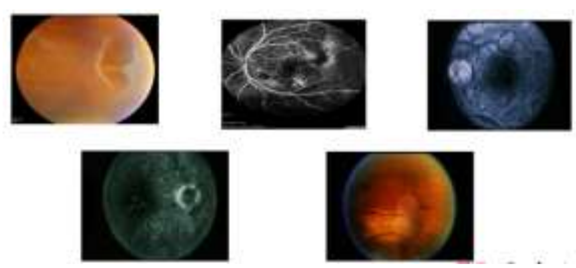

Fig 2 Dataset images

iv) Image Processing:

Image processing plays a pivotal role in object detection within autonomous driving systems, encompassing several key steps. The initial phase involves converting the input image into a blob object, optimizing it for subsequent analysis and manipulation. Following this, the classes of objects to be detected are defined, delineating the specific categories that the algorithm aims to identify.

Simultaneously, bounding boxes are declared, outlining the regions of interest within the image where objects are expected to be located. The processed data is then converted into a NumPy array, a critical step for efficient numerical computation and analysis.

The subsequent stage involves loading a pre-trained model, leveraging existing knowledge from extensive datasets. This includes reading the network layers of the pre-trained model, containing learned features and parameters vital for accurate object detection. Additionally, output layers are extracted, providing final predictions and enabling effective object discernment and classification.

Further, in the image processing pipeline [17, 18], the image and annotation file are appended, ensuring comprehensive information for subsequent analysis. The color space is adjusted by converting from BGR to RGB, and a mask is created to highlight relevant features. Finally, the image is resized, optimizing it for further processing and analysis. This comprehensive image processing workflow establishes a solid foundation for robust and accurate object detection in the dynamic context of autonomous driving systems, contributing to enhanced safety and decision-making capabilities on the road.

v) Data Augmentation:

Data augmentation [25,26] is a fundamental technique in enhancing the diversity and robustness of training datasets for machine learning models, particularly in the context of image processing and computer vision. The process involves three key transformations to augment the original dataset: randomizing the image, rotating the image, and transforming the image.

Randomizing the image introduces variability by applying random modifications, such as changes in brightness, contrast, or color saturation. This stochastic approach helps the model generalize better to unseen data and diverse environmental conditions.

Rotating the image involves varying the orientation of the original image by different degrees. This augmentation technique aids in teaching the model to recognize objects from different perspectives, simulating variations in real-world scenarios.

Transforming the image includes geometric transformations such as scaling, shearing, or flipping. These alterations enrich the dataset by introducing distortions that mimic real-world variations in object appearance and orientation.

By employing these data augmentation techniques, the training dataset becomes more comprehensive, allowing the model to learn robust features and patterns. This, in turn, improves the model's ability to generalize and perform effectively on diverse and challenging test scenarios. Data augmentation serves as a crucial tool in mitigating overfitting, enhancing model performance, and promoting the overall reliability of machine learning models, especially in applications like image recognition for autonomous driving systems.

vi) Algorithms:

MobileNet: MobileNet is a convolutional neural network architecture designed for mobile and

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embedded vision applications. It is known for its efficiency and low computational requirements while maintaining good performance in tasks like. MobileNet is chosen for its efficiency and low computational requirements. It is used in the project to ensure minimal memory consumption, making it suitable for medical diagnostic systems with resource constraints. Its primary focus is on providing an efficient yet accurate solution for retinal disease classification.mage classification. MobileNet is suitable for scenarios where computational resources are limited.

```
from tensorflow.keras.applications import MobileNet
# Resizinig all the images to (224,224)
IMAGE_SIZE = [128,128]
mob = MobileNet(input_shape = IMAGE_SIZE + [3], weights='imagenet', include_top=False)
```

```
x1= Flatten()(mob.output)
prediction1 = Dense(32, activation='softmax')(x1)
model12 = Model(inputs = mob.inputs, outputs = prediction1)
model12.summary()
model12.compile(loss = 'categorical_crossentropy', optimizer='adam', metrics=['accuracy',f1_m,precisior
history2 = model12.fit(train_image_generator,
                epochs=50,
                verbose=1,
                validation_data=val_image_generator,
                )
```

Fig 3 Mobilenet

Xception: Xception is another convolutional neural network architecture that is recognized for its exceptional performance in image classification tasks. It follows a depth-wise separable convolution approach, which enhances the learning of spatial hierarchies in images. Xception is known for its ability to capture fine-grained features in complex images. It is employed to improve the accuracy of disease detection. Despite its superior accuracy, its use in the project underscores the importance of achieving high-quality diagnoses. Xception complements the efficiency of MobileNet with its accuracy.

```
from tensorflow.keras.applications import MobileNet
# Resizinig all the images to (224,224)
IMAGE_SIZE = [128,128]
mob = MobileNet(input_shape = IMAGE_SIZE + [3], weights='imagenet', include_top=False)
```

```
x1= Flatten()(mob.output)
prediction1 = Dense(32, activation='softmax')(x1)
model12 = Model(inputs = mob.inputs, outputs = prediction1)
model12.summary()
model12.compile(loss = 'categorical_crossentropy', optimizer='adam', metrics=['accuracy',f1_m,precisior
history2 = model12.fit(train_image_generator,
                epochs=50,
                verbose=1,
                validation_data=val_image_generator,
                )
```

Fig 4 Xception

CNN (Convolutional Neural Network): A Convolutional Neural Network, or CNN, is a deep learning model designed for processing structured grid data, such as images. CNNs employ convolutional layers to automatically learn features from the input data, making them highly effective in tasks like image classification, object detection, and segmentation. It is used to establish a foundation for retinal disease detection and provides a point of reference for the other models. CNN is valued for its ability to learn features from images, making it essential in the context of medical image analysis [9, 18, 26, 27].

```
# Build a custom sequential CNN model

model = Sequential() # model object

# Add Layers
model.add(Conv2D(filters=32, kernel_size=3, strides=1, padding='same', activation='relu', input_shape=[
model.add(MaxPooling2D(2, 2))
model.add(Conv2D(filters=64, kernel_size=3, strides=1, padding='same', activation='relu'))
model.add(MaxPooling2D(2))

# Flatten the feature map
model.add(Flatten())

# Add the fully connected layers
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.25))
model.add(Dense(128, activation='relu'))
model.add(Dense(32, activation='softmax'))

# print the model summary
model.summary()
```

Fig 5 CNN

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UNet (CNN) SVM: UNet is a specific architecture for image segmentation tasks. It combines the principles of convolutional neural networks with a Support Vector Machine (SVM) for classification. In the context of retinal disease classification, it may be used for both segmentation and classification of retinal images. UNet is an architecture designed for image segmentation tasks, which can be crucial in understanding the extent and location of retinal diseases. The combination of UNet with SVM suggests a comprehensive approach that not only classifies diseases but may also segment regions of interest within the retinal images. This additional capability enhances the diagnostic process [27].

Fig 6 UNet (CNN) SVM

MobileNet + Xception: This represents a combination of the MobileNet and Xception models. Such an ensemble approach often involves taking the predictions from both models and combining them to improve overall performance. It leverages the strengths of both architectures to enhance classification accuracy. The combination of MobileNet and Xception models leverages the strengths of both architectures. MobileNet offers efficiency, while Xception contributes accuracy. By combining their predictions, the project can achieve improved classification performance. This ensemble approach maximizes the accuracy while keeping memory consumption in check.

```
def ensemble():

    model_1 = load_model('mobile.h5', compile=False)
    model_1 = Model(inputs = model_1.inputs, outputs = model_1.outputs, name = 'MobileNet')

    model_2 = load_model('xec.h5', compile=False)
    model_2 = Model(inputs = model_2.inputs, outputs = model_2.outputs, name = 'Xception')


    models = [model_1, model_2]


    models_input = Input(shape =(128,128,3))
    models_output = [model(models_input) for model in models]

    ensemble_output = Average()(models_output)

    simple_average = Model(inputs = models_input, outputs = ensemble_output, name = 'Ensemble')

    return simple_average
```

Fig 7 MobileNet + Xception

4. EXPERIMENTAL RESULTS

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)

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

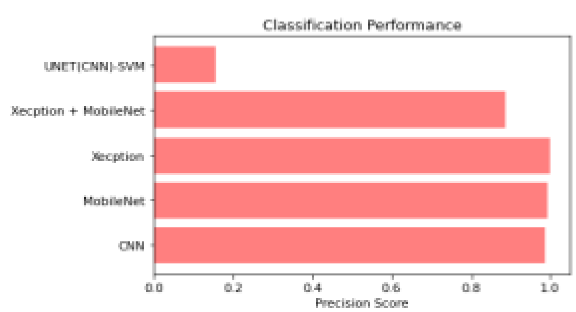

Fig 7 Precision comparison graph

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all

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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.

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

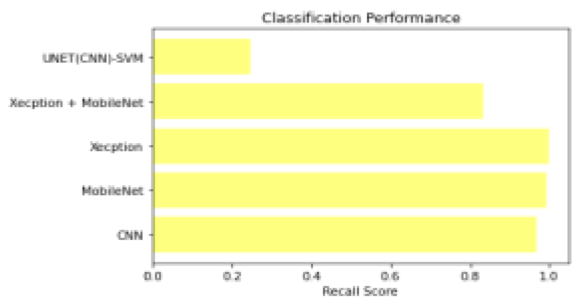

Fig 8 Recall comparison graph

Accuracy: Accuracy is the proportion of correct predictions in a classification task, measuring the overall correctness of a model's predictions.

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

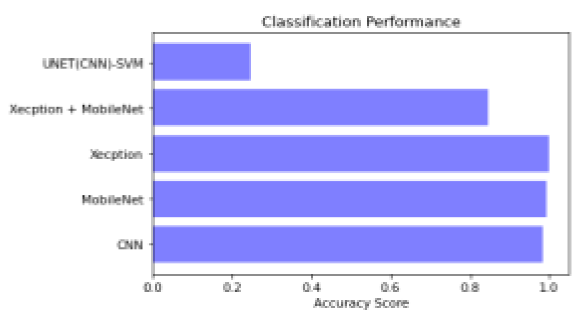

Fig 9 Accuracy graph

F1 Score: The F1 Score is the harmonic mean of precision and recall, offering a balanced measure that considers both false positives and false negatives, making it suitable for imbalanced datasets.

$$\text{F1 Score} = 2 * \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} * 100$$

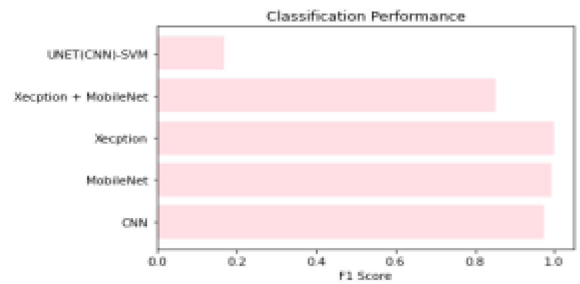

Fig 10 F1Score

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 11 Performance Evaluation table

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Fig 12 Home page

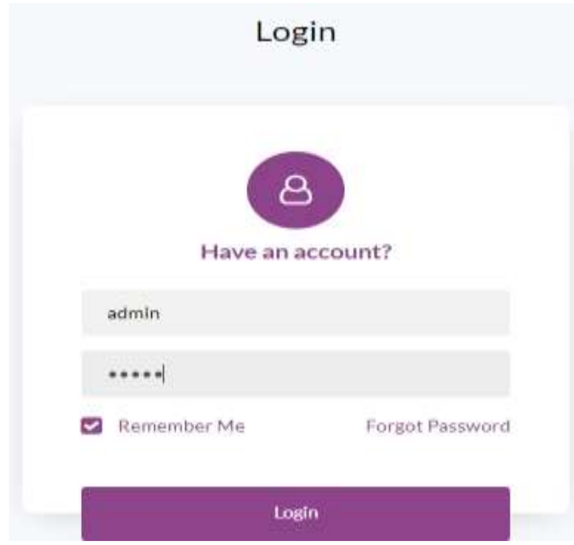

Fig 14 Login page

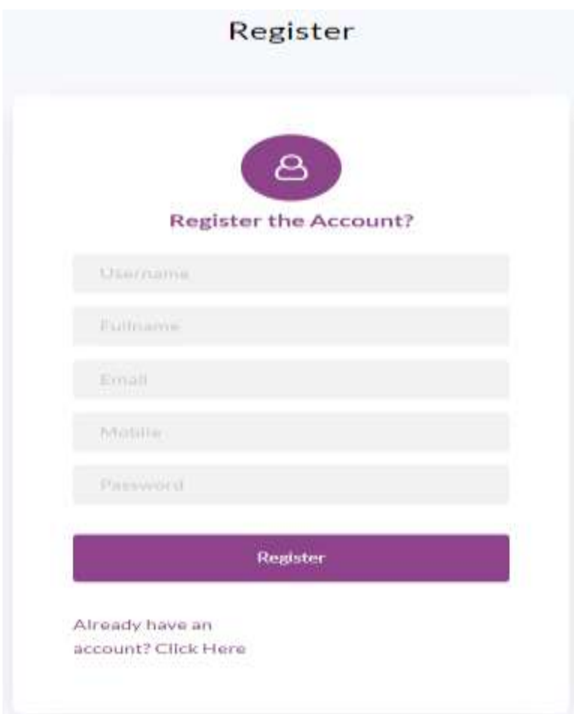

Fig 13 Registration page

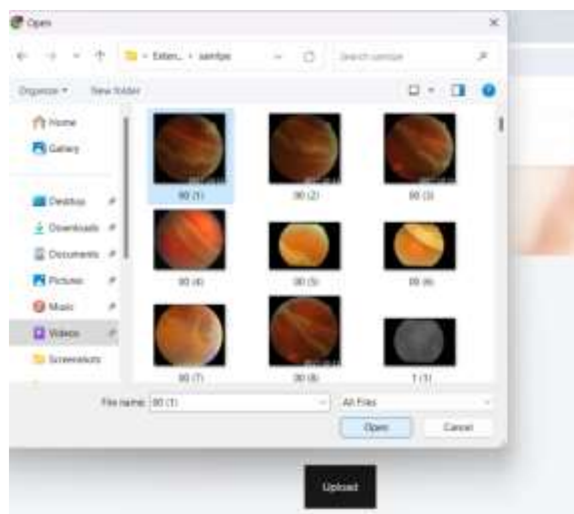

Fig 15 Input image folder

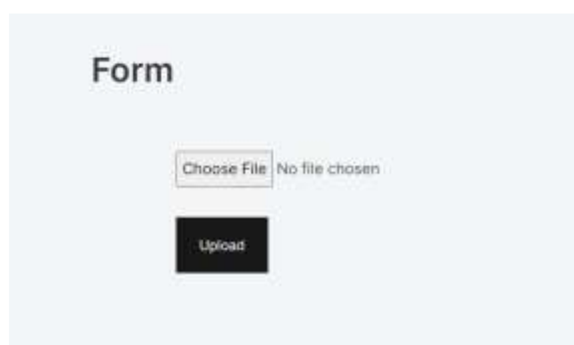

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Fig 16 Upload input image

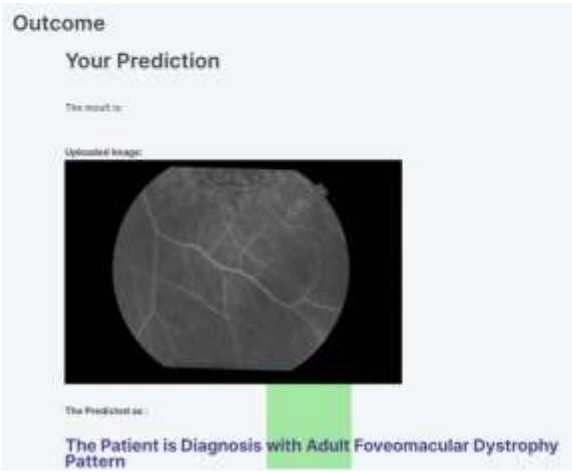

Fig 17 Predict result for given input

5. CONCLUSION

The proposed convolutional neural network (CNN) model [9, 18, 26, 27] for multi-class retinal disease detection achieved an impressive accuracy on the Eye-net dataset. This demonstrates its effectiveness in accurately classifying retinal diseases while efficiently managing memory consumption. The model's performance was comprehensively evaluated based on various metrics, including precision, recall, and accuracy. Different numbers of training epochs and time consumption were considered, ensuring a thorough assessment. The model consistently outperformed existing techniques in terms of memory management and accuracy. The noteworthy accuracy rates achieved by the MobileNet and Xception algorithms in retinal disease classification serve as a conclusive testament to their exceptional performance. These models outshine others, reaffirming their efficiency and positioning them as robust contenders for advancing the field of medical image classification. The model's performance was rigorously evaluated by comparing its categorization results with labels provided by ophthalmologists, reinforcing its accuracy and reliability. The deployment of the Flask framework for the front-end enabled a focused evaluation of our high-performing extension algorithm, the platform provided a controlled environment for systematically assessing and validating the robust performance of our algorithms with user inputs.

6. FUTURE SCOPE

The model can be extended to incorporate additional classes of retinal diseases, allowing for more comprehensive disease classification and diagnosis. Further research can focus on optimizing the model's memory consumption even more, potentially reducing the computational requirements and making it more accessible for real-time applications. [19, 33] The model can be integrated into existing medical imaging systems to assist ophthalmologists in the accurate and efficient diagnosis of retinal diseases. Collaboration with medical professionals and experts can help refine the model and validate its performance on a larger and more diverse dataset. The proposed model can serve as a foundation for developing automated screening systems for retinal diseases, enabling early detection and intervention, leading to improved patient outcomes.

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