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Diabetic Retinopathy Detection Using Deep Learning

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ABSTRACT

If left untreated, diabetic retinopathy, a condition brought on by chronic diabetes, can cause complete blindness. Therefore, early detection of diabetic retinopathy is crucial, as is medical intervention to avoid its negative consequences. Ophthalmologist detection by hand takes longer and causes significant discomfort when being examined. One of the most well-liked methods for enhancing performance in a number of fields, including medical image analysis and classification, is machine learning. Consequently, an automated system helps identify diabetic retinopathy early. This study provides machine learning for the extraction of exudates, hemorrhages, and micro-aneurysms using a combination of neural networks. With an Accuracy of 85%,an artificial neural network model was able to identify diabetic retinopathy. Diabetic retinopathy has been successfully identified by a convolution neural network model, which also provides information on the disease's severity. The model's achieved Accuracy is 95%.

KEYWORDS: Diabetic Retinopathy (DR), Machine Learning, Artificial Neural Networks and Deep Learning.

I. INTRODUCTION

Diabetes, or hyperglycemia, is the cause of diabetic retinopathy, an eye condition. In severe situations, it can result in complete blindness and vision loss. Early signs of diabetic retinopathy include cloudy eyes, blurred vision, dark patches of vision, and trouble identifying colors. In order to avoid complete blindness, diabetic retinopathy must be identified early. Diabetic retinopathy affects about one-third of the estimated 285 million people with diabetes worldwide. By 2030, there will be 191 million cases of diabetic retinopathy worldwide, up from 126.6 million in 2010.a type of early retinal disease known as non-proliferative diabetic retinopathy (NPDR)is distinguished by tiny red spots. The presence of DR is indicated by the appearance of different kinds of lesions on retinal images. If left untreated, diabetic retinopathy (DR), a complication of diabetes that damages the blood vessels in the retina, can result in blindness and vision loss. The risk of vision loss can be considerably decreased with early detection and prompt treatment. However, manually screening retinal images is a labor-intensive and time-consuming process that calls for expertise that is frequently lacking in environments with limited resources.

DR is a leading cause of blindness world wide, affecting millions of people with diabetes. Early detection and treatment can reduce the risk of vision loss by 90% [1]. Manual screening of retinal images is not feasible for widespread screening programs due to limited resources and expertise. Machine learning techniques[1] have shown promise in detecting DR from retinal images, achieving high Accuracy and sensitivity [2-4].Learning of deep models, such as convolution neural networks (CNNs), have been widely used for DR detection [5-7]. Transfer learning and ensemble methods have improved model performance [8-9].Limited availability of annotated datasets for training and validation. Variability in image quality and artifacts. Lack of interpretability and explainability of models. Develop a machine learning-based system to automatically detect DR from retinal images, addressing the limitations of current research. The system will use a deep learning model, leveraging transfer learning and ensemble methods, to classify retinal images into different stages of DR.

Dietterich and associates (2000), Machine Learning Ensemble Methods. Multiple Classifier Systems: Learning algorithms referred to as ensemble methods construct a set of classifiers and then classify new data points using a (weighted) vote of their predictions. Although bagging, boosting, and error-correcting output coding are more recent algorithms, Bayesian averaging was the original ensemble method.. In this paper, these techniques are reviewed and the reasons why ensembles frequently outperform individual classifiers are explained. In order to understand why ada- boost does not over fit quickly, some new experiments are presented and some earlier studies comparing ensemble methods are reviewed.
Hagos and associates. Using the 2500 fundus photos from the Kaggle DR recognition challenge dataset, a model was created to categorize images into two classes of DR using the pre-trained Inception V3 framework. bottom. They achieved 90.9%Accuracy and 3.94% loss when they applied the SGD Optimizer to their models. Alzami Farrikh, 2019 The MESSIDOR data set and fractal analysis Random Forest serve as the foundation for this diabetic retinopathy grade classification system after segmenting the image, your computer system computed the fractal dimension using a function. They were unable to distinguish between mild and severe diabetic retinopathy. Qomariah, 2019 Diabetic retinopathy and normal retina images are classified using convolution neural networks and support vector machines (SVM). Features include bleeding, exudates, and micro aneurysms.
The main Objective of this work:
1. Create a reliable machine learning model to categorize retinal images into the normal, mild, moderate, severe, and proliferative stages of DR.
2. To guarantee accurate DR detection, attain high sensitivity and specificity.
3. For training and validation, use publicly accessible datasets (like Kaggle and Eye PACS) or gather and annotate fresh data.
4. Provide a user-friendly interface that allows medical professionals to upload retinal images and get an immediate diagnosis.

II. Convolutional Neural Networks (CNNs):

Convolutional Neural Networks (CNNs) ar a form of deep learning artificial intelligence algorithm that is used to handle and analyze in a grid-like format, i.e., images. They perform well especially tasks related to image recognition, classification and object detection because they can automatically acquire spatial hierarchies of features.

Key Components of CNNs:

1. Convolutional Layer: This is the fundamental component of CNN. It uses a number of filters (also known as kernels) on the input image and pulls out important features such as edges, textures and patterns. These filters pass across the input data and give feature maps, which indicate the existence of certain features in varying positions.

2.Activation Function: Once convolution is performed, an activation function (usually ReLU -Rectified Linear Unit) is added to add non-linearity to the model. This enables CNN to get to know more complicated patterns.

3.Pooling Layer: The pooling layers decrease the size of feature maps spatially, decreasing the computational cost and enabling over fitting. One of the common techniques is the max pooling technique, in which the maximum value in a small area is considered to be the output.

4. Fully Connected Layer: The output of several convolutional and pooling layers is then flattened and overcome by fully connected (dense) layers. These layers carry out the final classification or prediction with reference to the features retrieved in the previous stages.

5. Output Layer: The last layer gives the prediction based on the likelihood of the input image being part of a particular class, e.g., on the use of soft max or sigmoid functions depending on task.

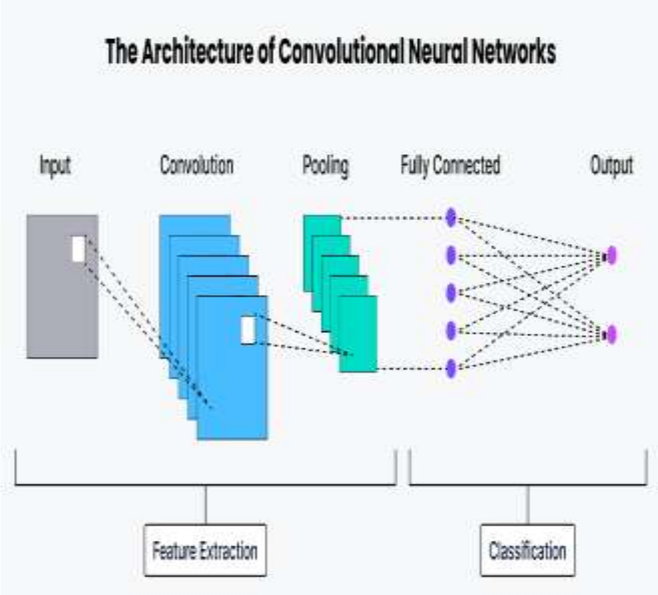


Fig2.1: The-Architecture of Convolutional Neural Networks.

- **Advantages of CNNs**
- **A**

utomatic Feature Extraction: CNNs do not require any manual feature engineering since they learn features in the form of raw data**.**

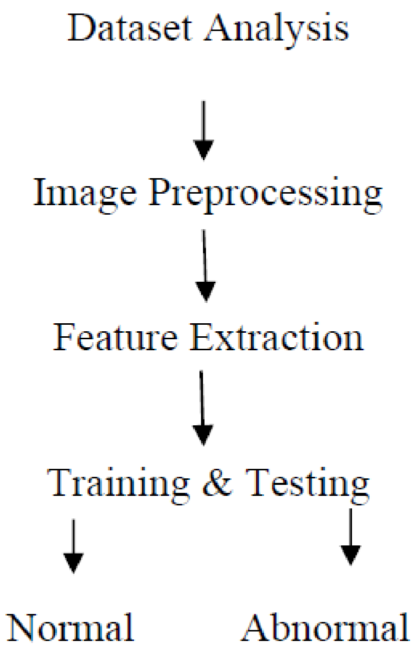
- **Parameters Sharing:** Sharing the same filter within the input decrease parameters in the network making it more efficient.
- **Translation Invariance**: CNNs are robust to changes in the position of objects within images, improving generalization.
- **CNNs are widely used in:**

➢ Image Processing applications
➢ Health sector
➢ Face and speech analysis
➢ Automation of cars ex: self driving cars

III. Artificial Neural Network(ANN):

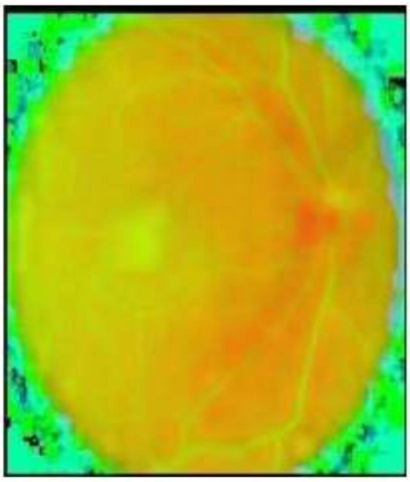
As a computing system, an artificial Neural Network (ANN) consists of basic, highly connected processing components that process intelligence based on their dynamic state in response to external inputs. The study of ANN models has become more and more important in recent years. This is due to their potential to provide answers to some of the issues in computer science and artificial intelligence that were previously unsolvable by conventional serial computers. Neural networks are particularly well-suited for human-like performance in robotic authority, machine vision, speech processing, and image acceptance, among other areas.

1V.Methodology:



- **Feature extraction and pre-processing:**
- The image from the dataset is first converted to an HSV image as part of image preprocessing to identify exudates. An image displayed in one color space can be changed into another using color space conversion. Saturation and value are channelized to hue in the designated image for red, blue, and green. The extraction of yellow exudates from the RGB image is helpful when converting RGB to HSV. The next steps are median filtering and edge zero padding. Figures 2and 3 depict the image prior to and following preprocessing, respectively.

Fig 4.1. Before Preprocessing



- **Fig4.2.A**fter Preprocessing

- Extraction of Features:

Here, binary classification employs two functions. Micro aneurysms are the second parameter, and the quantity of exudates is the first. Divide the number of white pixels in the preprocessed image by the total number of pixels in the image.

- Training Models:

Models with more than 20 epochs of training. A loop through a convolutional neural network's training dataset is called an epoch. Neural network training typically requires a significant amount of time. The ADAM optimizer was used to train the model. The optimizer is a method or instrument that modifies the learning rate and weights of neural networks in order to reduce losses. The best optimizer is ADAM since it is incredibly effective and requires very little time to train the model. A cross-entropy loss function, an activated soft max layer, and a batch size of 16 are used to train the model. Adam's standard parameter, a learning rate of 0.001, is applied.

- **Testing Models:** .

A fresh set of 200 retinal images that weren't part of the 1000 images used to train the model were used to test it. While the model is being tested, image preprocessing and feature extraction are carried out. 91.5 accuracy and 3.8% loss with 20 epochs. Parameters of Performance

- "Accuracy is the percentage of total accurate predictions which are based on the positive and negative classes."

- $\boldsymbol{Accuracy = (TP+TN)/(TP+FN+TN+FP)}$

where TP, TN, FP and FN are true positive, true negative, false positive and false negative respectively.

- **Recall/Sensitivity:** "Sensitivity is also called TPR (True Positive rate)" [1], which can be calculated as follows:
- $\boldsymbol{recall = TP/(TP+FN)}$

Precision: "It is the ratio of a truly classified number of samples and the given sum of True positive and False positive" [1]:

- **Precision = TP/(TP+FP)**
- **F1-Score:** It is "the harmonic mean of recall and precision"

- $\boldsymbol{F1 = 2\,(Precision)(recall)/(Precision+recall)}$

V. WORKFLOW

Step 1: Data Collection

- Download dataset from Kaggle (APTOS / EyePACS).

- Each image labeled as:
  - 0: No DR
  - 1: Mild
  - 2: Moderate
  - 3: Severe
  - 4: Proliferative DR

Step 2: Data Preprocessing

- Resize images (e.g., 224×224 or 299×299).
- Normalize pixel values (divide by 255).
- Remove noisy or low-quality images.
- Augment data (flip, rotate, zoom) to reduce over fitting.
- Split data into train, validation, and test sets.

Step 3: Model Building

Option A: Baseline CNN

- Build a 4–5 layer CNN with Conv, Pooling, Dropout, and Dense layers.

- Use Soft max for multi-class classification.

Option B: Transfer Learning

- Use pre-trained models (ResNet50, EfficientNetB0, or InceptionV3).

- Fine-tune last few layers for DR classification.

Step 4: Model Training

- Compile model with:

- Optimizer: Adam
- Loss: Categorical Cross entropy
- Metrics: Accuracy, Precision, Recall, F1-score, AUC

- Train for multiple epochs with early stopping and learning rate scheduler.

Step 5: Model Evaluation

- Evaluate using accuracy, confusion matrix, F1-score, and ROC-AUC.
- Visualize training curves (loss vs. epoch, accuracy vs. epoch).
- Optionally, visualize Grad-CAM heat maps for interpretability (to show which region of the retina the model focuses on).

Step 6: Deployment (Optional)

- Export trained model (.h5 or .pt).
- Create a web interface (Flask or Stream lit) to upload fundus images and predict DR stage.

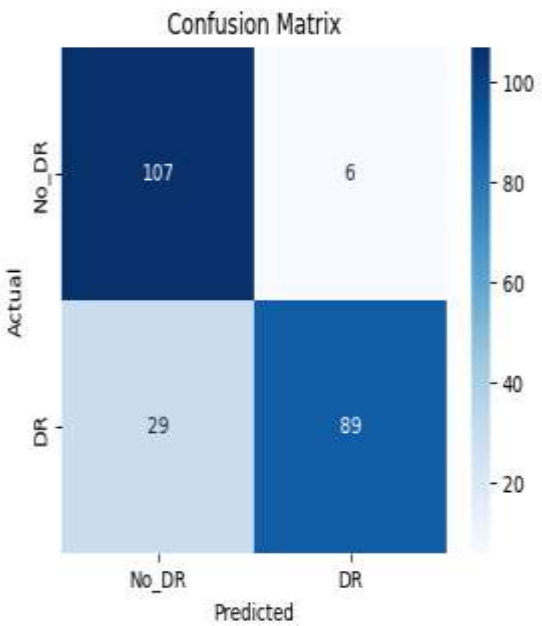


FIG 5.1 Confusion Matrix of ANN Model

TABLE 5.1 Classification Report of ANN model:

	precision	recall	f1-score	support
No_DR	0.79	0.95	0.86	113
DR	0.94	0.75	0.84	118
Accuracy	-	-	0.85	231
Avg of Macro	0.86	0.85	0.85	231
Avg wt	0.86	0.85	0.85	231

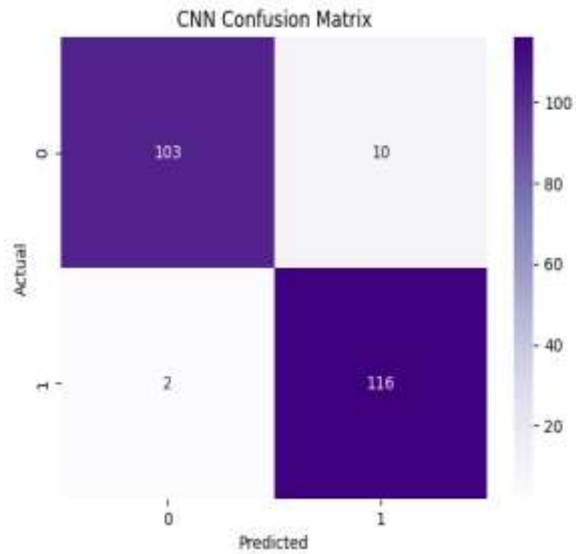


FIG 5.2 Confusion Matrix of CNN Model

TABLE 5.2 Classification Report of CNN model:

	precision	recall	f1-score	support
No_DR	0.98	0.91	0.94	118
DR	0.98	0.91	0.94	113
Accuracy	-	-	0.95	231
Avg of Macro	0.95	0.95	0.95	231
Avg wt	0.95	0.95	0.95	231

To RUN Web applications

Click on URL link in #Cell 12

🌍 Public URL: NgrokTunnel: "https://sultry-smudgedly-pearle.ngrok-free.dev" -> "http://localhost:8000"

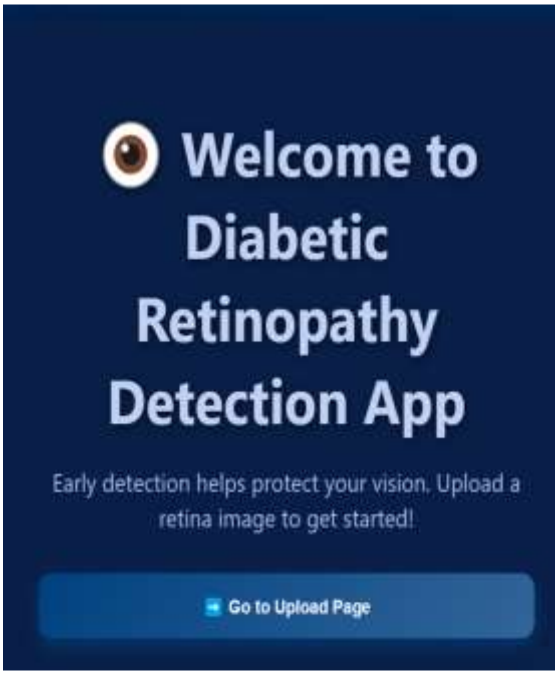


Fig 5.3 Choose file from "Diagnosis of Diabetic Retinopathy" in Computer

Fig 5.4 Click on Choose file to upload

Fig 5.5 Response for Test—No_DR image

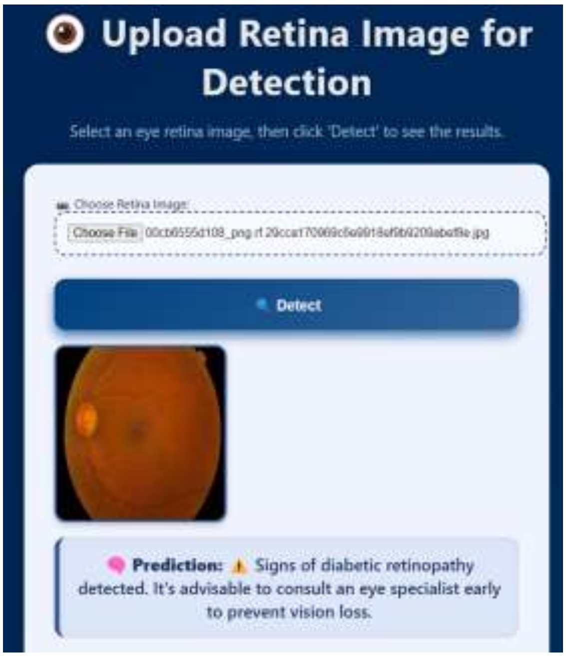


Fig 5.6 Response for Test—DR image

ANN Accuracy 85%

CNN Accuracy 95%

CONCLUSION

One of the diseases that has grown the fastest in recent years is diabetes. Studies show that people with diabetes have a 30% chance of getting diabetic retinopathy. Floater, blurred vision, and eventually blindness can result from the disease if it is not detected early. Diagnosing these photos by hand takes a lot of time, is complicated, and calls for highly skilled experts. With an Accuracy of 85%, an artificial neural network model was able to identify diabetic retinopathy. Diabetic retinopathy has been successfully identified by a convolution neural network model, which also provides information on the disease's severity. The model's achieved Accuracy is 95%. This model facilitates faster disease diagnosis for medical professionals. Other diseases, particularly those affecting the eyes, can be diagnosed using similar models. This helps identify such illnesses early and avoid permanent blindness.

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