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# SYSTEMATIC DEVELOPMENT OF AL-ENABLED DIAGNOSTIC SYSTEMS FOR GLAUCOMA AND DIABETIC RETINOPATHY

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***Abstract:*** The primary causes of vision impairment and blindness are retinal diseases, which include diabetic retinopathy, age-related macular degeneration, glaucoma, and retinal detachment. Correct and timely diagnosis of these illnesses is essential for efficient treatment and patient care. This abstract describes a novel use of convolutional neural networks (CNNs) for the diagnosis and prediction of various retinal diseases. A large dataset of retinal images covering a variety of retinal diseases is gathered and labelled with disease names in this study. To guarantee consistency and improve the model's capacity to pick up pertinent features, these photos go through a thorough preprocessing process. Techniques for data augmentation are used to diversify datasets more. The architecture of a CNN is intended for the categorization of retinal disorders. Convolutional layers are used in this architecture to extract features, and pooling layers are used to reduce dimensionality. Fully connected layers are then used to classify diseases such as Glaucoma and Multiple diabetics. Using supervised learning methods, the model is trained on the annotated dataset, optimizing the loss function and keeping an eye on validation performance to avoid overfitting. On a different test dataset, the CNN model's performance is evaluated using a number of evaluation metrics, such as accuracy, precision, recall, F1-score, and the AUC-ROC score. Additionally, post-processing steps are used to eliminate predictions with low confidence, increasing the model's clinical usefulness.

**Keywords:** Fundus images, Machine learning, Deep learning, Convolutional neural network algorithm, Retinal diseases.

## I. INTRODUCTION

The intricate and sensitive retina in humans is in charge of converting light into visual signals so that we can see our surroundings. Regrettably, a number of illnesses and disorders can affect the retina, such as age-related macular degeneration, glaucoma, diabetic retinopathy, and retinal detachment. If these conditions are not identified and treated, they can result in permanent vision loss or even blindness. Timely intervention and better patient outcomes are contingent upon an early and precise diagnosis of these retinal diseases. Convolutional neural networks (CNNs), one of the most recent developments in deep learning and artificial intelligence, have created new opportunities for the creation of automated diagnostic tools in the field of ophthalmology. CNNs are incredibly effective at image analysis tasks and have shown great promise in a number of medical applications, such as the identification and categorization of retinal disorders. The goal of this research is to use digital retinal images to predict and diagnose various retinal diseases by utilizing CNNs. Our goal is to train a CNN model that can accurately identify the presence and severity of different retinal diseases by using a well-annotated and diverse dataset of retinal images. Using CNNs in this situation has a number of benefits, such as the capacity to identify complex patterns and features in retinal images that may be invisible to human observers and the ability to speed up the diagnosis process so that clinical interventions can be made on time. Moreover, the implementation of automated systems can aid in filling the shortage of specialized ophthalmologists in areas with restricted access. Figure 1 shows the Retinal image with multiple parts for disease affected image.

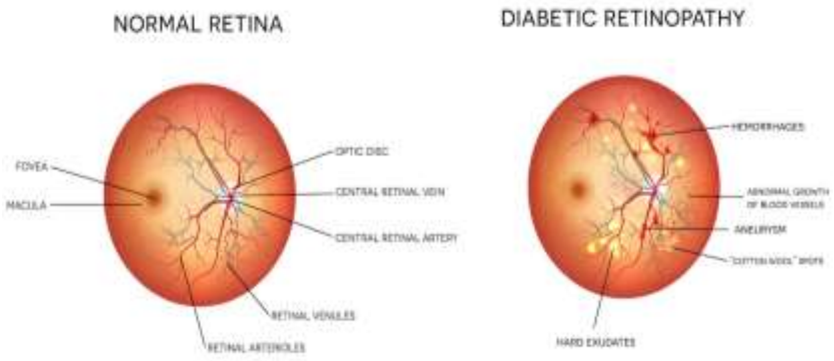



Figure 1: Normal Retina vs Diabetic retinal images

## II. RELATED WORK

Muhammad mateen, et.al,…[1] covered a detailed survey about the identification of diabetic retinopathy in the light of almost 150 research articles, summarized with the collection of retinal datasets, adoption of different kinds of methodologies to detect the diabetic retinopathy and select the performance evaluation metrics for the representation of their outcomes. Initially, retinal datasets are discussed and then several kinds of approaches have been explained to detect the retinal abnormalities including retinal neovascularization, hemorrhages, micro aneurysm, and exudates. In the literature, it was noted that most research work has been performed with the use of convolutional neural network models to develop deep multi-layer frameworks for the diagnosis of diabetic retinopathy using digital retinal fundus images, but on the other hand, the analysis and explanation of retinal photographs need ophthalmologists, which is time-consuming and very expensive task. Hence, it's necessary to introduce effective deep learning-based approaches that can learn by a limited retinal dataset

K. Shankar, et.al,….[2] implemented various DL models are available for DR classification, the hyperparameter tuning process of DL models are not extensively addressed. The hyperparameter tuning technique helps to properly select the parameter values and leads to better classification performance. In this view, this paper introduces a new automated Hyperparameter Tuning Inception-v4 (HPTI-v4) model for the prediction and classification of DR from color fundus images. The presented HPTI-v4 model is composed of diverse sub-processes like preprocessing, segmentation, feature extraction, and classification. Here, the segmentation process takes place by histogram-based segmentation, and the inception-v4-based feature extraction process takes place. For tuning the hyperparameters in inception-v4, the Bayesian optimization technique is involved. Finally, the classification process takes place under the application of multilayer perceptron (MLP).

Along He, et.al,…[3] presented a novel CABNet that combines CAB and GAB. CABNet can be trained in an end-to-end manner for fine-grained DR grading and learn discriminative features by the attention module. Extensive experiments on three datasets demonstrate that CABNet can achieve superior DR grading performance with different backbone networks, which shows the generality of our method. Our future work is to use generative adversarial networks (GANs) for synthesizing high-quality fundus images with labels. This is critical in the medical field since it is expensive to obtain annotated images. We could thus design a more effective model that can not only provide a grading score, but also indicate the lesion type. By using these synthetic datasets to pretrain the deep model and then fine-tuning on real retinal fundus datasets, we may further improve the DR grading performance.

Harshit kaushik, et.al,…[4] solved the non-ideal illumination and color degradation problems by using the gray world color constancy schema to desaturate the retinal images. This will enable ophthalmologists to use color of the images as a reliable cue for recognizing the DR signs and avoid the various distortions related to light distribution and color, which may hinder the diagnostic results. Scaling factor is an important step in color correction technique such as gray world in our case, therefore, the color channel with minimum mean is considered as a reference to calculate the gray world illuminant. To automate the diagnostic process and to make predictions using the desaturated images, a stacked generalization of three custom CNNs is developed, which is fed into a single meta-learner to extract the most optimum weights from the sub-networks to achieve better performance. This method differs from a usual voting classifier because the evaluation metrics (e.g. accuracy and mean squared error) are not averaged or voted, but rather the meta-learner model gets multiple

prediction probabilities as input, which are combined to generate better features and thus achieve accurate results.
Yi Zhou, et.al,…[5] proposed a large fine-grained annotated DR dataset, FGADR. Moreover, we conducted extensive experiments to compare different state-of-the-art segmentation models and explore the lesion segmentation task. Joint classification and segmentation methods were demonstrated to have better performance on the DR grading task. We also developed an inductive transfer learning method, DSAA, to exploit our DR dataset for improving ocular multi-disease identification. They are principally observed in the macular region, as the lipids coalesce and extend into the fovea. Soft exudates (SE), also sometimes referred to as 'cotton-wool spots' (CWS), are greyish-white patches of discoloration in the nerve fiber layer, or precapillary arterial occlusions. They usually appear in severe DR stages. Moreover, intra-retinal microvascular abnormalities (IRMAs) are areas of capillary dilatation and new intra-retinal vessel formation. A pre-proliferate DR stage can be predicted once IRMA is present in numbers. Neovascularization (NV) is a significant factor of proliferate DR. As the retina becomes more ischaemic, new blood vessels may arise from the optic disc or in the periphery of the retina. Therefore, identifying these related regions can be helpful for DR grading
S. GAYATHRI, et.al,…[6] implemented an automated approach for classifying DR is proposed in this work by integrating the features extracted using Haralick and ADTCWT. The extracted features using the proposed method made the classification task smoother. For performance analysis, the extracted features are given to four classifiers (SVM, Random Forest, Random Tree, J48) and evaluated the performance. According to the performance analysis, the Random Forest classifier with the proposed feature extraction outperforms all the other classifiers for the MESSIDOR, KAGGLE and DIARETDB0 databases. The DR is categorized as Nonproliferative DR (NPDR) and Proliferative DR (PDR). From the diagrams, the changes in the retina are clearly visible. If any of these conditions persist, then it is considered that the subject has DR. Generally, ophthalmologists are considering the mentioned lesions for the DR detection and to know about its severity.
Mohammad t. Al-antary, et.al,….[7] presented a novel deep learning model (MSA-Net) is proposed for the classification of the damage caused by DR on retina images. To improve the representation power of the network, the multi-scale attention mechanism on top of the high-level feature representation has been introduced. The multi-scale mechanism consists of the Atrous convolution which processed the input feature with different scales. The attention maps were produced with a series of convolutional layers. The attention maps were employed to focus on more informative parts of the multi-scale representation and suppress the weak ones. Furthermore, the multi-level and multiscale representation layers were included in the network to boost the performance. Training model in form of multitask learning achieved better performance than previous work described in the literature. The experimental results demonstrate the effectiveness and efficiency of the proposed model in diagnosing and classifying the DR disease
Yi Zhou, et.al,…[8] proposed an effective high-resolution DR image generation model which is conditioned on the grading and lesion information. The synthesized data can be used for data augmentation, particularly for those abnormal images with severe DR levels, to improve the performance of grading models. In our future work, more real annotated pixel-level lesion masks will be added for training DR-GAN better. Adopting such imbalanced data will make the model less sensitive to samples with higher DR severity levels and lead to overfitting. Although common data augmentation methods such as flipping and random cropping and rotation can mitigate the problem, the poor diversity of samples from those levels still limits model performance. Thus, in this paper, we propose an image generation model that synthesizes more miscellaneous DR images with different grading levels, and use these generated images to help train a grading model.
Eman abdelmaksoud, et.al,…[9] developed a novel ML-CAD system that can be applied on varied datasets to diagnose diabetic retinopathy grades. We used nine public benchmark datasets; DRIVE, CHASEDB1, STARE, HRF, IDRiD, DIARETDB1, MESSIDOR, and E-ophtha. At first, the proposed system filters and enhances the contrast. Then, it utilizes 11 texture feature descriptors by using GLRLM to determine the normal and DR images. Then, prepares the DR images by postprocessing steps for U-Net model. The U-Net model is trained four times on the four variations (hemorrhages, exudates, Blood Vessels, and microaneurysms). The system extracts 6 features; 2 for BV using GLCM with 11 descriptors and bifurcation point's count, 4 ROIs areas computations. Then, the system utilized the MLSVM for ML classification depending on the problem transformation. Finally, we computed 6 performance matrices averages of the proposed ML-CAD system. Our system proved that it is reliable and robust. It can be applied on the real world as it can be applied on different color fundus images with different cameras' settings, and different patients
Teresa araújo, et.al,…[10] propose an heuristic-based data augmentation scheme based on NV-like structures generation that compensate for the lack of PDR cases in DR-labeled datasets. The proposed neovessel synthesis algorithm relies on the general knowledge of common location and shape of these structures. NVs are generated and introduced in pre-existent retinal images which can then be used for enlarging deep neural

networks' training sets. Training with this type of data augmentation allows to increase detection of real NVs in independent test sets. However, part of the PDR images is still not detected since they do not present NVs but rather pre-retinal fibrosis or pre-retinal hemorrhages, which were poorly learned by the model. NVs which present an unusual shape or that are too slight are still being missed by the model, likely due to its lack of representation in the generated dataset. This study shows the potential of introducing NVs in retinal images for improving the detection of these proliferative DR signs, thus allowing to improve the performance of computer-aided DR grading methods and easing their clinical application.

## III. Exisitng Methodologies

Image processing, machine learning, and medical knowledge are all combined in the current multi-step method for predicting diabetic retinopathy from retinal images. First, using specialized equipment like retinal cameras or OCT scanners, high-quality retinal images are acquired. These pictures can be obtained as fluorescein angiography pictures, fundus photos, or OCT scans. The photos go through important preprocessing steps to improve quality after they are acquired. To maintain consistency, this calls for actions like noise reduction, contrast modification, and picture normalization. In order to ensure accurate analysis, image registration techniques can also be used to align images and adjust for any minor variations.

Feature extraction is a key system component. To determine whether diabetic retinopathy is present and how severe it is, several features are taken from the retinal images. These characteristics include a variety of markers, such as exudates, hemorrhages, microaneurysms, vessel tortuosity, and macular thickness. Every one of these characteristics adds a bit of knowledge to the overall evaluation of diabetic retinopathy. Image analysis algorithms are used in the feature extraction process, and these features are essential for allowing machine learning models to predict the disease.

Using retinal images, graph neural networks (GNNs) have shown promise in the prediction of diabetic retinopathy. For those who have diabetes, diabetic retinopathy is a serious concern. Early detection is essential to preventing vision loss. A wide range of retinal images, including those from people with and without diabetes, are carefully gathered for this study. Preprocessing is applied to these pictures in order to build a graph structure and extract pertinent features. Every retinal image is essentially converted into a graph, with edges encoding the spatial relationships between the various regions represented by nodes, which are individual pixels within the image. The model is able to extract contextual information and intricate interdependencies from the retinal data thanks to this graph representation.

## IV. Proposed System

The suggested Convolutional Neural Network (CNN) system for retinal disease prediction is a novel method to improve the precision and efficacy of diagnosing a variety of retinal diseases. The basis of the system is the collection of a large and varied dataset of retinal images that includes images of retinal diseases and conditions such as age-related macular degeneration, glaucoma, diabetic retinopathy, and retinal detachment. Preprocessing is done on these images in order to get them ready for analysis. This entails adjusting the brightness and contrast, rotating, flipping, and standardizing the image sizes and pixel values. It also involves applying data augmentation techniques. These actions are necessary to guarantee data consistency and supply a solid dataset to the CNN model.

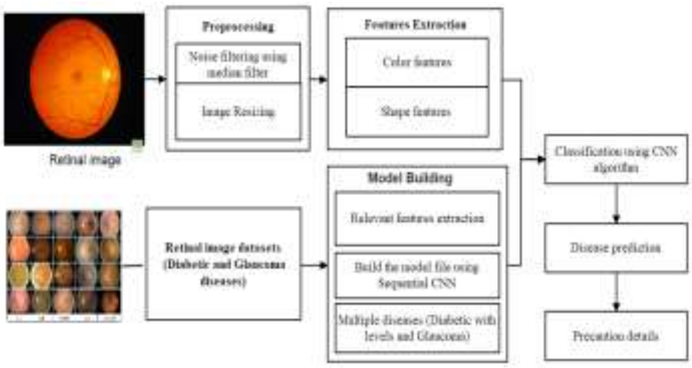



Figure 2: Proposed architecture diagram

### Image Acquisition

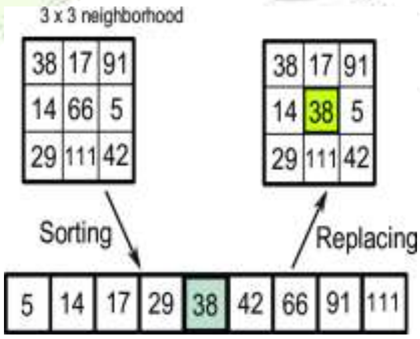
In this module is used to acquire a digital image. Retinal images of humans play an important role in the detection and diagnosis of cardiovascular diseases that including stroke, diabetes, arterio sclerosis, cardiovascular diseases and hypertension. Vascular diseases are often life critical for individuals, and present a challenging public health problem for society. The detection for retinal images is necessary and among them the detection of blood vessels is most important. The alterations about blood vessels such as length, width and branching pattern, can not only provide information on pathological changes but can also help to grade diseases severity or automatically diagnose the diseases. Upload the retinal images. The fundus of the eye is the interior surface of the eye, opposite the lens, and includes the retina, optic disc, macula and fovea, and posterior pole. The fundus can be examined by ophthalmoscope or fundus photography. The retina is a layered structure with several layers of neurons interconnected by synapses. In retina we can identify the vessels. Blood vessels show abnormalities at early stages also blood vessel alterations. Generalized arteriolar and venular narrowing which is related to the higher blood pressure levels, which is generally expressed by the Arteriolar to Venular diameter ratio., It constructed a dataset of images for the training and evaluation of our proposed method. This image dataset was acquired from publically available datasets such as DRIVE and STAR. Each image was captured using 24 bit per pixel (standard RGB) at 760 x 570 pixels. First, tested against normal images which are easier to distinguish. Second, some level of success with abnormal vessel appearances must be established to recommend clinical usage. As can be seen, a normal image consists of blood vessels, optic disc, fovea and the background, but the abnormal image also has multiple artifacts of distinct shapes and colors caused by different diseases.

## Preprocessing

To improve the image in ways that increases the chances for success of the other processes. Image sharpening refers to any enhancement technique that highlights edges and fine details in an image. Image sharpening is widely used in printing and photographic industries for increasing the local contrast and sharpening the images. In principle, image sharpening consists of adding to the original image a signal that is proportional to a high-pass filtered version of the original image. In this filter, the original image is first filtered by a high-pass filter that extracts the high-frequency components, and then a scaled version of the high-pass filter output is added to the original image, thus producing a sharpened image of the original. Note that the homogeneous regions of the signal, i.e., where the signal is constant, remain unchanged. Figure 3 display the median filtering algorithm process.

## Model Training Using CNN

The regions of interest in the images. The CNN model learns to automatically extract relevant features from the images and segment them based on these features. Once the CNN model has been trained, it can be evaluated on a separate test dataset to assess its accuracy and generalizability. The model can also be fine-tuned by adjusting its hyperparameters or by using transfer learning techniques to improve its performance. Overall, retinal image segmentation using CNN algorithm involves a combination of data collection, preprocessing, and machine learning techniques to develop accurate and reliable segmentation models. By automating the segmentation process, healthcare providers can save time and reduce errors when analyzing retinal images, leading to more accurate diagnoses and better patient outcomes.




## Classification

Diabetic and glaucoma classification using CNN involves using deep learning techniques to automatically classify retinal images as either diabetic or non-diabetic, as well as classify them as either glaucoma or non-glaucoma. The first step in this process is data collection. A large dataset of retinal images with corresponding diagnosis labels needs to be collected. The dataset should include both diabetic and non-diabetic retinal images, as well as both glaucoma and non-glaucoma retinal images. The dataset should be diverse enough to account for variations in age, sex, and ethnicity to ensure the algorithm can generalize well to different populations.

In a CNN, the input is a tensor with shape (number of images) x (image height) x (image width) x (input channels). After passing through a convolutional layer, the image becomes abstracted to a feature map, with shape (number of images) x (feature map height) x (feature map width) x (feature map channels). A convolutional layer within a neural network should have the following attributes:

Convolutional layers convolve the input and pass its result to the next layer. This is similar to the response of a neuron in the visual cortex to a specific stimulus. Each convolutional neuron processes data only for its receptive field. Although fully connected feed forward neural networks can be used to learn features and classify data, this architecture is impractical for images. It would require a very high number of neurons, even in a shallow architecture, due to the very large input sizes associated with images, where each pixel is a relevant variable. For instance, a fully connected layer for a (small) image of size 100 x 100 has 10,000 weights for each neuron in the second layer. Instead, convolution reduces the number of free parameters, allowing the network to be deeper. For example, regardless of image size, tiling 5 x 5 region, each with the same shared weights, requires only 25 learnable parameters. Using regularized weights over fewer parameters avoids the vanishing gradient and exploding gradient problems seen during back propagation in traditional neural networks.

**Pooling layers**

Convolutional networks may also include nearby or worldwide pooling layers to streamline the underlying computation. Pooling layers lessen the size of the statistics through combining the outputs of neuron clusters at one layer right into a unmarried neuron in the subsequent layer. Local pooling combines small clusters, commonly 2 x 2. Global pooling acts on all the neurons of the convolutional layer. There are commonplace varieties of pooling: max and common. Max pooling uses the most cost of each cluster of neurons at the previous layer, at the same time as common pooling alternatively makes use of the average cost.

**Fully connected layers**

Fully linked layers connect every neuron in one layer to each neuron in some other layer. It is similar to a conventional multi-layer perceptron neural community (MLP). The flattened matrix is going through a totally linked layer to categories the pictures.

**Receptive field**

In neural networks, every neuron receives input from a few quantities of locations within the preceding layer. In a fully related layer, every neuron gets input from each neuron of the previous layer. In a convolutional layer, each neuron gets input from only a confined vicinity of the previous layer referred to as the neuron's receptive area. Typically the vicinity is a square (e.g., five by way of five neurons). (So, in a completely linked layer, the receptive subject is the complete previous layer.) Thus in every convolutional layer, every neuron takes enter from a larger place of pixels in the enter image than previous layers. This is due to making use of the convolution time and again, which takes under consideration the fee of a pixel and its surrounding pixels.

**Weights**

Each neuron in a neural network computes an output cost by means of making use of a selected feature to the enter values coming from the receptive field within the previous layer. The function this is carried out to the input values is decided by means of a vector of weights and a bias (generally real numbers). Learning includes iteratively adjusting these biases and weights. The vector of weights and the bias are referred to as filters and constitute unique features of the enter (e.g., a selected shape). A distinguishing characteristic of CNNs is that many neurons can percentage the identical clear out. This reduces memory footprint because a single bias and a single vector of weights are used across all receptive fields sharing that filter, in place of every receptive field having its own bias and vector weighting. First $\alpha$,ITERmax, ERRmin, BATCHEStraining, SIZEbatch are initialized which are nothing but Learning rate, number of maximum iteration, minimum error, training batches, batch size respectively ;

According to $n1$ and $n5$; compute $n2$, $n3$, $n4$, $k1$, $k2$.
Randomly generate the weights $\theta$ of the CNN;
cnnModel = InitCNNModel($\theta$, [$n$1–5]);
iter = 0; err = +inf;
while err >ERRmin and iter<ITERmax do
err = 0;
for batch = 1 to BATCHEStraining do
[$\nabla\theta J(\theta)$, $J(\theta)$] = cnnModel_train (TrainingDataset, TrainingLabelsets), and $\theta$ should be updated;
err = err + mean($J(\theta)$);
end for
err = err/BATCHEStraining;

iter++;
end while
Save parameters $\theta$ of the CNN

The pooling process is similar to the convolution process in that it involves a sliding window similar to a filter, but the calculation is simpler. Mean pooling uses the average value in an image area as the pooled value of the area. This approach preserves the background of the image well. Max pooling takes the maximum value of the image area as the pooled value of the area and preserves the texture of the image well. The function of the fully connected layer is to integrate the multiple image maps obtained after the image is passed through multiple convolution layers and pooling layers to obtain the high-layer semantic features of the image for subsequent image classification. Figure 4 display the CNN algorithm layout.

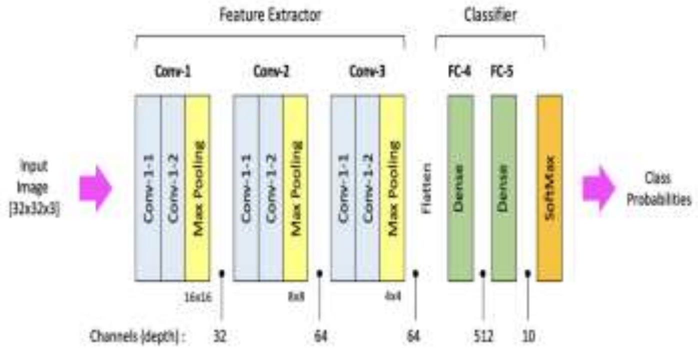


Figure 4: CNN Layers

**Disease Diagnosis**

0020Transfer learning techniques can also be used to fine-tune the deep learning model and improve its performance. Once the deep learning model has been trained, it can be evaluated on a separate test dataset to assess its accuracy and generalizability. The model can also be optimized by adjusting its hyperparameters or by using techniques such as data augmentation to improve its performance. In this module, we can classify the diseases whether it is diabetic or not and also identify the multi-level diabetics. And also predict the Glaucoma diseases with precaution details with improved accuracy rate.

## V. EXPERIMENTAL RESULTS

Retinal images are collected from KAGGLE datasets. Different performance measures such as accuracy, sensitivity, specificity, error rate and precision can be derived for analysing the performance of the system.

- True positive (TP): number of true positives - perfect positive prediction
- False positive (FP): number of false positives - imperfect positive prediction
- True negative (TN): number of true negatives - perfect negative prediction
- False negative (FN): number of true negatives - imperfect negative prediction

**Error rate:** Error rate (ERR) is computed as the fraction of total number of imperfect predictions to the total number of test data. The finest possible error rate is 0.0, whereas the very worst is 1.0. Minimization of this error rate will be the prime objective for any classifier.

$$. ERR = \frac{FP+FN}{TP+TN+FN+FP}$$

| ALGORITHM | ERROR RATE |
|---|---|
| RANDOM FOREST | 0.75 |
| GRAPH NEURAL NETWORK | 0.5 |
| CONVOLUTIONAL NEURAL NETWORK | 0.4 |

**Accuracy:** Accuracy (ACC) is found as the fraction of total number of perfect predictions to the total number of test data. It can also be represented as 1 – ERR. The finest possible accuracy is 1.0, whereas the very worst is 0.0.

$$ACC = \frac{TP+TN}{TP+TN+FN+FP} \text{ x } 100$$

| ALGORITHM | ACCURACY |
|---|---|
| RANDOM FOREST | 50% |
| GRAPH NEURAL NETWORK | 65% |
| CONVOLUTIONAL NEURAL NETWORK | 80% |

## VI. CONCLUSION

To conclude, the utilization of Convolutional Neural Networks (CNNs) in the diagnosis and prognosis of retinal diseases signifies a noteworthy progression in the domains of medical image analysis and ophthalmology. This technology has the potential to completely change how we identify and treat retinal diseases such as glaucoma, and diabetic retinopathy. The suggested system, which is based on CNNs, shows a lot of promise for raising disease prediction efficiency and accuracy. The system is capable of learning and identifying complex patterns and features that are essential for the precise diagnosis of retinal diseases thanks to the collection of various and carefully preprocessed retinal images. The precise classification of diseases and the extraction of crucial information are made possible by the utilization of CNN architectures customized to the unique needs of retinal image analysis. By avoiding overfitting and guaranteeing generalization to new data, the training and validation procedures make sure the model operates at peak efficiency. The implementation of this system in clinical environments and telemedicine platforms has the capacity to accelerate the identification of illnesses, facilitating prompt interventions that may have a substantial effect on patient outcomes.

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