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Residual Network-Based Deep Learning Framework for Diabetic Retinopathy Detection

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ABSTRACT

Artificial intelligence and machine learning have been transforming the health care industry in many areas such as disease diagnosis with medical imaging, surgical robots, and maximizing hospital efficiency. The Healthcare service market utilizing Artificial Intelligence is expected to reach 45.2 billion U. S. Dollars by 2026 from its current valuation, off $4.9 billion. Diabetic Retinopathy (DR) is a disease that results from complications of type one and Type two diabetes and affects patients' eyes. Diabetic retinopathy, if remains unaddressed, is one of the most serious complications of diabetes, resulting in permanent blindness. The disease has been affecting the lives of 347 million people worldwide. The paper aims to propose a residual network-based deep learning framework for the detection of diabetic retinopathy. The accuracy of our approach is 83% whereas the precision value for checking the absence of DR is 95%.

KEYWORDS

Artificial Intelligence, Diabetes, Diabetic Retinopathy, Machine Learning, Deep Learning

1. INTRODUCTION

The retina is a particularly sensitive or light-sensitive tissue at the back of our eyes that converts light into pictures. Diabetic Retinopathy is initiated by distorting the blood vessels in the retina of diabetics (DR). Diabetic retinopathy is characterized by double vision and impaired vision. Both eyes are frequently affected. Diabetic retinopathy may scar and destroy the retina if left untreated, resulting in partial or full blindness. Diabetic Retinopathy usually progresses in four phases. Mild, moderate, severe, or Proliferative non-proliferative retinopathy are the phases. Diabetic retinopathy (DR) is the most common cause of visual loss. Diabetes mellitus is connected to ophthalmoscopically undetected neurovascular damage that occurs before the onset of the first clinical signs of DR. Early surgical and nonvisible structural neuroretinal changes have been detected using, reduced contrast

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responsiveness primarily at low-frequency components and macular optical coherence tomography, unusual consequences in color vision and microperimetry tests, and a sustained implicit time documented by multifocal electroretinography.

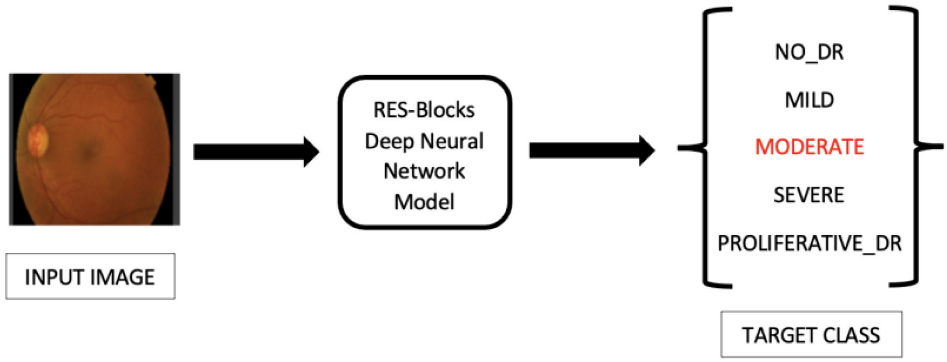
To diagnose the early stages of DR, vascular anomalies such as alterations in retinal artery caliber, morphological indices, and blood circulation have been studied. Early indicators of DR have been discovered as Optical Coherence Tomography Angiography findings, retinal vascular oxygen saturation trends, and higher levels of circulating markers and cytokines. It may lead to complications if not detected early enough. Regrettably, DR is not a curable condition, and therapy merely assists to slow the progression of vision loss. The risk of vision loss may be greatly reduced if DR is detected and treated early. Ophthalmologists must manually detect DR, which is difficult and time-consuming. As a result, automatic identification is necessary, and DR has been identified and categorized using machine and deep learning methods. Unlike computer-aided diagnostic approaches, manual diagnosis of DR retina fundus pictures by ophthalmologists takes time, effort, and money, and is prone to misdiagnosis. Deep learning has recently risen to prominence as one of the most popular approaches for improving performance in a variety of fields, notably medical image processing and classification. Convolutional neural networks are being increasingly commonly employed in medical image processing as a deep learning method, and they are quite successful. The retina images with all the four stages along with healthy retina images are shown in Figure 1. Therefore, we can say that Diabetic Retinopathy is the leading cause of blindness in the developing world as it can develop in people with both Type one and Type two diabetes. Also, the risk of developing diabetic retinopathy increases the longer one has diabetes.

As per WHO, currently, about 422 million people worldwide have diabetes and the majority of diabetic people are living in developing countries. Also, the number of diabetic people is continuously increasing.

Figure 1. Types of non-proliferative retinopathy

Diagnosis of DR is generally done by the eye doctor either by dilating the pupils or by injecting a fluorescent dye to see the images of blood vessels in the retina. But, the diagnosis of DR is very complex and needs to be performed by a trained retina specialist. With the help of a retina specialist, DR can be diagnosed at an early stage and the treatment can be started immediately which can stop the damage to the retina and prevent vision loss. But, due to the inadequate access to trained retina specialists in rural and semi-urban areas, most of the patients affected by DR visit a retina specialist only at a severe stage. Therefore, an intelligent diagnostic system is required that can perform a comprehensive eye test for diagnosing DR along with its current stage. AI-based tools can play an important role in the detection and identification of the severity of eye diseases. In the course of work, the authors perceived that AI can play a major role in the detection of diabetic retinopathy. In this research article, the authors have proposed a residual network-based deep neural network model for the detection of DR. As shown in Figure 2, the proposed model can not only detect DR but also detect the various stage of DR.

Figure 2. Input & output methodology



This research article is comprised of four different sections. In section 2, a detailed literature review has been presented. In section 3, the steps of working methodology have been discussed in detail. The results are presented and discussed in section 4. Lastly in section 5, the authors concluded the findings of the research.

2. LITERATURE SURVEY

The authors reviewed 215 research publications since 2018-2021 from IEEE and other referred journals. Then based on the papers, the authors segregated and classified research that presented Diabetic Retinopathy analysis using Artificial Intelligence and Machine Learning and shortlist 34 matching research with the proposed research. The work carried out in the shortlisted research articled is discussed below.

(Cao et al., 2018) analyzed and detected diabetic retinopathy using small pixel patches as inputs extracted from fundus image databases. The authors implemented neural network, support vector, and random forest machine algorithms and explored the use of reducing input dimensionality. Using machine learning, the authors proposed a unique method that outperformed existing deep learning detection methods (Jing et al., 1 C.E.). The authors also confirmed this using another online retinopathy dataset challenge. Results indicate this method has the potential to generalize to different datasets with consistent and better output. (Kolla & Venugopal, 2021) proposed a binary convolutional neural network model for a fast execution process and significantly reduce memory consumption against diabetic problems. The proposed model was efficient during Diabetic Retinopathy classification as well as hardware friendly for large-scale images. Research tests conducted with the Kaggle dataset displayed an increased runtime of almost fifty percent and reduced memory consumption by around thirty-seven percent as compared to the existing base model. (Qomariah et al., 2019) proposed a deep learning method for classification with extracting features for Diabetic Retinopathy with support vector machines from Messidor databases. The authors used the high-level features from the last fully connected layer based on transfer learning of convolutional neural network as input to classify the support vector machine. This process fine-tuned and performed classification to reduce the computation time. Results displayed accuracy of 95.24% for base 12 and 95.83% for base 13 databases. The authors also presented the use of machine learning to automate detection and provide fast reliable results. The authors even proved the severity and presence of diabetic retinopathy by exploring their retina photographs (some with low very resolution) with an accuracy of almost ninety percent. (Huda et al., 2019) identified the presence of diabetic retinopathy using machine learning algorithms such as Logistic Regression and Decision Tree, and Support Vector Machine for the prediction in the human eye. The authors classified and extracted optical features such as lesion microaneurysms & exudates, disk diameter, or the presence of hemorrhages in datasets. These were utilized to arrive at the final prediction decision on the presence of diabetic retinopathy with around ninety percent accuracy with higher precision and recall results of 92% and 97% respectively as compared to existing model results of 72% and 63%. This paper (SHIHAB et al., 2023) presents a comprehensive formula for the operational matrix of derivative for Spline Scaling Functions. Subsequently, it is employed to investigate a novel iterative parameterization direct method for roughly solving optimum control problems. The objective of this study (Ahmed & MOHAMMED, 2023) is to assess the feasibility of a system that utilises convolutional neural networks to identify breast cancer. The system categorises mammograms into five distinct classes: non-cancerous, benign calcification, malignant calcification, benign mass, and malignant mass.

The authors (Chowdhury et al., 2019) to simplify the identification procedure while still providing quick and, more crucially, trustworthy findings, used machine learning methods. This article uses a deep learning approach to assess the existence and intensity of DR in diabetic individuals by analyzing retinal images. Even when photos are collected or delivered in extremely low resolutions, the CNN-based algorithms are powerful enough to perform with an efficiency of up to 89.07 percent. Diabetic Retinopathy patients lose eyesight due to blood vessel damage at the back of the retina. Traditional detection methods involve time and effort, (Sharma et al., 2021) proposed diabetic retinopathy detection using Machine Learning with Image Processing. Input taken was from standard retinal image databases. The authors automated the process of detection using hybrid steps for image processing focusing on clear image feature extraction during pre-processing and then applied machine learning algorithms for image classification. This provided an accuracy of over eighty percent. Deep learning-based multi-classification framework as proposed by (Jiang et al., 2020) using Gradient weighted class activation and mapping. This model classified the different lesions and auto locates the regions. With over 3200 experimental images, five labels were pre-defined to design and test the model with the deep learning model architecture being based on ResNet. Results proved 93.9% sensitivity and 94.4% specificity for the diabetic retinopathy classification. (Wang et al., 2020) evaluated independent diabetic retinopathy test datasets using quadratic weighted kappa coefficient, analyzing with precision-recall and receiver operating characteristics. The authors compared the performance of this model with ophthalmologists of varied experience levels. The results provided the improved performance of diabetic retinopathy feature detection and severity diagnostics as compared to traditional deep learning models. The model performed similarly to a 5-year experienced ophthalmologist when diagnosing severity levels and similar to ten years of experiencing an ophthalmologist during the detection for diabetic retinopathy. (Shelar et al., 2021) presented solutions for late Diabetic Retinopathy detection based on Artificial Intelligence. Then authors identified the retina fundus images and performed binary classification as Proliferative, Moderate, and Normal staged disease. The images were classified using convolutional neural networks with a transferred learn algorithm. Results obtained displayed that the normal patients were classified with 85% accuracy whereas diabetic retinopathy cases displayed 84.12% accuracy with the proposed binary classification model. This study (Enbeyle et al., 2022) thoroughly investigated the predictive accuracy of advanced time series (ARIMA) models in projecting monthly water use. This work aims to determine the most suitable ARIMA models for accurately fitting the water consumption data in Tepi town, Southwestern Ethiopia, and efficiently predict future water consumption in the city. This examination (Younis et al., 2022) enables the visualisation of breast tissue using X-ray imaging for screening purposes. The utilisation of computational approaches is crucial in aiding medical practitioners in detecting this condition, hence enhancing the effectiveness of preventive and early diagnosis in the present circumstances.

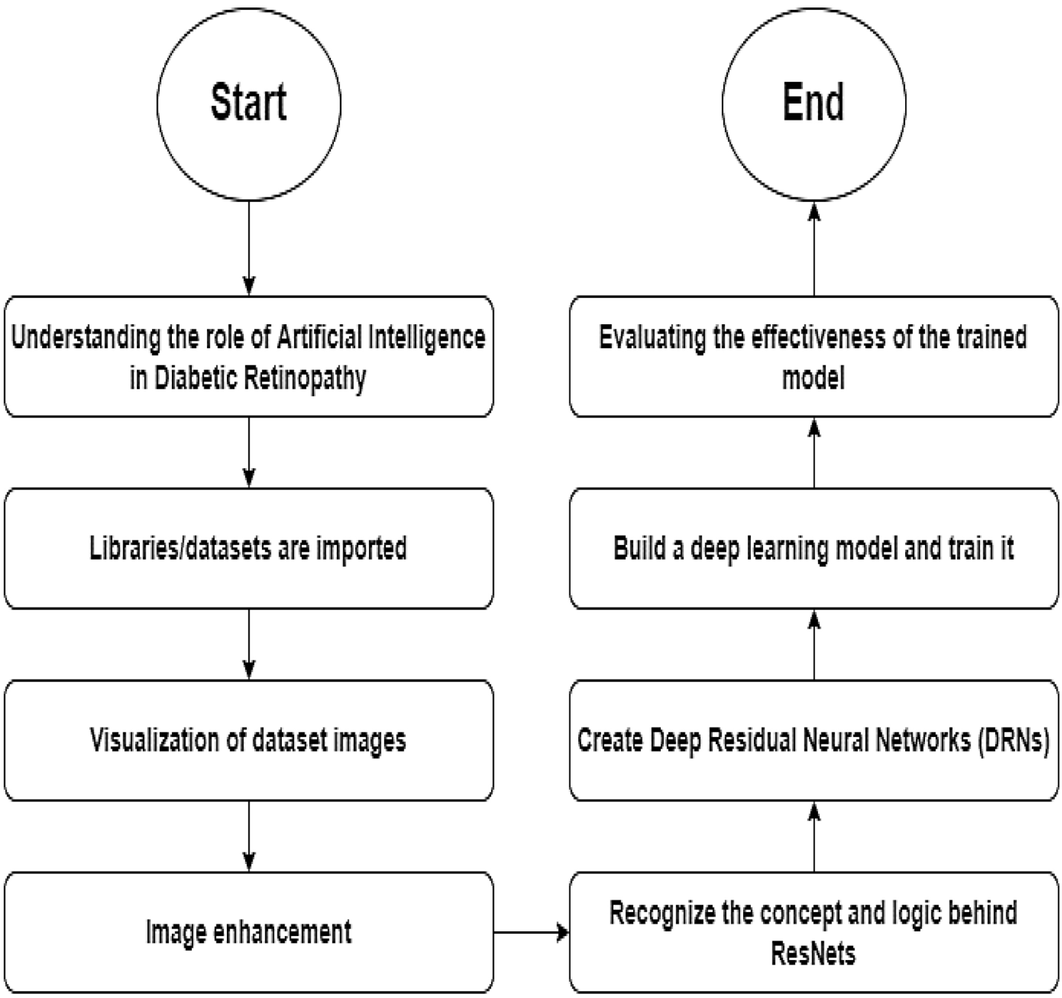
Classification and Feature selection has always played a critical role to determine, predict and classify diabetic retinopathy severity. (Meenakshi & Thailambal, 2021) presented methodologies by various researchers to categorize diabetic retinopathy and extract the characteristics using artificial intelligence (Dong et al., 1 C.E.), deep learning, and machine learning techniques (Ma et al., 1 C.E.). These technologies aid immensely to make decisions for the disease, predicting future actions, and screening diabetic retinopathy patients. The authors also compared metrics features to predict diabetic retinopathy for sensitivity, accuracy, and specificity. Future directions, challenges, advantages, and limitations of the classification techniques for diabetic retinopathy were also reviewed. (Chetoui et al., 2018) proposed an analysis of extracted texture features for acute diabetic retinopathy leading to complete blindness. The authors classified the extracted histogram using support vector machines and proposed the histogram binary scheme to represent the features. Experimental results indicated the proposed model performed with an accuracy of 90.4% using radial basis function kernel with SVM as well as ROC analysis curve displayed performance of 93.1% for the area under the curve. Detecting the different lesions related to diabetic retinopathy has a critical role in stage detection, prediction, and prevention. (Alves et al., 2020) designed deep learning neural network for the detection of lesions in digital retinal fundus images. This solution is built to be scaled and is a robust solution for resolving critical retina-related diabetes disease. Results from experiments using the Messidor dataset displayed higher performance, with 100% for the evaluation metrics taken into consideration. In terms of feature extraction time, the dataset delivered 17.63ms and 37.87ms acceptable time. (Emon et al., 2021) used feature extraction to predict diabetic retinopathy. The authors used machine learning algorithms to examine the dataset for optimum sensitivity and performance, true and false-positive rates, selectivity, and the receiver operating characteristic curve, which they obtained from the UCI repository. Sequential Minimal Optimization, Naive Bayes, Stochastic Gradient Descent, Logistic regression, bagging classifier, decision tree classifier, and random forest Classifiers are some of the machine learning techniques employed in this work. The best overall performance comes from logistic regression. (Arora & Pandey, 2019) offered a method to tackle the diabetic retinopathy problems that millions of people face around the world, yet medical practitioners and the technologies needed to detect diabetic retinopathy are in short supply. The use of machine learning to solve this problem has already been done, however, the efficacy of the machine learning method is dependent on the level of feature extraction, in which domain knowledge is needed. The approach provided in this study solves the issue by employing a deep learning algorithm that recognizes patterns and categorizes retina images into one of five classes. (Boral & Thorat, 2021) suggested a deep learning system to auto-identify photos and classify retinal fundus images into different categories using a recognition technique. The authors developed an algorithm that would incorporate a more efficient detecting mechanism. Different picture categorization functions of the Inception V3 can be adjusted using the transfer learning method. Fundus images are utilized for testing and training. The support vector machine technology is used to do the final classification, which divides the input images into two categories: diabetic retinopathy images and normal retinal images.

Using the Kaggle diabetic retinopathy dataset, (Patel & Chaware, 2020) developed a transfer learning strategy. To classify the different classes of diabetic retinopathy photos, the model was adjusted with global-average-pooling and classifier layers. The authors used weights of top layers to improve and fine-tune the model's performance after training the stacked layers, with the network having self-adapting features. The network training accuracy went from 70% to 91 percent, and the validation accuracy increased from 50% to 81 percent, indicating a significant improvement after fine-tuning. India is the world's diabetes capital, with the number of people with diabetes expected to reach 69.9 million by 2025. When we have too much sugar in our blood, the small blood vessels in our retina are clogged, and our retina becomes weak. The best way to safeguard our eyesight is to recognize DR early on. The goal of this research (Pm & Ranjana, 2020) is to provide several methodologies and current studies that use transfer learning to diagnose Diabetic Retinopathy in its early stages utilizing patient fundus photos. DR is a dangerous condition that, if left untreated, can result in total visual loss. Because diabetic retinopathy has few symptoms, a comprehensive eye examination is required to detect it. To diagnose diabetic retinopathy and enhance the existing healthcare system, research projects employing Deep Learning models have been conducted. (Prasad et al., 2021) examined current DR detection and classification methods to gain a better understanding of the subject and to guide future research.

3. METHODOLOGY

In this paper, a residual-based deep learning framework is implemented for the detection of diabetic retinopathy. As shown in Figure 3, the proposed methodology is divided into eight major steps.

Figure 3. Working methodology



Step 1: Recognize the Role of Artificial Intelligence in Diabetic Retinopathy

As eye examination grows more advanced, it's no wonder that artificial intelligence (AI) has risen in popularity in the eye care industry, with promising prospects for adoption in the coming years. AI is described as a machine's capacity to mimic intelligent behavior. AI has already shown to be quite useful in the understanding of much of the qualitative and quantitative testing that occurs in the vision care industry. OCT, glaucoma visual fields, electroretinography, and visual evoked perspective, for example, all provide AI results. These studies assist doctors in determining the severity of a wide range of eye disorders. An additional advantage of AI assessment tools is that they will certainly enhance the early identification of DR by putting the selection process in the control of a larger variety of health care providers. Early diagnosis leads to early treatment, which reduces the need for costly and intrusive treatments as well as follow-up consultations. It can also minimize the percentage of individuals who go undiagnosed with DR until it's too late, resulting in DR-related impairment. DR is an eye condition that causes moderate to severe vision loss and is the primary cause of visual impairment in persons of working age who have had diabetes for a long time. The enormous per capita expenditure adds to the health burden. As a result, there has been a growing interest in the creation of computerized analytic software for the assessment of retinal pictures in persons with diabetes utilizing computer machine learning and artificial intelligence (AI), therefore addressing at least a portion of the challenge.

Step 2: Importing Libraries and Dataset

The implementation is done in the python programming language and in this step, the necessary python libraries, and datasets are imported to start working. Packages like NumPy, pandas, TensorFlow, Matplotlib, seaborn, etc are used in the implementation. Initially, after importing all the necessary packages and libraries, the trained images are identified. There are 3662 trained images present in the dataset. The images are labelled as - 'Mild', 'Moderate', 'No_DR', 'Proliferate_DR', 'Severe'. The dataset used in the implementation is available at - https://www.kaggle.com/c/diabetic-retinopathy -detection. The algorithm for checking the list of image class names is given below. Jupiter themes are used for getting the list of images from the dataset available under the various class names

```
for i in os.listdir('./train'):
train_class = os.listdir(os.path.join('train', i))
for j in train_class:
img = os.path.join('train', i, j)
train.append(img)
label.append(i)
```

Step 3: Carry Out Visualization of Dataset Images

Once the image classes are listed then visualization of the images is performed. The data is explored just before training the model because there is a possibility that the data is messed up. The data should make some sense from a human perspective that is why the visualization of the data is carried out. Figure 5 shows the classification of various class names. The algorithm for the visualization of five images for each class in the dataset is shown below:

```
for i in os.listdir('./train'):
# get the list of images in a given class
train_class = os.listdir(os.path.join('train', i))
# plot 5 images per class
for j in range(5):
img = os.path.join('train', i, train_class[j])
img = PIL.Image.open(img)
axs[count][j].title.set_text(i)
axs[count][j].imshow(img)
count += 1
```

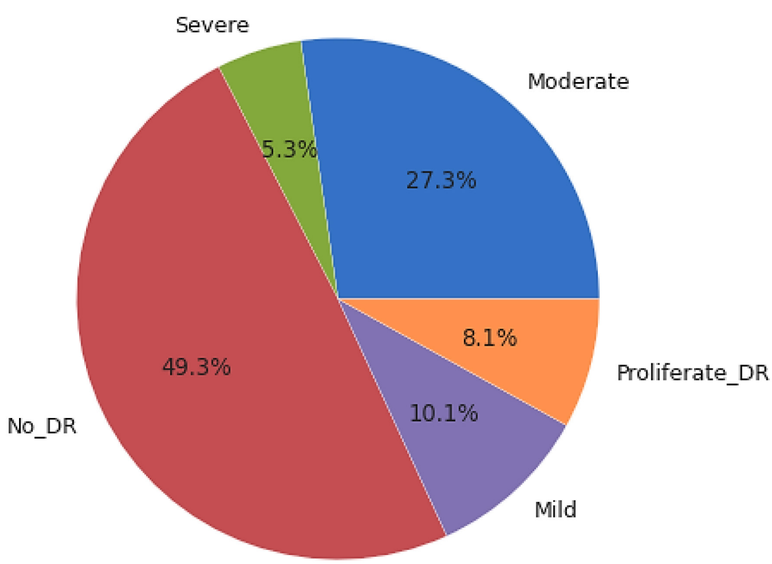
After visualization is done, then the number of available images in each class of the dataset is observed. The count of images for each class is shown in table 1 below.

Table 1. Count of images per class

Type of Image Class	Count of Images
Moderate	999
Mild	370
Proliferate_DR	295
No_DR	1805
Severe	193

The visualization of percentage samples per class is done in Figure 4 illustrates 49.3% of samples (~ 50% samples) that belong to No_DR means that do not have any diabetic retinopathy. Around 27.3% of samples come under the moderate class whereas 10.1% of images are of the mild class. The severe samples are around 5.3% whereas the proliferate_DR samples are 8.1%. The percentage visualization of samples per class gives us a good idea to manipulate the samples.

Figure 4. Percentage of samples per class



Step 4: Conduct Image Enhancement

In this step, the data is shuffled first and then it is split into two separate sets – training and testing data. The train and test datasets are equally divided to prevent any unequal distribution. After that, the run-time augmentation is done on the training and testing dataset. For generating the training data, normalization is done along with the addition of shear angle, horizontal flip, and zooming angle. The re-scaling is done according to the metrics below:

```
train = ImageGenerator(
rescaling = 1./255,
shear_range = 0.2,
validation_split = 0.15)
```

For generating the test dataset, only normalization is required. And that is done by executing *test = ImageGenerator(rescale = 1./255).*

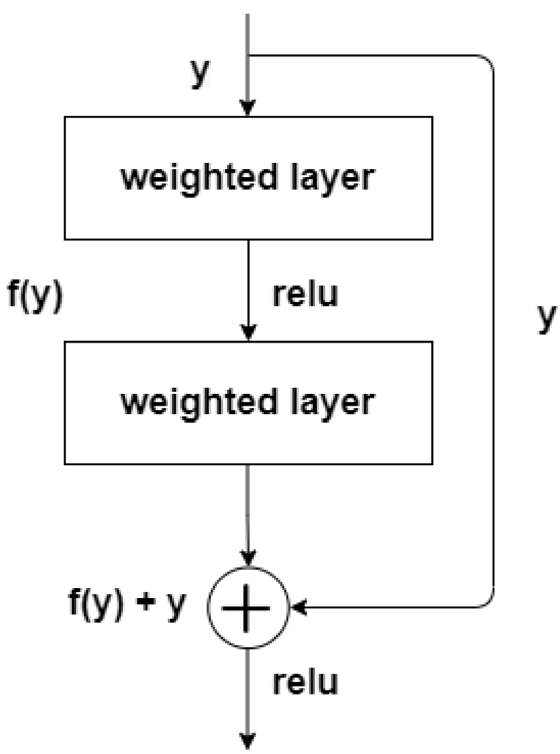
Consequently, the validation data is also generated along with the training and test dataset. It has been observed that 2490 validated images belong to five classes of images.

Step 5: Recognize the Concept and Logic Behind ResNet

In this step, the concept and logic behind the artificial neural networks, Convolution Neural Networks (CNN) and Residual Networks (ResNet) are recognized. In the previous step, we have been able to create our data generator and we created three different groups of images, we had our training data, we had our validation data, and we had our testing data as well. In artificial neural networks, we try to mimic the human brain, so our brain has hundreds of billions of neurons that communicate with each other with electrical and chemical signals. These connected neurons helped humans to see, think, create ideas, etc. The convolution neural network works well with images. An ideal convolution neural network has multiple convolution layers that are selected from various pooling filters. Once pooling filters are used for the selection then flattening is done to get the results.

The vanishing gradient tends to occur as the CNNs progress, which has a detrimental influence on network performance. When a gradient is back-propagated to older layers, a vanishing gradient develops, resulting in a very tiny gradient. The vanishing gradient problem is handled by the Residual Neural Network, which features a “skip connection” function that allows for the training of 152 layers. The ResNet algorithm works by layering “identity mappings” on top of the CNN. The ResNet is trained using ImageNet, which has 11 million pictures and 11000 classifications.

Figure 5. Residual network (ResNet)

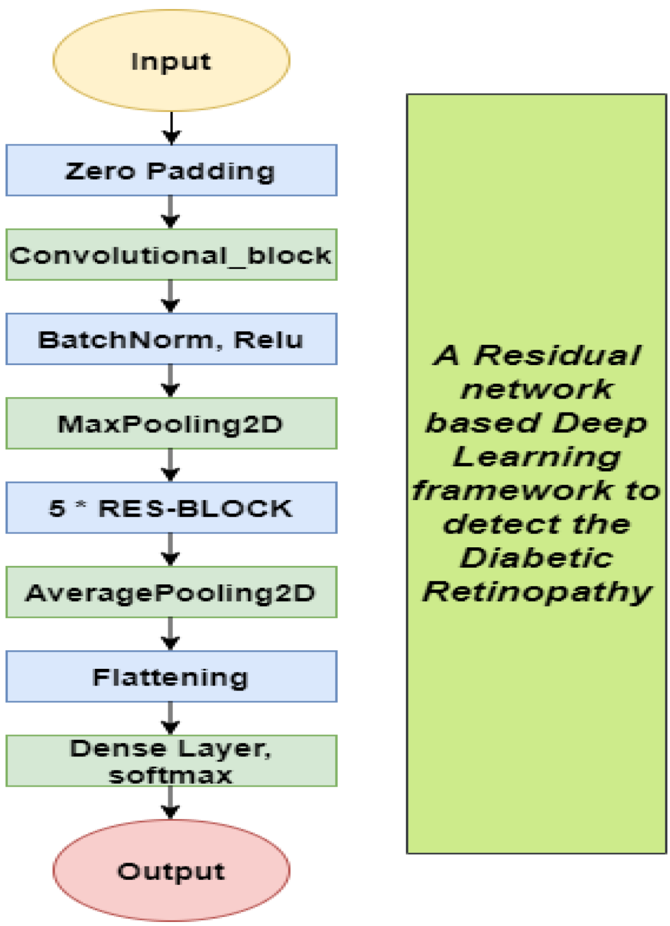


The working of ResNet is shown in Figure 5, and this model solves the problem of vanishing gradient. The "skip connection" feature can be used to reach out to the weighted layer. Initially, in the actual main network, we do zero-padding first and then followed by stage one. And in stage one, we come to the batch normalization activation, and then Max pooling. We have zero paddings, which comes to the batch normalization Max pooling 2D. And then we have the list of ResNet blocks afterward. We have the ResNet block followed by another ResNet block. If you want, you can add a stage here. Stage five ResNet block. We just ended up with only five ResNet blocks, followed by average pooling, flattening, and then dense or fully connected artificial neural network. Step by step working of the proposed methodology is described in the next step.

Step 6: Create Deep Residual Neural Networks (DRNNs)

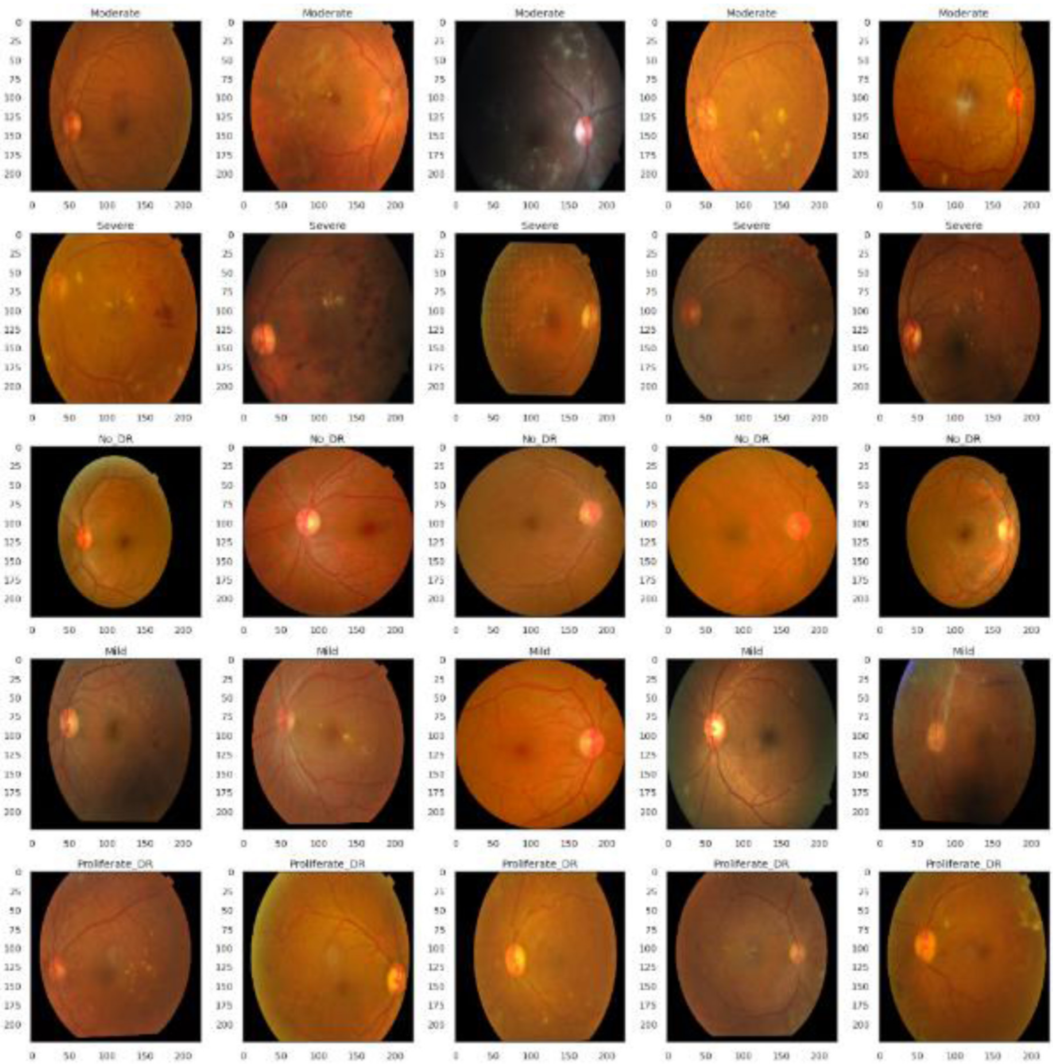
In the previous step, we have understood the concept of ResNet, now we create the deep residual neural network. The proposed framework is shown in Figure 6 and the algorithm used in the implementation of the proposed network is shown below. The implementation is performed in a staged systematic way. In stage 1, zero-padding is done, followed by batch normalization.

Figure 6. Proposed framework: Diabetic retinopathy detection



MaxPooling is done thereafter five stages of ResNet blocks are implemented sequentially as illustrated in Figure 7. At last, average pooling is done, followed by flattening and softmax activation function. The results are obtained, it has been observed that there are 4,987,525 total parameters, 4,967,685 trainable parameters, and 19,840 non-trainable params.

Figure 7. Classification of input images




```
Algorithm for the proposed framework
# Provide the shape of tensor
Y_input = Input(in_shape)
# Apply Zero-padding
Y = ZeroPadding2D((3,3))(Y_in)
# Stage-1
```

```
   Y = Conv2D(64, (7,7), strides= (2,2), name = 'conv1', kernel_
initializer= glorot_uniform(seed = 0))(Y)
   Y = BatchNorm(axis =3, name = 'bn_conv1')(Y)
   Y = Activation('relu')(Y)
   Y = MaxPooling2D((3,3), strides= (2,2))(Y)
   # Stage-2
   Y = resnet_block(Y, filter= [64,64,256], stage= 2)
   # Stage-3
   Y = resnet_block(Y, filter= [128,128,512], stage= 3)
   # Stage-4
   X = resnet_block(X, filter= [256,256,1024], stage= 4)
   # Stage-5
   # Y = resnet_block(Y, filter= [512,512,2048], stage= 5)
   # Apply Average Pooling
   Y = AveragePooling2D((2,2), name = 'Average_Pooling')(Y)
   # Final output layer
   Y = Flattening()(Y)
   Y = DenseLayer(5, activation = 'softmax', name = 'Dense_final',
kernel_initializer= glorot_uniform(seed=0))(Y)
```

Step 7: Create Deep Learning Model and Train It

In step 7, the deep learning model is created and trained, the Adam optimizer is used in the compilation of the model.

```
   model.compile(optimizer = 'adam', loss = 'categorical_
crossentropy', metrics= ['accuracy'])
```

If validation loss does not decrease after a given number of epochs, early stopping is used to end training.

```
   earlystopping = EarlyStopping(monitor='val_loss', mode='min',
verbose=1, patience=15)
```

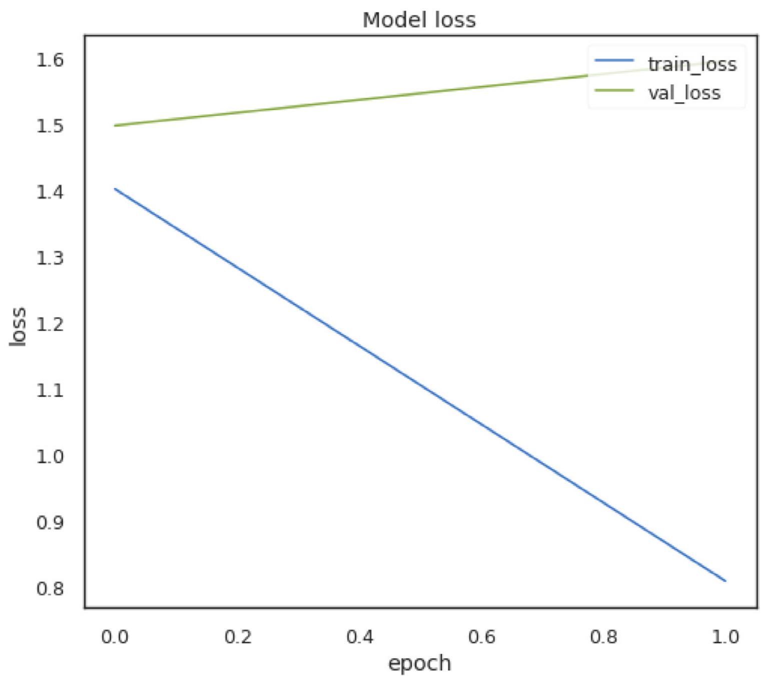
The best model with lower validation loss is saved to get the results.

```
   setcheckpoint = ModelCheckpoint(filepath="weights.hdf5",
verbose=1, save_best_only=True)
```

4. RESULTS AND DISCUSSION

In this section, the results obtained are elaborated and discussed. After creating the model in the previous sections, it was trained, and the training and validation loss is compared. As you can see in figure 8, the validation loss is going up whereas the training loss is decreasing with epochs. This ultimately shows that the model has attained a reduction in training loss. The training loss quantifies the disparity or deviation between the projected output and the desired objective during the training stage of a machine learning model. It quantifies the level of performance of the model on the training data. The objective during training is to minimise the loss, indicating that the model is acquiring the ability to generate more precise predictions on the training set. The loss is commonly computed using a loss function, which measures the discrepancy between the predicted values and the actual values. Validation loss is analogous to training loss, except it is computed on a distinct dataset known as the validation set. The validation set is separate from the training set and is excluded throughout the training phase. Instead, it functions as a separate dataset to assess the model's performance on unseen data. Monitoring the validation loss allows for the evaluation of the model's ability to generalise to novel, unseen data. The objective is to construct a model that exhibits high performance not just on the training data but also on novel, previously unobserved data.

Figure 8. Train loss v/s validation loss

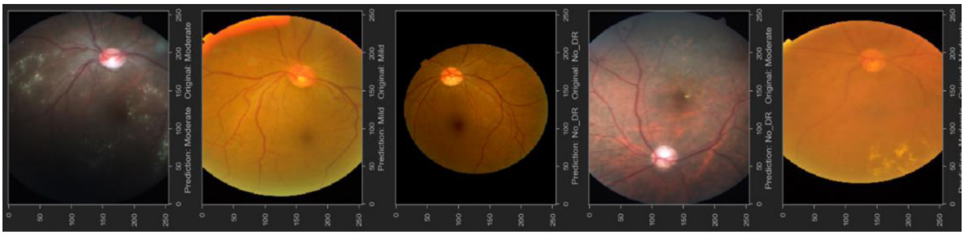


Finally, the effectiveness of the proposed model is evaluated. The test accuracy is calculated at 84.35% using the test_generator() method. After that, labels are assigned to the corresponding indexes e.g. 0: mild, 1: moderate, and so on. The formula used to get the test accuracy is given below:

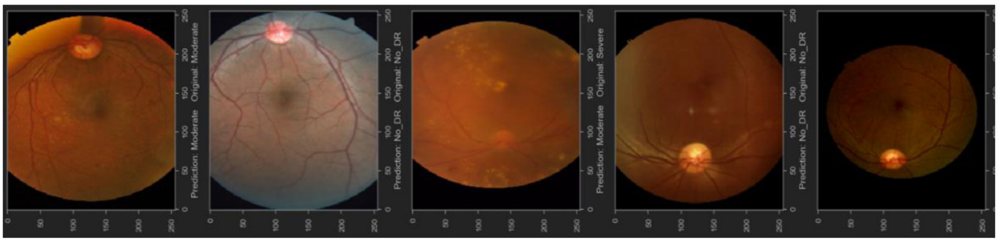
```
evaluate = model.evaluate(test_generator, steps = test_
generator.n // 32, verbose =1)
```

Thereafter, the images are loaded along with their predictions. It has been observed that the test accuracy came out to be 0.8417462482946794. Figures 9 a to d show the visualization of predicted v/s original images. Five samples from each class are displayed for visualization.

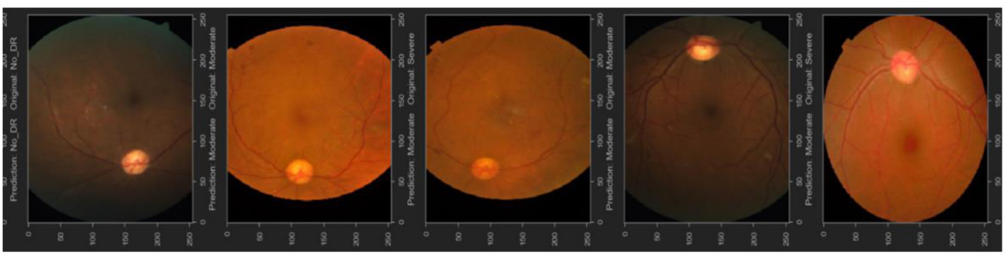
Figure 9. Prediction v/s original images



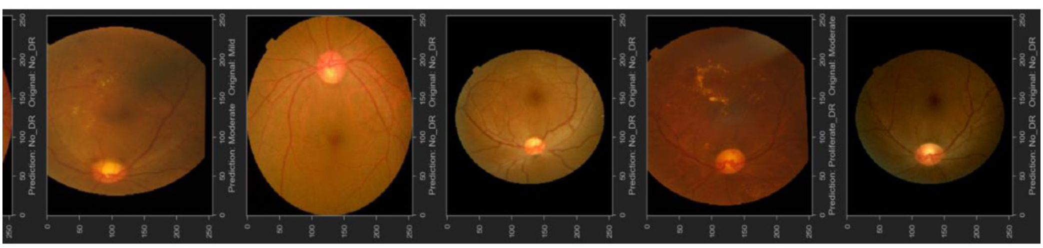
(a)



(b)



(c)



(d)

Figure 10 shows the confusion matrix of the predicted images v/s the original images.

Figure 10. Confusion matrix (predicted v/s original)

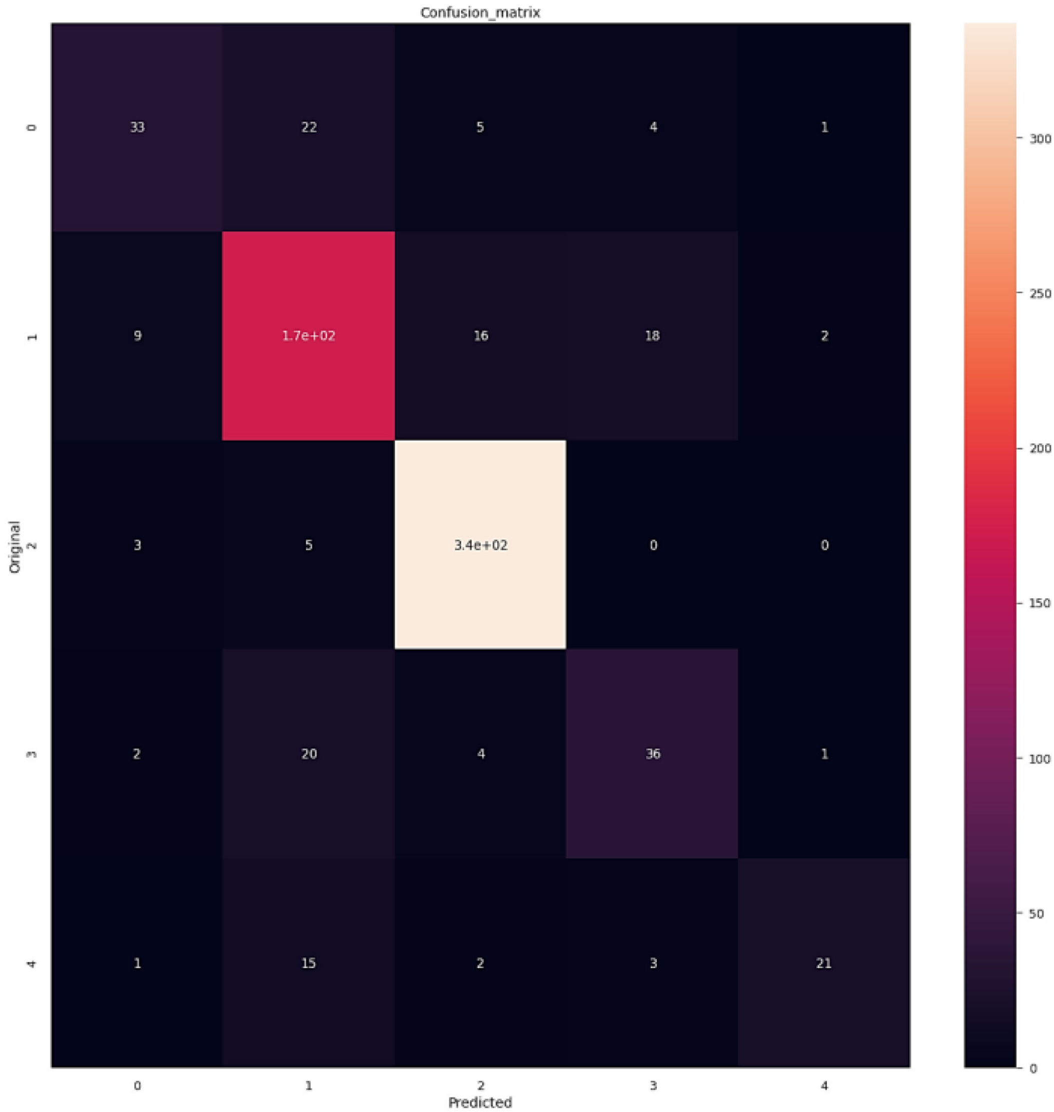


Table 2 shows the classification report of the proposed framework. The classification report shows the precision, recall, F1-score, and support of all five classes.

Table 2. Classification report

	Precision	Recall	F1-score	Support
Mild	0.74	0.54	0.62	65
Moderate	0.69	0.83	0.75	190

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Table 2. Continued

	Precision	Recall	F1-score	Support
No_DR	0.95	0.97	0.96	382
Proliferate_DR	0.58	0.52	0.55	58
Severe	0.82	0.51	0.51	38
Accuracy			0.83	733
Macro avg	0.76	0.64	0.68	733
Weighted avg	0.83	0.83	0.82	733

Table 3 highlights the comparative analysis of various latest papers that are related to Diabetic Retinopathy Detection using the Deep Learning approach. In this table, various parameters are taken for comparison and the major findings have been highlighted.

Table 3. Comparative analysis of latest papers related to diabetic retinopathy detection

Author	A	B	C	D	E	F	Major Findings
(Qiao et al., 2020)	✓	✓	✓	✓	✓	✓	The suggested system analyzes the existence of microaneurysms in fundus images utilizing deep neural networks methods with deep learning as a foundational element, which will conduct medical picture recognition and segmentation with low- and high interpretation. The fundus image is classified as normal or diseased using the semantic segmentation technique. To detect the characteristic of microaneurysm, semantic segmentation splits the picture pixels based on their shared connotation.
(Qummar et al., 2019)	✓	✓	✓	✓		✓	In this research, the authors offered an autonomous deep-learning-based technique for detecting the stage of diabetic retinopathy in the individual fundus using a single image. We also present a multistage transferable learning strategy, which uses comparable datasets with varied labeling. The proposed approach, which has a sensitivity and accuracy of 0.99 and ranks 54 out of 2943 competing methods, may be utilized as a screening tool for the early identification of diabetic retinopathy.
(Alyoubi et al., 2020)	✓	✓	✓	✓		✓	The latest state-of-the-art approaches for detecting and classifying DR color fundus pictures using convolutional neural networks have been studied and discussed in this paper. In addition, the color fundus retina datasets accessible on DR have been examined. Various difficult topics that demand more examination are also mentioned.
(Li et al., 2019)	✓	✓	✓	✓		✓	This research might aid ophthalmologists in evaluating and treating patients, lowering the incidence of vision loss, and allowing for a more quick and precise diagnosis. In this paper, the authors created and tested OCTD Net, a new deep network for DR detection in the early stage. One network retrieved characteristics from the original OCT picture, while the other fetched information from the retinal layer. The sensitivities, specificity, and accuracy were all 0.92, 0.90, and 0.95, respectively.
(Hacisoftaoglu et al., 2020)	✓	✓	✓	✓	✓	✓	In this paper, the deep learning approach is used to detect diabetic retinopathy, without changing the structure of the vein. The retina images from different datasets are used in this paper.

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Table 3. Continued

Author	A	B	C	D	E	F	Major Findings
(Rakhlin, 2018)	✓	✓	✓	✓		✓	In this paper, the author utilized a publicly accessible Kaggle data set to train our models. We utilized a subset of Kaggle data that had been excluded from training and the Messidor-2 ultimate source for testing. For training, neither withheld Kaggle pictures nor Messidor-2 was employed.
(Heisler et al., 2020)	✓	✓	✓	✓		✓	This paper, to see how well ensemble-learning approaches combined with deep learning can categorize DR in optical coherence tomography angiography pictures and their co-registered architectural pictures.

A: Diabetes B: Retinopathy C: Deep Learning D: Convolution Neural Networks E: Artificial Intelligence F: Fundus Image

5. THEORETICAL AND PRACTICAL CONTRIBUTIONS

A distinctive theoretical contribution is presented in this paper: a deep learning framework based on residual networks, especially tailored for the identification of diabetic retinopathy (DR) from retinal pictures. Our approach takes advantage of artificial intelligence (AI) and machine learning (ML) to address the pressing need for early detection and categorization of diabetic retinopathy (DR), the world's leading cause of blindness. The suggested architecture incorporates cutting-edge methods specifically designed to handle the intricacies of DR diagnosis while expanding on prior research in AI-driven medical imaging.

This research has significant and diverse practical implications. First off, with an astounding accuracy of 83%, our suggested deep learning architecture provides a very precise and effective way to identify DR from retinal pictures. This outperforms current approaches and gives medical professionals a trustworthy tool to quickly and correctly detect DR. Second, the robustness of our technique is highlighted by the accuracy value of 95% for determining the absence of DR, reducing the possibility of false negatives and guaranteeing accurate findings in clinical situations. This high level of precision is necessary for resource allocation and patient triage to be done effectively. Our framework's scalability and adaptability make it especially well-suited for implementation in resource-constrained situations, including rural locations where access to qualified medical professionals and medical screening may be restricted. Healthcare services can potentially reach millions of people who are at risk of vision loss and degeneration by utilizing AI technology to expand the scope of DR diagnosis and intervention.

This study provides a workable answer to an urgent medical problem, marking a substantial development in the use of AI and ML in healthcare. Our contribution to the continuous endeavors to boost healthcare outcomes and elevate the quality of life for people afflicted with diabetic retinopathy is to blend state-of-the-art technology with an exacting scientific approach.

6. CONCLUSION

In this work, the authors have implemented a deep residual neural networks-based learning framework. A dataset with 3662 retina images with 1805 No_DR images and 1857 images of five different stages of DR has been used in the proposed framework. Out of these 3662 retina images, 2929 pictures are taken for training purposes and 733 images are used to check the accuracy after training. The proposed framework has achieved an accuracy of 96% in classifying No_DR retina images. The accuracy of classifying the DR retina images into five different stages of DR ranges between 0.51 – 0.75. The proposed framework achieved an overall accuracy of 83%. The method used in this paper provided good results, we look forward to using the deep learning approach in detecting glaucoma or cataract in our future work.

CONFLICTS OF INTEREST

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

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