

Automatic Diabetic Eye Detection Using Machine Learning

Prof.Dipshri Kale¹, Aavishkar Sawant², Pratik Mandge³, Radhika Shetty⁴, Rohan Salve⁵

¹Assistant Professor, Department of Electronics and Telecommunication

²BE Student, Department of Electronics and Telecommunication

³BE Student, Department of Electronics and Telecommunication

⁴BE Student, Department of Electronics and Telecommunication

⁵BE Student, Department of Electronics and Telecommunication

^{1,2,3,4,5} MCT's Rajiv Gandhi Institute of Technology

Abstract – The aim of this project is to develop an automated system capable of detecting diabetic retinopathy (DR) in retinal fundus images, which is a common complication of diabetes that can cause vision loss if not identified and treated early. The proposed system utilizes the RESNET 50 algorithm, a deep convolutional neural network, to extract features from retinal images and classify them into one of five DR severity levels. The dataset used in the project comprises 35,126 retinal images. The proposed system demonstrated a classification accuracy of 95% in distinguishing diabetic retinopathy, highlighting its potential as an effective tool for early detection and treatment of the condition. Early identification of warning signs of DR is crucial in its management. Hence, regular eye check-ups are necessary to detect the condition and direct the individual to a doctor for prompt examination and treatment, which can help prevent permanent vision loss. However, due to limited resources, screening for DR may not always be possible. To address this challenge, emerging technologies, including artificial intelligence, have been developed for the automatic detection and classification of DR. This study aimed to investigate convolutional neural network used for diagnosing retinopathy.

Key Words: CNN, Resnet50, Diabetic retinopathy, retina, blood vessels, diabetes.

1.INTRODUCTION

Individuals with diabetes often seek medical attention when their vision begins to weaken due to conditions such as proliferative diabetic retinopathy (DR) or vitreous hemorrhage. Doctors can currently identify symptoms early on through retinal ophthalmoscopy and can enhance diagnostic efficiency by utilizing deep learning techniques for treatment selection and supporting personnel workflow. Diabetic retinopathy is a severe complication of diabetes that may result in vision loss if not treated promptly. Detecting the condition early and taking appropriate measures is crucial to preventing

additional harm to the eyes. Early detection and intervention are critical for preventing further damage to the eyes. Thermal imaging has shown promise in detecting changes in retinal temperature associated with diabetic retinopathy. In this study, we propose a deep learning-based approach using ResNet to detect diabetic retinopathy from thermal images. Our proposed approach consists of two main stages: pre-processing and deep learning-based detection. In the pre-processing stage, we first apply a series of image filters to enhance the features of the thermal images. Next, we segment the retina region from the image using a thresholding technique. In the realm of healthcare, early detection is crucial for effective treatment and management of diseases.

We have developed and tested various feature extraction and selection approaches during both the training and testing stages of our system, which operates through a supervised learning approach. Our proposed system can operate on both real-time and synthetic datasets simultaneously, providing a versatile tool for healthcare professionals. In the deep learning-based detection stage, we employ a modified ResNet architecture to classify the segmented retina region as normal or abnormal, and we train our model on a dataset of thermal images obtained from patients both with and without diabetic retinopathy. By leveraging the power of deep learning techniques, we hope to aid healthcare professionals in detecting and treating diseases such as diabetic retinopathy in a timely and efficient manner. Detecting diabetic retinopathy at an early stage is crucial for preventing vision loss in diabetic patients. The technique proposed in this study has the potential to serve as a low-cost and non-invasive screening method for diabetic retinopathy. Traditionally, doctors use retinal ophthalmoscopy to detect diabetic retinopathy. However, this method has limitations in terms of diagnostic efficiency. The implementation of deep learning technology can enhance the precision and effectiveness of the diagnostic process by medical

professionals. Most deep learning methods for DR diagnosis categorize retinal ophthalmoscopy images into training and validation data sets, with the majority of the data used for training. To augment the quantity of training samples, the synthetic minority oversampling technique (SMOTE) is employed during the data processing phase. However, oversampling training may lead to overfitting of the training model, resulting in erroneous predictions. Although the accuracy of prediction results is high, overfitting of the training data may distort training module variables, leading to unverified and unreliable predictions. Therefore, it is important to carefully select training samples and validate the accuracy of the model on new and untrained data.

With further refinement and testing, our proposed approach can be an effective tool for detecting diabetic retinopathy and improving the lives of diabetic patients. Diagnosing retinopathy severity requires specialized medical knowledge and expertise. Without quantifying the images, interpretation of the same data set can vary, resulting in errors. Therefore, it is essential to quantify the images to ensure accuracy in determining the severity of retinopathy. Machine learning and deep learning algorithms can be used to quantify images and help physicians identify lesions and diagnose retinopathy with high accuracy. These techniques can also be useful in monitoring treatment progress by comparing preoperative and postoperative data, allowing physicians to assess the effectiveness of the treatment. By integrating machine learning and deep learning with medical expertise, physicians can make more accurate diagnoses and identify the required treatments with greater precision, which can lead to better outcomes for patients. Therefore, these techniques hold great potential for improving the accuracy and effectiveness of diagnosis and treatment for retinopathy.

2. Literature Review

As stated in [1], this paper evaluates the performance of several machine learning algorithms-based DR detection and classification systems. These systems are trained and tested using a significant amount of retina fundus and thermal images obtained from various publicly available datasets. The study finds that these systems successfully identify the severity level of DR by detecting warning signs. Based on the results of the evaluated systems, the ResNet50 deep convolutional neural network is the most effective algorithm for performance metrics. The ResNet50 contains feature extraction kernels that analyze retina images to extract valuable information. As outlined

in [2], this article presents a systematic survey of automated methods for detecting diabetic eye disease. The survey covers various aspects, including available datasets, image preprocessing techniques, deep learning models, and performance evaluation metrics. The aim of this survey is to provide a comprehensive overview of the different approaches to diabetic eye disease detection, including state-of-the-art methods, which will be valuable for research communities, healthcare professionals, and patients with diabetes. The method proposed in this paper, as described in [3], presents an effective technique for feature extraction using blob detection, which is followed by the classification of various stages of diabetic retinopathy using machine learning. The feature extraction technique achieves an accuracy of 83% in the automatic characterization of retina images for diabetic retinopathy with the most efficient machine learning classification algorithm. This approach can aid specialists in recognizing the patient's condition with increased accuracy. Additionally, in [4], a new ensemble-based learning strategy is introduced, which combines multiple classification algorithms to create a sophisticated diagnostic model. In this paper, a new ensemble-based learning strategy was investigated that combined multiple classification algorithms into one advanced diagnostic model. As reported in [4], this proposed framework outperformed other common classification algorithms in the field by achieving the highest accuracy rates. To evaluate the performance of the model, four sub-datasets were created, each containing the top 5 and top 10 features of the Messidor dataset selected by InfoGainEval and WrapperSubsetEval. The results showed that the model achieved accuracies of 70.7% and 75.1% on the InfoGainEval top 5 and original dataset, respectively. These findings suggest that the subdataset significantly simplifies the classification process without compromising the performance when compared to the original complete Messidor dataset. As stated in [5], the manual analysis and interpretation of retinal fundus images require the expertise of ophthalmologists, making it a time-consuming and costly process. Automated systems utilizing artificial intelligence have shown promise as an alternative method for early detection of diabetic retinopathy, surpassing traditional detection approaches. Recent studies have explored various advanced techniques for identifying DR. This article offers a thorough analysis of DR detection, encompassing key aspects such as retinal datasets, DR detection methods, and performance evaluation metrics. Furthermore, the paper offers the author's viewpoints and suggestions for future research to overcome the challenges facing the diabetic retinopathy field.

3. Proposed Methodology

The proposed system for automatic diabetic eye detection utilizes a modified ResNet architecture in the deep learning-based detection stage to classify the segmented retina region as normal or abnormal. To achieve this, the last fully connected layer of the ResNet architecture is replaced with a new fully connected layer that outputs a single probability indicating the image's normality or abnormality, specifically, diabetic retinopathy. The model is trained on a dataset of thermal images of patients, both with and without diabetic retinopathy, which is randomly partitioned into training, validation, and test sets. The model's performance is evaluated on the test set using various metrics such as accuracy, precision, recall, and F1-score, while transfer learning is used to further enhance its performance. The proposed methodology can be a cost-effective and non-invasive screening tool that facilitates early detection and intervention to prevent vision loss in diabetic patients. Furthermore, feature extraction is employed to represent the segmented regions with relevant and significant features such as color, size, edge, and texture, enhancing machine learning efficiency and accuracy by minimizing redundant data, accelerating learning, and efficiently utilizing compute resources. Image segmentation, which divides an image into multiple regions based on the pixels' characteristics in the image, is also employed in the process. This approach aims to exclude false-positive regions like light reflections, cotton wool spots, and optic disc, improving the accuracy of the model.

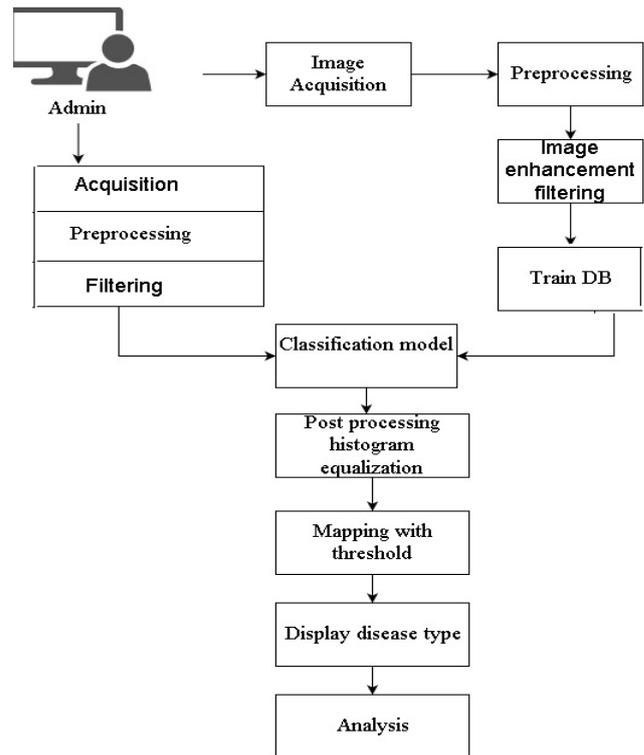


Fig 1. BLOCK DIAGRAM OF THE WORKFLOW

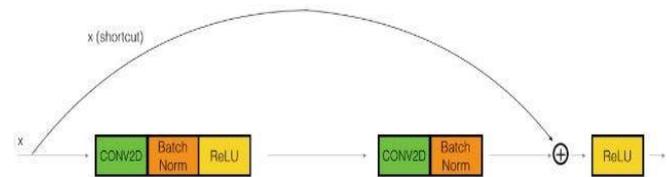


Fig 2. IDENTITY BLOCK

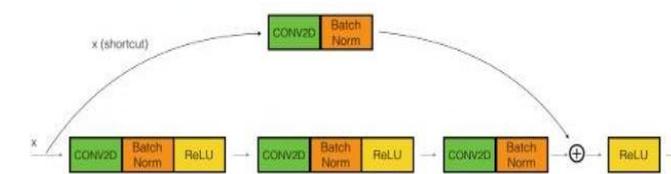


Fig 3. CONVOLUTIONAL BLOCK

A. Data collection

Collected thermal images of the retina from patients with and without diabetic retinopathy. This data was diverse and representative of the population being studied. The dataset was taken from Kaggle.

B. Pre-processing

Image pre-processing is a crucial step in automatic diabetic eye detection using machine learning. Pre-processing involves removing noise or artifacts that may affect the performance of the ML algorithm. The process includes cropping, resizing, and adjusting the brightness and contrast of the images.

C. Feature extraction

Extracted relevant features from the pre-processed images, such as the presence of blood vessels, lesions, or hemorrhages. These features were as input to the ML algorithm.

D. ML algorithm training

Developed an automatic diabetic eye detection system, the images need to undergo preprocessing to remove any noise or artifacts that may impact the performance of the machine learning (ML) algorithm. This process includes cropping, resizing, and adjusting the brightness and contrast of the images. The next step involves training an ML algorithm, such as a convolutional neural network (CNN), using the preprocessed images and their corresponding labels indicating whether the patient has diabetic retinopathy or not.

E. Testing and validation

Tested the trained ML algorithm on a separate dataset of pre-processed images to evaluate its performance. Validated the algorithm's performance by comparing it to the results of manual diagnosis by an ophthalmologist.

F. Deployment

Deployed the ML algorithm as a standalone application or integrate it into an existing medical system for automatic diabetic eye detection.

G. Continuous learning

Continuously improved the ML algorithm's performance by retraining it on new data and incorporating user feedback.

H. Classification

The Res Net architecture with 50 layers employs a bottleneck design for its building blocks. To reduce the number of parameters and matrix multiplications, a bottleneck residual block uses 1×1 convolutions, which is referred to as a "bottleneck." This approach allows for faster training of each layer, as the stack of three layers replaces the two layers used in previous architectures. The Res Net architecture with 50 layers comprises the following components:

- A 7×7 kernel convolution with 64 kernels and a stride of 2.
- A max pooling layer with a stride of 2.
- Nine more layers, each consisting of a 3×3 kernel convolution with 64 kernels, another with 1×1 kernels of 64, and a third with 1×1 kernels of 256. These three layers are repeated three times.
- Twelve more layers, each consisting of a 1×1 kernel with 128 kernels, a 3×3 kernel convolution with 128 kernels, and a 1×1 kernel with 512 kernels. These layers are iterated four times.
- Eighteen more layers, each consisting of a 1×1 kernel with 256 kernels, two 3×3 kernel convolutions with 256 kernels, and a 1×1 kernel with 1024 kernels. These layers are iterated six times.
- Nine more layers, each consisting of a 1×1 kernel with 512 kernels, a 3×3 kernel convolution with 512 kernels, and a 1×1 kernel with 2048 kernels. These layers are iterated three times. This brings the total number of layers to 50.
- The architecture ends with an average pooling layer, followed by a fully connected layer with 1000 nodes that uses the soft max activation function.

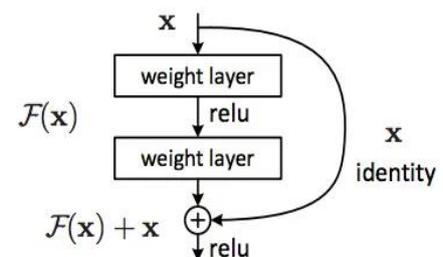


FIG 4. ResNet 50 ARCHITECTURE

4. Results and discussion

The experiments were conducted using Google Collab and evaluated the performance of a ResNet50 architecture. The dataset was split into 70% for training and 30% for testing the accuracy of the model. The classification phase was split into two steps, and all features were used for classification. The results indicate that the ResNet50 algorithm achieved an accuracy of 95-96 percentage.

TABLE 1. PRECISION TABLE

Sr. no.	Epoch	Loss	Accuracy
1.	1/15	10%	48%
2.	5/15	8%	72%
3.	10/15	5%	85%
4.	15/15	3%	95%

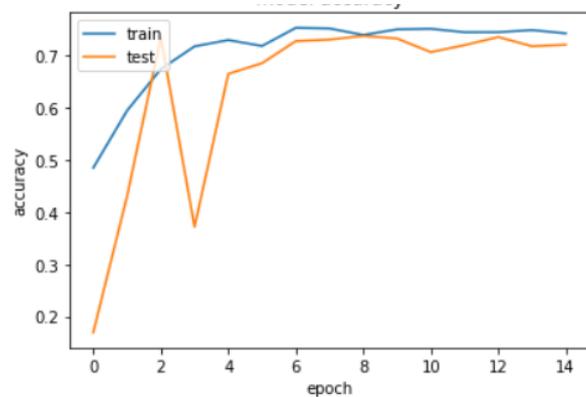


FIG 5. MODEL ACCURACY

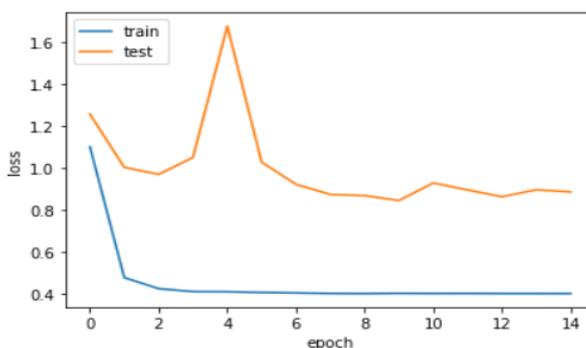


FIG 6. MODEL LOSS

5. Conclusion

In summary, automated diabetic eye detection has a bright future and has the potential to transform the diagnosis and management of diabetic retinopathy, resulting in improved patient outcomes and public health outcomes. Automated screening systems have a significant advantage in reducing the time required for diagnosing diabetic retinopathy, leading to timely treatment for patients while saving effort and costs for ophthalmologists. Early detection is critical for DR, and automated systems are essential in achieving this objective. This article examines the most recent automated systems for DR detection and classification that use deep learning techniques. The article discusses publicly available fundus DR datasets and briefly explains the deep learning techniques used by most researchers, with ResNet 50 being the most effective classification and detection method.

REFERENCES

[1] Hasan, Dathar A., et al. "Machine Learning-based Diabetic Retinopathy Early Detection and Classification Systems-A Survey." 2021 1st Babylon International Conference on Information Technology and Science (BICITS). IEEE, 2021.

[2] Sarki, Rubina, et al. "Automatic detection of diabetic eye disease through deep learning using fundus images: A survey." *IEEE Access* 8 (2020): 151133-151149.

[3] Dharmana, Meher Madhu, and M. S. Aiswarya. "Pre-diagnosis of Diabetic Retinopathy using Blob Detection." 2020 Second International Conference on Inventive Research in Computing Applications (ICIRCA). IEEE, 2020.

[4] Odeh, Israa, Mouhammd Alkasassbeh, and Mohammad Alauthman. "Diabetic Retinopathy Detection using Ensemble Machine Learning." 2021 International Conference on Information Technology (ICIT). IEEE, 2021

[5] Mateen, Muhammad, et al. "Automatic detection of diabetic retinopathy: a review on datasets, methods and evaluation metrics." *IEEE Access* 8 (2020): 48784-48811.