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A PRIVACY-PRESERVING FEDERATED CNN FOR DIABETIC RETINOPATHY DIAGNOSIS

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ABSTRACT

Diabetic Retinopathy is a common diabetic condition that, if left undressed, can affect in blindness and visual impairment. In this work, we present a new system for DR using a Federated Convolutional Neural Network (Fed CNN) that has been trained using the Adam supervised classification optimization algorithm. Decentralized model training on distributed datasets is made possible via federated learning, which protects patient privacy and enhances the model's conception. Multiple convolutional layers are used in Fed CNN armature to facilitate hierarchical representation learning and feature extraction. The Adam optimizer is used to adaptively alter the learning rates for specific parameters, perfecting both the speed of confluence and the delicacy of the model numerous healthcare installations work together to train the model, each furnishing a different collection of retinal images for the model to use. The proposed system is enforced using MATLAB software. By easing ongoing model enhancement without taking raw data sharing, the federated learning architecture allays privacy enterprises related to centralized styles. The proposed Fed CNN with Adam optimization system shows better delicacy with 98% which 2.25% is advanced when compared with FR-CNN, ANN and SVM. The issues of the trials show how well the suggested approach may classify the inflexibility degrees of DR. The federated CNN's improved individual capabilities and sequestration-conserving features are stressed by comparisons with other styles. The suggested frame advances telemedicine and customized healthcare by offering a scalable and private result for the opinion of DR, a serious consequence of diabetes. The primary research contribution of this study is the creation of a privacy-preserving and highly accurate diabetic retinopathy diagnosis system based on a Federated Convolutional Neural Network (Fed CNN) and the Adam optimisation algorithm. The work describes a way by which several healthcare institutions can train an AI model without sharing sensitive patient data, enhancing both data privacy and model performance.

Keywords: *Adam Optimization, Convolutional Neural Network, Diabetic Retinopathy, Federated Learning, Supervised Classification.*

1. INTRODUCTION

Images in the retina diagnosing DR involves the important application of classifying the condition. According to an International Health Organization report, diabetes affects a significant portion of the global population [1]. Diabetes mainly affects people over the age of thirty. Severe diabetes can produce DR, which is characterized by early-onset, treatable retinal anomalies such micro-aneurysms and other tiny lesions brought on by weak retinal capillaries [2]. The likelihood of visual loss decreases with the early recognition of DR. Nevertheless, it is hard to manage the late detection of this illness efficiently because the early signs are not evident. Furthermore, because it can be difficult to diagnose situations in retinal images, the diagnosis of this condition takes an important amount of experience and adequate skill on the part of the physician. In order to aid in the prompt discovery and efficient treatment of the condition, there is an even greater need for an efficient classification and screening system for retinopathy [3]. The field of medical image analysis has seen a significant increase in the use of deep learning-based techniques, whose capacity to identify and separate information allows for accurate illness diagnosis. The rising prevalence of the condition may provide significant challenges to the

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cure of retinal diseases when there are not enough retinal experts to assess each patient individual. Diabetes now happens when blood glucose levels rise, according to recent research. Extended periods of the same restriction balance might cause significant harm to blood vessels. For those who qualify, this also frequently results in a heart attack or stroke. Diabetic nephropathy is the term given to the injured area where blood glucose levels have increased. It can be described as a failure of the kidney's nephron and subsequent damage to the brain's neurons. Furthermore, Diabetic Retinopathy is another condition in which there is significant retinal damage [4]. According to WHO report, diabetes is expected to rank seventh among deadly diseases. Around the world, vision loss main contribution is DR and is thought to be a major factor in visual impairment in people between the ages of 25 and 75 [5].

For the majority of patients, symptoms do not manifest until they are severe. Early detection and medicine can assist slowly the disease's growth rate because of its fast progressive rate. Additionally, it shows that the number of diabetic patients has improved from over 10 lakhs to 40 lakhs. Therefore, diabetes may be present in an unexpected part of the body. A few prediction techniques, such as venous beading, micro aneurysms, bleeding, and so forth, can be used to identify it. It is thought to be more crucial to utilize. The term "micro aneurysm" refers to a circular blood clot measuring between 100 and 120 µm in size. The large volume of blood that is released from the affected area of the blood artery causes haemorrhage. Neovascularization is another term for the atypical growth of blood vessels [6]. Venous beading in this context refers to the veins' enlargement in the vicinity of obstructed arterioles. Both proliferative and non-proliferative DRs (NPDR and PDR) are categories for the DR. The NPDR is further classified into various phases based on the severity of diabetes, respectively. One consequence of diabetes is DR, which presents a major healthcare burden.

This disorder, which results from persistently high blood sugar, damages the retina and can cause blood vessel damage, fluid leakage, and even blindness. DR is a critical public health concern due to the rise in diabetes prevalence, particularly type 2 diabetes, which increases its occurrence [7]. Being the leading cause of blindness in adults of working age, the illness has a significant negative impact on people's quality of life and causes significant financial hardships [8]. The financial implications include both direct medical expenditures associated with diagnosis and treatment as well as indirect costs associated with lost productivity as a result of visual impairment. Since DR can be prevented by detecting the condition early, research projects use artificial intelligence, machine learning, and medical imaging to create automated methods that improve diagnostic precision. These developments have the potential to enhance patient outcomes, lessen the negative effects on society, and solve the complex issues that DR presents in the field of medicine.

Preventing irreversible visual impairment and blindness in DR requires prompt diagnosis. Early diagnosis enables timely intervention and therapy, which in turn helps medical professionals effectively control the disease's progression [9]. For people with diabetes, routine eye exams are essential because the early stages of DR may not show any symptoms. By using innovative algorithms to evaluate retinal medical images, machine learning significantly improves the early diagnosis process. It is possible to teach machine learning models to identify irregularities and subtle patterns in retinal pictures that might go unnoticed by the human eye. Through the process of learning from extensive annotated image datasets, these models are able to recognize distinctive characteristics linked to various phases of DR. Machine learning enables automated screening procedures that make it possible to process a huge number of photos quickly and efficiently. This makes it possible to identify those who are at danger in a timely manner and is especially helpful in healthcare systems with large patient loads. Furthermore, the subjectivity that comes with manual visual interpretation can be lessened with the help of machine learning models. Diagnosis consistency is essential, and machine learning algorithms can offer repeatable, standardized evaluations [10]. The total precision and dependability of DR assessments are improved by the incorporation of these technologies into the diagnostic process. It is crucial to diagnose DR as soon as possible, and machine learning is a useful technique for accomplishing this [11].

The goal of the project is to improve the efficiency and accuracy of identifying retinal anomalies linked to DR by utilizing innovative image analysis techniques. Through the use of an extensive dataset and cutting-edge supervised classification algorithms, the study aims to further the advancement of an automated system that can effectively screen for and diagnose DR early on. By enabling prompt interventions and lowering the risk of vision impairment and blindness connected to this common diabetic complication, the ultimate goal is to enhance patient outcomes. Diagnosing DR through manual evaluation of retinal pictures by ophthalmologists is a traditional method that can be laborious and prone to inter-observer variability. CNNs, in particular, are potent instruments for automated and effective DR detection due to these difficulties.

In this work, we present a federated learning method using a Fed CNN architecture for DR diagnosis. Federated learning eliminates the need to exchange private patient information by enabling the model to be trained across numerous dispersed local clients, such clinics or hospitals. In order to handle privacy issues and still contribute to the community knowledge for model improvement, each local client maintains ownership over its data. With an emphasis on supervised learning, the suggested Fed CNN makes use of CNNs' advantages in image classification tasks to reliably classify retinal pictures into various phases of DR. The Adam optimization technique, a well-liked option for deep neural network training, is used to optimize the model. By enhancing the model's performance and efficiency in identifying intricate patterns and features from retinal images, this method seeks to raise the diagnosis accuracy of DR.

The discovery holds relevance as it may lead to the development of an automated and federated diagnostic system that may help medical practitioners effectively recognize the various stages of DR. The model may take advantage of the pooled knowledge from several datasets while maintaining data security and privacy by utilizing federated learning. The findings of this work may have wider ramifications for the use of federated learning in medical image analysis by aiding in the creation of scalable and private-preserving methods for the diagnosis of DR.

The research study's principal contributions is given below

- Applying Gaussian filters and Contrast Limited Adaptive Histogram Equalization (CLAHE) are two important techniques of preprocessing that can be integrated to improve the quality of retinal fundus images.
- The implementation of a Federated CNN architecture is a ground-breaking measure to solve privacy issues related to medical data used in the diagnosis of DR. Through federated learning and the decentralization of local datasets across devices in a client-server architecture, the research guarantees the safe exchange of private patient data without compromising individual privacy.
- CNN model function as feature extractor, demonstrating the ability that CNNs are at recognizing spatial feature hierarchies from a variety of source data.
- The incorporation of the Adam optimization algorithm is one of the most significant contributions to the research, which shows a dedication to improving neural network training efficiency.

This research generated new knowledge in the following areas:

- Demonstrating that federated learning may be effectively used to diagnose diabetic retinopathy while maintaining patient anonymity.
- Showing that integrating Fed CNN architecture with the Adam optimiser enhances classification accuracy and convergence speed when compared to existing methods such as FR-CNN, ANN, and SVM.
- Providing proof that decentralised AI training can identify diabetic retinopathy at different severity levels with 98% accuracy.
- Introducing a scalable framework designed for telemedicine and personalised healthcare applications.

This research describes a federated deep learning framework for the classification of diabetic retinopathy that employs a Convolutional Neural Network optimised with the Adam algorithm. The suggested method prioritises privacy-preserving collaborative learning among many healthcare institutions, without sharing raw retinal image data. The work focuses on model construction, federated training architecture, MATLAB implementation, and performance evaluation based on classification accuracy. However, this study does not cover clinical treatment recommendations, real-time deployment in hospitals, hardware optimisation, or the identification of eye disorders other than diabetic retinopathy.

The following is the arrangement of the remained sections in this article: A summary of related studies is given in Section 2. The current system's problem statement is given in Section 3. In Section 4 of the study, the methodology and architecture of the proposed Adam enhanced Fed CNN for DR diagnosis and classification are described. The results of the study and the discussion that followed are presented in Section 5. Section 6 discusses the conclusion of the suggested model and its future application.

2. RELATED WORKS

Hemanth et al. [12] work aimed to diagnose diabetes-related retinopathy from fundus images of the retina using a different hybrid solution method. To be more specific, the hybrid approach relies on combining deep learning and image processing to achieve better outcomes. Retinal fundus image interpretation by hand involves a significant amount of labor, skill, and over processing time. Thus, visualization and computerized vision systems are essential to physicians, and the application of smart diagnosis systems is generally considered to be the next step. The study's suggested solution makes use of contrast-limited adaptable histogram equalization techniques as well as processing images with histogram equalization. Next, a CNN classification is used to make the diagnosis. The average values for the various performance evaluation criteria were 97% for accuracy, 94% for sensitivity, 98% for specificity, 94% for precision and 94% for F1-Score. The interpretability issue is one restriction when employing CNNs to enhance diagnosis-classification performance. This lack of interpretability may be a drawback, particularly in healthcare settings where establishing the model's acceptability in actual clinical situations and winning over medical professionals to the model are dependent on its transparency and interpretability.

A unique deep learning architecture was proposed by Islam et al. [13] to determine if an individual has diabetes or not based on the image of their retina. The research used a relatively small dataset to create a multiple stages convolutional neural network based model DiaNet, which achieves over 84% accuracy on this task and, as confirmed by medical experts, effectively recognizes the areas on the retina's images that are important to its decision-making process. This is a landmark study that emphasizes the retinal pictures' capacity to differentiate diabetic patients from the general population in Qatar. By evaluating DiaNet's performance against the current medical data-based field of machine learning models, researchers are able to determine that there is enough information in the retinal images to differentiate the diabetic cohort from the control population in Qatar. Furthermore, the research shows that predictive indicators for diabetic and other diseases like high blood pressure and ischemic cardiovascular disease may be present in retinal pictures. Based on the findings, experts feel that retinal scans should be used in the near future as part of the medical setup for diabetes diagnosis. The effectiveness of the model may be impacted by confounding variables or comorbidities that appear in the retina, which is one possible disadvantage of using retinal pictures for diabetes prediction. To guarantee the model's resilience and applicability to a range of demographics, confounding factors must be carefully taken into consideration.

Disease detection is challenging because early symptoms are scarce due to the disease's gradual course. Consequently, to support the early stages of the identification and screening process, an entirely computerized system is needed. Nazir et al. [14] Research presented an automated method for disease localization and segmentation using fuzzy k-means clustering and the Fast Region-based CNN algorithm. The bounding-box annotations are necessary for the FRCNN object detection method to function. A thorough comparison with the most recent techniques validates the approach's effectiveness for both disease identification and segmentation. The findings show that the suggested treatment was successful in achieving an average IoU of 95% and a mAP value greater than 94% in three different disorders. Furthermore, the suggested method can also be applied to address the various medical imaging segmentation problems. The method's sensitivity to changes in image quality was one possible flaw. The categorization performance is impacted if the input photos show a range of quality levels, including differences in image quality, contrast, or artifacts.

Yoo et al. [15] showed the way how few-shot learning with a GAN can increase the applicability of DL for diagnosing uncommon diseases with OCT. The study includes five uncommon illness categories with a few-shot dataset and four major classes with several datasets. We built GAN models to produce pathologic image data of each rare illness from normal OCT images prior to training the classifier. An expanded training dataset was used to train the Inception-v3 architecture, and an independent test dataset was used to evaluate the finished model. The distinguishing traits of each rare illness were extracted with the aid of synthetic photographs. The suggested DL model beat the Siamese network, prototype network, and classic DL models in terms of accuracy in the OCT detection of uncommon retinal disorders. Clinicians can reduce diagnostic delay and patient hardship by using FSL to diagnose uncommon retinal illnesses more accurately and prevent disregarding rare disorders with DL support. It's possible that the model will learn from these distortions and yield false findings if the results produced don't fairly depict the genuine variations within the uncommon retinal disorders is the drawback of the study.

The use of intelligent diagnosis techniques in advance analysis and disease detection is becoming widely acknowledged. An artificial neural network supervised learning strategy was presented by Chakraborty et al. [16] to enhance the accuracy of DR diagnosis results. The ANN-based classifier receives features that are taken out of the retinal pictures as input. Customized ANN architecture has been utilized to increase the method's accuracy by estimating multiple traditional ANN elements. In this work, an ANN architecture known as a feed-forward neural network with back propagation is adopted. The suggested method's accuracy was determined to be 97.13%. The findings imply that the suggested approach can successfully identify DR. The suggested method's drawback is that its efficacy could diminish if the images are not captured accurately and with exact features. The study's future objectives include capturing photos of DR patients, applying an appropriate feature extraction technique, and testing the method's accuracy on the patients.

The goal of diabetes-related retinal image classification is to automatically diagnose DR, and deep learning models have made significant progress in this regard. All of these techniques, however, rely on extensive annotated data sets for network training, which is highly labour-intensive when it comes to categorizing medical images. Luo et al. [17] work focuses on integrating a self-supervised framework into an unsupervised deep learning structure in an effort to address these shortcomings. In particular, we suggest utilizing a fuzzy self-supervision module, a feature learning module, and a reconstruction module to create a Self-supervised FCN. The network's representativeness is guaranteed by the characteristics learning and reconstruction modules, and the fuzzy self-supervision module is in the position of continuing to provide the training guidance for the entire network. Moreover, in an unsupervised way, the three losses of the rebuilding process, fuzzy supervision, and self-supervision work together to optimize the SFCN. We apply the network to three popular retinal image datasets in order to assess the efficacy of the suggested approach. The findings show that the network performs satisfactorily on an unsupervised retina image categorization job. The SFCN's sensitivity to changes in picture quality or artifacts found in medical imaging is one of its limitations. The SFCN may not generalize well to images with significant variations because medical images can occasionally exhibit a variety of characteristics, such as shifts in lighting conditions, focus, or artifacts introduced during the process of imaging. This could result in performance loss in real-world scenarios where the quality of input images varies.

The reviewed literature identifies a number of downsides with the suggested ways for classifying diabetic retinal images. A significant problem is that the approach is sensitive to the characteristics of the retinal images that are taken, which could affect in crimes when diagnosing rare retinal conditions. Likewise, the model's responsibility in practical scripts is impacted by differences in image quality, analogous as contrasts and vestiges. The study emphasizes the necessity for careful evaluation to ensure the model's performance across varied demographics by admitting the part of confounding variables and comorbidities in imaging the retina. The interpretability problem posed by CNN use makes them unpopular in remedial surrounds where openness is essential. Eventually, SFCN's perceptivity to variations in vestiges and image quality is limited, which hinders its capacity to generalize to a variety of images. These drawbacks point out areas where diabetic retinal image classification ways need to be improved.

3. PROBLEM STATEMENT

Diabetes retinopathy (DR) is a primary cause of blindness among diabetes individuals worldwide. Early detection and proper classification of DR are critical for preventing serious vision damage. Traditional methods of diagnosis necessitate the use of professional ophthalmologists and centralised medical data collecting, which can be time-consuming, expensive, and difficult to scale up. Existing machine learning and deep learning systems frequently use centralised datasets, raising serious concerns about patient privacy, data security, and regulatory compliance. Furthermore, traditional classification models such as ANN, SVM, and basic CNN approaches may have reduced accuracy and limited generalization when trained on isolated datasets from a single healthcare institution.

The challenges highlighted in the existing research suggest that DR diagnosis remains a significant challenge in healthcare, necessitating improved image processing and classification techniques. One of the most pressing challenges in the medical industry is ensuring the privacy and security of sensitive patient data during model training and data exchange operations. To address these restrictions, a new method based on the Federated

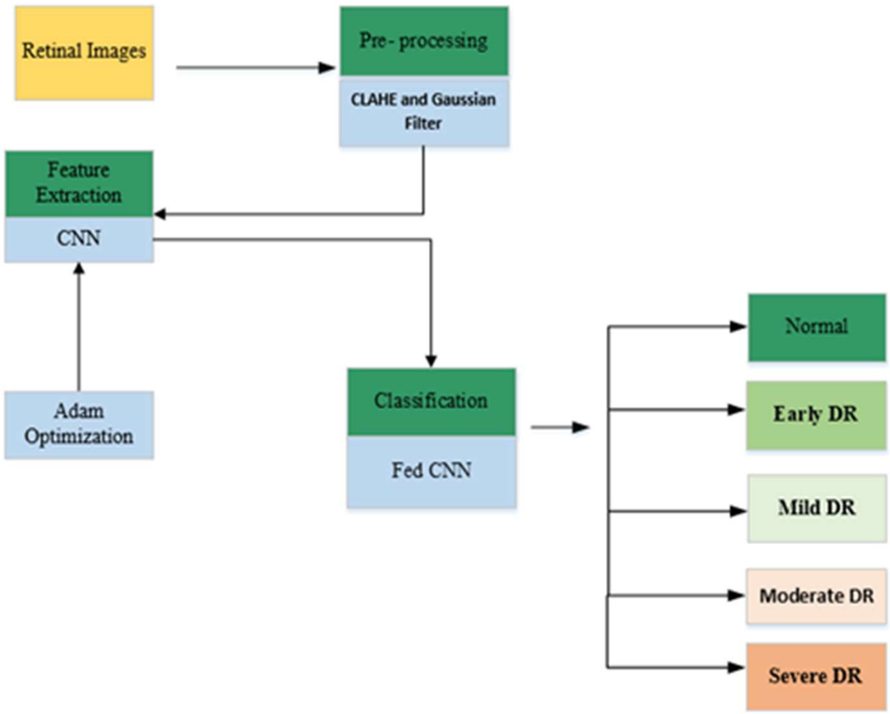

Figure 1: The Methodology Flow of the Adam Optimized Fed CNN Model

Convolutional Neural Network (Fed CNN) architecture is offered. The proposed method uses federated learning in a client-server context to enable decentralised training on local retinal image datasets dispersed across various healthcare facilities while protecting sensitive patient information.

Furthermore, CNNs are used as efficient feature extractors in retinal image analysis, and the Adam optimisation algorithm is used to improve training efficiency, convergence speed, and classification performance. The suggested technique seeks to create a scalable, privacy-preserving, and highly accurate DR diagnosis system that improves classification accuracy while maintaining medical data confidentiality. Finally, this framework aims to improve diabetic retinopathy diagnosis and contribute to better healthcare outcomes, including telemedicine support and personalised healthcare services.

Figure 1 shows the overall methodology flow illustration of the proposed model. It illustrates the successive way and processes involved in enforcing a federated Convolutional Neural Network (CNN) model optimized using the Adam optimization algorithm.

4. PROPOSED FED CNN FOR DR DIAGNOSIS AND SUPERVISED CLASSIFICATION

A thorough method for detecting DR has been described in this work. It includes gathering data, pre-processing methods such as Gaussian filter and CLAHE, and a Federated CNN architecture for feature extraction and classification. The high-resolution retinal images in the collection have severity labels that range from 0 to 4, which represent variances in real-world imaging. Pre-processing methods include reducing the size of the image and applying histogram equalization and

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CLAHE techniques to improve the quality of the image. The Gaussian filter is also used to lower noise in medical images, protecting the data integrity necessary for precise diagnosis. Moreover, by decentralizing local datasets and safely aggregating model updates, federated learning is integrated to solve privacy concerns related to medical data.

The architecture follows deep learning principles, which makes it easier to identify complicated patterns that are important for diagnosing DR. Additionally, for increased training efficiency, the study presents the integration of the Adam optimization algorithm, which combines the advantages of momentum and RMSprop. The performance of this integrated technique in the diagnosis of DR will now be examined, along with its potential implications for privacy-preserving medical data analysis and its effectiveness and accuracy.

4.1 Data Collection

Several high- resolution retinal images with markers indicating the inflexibility of DR (0 to 4) are included in the dataset. Images show both the left and right eyes of various cases, each with a distinct ID. Physicians estimated the inflexibility, and since different cameras produce varied views. Specially, the placements of the macula and optic nerve can be affected by the images that are moreover anatomically realistic or reversed. In anatomical perspectives, the optical nerve for the right eye is on the right, and the macula is on the left. The macula in inverted views may be below the midline of the optical nerve or may not have a notch. The miscellaneous dataset is delicate for automated analysis because it replicates real- world retinal imaging situations. For models to directly determine the inflexibility of DR, they must take into consideration fluctuations and identify symptoms of inversion.[18].

4.2 Data Pre-Processing Using CLAHE and Gaussian Filter

The research employs CLAHE image processing techniques to provide an alternative approach to improve retinal fundus images. When integrated into a single strategy, the well-known image enhancement technique CLAHE is rapid and easy to implement. In short, the study's steps were as follows: The target image sizes are first reduced to 150 by 225 pixels in order to decrease the amount of memory required by the deep learning process on computers. At the next stage, the retinal fundus imageries are divided into three image constituents: RGB. Following that, CLAHE is applied to each R, G, and B component, respectively. Finally, a concatenation approach is applied to the R, G, and B components to generate the colourful image that the CNN will use for deep learning. Further details on the two image processing technique (CLAHE) that were applied are given in the next subsections.

Images, especially those taken underwater, can be improved by applying a method called CLAHE. While CLAHE was originally developed for medical picture quality improvement, it may now be used for any type of image that requires improvement. When applied to conventional and medical photographs, CLAHE momentarily increases contrast significantly. CLAHE also does a fantastic job at compressing low-contrast images, such as those shot underwater. The following is a summary of the solution mechanism for the CLAHE: It splits the images into nominal partitions first, then applies the equalization of the histogram to each partition that is taken into consideration.

This process balances the grey value distribution of the target image. In this way, the image's hidden characteristics emerge more fully in line with its original form. The whole grey spectrum is now being used to describe the image. By carefully condensing the area borders, it is also possible to maintain sharp area margins. Selective condensation involves processing a picture just in the regions that are inside the boundary, after the area edge of the image has been determined. It is even feasible to lessen noise while maintaining the image's high spatial frequency content by combining the CLAHE, edges shaping, and median filtration. In technical terms, the amplification was limited by clipping the histogram at a specific value, and this was accomplished via CLAHE. The amount of noise in the histogram that is smoothed out that is, the contrast is enhanced is determined by that value [19]. Typically, the Rayleigh distribution is used to cut the histogram in the manner shown below.

$$h = h_{min} + [2(\propto^2)\, ln \frac{1}{1-p(f)})]^{0.5} \quad (1)$$

P (f) denotes the cumulative probability distribution in Eqn. (1), together with a nonnegative real scalar that serves as the distribution parameter. A minimal pixel value is defined by $\mathrm{h_{min}}$.

The most common causes of noise in medical images include irregular illumination that develop during imaging. The delicacy of the results could be significantly impacted by vestiges that arise from noise input into these images. Inaccurate discovery findings may ultimately arise from this. For this reason, the medical image analysis channel's noise removal step is essential. In order to insure the integrity of the data, noise must be excluded before employing point birth ways, which are pivotal for an accurate opinion. Gaussian is one of the most significant filters and frequently used pre-processing way for removing noise. Its primary purpose is to apply a blur to images, an extensively honoured system for minimizing noise and smoothing edges. The Gaussian sludge does this by trying to strike a delicate balance between emphasizing the image's most significant features and reducing insignificant or distracting details. This scrupulous tuning is necessary to enhance the overall superiority of the images and establish the foundation for a more accurate and dependable retinopathy categorization [20].

By effectively eliminating noise while preserving the essential components of the image, this filter for medical image analysis can yield more reliable results [21]

$$G(a,b) = \frac{1}{\sqrt{2\pi\rho^2}} e^{-\left(\frac{a^2+b^2}{2\rho^2}\right)} \qquad (2)$$

4.3 Feature Extraction and Classification Using Fed CNN Architecture for DR Diagnosis

Convolutional Neural Networks (CNNs) are an advanced and effective system for feature extraction from retinal pictures in DR opinion utilizing Supervised Classification. CNNs are particularly effective at relating complex patterns and features that are necessary for precise medical opinion since they're made for image- related conditioning. Because a CNN's architecture is so precisely designed to act the mortal visual system, it's especially useful for tasks like the discovery of DR. The input layer, which is the first layer of the CNN, is designed to fit the retinal pictures' confines. This makes it possible for the network to reuse the intricate spatial data set up in medical images directly. Also, several convolutional layers are used, each of which has activation functions for remedied Linear Units (ReLUs). As point sensors, these convolutional layers search the input image for different visual patterns at various sizes. By introducing on-linearity through the use of ReLU activation functions, the network is suitable to learn intricate correlations between pixels and features. Convolutional layers are followed by pooling layers, which are constantly enforced as maximum-pooling. In order to concentrate on the most important information and lessen computational load, maximum- pooling is used to down- test the spatial confines of the features. By keeping significant features while removing less important details, this medium aids the network in processing the most pivotal corridor of the retinal pictures for processing by the following layers. Completely connected layers also admit the convolutional and pooling layers' flattened affair. By incorporating the acquired data, these layers serve as classifiers, prognosticating whether or not DR will develop. Dropout layers are a voluntary addition that can help keep the model from over befitting and improve its capacity for conception. The affair layer partially uses a sigmoid activation algorithm to allow for double classification.

The model generates a probability that represents the possibility of DR, and the ultimate double choice can be made by applying a threshold. A careful layer arrangement is reflected in the intricate armature of the CNN in the environment of diagnosing DR, with each layer helping to extract material information from retinal pictures. Under the guidance of deep learning principles, this system enables the model to identify complex patterns that are essential for precise and timely opinion of DR. The federated learning integration and the architecture of CNN is explained in detail Figure 2.

The methodology integrates Federated Learning into the feature extraction and classification phase to mitigate privacy problems related to medical data. Federated Learning is a decentralized machine learning technique that makes use of the cooperative strength of several networks. Federated Learning, in contrast to conventional centralized models, has a distributed design that makes use of three different networks: A, B, and C. A portion of the entire dataset is stored in each network, and without sharing raw data, the model is trained cooperatively across these disparate datasets. The networks can share knowledge while maintaining data privacy due to this federated configuration. Networks A, B, and C facilitate cooperative training by combining information from several sources to create a more comprehensive and universal model. This method not only improves the performance of the model but also tackles issues with data security and confidentiality during the learning process. Local datasets are stored between devices in the established client-server architecture. The localization of raw data is maintained by this decentralization. Sensitive patient data can be shared without compromising patient privacy thanks to the communication protocol. In order to combine these updates on the central server and create a global model without jeopardizing the privacy of individual data, the aggregation process is carefully designed. In this situation, federated learning acts as a privacy-preserving paradigm that enables healthcare organizations to work together to jointly train a strong model without having to centralize patient data. This method addresses privacy issues related to the centralized processing and storage of

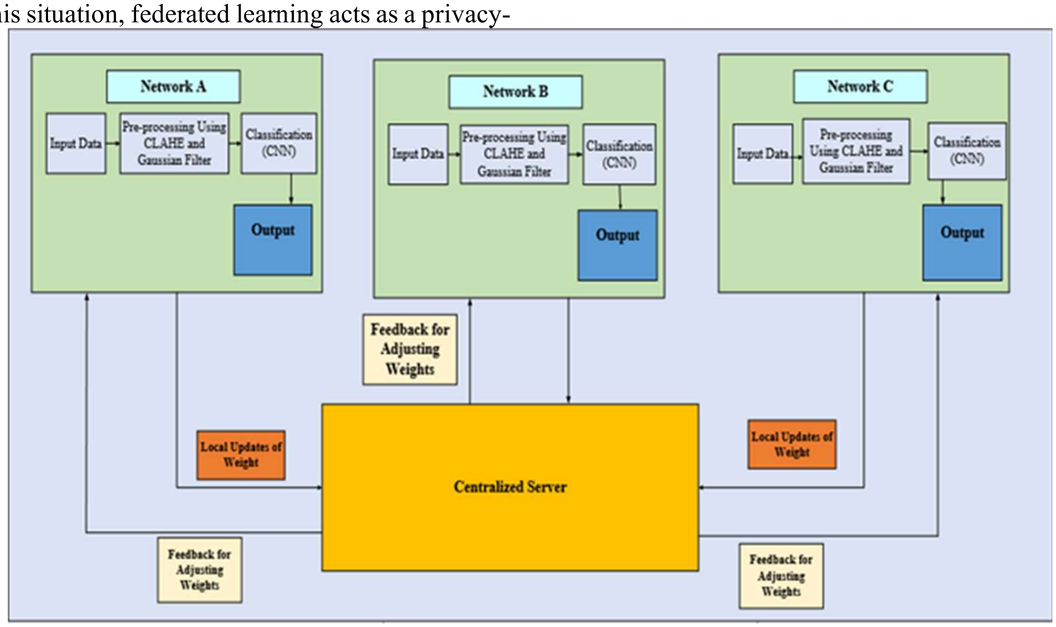


Figure 2: The Architectural Diagram of Fed CNN

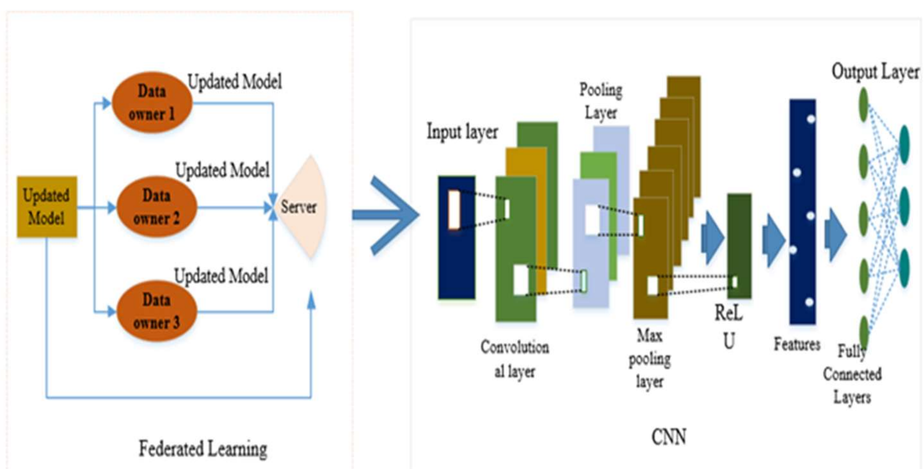


Figure 3: The Architectural Diagram of Fed CNN

sensitive medical data by carefully protecting the privacy of locally stored retinal images throughout the whole training process. The federated learning paradigm presents a cooperative and decentralized approach that is in perfect harmony with the need to protect patient privacy.

With each device or server storing a subset of the local dataset, the client-server architecture used in this integration is intended to disperse the learning process. By limiting raw patient data to its original site, this decentralization helps to mitigate the hazards that come with central repositories. Sharing of raw medical pictures is minimized because each device learns locally and the individual datasets function as discrete data silos. Federated learning relies heavily on the communication protocol that is set up between the local devices and the central server. With the help of this protocol, model updates can be securely exchanged without requiring the transmission of private raw data. The iterative communication mechanism keeps the raw patient data private while enabling each local device to make a contribution to the global model's improvement. This improves training process security and complies with stringent privacy laws protecting medical records.

One further important component that helps to protect sensitive medical data is the aggregation method, which gathers the model updates on the central server. Federated Learning, then, shows itself to be more than just a way to improve the model's diagnostic abilities. It turns into a pillar for establishing trust between patients and healthcare professionals. This innovative integration protects patient privacy and promotes a safer, more cooperative healthcare environment. In addition to advancing the field of DR Diagnosis Using Supervised Classification, the well - balanced combination of cutting-edge machine learning techniques with privacy-centric methodology establishes a precedent for privacy-preserving procedures in the wider setting of medical data analysis.

The architectural diagram of the Federated CNN (Fed CNN) likely illustrates the network's structure, showcasing its layers, connections, and data flow is shown in Figure 2. This visual representation aids in understanding the model's design and how information is processed across different nodes in a federated learning framework. Analyzing this diagram provides insights into the distributed nature of the model, crucial for collaborative learning across diverse datasets in healthcare facilities.

Another technique for extracting CNN features is transfer learning, which uses pre-trained CNN models as feature extractors. CNNs' architecture makes it possible for them to automatically and adaptively identify spatial feature hierarchies from the input data, making them particularly well-suited for jobs involving grid-like data, such as images and videos. The CNN is a widely used type of artificial neural network in deep learning for various computer vision applications. Tasks where CNNs must learn the spatial hierarchies of features from the source data in an independent and adaptable manner are especially well-suited for them.

Convolutional layers apply a series of "filters" on the original data. Each filter is designed to recognize a specific pattern or feature, such edges, corners, or, for deeper layers, more complex structures. The precise spots of the qualities as they travel over the image are displayed on a map that is made by these filters. A feature map, or description of the initial information with the filters applied, is the output of the convolutional layer. Convolutional layers can be loaded to generate more sophisticated models with a greater ability to retrieve minute details from images. The pixel of input, filter, and value at the position are represented by the Eqn. (3).

$$A(r,s) = \sum x \sum y\, B(r + x, s + y) * D(x, y) + b \quad (3)$$

Pooling layers is utilized to reduce the spatial dimension of user input and speed up processing. Following convolutional layers in the computational hierarchy are these. "Spatial dimensions" in the wider sense of the word refers to an image's height and width. Pixels are the basic building blocks of an image; they are made up of microscopic squares arranged in rows and columns. Pooling layers assist in minimizing the number of components or weights in the framework by lowering the spatial dimensions. This helps prevent overfitting and speeds up the model's training process. By reducing the function map, max pooling saves processing costs while making the framework invariant to tiny transitions. Max pooling is used to get the maximum value from each feature map. Within the pooling frame, max pooling successfully captures the most noteworthy attribute or characteristic. The total of every value in the pooling frame can be determined using average pooling. It gives an impression of common, rounded traits. The greatest pooling function can be found in Eqn. (4).

$$F(r,s) = \max\left(F(2p, 2q), F(2p, 2p + 1), F(2p + 1, 2q), F(2p + 1, 2q + 1)\right) \quad (4)$$

In a convolutional network, the fully connected layers are usually employed towards the end when the objective is to use the features acquired by the min and max layers of pooling to generate predictions, like labelling an input. When classifying images of creatures using a CNN, for example, the last fully connected layer may use the attributes that the previous layers had taught it to determine whether the image contained a dog, cat, bird, etc.

The completely linked layers are in charge of mapping the integrated properties to the anticipated outcomes, such as class labels in task categorization. The following Eqns. (5) and (6) represents the weighted sum and activation is given below.

Weighted sum: $Z = B.C + b$ (5)

Activation: A= softmax (Z) (6)

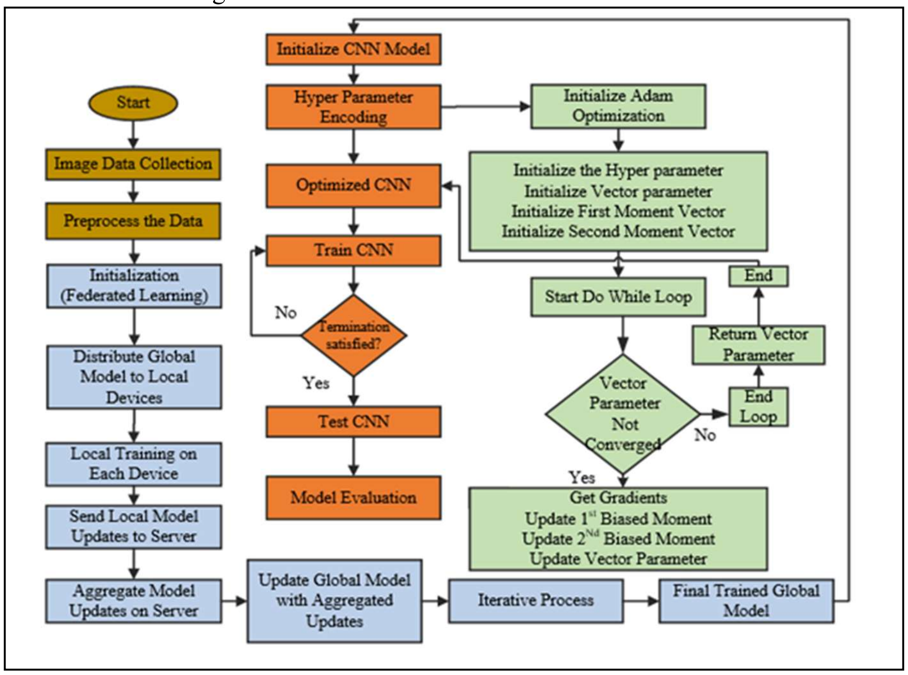


Figure 4: The Flow chart of the proposed Adam Optimized Fed CNN

It is possible to extract the final classification layers from a pre-trained model and use the output from its previous layers as features for a specific purpose. Compared to ordinary neural networks, CNNs have more layers. The depth, width, and height of each neuron are organized in the CNN based on volume. The convolutional, pooling, and connected layers make up the entirety of the CNN. An image with values per pixel makes up the input. For example, it has three dimensions: depth, width, and RGB channels [50 x 50 x 3]. The output of neurons associated to particular input local regions will be computed by the convolutional layer. Consequently, the process determines which filters to activate when it comes across a particular type of feature at a particular location in the user's input, creating a two-dimensional map of the filter's activation.

The amount of neurons (nodes) in the output layer for image categorization tasks is typically equal to the number of classes or groups that the algorithm is expected to classify. Common activation factors in the output layer for segmentation and classification tasks are Softmax, which converts the raw class scores into class probabilities, and Sigmoid, which classifies binary data. The Eqn. (7) represents the output probability (Z) is given below,

Output Probability(Z) = Sigmoid(Neuron Output (Y)) (7)

4.4 Integration of Adam Optimization into CNN for Improved Classification and Analysis

An optimization technique called Adaptive Moment Estimation, or Adam, is widely used for neural network training, particularly challenges involving in classification and diagnosis tasks. It combines the benefits of two previous optimization methods, Root Mean Square Propagation and momentum. By modifying the learning rates of specific parameters in accordance with the historical gradients, Adam performs admirably in a variety of machine learning settings [22].

The decay rate in the first moment estimate (β_1), and the decay rate in the second moment estimate (β_2) and the learning rate (α) are all set as hyperparameter during setup. At each iteration, the technique calculates the grade of the loss accordance to model parameters and updates the first and second moment estimates using exponential decay. In order to resolve biases towards zero, Adam provides terminology for bias correction.

Update the first moment estimate using exponential decay, and use the following Eqns. (8) and (9) to construct the second moment estimate.

$$n_i = \beta_1 . n_{i-1} + (1 - \beta_1). g_i \quad (8)$$

$$o_i = \beta_2 . o_{i-1} + (1 - \beta_2). (g_i)^2 \quad (9)$$

where n_i and o_i, respectively, stand for the initial and next moment estimations at iteration i, and g_i represents the gradient.

$$\widehat{n_i} = \frac{n_i}{1-\beta_1^i} \quad (10)$$

$$\widehat{o_i} = \frac{o_i}{1-\beta_2^i} \quad (11)$$

$$\theta_{i+1} = \theta_i - \alpha . \frac{\widehat{n}_i}{\sqrt{\widehat{v}_i + \epsilon}} \quad (12)$$

$\theta_i$represents the model variable at iteration t, α represents the learning rate, and ϵ is a small constant that keeps division by zero constant. Using the bias-corrected estimations, the model parameters are updated in the last step. Adam's versatility, effectiveness in the actual world, and blend of momentum and the RMSprop make it a potent optimizer. Its success is dependent on task-specific factors and hyper parameter selections, therefore achieving the optimal results requires trial and error. Adam's momentum integration and adaptive features make it a suitable neural network training optimizer. Figure 4 below shows the flow chart for the Adam-optimized Fed CNN.

5. RESULTS AND DISCUSSION

The federated CNN model performs admirably in reliably diagnosing DR severity levels, according to an evaluation of the model conducted using distributed datasets from several healthcare facilities. The model was trained utilizing the Adam optimization technique. The effectiveness of the proposed model effectiveness in many classification aspects, is provided by the thorough examination of key performance metrics. The discussion that follows explores the consequences of these findings, assesses how well the model generalizes across various datasets, and compares it with existing methods.

5.1 Performance Metrics

Accuracy: Accuracy is determined by comparing the predicted class labels generated by the CNN with the actual labels for the test dataset. Increase the "Number of Correct Predictions." After processing all the test images to ascertain correctness divide this amount by the "Total Number of Predictions" if the predicted label for an image in the test dataset equals the actual label. The following Eqn. (13) is frequently used to calculate accuracy.

(13)

Precision: Precision is a quantified quantity, mostly in statistics and ML. It assesses a model's capability to make optimistic predictions about the future. The fraction of correct estimates to all reliable estimates is known as precision.

$$Precision = \frac{True\ Positives}{(True\ Positives + False\ Positives)} \quad (14)$$

The level of precision has a range from 0 to 1.

F1-score: A popular metric for assessing sorting model performance is the F1-score, particularly for segmentation and classification-heavy models. When a dataset is imbalanced—that is, when one class greatly outnumbers the other—the F1 score comes in handy.

The Eqn. (16) is used to determine the F1-score.

$$F1\ Score = 2 \times \frac{(Precision \times Recall)}{(Precision + Recall)} \quad (16)$$

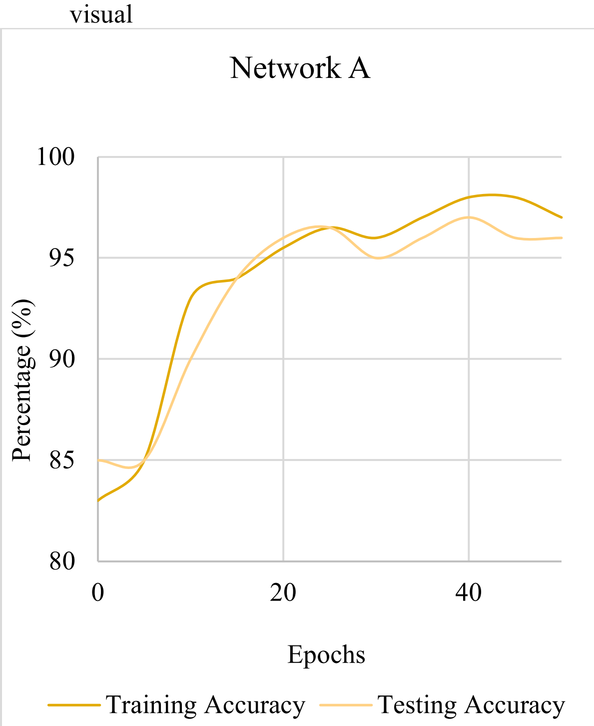
Figure 5 compares the Training and Testing Accuracy for Networks A, B, and C and shows how these networks learn and generalize across 100 epochs in different ways. With time, these losses diminish, suggesting that the model is acquiring up new skills and becoming more efficient. While the training accuracy increases more gradually over the course of the epochs, the testing accuracy also gradually increases like training accuracy and then on reaching further epochs. Figure 6 compares the Training and Testing Loss for Networks A, B, and C and shows how these networks learn and generalize across 100 epochs in different ways. With time, these losses diminish, suggesting that the model is acquiring up new skills and becoming more efficient. While the training loss declines more gradually over the course of the epochs, the testing loss begins at a greater value than the training loss and then abruptly declines before falling about epoch 20.

Figure 7 and Table 1 visually represents the performance metrics of the Adam-optimized Federated CNN compared with methods. This graphical illustration provides a clear and insightful overview of proposed model excels in metrics when compared it with the conventional approaches, emphasizing its superiority in DR diagnosis.

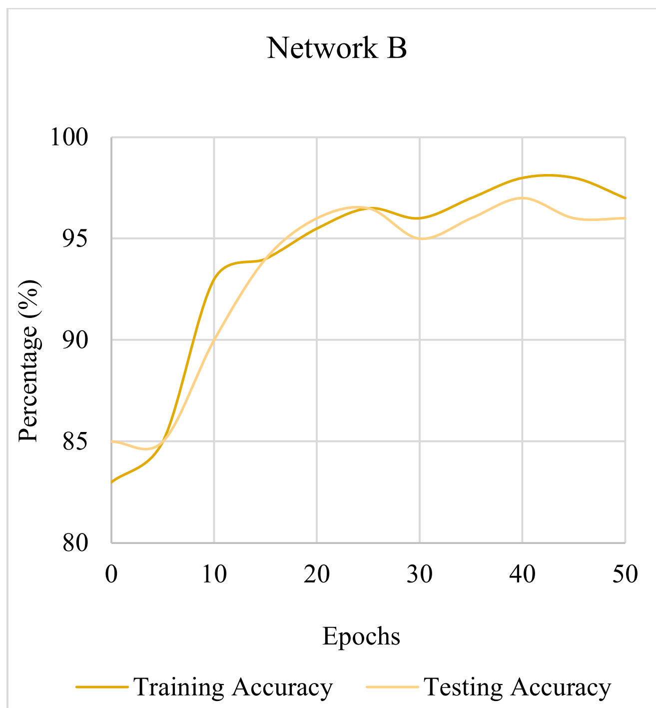
Table 1. *The Fed CNN Method's Performance Metrics are Compared with Existing Methods*

Method	*Accuracy (%)*	*Precision (%)*	*Recall (%)*	*F1Score (%)*
Faster R-CNN [14]	94	85.6	83.3	92.5
ANN [16]	97.13	89.3	89.93	97.94
SVM [23]	96.4	88.6	86.4	87.5
Proposed Adam optimized FedCNN	98	98.5	96.7	98.2

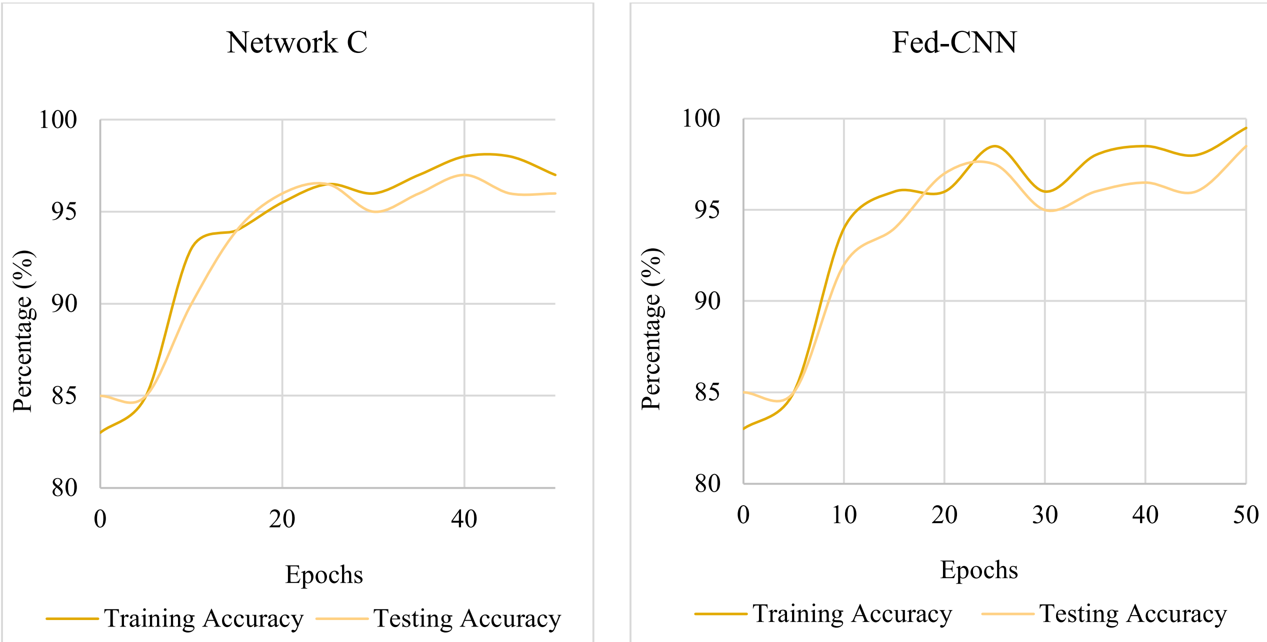
Figure 8 showcases the ROC curve for the proposed Adam- optimized Federated CNN, furnishing a visual



(a)



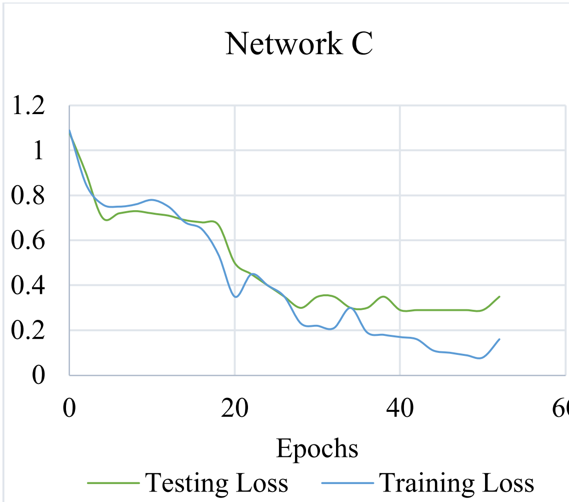
(b)



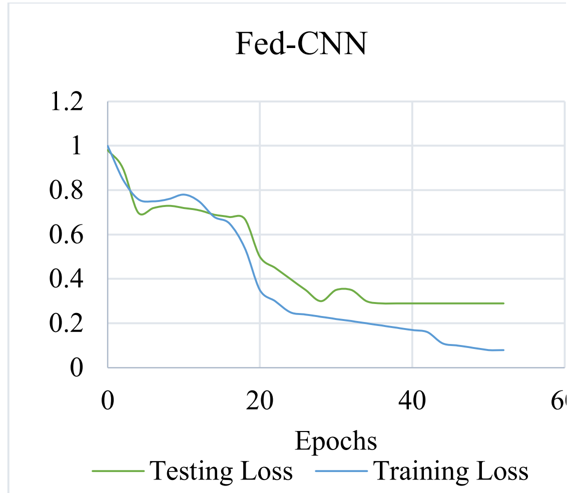
(c) (d)

Figure 5: Training and Testing Accuracy of CNN model for (a) network A, (b) network B, and (c) network C and (d) Fed-CNN model

(a) (b)



(c)



(d)

Figure 6: Training and Testing Loss of CNN model for (a) network A, (b) network B, and (c) network C and (d) Fed-CNN model

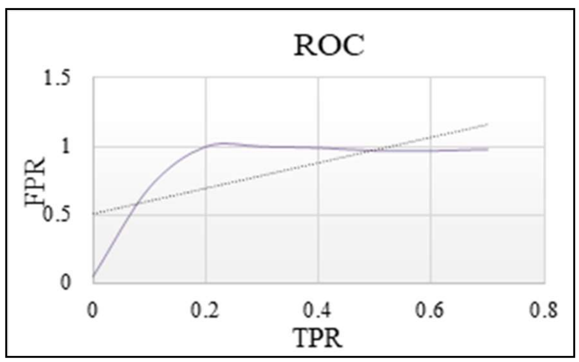


Figure 7: Illustration of the Performance Measures of the Adam Optimized Fed CNN Using Traditional Methods

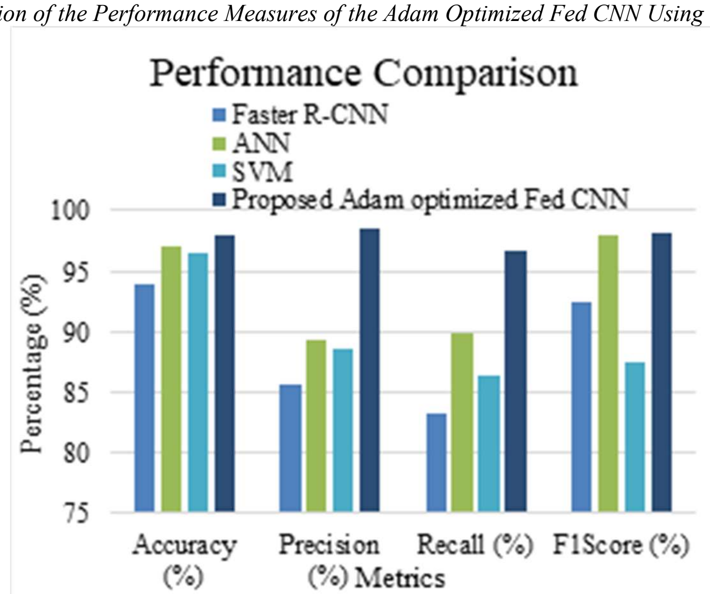


Figure 8: ROC curve of Proposed Adam Optimized Fed CNN Graphical Representation of Training and Testing loss

definition of the model's trade- off between perceptivity and particularity. This graphical representation is necessary in assessing the model's capability to distinguish between different DR inflexibility situations, offering precious perceptivity into its overall classification performance.

5.2 Discussions

The Adam-optimized federated CNN model performs well in diagnosing various severity levels of diabetic retinopathy (DR), as evidenced by evaluation utilising distributed datasets obtained from numerous healthcare institutions. The graphical analysis contrasts training and testing losses for Networks A, B, and C, offering a clear picture of how each model evolves over time. This visualisation aids in evaluating training convergence, stability, and generalisation ability across several data sources, demonstrating that the suggested federated strategy maintains consistent learning performance even in a decentralised setting. The evaluation is also supported by common performance indicators such as accuracy, precision, recall, and F1-score. The proposed model achieves an overall accuracy of 98%, outperforming previous approaches such as Faster R-CNN (94%) [14], ANN (97.13%) [16], and SVM (96.4%) [23]. Furthermore, the precision (98.5%), recall (96.7%), and F1-score (98.2%) show that the model is extremely dependable in correctly identifying positive DR cases while efficiently managing class imbalance in the dataset. The graphical representations of training and testing accuracy, loss curves, and ROC curves provide additional evidence that the model converges effectively during training and can clearly distinguish between distinct DR classes. Overall, these findings show that the proposed Adam-optimized federated CNN is a more accurate, stable, and resilient solution for DR detection than traditional techniques, making it a viable tool for secure and privacy-preserving medical image analysis.

6. CONCLUSION AND FUTURE SCOPE

In conclusion, this paper describes a privacy-preserving Diabetic Retinopathy (DR) detection system based on a Federated Convolutional Neural Network (Fed CNN) optimised with the Adam algorithm. The proposed approach facilitates collaborative learning across several healthcare institutions while protecting sensitive patient data and attaining high classification accuracy for various DR severity levels. The study emphasises the significance of combining federated and deep learning to create safe, scalable, and efficient AI-based healthcare solutions for telemedicine and personalised care. However, the current study is limited to certain retinal image datasets and focuses only on classification accuracy, leaving out real-world deployment difficulties such as communication overhead, computing complexity, and model explainability. Future work can improve the system by doing larger clinical validations, integrating real-time data, developing explainable AI approaches, and expanding to other medical diagnostic applications

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