ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25jun396

Optimizing Retinal Disease Diagnosis through ResNet-Based Deep Learning

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Publication Date: 2025/06/13

Abstract: DIABETIC Retinopathy is a serious eye condition. Beforehand Xdiscovery is pivotal for effective treatment. A special computer program can help descry Diabetic Retinopathy. The program uses images of the retina to make a diagnosis. This technology can prop croakers in relating the condition. Early discovery can help vision loss. Timely treatment can ameliorate patient issues. This technology has the implicit to help numerous people. The computer program uses a type of artificial intelligence. It analyzes images of the retina to descry abnormalities. The program provides accurate results. Different computer models were tested for their effectiveness. One model, called ResNet- 18, performed exceptionally well. It achieved high delicacy in detecting Diabetic Retinopathy. Diabetic Retinopathy is a significant health concern. Beforehand discovery and treatment can make a big difference. This technology can help croakers give better care.It can also ameliorate patient issues. Overall, this technology has great eventuality.

Keywords: *Diabetic Retinopathy, Early Detection, Retinal Imaging, Deep Learning, Medical Technology, Vision Loss, Patient Outcomes.*

How to Site: Dr. P. Sreedevi; B. Tabitha; (2025); Optimizing Retinal Disease Diagnosis through ResNet-Based Deep Learning. *International Journal of Innovative Science and Research Technology,* 10(6), 314-322. https://doi.org/10.38124/ijisrt/25jun396

I. INTRODUCTION

People who has diabetes can get an eye problem called diabetic retinopathy. This happens when small blood vessels in the back of the eye (the retina) get damaged. If it is not treated, it can make your vision blurry or even cause blindness. It is a common reason why many adults between 20 and 74 lose their vision. In the beginning, there are no clear signs. But later, it can start to hurt your eyesight. Here it has four stages like mild, moderate, severe, and poliferative. In the stage one, the tiny blood vessels will form in the back of the eye. In the moderate stage, that blood vessels may start to leak. If it starts to leak then it can make the vision blurry. If it gets worse and moves to the severe stage, more blood vessels are damaged, and vision loss becomes more likely. If we won't treat the disease it will reach to the final stage which cause the blindness.

This can cause serious problems, including blindness. Proliferative DR: Advanced stage with new, abnormal blood vessels that can cause blindness. Current Detection Method: Trained ophthalmologists examine fundus images to detect DR. However, this method can be time-consuming and may not detect DR early. Automating the screening process can help identify DR early. Our deep learning model leverages Convolutional Neural Networks (CNNs) with a ResNet architecture, enabling rapid and precise image analysis, while the ResNet design mitigates vanishing gradients to enhance overall accuracy.. The model uses the Swish activation function for better performance.

The goal is to develop a highly accurate model for detecting DR.Our model aims to outperform other architectures in accuracy Early detection can prevent vision loss and improve patient outcomes. The global prevalence of diabetic retinopathy poses a substantial challenge to public health, underscoring the need for awareness, prevention, and effective management of the condition. Accurate detection and treatment can prevent blindness. This model can assist medical professionals in making precise diagnoses of diabetic retinopathy, facilitating effective patient care. Early detection can improve treatment outcomes. Timely and precise identification of the condition can help prevent vision loss and support better health outcomes. This technology holds promise for supporting medical professionals in identifying and managing diabetic retinopathy, ultimately enhancing patient care.

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Diabetic Retinopathy is a serious complication of diabetes, Early detection and treatment are crucial, Our deep learning model shows promise in detecting DR accurately. Further research can improve the model's performance. This solution could have a profound effect on the diagnosis and management of diabetic retinopathy, leading to better health outcomes. It can help doctors diagnose DR more accurately. Early identification and intervention are made possible by this technology, which can lead to more effective management of the condition. This technology has the potential to make a significant impact.

II. LITERATURE SURVEY

Over the past few decades, many computer systems have been created to help find diabetic retinopathy (DR), especially for classifying the disease. Researchers have used deep learning (DL) and machine learning (ML) methods for this purpose. Majumder and his team created a deep learning system that combined two tasks—classification and prediction—so they could work together and improve results. Their model used a special type of neural network and got accuracy rates of 82% and 86% on the Eye PACS and APTOS datasets. Jod and team made a DR detection model that could explain its results by showing how much each part of the input affected the output. Akilesh and his team used transfer learning with a model called ResNet-v2 and added custom layers to improve DR detection. Mahmoud and coworkers used the CHASE dataset and built a hybrid ML system called HIMLA, which reached a high accuracy of 96.62%. Anupam Kumar and his team used a method with decision trees to find DR. They also used image tone mapping to keep important image details while balancing brightness. Features were selected using a genetic algorithm, and images were changed to grayscale to make the data easier to work with.

All of these efforts show how technology is getting better at helping doctors detect diabetic retinopathy. By using advanced image processing, transfer learning, and mixed models, accuracy and reliability are improving.

Alyobi et al. proposed a hybrid deep learning model that combines CNN512 with the YOLOV3 architecture.. In their system, YOLOv3 was employed to pinpoint DR-related lesions, while CNN512 was tasked with classifying diabetic retinopathy into five distinct stages. The integration of both models facilitated precise identification and categorization of DR abnormalities.

Kurilová et al. introduced a method aimed at detecting and analyzing hard exudates in retinal imagery. This technique supports accurate identification of these critical DR indicators. To enhance fundus image clarity, S.H. Abbood and co-researchers introduced a reprocessing approach that consists of two main stages. Next, a Gaussian blur was applied to heighten image contrast and suppress noise, which led to improved feature extraction and model prediction. They integrated a support vector machine (SVM) with a fast region-based convolutional neural network (R-CNN) in their model. A hybrid approach facilitated effective exudate detection with limited training data, while a transfer learning model based on Inception-v3 was adapted for predicting diabetic retinopathy. They applied histogram-based segmentation to extract features and enhanced image quality through CLAHE (Contrast Limited Adaptive Histogram Equalization). Akram et al. designed an ensemble classifier that combined Gaussian Mixture Models (GMM) with SVMs. Their strategy merged shape-based and intensity-based features to better identify retinal lesions and improve DR categorization. Mustafa et al. A deep learning approach utilizing multiple ensemble streams was used by researchers to evaluate and categorize the severity of diabetic retinopathy. To extract relevant visual patterns, they applied Principal Component Analysis (PCA) in conjunction with deep learning techniques. Deep features were utilized by ensemble classifiers to produce more stable and reliable outcomes. The model reached an accuracy of 95.58% on the Messidor-2 dataset and 85.46% on the EyePACS dataset for binary classification tasks Paul and colleagues introduced two methods for classifying diabetic retinopathy images into four categories: one utilized sequential multi-output models, and the other employed a series of single-output models a series of single-output models. The models categorized retinal images using four visual factors: overall appearance, eye laterality, image quality, and retinal features. The internal set included 7,743 images from a comprehensive UK-based DR risk assessment program. Additionally, they tested their approach on an external dataset of 1,479 retinal images from hospitals in Paraguay and Portugal. By analyzing gradient pixel attribution maps, they identified the key visual elements influencing the model's decisions. Their automated system demonstrated reliability in detecting DR across multiple image conditions and healthcare centers. This body of work highlights the growing capabilities of deep learning, ensemble methods, and image preprocessing in the advancement of DR detection and severity grading. A cosine tempering-based learning rate inspired by trigonometric functions was employed for training. The global channel attention mechanism enabled adaptive modification of the convolutional kernel. Another innovative model, GENet, was also proposed to improve DR image analysis. GENet was designed using a deep convolutional neural network as its foundational architecture. Its design focused on effectively analyzing colour images of the retina. Heat maps were used by GENet to highlight and draw attention to the most critical regions within images. This visualization aided in identifying signs system demonstrated reliability in detecting DR across multiple image conditions and healthcare centers. This body of work highlights the growing capabilities of deep learning, ensemble methods, and image preprocessing in the advancement of DR detection and severity grading. A cosine tempering-based learning rate inspired by trigonometric functions was employed for training. The global channel attention mechanism enabled adaptive modification of the convolutional kernel. Another innovative model, GENet, was also proposed to improve DR image analysis. GENet was designed using a deep convolutional neural network as its foundational architecture. Its design focused on effectively analyzing colour images of the retina. Heat maps were applied in GENet to draw attention to the most relevant image areas. GENet demonstrated high effectiveness across various evaluation metrics during testing.

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The system showed strong and reliable performance, reaching 95.6% in accuracy, precision, and sensitivity. This means it was very good at correctly finding signs of serious diabetic retinopathy. The model was trained and tested using a diabetic retinopathy dataset available on Kaggle. When tested, the GENet model gave consistent and strong results across different performance measures.

III. METHODOLOGY

In later a long time, neural systems have gotten to be essentially more complex, advancing from shallow designs with as it were a few layers to profound systems comprising over a hundred layers. One of the key benefits of such profound designs is their capacity to demonstrate exceedingly complex capacities. They are competent of learning highlights at shifting levels of abstraction—from recognizing fundamental edges in the early layers to recognizing more complex designs in the more profound layers. In any case, expanding profundity does not continuously ensure superior execution. One big problem in training deep neural networks is that the gradient values can get smaller as they pass through each layer. This makes it harder for the model to learn properly. Amid backpropagation, the slope values can decrease to close zero, particularly in the prior layers, which hampers the viability of angle plunge. This issue emerges due to the rehashed duplication of slope values by weight frameworks, possibly driving to exceptionally little or, in uncommon cases, too much expansive slope values (detonating gradients).

To address this issue, we utilized the ResNet-18 design upgraded with the wash actuation work, as appeared in Figure. This engineering was utilized in our approach to create a show for diabetic retinopathy (DR) discovery. ResNet helps solve this with its shortcut connections, which make the training process more stable. These connections allow us to train the model on large datasets without problems like overfitting or slow learning.

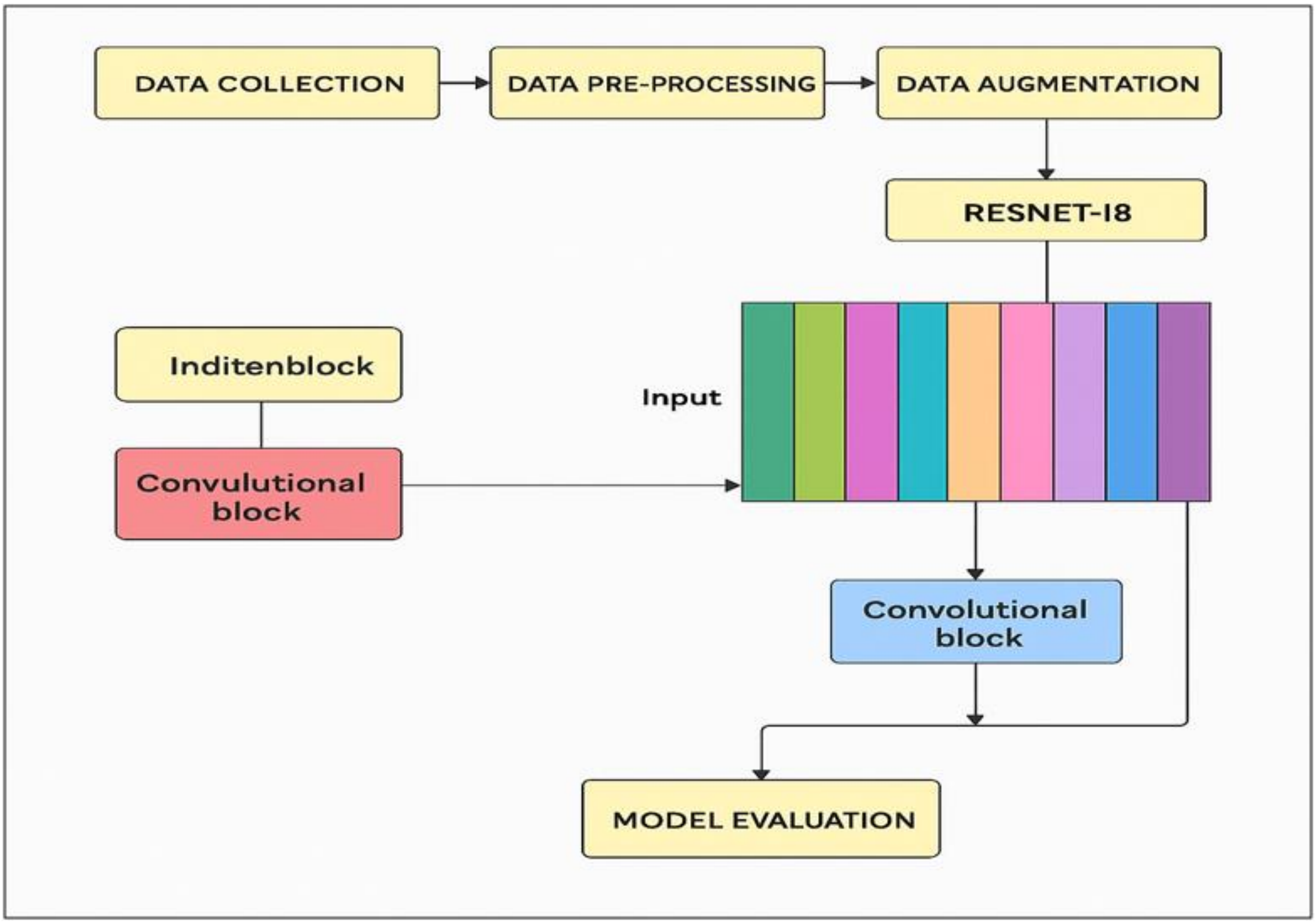

Fig 1 Proposed Framework

Compared to routine convolutional neural systems such as MobileNet, and VGG16, our ResNet-18 based show illustrated predominant execution. These comes about emphasize the down to earth utility of the ResNet engineering intending to real-world challenges like diabetic retinopathy conclusion. In our approach, we utilized ResNet-18, a convolutional neural network tailored for image classification tasks, developed using TensorFlow and adhering to established practices for deep neural network design. The architecture begins with a convolutional layer, then applies batch normalization, and proceeds with a pooling layer. There are eight blocks in total, made up of a mix of convolutional and identity blocks.

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The Swish function is applied as the activation method in these layers. After the block layers, the network features a global average pooling layer, ending with a fully connected layer that produces the final classification output.

The Swish function plays a key role in promoting better data flow through the network and accelerating the convergence during training. In deep networks, the activation function helps for gradient problem. Swish, in contrast, allows for small gradient updates to propagate effectively, enabling deeper network training. Mathematically, the Swish function is defined as:

$$f(x)=x*\text{sigmoid}(\beta x)$$

In this context, x denotes the input, while β is a parameter that modifies the shape of the function.

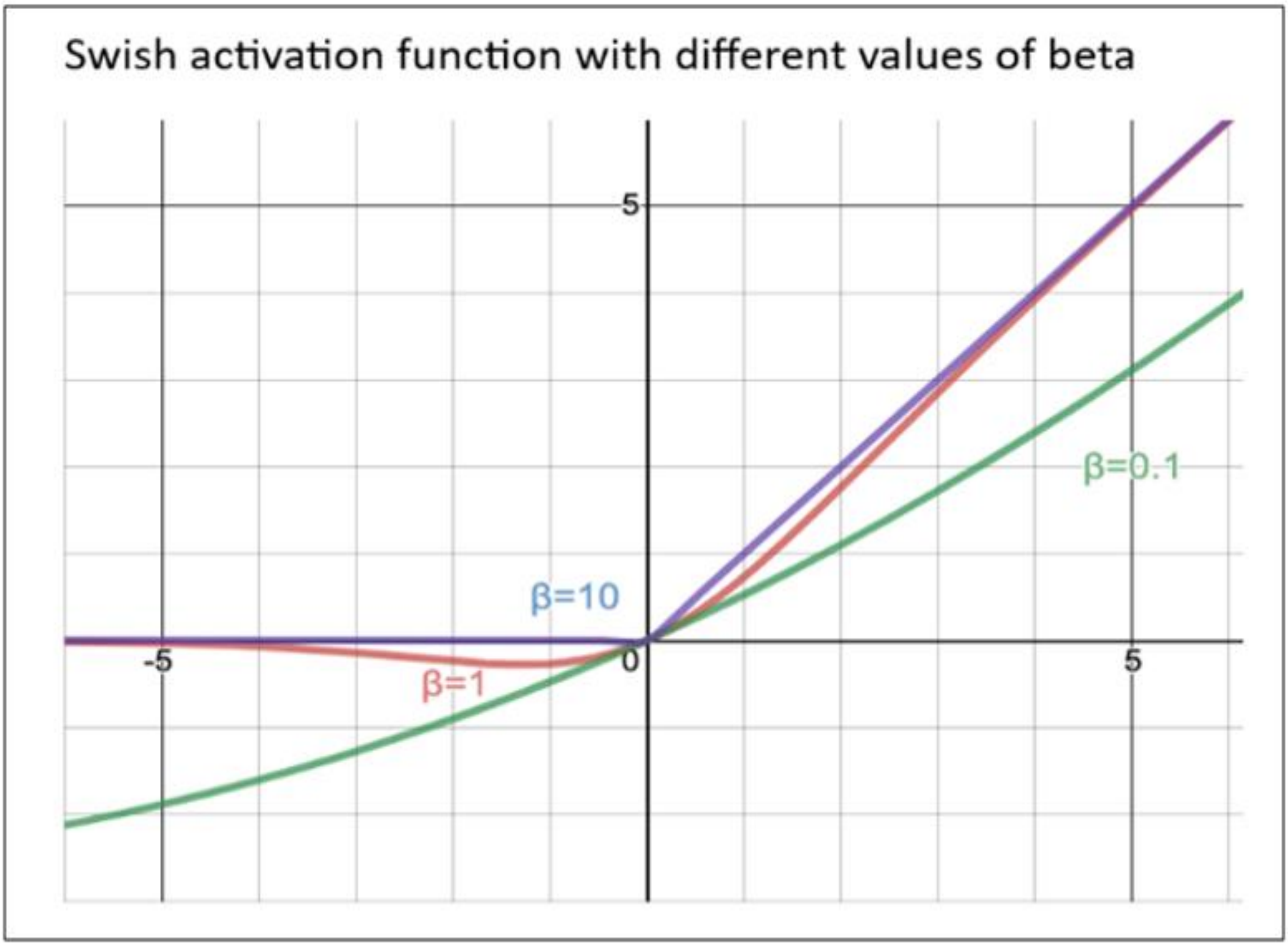

Fig 2 Swish activation function

The choice of β can significantly impact the model's performance, affecting accuracy, training time, and convergence behaviour. The figure illustrates how variations in the value of β affect the behavior of the Swish activation function.

To summarize, the Swish activation function stands out for its ability to help mitigate the vanishing gradient issue and, in certain cases, enhance model performance. The system utilizes the Adam optimization algorithm, a popular choice in deep learning, combined with a cyclical learning rate strategy. This approach dynamically adjusts the learning rate throughout training, promoting more efficient convergence. When compared to established architectures like MobileNet, and VGG16, the proposed model featuring an enhanced ResNet structure and the Adam optimizer with a cyclical learning rate—demonstrates superior accuracy and faster convergence in detecting diabetic retinopathy.

IV. DATA COLLECTION

This examine utilized retinal pictures gotten from the Kaggle organize, which offers a gigantic and moved set of pictures taken with unmistakable imaging procedures. These pictures are classified on a scale of 0 to 4, talking to changing stages of Diabetic Retinopathy (DR):

No DR (0) Mild DR (1) Moderate DR (2) Severe DR (3) and Proliferative DR (4)

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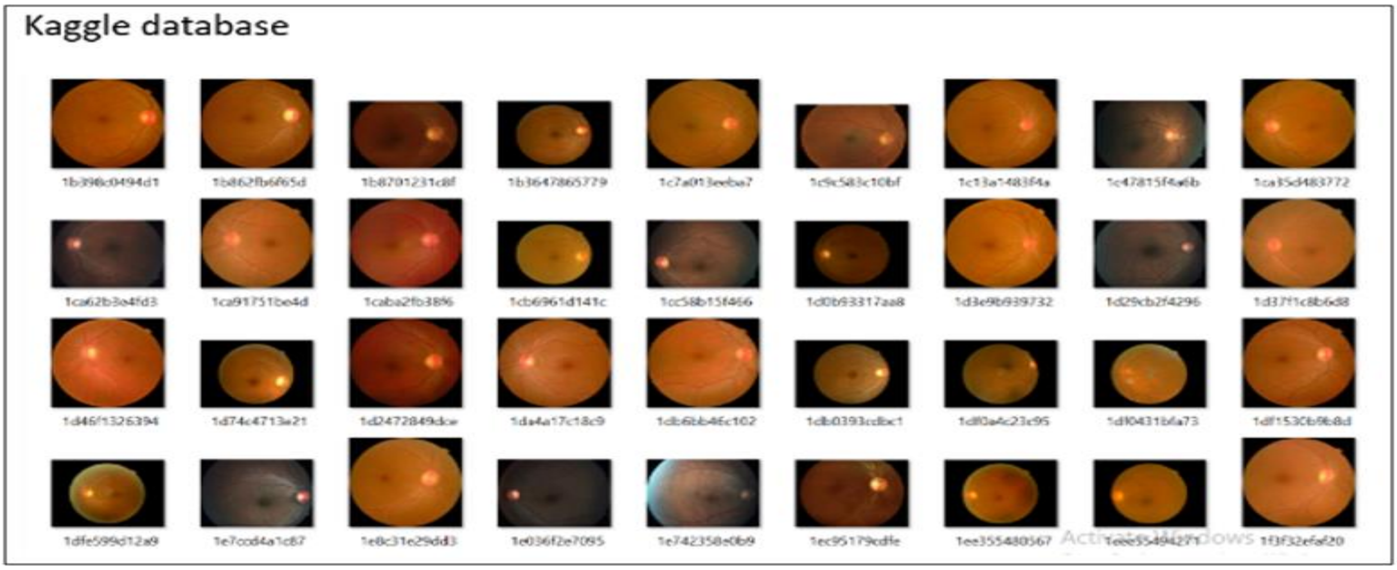

Fig 3 Kaggle database

V. RESULT AND DISCUSSION

➢ *Image Pre-Processing*

The images which are captured by the camera can vary the quality of the image in the presences of noise. It makes difficultly to see the blood vessels, small white patches. The images are arranged with different size due to contrast and brightness because of this the because of this we get to know how accurately they are classified. To solve this we use preprocessing methods which makes the image quality even more and helps for analyzing the images.

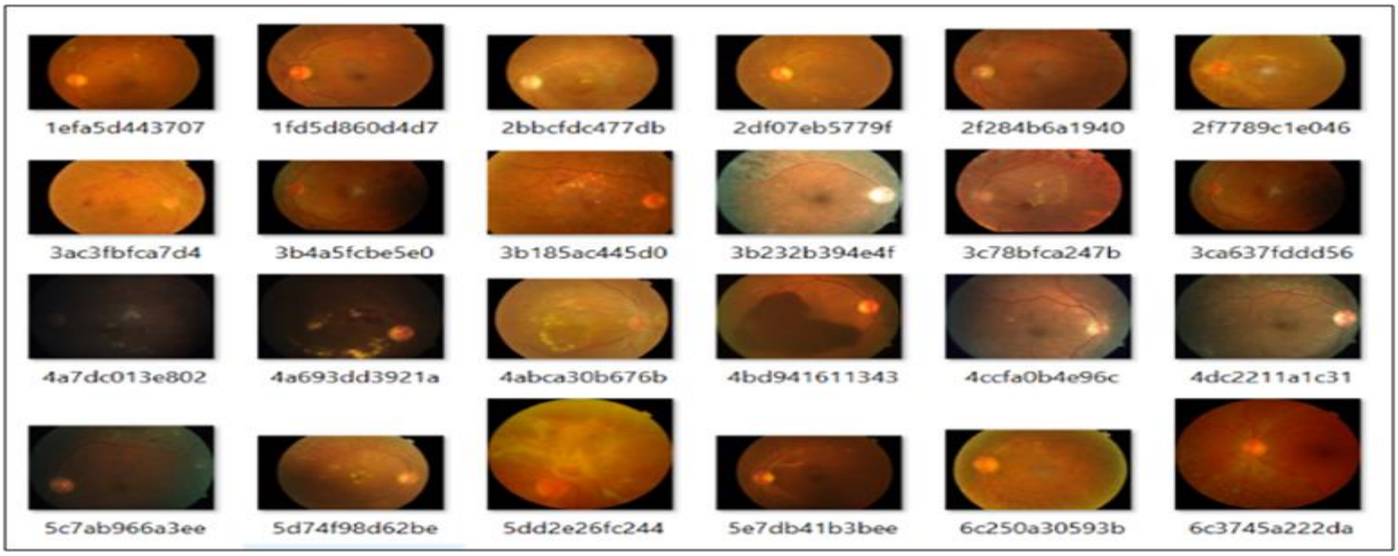

Fig 4 Funds Image before Pre-processing

The retinal images used the Gaussian filter under the grayscale as shown in the figure. This process reduced the noise thus improve the visibility of major components like, blood vessels and fluid, allowing the ability to examine the retinal structures better.

To improve the quality we use automatic cropping methods to remove the problems and focus. By increasing the photo structure it will help to express the image Accurately.

The final image appers better and successful in expressing the message when other elements removed and better colour is achieved. To address the issue of class imbalance, the dataset underwent augmentation using techniques such as zoom, rotation, and resizing. This process generated additional images, as illustrated in Figure, which helped to balance the distribution of images across the five classes.

By augmenting the dataset, the model was better equipped to learn from a more representative set of images, ultimately improving its performance and generalizability.

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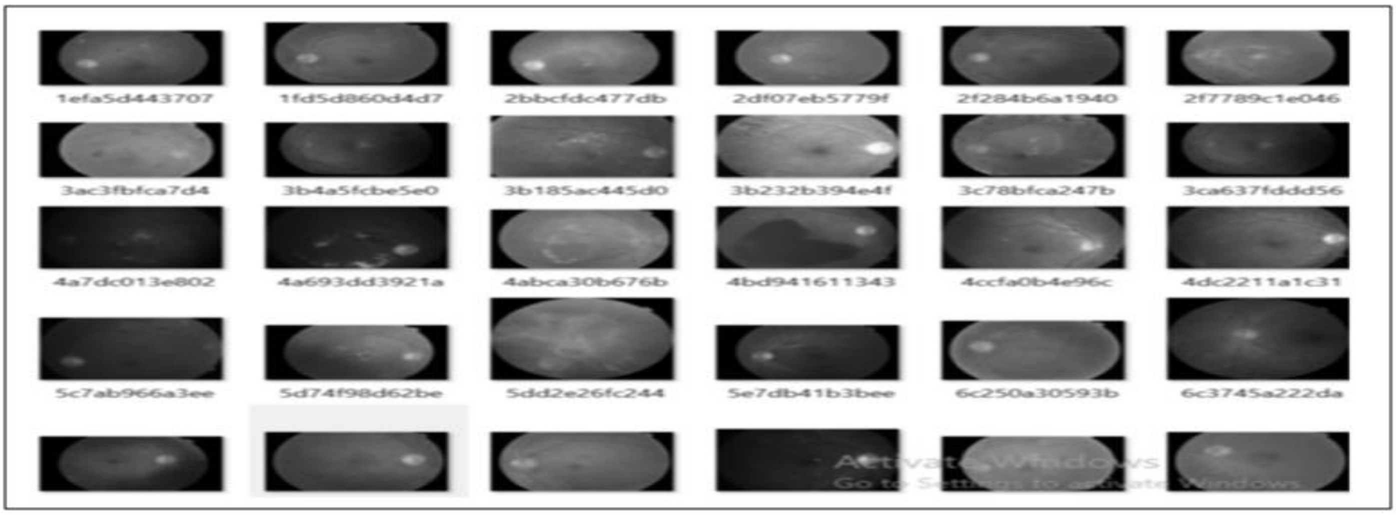

Fig 5 Funds Images after Pre-processing

➢ *ResNet18 using Swish Activation Function*

The figure shows about the Resnet18 model using the swish activation function. The dataset consist of 5,371 fundus images, here it were divided into 2 parts : 20% for testing and 80% for training. The model's performance in analysing the retinal images was illustrated by the noteworthy accuracy of 95.74% obtained with this configuration.

Layer (type)	Output Shape	Param #
conv2d_12 (Conv2D)	(1, 112, 112, 64)	1,792
batch_normalization_20 (BatchNormalization)	(1, 112, 112, 64)	256
max_pooling2d_1 (MaxPooling2D)	?	0
resnet_block_8 (ResnetBlock)	(1, 56, 56, 64)	42,176
resnet_block_9 (ResnetBlock)	(1, 56, 56, 64)	42,176
resnet_block_10 (ResnetBlock)	(1, 28, 28, 128)	101,376
resnet_block_11 (ResnetBlock)	(1, 28, 28, 128)	166,272
resnet_block_12 (ResnetBlock)	(1, 14, 14, 256)	399,360
resnet_block_13 (ResnetBlock)	(1, 14, 14, 256)	660,224
resnet_block_14 (ResnetBlock)	(1, 7, 7, 512)	1,585,152
resnet_block_15 (ResnetBlock)	(1, 7, 7, 512)	2,631,168
global_average_pooling2d_1 (GlobalAveragePooling2D)	?	0
flatten_1 (Flatten)	(1, 512)	0
dense_1 (Dense)	(1, 5)	2,565

Total params: 5,632,517 (21.49 MB)

Trainable params: 5,622,917 (21.45 MB)

Non-trainable params: 9,600 (37.50 KB)

Fig 6 Model Summary of ResNet18

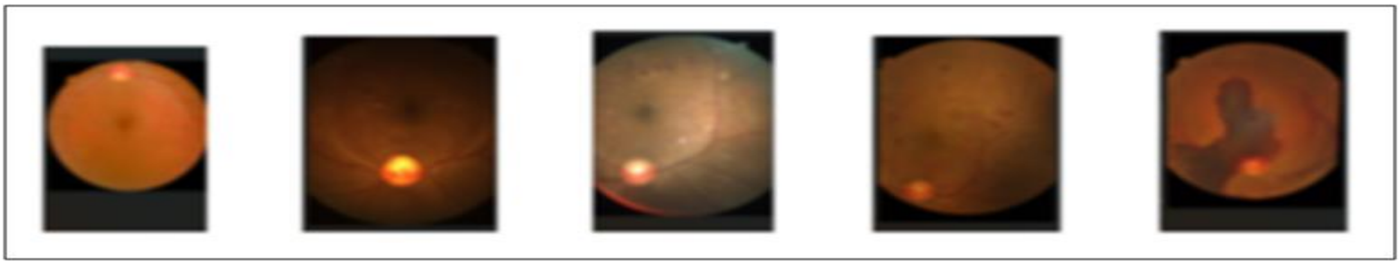

Fig 7 Classified Images samples

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The method works by choosing one image to represent each group, as shown in the figure.

VI. PERFORMANCE PARAMETERS

Model accuracy means how many predictions the model got right out of all the predictions it made. It shows how well the model correctly classifies things across all categories, as mentioned in related studies.

Accuracy = (TP+TN)/(TP+FP+TN+FN)

This tells us how many of the results the model said were "positive" were actually correct. This measure is commonly utilized to assess classification performance, providing insight into the model's accuracy in positive predictions.

Precision=TP/TP+FP

Sensitivity, also referred to as recall or true positive rate, quantifies a model's capability to correctly identify all actual positive instances within a dataset.

Sensitivity=TP/TP+FN

The F1-score mixes precision and recall (how many real positive cases the model found) into one number.

It helps us understand how good the model is overall, especially when we care about both correct and missed results.By calculating the harmonic mean of these two measures, the F1 score offers a comprehensive evaluation for classification tasks where both precision and recall are crucial.

F1-score=2*(Precision*Recall)/(Precision+Recall)

The performance results of the ResNet 18 architecture, utilizing the Swish activation function, are presented in Figure.

Table 1 Performance Metrics of ResNet

ResNet18	Training(%)	Testing(%) Kaggle Data
Accuracy	97.49	82.28
Precision	97.53	83.79
Sensitivity	97.40	82.06
F1 score	97.46	82.92

VII. COMPARISONPERFORMANCE METRICS

ResNet18 with Swish outperforms other deep learning models, achieving metrics of 97.49% accuracy, 97.53% precision, 97.40% sensitivity, and 97.46% F1-score, with detailed performance comparisons shown in figure.

Table 2 Comparison of Performance Metrics

Model Name	Accuracy(%)	Precision(%)	Sensitivity(%)	F1Score
Simple CNN	73.98	85.92	63.36	72.94
VGG-16	74.70	83.99	67.02	74.55
MobileNet-V2	75.75	84.02	67.30	80.80
ResNet18	97.49	97.53	97.40	97.46

VIII. CONCLUSION AND FUTURE SCOPE

This study showcases ResNet18's potential in classifying retinal images for diabetic retinopathy detection. Deep learning algorithms, especially ResNet18 with Swish, demonstrate high accuracy. Image processing effectively highlights critical retinal features, including blood vessels and exudates. The results indicate a promising future for Al-assisted DR diagnosis. A potential web-based screening platform could increase accessibility. Patients could upload fundus images and receive results quickly. This technology could benefit underserved populations. Collaboration with healthcare professionals is essential. ResNet18 with Swish shows promise for clinical applications. Further research can improve the model's performance. The potential impact on public health is substantial. Al-assisted DR diagnosis can save vision and improve lives. This study contributes to the growing field of medical Al.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25jun396

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Cite as:

Dr. P. Sreedevi, & B. Tabitha. (2025).

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