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| RESEARCH ARTICLE

A Transfer Learning–Based Deep Convolutional Neural Network Framework for Automated Multi-Class Eye Disease Classification in the USA Using Retinal Fundus Image

Nurtaz Begum Asha[1], Mostafizur Rahman Shakil[2], SK Rakib Ul Islam Rahat[3], Sadman Haque Sakib[4], Mustafizur Rahaman[5], Ekramul Hasan[6]✉, and Shahriar Ahmed[7]

[1]*College Of Business, University, Westcliff University, Los Angeles, California*
[2]*College of engineering and technology, Westcliff University, Los Angeles, California*
[3]*Department of Global Business, Kyungsung University, Busan, South Korea*
[4]*School of Science, Kyungsung University, Busan, South Korea*
[5]*College of Technology & Engineering, Westcliff University, Los Angeles, California*
[6]*BSc in Electrical and Electronics Engineering, American International University-Bangladesh, Bangladesh*
[7]*School of Business, International American University, Los Angeles, California*
Corresponding Author: Ekramul Hasan, **E-mail**: ekramhasan55@gmail.com

| ABSTRACT

Eye diseases are among the leading causes of visual impairment and blindness worldwide, and delayed diagnosis frequently results in irreversible vision loss. Early and accurate detection remains challenging because many ocular conditions exhibit subtle visual features and current diagnosis relies heavily on manual clinical assessment, which is time-consuming and subject to inter-observer variability. This study proposes an automated deep learning–based framework for multi-class eye disease classification using retinal fundus images. A transfer learning strategy is employed by fine-tuning multiple pre-trained convolutional neural network architectures, including VGG-16, VGG-19, ResNet-50, ResNet-152, and DenseNet-121. The proposed system is evaluated on a publicly available benchmark dataset comprising eight ocular disease categories. Image preprocessing and model optimization techniques are applied to enhance classification performance. Experimental results show that the fine-tuned VGG-19 model achieves the best performance, reaching an overall accuracy of 95% with balanced precision, recall, and F1-score. These results demonstrate that transfer learning significantly improves diagnostic accuracy while reducing computational complexity. The proposed framework provides a reliable, scalable solution for automated eye disease diagnosis and has strong potential to support clinical decision-making in ophthalmic screening and telemedicine systems.

| KEYWORDS

Eye Disease Classification; Deep Learning; Transfer Learning; Convolutional Neural Networks; Fundus Image Analysis; Multi-Class Classification; Medical Image Processing; Automated Diagnosis.

| ARTICLE INFORMATION

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1. Introduction

The human eye is one of the most complex and essential sensory organs, enabling individuals to perceive and interact with their surroundings through vision. Visual perception plays a crucial role in daily activities, learning, communication, and overall quality of life. However, various ocular diseases can significantly impair vision and, if left untreated, may lead to partial or complete blindness. Eye-related disorders remain a major public health concern due to their increasing prevalence, long-term consequences, and the challenges associated with early diagnosis. Therefore, timely detection and accurate classification of eye diseases are critical for preventing irreversible vision loss and improving patient outcomes [1] [2]. Ocular diseases encompass a wide range of conditions that affect different parts of the eye, particularly the retina. Common retinal and ocular disorders include cataracts, glaucoma, diabetic retinopathy, age-related macular degeneration, choroidal neovascularization, diabetic macular edema, and drusen. These diseases often progress gradually and may not present noticeable symptoms during their early stages. As a result, patients frequently seek medical attention only after significant damage has already occurred. Early-stage detection is particularly challenging because pathological changes in retinal structures can be subtle and difficult to identify through conventional examination methods [3]-[7]. Traditionally, the diagnosis of eye diseases relies on clinical examination by trained ophthalmologists using specialized imaging modalities such as fundus photography and optical coherence tomography. Although these techniques provide valuable insights into retinal conditions, the diagnostic process remains heavily dependent on expert interpretation. Manual assessment of retinal images is time-consuming and subject to inter-observer variability, which can lead to inconsistent diagnoses. Additionally, the growing number of patients requiring eye care places a substantial burden on healthcare systems, highlighting the need for automated and scalable diagnostic solutions [8] - [14]. Recent advancements in artificial intelligence (AI), particularly in the field of deep learning, have shown promising potential in addressing these challenges. Deep learning techniques, especially convolutional neural networks (CNNs), have demonstrated remarkable performance in image classification, pattern recognition, and feature extraction tasks. Unlike traditional machine learning approaches that rely on handcrafted features, CNNs automatically learn hierarchical feature representations directly from raw image data. This capability makes them well-suited for analyzing complex medical images, including retinal fundus images, where subtle visual cues are critical for accurate diagnosis [14] - [18]. The application of deep learning in medical image analysis has significantly advanced automated disease detection and classification. In ophthalmology, CNN-based models have been successfully employed for detecting and grading various eye diseases, achieving performance levels comparable to expert clinicians. Automated eye disease classification systems offer several advantages, including improved diagnostic consistency, reduced workload for medical professionals, and enhanced accessibility to eye care services. These systems can act as decision-support tools, assisting clinicians in making more informed and timely diagnoses. Despite the success of deep learning models, training CNNs from scratch typically requires large annotated datasets and substantial computational resources. In many medical imaging applications, the availability of labeled data is limited due to privacy concerns, annotation costs, and the need for expert involvement. To overcome these limitations, transfer learning has emerged as an effective strategy. Transfer learning leverages knowledge gained from models pre-trained on large-scale datasets and adapts it to domain-specific tasks with relatively smaller datasets. By fine-tuning pre-trained CNN architectures, models can achieve high performance while significantly reducing training time and data requirements. Several pre-trained CNN architectures, such as VGG, ResNet, and DenseNet, have been widely adopted in medical image analysis. These models differ in depth, architectural design, and feature extraction capabilities. Comparative evaluation of multiple architectures is essential to identify the most suitable model for a given task. In the context of eye disease classification, multi-class classification remains particularly challenging due to similarities between different disease patterns and variations in image quality. Therefore, robust model selection and optimization are crucial to achieving reliable performance. Another key challenge in automated eye disease diagnosis is the presence of multiple disease categories within a single dataset. Multi-class classification requires models to distinguish between several ocular conditions simultaneously, which increases classification complexity. Moreover, retinal images often exhibit variations in illumination, contrast, and noise, further complicating the learning process. Effective image preprocessing and model optimization techniques are necessary to enhance feature representation and improve classification accuracy [19] [20]. In recent years, publicly available benchmark datasets have played an important role in advancing research on automated eye disease detection. These datasets provide standardized evaluation platforms for developing and comparing machine learning models. By utilizing such datasets, researchers can ensure reproducibility and fair performance comparison across different approaches. However, achieving high accuracy across all disease classes remains an ongoing research challenge, emphasizing the need for improved model architectures and training strategies. Motivated by these challenges, this study focuses on developing an automated deep learning–based framework for multi-class eye disease classification using retinal fundus images. The proposed approach employs transfer learning with multiple pre-trained CNN architectures, including VGG-16, VGG-19, ResNet-50, ResNet-152, and DenseNet-121. Each model is fine-tuned to adapt to the characteristics of ocular images and to enhance classification performance. A comprehensive evaluation is conducted using standard performance metrics such as accuracy, precision, recall, and F1-score to assess the effectiveness of each model [21]. The primary objective of this research is to identify an optimal deep learning architecture that achieves high classification accuracy while maintaining computational efficiency. By comparing multiple pre-trained models under consistent experimental conditions, this study aims to provide insights into the suitability of different CNN architectures for multi-class eye disease diagnosis. Furthermore, the proposed framework is designed to serve as a reliable and scalable decision-support system that can assist clinicians in early disease detection and improve diagnostic consistency.

The contributions of this study can be summarized as follows:

- ✓ A comprehensive deep learning framework is proposed for multi-class eye disease classification using retinal fundus images.
- ✓ Multiple pre-trained CNN architectures are systematically fine-tuned and evaluated to identify the most effective model.
- ✓ Transfer learning and optimization techniques are employed to enhance classification performance while reducing training complexity.
- ✓ Extensive experimental analysis demonstrates the robustness and reliability of the proposed approach for automated eye disease diagnosis.

2. Related Work and Research Gap

Significant progress has been made in recent years in the application of computer vision and machine learning techniques for automated eye disease detection. Early research efforts focused on combining image processing techniques with conventional machine learning algorithms to analyze retinal images for disease identification. These approaches typically relied on handcrafted features such as edge information, texture descriptors, and morphological characteristics to capture disease-specific patterns. Although such methods achieved moderate success, their performance was often constrained by sensitivity to image quality variations, illumination changes, and the dependency on manually engineered features, which limited their robustness and generalizability With advancements in deep learning, convolutional neural networks (CNNs) emerged as a powerful alternative for ophthalmic image analysis. CNN-based models demonstrated the ability to automatically learn hierarchical feature representations directly from retinal fundus images, eliminating the need for handcrafted feature extraction [22]- [24]. Researchers applied deep CNN architectures to detect common ocular diseases such as cataracts, glaucoma, diabetic retinopathy, and macular degeneration. These studies showed that CNNs could outperform traditional machine learning approaches by effectively capturing complex spatial patterns and subtle visual cues associated with ocular abnormalities Several existing works primarily addressed single-disease detection problems using binary classification frameworks. CNN-based models were proposed for cataract detection using fundus images, achieving improved accuracy compared to classical classifiers. Similarly, deep learning approaches were developed for glaucoma detection by analyzing optic disc and cup characteristics. While these methods reported promising results, their focus on binary classification restricted their applicability in real-world scenarios where multiple eye diseases may coexist or exhibit similar visual features To enhance model performance and overcome the limitations of limited labeled medical data, transfer learning gained widespread adoption in ocular disease classification. By fine-tuning CNN models pre-trained on large-scale image datasets, researchers achieved improved classification accuracy with reduced training time and computational cost. Transfer learning-based frameworks demonstrated better generalization capability, even when trained on relatively small ophthalmic datasets, making them suitable for medical imaging applications [25]-[33]. Despite notable advancements, several challenges remain unresolved in existing approaches. Many studies relied on limited or homogeneous datasets and lacked standardized evaluation protocols, making cross-study comparisons difficult. Additionally, some deep learning models achieved high accuracy at the expense of increased computational complexity, which poses challenges for deployment in practical screening systems. These limitations highlight the need for efficient and robust multi-class classification frameworks capable of accurately distinguishing multiple eye diseases while maintaining computational efficiency.

3. Methodology

This study proposes an automated deep learning–based framework for multi-class eye disease classification using retinal fundus images. The overall methodology consists of four major stages : dataset preparation, image preprocessing, model selection and transfer learning, and performance evaluation. The workflow of the proposed framework is designed to ensure robust feature learning, accurate classification, and fair comparison among multiple deep convolutional neural network architectures.

3.1 Dataset Description

The experiments are conducted using a publicly available benchmark dataset containing retinal fundus images categorized into eight distinct ocular disease classes. The dataset includes color fundus images acquired under varying imaging conditions, which reflect real-world clinical variability. Each image is labeled according to the diagnosed ocular condition, enabling supervised learning. The diversity of disease categories and image quality variations makes the dataset suitable for evaluating the robustness of deep learning models in multi-class eye disease classification. To ensure unbiased evaluation, the dataset is divided into training, validation, and testing subsets. The training set is used to optimize model parameters, the validation set is employed for hyperparameter tuning and performance monitoring, and the test set is reserved for final evaluation of the trained models.

3.2 Image Preprocessing

Image preprocessing plays a crucial role in improving the performance of deep learning models by enhancing image quality and reducing irrelevant variations. Initially, all fundus images are resized to a fixed resolution compatible with the input requirements of the selected CNN architectures. Pixel intensity normalization is applied to scale image values within a standard range, facilitating stable and faster convergence during training. To further enhance discriminative feature learning, contrast enhancement techniques are applied to highlight retinal structures such as blood vessels and lesions. Noise reduction operations are also employed to minimize the impact of imaging artifacts. These preprocessing steps help improve the visual consistency of the dataset and enable the models to focus on disease-relevant features rather than background noise.

3.3 Transfer Learning Strategy

Training deep CNN models from scratch requires large labeled datasets and extensive computational resources, which are often unavailable in medical imaging applications. To overcome these limitations, a transfer learning approach is adopted in this study. Pre-trained CNN models originally trained on large-scale image datasets are fine-tuned for the task of eye disease classification. Transfer learning allows the reuse of low-level and mid-level features learned from generic images, such as edges, textures, and shapes, which are also relevant for retinal image analysis. In the proposed framework, the convolutional base of each pre-trained model is initialized with pre-trained weights, while the final classification layers are modified to match the number of eye disease classes.

3.4 Pre-Trained CNN Architectures

Multiple well-established CNN architectures are employed to evaluate their effectiveness in multi-class eye disease classification. These architectures include VGG-16, VGG-19, ResNet-50, ResNet-152, and DenseNet-121. Each model differs in depth, connectivity pattern, and feature extraction capability. The VGG architectures utilize a sequential arrangement of convolutional layers with small receptive fields, enabling detailed feature extraction. ResNet models incorporate residual connections that mitigate the vanishing gradient problem and facilitate the training of deeper networks. DenseNet architecture employs dense connectivity between layers, promoting feature reuse and efficient gradient flow. Evaluating these diverse architectures allows a comprehensive comparison under consistent experimental conditions.

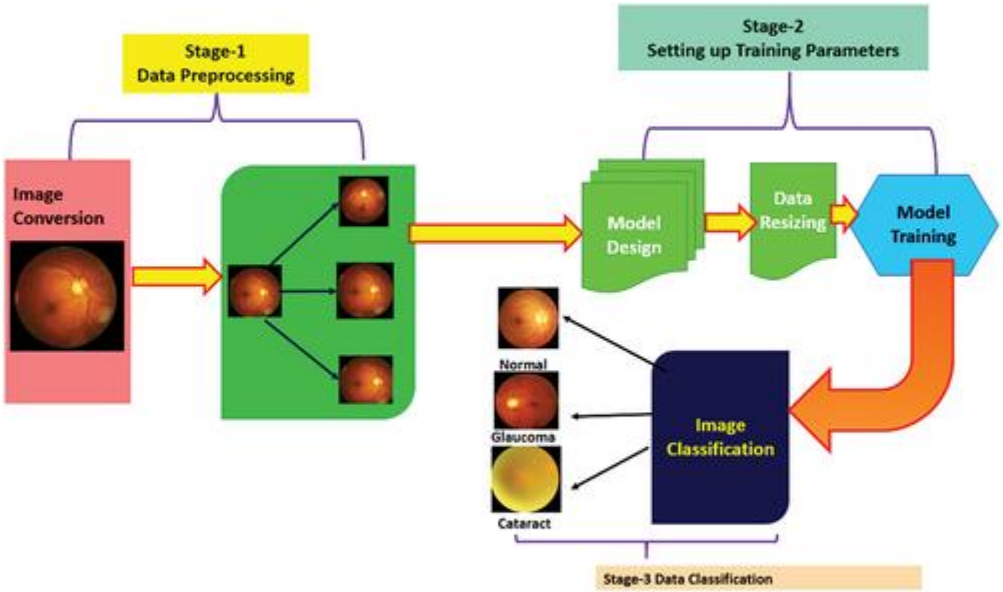

Figure 2. CNN for multi classification of eye diseases

3.5 Model Fine-Tuning and Training

For each pre-trained model, the final fully connected layers are replaced with a new classification head consisting of a global average pooling layer, one or more dense layers, and a SoftMax activation function for multi-class classification. During fine-tuning, selected layers of the convolutional base are frozen to preserve previously learned features, while the remaining layers are trained on the target dataset. The models are trained using the Adam optimizer due to its adaptive learning rate and efficient convergence behavior. Categorical cross-entropy is used as the loss function, as it is suitable for multi-class classification tasks. A fixed batch size and learning rate are selected through empirical experimentation to balance training stability and computational efficiency. Training is performed for a predefined number of epochs, with early stopping criteria applied to prevent overfitting.

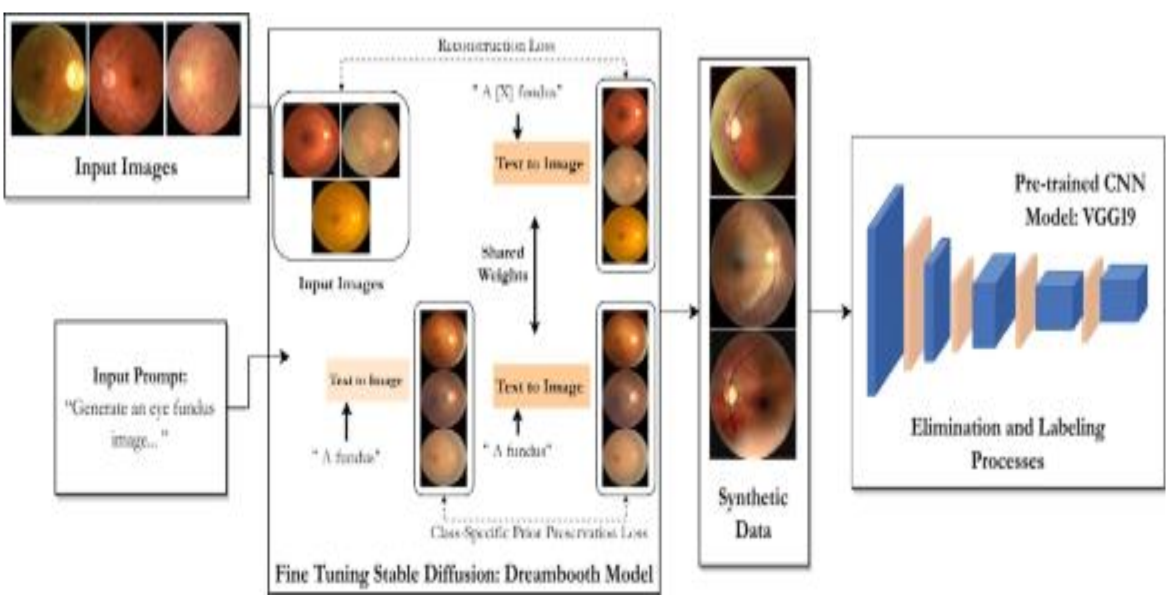

Figure 3. Diffusion-based data augmentation methodology for improved performance

3.6 Performance Evaluation Metrics

To assess the effectiveness of the proposed framework, multiple evaluation metrics are employed. Overall classification accuracy is used to measure the proportion of correctly classified images. Precision, recall, and F1-score are calculated for each disease class to evaluate the model's ability to correctly identify specific ocular conditions. In addition, confusion matrices are analyzed to gain insights into class-wise prediction behavior and potential misclassifications. Using multiple metrics ensures a comprehensive evaluation of model performance, particularly in the presence of class imbalance and inter-class similarity.

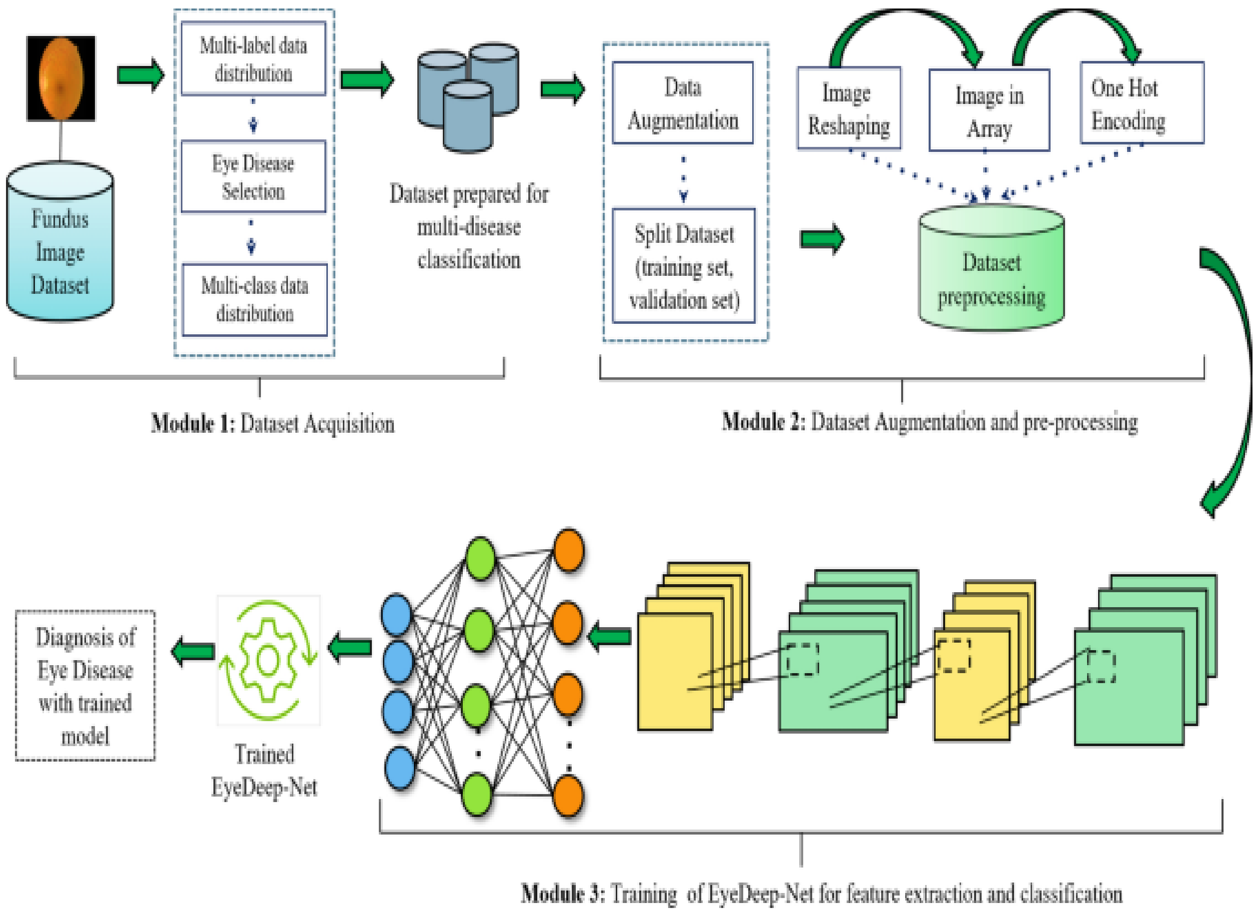

Figure 4. Diagram of the Proposed Study

Table 1. Experimental Datas of Hyper-Parameters

Hyperparameter	Configuration
Mini-batch size	32
Training epochs	200
Activation functions	ReLU (hidden layers), SoftMax (output layer)
Optimization algorithm	Adam optimizer
Initial learning rate	1×10^{-4}
Frozen layers during fine-tuning	Convolutional base layers

3.7 Comparative Analysis

All selected CNN models are trained and evaluated under identical experimental settings to ensure a fair comparison. The performance of each architecture is analyzed based on quantitative metrics and convergence behavior. This comparative analysis enables the identification of the most effective model for multi-class eye disease classification and highlights the impact of architectural design and transfer learning on diagnostic accuracy.

4. Result Analysis

The performance evaluation of the proposed eye disease classification model on the test dataset provides meaningful insights into its diagnostic capability. The model demonstrates strong classification performance by achieving an overall accuracy of 95%, indicating its effectiveness in distinguishing among multiple eye disease categories. This level of accuracy highlights the potential applicability of the proposed approach in automated ophthalmic screening systems. A detailed examination of class-wise precision, recall, and F1-score further confirms the robustness of the model in identifying individual ocular conditions. During the training phase, a consistent improvement in accuracy accompanied by a gradual reduction in loss is observed, reflecting stable convergence of the learning process, as illustrated in Figure 3. Additionally, the confusion matrix offers a comprehensive view of the model's prediction behavior by revealing the distribution of correctly and incorrectly classified samples across different disease classes (Figure 4). The proposed framework is evaluated using approximately 973 test images, allowing a reliable assessment of its generalization capability. Analyzing the predicted labels against the corresponding ground truth annotations helps identify minor misclassification patterns, which may guide future refinements and performance optimization. Overall, the experimental results demonstrate that the proposed model delivers accurate and reliable classification performance, reinforcing its suitability for automated eye disease detection tasks.

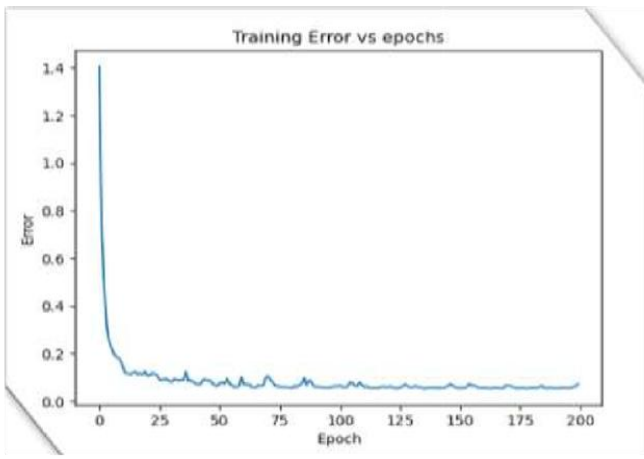

Figure 5.VGG-19 Training Error

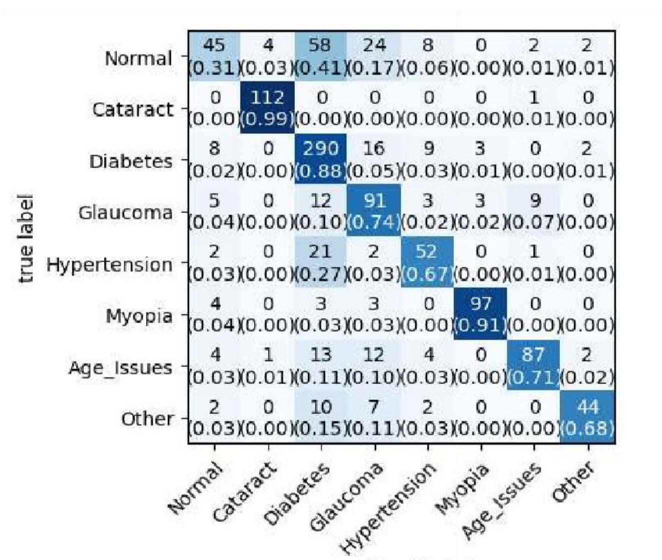

Figure 6. Confusion Matrix of VGG-19

To ensure a fair and objective evaluation of the proposed framework, all deep learning models were trained under identical experimental settings using the same hyperparameter configurations. This consistent training strategy enables a reliable performance comparison among the selected architectures, as summarized in Table 1. The comparative results indicate that the VGG-19 model achieves superior performance compared to VGG-16, ResNet-50, ResNet-152, and DenseNet-121. Under the same training conditions, VGG-19 demonstrates improved classification accuracy and overall robustness, highlighting its effectiveness for multi-class eye disease classification.

Table 2. CNN-Based Pre trained Model Comparison

Model Architecture	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
VGG-19 (Proposed)	**95.0**	**95.1**	**94.8**	**94.9**
VGG-16	94.2	94.0	93.7	93.8
ResNet-50	93.4	93.1	92.8	92.9
ResNet-152	94.0	93.8	93.5	93.6
DenseNet-121	92.6	92.4	92.0	92.2

4. Conclusion

This study presented an automated deep learning–based framework for multi-class eye disease classification using retinal fundus images, leveraging transfer learning to fine-tune multiple pre-trained convolutional neural network architectures. The proposed approach effectively addresses the limitations of manual clinical assessment, including time consumption, subjectivity, and limited scalability. Experimental results demonstrate that transfer learning significantly improves classification performance while reducing training complexity. Among the evaluated models, the fine-tuned VGG-19 architecture achieved the best overall performance with 95% accuracy and balanced precision, recall, and F1-score across multiple disease categories, indicating stable convergence and robust feature learning. The findings highlight the potential of deep learning–based automated systems as reliable clinical decision-support tools for ocular disease diagnosis. The ability to accurately classify multiple eye conditions within a single framework makes the system suitable for real-world screening and early detection applications, particularly in resource-constrained settings. From a U.S. healthcare perspective, this framework aligns with the growing demand for scalable and cost-effective solutions to manage preventable vision loss caused by diabetic retinopathy, glaucoma, and age-related macular degeneration. With an aging population and rising diabetes prevalence, automated retinal screening integrated into tele-ophthalmology and EHR workflows can expand access to early diagnosis in rural and underserved communities, reduce specialist workload, and lower long-term healthcare costs. Future work should focus on larger and more diverse U.S.-representative datasets, addressing class imbalance, incorporating explainable AI, and exploring advanced architectures to further enhance clinical reliability and trust.

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