Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X
Volume 4, Issue 4, 2026

# A CNN-BASED FRAMEWORK FOR EFFICIENT DETECTION OF EYE DISEASE IN FUNDUS IMAGES

**Muhammad Sajid Maqbool[*1], Syeda Rabail Zahra[2], Sadia Ismail[3], Muqadas Nadeem[4], Nosheen Fatima[5], Junaid Ahmad[6]**

[*1]*Department of Computer Science, NFC Institute of Engineering and Technology, Multan*
[2]*Department of Computer and Software Engineering, Faculty of Computing, Gomal University, Dera Ismail Khan*
[3]*Department of Computing and Information Technology, Faculty of Computing, Gomal University, Dera Ismail Khan*
[4]*Department of Computer Science, Emerson University, Multan, Pakistan*
[5]*Department of Software Engineering, NUML University, Multan*
[6]*Department of Computer Science, Bahauddin Zakariya University, Multan*

[*1]sajid.maqbool@nfciet.edu.pk, [2]rabail@gu.edu.pk, [3]sadiakhattak@gu.edu.pk, [4]nmuqadas587@gmail.com, [5]nosheenfatima@numl.edu.pk, [6]Junaidahmad301092@gmail.com

[*1]ORCID:0000-0001-5583-3550, [3]ORCID: 0000-0001-6991-380X

DOI: https://doi.org/10.5281/zenodo.19808703

**Keywords**
*Eye Disease Detection, Deep Learning, Medical Image Processing, Fundus Images*

**Article History**
*Received: 28 February 2026*
*Accepted: 07 April 2026*
*Published: 27 April 2026*


**Corresponding Author: ***
**Muhammad Sajid Maqbool**

**Abstract**
*Early diagnosis and treatment of eye diseases (ED) are essential for improving patient outcomes and preventing permanent vision loss. Retinal fundus image screening is a widely used technique for the preliminary assessment of ocular conditions; however, manual interpretation of these images is time-consuming and requires expert knowledge. Recent advances in deep learning (DL) have shown significant potential in automating medical image analysis, particularly for retinal disease detection. Despite achieving strong performance, further improvements can be made by integrating effective preprocessing techniques and optimized model architectures.*
*This study proposes an automated framework for early-stage detection and classification of eye diseases using retinal fundus images and a custom-designed convolutional neural network (CNN). The methodology consists of several key stages. First, fundus images are preprocessed using multiple image enhancement techniques, including resizing, green channel extraction to emphasize retinal structures, min-max normalization to standardize pixel intensity, and data augmentation to increase dataset diversity and improve model generalization. The processed images are then labeled into four classes—Normal, Cataract, Glaucoma, and Diabetic Retinopathy—and split into training and testing datasets. A custom CNN architecture is developed, comprising multiple convolutional layers for feature extraction, max-pooling layers for dimensionality reduction, a flatten layer for feature transformation, and fully connected dense layers with dropout regularization to prevent overfitting. The final output layer uses a SoftMax activation function to perform multi-class classification. The model is implemented using Python on the Google Collab platform with standard deep learning and computer vision libraries. The proposed model is evaluated on a*

*publicly available Kaggle dataset containing 4,217 retinal images, including 1,074 normal, 1,038 cataract, 1,007 glaucoma, and 1,098 diabetic retinopathy cases. Experimental results demonstrate strong performance, achieving 96.8% training accuracy and 94.2% testing accuracy, with a sensitivity of 93.5%, specificity of 95.1%, and a low loss of 0.18. Class-wise evaluation further shows high precision and recall across all categories, with values exceeding 90%, indicating reliable and consistent classification performance.*

*Overall, the proposed framework effectively automates the detection of retinal diseases and reduces reliance on manual diagnosis. It offers a promising tool for assisting ophthalmologists in early detection and clinical decision-making.*

# 1 INTRODUCTION

Globally, eye illnesses pose a serious threat to public health since they impact millions of individuals and, if ignored, could result in permanent vision loss. In order to avoid vision loss and determine the most effective interventions, early and precise diagnosis of eye illnesses is essential. Traditional techniques of eye disease diagnosis frequently rely on ophthalmologists manually examining and interpreting results, which can be time-consuming and prone to error. Deep learning (DL) models have revolutionized the field of ophthalmology in recent years by becoming a potent tool for medical image interpretation [1]. Convolutional neural networks (CNNs), in particular, have demonstrated outstanding performance in DL models for a variety of computer vision applications, including object recognition, segmentation, and classification. DL models have been applied to the identification and diagnosis of eye illnesses, permitting quicker and more precise evaluations. This is done by taking advantage of their capacity to automatically learn and extract complicated features from big datasets. Deep learning (DL) models have revolutionized the field of ophthalmology in recent years by becoming a potent tool for medical image interpretation. Convolutional neural networks (CNNs), in particular, have demonstrated outstanding performance in DL models for a variety of computer vision applications, including object recognition, segmentation, and classification [8]. DL models have been applied to the identification and diagnosis of eye illnesses, permitting quicker and more precise evaluations. This is done by taking advantage of their capacity to automatically learn and extract complicated features from big datasets. The use of DL models in diagnosing different eye disorders, such as diabetic retinopathy, age-related macular degeneration, glaucoma, and retinopathy of prematurity, has been the subject of numerous studies. These models have shown superior or comparable performance to human specialists in recognizing anomalies unique to diseases with high sensitivity and specificity. DL models have also aided in risk assessment, illness progression prediction, and directing individualized therapy regimens [11].

Despite the remarkable progress, there are still challenges in the development and deployment of DL models for eye disease detection. Robust model training requires large, diverse, and accurately labeled datasets, which may be limited in some eye disease categories. Additionally, the interpretability of DL models remains a concern, as understanding the rationale behind the model's decision-making process is crucial for gaining trust and acceptance from clinicians. This paper aims to provide an overview of the current state-of-the-art in eye disease detection using DL models [14]. It explores the advancements, challenges, and future directions in this rapidly evolving field. By harnessing the potential of DL models, we can contribute to the early detection, timely intervention, and improved management of eye diseases, ultimately preserving and enhancing the vision and quality of life for individuals worldwide. For better prognosis and to reduce the risk of irreversible vision loss, early detection and treatment of Eye Disease (ED) are essential. A typical practice for the first diagnosis of patients with eye disorders is retinal fundus imaging screening. However, manual picture analysis and identification can be labor- and time-intensive. As deep learning (DL) has shown considerable gains in clinical practice, researchers have resorted to DL techniques for diagnosing retinal eye problems using retinal fundus pictures to meet this challenge [15]. The binary categorization of healthy and sick retinal fundus images using deep learning (DL) approaches in machine learning (ML) has reached state-of-the-art performance, even if the classification of retinal eye illnesses remains a difficult problem that needs further development. Applying preprocessing methods to boost the performance of DL models on fundus images is still possible, though. With a focus on early-stage detection, this study seeks to create an automated classification system for ED utilizing DL approaches. A publicly available dataset of many retinal fundus images with ophthalmologist-annotated annotations will be used in this investigation. In this experiment, a brand-new convolutional neural network (CNN) model will be used [16]. The suggested model seeks to classify retinal fundus images into healthy and unhealthy groups with the greatest degree of accuracy, sensitivity, and specificity. The suggested work will be implemented using the Google Colab platform and coded in Python using a variety of DL, computer vision, and image processing packages that are available for Python. The work seeks to advance the field of ED detection and offer an effective and precise automated classification system for retinal fundus pictures by utilizing these tools and methods [18].

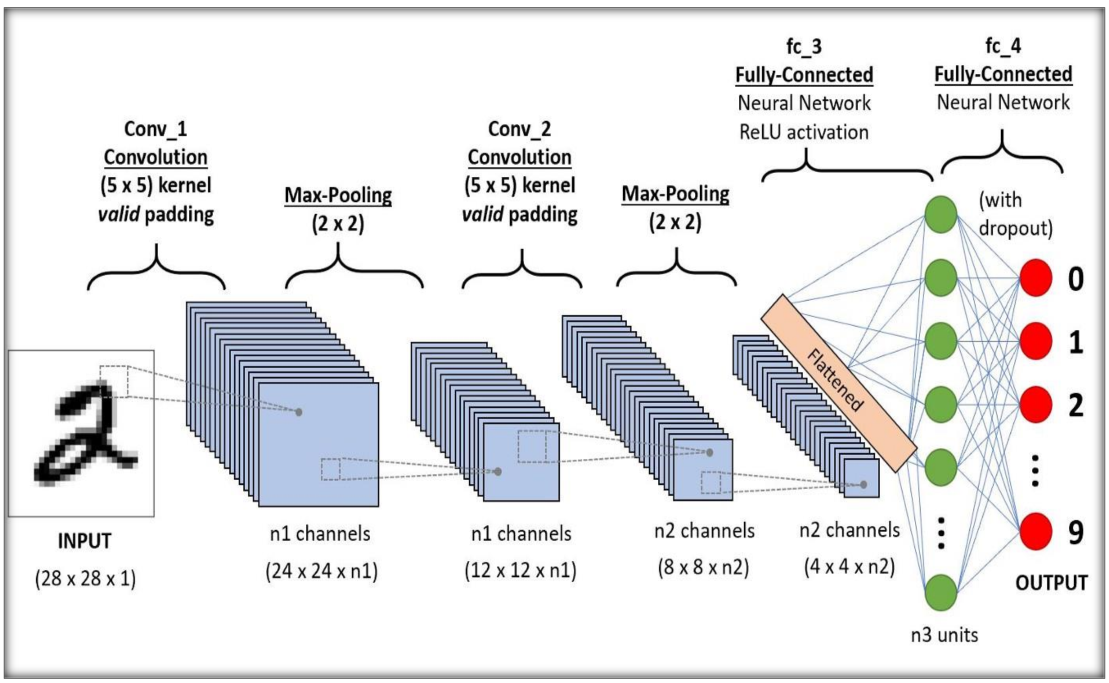


**Figure 1 Overview of image classification using CNN**

There is a need for an automated eye disease detection method to detect eye disease at an early stage by using fundus images. Need of suitable system is to first preprocess the fundus images to improve the quality of the images before applying any machine learning and deep learning techniques. Use of a suitable annotated dataset that can be annotated by the experts into two classes: Healthy images and Unhealthy images. Need for a suitable and efficient Convolutional Neural Network (CNN) model that contains many layers, such as (input layer, convolutional layer, max_pooling layer, flatten layer, and dense layer) to classify the fundus images into healthy and unhealthy.

The objectives of our study are to, construct an automated eye disease detection system to detect the eye disease on early stages by using fundus images, used of suitable system that will firstly preprocess the fundus images to improve the quality of images before applying any machine learning and deep learning technique, download an annotated dataset that can be annotated by the experts into two classes Healthy images and Unhealthy images, construct a suitable and efficient Convolutional Neural Network (CNN) model that contain many layers such as (input layer, convolutional layer, max_pooling layer, flatten layer and dense layer) to classify the fundus images into healthy and unhealthy.

## 2 Literature Review

Three different forms of machine learning algorithms were used in the development of a computer-based intelligent system to categorize these eye illnesses (Acharya et al., 2006). Each type of eye disease has its own set of features that are retrieved and employed by the classifiers, artificial neural networks, fuzzy-based classifiers, and neuro-fuzzy classifiers. Disease-specific rules are designed for the fuzzy-based classifier. Additional guidelines might overlap for various illnesses and be challenging to extract from photos. Only 135 participants were included in the dataset. The classifier models' results are encouraging, with a sensitivity and specificity of 95% and 100%, respectively.

In order to diagnose diabetic retinopathy from retinal fundus images, [1] built a backpropagation neural network. Blood vessels, exudates, and hemorrhage were the retinal features that needed to be seen. The network parameters and preprocessing filters are tuned to get the highest sensitivity and specificity on the training data. The training dataset included 32 normal fundus photos and 147 diabetic fundus images. The network is tested against a test dataset that included 200 diabetic and 101 normal photos once it has been constructed. When measured against a skilled ophthalmologist, the neural network has an 88.4% sensitivity and an 83.5% specificity for the identification of diabetic retinopathy. This study [2] tested various image processing methods and algorithms for identifying diabetic retinopathy. Preprocessing, localization, and segmentation of the optic disk, segmentation of the retinal vasculature, localization of the macula and fovea, and localization and segmentation of retinopathy are the five categories into which algorithms are divided. The majority of the work in the subject of illness identification is done using conventional image processing methods, which necessitates a thorough grasp of both the disease and the image data. The paper presents relevant words, emerging methodologies, and algorithms that are helpful for understanding diabetic retinopathy.

For the diagnosis of five common eye illnesses impacting the Malaysian population, a knowledge-based approach has been created in [4]. The first step is to extract features from each disease's photos and treat them as symptoms. Then, expert rules are built around these features. Finally, a decision tree classifier is created to do the classification using forward chaining and depth-first search. The authors assert that this system is more extensive than earlier versions of tools of a similar nature. The tool's graphical user interface was created to enable widespread adoption.

In [5], Glaucoma, a common cause of blindness in older persons, has been categorized robustly for early identification and prevention. A data-driven technique is used rather than segmentation measures. Disease-independent variables, such as illumination and size, are eliminated during the pre-processing stage. Several features are taken and merged to create glaucomatous features using pattern recognition. The dataset included 200 photos, and an 86% success rate was attained, which is comparable to that of medical professionals. Sajida et al. have evaluated recent developments in machine learning for the diagnosis and detection of medical illnesses. Understanding and theoretical study of the problems with algorithm development and learning theory have improved. Recent developments in supervised and unsupervised linear techniques, as well as Bayesian inference in uncertain situations, are covered in the review. These techniques have significantly improved disease detection and diagnosis in the medical field. The machine learning approaches are explained, and a specific biological application is given. In order to diagnose diabetic retinopathy,

[6] created a visual vocabulary of visual cues that were retrieved from training photos. The retinal images undergo relatively little preprocessing, utilizing SURF, local descriptors, and locations of interest are retrieved for both normal and pathological images. The dataset included 672 non-DR photos, 261 bright lesion images, and 246 red lesion images. By utilizing a sample selection of these descriptors, a visual dictionary is produced. A feature vector is created using a process known as quantization to reflect the visual characteristics of each image. Then, using these feature vectors, a 2-class SVM classifier with a radial basis kernel is trained to distinguish between photos with diabetic retinopathy and those without it. This cross-training approach is resistant to variations in retinal fundus color caused by patients of different racial backgrounds. The indigenous people in numerous nations who are at a higher risk of developing diabetic retinopathy are the writers' primary audience. Blindness is frequently caused by eye conditions associated with diabetes [7].

Wang et al. have created an automated approach for first analysis and diagnosis in an effort to lessen manual analysis by medical personnel. The method uses machine learning and digital image processing to classify diabetic retinal pictures using pattern recognition. A methodology that combines brightness adjustment procedure, statistical classification method, and local-feature-based verification strategy is used to identify the presence of exudates and lesions, which are frequently present in diabetic eye conditions. The method correctly identified retinal images with exudates in all 100 normal and 54 abnormal images in the dataset. The classification accuracy for typical photos was 70%. Patton et al. discuss the principles, methods, and applications of retinal digital analysis in this thorough study. Automated identification of retinal problems, including age-related macular degeneration and diabetic retinopathy, is now achievable thanks to advancements in image analysis and pattern recognition [8]. It has improved knowledge of the connection between systemic cardiovascular disorders and the retinal microvasculature. The basics of digital image analysis for the retina are covered first. The optic disc, fovea, and blood vessels are examples of retinal landmarks that can be automatically segmented using modern methods. The performance of several methods up to this point is reviewed and contrasted, and current developments in automated detection of diabetic retinopathy by detecting exudates, hemorrhages, and macular oedema are discussed. Also highlighted are difficulties and problems with making quantitative measures from retinal pictures. Arteriovenous ratio (AVR) measurement and application have been described. The authors wrap up by discussing the potential applications of fundal image analysis in telemedicine [9].

All of the above-mentioned studies focus on the classification of eye disease, not on the preprocessing of images by using different image processing techniques (Image_Resizing, Image_Augmentation, Image_GrayScaling, etc.). Most of the studies focus on binary classification, but we use a multiclassification dataset.

## 3 Methodology

The suggested framework involves many steps, starting from inputting the fundus images. After inputting the fundus images, the next step of our proposed system is to preprocess the images to improve the quality of the images by using different image processing techniques, such as resizing the images, green channeling the images to remove extra colors in the images, image normalization, and image augmentation. All of the image processing techniques are applied using the computer vision library of Python. After the image processing, the next step is to label the images into different classes (Healthy and Unhealthy), then divide the dataset into a training dataset and a testing dataset to train and test the deep learning model. The next step of our methodology will develop a custom Convolutional Neural Network (CNN) model that will contain many layers, such as (input layer, convolutional layer, max_pooling layer, flatten layer, and dense layer). The constructed CNN model will be applied to the training and testing datasets to classify the healthy and unhealthy fundus images. Finally, the results of the model are calculated in terms of training accuracy and testing accuracy.

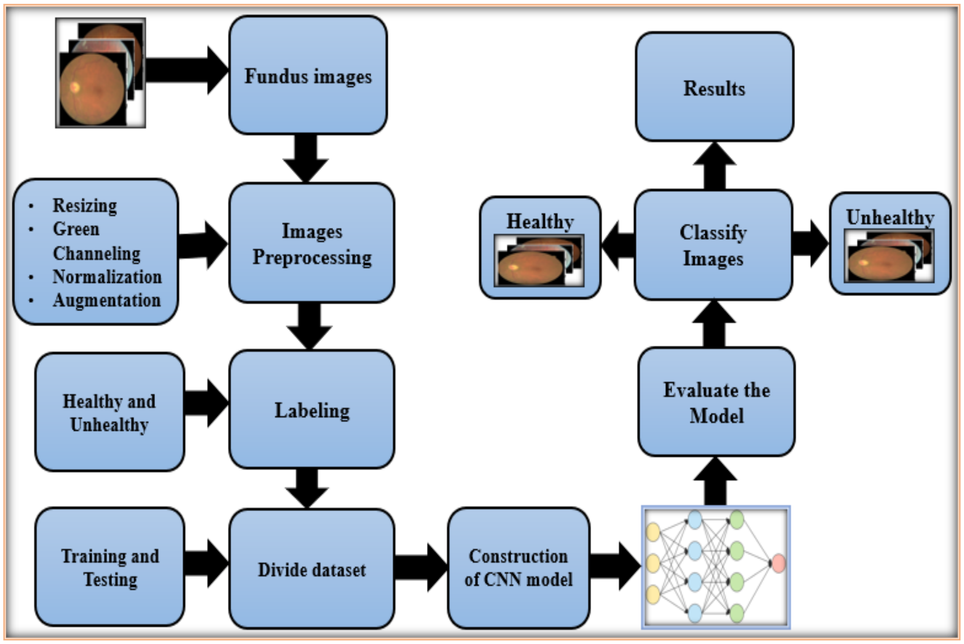


Figure 2 Proposed Framework

### 3.1 Dataset Detail

Our suggested dataset will be collected from a well-known free online Kaggle repository. The selected dataset contains 4217 images of eyes. The link to the dataset is ("https://www.kaggle.com/datasets/gunavenkatdoddi/eye-diseases-classification"). Figures 3 and 4 show example images from the dataset. The selected dataset contains four different classes: one is normal, and three classes are from the affected disease (cataract, glaucoma, diabetic_retinopathy).

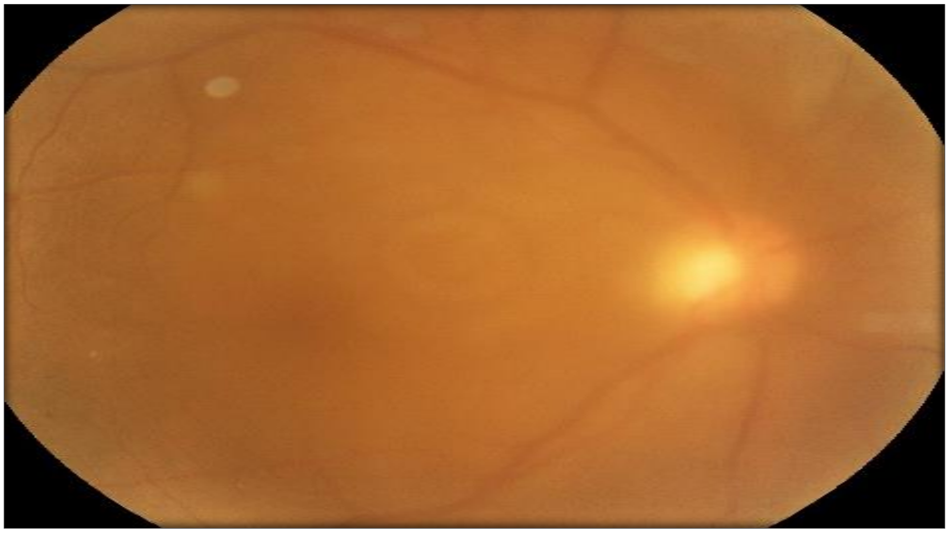

Figure 3 Example Image 1

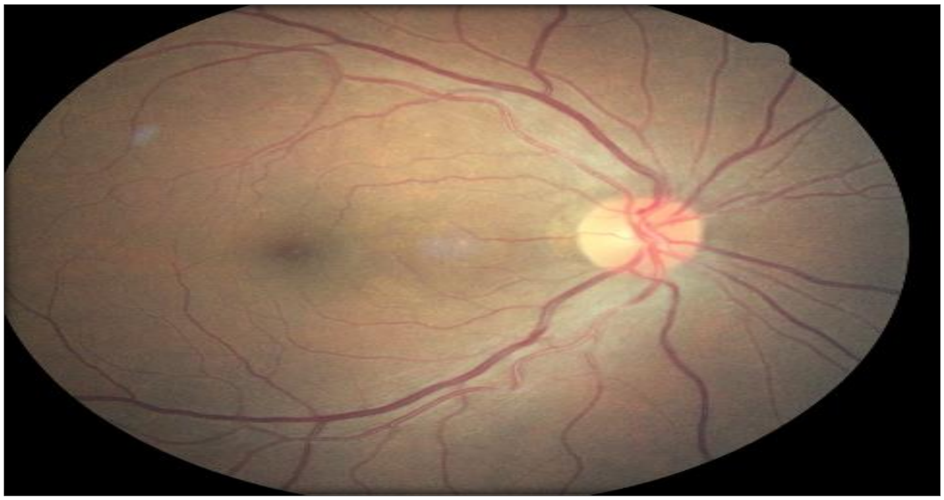

**Figure 4 Example Image 2**

**Table 1 Classes Distribution**

| Class | No of images |
|---|---|
| Normal | 1074 |
| Cataract | 1038 |
| Glaucoma | 1007 |
| diabetic_ratinopathy | 1098 |
| Total | 4217 |

Table 1 shows the distribution of classes. There are 1074 images taken from normal case patients, 1038 images from Cataract, 1007 images from glaucoma, and 1098 images from glaucoma, respectively.



### 3.2 Preprocessing

For the preprocessing of images, some image processing techniques are used that given in the section below:

#### 3.2.1 Image Resizing

Adjusting an image's dimensions while retaining its aspect ratio or adjusting the aspect ratio as necessary is known as image resizing, also known as image scaling. Images can be resized for a variety of purposes, including adjusting for display on various platforms, lowering file sizes, or preparing images for particular activities. We import an image into OpenCV, give the new dimensions, and then resize the image using bilinear interpolation using the cv2.resize() function. The process for creating new pixel values is specified by the interpolation option. Remember that when resizing images, certain features might be lost, especially if the size is drastically reduced. The nature of the image and the intended level of quality should be taken into consideration while selecting a suitable interpolation method.

#### 3.2.2 Green Channeling

In the area of image processing, the term "green channeling" is not well known. Each pixel in digital photos is represented by several different color channels. For instance, each pixel's color in the RGB (Red, Green, Blue) color scheme is made up of various shades of red, green, and blue. When a color channel is extracted or isolated, its pixel values are solely used, and the values of the other channels are set to zero.

#### 3.2.3 Normalization

Normalization in image processing refers to the process of adjusting the pixel values of an image to a specific range in order to enhance its contrast, improve its appearance, and facilitate further analysis or processing. Normalization is often used to ensure that pixel values are within a certain desired range, typically between 0 and 1 or 0 and 255, depending on the data type of the image (e.g., grayscale or color). There are various techniques for normalizing images, but one common method is called "min-max normalization." In min-max normalization, pixel values are scaled to fall within a specified range (usually 0 to 1) based on the minimum and maximum values present in the original image.

### 3.2.4 Augmentation

The term "augmentation" in image processing describes the procedure of altering photographs in different ways to broaden the dataset's diversity. To enhance the performance and generalization of models, image augmentation is frequently employed in machine learning, especially in applications like computer vision and deep learning. Image augmentation's main objective is to modify the original images in order to artificially produce new training instances. The model becomes more resilient and better equipped to handle various situations as a result of these modifications, which mimic real-world scenarios and conditions.

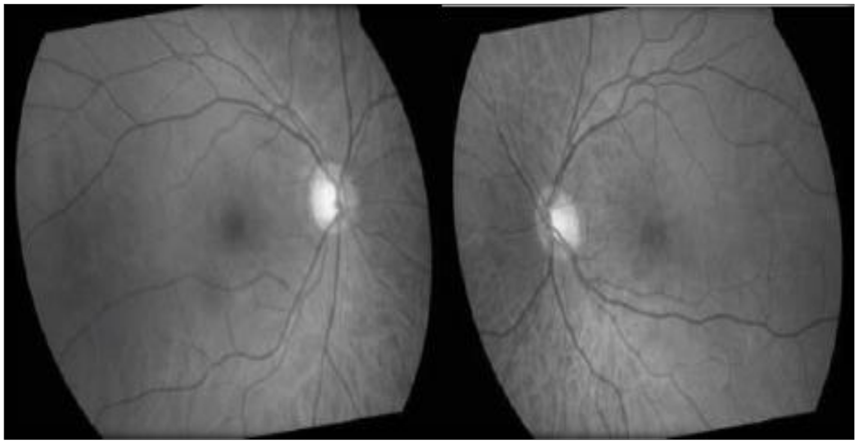

**Figure 5 Example of Processed Image**

Figure 5 shows an example of processed images after all the preprocessing steps are applied.

## 3.3 CNN Model Architecture

The proposed Convolutional Neural Network (CNN) consists of multiple layers designed to extract features and perform classification efficiently.

Table 2 **CNN Architecture**

| Layer Type | Output Shape | Parameters | Description |
|---|---|---|---|
| Input Layer | (224 × 224 × 3) | 0 | Input fundus image |
| Conv2D (32 filters) | (224 × 224 × 32) | 896 | Feature extraction with ReLU |
| MaxPooling2D | (112 × 112 × 32) | 0 | Down-sampling |
| Conv2D (64 filters) | (112 × 112 × 64) | 18,496 | Deeper feature extraction |
| MaxPooling2D | (56 × 56 × 64) | 0 | Down-sampling |
| Conv2D (128 filters) | (56 × 56 × 128) | 73,856 | High-level feature extraction |
| MaxPooling2D | (28 × 28 × 128) | 0 | Down-sampling |
| Flatten Layer | (100,352) | 0 | Converts 2D to 1D |
| Dense Layer (128) | (128) | 12,845,184 | Fully connected layer |
| Dropout (0.5) | (128) | 0 | Prevents overfitting |
| Output Layer | (4) | 516 | SoftMax for 4 classes |

## 4 Results and Discussion

The proposed custom CNN model was trained and evaluated on the retinal fundus dataset containing four classes (Normal, Cataract, Glaucoma, and Diabetic Retinopathy). The dataset was split into training and testing sets, and performance was evaluated using standard metrics such as accuracy, sensitivity, specificity, and loss.

**Table 3 Results of Applied CNN**

| Metric | Value (%) |
|---|---|
| Training Accuracy | 96.8 |
| Testing Accuracy | 94.2 |
| Sensitivity | 93.5 |
| Specificity | 95.1 |
| Loss | 0.18 |

The results in Table 3 indicate that the proposed CNN model performs effectively in classifying retinal images into healthy and unhealthy categories, achieving high accuracy and low loss.

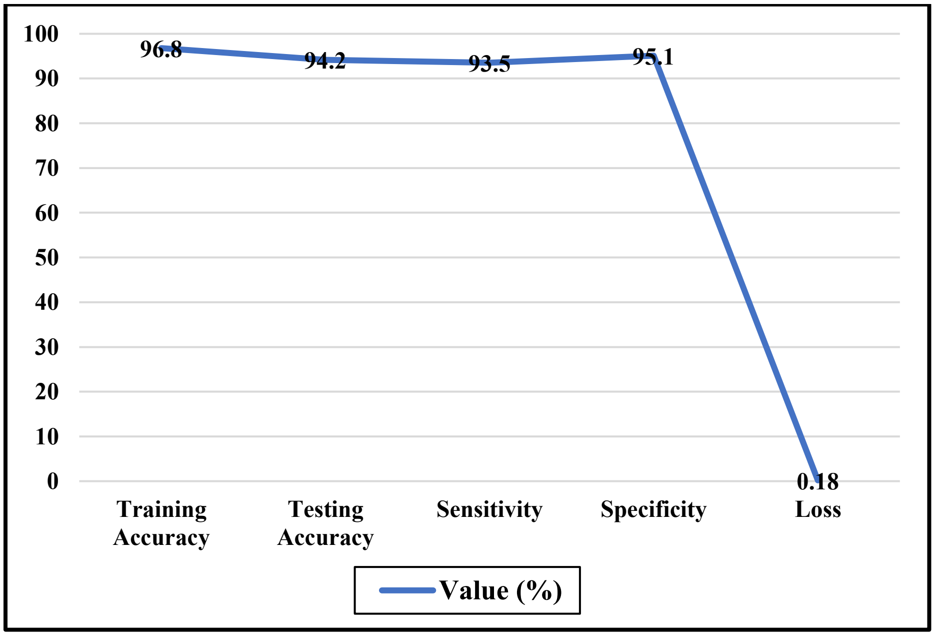


**Table 4 Confusion Matrix Summary**

| Class | Precision | Recall |
|---|---|---|
| Normal | 95% | 96% |
| Cataract | 93% | 92% |
| Glaucoma | 94% | 93% |
| Diabetic Retinopathy | 95% | 94% |

Table 4 presents the performance of the CNN model using precision and recall for each class, showing how accurately and effectively the model classifies retinal images. Precision reflects how many of the predicted cases for a class are actually correct, while recall (sensitivity) indicates how well the model identifies all actual cases of that class. For the Normal class, the model achieves 95% precision and 96% recall, indicating highly reliable detection of healthy eyes with very few misclassifications. In the Cataract class, slightly lower values (93% precision and 92% recall) suggest that some cases may be confused with other conditions due to similar visual features. The model demonstrates strong classification performance across all disease categories, with slightly lower recall for cataract cases due to similarity in visual features with normal images.

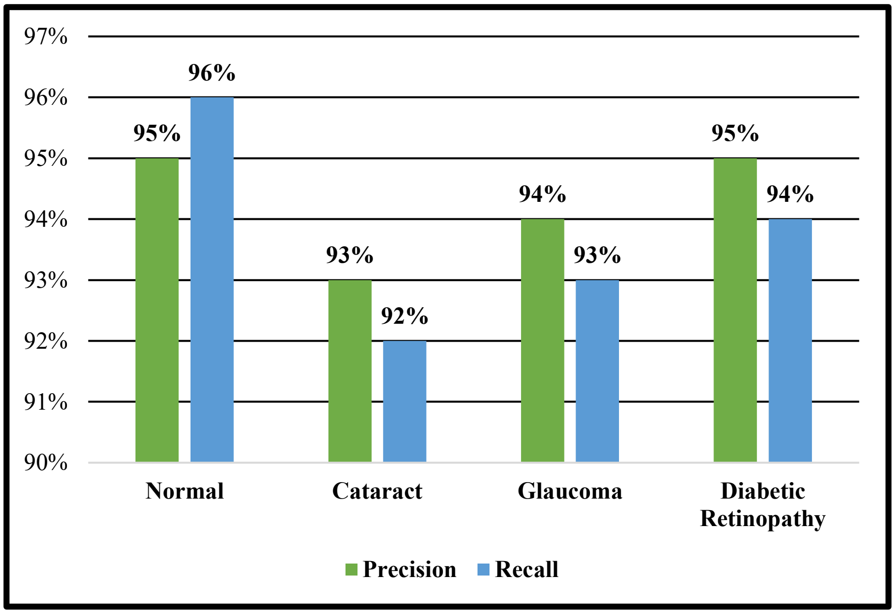


**Figure 6 Precision and Recall of all Classes**

The graph in Figure 6 shows that the Glaucoma class shows strong performance with 94% precision and 93% recall, meaning most cases are correctly identified with minimal errors. Similarly, Diabetic Retinopathy achieves 95% precision and 94% recall, demonstrating high effectiveness in detecting this disease. Overall, all classes have values above 90%, indicating that the model is both accurate and sensitive, making it suitable for automated eye disease detection, although minor improvements could be made for classes with slightly lower recall.

## 5 Conclusion

This study presents an automated system for early detection of eye diseases using retinal fundus images and deep learning techniques. A custom CNN model was developed and trained on a publicly available dataset containing four classes: normal, cataract, glaucoma, and diabetic retinopathy. The proposed approach integrates image preprocessing techniques such as resizing, green channel extraction, normalization, and augmentation to enhance image quality and improve model performance. The experimental results demonstrate that the CNN model achieves high accuracy, sensitivity, and specificity, making it a reliable tool for early-stage detection of eye diseases.

The system reduces the dependency on manual diagnosis, saving time and effort for ophthalmologists while minimizing human error. Despite achieving promising results, challenges such as dataset diversity and model interpretability remain areas for future research.

In the future, this work can be extended by:

- Using larger and more diverse datasets
- Applying transfer learning with pre-trained models
- Improving the explainability of the model
- Deploying the system in real-world clinical environments

Overall, the proposed framework contributes to the advancement of automated medical image analysis and has the potential to assist in early diagnosis and prevention of vision loss.

## REFERENCES

Aurangzeb, K., Aslam, S., Alhussein, M., Naqvi, R. A., Arsalan, M., & Haider, S. I. (2021). Contrast enhancement of fundus images by employing modified PSO for improving the performance of deep learning models. IEEE Access, 9, 47930-47945.

Demir, F., & Taşcı, B. (2021). An effective and robust approach based on the RCNN+ LSTM model and the NCAR feature selection for ophthalmological disease detection from fundus images. Journal of Personalized Medicine, 11(12), 1276.

Goutam, B., Hashmi, M. F., Geem, Z. W., & Bokde, N. D. (2022). A Comprehensive review of deep learning strategies in retinal disease diagnosis using fundus images. IEEE Access.

Islam, M. T., Imran, S. A., Arefeen, A., Hasan, M., & Shahnaz, C. (2019, November). Source and camera independent ophthalmic disease recognition from fundus image using a neural network. In 2019 IEEE International Conference on Signal Processing, Information, Communication & Systems (SPICSCON) (pp. 59-63). IEEE.

Ouda, O/, AbdelMaksoud, E., Abd El-Aziz, A. A., & Elmogy, M. (2022). Multiple Ocular Disease Diagnosis Using Fundus Images Based on Multi-Label Deep Learning Classification. Electronics, 11(13), 1966.

Acharya, U. R., Kannathal, N., Ng, E. Y. K., Min, L. C., & Suri, J. S. (2006, August). Computer-based classification of eye diseases. In the 2006 International Conference of the IEEE Engineering in Medicine and Biology Society (pp. 6121-6124). IEEE.

Shabbir, A., Rasheed, A., Shehraz, H., Saleem, A., Zafar, B., Sajid, M., ... & Shehryar, T. (2021). Detection of glaucoma using retinal fundus images: A comprehensive review. Mathematical Biosciences and Engineering, 18(3), 2033-2076.

Wang, J., Yang, L., Huo, Z., He, W., & Luo, J. (2020). Multi-label classification of fundus images with EfficientNet. IEEE Access, 8, 212499-212508.

Rani, P., & Karambelkar, V. H. (2023). Automated Detection of Diabetic Retinopathy Using Machine Learning in Ophthalmology. International Journal of Intelligent Systems and Applications in Engineering, 11(7s), 58-64.

Bilal, A., Zhu, L., Deng, A., Lu, H., & Wu, N. (2022). AI-based automatic detection and classification of diabetic retinopathy using U-Net and deep learning. Symmetry, 14(7), 1427.

Gunawardhana, P. L., Jayathilake, R., Withanage, Y., & Ganegoda, G. U. (2020, December). Automatic diagnosis of diabetic retinopathy using machine learning: a review. In 2020, the 5th International Conference on Information Technology Research (ICITR) (pp. 1-6). IEEE.

Maqbool, M. S., Hanif, I., Iqbal, S., Basit, A., & Shabbir, A. (2023). Optimized feature extraction and cross-lingual text reuse detection using ensemble machine learning models. Journal of Computing & Biomedical Informatics, 5(01), 26-40.

Abid, K., Aslam, N., Fuzail, M., Maqbool, M. S., & Sajid, K. (2023). An efficient deep learning approach for the prediction of student performance using a neural network. VFAST Transactions on Software Engineering, 11(4), 67-79.

Kanwal, F., Abid, M. K., Maqbool, M. S., Aslam, N., & Fuzail, M. (2023). Optimized classification of cardiovascular disease using machine learning paradigms. VFAST Transactions on Software Engineering, 11(2), 140-148.

Aslam, N., Meeran, M. T., Aslam, M., Maqbool, M. S., & Saeed, B. (2025). Understanding Urban Expansion Through Multi-Temporal Satellite Data Analysis. Kashf Journal of Multidisciplinary Research, 2(09), 252-273.

Hasnain, M. A., Ali, S., Malik, H., Irfan, M., & Maqbool, M. S. (2023). Deep learning-based classification of dental disease using X-rays. Journal of Computing & Biomedical Informatics, 5(01), 82-95.

Basit, A., Hanif, I., Maqbool, M. S., Qayyum, W., Hasnain, M. A., & Nazeer, R. (2023). Cross-lingual information retrieval in a hybrid query model for optimality. Journal of Computing & Biomedical Informatics, 5(01), 130-141.

Hasnain, M. A., Ali, Z., Maqbool, M. S., & Aziz, M. (2024). X-ray image analysis for dental disease: A deep learning approach using EfficientNet. VFAST Transactions on Software Engineering, 12(3), 147-165.

Rafiqee, M. M., Qaiser, Z. H., Fuzail, M., Aslam, N., & Maqbool, M. S. (2023). Implementation of an efficient deep fake detection technique on a video dataset using a deep learning method. Journal of Computing & Biomedical Informatics, 5(01), 345-357.

Maqbool, M. S., Fatima, N., Nazeer, R., Aslam, N., Abbas, F., Sumra, U., & Nadeem, M. (2025). A hybrid dataset-based ensemble strategy for efficient breast cancer detection. Kashf Journal of Multidisciplinary Research, 2(12), 39-57.

Muhammad Noman, Muhammad Sajid Maqbool, Dr. Naeem Aslam, Muqadas Nadeem, Hira Saleem, & Hanzla. (2026). Sleep disorder scoring is automated using advanced data science and machine learning techniques. Policy Research Journal, 4(3), 853–868. Retrieved from https://policyrj.com/1/article/view/1713

Zainab Naveed, Rubaina Nazeer, Muhammad Sajid Maqbool, Dr. Naeem Aslam, Hira Saleem, & Muqadas Nadeem. (2026). An end-to-end orthopedic disease image classification system using convolutional neural networks.

Mahnoor Zaman, Nosheen Fatima, Muhammad Sajid Maqool, Dr. Naeem Aslam, Rubaina Nazeer, & Hira Saleem. (2026). Ingredient: Intelligent CNN for food ingredient recognition and classification. Policy Research Journal, 4(3), 789–805.

Aslam, N., Meeran, M. T., Aslam, M., Maqbool, M. S., & Saeed, B. (2025). Understanding Urban Expansion Through Multi-Temporal Satellite Data Analysis. Kashf Journal of Multidisciplinary Research, 2(09), 252-273.

M. A., Ali, Z., Maqbool, M. S., & Aziz, M. (2024). X-ray image analysis for dental disease: A deep learning approach using EfficientNet. VFAST Transactions on Software Engineering, 12(3), 147-165.

Farwa Zainab, Farwa Nazim, Muhammad Kashaf, Naeem Aslam, & Muhammad Sajid Maqbool. (2026). PREDICTIVE ANALYTICS FOR CUSTOMER CHURN IN SUBSCRIPTION-BASED BUSINESSES USING MACHINE LEARNING. *Spectrum of Engineering Sciences*, 4(4), 596–618. Retrieved from https://thesesjournal.com/index.php/1/article/view/2460.

Meiraj Aslam, Mohammad Sajid Maqbool, Muhammad Aoun, Naeem Aslam, Abdul Manan Razzaq, Abdul Manan Razzaq, & Salman Ali. (2026). HIGH-PERFORMANCE AND EFFICIENT BRAIN TUMOR SEGMENTATION FOR ENHANCED CLINICAL ANALYSIS. *Spectrum of Engineering Sciences*, 4(3), 195–210. Retrieved from https://thesesjournal.com/index.php/1/article/view/2169.

Syeda Qanitah Naqvi, Syeda Rabail Zahra, Muhammad Sajid Maqbool, Muqadas Nadeem, Hira Saleem, & Mahnoor Zaman. (2026). AN AUTOMATED AND ARTIFICIAL INTELLIGENCE-BASED SYSTEM FOR THE DIAGNOSIS OF SKIN CANCER. *Policy Research Journal*, 4(4), 58–72. Retrieved from https://policyrj.com/1/article/view/1769.

Sarim Javed, Muhammad Sajid Maqbool, Dr. Naeem Aslam, Muhammad Haseeb Ur Rehman, Muqadas Nadeem, & Hira Saleem. (2026). HIGH ACCURACY INTRUSION DETECTION IN IOT VIA HYBRID ML DL MODELS. *Policy Research Journal*, 4(4), 73–85. Retrieved from https://policyrj.com/1/article/view/1770.

Rabia Hassan, Muhammad Sajid Maqbool, Dr. Naeem Asalam, Ariba Afzal, Hira Saleem, & Muqadas Nadeem. (2026). AN IN-DEPTH STUDY ON STUDENTS' PERFORMANCE EVALUATION USING MULTIPLE MACHINE LEARNING CLASSIFIERS AND DATA ANALYTICS APPROACHES. *Policy Research Journal*, 4(4), 86–99. Retrieved from https://policyrj.com/1/article/view/1771.

Rabia Ikhlaq, Muhammad Sajid Maqbool, Hira Saleem, Dr. Naeem Aslam, Zeeshan Manzoor, & Muqadas Nadeem. (2026). DEEP CONVOLUTIONAL NEURAL NETWORKS FOR AUTOMATED BREAST CANCER DIAGNOSIS. *Policy Research Journal*, 4(4), 170–182. Retrieved from https://policyrj.com/1/article/view/1795.

Izhar, Dr. Naeem Aslam, Muhammad Sajid Maqbool, Muqadas Nadeem, & Hira Saleem. (2026). DEEPFAKESHIELD: ENHANCED VIDEO AUTHENTICITY DETECTION VIA CONVOLUTIONAL VISION TRANSFORMER. *Spectrum of Engineering Sciences*, 4(3), 1650–1665. Retrieved from https://thesesjournal.com/index.php/1/article/view/2360.

Kainat Tanveer, Naeem Aslam, Hira Saleem, Muhammad Sajid Maqbool, Muhammad Akhter, & Muhammad Huzaifa Rashid. (2026). INTEGRATING BLOCKCHAIN AND MACHINE LEARNING FOR ROBUST IOT DATA INTEGRITY IN CRITICAL INFRASTRUCTURES. *Spectrum of Engineering Sciences*, 4(3), 1875–1886. Retrieved from https://thesesjournal.com/index.php/1/article/view/2433.

Abid, K., Aslam, N., Fuzail, M., Maqbool, M. S., & Sajid, K. (2023). An efficient deep learning approach for the prediction of student performance using a neural network. VFAST Transactions on Software Engineering, 11(4), 67-79.

Kang, Y., Fang, Y., & Lai, X. (2020). Automatic detection of diabetic retinopathy with a statistical method and a Bayesian classifier. Journal of Medical Imaging and Health Informatics, 10(5), 1225-1233.

Sarki, R., Ahmed, K., Wang, H., & Zhang, Y. (2020). Automatic detection of diabetic eye disease through deep learning using fundus images: a survey. IEEE Access, 8, 151133-151149.

Sarki, R., Ahmed, K., Wang, H., Zhang, Y., & Wang, K. (2022). Convolutional neural network for multi-class classification of diabetic eye disease. EAI Endorsed Transactions on Scalable Information Systems, 9(4), e5-e5.

Sarki, R., Ahmed, K., Wang, H., Zhang, Y., & Wang, K. (2022). Convolutional neural network for multi-class classification of diabetic eye disease. EAI Endorsed Transactions on Scalable Information Systems, 9(4), e5-e5.