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Retinal Eye Disease Detection Using Deep Learning

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Abstract: Globally this second blinding condition which affects millions of people is the reason for the advocacy of early diagnosis and treatment needed to stop these conditions from gettiong worse in the future Deep Learning as a Sustainable Technology to Detect Retinal Diseases: In this article, we touch on the elements of retinal disease diagnosis using the deep learning models. The tool, which adopts an ensemble of optimized state-of-the-art neural network architectures including MobileNetV2, ResNet50, InceptionV3, and DenseNet, will undergo a detailed evaluation of their respective performance with classifying retinal images. The strategy set behind our preprocessing steps, resize images, convert grayscale to RGB and extensive training cycles gives rise in the evolution of a top model. Interestingly all the results showcase ResNet50 the best persoiling which produces accuracy of 0.89; consequently, setting a new mark on retinal scan analysis. This research yields up a valular aspect of early retinal disease detection; we end up having an increased chance of conducting a precise diagnosis and improved patient outcomes.
Using retinal fundus pictures, ophthalmologists may diagnose retinal issues with great precision. Early detection helps avoid blindness and increase the likelihood of a cure. Medical professionals can diagnose retinal fundus images to help with conditions including diabetic retinopathy and retinitis pigmentosa. Machine learning research has recently concentrated on using feature extraction and image classification to diagnose conditions such as diabetic retinopathy. Our objective in this work is to automatically identify, without explicit segmentation or feature extraction, photos with retinal abnormalities from those of the healthy. Instead, we automatically categorise every retinal fundus image as healthy or sick using a deep learning algorithm

Keywords: Retinal abnormalities, disease detection, deep learning, ResNet50, MobileNetV2, InceptionV3, DenseNet.

1. INTRODUCTION

Diabetic retinopathy (DR), a significant consequence of the global diabetes epidemic, emerges as a primary cause of adult blindness in the United States. This condition arises from the deleterious effects of diabetes mellitus, leading to various complications. The risk for the appearance of DR grows longer the term of diabetes is, the higher the blood sugar levels are and better the positive pressure the arterial hypertension leads to [1] [2]. Firstly, DR forms the circle of a great number blood vessels in the retina with a purpose to send light to the brain. Adding to this, the sustained exposure to high glucose levels directly affects the permeability of blood vessels to macromolecules. First, it causes endothelial damage that permits the increase of capillary cell permeability, further scaling the process of capillary obstruction [3].

Diabetic retinopathy, impacting a vast global population, is a severe visual impairment stemming from a range of diabetes-related complications. Eye exams are crucial for detecting this condition, but the large number of retinal images requires careful analysis for accurate diagnosis. In this digital era, computer-assisted decision-support systems provide a valuable tool for precise and efficient diagnostic evaluations. This study explores recent computer-assisted research focused on DR. The impact of diabetes extends beyond the retina, affecting organs like the heart and kidneys [4] [5]. The International Diabetes Federation reports that out of 537 million people with diabetes worldwide, about 90 million suffer from DR [6]. DR affects the retina by causing vascular inflammation and fluid accumulation, leading to vision impairment and potentially irreversible blindness. DR is responsible for approximately 2.6% of global blindness cases [7] [8]. The fig. 1 contrasts the anatomical

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differences between a normal eye and an eye affected by Diabetic Retinopathy (DR). On the left, the 'Normal Eye' is depicted with clear, healthy blood vessels within the retina, which is the light-sensitive layer at the back of the eye. On the right, the 'Eye with Retinopathy' demonstrates the characteristic changes of DR, including the presence of tiny blood vessels that have begun to leak fluid into the retina. This leakage is a hallmark of the disease, leading to the potential for significant visual impairment.

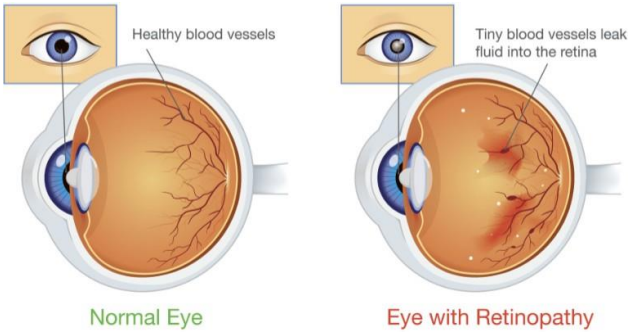


Figure 1: Diabetic Retinopathy

Diabetic retinopathy is a multifaceted disorder in which diabetes adversely affects the retina, and a combination of various visual disturbances eventually results in irreversibility blindness [9]. Early detection of DR is of the essence in the prevention of blindness and re-establishment of the health of the retina [10]. High volumes of data and errors in the misclassification of the traditional diagnostic procedures limit their application in detecting DR [11]. Computer-aided decision-making tools have shown a great deal of accuracy in detecting DR [12]. A majority of the people living with DR reside in socio-economically disadvantaged countries [13], which brings to the fore the importance of effective diagnostic solutions in these countries. The diagnosis and assessment of the severity of DR crucially rely on a detailed analysis of retinal images in search of some specified lesions such as hemorrhages, microaneurysms, and exudates [14].

Before 1961, diagnosis of diabetic retinopathy included some assessment of visual acuity and, in dilated examinations, for the retina and the optic nerve. Other methods included estimating the intraocular pressure with tonometry and finding abnormalities in the results [15]. Advanced imaging technology in diabetic retinopathy was initiated by introducing fluorescein angiography. This was the earliest time when a fluorophore was injected into the bloodstream, and its distribution and concentration were mapped and imaged using a fundus camera. Vascular leakage in the retina is outlined by vessels highlighting with the fluorescent dye [16] [17]. Although effective, fluorescein angiography has eventually been outstripped by optical coherence tomography (OCT), a method allowing to get extremely detailed 3D images of the retina, without pupil dilation, and working well in combination with diverse telemedicine approaches [18, 19].

The newer fundus photography innovations of recent years include techniques like ultra-widefield (UWF) retinal imaging, such as those provided by the Optos 200 Tx from Optos plc. Such methods enable the observation of the retina through 200 degrees, which is helpful for proper diagnosis other than fast image processing and manipulation. The field that has seen the most significant impact from deep learning has been the field of machine learning applied to medical diagnostics. Medical Image Analysis: Deep learning models using multi-layered architectures in analyzing the images have been quite successful and can be well demonstrated by the research work of LeCun et al. [20], Liu et al. [21], and Litjens et al. [22]. Most of the research work carried out on OCT images is related to the recognition of critical features and stages of the condition with the help of classifiers. Besides, the recent works of Pratt et al. [23] and Sangeethaa et al. [24] have recently even made use of Convolutional Neural Networks (CNNs) for DR diagnosis. Due to the automatic capability of feature extraction and adaptability for many classifications of tasks, many Convolutional Neural Networks used for analyzing OCT images employed for DR have been of interest. What remains to be further explored is that they have not been applied to UWF fundus images or the diagnosis of the various stages of DR.

In this article, we propose to create a comprehensive model for detecting retinal eye diseases using advanced deep learning techniques, with a focus on transfer learning. Acknowledging the difficulties in obtaining large, varied, and annotated retinal datasets, along with the significant computational resources needed for training deep neural networks, we plan to utilize pre-trained models. By fine-tuning these models, which have already been trained on extensive datasets, for the specific task of retinal disease detection, we aim to enhance the efficiency and effectiveness of our approach. Our objectives include assessing various pre-trained models for their suitability, adapting them to identify disease-specific features in retinal datasets, and thoroughly comparing our model's performance with traditional methods. Ultimately, our research aspires to deliver a model that not only improves the accuracy and speed of diagnosing retinal diseases but also offers scalable and accessible diagnostic tools for diverse global populations.

2. RELATED WORKS

Retinal eye diseases play a major role in the incidence of vision problems in different corners of the globe; hence, the need for early diagnosis is fundamental in avoiding vision loss. In recent years, deep learning within the world of ophthalmology has ushered in a whole new wave of opportunities, for not just fast, but also accurate

diagnosis of these illnesses. This domain-specific field has many related works that have been using deep learning techniques to identify and evaluate retinal diseases.

In [25] a system is being automated which is used for grading the severity of DR images that deal with variations in the light and eye field range. Machine learning models including CNN, VGG-16, and VGG-19 were employed by researchers to classify images into five severity grades that represent no DR and proliferative DR. The sensitivity was 20%, specificity was 22% and accuracy was 22% though AUC was 0.904.

Another research [26] presented an automatic deep-learning method for staging DR using a single fundus photograph. They introduced a multistage transfer learning approach that takes advantage of datasets with various labeling styles. This method, particularly useful for early DR screening, attained impressive sensitivity and specificity of 0.99 and ranked 54th out of 2943 methods in the APTOS 2019 Blindness Detection Dataset, achieving a quadratic weighted kappa score of 0.925466.

In a different approach [27], researchers introduced a novel DR monitoring model that first enhances image quality using the Contrast Limited Adaptive Histogram Equalization technique. The model then employs the EfficientNet-B5 architecture for classification, known for its uniform scaling. This model showed significant improvements in AUC metrics when trained and evaluated on combined datasets of Messidor-2 and IDRiD, and Messidor-2 and Messidor, outperforming previous models.

Another team [28] utilized a CNN leveraging the pre-trained VGG-16 model for refined DR severity classification. Implementing advanced deep learning strategies like data augmentation, batch normalization, dropout layers, and learn-rate scheduling on high-resolution images, they achieved an average class accuracy of 74%, a sensitivity of 80%, a specificity of 65%, and an AUC of 0.80, surpassing previous studies using other pre-trained networks or models.

Further, researchers [29] employed the Densely Connected Convolutional Network, particularly DenseNet-169, for early DR detection. They categorized fundus images into varying severity levels and used datasets from Diabetic Retinopathy Detection 2015 and Aptos 2019 Blindness Detection. Their process included data collection, preprocessing, augmentation, and modeling, resulting in a 90% accuracy rate for the primary model and 78% accuracy for a supplementary regression model, aiming to establish an effective system for automatic DR detection.

A study [30] introduced a deep learning-based method to classify DR severity using variations of the EfficientNet. This method trained on diverse datasets and the most proficient model achieved a quadratic kappa score of 0.924377 on the APTOS test dataset, demonstrating the model's potential in hastening DR diagnoses for early detection.

Another novel model, the Hinge Attention Network (HANet) [31], was presented, incorporating multiple attention stages and a pre-trained VGG16 base. This model, enhanced with a Convolutional LSTM layer, achieved accuracies of 85.54% and 66.41% on Kaggle APTOS and IDRiD datasets, respectively.

In [32] method, deep learning model as well as automatic detection of diabetic retinopathy was introduced. The processing adopted deformable registration and image classification with four models of CNN where the classification accuracy was 85.28% on APTOS 2019 dataset.

In [33], the approach was to use 28 hybrid models in comparison with 7 deep learning models to classify images for DR. The best hybrid of SVM and MobileNet V2 approach showed the accuracy levels of up to 88.80%, thus playing a proof of the validity of this mixing of deep learning feature extraction and the classical machine learning classification algorithms.

Table 1: RELATED WORKS

Ref	Methods	Dataset	Results
[25]	Transfer learning of VGG16 and VGG19	Kaggle competition dataset 2015	Accuracies: 71% (VGG16), 73% (VGG19), Improved to 83% after modification
[26]	Three-head CNN	APTOS 2019 Blindness Detection Dataset	Sensitivity: 99%
[27]	EfficientNet B5	MESSIDOR, MESSIDOR-2, IDRiD	AUC: 0.94 (MESSIDOR), 0.93 (IDRiD)
[28]	VGG-16	Kaggle EyePACS	Accuracy: 74%, Sensitivity: 80%, Specificity: 65%
[29]	DenseNet-169	Diabetic Retinopathy Detection 2015, Aptos 2019 Blindness	Accuracy: 90%
[30]	Ensemble of EfficientNet models	Kaggle APTOS	EfficientNet-B3 performed better than the ensemble and other models
[31]	Hinge Attention Network (HANet)	IDRid	Accuracy: 66.4%
[32]	DenseNet-121, Xception, InceptionV3, ResNet-50	Kaggle APTOS	Best accuracy: 85.28%
[33]	SVM-MobileNet V2	APTOS, Kaggle DR, and Messidor-2	Accuracy: 88.80%

3. MATERIALS AND METHODS

A. Proposed Retinal Eye Disease model

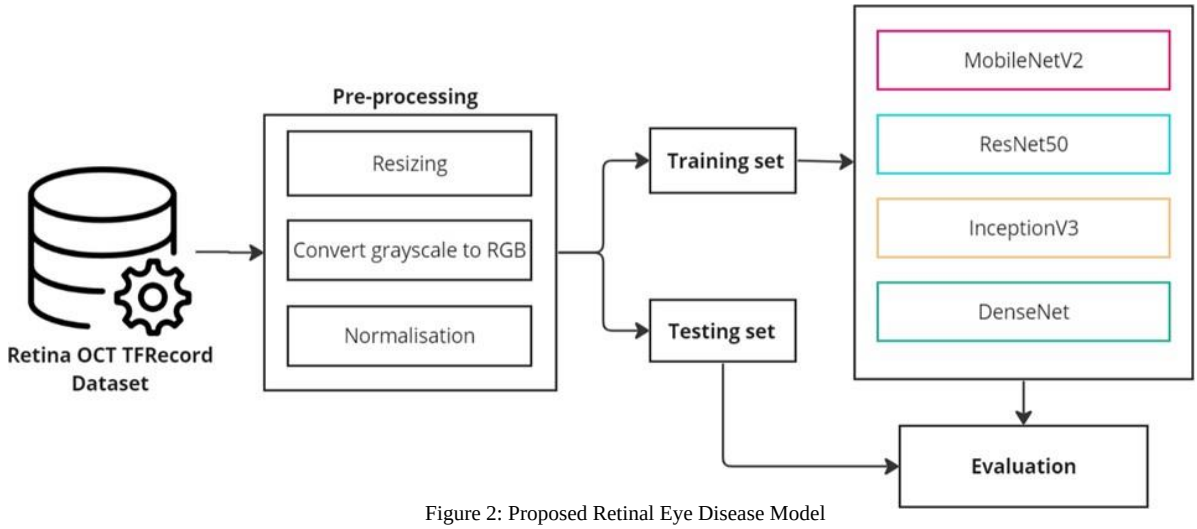


Figure 2: Proposed Retinal Eye Disease Model

In our proposed model (Fig.2), we adopt the Retinal Optical Coherence Tomography (OCT) dataset if researches have done great job in collecting a massive catalog of such scans. This OCT image is our key component used for the development of deep learning framework. Before thoroughly integrating the dataset into the neural networks, we perform a few preprocessing operations to have cleaner data that will work better for the model. These stages include image resizing to have uniform standard, converting grayscale images to the RGB format to standardize the input and capture the subtle differences near around a center of symmetry, and finally, a normalization of pixel values for the purpose of speeding up convergence and reducing the chance of local optimization during training.

For the model's training, we employ an ensemble of advanced neural network architectures: MobileNetV2, ResNet V50, Inception V3, and DenseNet are some of the networks used. Every single network that is capable of image classification is intently trained on the 'train set' folder using the dataset of OCT. This diversity of structures provides the capability of the model of achieving a higher depth and accuracy of analytics. In the last step, these models are exercised using random query in the 'test set' folder of the dataset to check their performance and to point out potential errors. The goal of the all our methods is to create the novel strategy to detect the retinal diseases and analysis it by utilizing the best qualities of different architectures on the OCT dataset.

B. Dataset Description

The Retinal Optical Coherence Tomography (OCT) dataset, available on Kaggle[1], features detailed cross-sectional images of retinas from living patients, with an annual volume of approximately 30 million scans. This extensive dataset includes over 84,000 images, classified into four categories: choroidal neovascularization (CNV), diabetic macular edema (DME), drusen (early age-related macular degeneration or AMD), and normal retinas. The dataset is thoughtfully divided into training, validation, and testing segments. Collected from various medical institutions between 2013 and 2017, these images have been meticulously evaluated and labeled through a comprehensive grading system by multiple trained graders, ensuring the reliability of the diagnostic categories.

C. Data pre-processing

In our dataset, we first organize the retinal images, stored in the .tfrecord format, by grouping and sorting them based on their prefix before the 'tfr' tag. This initial step involves creating directories for each prefix and relocating corresponding files, setting the stage for efficient preprocessing. Each .tfrecord file contains key features like the image in binary string format, encoded label, and class indication (NORMAL, CNV, DME, or DRUSEN). We then create a TFRecordDataset from these paths for further processing.

The primary goal of preprocessing is to convert raw retinal images into a format suitable for deep learning models. We begin by resizing the images to a uniform dimension of 224×224 pixels to ensure consistency across the dataset and compatibility with popular deep

[1] https://www.kaggle.com/datasets/harshsoni/retina-oct-tfrecord-dataset/data

learning architectures. This resizing is crucial for leveraging pre-trained models and reducing computational demands. Next, we convert any grayscale images to RGB format.

This step is critical as many neural networks are designed for 3-channel input and this conversion maintains the grayscale information across all three channels, aligning with standard input structures.

Normalization is another key step where pixel values are scaled, aiding in faster convergence of the neural network and reducing the likelihood of getting trapped in local optima. To align with the categorical nature of our problem, we employ one-hot encoding to transform class labels into a binary matrix, facilitating effective classification by the neural network.

D. Deep Learning Models

Deep learning has revolutionized medical diagnostics, especially in detecting retinal eye diseases. This technology employs advanced neural network architectures to interpret complex patterns in medical imagery, thereby enhancing diagnostic precision. This section focuses on evaluating four deep learning models: MobileNetV2, ResNet50, InceptionV3, and DenseNet. Renowned for their architectural uniqueness and proficiency in image classification, these models are scrutinized for their suitability and performance in retinal disease detection. This exploration sets the groundwork for advancing ophthalmic diagnostic methods.

1) MobileNetV2 Method: MobileNetV2 stands out due to its inverted residuals and linear bottlenecks, making it both compact and computationally efficient.

We use it primarily as a feature extractor, leveraging its depthwise separable convolutions to identify crucial features in retinal images. To tailor MobileNetV2 for our needs, we modify it by removing its top classification layers, transforming it into a potent feature extractor pre-trained on ImageNet data. To avoid overfitting and optimize training, most layers are frozen, allowing only the final two layers to be fine-tuned for our specific dataset. Our custom layering includes a global average pooling layer followed by a dense layer with 128 neurons and ReLU activation, a dropout layer for regularization, and a final dense layer with softmax activation for binary classification.

$$\mathrm{ReLU}(x) = \max(0, x) \qquad (1)$$

This means that if x is positive, the function returns x; if x is negative, the function returns 0.

$$Softmax(xi) = \frac{e^{x_i}}{\sum_{j=1}^{k} e^{x_j}} \qquad (2)$$

where, x is the input vector to the softmax function ,x_i is the i-th element of this vector, and K is the number of classes. We employ the 'adam' optimizer for its effectiveness with sparse gradients and the categorical cross-entropy loss function to guide model training. An early stopping mechanism is also implemented, monitoring validation loss to prevent overtraining and maintain generalization. This combination of the modified MobileNetV2 architecture, custom layers, and optimization strategy creates a model finely tuned for accurate and efficient retinal image analysis.

2) ResNet50 Method: The ResNet50 architecture, a key member of the Residual Network family, is notable for its innovative solution to the vanishing gradient problem in deep neural networks. Featuring 50 layers and distinctive "skip connections" that bypass layers during propagation, ResNet50 effectively learns identity functions, allowing for deeper networks without performance degradation.

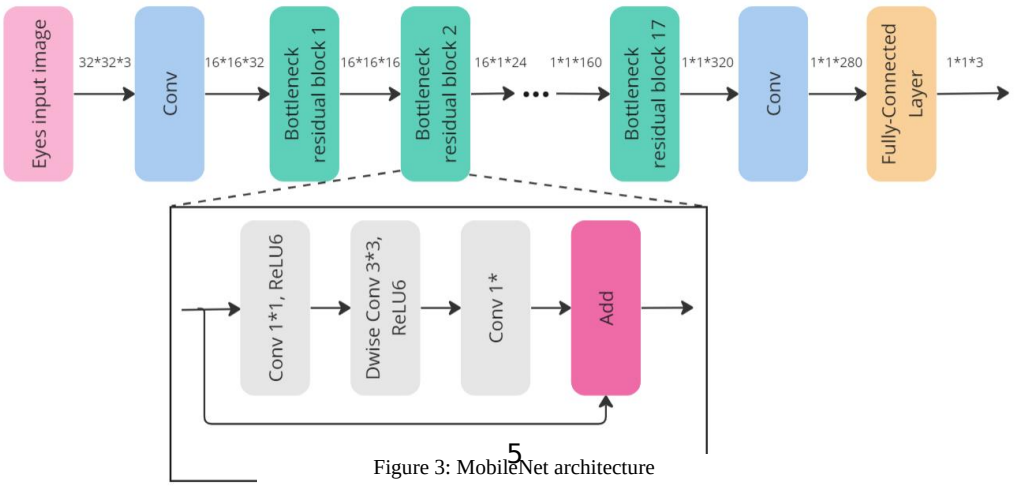


Figure 3: MobileNet architecture

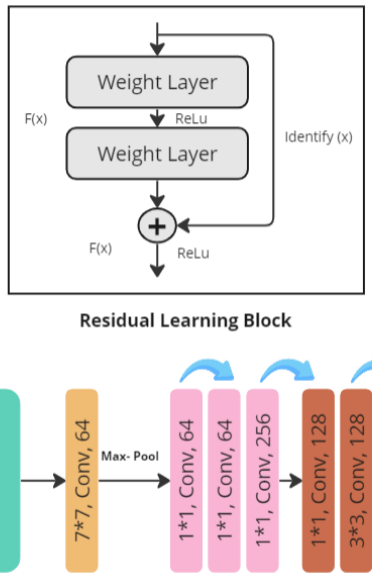


Figure 4: ResNet50 architecture

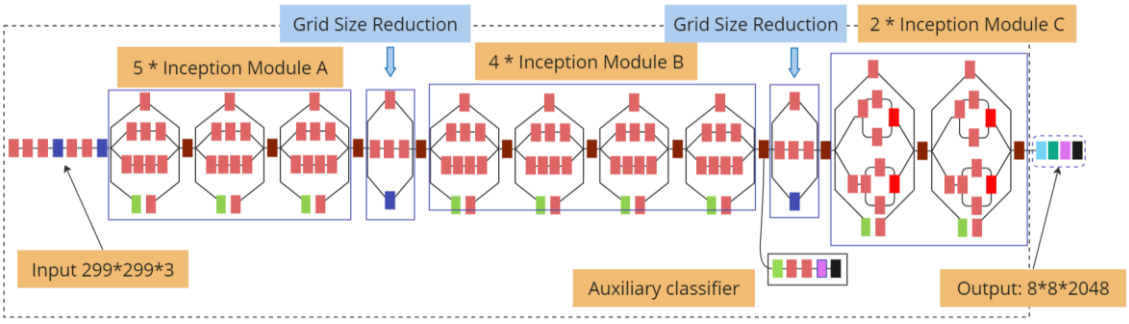


Figure 5: InceptionV3 architecture

In our study, we adapt ResNet50 as a core element of our model, leveraging its pre-trained weights from ImageNet and repurposing it as a feature extractor for retinal images. To fit our dataset and avoid overfitting, most ResNet50 layers are non-trainable, maintaining their weights during training. Our model includes a customized classification head on top of ResNet50. Following a Global Average Pooling layer to reduce dimensions and retain critical features, a Dense layer with 128 neurons and ReLU activation introduces non-linearity. A Dropout layer (0.2 rate) is added to prevent overfitting. The architecture concludes with a final Dense layer with softmax activation for binary classification. We use the 'adam' optimizer for efficient, accurate learning and categorical crossentropy loss to measure performance. An early stopping mechanism, tracking validation loss, prevents overtraining, ensuring the model retains its best weights. This integration of ResNet50's deep network capabilities with our specialized layers aims to achieve new heights in retinal image analysis, focusing on depth and precision.

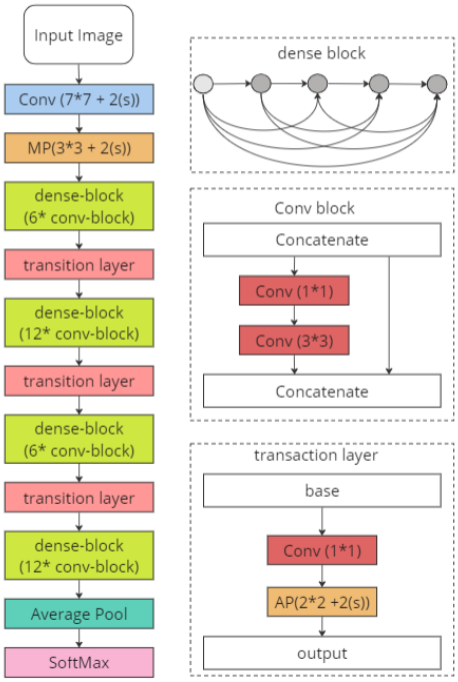
Table 2: CONFIGURATION AND TRAINING PARAMETERS FOR THE RESNET50 BASED RETINAL IMAGE ANALYSIS MODEL

Parameter	**Value**
Pre-trained Weights	ImageNet
Include Top Layers	False
Input Shape	(224, 224, 3)
Trainable Base Layers	None (All frozen)
Global Average Pooling	Yes
Dense Layers	128 (ReLU), 2 (Softmax)
Dropout Rate	0.2
Optimizer	Adam
Loss Function	Categorical Cross-Entropy
Metrics	Accuracy
Early Stopping Monitor	Validation Loss
Early Stopping Patience	10 epochs
Training Epochs	100 (max, with early stopping)
Batch Size	32
Validation Split	20%
Shuffle Training Data	True

3) *InceptionV3 Method:* The InceptionV3 architecture, part of the Inception series, is renowned for its innovative ”network within a network” design. This design utilizes multiple filter sizes and a mix of 1x1, 3x3, and 5x5 convolutions at the same level, enabling effective capture of spatial hierarchies. InceptionV3 also features ”bottleneck” layers that reduce parameter count, thus speeding up training without sacrificing feature extraction capabilities.

In our study, InceptionV3 is crucial, acting as a feature extractor with pre-trained weights from ImageNet. To tailor it to our dataset, the top classification layers are removed, leaving the base layers skilled in pattern recognition. The layers of the InceptionV3 base model are frozen to maintain their pre-trained weights during training. We then add custom classification layers to the InceptionV3 base. This includes a Global Average Pooling layer for dimensionality reduction, a Dense layer with 128 neurons and ReLU activation for non-linearity, and a Dropout layer (0.2 rate) to reduce overfitting. The architecture concludes with a Dense layer featuring soft-max activation for binary classification. For optimization, the ’adam’ optimizer is used for its adaptability, and categorical cross-entropy loss measures training performance. An early stopping mechanism, monitoring validation loss, halts training when no improvement is observed, ensuring the preservation of the best model weights. This integration of InceptionV3’s advanced architecture with our customized layers aims to create a model uniquely suited for precise and in-depth retinal image analysis.

4) *DenseNet121 Method:* part of the Dense Convolutional Network family, revolutionizes deep learning architecture with its unique connectivity pattern. Each layer is directly con- nected to all preceding layers, enhancing depth and improving gradient flow, thus mitigating the vanishing gradient problem typical in deep networks.



In our research, DenseNet121 serves as a critical component of our model, functioning as a feature extractor with pre- trained weights from ImageNet. To tailor it to our dataset, we remove its top classification layers, focusing on the base feature-learning layers. The layers of the DenseNet121 base model are frozen to prevent overfitting and maintain their weights during training. Our custom layering includes a Global Average Pooling layer for dimension reduction, followed by a Dense layer with 128 neurons and ReLU activation for non-linearity. A Dropout layer (0.2 rate) is included to combat overfitting. The architecture ends with a Dense layer for binary classification using softmax activation. We use the ’adam’ optimizer for effective and precise optimization, with categorical cross-entropy loss as the performance metric. An early stopping mechanism, tracking validation loss, halts training when no further improvement is detected, ensuring optimal model weights. This combination of DenseNet121’s deep architecture with our specialized layers aims to create a model adept in retinal image analysis, balancing depth and precision.

4. Results and Discussion

A. *Evaluation Metrics*

In the classification tasks delineated in this chapter, a comprehensive suite of evaluation metrics, namely accuracy, precision, recall, and F1-score, is employed to rigorously assess the model’s performance. To provide a holistic view, we will also present the confusion matrix for each model evaluation. Accuracy serves as a cornerstone metric, quantifying the proportion of correctly classified samples to the total sample count, represented as:

$$ACC = \frac{TP+TN}{TP+FP+TN+FN} \quad (3)$$

Moreover, precision and recall refine the notions. Precisely, precision wraps the definition of aa model’s ability to correctly predict positive samples as follows:

$$Pre = \frac{TP}{TP+FP} \quad (4)$$

where TP is a number of true positives, and FP is false positives. In turn, recall defines a model’s competence to include all possible positive samples, and is mathematically expressed as:

$$Recall = \frac{TP}{TP+FN} \quad (5)$$

FN is false negatives. Finally, the F1-score considers the balance perception of the model's relevancy, especially regarding class imbalance, which is presented as follows:

$$F1 = 2 * \frac{Pre * Recall}{Pr + Recall}$$

Aggregate measure is provided that takes into account not only false positives, but also false negatives. By using this comprehensive set of parameters, we intend to provide our audience with a detailed and comprehensive measure of the model's performance. This matrix provides a short visual representation of how well the model's predictions correspond to the actual labels. Given our specific task, the two categories are presented as "ABNORMAL" , which is denoted by 0, and "NORMAL" , which has a label of 1:

Figure 6: DenseNet121 architecture

TABLE 3: CONFUSION MATRIX

	Predicted: 0	**Predicted: 1**
Actual: 0	TN	FP
Actual: 1	FN	TP

Here, True Negative (TN) represents the count of 'ABNORMAL' samples accurately predicted as such, while True Positive (TP) signifies the 'NORMAL' samples correctly identified. Conversely, False Positive (FP) indicates 'ABNORMAL' samples misclassified as 'NORMAL', and False Negative (FN) denotes 'NORMAL' samples incorrectly predicted as 'ABNORMAL'. This matrix provides an insightful breakdown, enabling a comprehensive understanding of the model's accuracy, precision, recall, and specificity for our Retinal Eye Disease Detection task.

B. Evaluation Methods

The evaluation of our proposed deep learning models reveals insightful performance metrics, particularly in the context of retinal image classification.

MobileNetV2: The MobileNetV2 model's performance, as shown in Fig.7 analysis of the MobileNetV2 model over 45 epochs reveals significant training improvements, with loss decreasing from 0.5510 to 0.1010, and accuracy increasing from 0.7183 to 0.9638, demonstrating the model's learning effectiveness. In contrast, validation metrics show variability; although accuracy peaks at 0.8817, it also presents fluctuations that may indicate overfitting.

Figure 7: Training and Validation Accuracy and Loss Trends for MobileNetV2 Model over 45 Epochs

Figure 8: Training and Validation Accuracy and Loss Trends for ResNet50 Model over 16 Epochs

Similarly, validation loss varies, with its nadir at the 26th epoch, followed by irregular increases, suggesting a need for vigilant model refinement.

ResNet50: In our study focusing on Retinal Eye Disease Detection, the ResNet50 model's training and validation performance was critically examined. Fig.8 illustrates the model's accuracy and loss across epochs. The training accuracy commenced at 83.35% with a corresponding validation accuracy of 85.08%, both displaying an up-ward trajectory as epochs advanced, reflecting positive learning. Nonetheless, vigilance is necessary to prevent overfitting, which is suggested when training accuracy rises while validation accuracy does not improve. The initial training and validation loss were 0.3670 and 0.3564, respectively, with the model's objective to reduce these as a sign of improving prediction accuracy. Steady decrease in loss is indicative of effective parameter optimization, while any irregularities may point towards convergence problems or overfitting.

InceptionV3: The InceptionV3 model's training and val idation performance over 27 epochs, shown in Fig.9, reveals a complex learning pattern. Training accuracy begins at 67.35%, showing some early gains followed by notable fluctuations, while validation accuracy starts at a lower 38.08%, also fluctuating as epochs progress. These variations suggest the model struggles to consistently learn from the data. Training loss decreases from a high of 2.0672, indicating progress, yet validation loss startsat 1.0032 and varies, sometimes increasing, which could imply that the model's generalization to new data is unstable.

DenseNet121: The DenseNet121 model showcased in Fig.10 notable performance over 13 epochs, as training and validation accuracies steadily climbed, reflecting its capability to learn and generalize effectively. Training accuracy peaked at around 86%, while validation accuracy closely followed at approximately 88%, indicating the model's proficiency in recognizing patterns in the retinal

images. Concurrently, both training and validation losses consistently declined, signifying successful optimization and the model's convergence towards an optimal state.

Our analysis, as detailed in Table IV, includes models such as MobileNetV2, ResNet50, InceptionV3, and DenseNet121, with a primary focus on their accuracy scores.

ResNet50 stands out with the highest accuracy of 0.89, indicating its exceptional capability in distinguishing between normal and abnormal retinal images. This near 90% accuracy can be attributed to ResNet50's deep architecture and the effectiveness of its skip connections in capturing complex image features. This result underscores the model's robustness and its

Figure 19: Training and Validation Accuracy and Loss Trends for InceptionV3 Model over 27 Epochs

Figure 10: Training and Validation Accuracy and Loss Trends for DenseNet121 Model over 27 Epochs

potential utility in clinical settings for retinal disease diagnosis.

DenseNet121 follows closely, showcasing an accuracy of 0.81. This performance demonstrates DenseNet121's efficiency in image classification, likely benefiting from its densely connected layers which facilitate feature reuse and consolidation, leading to over 80% accuracy.

In comparison, MobileNetV2 and InceptionV3 achieved slightly lower accuracies of 0.79 and 0.77, respectively. MobileNetV2's slightly lower accuracy might stem from its trade-off between efficiency and depth, as it prioritizes a lightweight architecture. InceptionV3, despite its sophisticated design, seems to have encountered challenges in capturing the nuanced features of retinal images, which might explain its modest performance.

C. Comparision Results

Our research undertakes this crucial task, presenting a comprehensive comparison of our proposed ResNet50-based model with several established models in the field. Table V compares the accuracy of various existing diabetic retinopathy (DR) detection models with our ResNet50-based model.

TABLE 4: COMPARISON RESULTS

Models	Accuracy
MobileNetV2	0.79
ResNet50	0.89
InceptionV3	0.77
DenseNet121	0.81

We note that earlier models cited in research works [25] and [28], which utilized architectures like VGG-16 and VGG-19, achieved accuracies of 82% and 74%, respectively. These figures, while respectable, fall short of the 89% accuracy attained by our ResNet50 model, underscoring our model's enhanced performance.

Additionally, studies [31] and [32] reported accuracies of 85.54% and 85.28%, respectively, employing advanced models like HA-Net with multiple attention stages and an ensemble of CNN models, including DenseNet-121, Xception, Inception-v3, and ResNet-50. Notably, recent research [33] incorporating a hybrid approach by fusing a SVM with MobileNet V2 architecture has reached an impressive 88.80% accuracy. This hybrid model underscores the potential of integrating deep learning with traditional classifiers for feature extraction in DR classification. Despite these sophisticated approaches, our ResNet50 model still achieves a higher accuracy, evidencing its effectiveness in DR detection.

TABLE 5: COMPARISON WITH EXISTING WORKS

Reference	Accuracy
[25]	82%
[28]	74%
[31]	85.54%
[32]	85.28%
[33]	88.8%
Our ResNet50	**89%**

The standout feature of our ResNet50 model is its remarkable 89% accuracy, which surpasses existing models by a significant margin. This implies that the deep architecture with the use of skip connections of ResNet50 are skillful at extracting information about the minute features in the fundus pictures. Such high accuracy is extremely vital for early detection and management of diabetic retinopathy, which indeed indicates that our ResNet50-based approach not only provides higher accuracy but may be even more reliable than those are usually used in the clinical applications in diagnosing various degrees of DR.

5. CONCLUSION

The presence of Retinal Eye Disease and in its role as one of the complications of chronic diabetes has been a major problem in the field of ophthalmology and healthcare. Prompt detection and timely management proves to be the basic factor in inhibiting the loss of vision and providing the best care for the patient. This article has really shone the light on different aspects of diabetic retinopathy, including the difficulties in its diagnosis and the emerging solutions by the advanced technology. Our proposed deep learning based model with various neural network architectures show clear progress towards the fight against this disease. Through equally careful data preprocessing and thorough training, the model becomes an excellent example of the ability to accurately discriminate and identify diabetic retinopathy. The standout performance of our ResNet50-based model, achieving an accuracy of 89%, signifies a notable leap forward in setting new standards for the field. This achievement not only underscores the effectiveness of our model but also highlights its potential impact on the early diagnosis and management of diabetic retinopathy, offering new avenues for improved patient outcomes in ophthalmiccare.

Future enhancements to our research include expanding the dataset for better model generalization and exploring transfer learning techniques for more robust diagnostics. Additionally, integrating model interpretability will build trust and offer valuable insights, while incorporating telemedicine applications could improve patient outcomes through timely interventions.

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