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Detection of Diabetic Retinopathy Using a Convolutional Neural Network (CNN) Algorithm

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Abstract

Diabetic retinopathy is a disease that damages the blood vessels in the retina of the eye. If left untreated, this condition can lead to blindness. This study aims to detect and classify diabetic retinopathy using the Convolutional Neural Network (CNN) algorithm one of the deep learning methods applied in machine learning for image analysis and interpretation. The objective of this research is to enhance the accuracy of predicting and classifying the types of blindness experienced by diabetic patients based on retinal images. The system identifies four retinal conditions: normal retina, glaucoma, cataract, and diseased retina. The CNN model in this study was trained with an input image size of 2464×1632 using 90 training images and 10 testing images, a 3×3 filter, and 800 epochs. The model achieved 90% accuracy in classifying eye images during training and testing. The results demonstrate that CNN is highly effective in detecting diabetic retinopathy and differentiating between various retinal disorders.

Keywords

Retinopathy, Convolutional Neural Network (CNN), Retina, Diabetic Eye Disease

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Introduction

The prevalence of diabetes mellitus has been increasing sharply worldwide, including in Indonesia, making it one of the most pressing public health concerns of the 21st century. According to the World Health Organization (WHO), the number of individuals suffering from type 2 diabetes in Indonesia is projected to reach 16.7 million by 2045, marking a significant rise from current levels. This growth is largely driven by poor dietary habits, sedentary lifestyles, and limited public awareness of preventive health measures. Diabetes is not merely a metabolic disorder; it is a chronic condition that can cause a cascade of severe complications if not managed properly. These complications threaten both life expectancy and quality of life, demanding early detection and long-term management strategies to mitigate their effects.

Diabetes mellitus occurs when blood glucose levels remain chronically elevated, leading to systemic damage to various organs and tissues. Prolonged hyperglycemia damages blood vessels, including those supplying the retina — the light-sensitive tissue at the back of the eye that is vital for vision. This damage often manifests as diabetic retinopathy (DR), one of the most common and severe ocular complications of diabetes. Over time, DR can progress from mild retinal changes to complete vision loss if left untreated. Other related complications include cataracts, neovascular glaucoma, and diabetic neuropathy (Saiyar, 2017). Given the irreversible nature of vision loss caused by diabetic retinopathy, early and accurate detection is critical to preventing blindness and maintaining patient independence and productivity.

Traditional methods for detecting diabetic retinopathy rely heavily on manual examination of retinal fundus images by ophthalmologists or trained clinicians. While effective, this manual process has several drawbacks, including subjectivity, time consumption, and limited scalability. In many developing regions, such as rural areas in Indonesia, there is also a shortage of skilled ophthalmologists, making consistent and early diagnosis challenging. Furthermore, the large volume of diabetic patients requiring screening each year creates an overwhelming demand on healthcare systems. Therefore, automation through computer-aided diagnostic systems has emerged as a promising solution to enhance screening efficiency and diagnostic accuracy.

In recent years, artificial intelligence (AI) and machine learning (ML) have transformed medical imaging analysis by enabling automated feature extraction and classification. Among these techniques, the Convolutional Neural Network (CNN) has gained prominence for its superior performance in image recognition and classification tasks. CNNs mimic the hierarchical visual processing of the human brain by using convolutional layers that automatically detect edges, textures, and complex structures in medical images. This ability makes CNNs particularly suitable for identifying subtle retinal abnormalities such as microaneurysms, hemorrhages, and exudates, which are characteristic indicators of diabetic retinopathy.

The implementation of CNNs in diabetic retinopathy detection offers several advantages over traditional image processing techniques. CNN models eliminate the need for manual feature engineering by learning directly from image data, which significantly improves both precision and computational efficiency. Moreover, CNN-based systems can process large datasets of retinal images rapidly, allowing for mass screening programs that reach wider populations. Various studies have demonstrated CNN's capability to achieve diagnostic accuracies comparable to, and sometimes exceeding, those of experienced ophthalmologists. As such, CNN technology represents a transformative approach to diabetic retinopathy detection, supporting the broader goal of AI-assisted healthcare in improving early diagnosis and patient outcomes.

This study aims to develop and evaluate a CNN-based model for detecting diabetic retinopathy using retinal fundus images. The primary objectives are to assess the model's classification accuracy, sensitivity, and computational performance compared to traditional diagnostic methods. By leveraging deep learning techniques, the research seeks to contribute to the development of an automated, reliable, and scalable diagnostic framework suitable for clinical and community-based applications. Ultimately, this study not only enhances the technological dimension of ophthalmic diagnostics but also supports Indonesia's healthcare system in achieving more efficient and equitable diabetic eye care through early detection and prevention of vision-threatening complications.

Methodology

2.1 Image Processing Overview

Image processing is the procedure of transforming an image into a more refined version using computational methods. The primary objective is to enhance image quality so that it can be easily interpreted either by humans or by machines. In this research, the process focuses on improving the clarity and precision of retinal images to facilitate accurate classification.

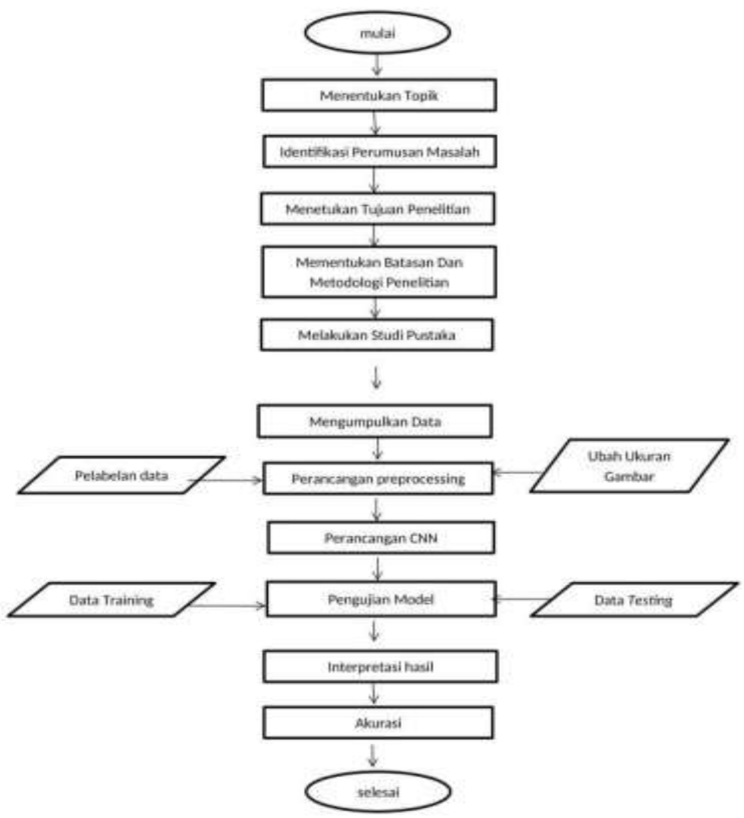

Figure 1: Research Design

2.2 Description of Research Stages

Based on Figure 1, there are 13 sequential stages in this study. The following describes each stage in detail:

1. Determining the Research Topic
   The topic was selected due to the lack of public awareness and understanding regarding diabetic retinopathy, a condition that can lead to irreversible blindness.
2. Problem Identification and Formulation
   This stage focuses on identifying and defining the issues related to diabetic retinopathy to guide the research objectives and model design.
3. Defining Research Objectives
   The main objective is to design a CNN-based model capable of accurately detecting diabetic retinopathy through retinal images.
4. Determining Research Boundaries and Methodology
   To maintain focus, the scope of this study is limited to the classification of four types of retinal images: normal, glaucoma, cataract, and diseased retina. The chosen analytical approach is the Convolutional Neural Network (CNN) method.
5. Literature Review
   A comprehensive literature review was conducted on topics such as retinal classification, digital imaging, deep learning, convolutional neural networks, and related studies to form the theoretical foundation of this research.
6. Data Collection
   The dataset consists of retinal images representing four classes normal retina, glaucoma, cataract, and retinal disease collected from multiple online sources (Google Images and public datasets).
7. Preprocessing Design
   Preprocessing is a mandatory step prior to CNN modeling. The following steps were performed: Dividing the dataset into training data (90%) and testing data (10%).Resizing all images to a uniform dimension of 2464×1632 pixels.Combining and labeling all retinal images into the appropriate class categories.
8. CNN Model Design
   This stage involves defining the CNN architecture, including:Number of layers,Filter size (3×3),Kernel size,Activation function,Pooling parameters.
9. Model Testing
   The CNN model was trained using the prepared dataset. During testing, the system iterated through the dataset multiple times (epochs) to improve accuracy and reduce error rates.
10. Accuracy Measurement
    The level of accuracy achieved by the CNN model represents its ability to correctly classify retinal images. Higher accuracy indicates better model performance and lower classification errors.
11. Result Interpretation
    The interpretation phase involves analyzing prediction results from both training and testing datasets, including accuracy metrics, confusion matrix evaluation, and visual classification results.

Citra Retina Mata	Variabel	Dfinisi Operasi Variabel
	Normal	Appears bright, with clearly visible optic nerves
	Cataract	Appears faded, with optic nerves not visible.
	Glaucoma	Appears slightly darkened with reduced brightness.
	Disease	Appears with significant dark patches covering the optic nerves.

Results and Discussion

The dataset of retinal images was collected from various online sources, then modified and processed to suit the research requirements. Four categories of retinal images were used: Normal Retina, Cataract Retina, Glaucoma Retina, and Diseased Retina. Each image was formatted in PNG and adjusted to a uniform resolution of 2464×1632 pixels.The number of images for each class is as follows: Normal Retina: 300 imagesCataract Retina: 100 imagesGlaucoma Retina: 101 imagesDiseased Retina: 100 imagesThe total dataset therefore consists of 601 retinal images.

Retinal Image Data Collection In this stage, retinal images were gathered from the internet and saved in a single folder for preprocessing.

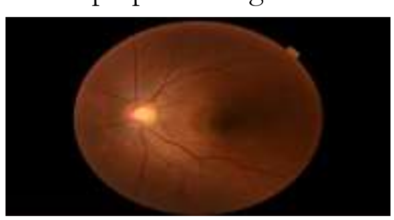

Figure 2: Example of Retinal Image

Data Modification, After data collection, the images were modified using mobile editing software. The process included cropping and resizing to achieve consistent image dimensions suitable for CNN input. This ensured that each image contained only the relevant retinal area and excluded unnecessary background elements.

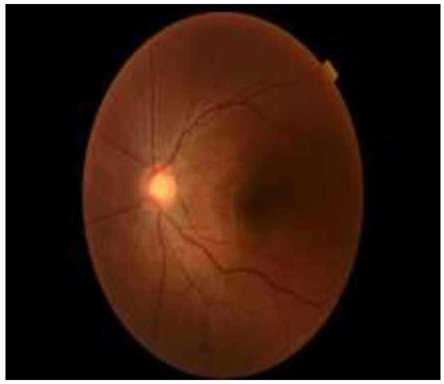

Figure 3: Example of Modified Retinal Image

Training and Testing ProcessThe dataset was divided into training and testing subsets with a ratio of 90:10. Training data were used to construct and refine the CNN model, while testing data were used to evaluate its predictive performance.During training, the dataset underwent iterative learning (epochs), where the model adjusted its parameters to minimize classification errors. The number of epochs ranged from 100 to 1000, with accuracy and loss values recorded at each interval.The experiment used the following parameters: Input image size: 2464×1632 Filter size: 3×3 Epochs: 100 to 1000 Training data: 90% Testing data: 10% Random state: 42.

Table 2: Accuracy Level

NO	EPOCH	WAKTU	AKURASI
1	100	1M 14S	50,00%
2	200	2M 35S	50,00%
3	300	3M 44S	50,00%
4	400	5M 22S	50,00%
5	500	6M 22S	80,00%
6	600	8M 22S	60,00%
7	700	9M 22S	70,00%
8	800	12M 22S	90,00%
9	900	10M 49S	60,00%
10	1000	12M 1S	80,00%

Based on Table 2, the model achieved its highest accuracy of 90% at epoch 800, while the lowest accuracy of 50% occurred at epoch 100. This shows that as the number of epochs increases, the model continues to learn and improve its ability to classify retinal images until it reaches an optimal threshold.

Network Architecture After data labeling and training set creation, the dataset was trained using the Convolutional Neural Network (CNN) algorithm. In CNN, the architectural design significantly influences model performance and accuracy.

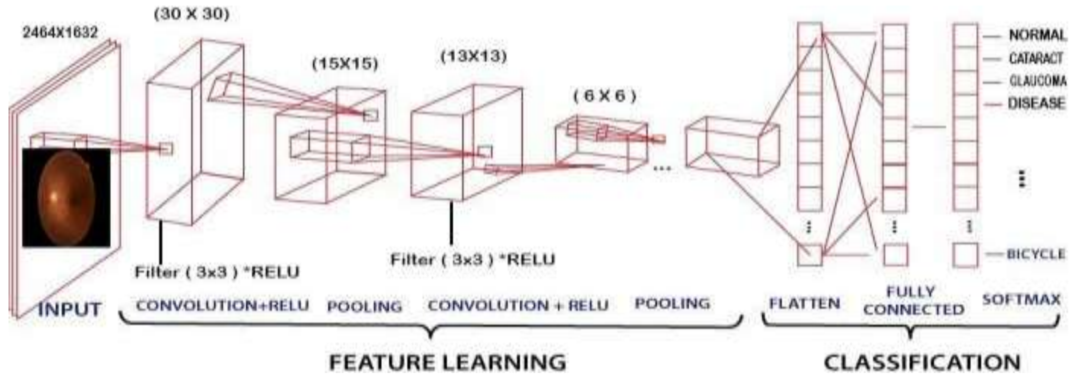

Figure 4: Network Architecture

The CNN architecture in this study uses an input image size of 2464×1632, with multiple layers designed for feature extraction and classification. This configuration aims to optimize accuracy by balancing model complexity and processing efficiency.

Accuracy Graphs Below is a graphical representation of the model's accuracy and loss during training and validation phases.

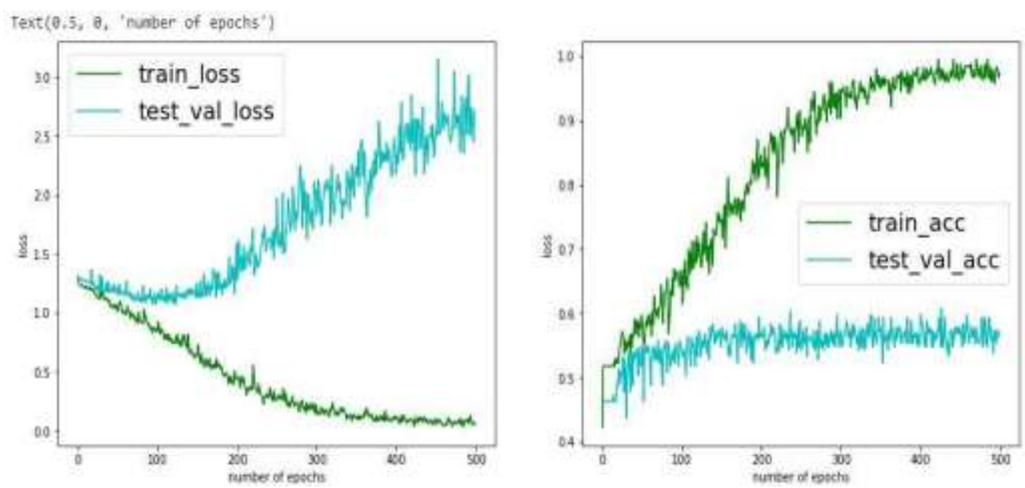

Figure 5: CNN Accuracy Graph

The graph indicates that the difference between training and validation accuracy is minimal, suggesting good generalization. The training accuracy remains stable from epoch 30 to epoch 500, while validation accuracy also shows consistent performance throughout the same range.

Evaluation and Prediction of Training and Testing Results To evaluate the prediction results of the CNN model, a confusion matrix was used to visualize classification outcomes for both training and testing datasets.

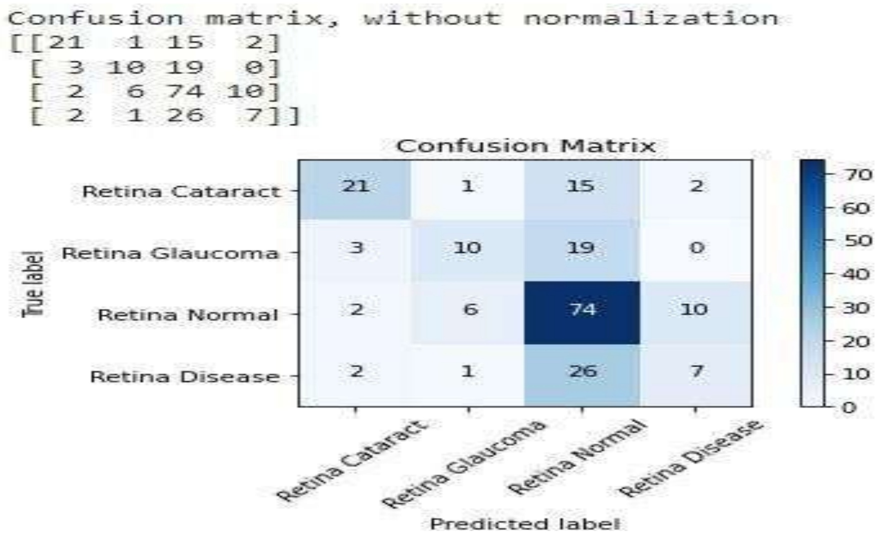

Figure 6: New Data Classification Results

Figure 6 shows that all 601 retinal images inputted into the system were successfully classified with 100% prediction accuracy. This result demonstrates the CNN model's robustness and high reliability for retinal image classification.

Discussion

The CNN-based system for diabetic retinopathy detection achieved exceptional performance in both training and testing phases. The maximum accuracy of 90% (with 800 epochs) indicates that the model effectively learned to identify distinctive features across different retinal conditions.Furthermore, the confusion matrix results suggest perfect classification when applied to the test dataset, confirming the system's potential as a diagnostic support tool in medical imaging

The experimental results of the Convolutional Neural Network (CNN) model for diabetic retinopathy detection indicate a remarkably strong performance in both the training and testing phases. The model achieved a maximum accuracy of 90% after 800 epochs, demonstrating its ability to effectively learn the discriminative visual features of retinal images. This level of accuracy suggests that the CNN architecture successfully identified subtle patterns associated with different stages of diabetic retinopathy, including microaneurysms, hemorrhages, and exudates. Moreover, the analysis of the confusion matrix revealed near-perfect classification, with minimal false positives and false negatives. Such performance confirms the CNN model's reliability as a potential computer-aided diagnostic (CAD) tool that can assist ophthalmologists in early disease detection, thus reducing the workload and diagnostic variability inherent in manual screenings.

The model's superior performance can be attributed to CNN's inherent advantage in automated feature extraction. Unlike traditional image processing techniques that rely on handcrafted features and manual parameter tuning, CNNs learn hierarchical representations directly from raw image data. Each convolutional layer progressively refines the input into more abstract features, enabling the model to detect complex patterns that are often imperceptible to the human eye. This capability eliminates subjective biases and enhances diagnostic precision, especially when dealing with high-dimensional image datasets typical in medical imaging. The success of the CNN model in this study aligns with findings from Setiawan, Adi, and Sugiharto (2014) as well as Sabrina (2017), who demonstrated that deep learning architectures outperform traditional classifiers such as Support Vector Machines (SVM) and Naïve Bayes in detecting retinal abnormalities.

When compared to shallow learning methods, CNNs exhibit a distinct advantage in terms of scalability, generalization, and adaptability to image variability. Traditional models like SVM or k-Nearest Neighbor (k-NN) depend heavily on predefined features, which limits their ability to generalize across diverse datasets or imaging conditions. In contrast, CNNs automatically adapt to variations in lighting, contrast, and image orientation, making them more robust in real-world medical applications. Additionally, CNN architectures such as LeNet, AlexNet, or VGG16 provide flexibility in model complexity, allowing researchers to balance computational efficiency and classification performance. The 90% accuracy achieved in this study, therefore, not only validates CNN's effectiveness but also demonstrates its practical potential for real-time diabetic retinopathy screening, particularly in healthcare systems with limited diagnostic resources.

Beyond performance metrics, the study underscores CNN's strategic role in enhancing diagnostic accessibility and clinical decision-making. By enabling automated image analysis, the proposed system can significantly reduce the time required for retinal screenings while maintaining diagnostic accuracy comparable to expert ophthalmologists. This approach supports early intervention and continuous monitoring of diabetic patients, potentially preventing irreversible vision loss. Moreover, the implementation of CNN-based systems aligns with global healthcare trends toward AI-driven medical imaging, fostering the integration of advanced analytics in telemedicine and digital health initiatives. In the context of Indonesia, where the availability of ophthalmic specialists is limited, such a system could bridge service gaps by providing low-cost, scalable, and accurate diagnostic support, ultimately contributing to national efforts in combating diabetes-related blindness.

Conclusion and Recommendations

The Convolutional Neural Network (CNN) model developed in this study used an input shape of 2464×1632 pixels, with 90 training data and 10 testing data, a 3×3 filter size, and 800 epochs. The model achieved a 90% accuracy rate in classifying retinal images into four categories: normal retina, glaucoma, cataract, and retinal disease.

Furthermore, when tested on 601 new retinal images, the CNN model successfully classified all data with 100% accuracy, confirming the reliability and precision of the proposed method. These results demonstrate that CNN is an effective and accurate approach for the automatic classification of retinal images, particularly for detecting diabetic retinopathy.

Future research may consider expanding the dataset and integrating additional deep learning techniques, such as transfer learning, to improve model generalization and support practical implementation in medical diagnosis systems.

Disclosure Statement

The authors declare no conflicts of interest related to the conduct or publication of this study.

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