MAJOR PROJECT-2 REPORT

THE MEDICAL IMAGE CLASSIFICATION USING RNN, CNN, LSTM.

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Declaration

This is to certify that the Major project-2 report titled **"The Medical Image Classification using RNN, LSTM, CNN "** which is submitted by me in partial fulfillment of the requirement for the award of degree M.Tech. in Computer Science to USICT, GGSIP University, Dwarka, Delhi, comprises only my original work, and due acknowledgment has been made in the text to all other material used.

Date:

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Certificate

This is to certify that the Major project-2 report entitled **"The Medical Image Classification using RNN, LSTM, CNN."** submitted by Sashwat Ranjan Shukla in partial fulfillment of the requirement for the award of the degree M.Tech CSE at USICT, GGSIP University, Dwarka, Delhi, is to the best of my knowledge, a record of the candidate's own work conducted under my supervision.

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Supervisor

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1. Abstract

In this study, we explore the integrating machine learning (ML) in the medical field has significantly improved disease detection, diagnosis, and treatment planning. Diabetes, also known as Diabetes Mellitus (DM), is a metabolic disorder that occurs due to elevated blood sugar levels in the body, this leads to the eye deficiency **Diabetic Retinopathy (DR) detection** which is a leading cause of vision loss. This project using **image classification techniques** to aid early diagnosis and prevent vision impairment. Diabetic Retinopathy is a severe complication of diabetes that affects the retina, leading to blindness if not diagnosed and treated in time.

To achieve accurate detection, this project employs various machine learning and deep learning algorithms, including Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and Transfer Learning. Each algorithm is applied to a dataset of retinal images to classify different stages of Diabetic Retinopathy. The performance of these models is evaluated based on key metrics such as accuracy, precision, recall, F1 score, and computational efficiency.

By comparing these techniques, this study aims to determine the most effective algorithm for Diabetic Retinopathy detection in terms of both accuracy and practicality. The findings from this research will contribute to the advancement of AI-driven medical imaging solutions, potentially assisting ophthalmologists in faster and more reliable diagnoses. Ultimately, this project highlights the role of machine learning in **enhancing automated medical diagnostics**, reducing manual workload, and improving patient outcomes.

2. Introduction

Here we explore the **implementation of machine learning (ML) in the medical field** and its growing impact on various healthcare sectors. The medical industry faces a significant challenge: while the number of patients continues to rise, the availability of healthcare professionals, including doctors and radiologists, remains limited. As a result, medical experts are increasingly burdened with analysing **X-rays, MRIs, retinal images, and diagnostic reports** a time-consuming process that requires precision and expertise.[1]

To address these challenges, **machine learning algorithms** are being integrated into medical diagnostics to enhance efficiency, accuracy, and speed. These advanced models can process vast amounts of medical data in minimal time, enabling early disease detection and assisting doctors in making informed decisions. By automating the classification and analysis of medical images and reports, ML helps optimize healthcare workflows, reduce human error, and improve patient outcomes. This study delves into the various **ML techniques used in medical diagnostics**,[2] examining their implementation, effectiveness, and transformative potential in revolutionizing healthcare. By leveraging artificial intelligence, the medical industry can enhance diagnostic accuracy, streamline processes, and ultimately provide better and faster care for patients.

Diabetic Retinopathy (DR), also known as **diabetic eye disease**, is a serious complication of diabetes mellitus that affects the retina and can lead to vision impairment or blindness if left untreated. Studies show that **individuals who have had diabetes for over 20 years** develop some form of DR. One of the biggest challenges in detecting DR is that it often has **no early warning signs**, making early diagnosis crucial for preventing irreversible vision loss.

Traditionally, **retinal photography** with **manual interpretation** has been used as a standard screening method for doctors. In many cases, it has been shown to be even more effective than **in-person dilated eye examinations**.[3] However, manual analysis is time-consuming and requires expert ophthalmologists, making it impractical for large-scale screenings. To overcome this challenge, **machine learning and deep learning** techniques are being explored to **automate the detection and classification of DR**, enabling faster and more accurate diagnoses.

This project focuses on **retinal image classification** to detect **Diabetic Retinopathy** at an early stage. By leveraging deep learning models, the goal is to develop an automated system that can analyse retinal images and identify diseases accurately. The primary focus is on using three different deep learning architectures CNN, RNN, and LSTM individually to compare their effectiveness in disease classification.

Machine Learning Models Used in this project to classify the image for diabetic retinopathy detection.

1. **CNN (Convolutional Neural Network)**
    - Designed to detect spatial patterns in medical images.
    - Uses convolutional layers to extract important features and pooling layers to reduce dimensionality while preserving key details.
    - Well-suited for recognizing visual patterns in retinal images and distinguishing between different diseases.[2]
2. **RNN (Recurrent Neural Netxwork)**
    - Analyzes sequential data by processing pixel values in a structured order.
    - Helps in identifying temporal dependencies within image sequences, providing a unique approach to classification.
3. **LSTM (Long Short-Term Memory – A Variant of RNN)**
    - A specialized form of RNN that mitigates vanishing gradient issues and effectively processes long-range dependencies.
    - Useful in learning complex patterns in retinal images for better disease classification.

With the increasing prevalence of diabetes worldwide, the risk of developing Diabetic Retinopathy (DR) has become a major concern in the medical field. Early detection is crucial to prevent severe complications, including vision loss and blindness. This project aims to develop an automated diagnostic system that leverages deep learning techniques to analyze retinal images and classify them based on the severity of DR. By utilizing Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) models, the system will process medical images to identify patterns associated with DR progression. The objective is to compare the performance of these models in accurately detecting and classifying DR cases, providing a reliable AI-assisted tool for ophthalmologists. [4], [5]This project not only enhances early disease detection but also contributes to the advancement of AI-driven healthcare solutions, making diagnostics more accessible, efficient, and scalable for large-scale screenings.

The models are trained on a labelled dataset of retinal images, with preprocessing techniques such as image resizing, normalization, and augmentation applied to enhance learning efficiency. Performance evaluation is conducted using key metrics, including accuracy, precision, recall, F1-score, and confusion matrix analysis.

In this project, retinal images are classified based on the severity of **Diabetic Retinopathy** using a dataset where a clinician has rated the presence of DR in each image on a scale of 0 to 4, as follows: 0 - No DR,1 – Mild,2 – Moderate,3 – Severe,4 - Proliferative DR

My task is to develop an automated analysis capable of assigning a severity score based on this scale. This system will analyze retinal images, determine the patient’s condition, and compare the performance of different deep learning models (CNN, RNN, and LSTM) to identify the most efficient technique for this approach.

By developing an AI-driven diagnostic tool, this project aims to help doctors and patients:

- Improve early detection of retinal diseases, reducing the risk of vision loss.
- Assist ophthalmologists in faster and more reliable diagnoses.
- Compare the efficiency of CNN, RNN, and LSTM models to determine the most accurate approach for medical image classification.

This study highlights the potential of deep learning in medical imaging, demonstrating how AI can revolutionize early disease detection and treatment planning in healthcare sector.

3. Diabetes Mellitus and Diabetic Retinopathy:

Diabetes Mellitus and Its Impact

Diabetes Mellitus (DM) is a chronic metabolic disorder characterized by persistently high blood glucose levels due to insufficient insulin production or the body's inability to use insulin effectively. Over the past few decades, diabetes cases have surged dramatically, increasing from **108 million in 1980 to over 422 million in 2014**.[1][6] The disease affects multiple organs, including the **heart, kidneys, liver, joints, and eyes**, leading to severe complications if left unmanaged.

One of the most serious complications of diabetes is **Diabetic Retinopathy (DR)** a progressive eye disease that damages the blood vessels in the retina, potentially leading to vision impairment or blindness. In fact, DR is the leading cause of blindness among individuals under 50. If not detected and treated early, the condition can advance to severe stages, causing irreversible vision loss.[7]

What is Diabetic Retinopathy?

Diabetic Retinopathy occurs when prolonged high blood sugar damages the delicate retinal blood vessels, causing them to swell, leak, or become blocked. As the disease progresses, the retina may develop abnormal new blood vessels (neovascularization), leading to hemorrhages, retinal detachment, and eventual blindness. The risk of DR increases with longer diabetes duration, poor blood sugar control, and high blood pressure.[8]

According to the World Report on Vision, approximately **11.9 million people suffer from visual impairment due to DR, glaucoma, and trachoma**. Globally, DR accounts for **2.6% of all blindness cases**.[6] Given its progressive nature, early detection is crucial to prevent vision deterioration.

Stages and Classification of Diabetic Retinopathy

Diabetic Retinopathy progresses through two main stages:

1. **Non-Proliferative Diabetic Retinopathy (NPDR):**
    - The early stage of DR, where abnormal retinal blood vessels leak fluids, leading to swelling and microaneurysms.

- Characterized by hemorrhages, microaneurysms, hard exudates, and venous beading.
- Severity increases from mild to moderate to severe NPDR.[9]

2. **Proliferative Diabetic Retinopathy (PDR):**
   - The advanced stage, where the retina develops abnormal blood vessels (neovascularization) due to oxygen deprivation.
   - These fragile vessels rupture easily, causing vitreous hemorrhages, scarring, and retinal detachment.
   - This stage significantly increases the risk of permanent blindness.

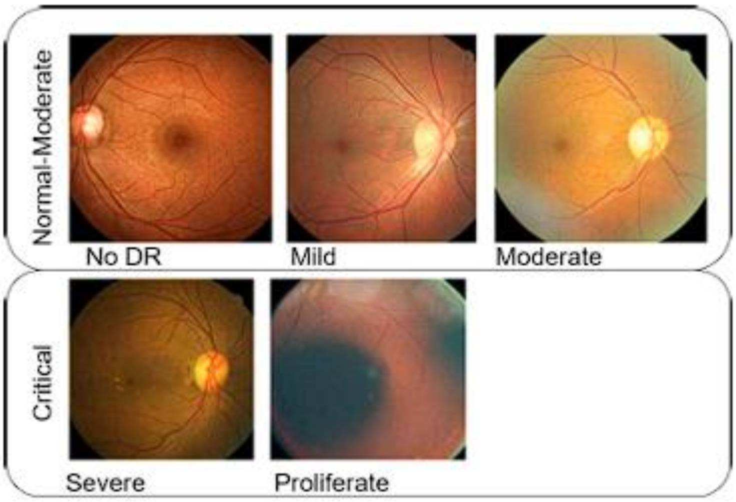

Figure 1: Stages of Diabetic Retinopathy[6]

Clinicians grade DR on a **scale of 0 to 4**, based on disease severity:

- **0 - No DR** (Healthy retina)
- **1 - Mild DR** (Microaneurysms present)
- **2 - Moderate DR** (Increasing damage but no neovascularization)
- **3 - Severe DR** (Extensive hemorrhages, venous abnormalities)
- **4 - Proliferative DR** (Neovascularization with high blindness risk)

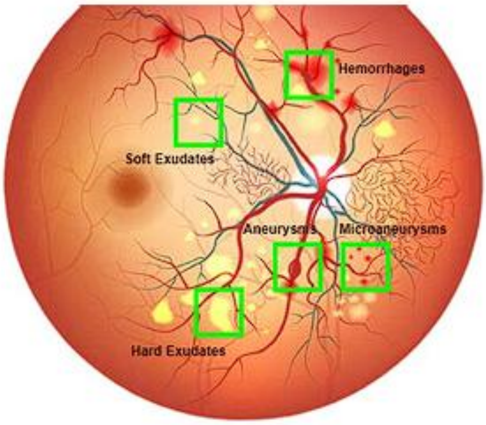

Figure 2: Retina, showing Microaneurysms, Hemorrhages, and Exudates.[6]

Key Retinal Lesions in DR:

Diabetic Retinopathy is diagnosed based on the presence of specific retinal lesions, including:

- **Microaneurysms (MA):** Small, round, red dots due to weakened blood vessel walls.
- **Hemorrhages (HM):** Large, irregular red spots from ruptured vessels, classified into flame-shaped and blot hemorrhages.
- **Hard Exudates (EX):** Yellow deposits caused by plasma leakage, often forming in clusters.
- **Soft Exudates (Cotton Wool Spots):** White, oval-shaped lesions due to nerve fiber swelling.[1], [2], [6]

In **Non-Proliferative DR**, microaneurysms and hemorrhages are commonly observed, whereas **Proliferative DR** is marked by extensive neovascularization, leading to severe complications.

4. Automated diagnosis and Need for Early Detection of Diabetic Retinopathy

Early detection of DR is crucial to prevent **progressive vision loss**. Traditionally, diagnosis is performed by **ophthalmologists analysing retinal images** for lesion patterns. However, manual diagnosis is time-consuming, subject to human error, and highly dependent on expert availability. Advancements in Artificial Intelligence (AI) and Deep Learning have revolutionized DR detection by enabling automated classification of retinal images with high accuracy.

Advanced automated analysis system capable of accurately classifying Diabetic Retinopathy (DR) severity based on a standardized grading scale ranging from 0 (No DR) to 4 (Proliferative DR). This system will leverage deep learning techniques to analyze retinal images, assess the severity of the disease, and provide an objective, consistent evaluation of a patient's condition.

The core functionality of this system involves processing and interpreting retinal fundus images to detect key retinal abnormalities, such as microaneurysms, hemorrhages, and exudates, which are indicative of DR progression. By automating this process, the system aims to enhance early diagnosis, reduce reliance on manual screening, and minimize the risk of human error in disease assessment[10]. A critical aspect of this project is the comparative analysis of Machine Learning models such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks have been extensively used for DR diagnosis. The system will be trained on a labeled dataset where each image has been rated by clinicians on the DR severity scale. The ultimate objective is to determine which deep learning model delivers the highest accuracy, efficiency in classifying DR severity.

5. Algorithms

The core objective of this system is to analyze **retinal fundus images** and assign a severity score based on DR progression. The system will explore the following deep learning models:

5.1. Convolutional Neural Networks (CNNs) for DR Detection

CNNs are widely used for image classification and pattern recognition due to their ability to automatically extract meaningful features from images without manual intervention. Unlike traditional machine learning approaches that require handcrafted feature extraction, CNNs can learn relevant low-level (edges, textures) and high-level (shapes, structures) features directly from raw images. This makes CNNs an ideal choice for Diabetic Retinopathy (DR) detection, where the identification of lesions, microaneurysms, hemorrhages, and exudates plays a crucial role in grading the severity of the disease.[2][11]

DR progresses through five severity levels, ranging from No DR (Normal) to Proliferative DR (Most Severe Stage). CNNs can differentiate between these stages by recognizing specific visual patterns and abnormalities in retinal fundus images. They have the ability to process large-scale medical image datasets and classify images with high accuracy, reducing the dependency on manual diagnosis by ophthalmologists.[11]

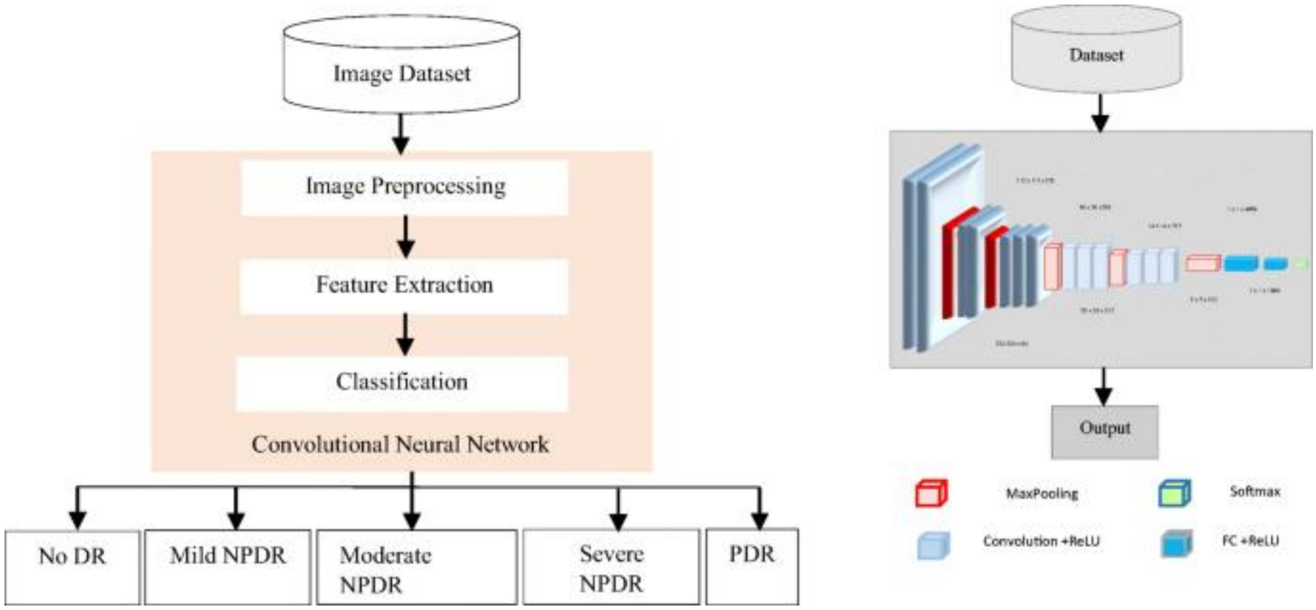

Figure 3: flow diagram of CNN Classify Diabetic Retinopathy[2]

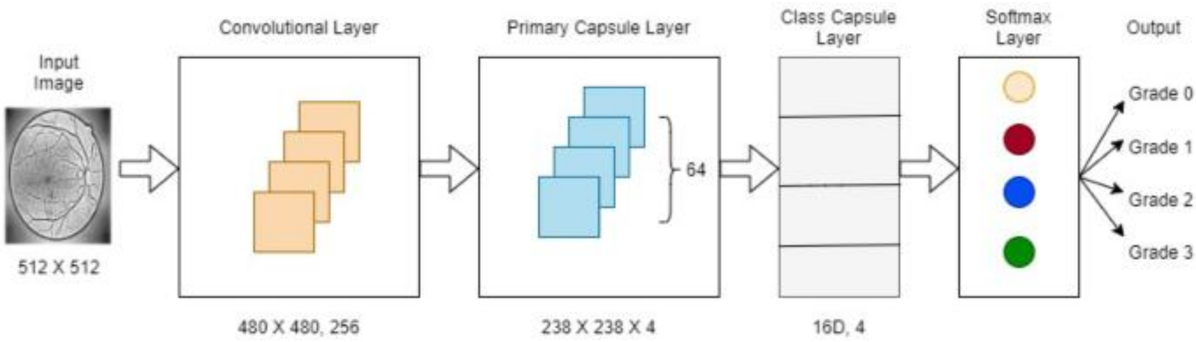

Figure 4: CNN working in classification of Diabetic retinopathy (DR)[12]

CNN Works for DR Detection by:

a. **Input Processing:** Retinal fundus images are fed into the CNN for analysis.

b. **Feature Extraction (Convolutional Layers):** Convolutional layers apply filters (kernels) to detect edges, textures, and important patterns such as blood vessels and abnormalities in the retina.

c. **Feature Selection (Pooling Layers):** Pooling layers reduce the spatial size of the extracted feature maps while retaining important information.

d. **Classification (Fully Connected Layers):** The extracted features are passed through dense layers, and the final **softmax layer** assigns a probability score to each DR severity level:

- No DR (Normal)
- Mild DR
- Moderate DR
- Severe DR
- Proliferative DR (Most Severe Stage)

5.2. Recurrent Neural Networks (RNNs) for DR Detection

Recurrent Neural Networks (RNNs) are specialized for handling sequential data, making them an interesting approach for analyzing progressive retinal changes in Diabetic Retinopathy (DR) patients. Unlike Convolutional Neural Networks (CNNs), which treat images as static, RNNs process the data sequentially, capturing spatial and temporal dependencies. This characteristic allows RNNs to track how retinal abnormalities evolve over time, which is especially useful for monitoring DR progression in patients undergoing regular screenings.[8]

In traditional image processing tasks, CNNs dominate because they can extract spatial features effectively. However, CNNs primarily focus on detecting localized patterns in an image without considering sequential relationships between pixels or time-dependent changes. DR is a progressive disease, meaning it does not appear suddenly but instead develops over time with increasing severity. This progression involves the gradual formation and expansion of microaneurysms, hemorrhages, exudates, and neovascularization. A model that can process sequential dependencies between different areas of the retina—or even between multiple patient scans over time—offers a powerful tool for predicting disease progression rather than just diagnosing a static image.[5]

RNNs provide this advantage by maintaining a memory of previously processed information. They analyze retinal images in a step-by-step manner, with each processing step being influenced by the previous one.[13] This allows RNNs to capture hidden relationships between different retinal features and detect early warning signs that might be overlooked in a single-image analysis. Additionally, if multiple fundus images are available for a patient over different timeframes, RNNs can be used to compare retinal changes between visits, making them a valuable tool for long-term DR monitoring and early intervention.

RNN Works for DR Detection by:

a. **Image Flattening:** The retinal image is converted into a sequence of pixel intensity values.

b. **Recurrent Processing:** RNN neurons process one pixel at a time, while the hidden state retains memory of previous pixels. A hidden state retains memory of previous pixels, enabling the model to recognize complex patterns like microaneurysms, hemorrhages, and exudates spread across different regions of the retina.

c. **Final Classification:** After processing the entire sequence, the network predicts the severity level of DR (No DR, Mild, Moderate, Severe, or Proliferative DR).

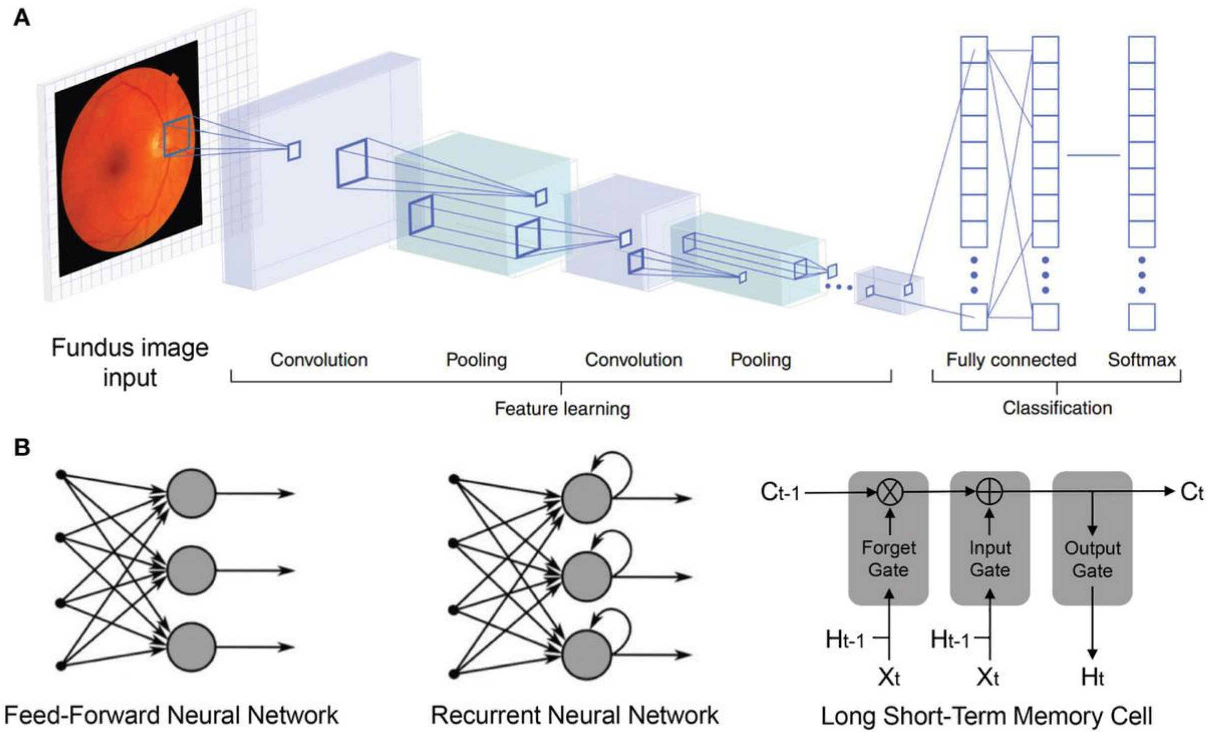

Figure 5:Diabetic Retinopathy for RNN and LSTM [14]

5.3. Long Short-Term Memory Networks (LSTMs) for DR Detection

Long Short-Term Memory (LSTM) networks are a specialized type of Recurrent Neural Networks (RNNs) designed to address the vanishing gradient problem that traditional RNNs suffer from. Unlike standard RNNs, which struggle to retain long-term dependencies, LSTMs incorporate memory control mechanisms that help in remembering important information over longer sequences. This makes them highly effective for analyzing progressive retinal changes in Diabetic Retinopathy (DR) patients, where lesion evolution occurs gradually over time. By leveraging gated memory units, LSTMs can track DR progression more efficiently and improve the classification of severity stages.[15]

LSTMs operate by maintaining a cell state, which acts as a long-term memory storage unit, allowing the model to selectively retain, update, or discard information. This is crucial in DR detection, where minor abnormalities such as **microaneurysms, hemorrhages, and exudates** may appear at different stages and locations in the retina. Unlike CNNs, which process the image as a static object, LSTMs treat retinal images as **sequential data**, enabling them to model disease progression over time by recognizing the sequential relationships between different lesion patterns.[3]

LSTMs are particularly useful in cases where a patient undergoes multiple screenings over time, as they can track gradual retinal deterioration by analyzing a sequence of retinal images. This ability makes LSTMs an ideal choice for longitudinal studies and real-time DR monitoring, helping ophthalmologists detect disease progression earlier and more accurately than traditional static models.[16]

LSTM Works for DR Detection by:

a. **Input Processing:** The retinal image is converted into a sequential dataset.

b. **Memory Management Using Gates:**

    - **Forget Gate:** Discards unnecessary past information.
    - **Input Gate:** Selects new important information to be stored.
    - **Cell State:** Stores long-term memory of lesion patterns.
    - **Output Gate:** Extracts relevant features for classification.

c. **Final DR Classification:** The LSTM predicts DR severity levels based on learned long-term dependencies.

6. Conclusion

Diabetic Retinopathy (DR) is a significant global health concern, leading to vision loss and blindness, particularly among individuals with prolonged diabetes. As diabetes cases continue to rise worldwide, early detection and timely intervention are essential to prevent severe visual impairment. However, conventional DR screening methods depend on expert ophthalmologists, making widespread screening difficult and often leading to delayed diagnosis and treatment. Without prompt detection, DR can progress to advanced stages, increasing the risk of macular edema, retinal detachment, and permanent blindness.

Advancements in artificial intelligence (AI) and deep learning have paved the way for automated DR detection systems, offering a promising solution to these challenges. Deep learning models such as CNNs, RNNs, and LSTMs have shown high accuracy in retinal image analysis, enabling more efficient and reliable DR classification. These AI-driven techniques can minimize misdiagnosis, accelerate screening processes, and support early disease detection, particularly in regions with limited access to specialized eye care professionals. By utilizing real-time image processing and predictive analytics, AI-based solutions can make DR diagnosis faster, more consistent, and cost-effective.

This report is cantered on developing an AI-powered system that employs CNN, RNN, and LSTM models to detect Diabetic Retinopathy from retinal images. By implementing and analyzing these deep learning techniques, the project seeks to determine the most effective approach for accurate DR identification and classification. A comparative evaluation will be conducted to assess each model's accuracy, efficiency, and computational performance, ultimately identifying the optimal algorithm for DR detection. The findings from this study will contribute to the enhancement of AI-driven medical imaging technologies, supporting the integration of automated DR screening systems into healthcare for earlier diagnosis and better patient care.

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