International Journal of Recent Engineering Research and Development (IJRERD)
ISSN: 2455-8761
www.ijrerd.com || Volume 09 – Issue 02 || Mar - Apr 2024 || PP. 34-44

Multiple Instance Learning for Diabetic Retinopathy Classification

Surya Nivash T, Girinath N, Vinoth Kumar V
UG Scholar
Department of Biomedical Engineering
Paavai College of Engineering
Namakkal, India

Sundhararaj V
Assistant professor
Department of Biomedical Engineering
Paavai College of Engineering
Namakkal, India

Abstract: The eye is sometimes said to provide a window into the health of a person for it is only in the Diabetic retinopathy (DR) is a serious eye disease originating from diabetes mellitus that one can actually see the exposed flesh of the subject without using invasive procedures. There are a number of diseases, particularly vascular disease that leave tell-tale markers in the retina. Microaneurysms (MAs) are early signs of DR. So, the detection of these lesions is essential in an efficient screening program to meet clinical protocols. Retinal images provide considerable information on pathological changes caused by local ocular disease which reveals diabetes, hypertension, arteriosclerosis, cardiovascular disease and stroke. Computer-aided analysis of retinal image plays a central role in diagnostic procedures. However, automatic retinal segmentation is complicated by the fact that retinal images are often noisy, poorly contrasted, and the vessel widths can vary from very large to very small. It presents image processing techniques such as dark object detection to analyze the condition or enhance the input image in order to make it suitable for further processing and improve the visibility of vessels in color fundus images. Its implement to automate classification algorithm named as Convolutional neural network (CNN) algorithm. The CNN architecture is designed to effectively extract features from retinal images, capturing intricate patterns associated with diabetic retinopathy. The model is trained using a combination of loss functions and optimization techniques to ensure convergence and generalization. Hyperparameter tuning is performed to optimize the model's performance on the validation set. The trained CNN evaluated on a separate test sets and its performance metric includes accuracy, precision, recall, F_1 score. Additionally, the model's interpretability is to explore to understand the features contributing to predictions.

Keywords: Diabetic retinopathy (DR), Eye disease, Retinal images, Microaneurysms(MAs), Vascular disease, Computer-aided analysis, Image processing techniques, Dark object detection, Convolutional neural network (CNN), Feature extraction, Optimization techniques, Hyperparameter tuning, Performance metrics, Interpretability Classification algorithm.

I. INTRODUCTION

Diabetic retinopathy (DR) is a serious complication of diabetes mellitus and a leading cause of vision impairment and blindness globally. This microvascular complication affects the retina, the light-sensitive tissue at the back of the eye, and is characterized by progressive damage to the blood vessels within the retina. The prevalence of diabetes is rising at an alarming rate, with an estimated 463 million adults affected worldwide in 2019, and this number is expected to reach 700 million by 2045 according to the International Diabetes Federation. The retina plays a crucial role in vision, capturing and processing light signals that are then transmitted to the brain for interpretation. In individuals with diabetes, prolonged exposure to elevated blood glucose levels can lead to damage of the retinal blood vessels, causing leakage and swelling. As the condition progresses, abnormal blood vessels may form, leading to a variety of complications such as hemorrhages, exudates, and, in severe cases, retinal detachment. Early detection and intervention are paramount in preventing irreversible vision loss due to diabetic retinopathy. Traditional screening methods involve manual examination of retinal images by ophthalmologists, a time-consuming process that may not be scalable given the increasing prevalence of diabetes. Consequently, there is a growing interest in leveraging advanced technologies, such as deep learning and computer vision, to develop automated systems for the early detection and classification of diabetic retinopathy.

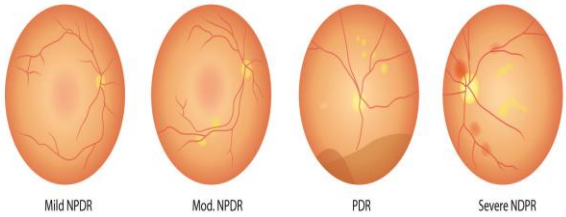


Fig 1.1: Diabetic Retinal images

Deep learning is a subset of machine learning, which is essentially a neural network with three or more layers. These neural networks attempt to simulate the behaviour of the human brain—albeit far from matching its ability—allowing it to “learn” from large amounts of data. While a neural network with a single layer can still make approximate predictions, additional hidden layers can help to optimize and refine for accuracy. Deep learning drives many artificial intelligence (AI) applications and services that improve automation, performing analytical and physical tasks without human intervention. Deep learning technology lies behind everyday products and services (such as digital assistants, voice-enabled TV remotes, and credit card fraud detection) as well as emerging technologies (such as self-driving cars).

Deep learning is a subfield of machine learning that uses artificial neural networks to model and solve complex problems. It has emerged as one of the most promising areas of research in artificial intelligence and has been applied to a wide range of applications such as image and speech recognition, natural language processing, and robotics. Deep learning models are based on artificial neural networks that are inspired by the structure and function of the human brain. These networks consist of layers of interconnected nodes, each of which performs a mathematical operation on the input data. The output of each node is passed on to the next layer of nodes, where it is combined with the outputs of other nodes and further processed. This process continues until the output of the final layer is produced, which represents the prediction or classification of the input data.

One of the key advantages of deep learning is its ability to learn complex patterns and relationships in the data. This is achieved by using multiple layers of nodes, each of which learns a different set of features from the input data. The first layer learns low-level features such as edges and corners, while subsequent layers learn higher-level features such as textures and shapes. This hierarchical learning process enables deep learning models to capture complex patterns and relationships in the data, making them highly effective in solving complex problems. Another advantage of deep learning is its ability to learn from large amounts of data. Deep learning models require large amounts of data to train effectively, but once trained, they can make accurate predictions on new, unseen data. This makes deep learning particularly well-suited for applications such as image and speech recognition, where large amounts of labeled data are available.

1.1 Challenges in the System

Interpretability and explain ability pose significant challenges in the deployment of CNNs for medical applications. The inherently complex nature of these models raises concerns about their transparency and the ability to comprehend decision-making processes, especially in healthcare contexts where understanding predictions is critical. Overfitting, the risk of the model performing exceptionally well on the training data but failing to generalize to new data, is a common hurdle that necessitates the development of strategies to enhance generalization and real-world applicability. Ethical considerations, including patient privacy, informed consent, and potential biases in predictions, require careful attention to ensure the responsible deployment of the system in healthcare settings. Integrating the automated system seamlessly into existing clinical workflows is a challenge that demands careful planning. The system must align with the routines of healthcare professionals without causing disruptions or adding undue complexity to their processes.

Additionally, addressing hardware and resource constraints, given the substantial computational requirements of CNNs, is vital for practical implementation. Navigating these challenges will be crucial in developing a robust, effective, and ethically sound automated system for diabetic retinopathy prediction that can seamlessly integrate into clinical practice.

The project on predicting diabetic retinopathy using Convolutional Neural Networks (CNNs) encompasses a multifaceted scope aimed at advancing automated healthcare diagnostics. A primary focus lies in the meticulous development and optimization of a specialized CNN model, fine-tuned to accurately predict the severity of diabetic retinopathy. This involves exploring various model architectures, optimizing hyperparameters, and implementing strategies to enhance the model's ability to generalize across diverse retinal images.

II. LITERATURE SURVEY

[1] Muhammad Mateen et al:

The retina is a sphere-shaped structure, composed of a thin layer, located in the backside of an eye. The function of a retina is to transfer the light into the neural signals and coordinate with the brain to process the visual information. The retina is placed beside the optic nerve, and a dark circular part located in the center of the retina is called macula. The fovea is a central part of the macula, which provides a clear vision. All over the world, diabetes is a widespread disease. The diabetic patients between 20 to 74 years old can suffer blindness because of hysterical diabetes and this kind of disease is called diabetic retinopathy. In the human body, retinal tissue, similar to all the other tissues, receives blood supply via the body's vasculature. Additionally, the retinal tissue receives the blood through micro blood vessels and needs to retain the blood sugar level with the uninterrupted flow of blood. The abnormal condition of the sugar level in the retinal blood vessels leads to microaneurysms (MAs). MA is an early sign of diabetic retinopathy, which can be considered as a basic element of diabetic retinopathy. The shape of MAs is almost circular with darkish color and tiny in size. Later, the abnormal retinal blood vessels may breakdown into the form of micro vascular networks, which is called retinal neovascularization. Diabetic retinopathy also contains some other abnormalities including cotton wool spots, hemorrhages, exudates which lead to non-reversible blindness and vision impairment.

[2] K.Shankar et al:

In past decades, diabetes is caused because of the excess growth of glucose in the blood. If the same condition is retained for a long time, it results in severe blood vessel damage. A person affected with diabetes is vulnerable to kidney failure, loss of eyesight, bleeding teeth, lower limb confiscation, nerve failures, and so on. It also leads to a heart attack as well as stroke in diabetic affected individuals. The nephrons present in the kidney are damaged and leads to diabetic neuropathy while neurons present in the brain get damaged, and cause diabetic retinopathy (DR) which results in the retinal infection. An efficient DR disease diagnosis model called the HPTI-v4 model has been presented. The presented HPTI-v4 model involves the segmentation process by the feature extraction processes based on histogram and Inception v4. For tuning the hyperparameters in Inception v4, the Bayesian optimization technique is involved. Finally, the classification processes are performed by the use of MLP. The experimental outcomes stated that the presented HPTI-v4 model showed extraordinary results with the maximum accuracy, sensitivity, and specificity of 99.49%, 98.83%, and 99.68% respectively. At the initial stage, the vision gets affected slowly. Consequently, it is compulsory for diabetic patients must undertake a systematic eye checkup where the retina should be observed by an ophthalmologist. There are various techniques for detecting the affected eye, some of them are slit lamp bio-microscopy, optical coherence tomography (OCT), fundus fluorescein angiography (FFA), and fundus images

[3] Along He et al:

The blindness caused by DR can be prevented through regular fundus examinations. In clinical diagnosis, DR screening mainly relies on ophthalmologists examining colored fundus images. However, the large number of patients with DR brings a great burden for limited number of ophthalmologists. As the number of diabetic people increases, the amount of fundus images is increasing and becoming more and more difficult to be real-time analyzed manually. Thus, it is necessary to use computer aided diagnosis to reduce the burden on ophthalmologists and examination time, making patients keep abreast of their illness. In this paper, we present 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.

[4] Harshit Kausik et al:

Different techniques have been presented by researchers to deal with retinal image normalization, balancing luminosity distribution, contrast normalization, and computer-aided diagnostic systems, which have proved to be of great importance in the field of retinal imaging. The literature survey of this study covers two major categories of DR works to ensure that an overall view is given for better understanding. The works of each category were evaluated based on different performance metrics and design attributes based on the data pattern and proposed experimental design. Since most of the proposed approaches focused mostly on machine learning, deep learning, and image processing techniques to extract candidate features such as lesions, hemorrhages, exudates and cotton-wool spots but they ignored solving the variance in scene illumination and light degradation, which affects the performance and may result in biased prediction results. In our proposed method, we have used a dataset that has multi-sourced images. Therefore, various types of noise and distortions are encountered in the images. To overcome such issues, we aim to explore the research area of combining artificial intelligence and image processing to develop a complete illumination proof diagnostic tool for DR. We proposed to solve the problem of non-ideal illuminations in the retinal fundus images using the gray world algorithm and to develop an automated DR prediction system. A stack generalization-based ensemble model is prepared using three different CNNs. The performance of image normalization is measured using statistical metrics such as the PSNR and MSE of the original and enhanced images

[5] Yi Zhou et al:

Diabetic retinopathy (DR) is a type of ocular disease caused by high levels of blood glucose and high blood pressure, which can damage the blood vessels in the back of the eye (retina) and lead to blindness. One-third of people living with diabetes have some degree of diabetic retinopathy, and every person who has diabetes is at risk of developing it. Accurately grading diabetic retinopathy is time-consuming for ophthalmologists and can be a significant challenge for beginner ophthalmology residents. Therefore, developing an automated diagnosis system for diabetic retinopathy has significant potential benefits. Since there exists feature distribution difference between the source and target domain (introduced by the different data sources), we aim to adapt the representations of the two domain data so that the segmentation module trained on source domain data can fit the target domain data and extract better multi-scale transferred features. Such transferred knowledge of disease patterns shared between the two domains can improve the results of the target domain task. To promote research in medical image segmentation, classification, and transfer learning, particularly for the community of diabetic retinopathy diagnosis, in this paper, we 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.

III. METHODOLOGY

3.1 Existing System

Diabetic retinopathy can be broadly classified as non-proliferative diabetic retinopathy diabetic patient’s retina is very important. And, automated or computer assisted analysis of diabetic patients’ retina can help eye care specialist to screen larger populations of patients. With a large number of patients, the workload of local ophthalmologists is highly unsubstantial. One of the most important steps in the automated detection of DR is the detection of microaneurysms. Microaneurysms are amongst the earliest observable signs of the presence of diabetic retinopathy. Due to a large number of patients, the available ophthalmologists are not sufficient in handling all the patients, especially in rural areas. The development of an existing system for diabetic-based retinal diseases using Graph Neural Networks (GNNs) involves representing retinal data as a graph, where nodes correspond to different features or elements, and edges capture relationships between them. The GNN architecture is designed to leverage these structured relationships, with layers of graph convolutional operations extracting hierarchical features from the retinal graph. The primary objective is typically classification or regression tasks related to diabetic retinopathy, such as predicting disease severity or categorizing images into different stages. Training the GNN involves optimizing its parameters using labeled datasets, and the model's generalization performance is evaluated on separate validation and test datasets. Ensuring interpretability of GNN predictions is critical, especially in medical applications, to provide insights into decision-making processes. Ethical considerations, encompassing patient privacy, informed consent, and bias mitigation, are integral aspects of system development. Continuous awareness of advancements in GNN research and a multidisciplinary approach involving data scientists, healthcare professionals, and ethicists contribute to the system's efficacy in addressing diabetic-based retinal diseases.

The advantages of this system include

- Only classify the grade of uploaded images
- Extract the retinal features like vessels, optic disc, microaneurysms, hemorrhage, exudates (including hard exudates and soft exudates)
- There is no algorithm for predicting diseases

- Does not support large datasets

3.2 Proposed System

A proposed system for diabetic and glaucoma prediction from retinal images using Convolutional Neural Networks (CNNs) involves several key steps. Firstly, a large dataset of retinal images with corresponding diagnosis labels for both diabetic and glaucoma patients' needs to be collected. The dataset should be diverse enough to account for variations in age, sex, and ethnicity. Next, the dataset needs to be pre-processed to remove any artifacts and enhance the quality of the images. This can involve techniques such as noise reduction, contrast enhancement, and normalization. The pre-processed images can then be segmented to extract regions of interest, such as the optic nerve head and retinal blood vessels. Once the images have been preprocessed and segmented, they can be used to train a CNN model. CNNs are particularly suited to image classification tasks as they are able to automatically extract relevant features from the images. The CNN model can be trained using a combination of labeled retinal images and corresponding diagnosis labels. After training the CNN model, 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. In addition to training the CNN model, it's important to also visualize the features learned by the model to gain insights into the diagnostic process. This can involve techniques such as activation mapping, which highlights the regions of the image that are most important for the model's prediction. Visualizing the features can help to identify the key characteristics of retinal images that are indicative of diabetic retinopathy or glaucoma. Furthermore, it's important to consider the interpretability of the CNN model in a clinical setting. While CNNs have shown excellent performance in image classification tasks, their "black box" nature can make it difficult to interpret their predictions. One approach to increasing the interpretability of the model is to use techniques such as saliency mapping or class activation mapping, which highlight the regions of the image that contribute most to the model's prediction. This can help clinicians to better understand the model's reasoning and make more informed decisions about patient care. Finally, the trained CNN model can be deployed in a clinical setting to provide early diagnosis and treatment to patients with diabetic retinopathy.

The advantages of this system include

- Implemented in real time
- Detect the diabetic diseases with multiple levels
- Dark objects are identified easily for Glaucoma detection
- Provide the diagnosis information

3.3 System Architecture

In this architecture, split the images into training and testing phase. Training phase input the retinal image datasets that are collected from KAGGLE website. Then train the models with 5 classes using Convolutional neural network algorithm. In testing phase, input the retinal images and perform noise filtering to remove the noises from images and resize the images. Then extract the features maps using CNN and classify the feature map with model file. Finally classify the disease with improved accuracy rate

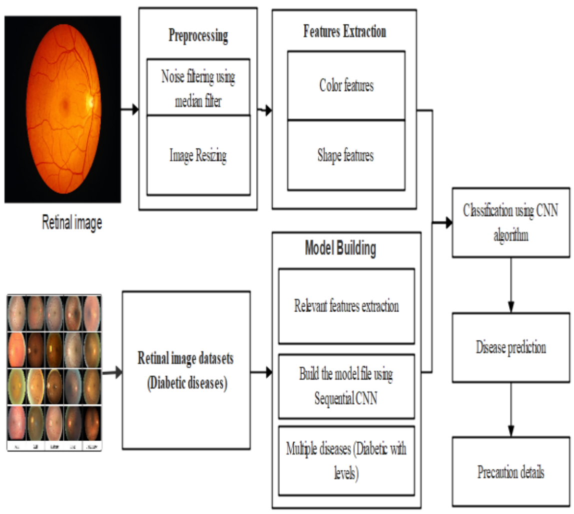


Fig 3.1 System Architecture

The main purpose of a use case diagram is to portray the dynamic aspect of a system. It accumulates the system's requirement, which includes both internal as well as external influences. It invokes persons, use cases, and several things that invoke the actors and elements accountable for the implementation of use case diagrams. It represents how an entity from the external environment can interact with a part of the system.

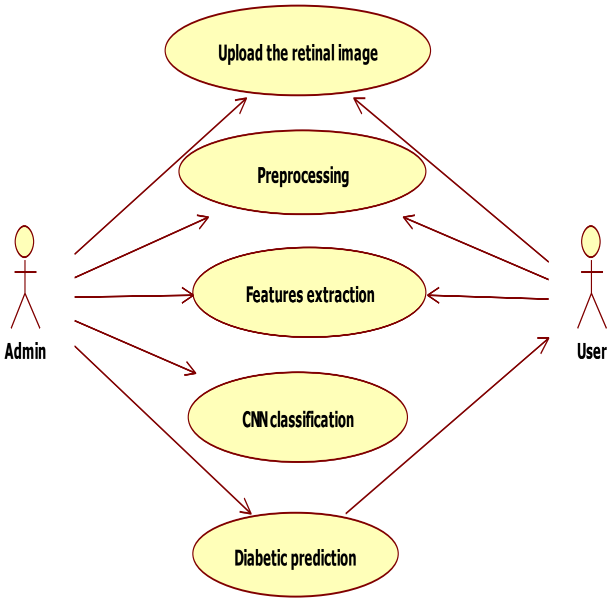


Fig 3.2 Flow Chart

3.4 Approach

The problem identification for diabetic prediction and glaucoma prediction from retinal images involves developing machine learning models that can accurately classify retinal images as either diabetic or non-diabetic, and as either having glaucoma or not having glaucoma. For diabetic prediction, the model needs to be trained to identify specific changes in the retinal images that are indicative of diabetic retinopathy, such as microaneurysms, hemorrhages, and exudates. The model should also be able to differentiate between early and advanced stages of diabetic retinopathy. For glaucoma prediction, the model needs to be trained to detect characteristic changes in the optic nerve head and retinal nerve fiber layer, which are typically associated with glaucoma. The model should also be able to distinguish between different stages of glaucoma. In order to develop accurate machine learning models for diabetic and glaucoma prediction, a large dataset of retinal images with corresponding diagnosis labels is required. The dataset needs to be carefully curated to ensure that it includes a representative sample of both diabetic and non-diabetic patients, as well as patients with and without glaucoma. Additionally, the dataset should be diverse enough to account for variations in age, sex, and ethnicity. Data collection is a crucial step in developing accurate machine learning models for diabetic and glaucoma prediction from retinal images. The success of these models largely depends on the quality and quantity of data used for training. Retinal images can be obtained through various imaging techniques such as fundus photography, optical coherence tomography (OCT), and scanning laser ophthalmoscopy (SLO). The images need to be carefully curated to ensure that they include a representative sample of both diabetic and non-diabetic patients, as well as patients with and without glaucoma. Additionally, the dataset should be diverse enough to account for variations in age, sex, and ethnicity. Data augmentation techniques can also be used to increase the size of the dataset and improve the generalizability of the models. However, it's important to ensure that the augmented data is realistic and reflects the real-world variations in retinal images. Overall, collecting a high-quality dataset is a critical step in developing accurate and reliable machine learning models for diabetic and glaucoma prediction from retinal images. Overall, the goal of diabetic and glaucoma prediction from retinal images is to provide early diagnosis and treatment to prevent the progression of these diseases and minimize the risk of vision loss.

3.4.1. 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.

3.4.2. Pre-Processing:

The provided content discusses techniques for improving image quality, particularly in the context of retinal image processing. It begins by highlighting the importance of grayscale conversion to identify black and white illumination, followed by the use of median filters to reduce noise caused by distorted colors and noisy pixels in colored retinal images. These preprocessing steps are crucial for enhancing and sharpening the vascular pattern, which aids in blood vessel segmentation. Furthermore, it emphasizes the significance of high-frequency components in human perception, noting that enhancing these components can greatly improve visual quality. Image sharpening techniques, such as adding a signal proportional to a high-pass filtered version of the original image, are described. This process highlights edges and fine details, increasing local contrast and overall image sharpness. Overall, these techniques are essential for enhancing image quality and aiding in various image processing tasks, particularly in medical diagnosis and research involving retinal images**.**

3.4.3 Segmentation:

Retinal image segmentation using CNN algorithm involves using deep learning techniques to automatically identify and segment the regions of interest in retinal images. 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 be diverse enough to account for variations in age, sex, and ethnicity to ensure the algorithm can generalize well to different populations. Once the dataset has been collected, it needs to be preprocessed to remove any artifacts and enhance the quality of the images. This can involve techniques such as noise reduction, contrast enhancement, and normalization. The preprocessed images can then be segmented to extract regions of interest, such as the optic nerve head and retinal blood vessels. After preprocessing and segmentation, a CNN model can be trained to accurately segment the retinal images. The CNN model can be trained using a combination of labeled retinal images and corresponding segmentation masks that indicate the location of 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.

3.4.4 Classification:

Retinal image segmentation with CNNs employs deep learning to automatically identify and delineate regions of interest in retinal images. The process starts with collecting a diverse dataset of retinal images with corresponding diagnosis labels, ensuring representation across demographics. Preprocessing follows, including noise reduction, contrast enhancement, and normalization to improve image quality and remove artifacts. Segmentation involves extracting areas like the optic nerve head and retinal blood vessels. A CNN model is then trained on labeled images and segmentation masks to learn feature extraction and segmentation. Evaluation on a separate test dataset gauges accuracy and generalization, with fine-tuning options like hyperparameter adjustment and transfer learning to enhance performance. Automating segmentation saves time, reduces errors, and improves diagnostic accuracy, benefiting patient care outcomes.

3.4.5 Disease Diagnosis:

The content outlines the process of predicting glaucoma disease from retinal images using machine learning algorithms. It begins with data collection, followed by preprocessing steps like noise reduction and contrast enhancement to improve image quality. Machine learning models, particularly deep learning ones, are then trained on labeled retinal images and corresponding glaucoma diagnosis labels to automatically extract features and predict the likelihood of developing glaucoma. Transfer learning techniques may be applied to enhance model performance, and evaluation on a separate test dataset is conducted to assess accuracy and generalization. Additionally, optimization methods like adjusting hyperparameters and employing data augmentation can further improve model performance. The module aims to classify whether a disease is diabetic or not and identify disease levels such as No DR, Mild, Moderate, Severe, and Proliferative DR. This comprehensive approach utilizes advanced machine learning techniques to aid in early detection and management of glaucoma, potentially preventing vision loss and improving patient outcomes.

IV. Implementation

A convolutional neural network is a feed-forward network with the ability of extracting topological properties from the input image. It extracts features from the raw image and then a classifier classifies extracted features. CNNs are invariance to distortions and simple geometric transformations like translation, scaling, rotation and squeezing. Convolutional Neural Networks combine three architectural ideas to ensure some degree of shift, scale, and distortion invariance: local receptive fields, shared weights, and spatial or temporal sub-sampling. The network is usually trained like a standard neural network by back propagation. A convolutional layer is used to extract features from local receptive fields in the preceding layer.. In a network with a 5×5 convolution kernel each unit has 25 inputs connected to a 5×5 area in the previous layer, which is the local receptive field. A trainable weight is assigned to each connection, but all units of one feature map share the same weights. This feature which allows reducing the number of trainable parameters is called weight sharing technique and is applied in all CNN layer. With local receptive fields, elementary visual features including edges can be extracted by neurons. To extract the same visual feature, neurons at different locations can share the same connection structure with the same weights. The output of such a set of neurons is a feature map. This operation is the same as a convolution of the input image with a small size kernel. Multiple feature maps can be applied to extract multiple visual features across the image. Subsampling is used to reduce the resolution of the feature map, and hence reduce the sensitivity of the output to shifts and distortions. In our proposed CNN structure, multiple features can be extracted from each original eye data, and each feature has □3 dimensions.

Constructing the CNN Model

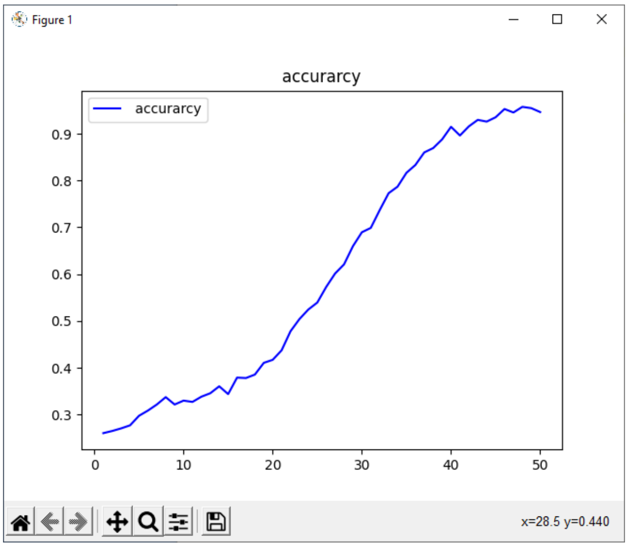
```
function INITCNNMODEL (□, [□1–5])
layerType = [convolution, max-pooling, fully-connected, fully-connected];
layerActivation = [tanh(), max(), tanh(), softmax()]
model = new Model();
for□=1 to 4 do
layer = new Layer();
layer.type = layerType[□];
layer.inputSize = □□
layer.neurons = new Neuron [□□+1];
layer.params = □□;
model.addLayer(layer);
end for, return model;  end function
```

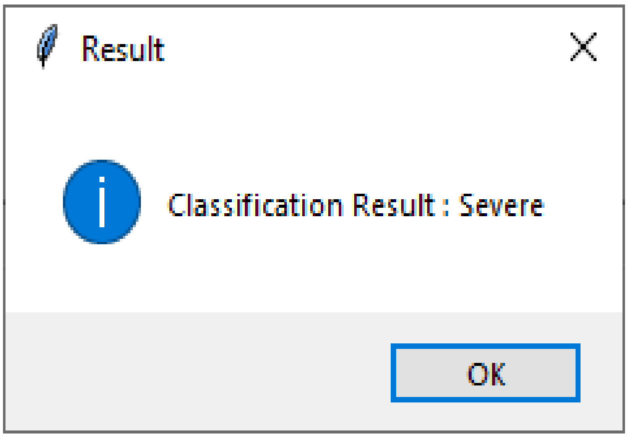
Training the CNN Model

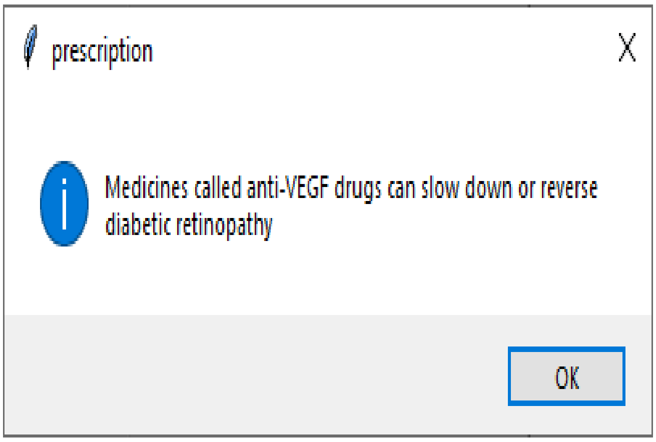
```
Initialize learning rate □, number of max iteration ITERmax, min error ERRmin, training batchsBATCHEStraining, bach size SIZEbatch, and so on;
Compute □2, □3, □4, □1, □2, according to □1 and □5;
Generate random weights □ of the CNN;
cnnModel = InitCNNModel(□, [□1–5]);
iter = 0; err = +inf;
while err >ERRmin and iter<ITERmax do
err = 0;
```

forbach = 1 to $BATCHES_{training}$ do
[∇ □□(□), □(□)] = cnnModel.train (TrainingDatas, TrainingLabels), as (4) and (8); Update □ using (7);
err = err + mean(□(□));
end for err = err/$BATCHES_{training}$;
iter++;
end while , Save parameters □ of the CNN

V. RESULTS AND DISCUSSIONS







VI. CONCLUSION

In conclusion, retinal image analysis using deep learning techniques has shown great potential in the early detection and prediction of several eye diseases such as diabetic retinopathy. With the increasing prevalence of these diseases worldwide, there is a growing need for more effective and efficient screening methods. Deep learning-based approaches can not only improve the accuracy and speed of diagnosis but also reduce the burden on healthcare systems and improve patient outcomes. The proposed system using CNN algorithms for retinal image segmentation, diabetic classification can help healthcare providers to make more informed decisions and provide personalized treatment plans. The combination of deep learning algorithms and retinal imaging has the potential to revolutionize the way we diagnose and manage these diseases, leading to better patient outcomes and a reduction in the overall healthcare burden. With the help of deep learning algorithms, medical professionals can process complex retinal images more efficiently, which can result in faster and more accurate diagnoses. Moreover, these approaches can help overcome the challenges associated with subjective interpretations of medical images. Human error and inter-observer variability can lead to inconsistencies in the interpretation of medical images, which can have a significant impact on patient outcomes. By leveraging machine learning algorithms, we can obtain more objective and standardized results that can help improve the quality of care.

VII. REFERENCES

[1]. Mateen, Muhammad, et al. "Automatic detection of diabetic retinopathy: a review on datasets, methods and evaluation metrics." IEEE Access 8 (2020): 48784-48811.
[2]. Shankar, K., et al. "Hyperparameter tuning deep learning for diabetic retinopathy fundus image classification." IEEE Access 8 (2020): 118164-118173.
[3]. He, Along, et al. "CABNet: category attention block for imbalanced diabetic retinopathy grading." IEEE Transactions on Medical Imaging 40.1 (2020): 143-153.
[4]. Kaushik, Harshit, et al. "Diabetic retinopathy diagnosis from fundus images using stacked generalization of deep models." IEEE Access 9 (2021): 108276-108292.
[5]. Zhou, Yi, et al. "A benchmark for studying diabetic retinopathy: segmentation, grading, and transferability." IEEE Transactions on Medical Imaging 40.3 (2020): 818-828.
[6]. Gayathri, S., et al. "Automated binary and multiclass classification of diabetic retinopathy using haralick and multiresolution features." IEEE Access 8 (2020): 57497-57504.
[7]. Al-Antary, Mohammad T., and Yasmine Arafa. "Multi-scale attention network for diabetic retinopathy classification." IEEE Access 9 (2021): 54190-54200.
[8]. Zhou, Yi, et al. "DR-GAN: conditional generative adversarial network for fine-grained lesion synthesis on diabetic retinopathy images." IEEE Journal of Biomedical and Health Informatics (2020).
[9]. Abdelmaksoud, Eman, et al. "Automatic diabetic retinopathy grading system based on detecting multiple retinal lesions." IEEE Access 9 (2021): 15939-15960.
[10]. Araújo, Teresa, et al. "Data augmentation for improving proliferative diabetic retinopathy detection in eye fundus images." IEEE Access 8 (2020): 182462-182474.
[11]. T. Saba, ‘‘Recent advancement in cancer detection using machine learning: Systematic survey of decades, comparisons and challenges,’’ J. Infection Public Health, vol. 13, no. 9, pp. 1274–1289, Sep. 2020.
[12]. S. A. Hassan, S. Akbar, A. Rehman, T. Saba, H. Kolivand, and S. A. Bahaj, ‘‘Recent developments in detection of central serous retinopathy through imaging and artificial intelligence techniques—A review,’’ IEEE Access, vol. 9, pp. 168731–168748, 2021.
[13]. S. Akbar, S. A. Hassan, A. Shoukat, J. Alyami, and S. A. Bahaj, ‘‘Detection of microscopic glaucoma through fundus images using deep transfer learning approach,’’ Microsc. Res. Technique, vol. 85, no. 6, pp. 2259–2276, Jun. 2022.
[14]. A. Shoukat, S. Akbar, S. A. E. Hassan, A. Rehman, and N. Ayesha, ‘‘An automated deep learning approach to diagnose glaucoma using retinal fundus images,’’ in Proc. Int. Conf. Frontiers Inf. Technol. (FIT), Dec. 2021, pp. 120–125.
[15]. T. Saba, S. Akbar, H. Kolivand, and S. Ali Bahaj, ‘‘Automatic detection of papilledema through fundus retinal images using deep learning,’’ Microsc. Res. Technique, vol. 84, no. 12, pp. 3066–3077, Dec. 2021.
[16]. O. M. A. Hazaimeh, K. M. O. Nahar, B. A. Naami, and N. Gharaibeh, ‘‘An effective image processing method for detection of diabetic retinopathy diseases from retinal fundus images,’’ Int. J. Signal Imag. Syst. Eng., vol. 11, no. 4, p. 206, 2018, doi: 10.1504/IJSISE.2018.10015063.
[17]. L. Zhou, Y. Zhao, J. Yang, Q. Yu, and X. Xu, ‘‘Deep multiple instance learning for automatic detection of diabetic retinopathy in retinal images,’’ IET Image Process., vol. 12, no. 4, pp. 563–571, Apr. 2018.

[18]. M. Leeza and H. Farooq, ‘‘Detection of severity level of diabetic retinopathy using bag of features model,’’ IET Comput. Vis., vol. 13, no. 5, pp. 523–530, Aug. 2019, doi: 10.1049/IET-CVI.2018.5263.

[19]. O. M. Al-Hazaimeh, M. Al-Nawashi, and M. Saraee, ‘‘Geometrical based approach for robust human image detection,’’ Multimedia Tools Appl., vol. 78, no. 6, pp. 7029–7053, Mar. 2019, doi: 10.1007/S11042-018-6401-Y.

[20]. I. Qureshi, J. Ma, and K. Shaheed, ‘‘A hybrid proposed fundus image enhancement framework for diabetic retinopathy,’’ Algorithms, vol. 12, no. 1, p. 14, Jan. 2019. [18] S. Simon, ‘‘Retinal image enhancement and eye disease identification,’’ in Proc. Int. Conf. Syst., Energy Environ., 2019, pp. 1–7