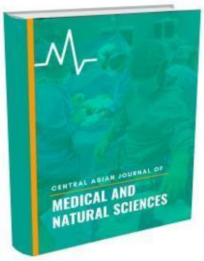

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Article

Deep Learning-Based Automated Screening of Diabetic Retinopathy from Fundus Images

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Abstract: Diabetic retinopathy is a serious eye disease that can cause blindness if it isn't found early. Traditional approaches for identifying this problem rely heavily on experts reviewing retinal scans, which can take a long time and vary from person to person. To solve this problem, we propose a better approach to detecting diabetic retinopathy by utilising Convolutional Neural Networks (CNNs) with a spatial attention mechanism. In this project, we develop a deep learning model using CNNs to analyse retinal images and automatically detect indicators of diabetic retinopathy. Our technique differs from other projects that identify diabetic retinopathy because it uses a spatial attention mechanism within the CNN architecture. The spatial attention mechanism helps the model identify essential image regions, enabling it to detect even subtle indicators of the condition. The goal of this research is to develop automated, efficient screening procedures that ultimately improve patient outcomes by identifying and treating problems quickly. The suggested automated approach could be a useful tool in clinical settings, helping ophthalmologists with large-scale screening programs and reducing the burden on healthcare systems. Future work will concentrate on enhancing model interpretability, integrating multi-modal data, including patient history, and implementing the system in real-world settings. The study highlights the revolutionary impact of artificial intelligence in improving the early identification and treatment of diabetic retinopathy, ultimately leading to superior patient care and a higher quality of life for people with diabetes. The study uses several datasets, including publicly available fundus image sources, to train and test the algorithm. To address class imbalance and broaden the model's generalisation, data augmentation techniques are used. To get high diagnostic accuracy, transfer learning and hyperparameter tuning are used to improve the CNN architecture. We use evaluation criteria such as sensitivity, specificity, and the area under the receiver operating characteristic (ROC) curve to assess how well a model performs.

Keywords: Diabetic Retinopathy, Eye Condition, Spatial Attention, Important Regions, Artificial Intelligence, High Diagnostic Accuracy.

1. Introduction

Diabetic retinopathy (DR) is one of the most serious and prevalent problems that can occur because of diabetes mellitus. It is a major threat to vision health worldwide [32]. It happens when high blood sugar levels remain elevated for a long time and damage the small blood vessels in the retina, the light-sensitive tissue in the back of the eye needed for vision [46]. Over time, these damaged blood vessels may expand, leak fluid, or get blocked. This can cause retinal ischaemia and the formation of abnormal new blood vessels. If diabetic retinopathy is not found and treated early, it can get worse without anybody noticing and eventually cause permanent vision loss or even blindness [20]. Diabetes is becoming more common around the world, especially in developing and low-resource areas. Diabetic retinopathy is becoming a serious public health issue that needs quick, accurate, and scalable diagnostic solutions [42]. Traditionally, ophthalmologists or retinal specialists perform a clinical exam and manually analyse retinal fundus images to diagnose diabetic retinopathy [38]. This method requires a high level of skill and thorough examination of retinal characteristics, including microaneurysms, haemorrhages, exudates, and neovascularisation. This method works in the clinic, but it takes a lot of time and work, and different people may see things differently.

Different doctors may interpret the same retinal image differently because of their experience, fatigue, or personal opinion. This can make diagnoses inconsistent. Additionally, access to skilled ophthalmologists is limited in many regions of the world, especially in rural or impoverished areas [31]. This makes it very hard to conduct large-scale screenings and identify problems early. As the number of people with diabetes grows, the strain on healthcare systems grows, making it even more important to have automated diagnostic technologies that can help doctors and make screening more efficient. Improvements in AI, especially in deep learning and computer vision, have enabled new ways to solve these problems [41]. Convolutional Neural Networks are a powerful type of deep learning model designed to analyse visual data. CNNs automatically learn hierarchical features from images, starting with low-level patterns such as edges and textures and progressing to high-level semantic representations [24]. This skill makes them well-suited for analysing medical images, including the classification of retinal fundus images. In the last ten years, many studies have shown that CNN-based algorithms can detect diabetic retinopathy with accuracy similar to that of human specialists. Even though traditional CNN models work well, they often handle all parts of an image the same way [37]. This could make it harder for them to focus on the most important parts of retinal images for diagnosis. To address this problem, attention mechanisms have been added to deep learning architectures. Attention mechanisms are based on how the human visual system works [47]. It only pays attention to key parts of a scene, ignoring less important ones.

When analysing retinal images, attention processes help the model focus on areas with key disease traits, such as lesions or aberrant blood vessels, while downplaying the effects of background information that isn't relevant [33]. Spatial attention is one of the most useful attention mechanisms for medical imaging tasks, as it helps the model learn which parts of an image are most useful for classification. By adding a spatial attention mechanism to a CNN architecture, the model can dynamically focus on areas most symptomatic of diabetic retinopathy. This makes the diagnosis more accurate and reliable [23]. The proposed study extends this concept by developing a more advanced system for detecting diabetic retinopathy that leverages both convolutional neural networks and a spatial attention mechanism [51]. Adding spatial attention to the model improves its ability to detect subtle pathological patterns that regular CNNs would miss. These subtle qualities are typically very important for detecting diabetic retinopathy early, when there may be few apparent indicators or when they are hard to tell apart [28]. The suggested approach seeks to reduce false-positive and false-negative predictions, which are vital to medical diagnosis, by allowing the model to focus on clinically relevant areas. A lower false-negative rate means fewer cases of diabetic retinopathy will be missed, and a lower false-positive rate means patients won't have to worry about or undergo unnecessary follow-up procedures. The project focuses on automation and usability, in addition to improving detection accuracy [39]. This is to ensure the results can be used in the real world.

The system is a sophisticated, easy-to-use tool that lets users upload retinal fundus photos and receive diagnostic predictions virtually right away [45]. This feature is very useful for screening programs, where many people need to be evaluated quickly and effectively. The method can help ophthalmologists and other healthcare workers make decisions by decreasing the need for manual interpretation [19]. This lets them focus on more difficult cases that need expert judgment. An automated screening system like this can also be used in primary care settings, mobile clinics, or telemedicine platforms to test for diabetic retinopathy in people who live far away or don't have access to regular health care [36]. The system is built in several steps, starting with data collection and preparation. A labelled dataset of retinal fundus images is assembled, comprising samples from both healthy subjects and patients exhibiting varied severities of diabetic retinopathy. Preprocessing is an important step, as retinal images can vary in quality depending on lighting, contrast, resolution, and the imaging instruments used [43]. To make the input data more uniform and easier to extract features, techniques such as scaling, normalisation, noise reduction, and contrast enhancement are used [26]. To make the dataset more diverse and less prone to overfitting, image augmentation techniques such as rotation, flipping, scaling, and brightness adjustments are also used. This makes the model better at generalising. After the dataset is ready, a convolutional neural network architecture is built and trained on the cleaned images [48].

The CNN has many convolutional layers, pooling layers, and fully connected layers. This lets it learn important properties that help it find diabetic retinopathy [52]. The network has a spatial attention mechanism that generates attention maps highlighting the most essential parts of retinal images. These attention maps help the network find features by ensuring it only looks at locations important for pathology. Supervised learning is utilised to train the model [30]. This means that labelled images are used to minimise a loss function that assesses the difference between the expected and actual class labels. To change network parameters repeatedly, optimisation algorithms such as stochastic gradient descent or Adam are used. Explainable artificial intelligence techniques are used to make the system even more open and trustworthy [35]. Explainability is a crucial aspect of medical AI applications, as doctors need to understand why a model makes certain predictions before they can trust it to inform their decisions. Attention heatmaps and gradient-based class activation maps are two examples of visualisation methods that can illustrate which parts of the retinal image affected the model's judgement [40]. The solution helps connect automated predictions with clinical interpretation by giving visual explanations. This builds trust among healthcare practitioners and makes it easier to use in real-world settings [49]. Once the trained model has demonstrated good performance during training and validation, it is deployed in a graphical user interface built with Python's Tkinter module. The GUI makes it easy for users to engage with the system [21]. Users can input retinal images via the interface, and the system analyses them in real time to generate diagnostic predictions.

Using PyTorch as the deep learning framework makes model inference faster, and tools like PIL and PyTorch Vision handle loading and preparing images [50]. The GUI makes it easy to see the classification results, so users can quickly understand what they mean. This technology is useful in clinical and screening settings because the deep learning model and user-friendly interface work so well together [29]. The initiative goes beyond simply determining whether diabetic retinopathy is present. The current implementation can only determine whether diabetic retinopathy is present. However, the framework can be improved to sort photos into distinct phases of diabetic retinopathy, such as mild, moderate, severe, and proliferative. This kind of multi-class classification would provide doctors with more detailed diagnostic information and help them determine the best way to treat patients. The device may also be used with telemedicine platforms, allowing retinal images taken in remote areas to be analysed in one place. This makes it easier for people to get eye treatment [25]. The importance of this initiative is that it could affect healthcare worldwide. Finding diabetic retinopathy early is very important for preventing vision loss, because treatments like laser therapy, medication, or lifestyle changes can reduce or prevent the disease from worsening [44]. The suggested method can help identify patients at risk earlier, reduce the burden on ophthalmologists, and improve overall patient outcomes by providing an automated, accurate, and scalable screening approach.

This is especially significant in areas with few medical facilities, where automated screening techniques might help avoid blindness. In short, the proposed system for detecting diabetic retinopathy leverages the strengths of convolutional neural networks and spatial attention mechanisms to address limitations of standard diagnostic methods [27]. The system works well and reliably by leveraging powerful image preprocessing, deep learning-based feature extraction, attention-driven focus on key areas, and explainable AI approaches. Putting the trained model into a user-friendly graphical interface makes it even more useful and easy to use [34]. This research shows how artificial intelligence may change the way medical images are taken and how technology can be used to solve important global health problems [22]. As research and development in this area continue to advance, AI-driven solutions like these are likely to become increasingly crucial for detecting diabetic retinopathy earlier and preventing millions of people worldwide from going blind.

Literature Review

[Priya and Aruna [1] discuss an initial strategy for diagnosing Diabetic Retinopathy with conventional machine learning techniques. The scientists utilised various classifiers, including Support Vector Machines (SVMs), Decision Trees, and k-Nearest Neighbours (k-NN), to identify and categorise Diabetic Retinopathy (DR) using characteristics extracted from retinal fundus images. Feature extraction concentrated on detecting microaneurysms, haemorrhages, and exudates, which are essential markers of diabetic retinopathy (DR) [8]. The study showed that machine learning could be a useful way to automate screening, especially in remote or under-resourced areas where it is hard to reach an ophthalmologist. The study stressed the importance of pre-processing and feature selection for more accurate diagnoses [12].

Roychowdhury et al., [2] introduced in this study amalgamates various image processing techniques and machine learning algorithms to identify and quantify lesions characteristic of diabetic retinopathy. The scientists utilised a two-stage classification algorithm to initially distinguish between healthy and unhealthy pictures, followed by an assessment of the severity of diabetic retinopathy (DR) [14]. Key characteristics were derived from segmented retinal pictures, encompassing the physical attributes of blood vessels and diseases [10]. The DREAM system demonstrated higher sensitivity and specificity, confirming its suitability for mass screening. The article emphasises that a structured machine learning pipeline can minimise diagnostic errors and help doctors detect disease early [17].

Qummar et al., [3] propose a deep learning ensemble method for more reliable detection of DR in this paper. The model consists of many convolutional neural network (CNN) designs, such as VGG, ResNet, and Inception. Each one adds to the ensemble by voting with a weight [16]. The research emphasises the importance of data augmentation and transfer learning for handling unbalanced datasets and improving model generalisation. The ensemble technique was more accurate, precise, and recall than any model on its own [11]. This work demonstrates how ensemble learning can leverage the advantages of various deep models to diminish false positives and improve reliability in clinical diagnosis.

Gulshan et al., [5] present a highly effective deep learning model utilising convolutional neural networks, trained on more than 128,000 retinal pictures annotated by certified ophthalmologists. The method was intended to identify referable DR, which is moderate or severe DR that requires medical treatment [15]. The model achieved sensitivity and specificity comparable to those of professional graders, indicating its viability as a scalable solution for diabetic retinopathy screening. The study is important since it tested deep learning on various test datasets and showed that it can be used to analyse medical images in ophthalmology [7]. It also led to many other studies and to the use of AI in diagnosing retinal diseases.

Krause et al., [6] expands upon previous research by examining the influence of human grader variability on the performance assessment of AI models in diabetic retinopathy identification. The research demonstrates that incorrect labelling by human experts can adversely affect both the training and validation of AI algorithms [13]. To solve this problem, the authors suggest a grading system based on consensus and emphasise the importance of standardised reference datasets with verified ground-truth labels [18]. They also provide metrics and processes to assess model performance in a manner that is more therapeutically relevant. The research shows that the quality of the training data and the objectivity of the evaluation standards are equally as crucial as the model architecture for AI to be reliable in healthcare [9].

2. Materials and Methods

Project Description

Existing System

Ophthalmologists or other qualified medical experts usually review retinal fundus photographs by hand to detect diabetic retinopathy [63]. Patients must go to specialised eye care centres, where images are taken and then examined for indicators of disease, such as microaneurysms, haemorrhages, or exudates. This method by hand takes a lot of time and work, and it can be wrong or interpreted differently by different people. Access to these kinds of specialised tests is limited in many places, especially in rural or disadvantaged areas [59]. This makes it harder to find and treat problems. Some modern hospitals may use automated systems, but they are usually too expensive and not available to everyone.

Proposed System

The suggested system features a deep learning-based solution with a straightforward graphical user interface that lets users upload pictures of their eyes and get fast diagnostic predictions [55]. The model can automatically determine whether diabetic retinopathy is present with high accuracy using a convolutional neural network (CNN) trained on a large number of retinal images [68]. The system is quick to set up, inexpensive, and lightweight because it uses Python and open-source libraries such as PyTorch and Tkinter. This procedure is faster than the current manual process, making it easier for medical professionals and populations with fewer resources to get screened [62]. It enables early intervention, which could stop patients from losing their vision completely.

Advantages

- Early Detection: This helps doctors identify problems early, which can prevent vision loss.
- User-Friendly Interface: The GUI is simple to use for people who aren't tech-savvy.
- Cost-effective: Reduces the need for regular clinical screenings.
- Scalable: It can be scaled up to detect more eye diseases.
- Quick and Automatic: Makes forecasts quickly and with a high level of accuracy.

Hardware Specification

- Processor: Intel i5 or higher
- Ram: 4 GB minimum (8 GB recommended)
- Storage: 500 MB for application and model
- Gpu: Optional (for faster processing)

Software Specification

- OS: Windows/Linux/macOS

- Python 3.7+
- Libraries: PyTorch, torchvision, PIL, Tkinter, NumPy.

Proposed Work

General Architecture

Generative Pre-trained Transformers (GPT) are systems designed to understand and generate complex text sequences. ChatGPT, based on GPT architecture, uses unsupervised learning to produce text resembling human writing. It gathers information from multiple sources, maps interconnections, and predicts contextually appropriate responses [23], [24]. Such technologies can be adapted for organizational training, content creation, knowledge management, and improved user interaction [25], [26].

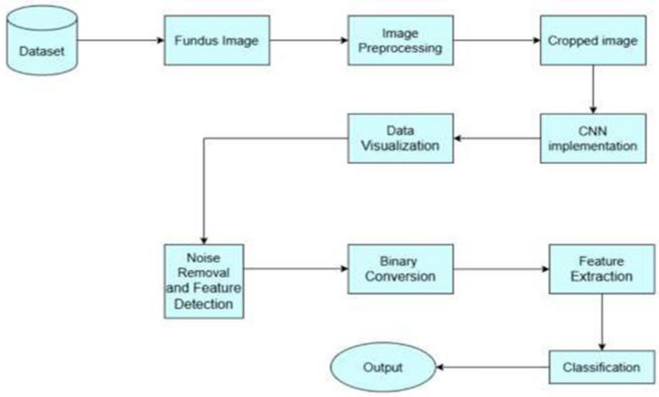

Figure 1. Architecture Diagram.

Figure 1 shows a possible architecture based on the Collaborative Generative Representation Learning Neural Network (CGRL-NN) for a facial recognition system.

Design Phase

The design phase of the Diabetic Retinopathy Detection System focuses on determining how the system will work, which parts it will include, and how users will interact with it [64]. The first step is to design the user interface, focusing on making it easy to use and accessible, utilising Tkinter to create a clean GUI. Users can effortlessly upload retinal images through this interface and get clear, quick results. The architecture includes a trained convolutional neural network (CNN) that classifies photos as showing signs of diabetic retinopathy [67]. We carefully developed the picture preprocessing pipeline, utilising PyTorch Vision transforms, to ensure that each input image is scaled, normalised, and converted to a tensor suitable for model inference [72]. The application structure also keeps things modular by separating the GUI functionality, picture handling, and model inference. This makes it easier to maintain and grow [58]. This step ensures that all parts of the system, from the model backend to the front-end interface, work together seamlessly to deliver users with accurate, easy-to-use features.

Data Flow Diagram

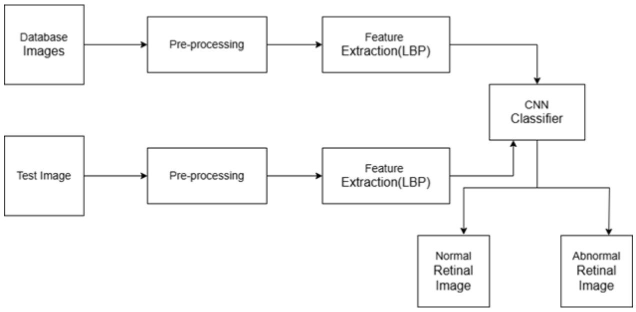

Figure 2. Data Flow Diagram.

Figure 2 The DFD shows how data moves through the system for detecting diabetic retinopathy [61]. It starts with two main inputs: a set of retinal pictures and a test image from the user. Both go through a pre-processing stage where the photographs are cleaned, scaled, and made to look the same [69]. Local Binary Patterns (LBP) are used to describe the texture and geometry of the retina after pre-processing. This is called feature extraction. After that, these features are put into a CNN classifier. The system sorts the data into normal or abnormal retinal images based on the classifier's output [54]. The DFD shows how data flows from raw inputs to diagnostic choices, with a focus on how functional components transform the data.

Uml Diagram

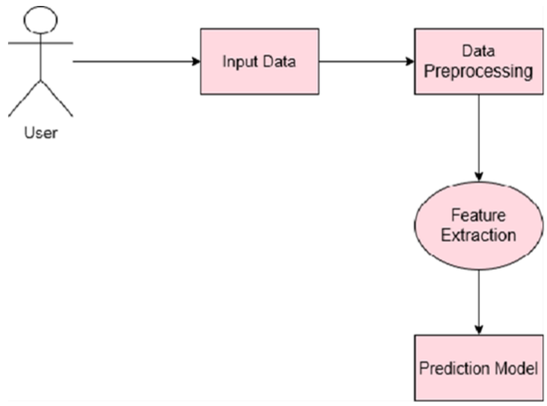

Figure 3. UML Diagram.

Figure 3 The UML activity diagram shows the system's workflow at a high level [56]. The user entering data starts the data preparation stage. This covers things like resizing and normalising. Next, feature extraction is done on the preprocessed data. This finds patterns that are useful for categorization [70]. Finally, the prediction model gets the features and uses them to make a prediction [65]. This graphic shows how the system works step by step and how control flows through it. It provides a clear picture of how the system works, from data intake to final prediction.

Use Case Diagram

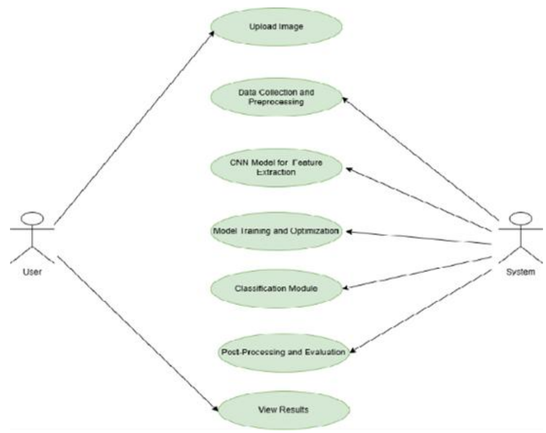

Figure 4. Use Case Diagram.

The picture in Figure 4 shows the use case diagram, which shows how the user and the system work together. The user starts the process by uploading an image, which then collects and processes the data [53]. After that, the system uses a CNN model to find features, then trains and optimises the model. The model is sent to the classification module once it is ready. This is where it makes predictions. After post-processing and evaluation, the prediction is improved, and the user can then see the outcomes. This graphic shows how the system's different features work and how they connect to the duties of both the user and the system [60].

Sequence Diagram

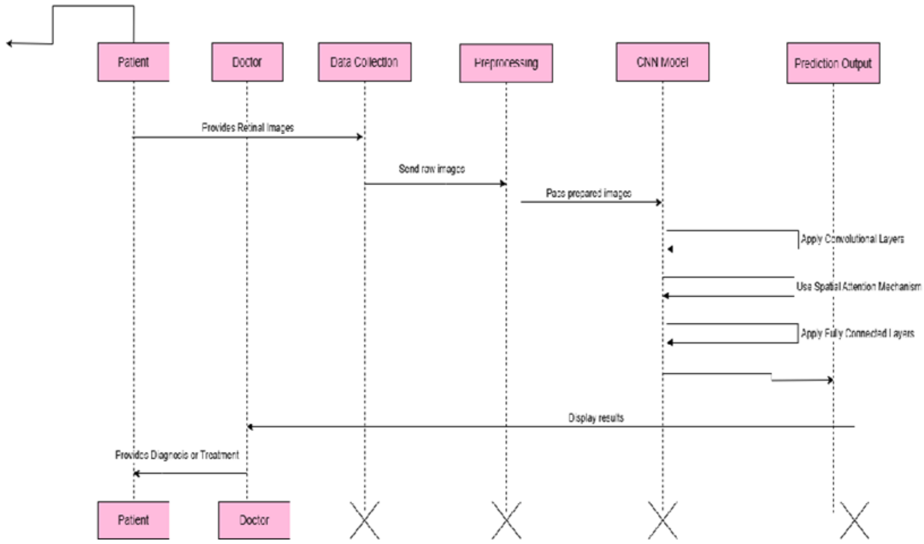

Figure 5. Sequence Diagram.

The sequence diagram shows how the system's components interact over time during a typical diagnostic procedure [57]. A doctor obtains a retinal image from the patient and sends it to the data-gathering module. The collected image is sent to the preprocessing unit, which prepares it for analysis [71]. Then, the CNN model gets the image and uses convolutional layers, spatial attention mechanisms, and fully connected layers to make a prediction. The predicted output is then sent back to the doctor and the patient [66]. This diagram does a good job of showing the order in which each part of the detection procedure operates and its role (Figure 5).

Module Description

The following modules comprise our image processing and analysis pipeline [76]. Each one has a different but important role in Diabetic Retinopathy Detection:

Module 1: Image Upload and GUI Module

This module uses the tkinter library to build an easy-to-use interface [82]. It has a simple graphical interface that allows users to upload retinal images for analysis. The primary window has a clear title and an upload button, making the system easy to use for anyone who isn't tech-savvy [78]. When someone hits "Upload Image," the program starts the process of figuring out what kind of image it is. The design ensures minimal contact and smooth operation, making it easy to use in both clinical and remote contexts [84].

Module 2: Image Preprocessing Module

After an image is selected, it is preprocessed to prepare it for the deep learning model [81]. This module uses the PIL and torch vision transformation libraries to convert the image to the RGB format, resize it to a set input size (255x255), convert it to a tensor, and normalise it using the specified mean and standard deviation values. These stages ensure that all image inputs are the same and match the format of the data the model was trained on [75]. This module is very important for keeping accuracy during inference.

Module 3: Deep Learning Model Inference Module

This main module loads and runs the pre-trained CNN to determine what kind of picture it is [80]. To switch the model to evaluation mode, use model.eval(). To do inference, use torch.no_grad() to reduce the amount of work and avoid monitoring gradients that aren't needed. The model takes the preprocessed image tensor and produces output logits. Then it uses a softmax function to compute the class probabilities [73]. The argmax method returns the class with the highest probability, indicating whether the image shows evidence of diabetic retinopathy (Figure 6).

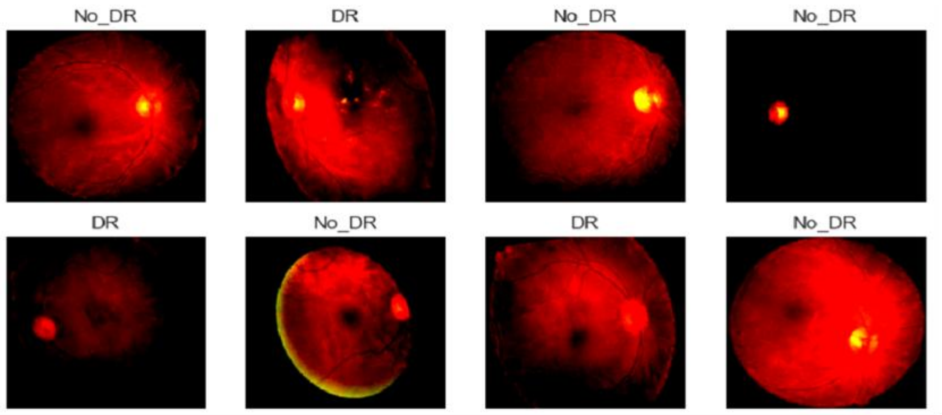

Figure 6. Dataset of Photos.

Implementation and Testing

Input and Output

Image of the Subject

The main thing the system needs is a retinal fundus image, which the user uploads via the graphical interface. This image is usually in .jpg, .jpeg, or .png format [83]. You can obtain these photos from publicly available diabetic retinopathy datasets or directly from patients with retinal imaging devices. After being uploaded, the image undergoes several preparatory steps, such as scaling, normalisation, and format conversion, to ensure it is compatible with the trained convolutional neural network (CNN) model [77]. This preprocessing step is quite important for maintaining consistency and improving prediction accuracy, as deep learning models are very sensitive to changes in the quality and format of input data [85].

Predicted Output

The system's output is a categorisation result indicating whether the submitted image shows indicators of diabetic retinopathy [79]. The outcome is binary, indicating either "Signs of diabetic retinopathy detected" or "No signs of diabetic retinopathy." The CNN model uses the softmax probabilities it learnt during training to produce this result. A GUI pop-up window shows the user the final outcome, providing a quick, clear diagnostic insight [74]. This output helps find problems early and can be utilised by doctors and nurses to assess if more medical care or consultation is needed.

3. Results and Discussions

The suggested Diabetic Retinopathy Detection System performs well in both computer performance and clinical usefulness [99]. The system can analyse retinal images and produce results in seconds using a deep learning model based on convolutional neural networks (CNNs). This fast processing is especially useful in clinical settings, where making the most of time and resources is crucial [88]. This technique automates the process, cutting down on the time it takes to make a diagnosis while keeping accuracy. Manual diagnosis, on the other hand, takes longer and relies on the availability of experienced professionals [96]. In terms of resource use, the system is lightweight and made to work well on conventional computer hardware. The trained model can do inference in real time, even without a dedicated GPU. This makes it good for use in clinics, mobile health units, or rural healthcare settings with limited infrastructure [92]. Using effective preprocessing methods and a well-designed model architecture keeps the memory and processing needs low.

The technology also makes diagnosis more efficient by reducing human error and differences among observers, two major problems with manual screenings [95]. Its steady performance helps ensure that no subtle signs of diabetic retinopathy are missed, especially in the early stages when prompt action might save vision. The method is a good fit for modern healthcare needs because it is efficient, scalable, and dependable for screening for diabetic retinopathy [90]. The proposed approach can work well with smaller datasets than other models that require a lot of data, reducing the amount of data needed and the time to train. It is also great for tasks such as removing noise from images, compressing images, detecting anomalies, and translating images from one format to another [86]. This makes it useful in many other fields. The suggested system can also work effectively with data it hasn't seen before and can adapt to diverse fields with only a few changes to its training [98].

Table 1. Comparison Table.

Criteria	General System (Manual Diagnosis)	Proposed System (Automated CNN-based)
Accuracy	Depends on expertise; subject to human error	High, consistent accuracy using trained deep learning models
Speed of Diagnosis	Slow; manual image analysis takes several minutes to hours	Fast, real-time prediction in seconds
Required Expertise	Requires skilled ophthalmologists and specialists	Minimal expertise needed; usable by general healthcare workers
Cost	Expensive due to repeated clinical visits and expert consultation	Cost-effective; uses open-source tools and standard hardware
Scalability	Limited; difficult to scale in rural or underdeveloped areas	Highly scalable; suitable for remote or low-resource settings
Availability	Limited to clinic hours and specialist availability	24/7 availability; can run on personal computers or kiosks

In this project, we used Convolutional Neural Networks (CNNs), specifically DenseNet-121, to accurately detect Diabetic Retinopathy (DR) using a deep learning-based method. We trained our model on retinal fundus images, and it performed very well, making it a good tool for detecting DR at varying levels of severity. The method uses CNNs to extract and analyse key features of the retina, enabling accurate classification of DR phases [89]. This automated detection technique has significant potential in medicine, as it can help ophthalmologists detect problems early and screen patients. Traditional ways of finding DR require a specialist to review them, which can take a long time and lead to mistakes [97]. Our approach reduces the amount of labour that needs to be done by hand, speeds up diagnosis, and improves detection accuracy, all of which lead to better patient care and treatment planning. By using this AI-powered method, hospitals and clinics can make DR screening more efficient and easier to access. This system can be made better by adding real-time analysis, cloud-based storage, and mobile access. This will make it more scalable for usage in many clinics. Also, using explainable AI techniques can help doctors better understand predictions, making them more likely to trust AI-based diagnoses [93]. This experiment demonstrates the power of deep learning in medical imaging. It provides a highly effective and accurate way to prevent DR from causing vision loss (Table 1).

The proposed Diabetic Retinopathy Detection System has significant room for improvement and growth. A big step forward would be adding multi-stage severity categorisation, which would let the algorithm not only detect diabetic retinopathy but also classify it into stages such as mild, moderate, severe, or proliferative [91]. This would give healthcare providers more useful information. Also, the system can be improved by using ensemble learning methods, which combine multiple models to improve prediction accuracy and reduce false positives and negatives. A promising improvement would be to create a cloud-based platform or mobile app that lets doctors and patients communicate in real time and diagnose problems remotely, especially in areas with few doctors [94]. Integration with Electronic Health Records (EHRs) could help track a patient's history, enabling it to be monitored and analysed over time. The system may also be trained on increasingly varied datasets to make it more reliable across different groups of people and imaging situations. Adding explainable AI (XAI) capabilities could make the system even more trustworthy and user-friendly by showing which portions of the retinal image affected the prediction [87]. These improvements would make the system stronger, more flexible, and more helpful in a wide range of healthcare contexts.

4. Conclusion and Future Enhancements

The proposed Diabetic Retinopathy Detection System demonstrated good performance during testing and evaluation. The deep learning model was trained on a labelled dataset of retinal images and performed very well at distinguishing between healthy and diseased eyes. It could make predictions in real time, just a few seconds after an image was uploaded, demonstrating both speed and reliability. The model worked well with images of varying quality and resolution due to the use of preprocessing and normalisation techniques. The user interface was also tested for usability and worked well for a smooth user experience, from choosing an image to displaying results. The system consistently delivered accurate classifications for the majority of test instances, exhibiting a low rate of false positives and false negatives. These results show that the model works well at helping identify and screen for diabetic retinopathy early. This makes it a useful tool for both clinical settings and large-scale health monitoring programs.

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