Journal of Electronics, Electromedical Engineering, and Medical Informatics
Multidisciplinary: Rapid Review: Open Access Journal Vol. 7, No. 2, April 2025, pp: 471-483; eISSN: 2656-8632

RESEARCH ARTICLE OPEN ACCESS

Manuscript received January 15, 2025; Accepted March 15, 2025; date of publication April 23, 2025
Digital Object Identifier (**DOI**): https://doi.org/10.35882/jeeemi.v7i2.717

How to cite: Nitesh Sureja, Hemant Patel, Vruti Parikh, Ajaysinh Rathod, Priya Patel and Heli Sureja, "Explainable Artificial Intelligence based Deep Learning for Retinal Disease Detection", Journal of Electronics, Electromedical Engineering, and Medical Informatics, vol. 7, no. 2, pp. 471-483, April 2025.

# Explainable Artificial Intelligence-based Deep Learning for Retinal Disease Detection

**Nitesh Sureja[1], Hemant Patel[2], Vruti Parikh[1], Ajaysinh Rathod[3], Priya Patel[3] and Heli Sureja[4]**
[1]Department of Computer Science and Engineering, Krishna School of Emerging Technology and Applied Research, KPGU, Vadodara, INDIA
[2]Department of Computer Science & Engineering, Dr. Subhash University, Junagadh, INDIA
[3]Department of Computer Science & Design, Sardar Vallabhbhai Patel Institute of Technology, GTU, Vasad, INDIA
[4]MS Student, Department of Computer & Data Science, Tagliatela College of Engineering, University of New Haven, CT, USA

**Corresponding author: Nitesh Sureja (e-mail: nmsureja@gmail.com).**

This work did not receive any financial support.

**ABSTRACT** This research focuses on the automated identification of retinal diseases. To address this challenge, an artificial intelligence-based approach developed utilizing five deep learning models namely Xception, InceptionV4, EfficientNet-B4, SqueezeNet, and ResNet-264. The model leverages transfer learning to enhance its performance. It is trained on a dataset of optical coherence tomography (OCT) images to classify retinal conditions into four categories: (1) diabetic macular edema, (2) choroidal neovascularization, (3) drusen, and (4) normal. The training dataset, sourced from publicly available repositories, comprises 1,08,312 OCT retinal images covering all four categories. The proposed models achieved good results. InceptionV4 outperformed other models across multiple metrics, achieving the highest accuracy (99.50%), precision (100%), recall (100%), AUC (100%), and F1 score (100%). It surpassed SqueezeNet (accuracy: 98.00%, precision: 98.00%, recall: 98.00%), EfficientNet-B4 (accuracy: 98.50%, precision: 98.50%, recall: 98.50%), Xception (accuracy: 78.25%, precision: 80.36%, recall: 77.75%, F1 score: 99.50%), and ResNet-264 (accuracy: 87.75%, precision: 87.94%, recall: 87.50%, F1 score: 87.98%). The results highlight the effectiveness of deep learning models combined with transfer learning in achieving accurate and efficient retinal disease detection. Future research could focus on expanding the dataset and exploring hybrid architectures to enhance classification accuracy and improve generalization across various retinal conditions.

**INDEX TERMS** Convolution neural network, Deep learning, Explainable artificial intelligence, Machine learning, Medical image analysis, Retinal diseases.

## I. INTRODUCTION

The application of deep learning (DL) in medical image analysis has significantly enhanced the accuracy and efficiency of disease detection and diagnosis. Traditional scientific approaches to disease identification were often time-consuming, less reliable, and susceptible to errors. However, with advancements in deep learning, the biomedical field has increasingly adopted automated techniques for disease detection, leading to more precise and timely results. One of the leading causes of early vision loss is retinal disease or damage, which adversely affects the retina—a delicate layer located at the inner back of the human eye. This study explores computer-assisted methods for the automated detection of retinal diseases, including drusen, diabetic macular edema (DME), choroidal neovascularization (CNV), and normal retinal conditions, through the use of transfer learning [1-4]. Figure 1 presents sample OCT images illustrating these three retinal diseases alongside a normal retina.

Detecting retinal diseases is a well-established classification challenge in deep learning. This study addresses the problem by automating the identification of retinal conditions using optical coherence tomography (OCT) images. The model classifies retinal states into four categories: diabetic macular edema (DME), choroidal neovascularization (CNV), drusen, and normal [5-7]. With the increasing adoption of OCT imaging in medical diagnostics, a computer-assisted system for retinal disease detection can enhance reliability, aid in treatment, and facilitate disease monitoring. Traditional automated diagnosis methods require extensive image pre-processing before feeding data into shallow neural networks, making the process time-consuming. To overcome these limitations, this research employs transfer learning techniques. The motivation behind this work stems from the challenges researchers face in diagnosing retinal diseases effectively.

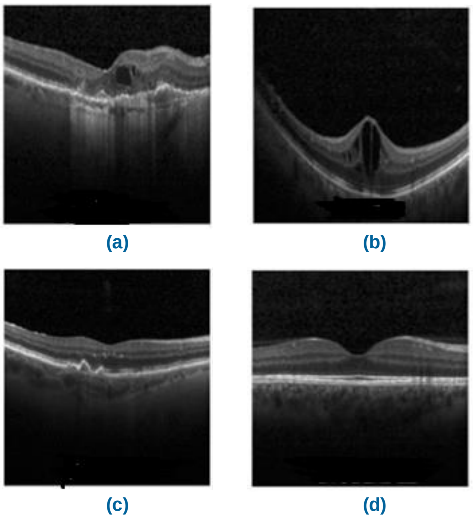



**FIGURE. 1 Sample Retina OCT Images ((a) CNV (b) DMV (c) DRUSEN (d) Normal**

Deep learning (DL) and machine learning (ML) models have demonstrated strong performance in retinal disease diagnosis. In this study, DL techniques are preferred due to their ability to process complex biological data and extract high-level abstract features from retinal images. The primary objective is to implement a transfer learning approach using five different deep learning models pre-trained on the ImageNet dataset. The model's performance is evaluated and compared with existing methods for retinal disease classification. To ensure robust validation, the proposed model is tested on an external dataset—Large Dataset of Labeled Optical Coherence Tomography (OCT) and Chest X-ray Images—which comprises 1,08,312 OCT retinal images. This dataset is compiled by Daniel Kermany, Michael Goldbaum, and Kang Zhang. The overarching goal of this research is to advance automated retinal disease detection and support computer-assisted diagnosis for conditions such as macular edema, age-related macular degeneration, and diabetic retinopathy. The key contributions of this study are as follows.

- The proposed study presents an approach for retinal disease detection by evaluating multiple deep learning architectures, including Xception, InceptionV4, EfficientNet-B4, SqueezeNet, and ResNet-264 architectures.
- All above models evaluated within a transfer learning framework which improved the performance of all deep learning models when utilized on a separate OCT image dataset compared to existing state-of-the-art methods.
- Additionally, transfer learning with pre-trained deep models has been shown to effectively mitigate overfitting challenges in medical image classification. Therefore, this study employs all models, pre-trained on ImageNet, a large-scale dataset of natural images.
- The primary objective of developing this approach is to conserve resources, minimize overfitting, and optimize computational efficiency.

Saha et al. created a system for detecting AMD symptoms from OCT images. The proposed system used a transfer learning algorithm, eliminating the need for thousands of images or a highly specialized deep learning machine [8]. De Fauw et al. developed a novel deep learning architecture applied to three-dimensional OCT images, demonstrating performance that matched expert detection in some retinal diseases [9]. Lu et al. proposed a method combining four binary classifiers within a deep convolutional neural network (DCNN) framework to differentiate retinal abnormalities in OCT images [10]. An et al. introduced a machine learning technique for detecting glaucoma. The authors used three-dimensional (OCT) data as well as color fundus images to detect the abnormal features of eye retina. A segmentation algorithm was used to generate thickness and deviation maps. Then (CNN) transfer learning was applied to a set of input images such as gray-scale optic disc fundus image, retinal nerve fiber layer, and retinal ganglion cell complex. CNN is trained using data augmentation. Then a random forest (RF) was trained by combining the results of each CNN model. Their model showed high accuracy to detect glaucomatous subjects based on features extracted from images [11]. Fang et al. introduced a lesion-sensitive CNN method for classifying retinal OCT images. They originally designed a grid to detect lesions and then generated an attention map from the OCT image using this grid. This attention map was subsequently incorporated into the classification network [12]. Wang et al. proposed a fully automated CNV segmentation and diagnosis algorithm using a CNN. They employed a clinical dataset that included eye scans of both CNV and non-CNV patients, achieving a specificity of 95% in their test data [13]. Shih and Patel presented a new deep learning classification technique applied to OCT retinal images, with the dataset comprising one normal and three most common retinal disease scans. They evaluated several parameters and different classifiers in the training network architecture [14]. Sunija et al. proposed a deeply separable convolution model to classify glaucoma and healthy images using Spectral-Domain OCT (SD-OCT) images. This proposed network resulted in a higher overall achievable accuracy with less computational complexity and produced effective results [15].

Adel et al. proposed a multiclassification model based on OCT images to detect retinal eye diseases. They used transfer learning over direct CNN, employing the Xception and InceptionV3 transfer learning models. They opted for the categorical hinge loss function (known as SVM loss) over softmax loss to classify four eye diseases [16]. Elsharkawy et al. proposed a computer-assisted diagnostic method to detect DR using structural 3D retinal scans. They used prior shape information to segment retinal layers from 3D-OCT images. Several studies have also binary-classified DME, Drusen, and CNV retina images against healthy retina images [17]. Berrimi and Moussaoui proposed a new CNN classification architecture based on deep learning and transfer learning, using retinal images obtained from the OCT device. They compared their architecture's performance with pre-trained models such as VGG16 and InceptionV3 and achieved 98.5% accuracy on the test set [18]. Jin et al. developed a multimodal deep learning model using Optical Coherence Tomography Angiography (OCTA) and OCT images to assess CNV in AMD patients, achieving 95.5% accuracy for the dataset in their study [19]. Rong et al. proposed a surrogate-assisted classification method to automatically classify retinal OCT images based on CNN. They first reduced the noise in the images, removed the masks by applying morphological thresholding and broadening, and used these images to create surrogate images. The test images were then estimated by averaging the outputs from the CNN model trained on representative images [20]. Daghistani employed a method that includes a CNN for the DME classification task. Five models consisting of different convolution layers were created to demonstrate the effect of convolution. The CNN model with five convolutional layers exhibited the best performance in classifying DME, corroborating the notion that a higher number of convolution layers enhances the accuracy of the model. Several studies in the literature, akin to our own, discuss machine learning methods used to detect individuals with CNV, DME, drusen, and healthy individuals from OCT images [21]. Rastogi et al. endeavored to detect DME, CNV, and drusen from OCT images. They proposed a detection model based on deep learning architectures to detect retinal diseases, utilizing a Dense Connected Convolutional Neural Network (DenseNet) and achieved 98% accuracy on the training set [22].

Hwang et al. integrated cloud computing with AI and telemedicine in their study for the diagnosis of AMD. They designed a user-friendly cloud system website, enabling anyone with an internet connection and a computer to use the AI model [23]. Li et al. proposed a model that categorizes retinal patients into four classes: DME, CNV, normal, and drusen, using the pre-trained deep learning method VGG16. They achieved a prediction accuracy of 98.6% on a validation dataset of 1,000 images [24]. Saleh et al. used OCT images to classify patients as drusen, DME, normal, and CNV. They used transfer learning-based SqueezeNet and InceptionV3 techniques to classify retinal diseases, achieving high performance as a result of their study [25]. Yan et al. developed a classification system based on OCT images, dividing them into four categories: drusen, inactive CNV, active CNV, and normal. They trained a ResNet-34 deep learning model containing a Convolutional Block Attention Module (CBAM) on the dataset [26]. Gupta et al. aimed to design an AI-based automated network to help ophthalmologists more accurately identify and categorize eye diseases from OCT images, such as drusen, DME, and CNV. They achieved 83.66% accuracy performance for test images using a CNN architecture [27].

The structure of this paper is as follows: Section 2 provides an outline of the research methodology in detail, along with the databases an evaluation metrics used in this study. Section 3 presents the results obtained from the experiments. Section 4 discusses the outcomes of the study. Finally, Section 5 concludes the study and suggests potential future research directions.

## II. MATERIAL AND METHODS

The proposed methodology consists of five key stages: data collection, augmenting the data, preprocessing of data, training the model, and model evaluation. First stage involves acquiring images of diseased and normal retina images. Due to non-availability of sized data, augmentation technique was applied to create additional images. To improve accuracy in detecting retina diseases, five widely used deep learning models— Xception, InceptionV4, EfficientNet-B4, SqueezeNet, and ResNet-264—were selected and assessed. These algorithms demonstrate high accuracy in identifying diseases, making the method a valuable tool for fast and precise retina disease diagnosis in medical image analysis tasks. The stages and processes in the methodology are illustrated in Figure 2.

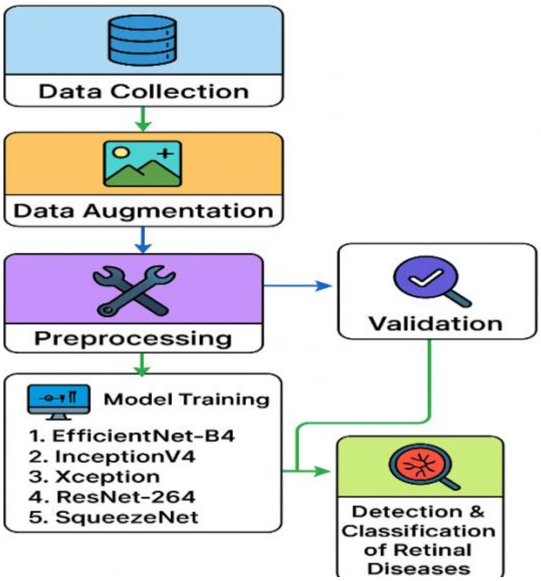



FIGURE 2. Proposed Methodology

### A. DATA COLLECTION

This study utilizes the "Large Dataset of Labeled Optical Coherence Tomography (OCT) and Chest X-ray Images", which is publicly accessible on Mendeley Data for research purposes. The dataset was compiled by Daniel Kermany, Michael Goldbaum, and Kang Zhang and is structured into three main sections: training, testing, and validation. Each section is further divided into four categories based on image classification: Normal, CNV, DRUSEN, and DME [28]. The dataset comprises approximately 1,08,312 retinal OCT scan images in JPEG format. These images were collected from adult patients over a period spanning July 1, 2013, to March 1, 2017, across multiple medical institutions, including the California Retinal Research Foundation, Shiley Eye Institute at the University of California, Beijing Tongren Eye Center, Medical Center Ophthalmology Associates, and the Shanghai First People's Hospital [29]. The description of the dataset is given in TABLE 1.

TABLE 1
DATASET Description

| Large Dataset of Labeled Optical Coherence Tomography (OCT) and Chest X-ray Images. [28][29] | | |
|---|---|---|
| **Classes** | **Number of Images** | **Number of Images used** |
| NORMAL | 51390 | 1250 |
| DRUSEN | 8867 | 1250 |
| CNV | 37456 | 1250 |
| DME | 11599 | 1250 |
| Total Images | 108312 | 5000 |

## B. PREPROCESSING

In image analysis, preprocessing is a critical step as it improves the quality and consistency of the dataset. This study employed different preprocessing techniques such as data augmentation, image normalization, and image scaling. Images in the dataset are resized in 150 × 150 format to confirm uniform dimensions and simplify data processing by the model. Image normalization was performed to decrease the effect of contrast and light variations by scaling values of pixels in the interval of 0 to 1. Data augmentation techniques such as cropping, rotation, and flipping are used for expanding the database and removing overfitting. These methods increase the diversity of the data and enhanced the model's performance. Common data augmentation strategies, including zooming, rotating, shifting (height and width), shearing, and vertical flipping, are used to generate new images by introducing minor changes to the original ones. This approach creates a bigger and varied database, which helped train DL (deep learning) method more effectively.

As the dataset used in this research is already preprocessed and augmented, we have not performed any preprocessing. We have selected 1250 images of each class for our task. We adopt a 70-20-10 split for training, testing, and validation to ensure effective model learning, evaluation, and fine-tuning. The training set (70%) is used to learn patterns from the data, the test set (20%) is reserved for final model evaluation to assess generalization, and the validation set (10%) is used for hyperparameter tuning and model selection to prevent overfitting.

## C. MODEL SELECTION AND TRAINING

The DL (deep learning) methods used in this study—EfficientNet-B4, Xception, InceptionV4, SqueezeNet, and ResNet164—were selected based on their ability to optimize model performance across different dimensions, including accuracy, computational efficiency, and feature extraction capabilities. The criteria for selecting these models are detailed below:

- EfficientNet-B4: Based on a compound scaling approach, EfficientNet-B4 achieves high accuracy with significantly fewer parameters, making it an ideal choice for balancing efficiency and performance [30][31].
- Xception: Utilizing depthwise separable convolutions, Xception reduces computational complexity while enhancing feature extraction, making it highly effective for complex image classification tasks [32].
- InceptionV4: Designed with multiple parallel convolutional filters, InceptionV4 captures multi-scale features efficiently, improving the model's ability to detect fine-grained patterns in images [33].
- SqueezeNet: A lightweight architecture that uses Fire modules to achieve comparable accuracy to larger models with significantly fewer parameters, making it suitable for low-resource environments [34].
- ResNet164: Leveraging deep residual learning, ResNet164 addresses vanishing gradient issues and improves feature learning by allowing deeper network training without performance degradation [35].

Leveraging model's pretrained weights allowed for faster convergence, even with a relatively limited dataset size. We trained all these models with preprocessed data, which enhanced their ability to learn distinguishing features effectively.

### 1) EFFICIENTNET-B4

EfficientNetB4 is one of the scaled variants of the original EfficientNet architecture, which is designed using Neural Architecture Search (NAS) to optimize accuracy and efficiency across a range of computational budgets. The foundation of EfficientNet lies in its compound scaling method, which uniformly scales depth (d), width (w), and input resolution (r) using a compound coefficient φ. The scaling is governed by the Eq. (1) and Eq. (2) [30] [31].

$$d = \alpha^{\varphi}, \quad w = \beta^{\varphi}, \quad r = \gamma^{\varphi} \tag{1}$$

$$\alpha \cdot \beta^2 \cdot \gamma^2 \approx 2, \quad \text{where } \alpha, \beta, \gamma > 0 \tag{2}$$

This method allows for a principled and balanced scaling of all three dimensions, unlike conventional approaches that scale arbitrarily. EfficientNetB4 corresponds to a higher value of φ, specifically φ = 4, meaning it has greater depth, width, and input resolution than baseline EfficientNetB0, leading to higher accuracy at the cost of increased computation. The architecture relies on MBConv blocks (Mobile Inverted Bottleneck Convolution), which combine depthwise separable convolutions and squeeze-and-excitation (SE) modules to efficiently capture spatial and channel-wise information. The network is trained using categorical cross-entropy loss given by Eq. (3) [30][31].

$$L = -\sum_{i=1}^{C}(y_i \log(\hat{y}_i)) \quad (3)$$

where $y_i$ and $\hat{y}_i$ are the ground-truth and predicted probabilities for class i, and C is the number of classes. EfficientNetB4 achieves state-of-the-art performance on image classification benchmarks such as ImageNet, making it highly suitable for complex tasks like skin disease classification, where fine-grained details are critical.

#### 2) XCEPTION

Xception (Extreme Inception) is a deep convolutional neural network architecture that improves upon Inception modules by completely replacing them with depthwise separable convolutions. The architecture is based on the assumption that spatial and cross-channel correlations can be mapped separately. A depthwise separable convolution consists of a depthwise convolution followed by a pointwise (1x1) convolution. This operation is mathematically using Eq. (4) [32].

$$y = pw(dw(x)) \quad (4)$$

where $dw$ denotes depthwise convolution and $pw$ denotes pointwise convolution. Xception uses residual connections as per Eq. (5) [32] and is trained with the categorical cross-entropy loss calculated by Eq. (6) [32]

$$y = F(x) + x \quad (5)$$

$$l = -\sum y_i * \log(\hat{y}_i)) \quad (6)$$

Xception achieves high performance with fewer parameters, making it ideal for resource-constrained environments and high-accuracy requirements such as skin disease detection.

#### 3) INCEPTIONV4

InceptionV4 is a convolutional neural network (CNN) that builds upon the Inception architecture by combining the benefits of deeper networks with efficient computation. It integrates the design principles of Inception-ResNet modules and increases the network's depth with residual connections. The core building blocks of InceptionV4 are Inception-A, Inception-B, and Inception-C modules, which are optimized for capturing multi-scale features through parallel convolutions. Each module contains different filter sizes (1x1, 3x3, 5x5) and pooling operations that operate in parallel and concatenate their outputs. Residual connections improve gradient flow, defined as per Eq. (7) [33].

$$y = F(x) + x \quad (7)$$

where $F(x)$ is the output of the Inception module and $x$ is the input. The model is trained using cross-entropy loss using Eq. (8) [33].

$$l = -\sum y_i * \log(\hat{y}_i)) \quad (8)$$

InceptionV4 strikes a balance between computational complexity and classification performance, making it suitable for fine-grained image classification tasks like medical image analysis.

#### 4) SQUEEZENET

SqueezeNet is a lightweight convolutional neural network designed for high accuracy with very few parameters. It employs a unique 'fire module' that includes a squeeze layer (1x1 convolutions) followed by expand layers (a mix of 1x1 and 3x3 convolutions). The squeeze layer reduces input channels, while the expand layer increases them, reducing overall model size. The fire module is computed using Eq. (9) [34].

$$y = \text{Expand}(\text{Squeeze}(x)) \quad (9)$$

SqueezeNet achieves AlexNet-level accuracy with 50x fewer parameters. It is particularly suited for embedded systems and mobile applications. The network is trained using the cross-entropy loss using Eq. (10) [34].

$$l = -\sum y_i * \log(\hat{y}_i)) \quad (10)$$

Its small footprint and decent accuracy make it a candidate for real-time medical diagnosis on mobile devices.

#### 5) RESNET-264

ResNet264 is a very deep variant of the Residual Network (ResNet) family, designed to learn extremely complex features without suffering from vanishing gradients. It utilizes identity shortcut connections that allow gradients to flow directly through the network. A residual block in ResNet264 is expressed as per Eq. (11) [35].

$$y = F(x, \{w_i\}) + x \quad (11)$$

where $F(x, \{w_i\})$ represents the residual mapping to be learned. Batch normalization and ReLU activations follow each convolution. Due to its depth, ResNet264 captures intricate hierarchical features in images. Training is done using categorical cross-entropy using Eq. (12) [35].

$$l = -\sum y_i * \log(\hat{y}_i)) \quad (12)$$

ResNet264 is highly suitable for tasks demanding fine-grained detail, such as skin disease classification from dermoscopic images.

#### 6) TRANSFER LEARNING

Transfer learning has proven to be an effective strategy in deep learning-based classification tasks, particularly when working with complex architectures such as EfficientNet-B4, Xception, InceptionV4, SqueezeNet, and ResNet164. These models have been pre-trained on large-scale datasets such as ImageNet, allowing them to learn hierarchical feature representations that can be effectively transferred to domain-specific tasks [30][36]. Transfer learning is used in this work to achieve following benefits from two key advantages:

1. Computational Efficiency – Training deep CNNs from scratch requires extensive computational resources and large amounts of labeled data. By using pre-trained models, we significantly reduce the training time and computational cost while still achieving high accuracy.
2. Improved Performance and Generalization – The pre-trained models provide a strong feature extraction foundation, reducing the risk of overfitting, especially when working with limited datasets. Studies have shown that fine-tuning these models can lead to improved accuracy and robustness in classification tasks [33] [35].

For this study, we fine-tune the pre-trained models on our dataset while preserving the lower-level feature extraction layers. This ensures that the models retain their learned representations while adapting to the specific characteristics of our data.

### 7) EXPLAINABLE ARTIFICIAL INTELLIGENCE (XAI)

Explainable Artificial Intelligence (XAI) plays a crucial role in interpreting neural networks. While deep learning models have excelled at handling complex tasks, their intricate architectures and extensive parameterization often make them incomprehensible, earning them the label of "black boxes." Interpreting these models is essential to building trust, fostering transparency, and ensuring accountability, particularly in high-stakes real-world applications [37][38].

XAI provides insights into the decision-making processes of neural networks, shedding light on the key factors and patterns that influence their outcomes. This capability helps identify and address biases, ensures compliance with ethical and legal standards, and supports model optimization, validation, and debugging. By improving fine-tuning and enhancing capacity, XAI enables effective use of deep learning's full potential, confirming that decisions in important areas are ethical, informed, and reliable. To enhance the trust and consistency of our presented models, we employed Grad CAM, Grad CAM++, Eigen CAM and LIME Class Activation Mapping (CAM) techniques, to visually explain the model's decision-making process. This approach provides a clear, visual representation of influential factors, promoting better understanding in the system. Grad-CAM is a powerful technique for identifying instances associated with a specific class. The heatmaps it generates are anticipated to provide greater accuracy in highlighting precise areas corresponding to a specific class in an image. By integrating Grad-CAM++, the visualization of predictions made by CNN models is further refined. The mathematical formulation of Grad-CAM++ can be represented as follows Eq (13) [37][38].

$$W_k^c = \sum_i \sum_j \propto_{i,j}^{kc} ReLU\left(\frac{\partial Y^c}{\partial A_{i,j}^k}\right) \quad (13)$$

where, $W_k^c$ represents the weights of neurons, $\propto_{i,j}^{kc}$ denotes the significance of location $(i, j)$, $A^k$ refers to the activation map, $c$ stands for the target class, and $Y^c$ represents the score of class $c$.

### 8) EVALUATION METRICS

To assess the effectiveness of the deep learning models, we utilize multiple evaluation metrics, ensuring a comprehensive and fair assessment of classification performance [39]. The performance was assessed using a confusion matrix. The Eq. (14) [39], Eq. (15) [39], Eq. (16) [39], Eq. (17) [39], and Eq. (18) [39] were applied to compute accuracy, precision, recall, F1-score, and AUC based on the confusion matrix.

$$\text{Accuracy} = (\text{TN} + \text{TP})/(\text{TN} + \text{FP} + \text{TP} + \text{FN}) \quad (14)$$

$$\text{Precision(Pre)} = \text{TP} / (\text{TP} + \text{FP}) \quad (15)$$

$$\text{Recall(Rec)} = \text{TP}/(\text{TP} + \text{FN}) \quad (16)$$

$$\text{F1 Score} = (2 \text{ x Pre} * \text{Rec}) / (\text{Pre} + \text{Rec}) \quad (17)$$

$$\text{AUC} = \frac{1}{2}\left(\frac{\text{TP}}{\text{TP+FN}} + \frac{\text{TN}}{\text{TN+FP}}\right) \quad (18)$$

In these calculations, true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) are used as the key components. Keras was employed to implement all deep learning models and explainable AI (XAI), with TensorFlow serving as the backend. These experiments were carried out in PyCharm Community Edition (2021.2.3). The model training and evaluation were performed on a PC equipped with an 11th generation Intel® Core™ i3 CPU (2.50GHz), 128GB of RAM, and a 24GB GPU, running 64-bit Windows 11.

## III. RESULTS

The research was conducted using the Python language and the TensorFlow. Table 1 details the training parameters used. The models were trained using training data and validated with validation data to ensure proper training. After training, the model was evaluated using test data. TABLE 2 gives the information about the various training parameters used.

**TABLE 2**
**Training Parameters**

| Models: EfficientNet-B4, Xception, InceptionV4, SqueezeNet, and ResNet164 | |
|---|---|
| Image Size | 150 x 150 |
| Batch Size | 32 |
| Epochs | 40 |
| Learning Rate | 0.001 |
| Loss Function | Categorical Crossentropy |
| Optimizer | Adam |

**TABLE 3**
**Performance of the classifier models**

| Model | Accuracy | Precision | Recall | AUC | F1 Score |
|---|---|---|---|---|---|
| Xception | 78.25 | 80.36 | 77.75 | 94.53 | 99.50 |
| InceptionV4 | 99.50 | 100 | 100 | 100 | 100 |
| ResNet-264 | 87.75 | 87.94 | 87.50 | 96.33 | 87.98 |
| EfficientNet-B4 | 98.50 | 98.50 | 98.50 | 99.64 | 98.50 |
| SqueezeNet | 98.00 | 98.00 | 98.00 | 98.80 | 98.00 |

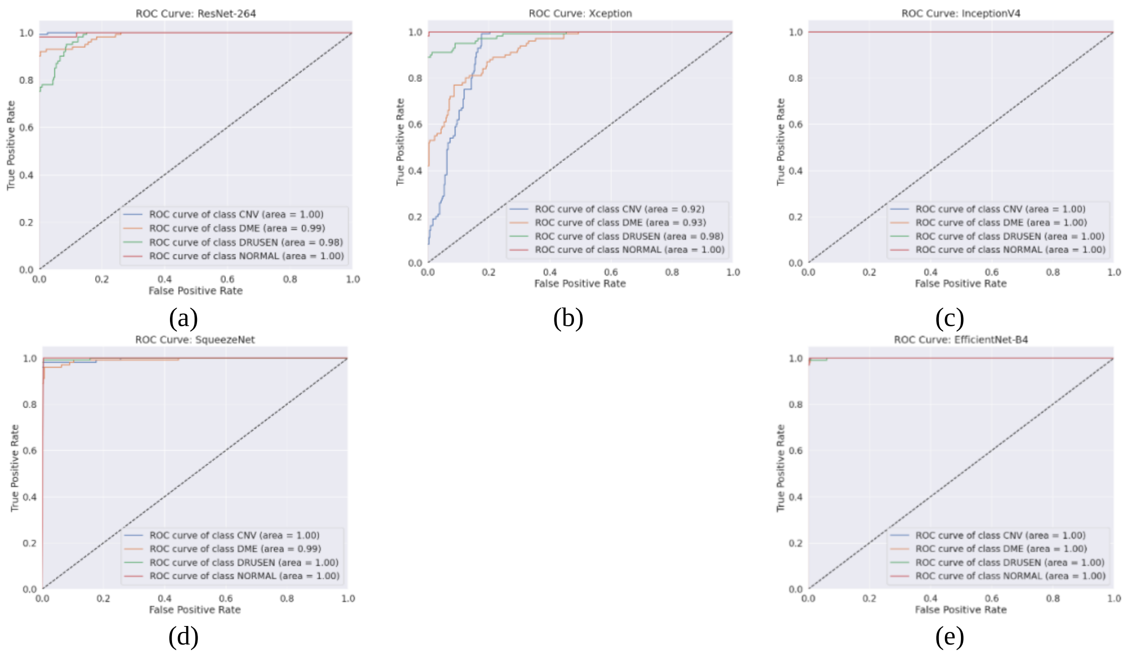
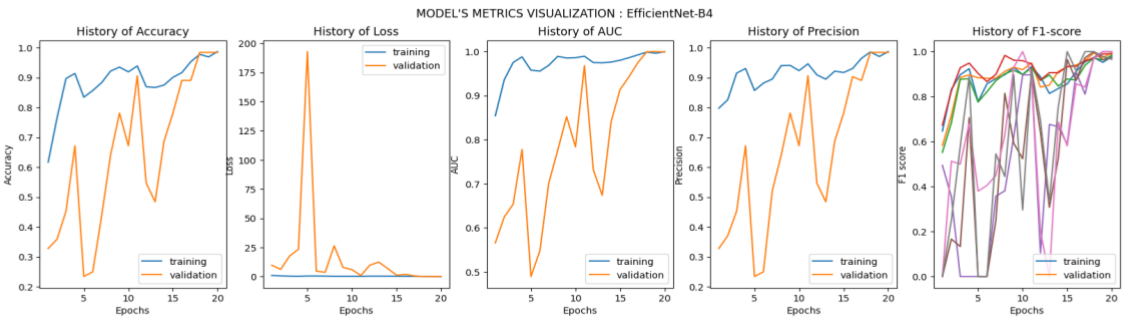



**FIGURE 3. ROC curve (a) ResNet-264, (b) Xception, (c) InceptionV4, (d) SqueezeNet, (e) EfficientNet-B4**

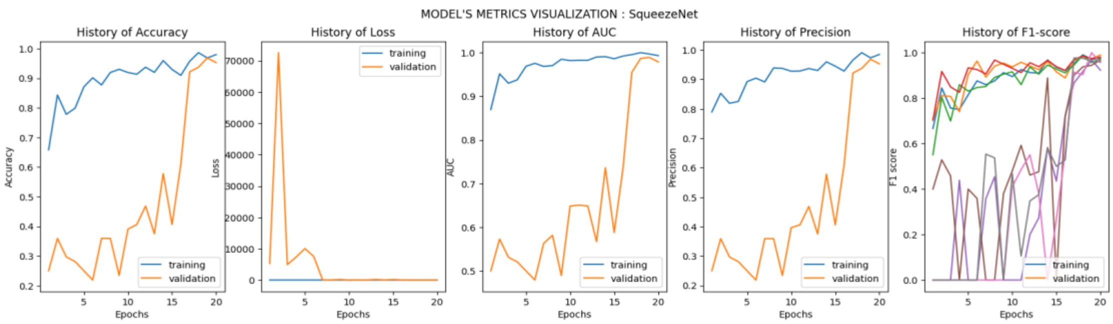
TABLE 3 shows the details of classification and detection performances of all proposed models. InceptionV4 achieved the highest accuracy of 99.50%, surpassing other models: SqueezeNet (98.00%), EfficientNet-B4 (98.50%), Xception (78.25%), and ResNet-264 (87.75%). InceptionV4 achieved the highest precision of 100% surpassing other models: SqueezeNet (98.00%), EfficientNet-B4 (98.50%), Xception (80.36%), and ResNet-264 (87.94%). InceptionV4 achieved the highest recall of 100% surpassing other models: SqueezeNet (98.00%), EfficientNet-B4 (98.50%), Xception (77.75%), and ResNet-264 (87.50%). InceptionV4 achieved the highest AUC of 100% surpassing other models: SqueezeNet (98.80%), EfficientNet-B4 (99.64%), Xception (94.53%), and ResNet-264 (96.33%). InceptionV4 achieved the highest f1 score of 100% surpassing other models: SqueezeNet (98.00%), EfficientNet-B4 (98.50%), Xception (99.50%), and ResNet-264 (87.98%). The results demonstrate that the InceptionV4 model outperformed the other models.

Figures 3 presents the ROC curves four classes across five models, illustrating the trade-off between True Positive Rate (TPR) and False Positive Rate (FPR). A higher ROC value (close to 1) indicates strong classification, while values near 0.5 suggest poor distinction. The results confirm that InceptionV4, EfficientNet-B4 and SqueezeNet models have strong performance across most classes.

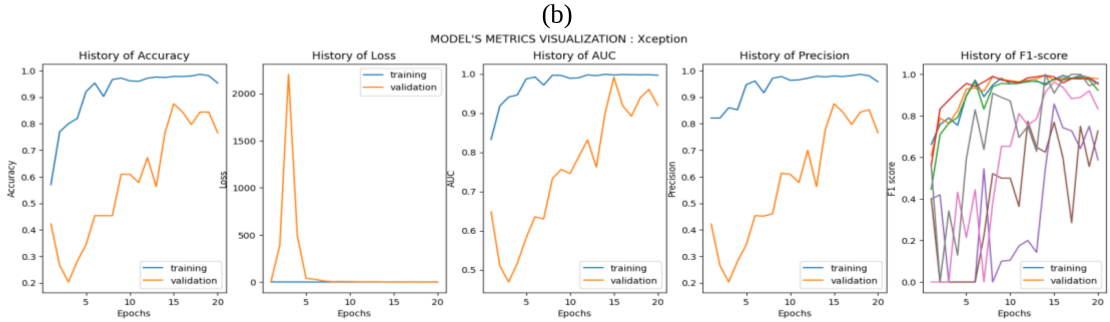
FIGURE 4 show plots for the training and validation losses, as well as the accuracies, precision, recall, AUC, and F1 score of all models. To avoid unnecessary computations, training is halted if results stagnate for three consecutive epochs, indicating the best performing epoch. FIGURES 5 presents confusion matrices drawn based on the performance of models employed in this research. The matrices give the count information of various classes classified by the model as an actual prediction and different prediction. FIGURE 6 presents original and predicted image visualization of Grad-Cam, Grad Cam++, Eigen-Cam and LIME. FIGURE 7 shows the wrong predictions. FIGURE 8 presents evaluation results achieved with test set graphically.



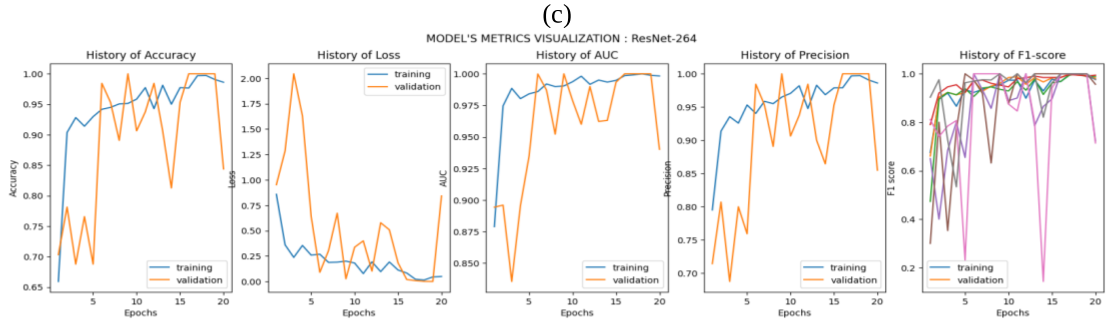

(a)



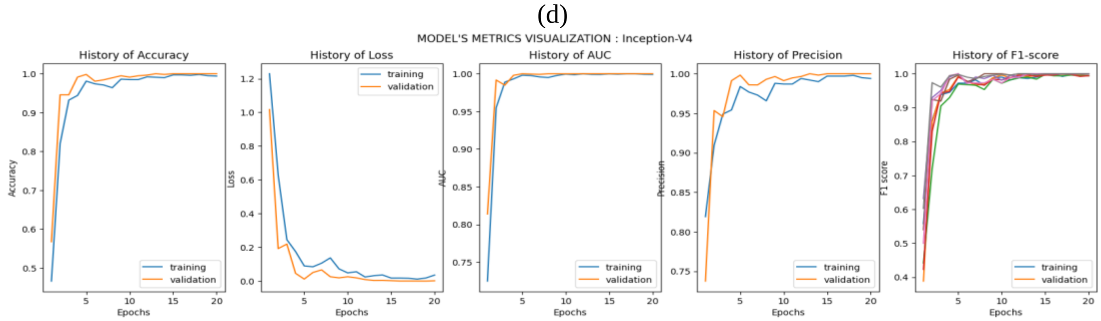

(b)




(c)




(d)




(e)

**FIGURE 4.** **Accuracy, Loss, AUC, Precision and F1-score graph (a) EfficientNetB4, (b) SqueezeNet, (c) Xception, (d) ResNet-264, (e) InceptionV4**

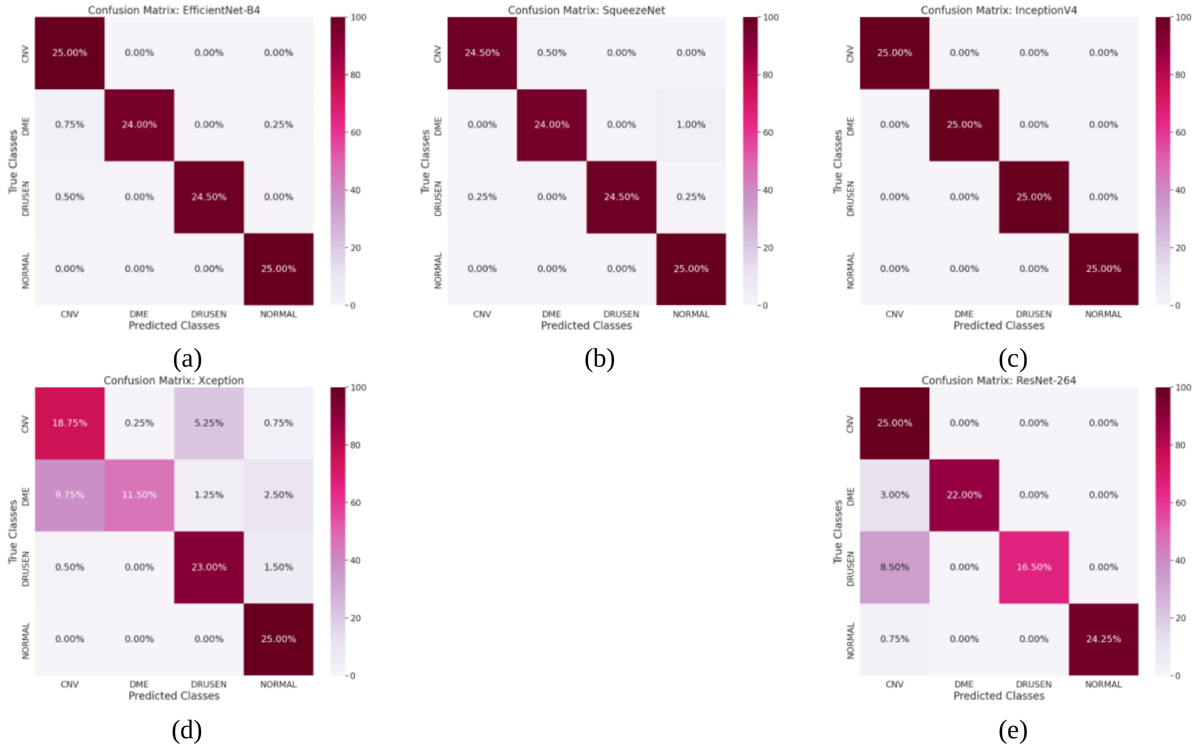



**FIGURE 5. Confusion Matrix (a) EfficientNetB4, (b) SqueezeNet, (c) InceptionV4, (d) Xception, (e) ResNet-264**

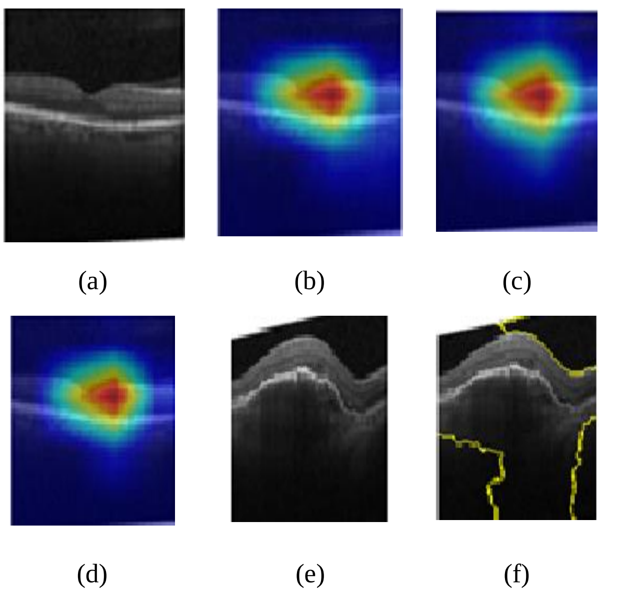



**FIGURE 6. Confusion Matrix (a) EfficientNetB4, (b) SqueezeNet, (c) InceptionV4, (d) Xception, (e) ResNet-264**

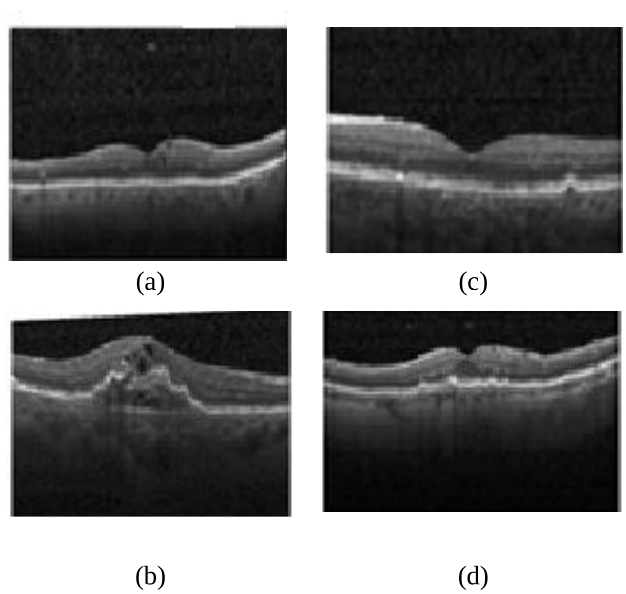



**FIGURE 7. Original and predicted Images (a) True: DME Predicted: NORMAL (b) True: CNV Predicted: DME (c) True: DRUSEN Predicted: NORMAL (d) True: DRUSEN Predicted: CNV**

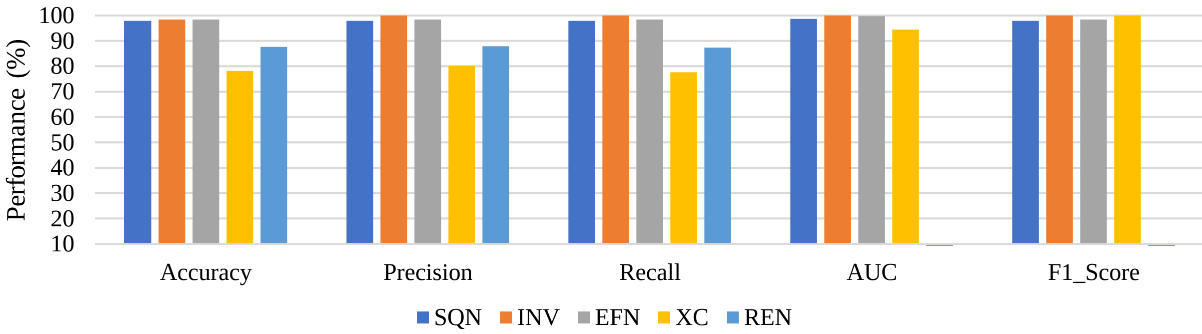



**FIGURE. 8** **Performance of the classifier (SQN = SqueezeNet, EFN = EfficientNet-B4, XC = Xception, INV = InceptionV4, REN = ResNet-264)**

## IV. DISCUSSION

This work uses ISIC 2017 data to assess the performance of deep CNN models in retinal illness classification. We validated the performance of the suggested models by matching their outcomes with those of current literature studies. Preprocessing activities including data augmentation to boost dataset diversity and reduce overfitting followed data capture. Unneeded areas were eliminated via cropping, therefore freeing the model to concentrate on the area of interest (ROI). All photos were downsized to a consistent dimension of 150 × 150 × 3 since the dataset comprised photographs with differing resolutions. Several deep CNN architectures were applied in feature extraction. The models obtained testing accuracy between 78.25% and 99.50%. With 99.50%, InceptionV4 produced the best accuracy followed by EfficientNet B4 (98.50%), SqueezeNet (98.00%), ResNet0264 (87.75%), and Xception (78.25%). TABLE 4 offers a comparison with other currently used techniques. InceptionV3 (94.46%) by Boix et al. [40], CNN with InceptionV3 (98.00%) by Choudhary et al. [41], RFT with CNN layers (83.78%) by Alwakid et al. [42], and ResNet50 (93.60%) by Abood et al. [43] have demonstrated varied degrees of accuracy depending on different models. Additional noteworthy studies include DenseNet 169 (90.00%) by Mushtaq et al. [44], DenseNet 121 (98.40%) by Mostari et al. [45], and a combination of VGG16 and VGG19 (90.16%) by Menaouer et al. [46]. Further underlining the better performance of our approach are additional comparisons with retinal illness classifiers as EyeDeep-Net (91.00%) by Senger et al. [47] and models constructed by Das et al. [48] and Nguyen et al. [49] with respective accuracies of 89.10% and 89.17%, respectively. With an average accuracy of 95.04%, the enhanced Deep CNN models developed by Ejaz et al. likewise produced comparable results. Our approach exceeded all previous findings with a 99.50% accuracy by combining five DL models with transfer learning and Dropout regularization.

By mimicking dataset diversity which is essential in the medical field where data shortage is common data augmentation significantly improved model robustness. Analyzing several deep learning models revealed their respective strengths and shortcomings for the retinal illness classification. Especially, the addition of several illness classes alongside healthy controls improves the clinical relevance of the model by more precisely replicating real-world diagnostic circumstances than binary classification systems. At last, a thorough analysis of important criteria accuracy, sensitivity, specificity, and precision offers a whole picture of every model's diagnostic power. This helps one to find places where models shine or call for more improvement. The results confirm that, in retinal disease detection, well tuned deep CNNs together with suitable preprocessing and training techniques can attain better performance than current approaches.

**TABLE 4**
**Comparison of results with state-of-the-art models**

| Reference | Model | Accuracy |
|---|---|---|
| Boix et al. [40] | InceptionV3 | 94.46 |
| Choudhary et al. [41] | InceptionV3, CNN | 98.00 |
| Alwakid et al. [42] | RFT, CNN | 83.78 |
| Abood et al. [43] | ResNet-50 | 93.6% |
| Mushtaq et al. [44] | DenseNet-169 | 90.00% |
| Mostari et al. [45] | DenseNet-121 | 98.40% |
| Menaouer et al. [46] | VGG16 and VGG19 | 90.60%. |
| Sengar et al. [47] | EyeDeep-Net | 91.00% |
| Das et al. [48] | Deep Learning | 89.10% |
| Nguyen et al. [49] | ResNet152 | 89.17% |
| Ejaz et al. [50] | CNN-3 | 95.04% |
| Proposed Model | Xception, ResNet-264, EfficientNet-B4, SqueezeNet, InceptionV4 | 99.50% InceptionV4 |

By mimicking dataset diversity which is essential in the medical field where data shortage is common data augmentation significantly improved model robustness. Analyzing several deep learning models revealed their respective strengths and shortcomings for the retinal illness classification. Especially, the addition of several illness classes alongside healthy controls improves the clinical relevance of the model by more precisely replicating real-world diagnostic circumstances than binary classification systems.

At last, a thorough analysis of important criteria accuracy, sensitivity, specificity, and precision offers a whole picture of every model's diagnostic power. This helps one to find places where models shine or call for more improvement. The results confirm that, in retinal disease detection, well tuned deep CNNs together with suitable preprocessing and training techniques can attain better performance than current approaches.

This study, while promising, suggests that further research is needed to fully realize the potential of deep learning models in retinal disease detection. Future investigations could focus on integrating additional variables, such as patient demographics or clinical histories, to better understand how these factors influence the accuracy of predictions. Exploring the applicability of these models across different healthcare settings and for various stages of retinal diseases would undoubtedly broaden our understanding of their utility and scalability. A key limitation of this study is its reliance on a single dataset. The generalizability of the results could be improved by validating these models with diverse datasets from different populations and clinical environments. While deep learning models show superior performance compared to traditional methods, the "black box" nature of these models remain a significant challenge, making them difficult to interpret when applied to specific clinical decisions. Efforts to enhance the transparency of the decision-making process in deep learning models, or to develop more interpretable models without compromising performance, would provide valuable insights for clinicians. This study demonstrates that deep learning models, especially convolutional neural networks (CNNs), could be highly effective in detecting retinal diseases, paving the way for greater integration of technology in medical diagnostics. Further refinement of these models, along with the exploration of practical applications in clinical practice, will be critical in advancing toward more personalized and accurate detection systems. Such advancements could help optimize patient care by providing timely diagnoses, improving treatment plans, and ultimately enhancing overall healthcare outcome.

This study emphasizes the significant potential of machine and deep learning models, particularly algorithms like EfficientNet-B4, Xception, InceptionV4, SqueezeNet, and ResNet164, in retinal disease detection. The superior performance of these models suggests they could play a pivotal role in developing predictive tools for identifying various medical illnesses. Such tools would allow medical practitioners to take proactive measures and offer a very good medical support tailored to different diseases. Furthermore, the insights generated from these models could help design treatment plan, resource allocation, and the creation of methods that promote an inclusive and effective medical environment. This approach not only boosts disease detection but also ensures that medical practices are grounded in data, making them adaptable to the diverse needs of the different diseases.

## V. CONCLUSION

The aim of this research was to enhance deep learning-based techniques for retina disease detection to attain superior accuracy compared to current algorithms. A transfer learning approach utilizing Xception, InceptionV4, EfficientNet-B4, SqueezeNet, and ResNet-264 models was introduced and demonstrated the maximum performance, with an accuracy score of 100% (InceptionV4). The proposed strategy demonstrated superior performance compared to methods outlined in earlier research. This approach may be utilized in the future for real-time detection and forecasting of retina disease detection on smartphones. To substantiate the model's feasibility, further investigations may require the examination of greater image sizes. We believe that this study and further related studies will facilitate the rapid identification, categorization, and management of retina disease detection. Our findings are encouraging, indicating that our model may represent a cutting-edge DL (Deep learning) method for the early identification of retina diseases. Our model attained a significant degree of accuracy in classifying retina diseases within both test and training datasets, rendering it possibly a relevant instrument for rapid and precise disease detection in medical analysis environments.

## ACKNOWLEDGMENT

We consider it an immense pleasure to convey our deep sense of gratitude to all who have helped us during this research directly or indirectly.

## REFERENCES

[1] K. L. Pennington and M. M. DeAngelis, "Epidemiology of age-related macular degeneration (AMD): associations with cardiovascular disease phenotypes and lipid factors," *Eye and Vision*, vol. 3, no. 1, Dec. 2016, doi: 10.1186/s40662-016-0063-5.
[2] G. Atteia, N. A. Samee, and H. Z. Hassan, "DFTSA-Net: Deep Feature Transfer-Based Stacked Autoencoder Network for DME diagnosis," *Entropy*, vol. 23, no. 10, p. 1251, Sep. 2021, doi: 10.3390/e23101251.
[3] Q. D. Nguyen, S. M. Shah, E. Van Anden, J. U. Sung, S. Vitale, and P. A. Campochiaro, "Supplemental oxygen improves diabetic macular edema: a pilot study," *Investigative Ophthalmology & Visual Science*, vol. 45, no. 2, p. 617, Jan. 2004, doi: 10.1167/iovs.03-0557.
[4] G. Rajesh, X. M. Raajini, K. M. Sagayam, and H. Dang, "A statistical approach for high order epistasis interaction detection for prediction of diabetic macular edema," *Informatics in Medicine Unlocked*, vol. 20, p. 100362, Jan. 2020, doi: 10.1016/j.imu.2020.100362.
[5] J. W. Crabb et al., "Drusen proteome analysis: An approach to the etiology of age-related macular degeneration," in *Proceedings of the National Academy of Sciences*, vol. 99, no. 23, pp. 14682–14687, Oct. 2002, doi: 10.1073/pnas.222551899.
[6] S. Loukovaara et al., "Indications of lymphatic endothelial differentiation and endothelial progenitor cell activation in the pathology of proliferative diabetic retinopathy," *Acta Ophthalmologica*, vol. 93, no. 6, pp. 512–523, Apr. 2015, doi: 10.1111/aos.12741.
[7] T. A. Ciulla, A. G. Amador, and B. Zinman, "Diabetic retinopathy and diabetic macular edema," *Diabetes Care*, vol. 26, no. 9, pp. 2653–2664, Sep. 2003, doi: 10.2337/diacare.26.9.2653.
[8] S. Saha et al., "Automated detection and classification of early AMD biomarkers using deep learning," *Scientific Reports*, vol. 9, no. 1, Jul. 2019, doi: 10.1038/s41598-019-47390-3.
[9] J. De Fauw et al., "Clinically applicable deep learning for diagnosis and referral in retinal disease," Nature Medicine, vol. 24, no. 9, pp. 1342–1350, Aug. 2018, doi: 10.1038/s41591-018-0107-6.
[10] W. Lu, Y. Tong, Y. Yu, Y. Xing, C. Chen, and Y. Shen, "Deep Learning-Based Automated Classification of Multi-Categorical

Abnormalities from optical coherence tomography images," *Translational Vision Science & Technology*, vol. 7, no. 6, p. 41, Dec. 2018, doi: 10.1167/tvst.7.6.41.

[11] G. An et al., "Glaucoma Diagnosis with Machine Learning Based on Optical Coherence Tomography and Color Fundus Images," *Journal of Healthcare Engineering*, vol. 2019, pp. 1–9, Feb. 2019, doi: 10.1155/2019/4061313.

[12] L. Fang, C. Wang, S. Li, H. Rabbani, X. Chen, and Z. Liu, "Attention to Lesion: Lesion-Aware Convolutional Neural Network for Retinal Optical coherence Tomography image classification," *IEEE Transactions on Medical Imaging*, vol. 38, no. 8, pp. 1959–1970, Feb. 2019, doi: 10.1109/tmi.2019.2898414.

[13] J. Wang et al., "Automated diagnosis and segmentation of choroidal neovascularization in OCT angiography using deep learning," *Biomedical Optics Express*, vol. 11, no. 2, p. 927, Jan. 2020, doi: 10.1364/boe.379977.

[14] F. Y. Shih and H. Patel, "Deep Learning classification on optical coherence tomography retina images," *International Journal of Pattern Recognition and Artificial Intelligence*, vol. 34, no. 08, p. 2052002, Sep. 2019, doi: 10.1142/s0218001420520023.

[15] P. Sunija, V. P. Gopi, and P. Palanisamy, "Redundancy reduced depthwise separable convolution for glaucoma classification using OCT images," *Biomedical Signal Processing and Control*, vol. 71, p. 103192, Oct. 2021, doi: 10.1016/j.bspc.2021.103192.

[16] Adel, M. M. Soliman, N. E. M. Khalifa, and K. Mostafa, "Automatic classification of retinal eye diseases from optical coherence tomography using transfer learning," in *16th International Computer Engineering Conference*, Cairo, Egypt, pp. 37–42, Dec. 2020, doi: 10.1109/icenco49778.2020.9357324.

[17] M. Elsharkawy et al., "A novel Computer-Aided diagnostic System for early detection of diabetic retinopathy using 3D-OCT Higher-Order Spatial Appearance model," *Diagnostics*, vol. 12, no. 2, p. 461, Feb. 2022, doi: 10.3390/diagnostics12020461.

[18] M. Berrimi and A. Moussaoui, "Deep learning for identifying and classifying retinal diseases," in *2020 2nd International Conference on Computer and Information Sciences (ICCIS)*, Sakaka, Saudi Arabia, 2020, pp. 1-6, doi: 10.1109/ICCIS49240.2020.9257674.

[19] K. Jin et al., "Multimodal deep learning with feature level fusion for identification of choroidal neovascularization activity in age-related macular degeneration," *Acta Ophthalmologica*, vol. 100, no. 2, Jun. 2021, doi: 10.1111/aos.14928.

[20] Y. Rong et al., "Surrogate-Assisted Retinal OCT image classification based on convolutional neural networks," *IEEE Journal of Biomedical and Health Informatics*, vol. 23, no. 1, pp. 253–263, Feb. 2018, doi: 10.1109/jbhi.2018.2795545.

[21] T. Daghistani, "Using Artificial Intelligence for Analyzing Retinal Images (OCT) in People with Diabetes: Detecting Diabetic Macular Edema Using Deep Learning Approach," *Transactions on Machine Learning and Artificial Intelligence*, vol. 10, no. 1, pp. 41–49, Feb. 2022, doi: 10.14738/tmlai.101.11805.

[22] D. Rastogi, R. P. Padhy, and P. K. Sa, "Detection of Retinal Disorders in Optical Coherence Tomography using Deep Learning," in *2022 13th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, pp. 1–7, Jul. 2019, doi: 10.1109/icccnt45670.2019.8944406.

[23] D.-K. Hwang et al., "Artificial intelligence-based decision-making for age-related macular degeneration," *Theranostics*, vol. 9, no. 1, pp. 232–245, Dec. 2018, doi: 10.7150/thno.28447.

[24] F. Li et al., "Deep learning-based automated detection of retinal diseases using optical coherence tomography images," *Biomedical Optics Express*, vol. 10, no. 12, p. 6204, Nov. 2019, doi: 10.1364/boe.10.006204.

[25] N. Saleh, M. A. Wahed, and A. M. Salaheldin, "Transfer learning-based platform for detecting multi-classification retinal disorders using optical coherence tomography images," *International Journal of Imaging Systems and Technology*, vol. 32, no. 3, pp. 740–752, Nov. 2021, doi: 10.1002/ima.22673.

[26] Y. Yan et al., "Attention-based deep learning system for automated diagnoses of age-related macular degeneration in optical coherence tomography images," *Medical Physics*, vol. 48, no. 9, pp. 4926–4934, May 2021, doi: 10.1002/mp.15002.

[27] R. Gupta, V. Tripathi, and A. Gupta, "An Efficient Model for Detection and Classification of Internal Eye Diseases using Deep Learning," in *2021 International Conference on Computational Performance Evaluation (ComPE)*, pp. 045–053, Dec. 2021, doi: 10.1109/compe53109.2021.9752188.

[28] Kermany, D.; Zhang, K.; Goldbaum, M. Large Dataset of Labeled Optical Coherence Tomography (OCT) and Chest X-ray Images. Mendeley Data 2018, 3, 10–17632.

[29] Yang, J.; Fong, S.; Wang, H.; Hu, Q.; Lin, C.; Huang, S.; Zhao, Q. Artificial intelligence in ophthalmopathy and ultra-wide field image: A survey. *Expert Syst. Appl.* 2021, 182, 115068.

[30] Tan, M. and Le, Q., "Efficientnet: Rethinking model scaling for convolutional neural networks." in *international conference on machine learning*, Long Beach, California, May 2019, pp. 6105-6114, PMLR.

[31] R. Pillai, N. Sharma, and R. Gupta, "Fine-Tuned EfficientNeTB4 Transfer Learning Model for weather Classification," in *2023 3rd Asian Conference on Innovation in Technology (ASIANCON)*, India, pp. 1–6, Aug. 2023, doi: 10.1109/asiancon58793.2023.10270698.

[32] F. Chollet, "Xception: Deep Learning with Depthwise Separable Convolutions," in *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Honolulu, HI, USA, 2017, pp. 1800-1807, doi: 10.1109/CVPR.2017.195.

[33] Szegedy, S. Ioffe, V. Vanhoucke, and A. Alemi, "Inception-V4, Inception-ResNet and the impact of residual connections on learning," in *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 31, no. 1, Feb. 2017, doi: 10.1609/aaai. v31i1.11231.

[34] F. N. Iandola, S. Han, M. W. Moskewicz, K. Ashraf, W. J. Dally, and K. Keutzer, "SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and <0.5MB model size," *arXiv-Cornell University*, Jan. 2016, doi: 10.48550/arxiv.1602.07360.

[35] K. He, X. Zhang, S. Ren and J. Sun, "Deep Residual Learning for Image Recognition," in *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Las Vegas, NV, USA, 2016, pp. 770-778, doi: 10.1109/CVPR.2016.90.

[36] Kornblith, S., Shlens, J. and Le, Q.V., 2019. Do better Imagenet models transfer better? In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, Long Beach, CA, USA, June 2019, pp. 2661-2671, ISBN: 978-1-7281-3293-8.

[37] A. Adadi and M. Berrada, "Peeking Inside the Black-Box: A Survey on Explainable Artificial Intelligence (XAI)," *IEEE Access*, vol. 6, pp. 52138-52160, 2018, doi: 10.1109/ACCESS.2018.2870052.

[38] A. B. Arrieta et al., "Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI," *Information Fusion*, vol. 58, pp. 82–115, Dec. 2019, doi: 10.1016/j.inffus.2019.12.012.

[39] Powers, David & Ailab., "Evaluation: From precision, recall and F-measure to ROC, informedness, markedness & correlation.", *J. Mach. Learn. Technol.*, Vol. 2, 2011, pp. 2229-3981, doi:10.9735/2229-3981.

[40] V.V Boix and D.R. Fernandez, "Diabetic retinopathy detection through convolutional neural networks with synaptic metaplasticity," *Comput. Methods Programs Biomed*. 2021, 206, 106094.

[41] A. Choudhary et al., "A Deep Learning-Based Framework for Retinal Disease Classification," *Healthcare* 2023, 11, 212. doi.org/10.3390/healthcare11020212

[42] G. Alwakid et al., "Deep Learning-based prediction of Diabetic Retinopathy using CLAHE and ESRGAN for Enhancement," *Healthc MDPI*., 2023. pp:863. doi: 10.3390/healthcare11060863

[43] S. Abbood et al., "Hybrid retinal image enhancement algorithm for diabetic retinopathy diagnostic using deep learning model," *IEEE Access*. 2022, Vol. 10, pp. 73079–73086.

[44] G. Mushtaq and F. Siddiqui, "Detection of diabetic retinopathy using deep learning methodology," in *IOP Conference Series: Materials Science and Engineering*. 2021, p. 012049.

[45] A.M. Moustari et al. "Two-stage deep learning classification for diabetic retinopathy using gradient weighted class activation mapping," *Automatika*, 2024, vol. 65, no. 3, pp. 1284–1299.

[46] B. Menaouer et al.," Diabetic retinopathy classification using hybrid deep learning approach," *SN Comput. Sci.*, vol. 3, no. 5, p. 35, 2022.

## AUTHOR BIOGRAPHY

**NITESH SUREJA** has a good academic background in Computer Engineering. He is currently employed with Drs. Kiran & Pallavi Patel Global University (KPGU), Vadodara, Gujarat, INDIA. He is working as a professor in the Krishna School of Emerging Technology and Applied Research, one of the constitute institute of KPGU. His current research interests include machine learning, data science, artificial intelligence, and algorithms inspired by nature. He has been a teacher for more than 24 years. More than 35 International publications with SCOPUS/Google indexes have published as his study findings. He has invited as a keynote speaker at numerous international conferences. He has mentored two PhD candidates. Also, he is currently mentoring eight PhD students. He has two books in his name. he is a lifetime member of ISTE.

**HEMANT PATEL** has a strong background in Computer Engineering. He currently holds the position of Head and Associate Professor at Dr. Subhash University in Junagadh. Dr. Hemant Patel, with over 13 years of academic experience, has made remarkable contributions to the field through his research and publications. His keen research interests encompass machine learning, data science, ontology and NLP. His expertise in these areas is evident through the publication of numerous papers that delve into these captivating subjects. He has total eight research publications. He is currently guiding three Phd Students.he has been a part of many committes at Dr. subhash university.

**AJAYSINH RATHOD** is wotking as associate professor and HOD in department of computer science and design at sardar vallabhbhai patel institute of technology, vasad, gujarat, india. He received the B.E. in IT and M.E. in CSE degrees from the north gujarat university, patan and Rajasthan Technical University, Kota, Rajasthan respectively. He received his Ph.D. degree in CSE from C U Shah university, Wadhwancity, gujarat , India. He has mort than 15 years of academic experience. He has made remarkable contributions to the field through his research and publications. His keen research interests encompass information security & privacy, location-based privacy, IoT, privacy issues in data Mining, privacy Issues in big data and big data analytics. His expertise in these areas is evident through the publication of numerous papers that delve into these captivating subjects.

**PRIYA PATEL** is currently holds the position of Assistant Professor in department of computer science and design at sardar vallabhbhai patel institute of technology, vasad, gujarat, India. She is pursuing PhD from KPGU university, vadodara, india. Priya Patel, with over 8 years of academic experience, has made remarkable contributions to the field through her research and publications. His keen research interests encompass blockchain, data science, artificial intelligence, and big data analytics. Her expertise in these areas is evident through the publication of papers that delve into these captivating subjects. His keen research interests encompass Artificial Intelligence, Data Mining, IoT, and Big Data Analytics.

**VRUTI PARIKH** Vruti Parikh is currently working as an assistant professor with Drs. Kiran and Pallavi Patel Global University (KPGU), Vadodara, Gujarat, India. She is pursuing her Phd from the same university. She has published three papers in scopus indexed journals. Her current research interests include data deduplication, data optimization, machine learning, big data analytics and data science. Her research pursuits reflect her dedication to exploring innovative solutions in these areas, contributing to advancements in the field of data management and analytics. She is assisting students with various training and placement activities. She worked on various live projects during her industrial experience.

**HELI SUREJA** Heli Sureja is currently a MS Student in Department of Computer & Data Science at Tagliatela College of Engineering, University of New Haven, CT, USA. She has completed her B.E. in computer science and engineering from babaria institute of technology, vadodara, Gujarat technological university, Gujarat, INDIA. Her current research interests include data science, data analytics, machine learning, deep learning and nature inspired algorithms. Her research pursuits reflect her dedication to exploring innovative solutions in these areas, contributing to advancements in the field of data science and analytics. She has published three scopus indexed papers with one scopus book chapter.