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Eye Disease Classification and Detection using Deep Learning

Jella Surya Prakash[1], Dr. K. Shahu Chatrapati[2]

[1] M.Tech Student, Department of Computer Science and Engineering, JNTUHUCEST Hyderabad, Telangana, India
[2] Professor of CSE, Department of Computer Science and Engineering, JNTU Hyderabad, Telangana, India

Abstract
Diabetic retinopathy, glaucoma, and cataract are the most common eye diseases that are difficult to detect manually in their early stages. If these diseases are not detected early, they can cause permanent vision loss. Manual detection of eye diseases may result in incorrect diagnoses. This project aims to build an efficient model for eye disease classification and detection using deep learning techniques. Machine learning algorithms were previously used for eye disease classification and detection. Support vector machines, convolutional neural networks, and ResNet50 were previously used for eye disease detection. These existing models are complex and work efficiently only for small datasets. The primary objective of this project is to predict whether a person has eye disease or not based on his or her retinal fundus imaging data. The proposed system will use the Visual Geometry Group 19 deep learning algorithm for eye disease classification and detection. The proposed system is to enhance the test accuracy and work with larger datasets. The proposed VGG19 model achieved a high accuracy of 94%, demonstrating its effectiveness in capturing relevant features for distinguishing between diabetic retinopathy, glaucoma, and cataract eye diseases. The proposed system results in an increase in early detection rates, ultimately leading to better patient management.

Keywords: Diabetic Retinopathy, Glaucoma, Cataract, Visual Geometry Group 19, Deep Learning

1. Introduction

The eye is made up of different parts, such as the cornea, retina, lens, and optic nerve, all working together to process visual information. We should protect our eyes by keeping them clean, maintaining proper hygiene, and taking help from doctors when necessary. Diabetic retinopathy, glaucoma, and cataract are the most common eye diseases. Eye diseases cause several conditions that affect the eyes and may lead to vision impairment or perhaps blindness. Eye diseases can impact anyone and might be caused by several factors, including genetics, environmental influences, and lifestyle choices. These diseases could cause blurred or distorted vision, discomfort, redness, or discharge from the eyes. Consult a doctor if you see any of these symptoms or changes in your eyesight so that you receive the required diagnosis and treatment. If these diseases are not detected early, they can cause permanent vision loss. Many eye disorders can be avoided or treated by good eye care and regular eye checks, which can detect early disease indications and support people in preserving their eyesight. Studies and investigations conducted in recent years with technological advancements show that deep learning, machine learning,

and artificial intelligence have the potential to play significant roles in the prevention, diagnosis, and treatment of eye diseases. These technologies have aided in the early diagnosis of eye diseases. Deep learning can be applied to examine medical images, such as retinal scans, to detect early signs of eye diseases such as diabetic retinopathy, glaucoma, and cataract. This project uses the Visual Geometry Group deep learning algorithm for eye disease classification and detection that predicts whether a person has eye disease or not based on their retinal fundus imaging data.

The early and accurate detection of eye diseases such as diabetic retinopathy, glaucoma, and cataract remains a significant challenge in the medical field. These conditions often progress without noticeable symptoms in the early stages, making manual diagnosis both time-consuming and prone to errors, especially in areas lacking experienced ophthalmologists. Inaccurate or delayed diagnoses can lead to irreversible vision loss, emphasizing the need for automated and reliable diagnostic tools. This project addresses the problem by developing a deep learning-based system for eye disease classification and detection using the Visual Geometry Group 19 (VGG19) algorithm. The aim is to improve diagnostic accuracy, reduce human error, and enable faster detection by leveraging retinal fundus images, ultimately contributing to more effective and timely eye disease management. The primary objective of this project is to develop an accurate and reliable deep learning model for the classification and detection of diabetic retinopathy, glaucoma, and cataract using retinal fundus imaging data. As the manual diagnosis of these eye diseases remains slow and prone to errors, there is a growing need for an intelligent and automated solution that can support doctors. This project applies the VGG19 deep learning algorithm to enhance diagnostic accuracy, reduce detection time, and minimize human error. It also focuses on working with larger, more diverse datasets, supporting early diagnosis, ensuring scalability, and making the model suitable for clinical deployment to improve patient care outcomes.

2. Literature Survey

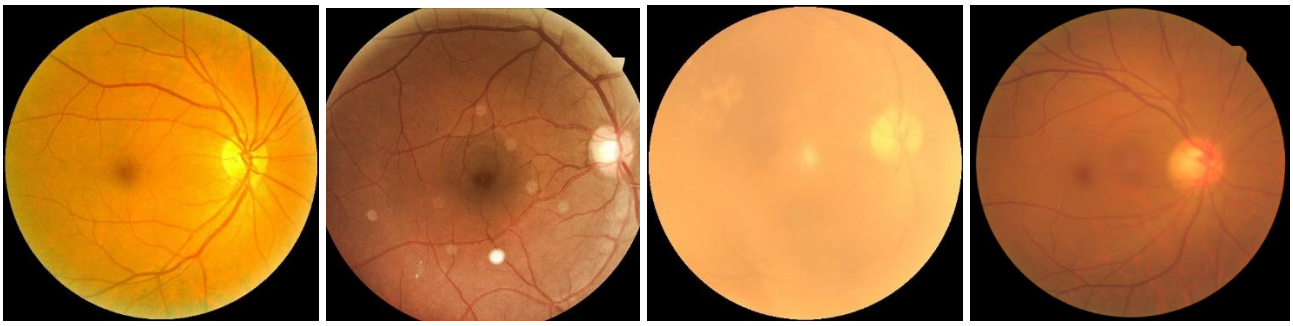
Deep learning has become a revolutionary technology in the area of medical image analysis, especially in ophthalmology, in recent years. Several research efforts have focused on the classification and detection of eye diseases using various deep learning models. S. A. Gamel, I. S. Alansari, S. S. Saleh, and H. A. Khater explored the application of the VGG16 model in their project on Transforming Ophthalmic Care: The Role of AI in Accurate Eye Disease Classification[1]. This model works efficiently on small datasets. However, it was not implemented on large datasets. Helmi Imaduddin, Ihsan Cahyo Utomo, and Dimas Aryo Anggoro used the ResNet50 architecture in their report on Fine-tuning ResNet50 for the Classification of Visual Impairments from Retinal Fundus Images[2]. This model has a high computational cost, and there is a need to improve the accuracy. G. Verma studied Retinal Image Analysis for Disease Classification using Convolutional Neural Networks[3]. There is a need to improve the accuracy in multi-class classification of eye diseases. Maneesha Vadduri and P. Kuppusamy used EfficientNetB7 architecture in their study on Enhancing Ocular Healthcare: Deep Learning Based Multi-Class Diabetic Eye Disease Segmentation and Classification[4]. Their model has a good performance in classification tasks, making it suitable for multi-class diabetic eye disease detection. Nonetheless, the model's complexity and high memory and computational requirements pose barriers to deployment on standard clinical hardware. The existing models offer promising results, but their performance is limited by dataset size, computational costs, or the complexity of the medical data[5]. Hence, there is a need for efficient models to enhance diagnostic accuracy.

3. Proposed Methodology

The proposed system is to apply the Visual Geometry Group 19 deep learning algorithm for eye disease classification and detection. The proposed system predicts whether a person has eye disease or not based on his or her retinal fundus imaging data. The proposed system is designed with several important goals. One of the main objectives is to create a system that is both accurate and easy to use. This would allow the system to be used in a variety of healthcare settings, from large hospitals to small clinics, so that more people can benefit from advanced diagnostic tools. The system also focuses on improving the accuracy of current methods, handling large amounts of data, and increasing the chances of detecting eye diseases early. It is built to make predictions using retinal fundus images, which are commonly used in eye examinations. The proposed system works well with both small and large datasets, making it flexible for different situations. Compared to other existing systems, it is less complex, which makes it easier to use. The model is smaller in size, so it can be loaded quickly and used to make fast predictions. This helps reduce the time needed for diagnosis and improves the rate of early detection. The system also provides high accuracy and is effective in identifying multiple types of eye diseases at once, making it a strong tool for modern eye care.

Dataset: The eye disease dataset used in this project is taken from Kaggle. The dataset used in this study comprises retinal fundus imaging data from the patients diagnosed with diabetic retinopathy, glaucoma, and cataract eye diseases and retinal fundus imaging data from healthy people. There are 1074 Normal, 1038 Cataract, 1007 Glaucoma, and 1098 Diabetic Retinopathy images in the dataset[6]. Figure 1 shows retinal fundus images of a normal eye and eyes affected by diabetic retinopathy, cataract, and glaucoma.

Figure 1: Retinal Fundus Image of Normal, Diabetic Retinopathy, Cataract, and Glaucoma



4. Architecture

VGG19 is a deep convolutional neural network architecture, primarily designed for image classification tasks, and is a variant of the VGG model developed by the Visual Geometry Group at the University of Oxford[7]. The VGG19 deep learning model consists of 19 layers, including 16 convolutional layers and 3 fully connected layers. VGG19 is characterized by its simplicity and uniformity, using small 3x3 convolutional filters stacked on top of each other, which allows it to capture intricate features from the input images.

Figure 2: VGG19 Architecture

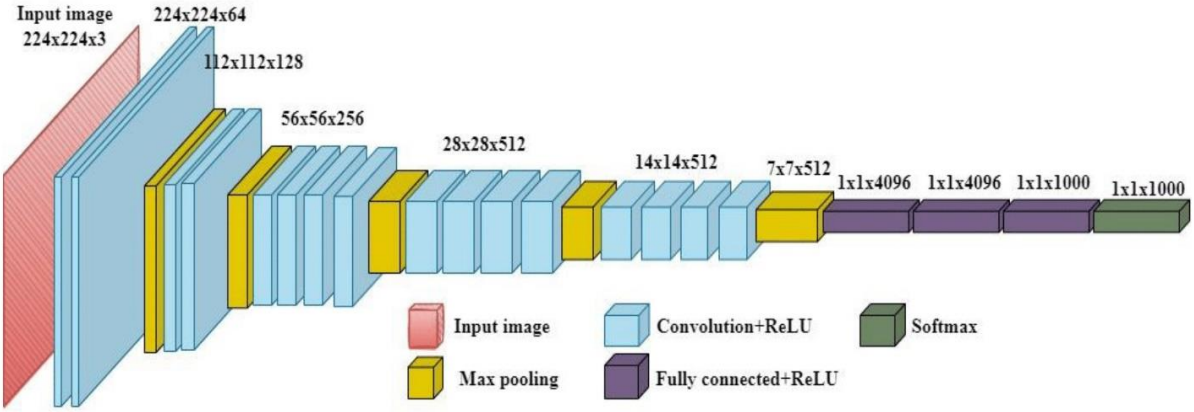


Figure 2 shows the architecture of the VGG19 deep learning algorithm. The architecture follows a straightforward pattern, where the convolutional layers are followed by max-pooling layers, and at the end, the fully connected layers are used for classification. The architecture concludes with a softmax layer for classification[8]. Due to its depth and high performance, VGG19 has become one of the best deep learning algorithms. VGG19's architecture is easy to implement because it uses only 3x3 convolutional layers with stride 1 and padding. VGG19's deep architecture enables it to capture more intricate features, making it effective for image classification tasks.

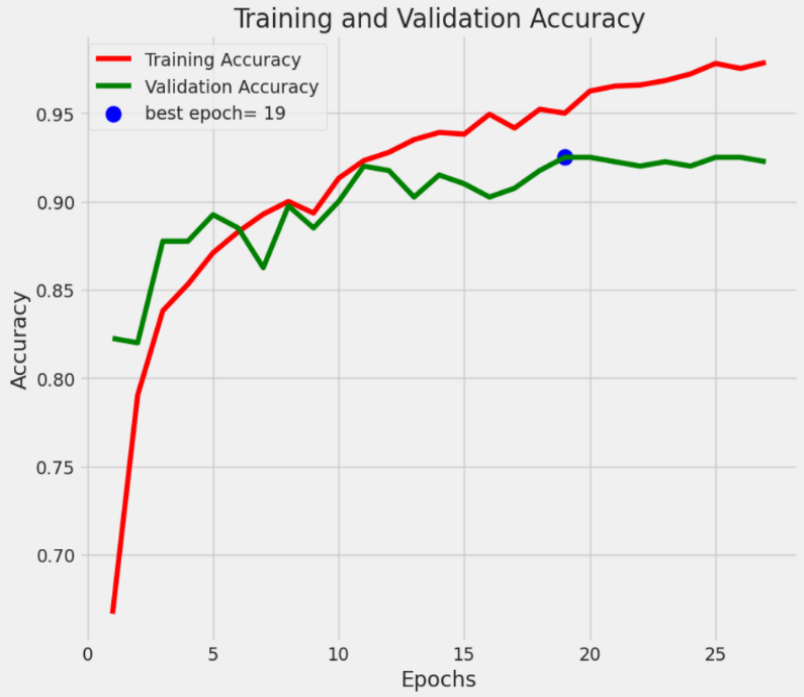
5. Implementation

The dataset is divided into training, validation, and test sets. Eighty percent of the data is allocated for training, while the remaining twenty percent is equally split between testing and validation. To ensure randomness and reproducibility, the splits are shuffled using a fixed random seed. The images are loaded in RGB format. Horizontal flipping is applied to augment the training dataset. The VGG19 base model is loaded with pre-trained weights from the ImageNet dataset, and the top layers are removed. To preserve the features already learned, the base model is initially frozen. The flattening operation is done to transform the three-dimensional tensor into a one-dimensional vector that is sent to a fully connected layer for additional processing. A dense layer with 256 units is added, along with L2 regularization to reduce overfitting. This is followed by a batch normalization layer and a dropout layer with a 0.5 dropout rate. Another dense layer with 128 units is added, followed by batch normalization and a 0.35 dropout rate. The last output layer is a softmax layer, which is used for multi-class classification of eye diseases. The proposed VGG19 model is compiled using the AdamW optimizer with a low learning rate of 0.0001. The loss function used is categorical crossentropy, and accuracy is chosen as the metric. The ReduceLROnPlateau callback decreases the learning rate if the validation loss does not improve after a few epochs. The EarlyStopping callback stops training if there is no progress for several epochs and restores the best weights to prevent overfitting. During fine-tuning, only the layers from block 4 and block 5 are set as trainable to allow deeper feature learning. The rest of the layers remain frozen. The model is then recompiled with a smaller learning rate to avoid large weight updates during fine-tuning. This step helps improve the model's performance by allowing it to learn more task-specific features while keeping the learned features from earlier layers intact.

6. Results

Figure 3 shows the relationship between the number of training epochs and the validation accuracy of the proposed VGG19 model. An epoch represents a complete pass through the whole training dataset[9].

Figure 3: Accuracy vs Epoch



As the model trains over multiple epochs, it updates its weights to minimize the loss function, ideally improving its performance on the task. Initially, as epochs increase, the model's accuracy typically rises, reflecting its ability to learn from the data. However, this trend can plateau or even decline due to overfitting, where the model becomes too tailored to the training data and loses generalization capability on new, unseen data. Plotting accuracy against epochs helps visualize this learning process, indicating how well the model is training and when it might be necessary to implement techniques like early stopping to prevent overfitting. This visualization is crucial for fine-tuning the model's training parameters and achieving optimal performance.

Figure 4: Confusion Matrix of the Proposed VGG19 Model

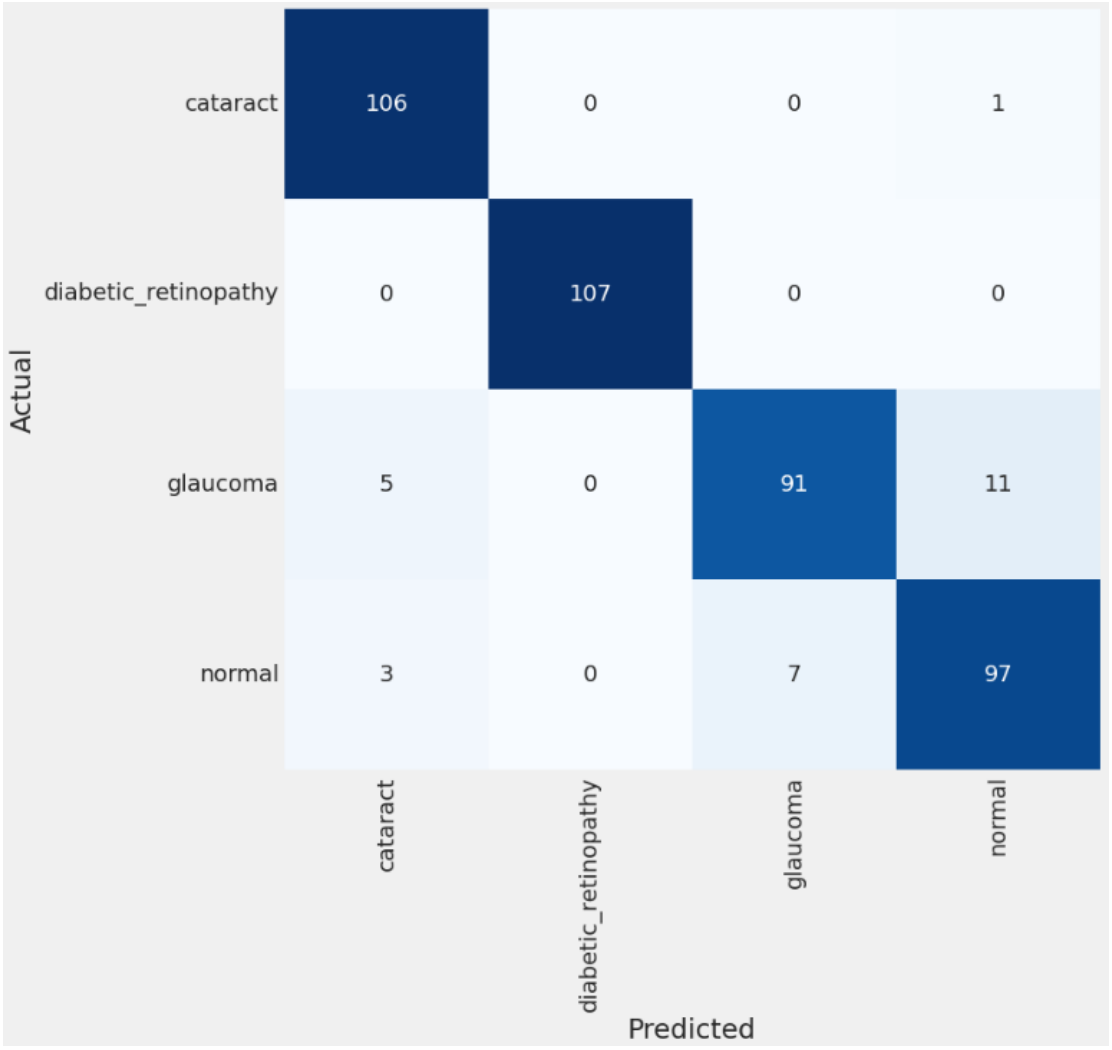


Figure 4 illustrates the confusion matrix that tabulates the predicted and actual classifications of a model's predictions. In the confusion matrix, the actual labels are represented by rows, and the predicted labels are represented by columns. The confusion matrix helps to understand the performance of the proposed system by showing the correct and incorrect predictions for each class. The main diagonal of the confusion matrix shows the number of correct predictions for each class, while off-diagonal elements indicate misclassifications. Figure 5 shows the classification report of the proposed VGG19 model, which provides a comprehensive evaluation of its performance in categorizing data across multiple classes. The classification report contains precision, recall, F1-score, and support values for each class. Precision measures the accuracy of positive predictions, recall gauges the model's ability to correctly identify positives, and the F1-score balances these metrics into a single value. The support shows the number of samples for each class, offering insights into the dataset's distribution.

Figure 5: Classification Report of the Proposed VGG19 Model

	precision	recall	f1-score	support
cataract	0.93	0.99	0.96	107
diabetic_retinopathy	1.00	1.00	1.00	107
glaucoma	0.93	0.85	0.89	107
normal	0.89	0.91	0.90	107
accuracy			0.94	428
macro avg	0.94	0.94	0.94	428
weighted avg	0.94	0.94	0.94	428

The proposed VGG19 model achieved a high accuracy of 94 percent on the test dataset. The results demonstrate that the proposed VGG19 model can effectively classify and detect eye diseases based on retinal fundus imaging data. The high accuracy indicates that VGG19 captures relevant features that distinguish between diabetic retinopathy, glaucoma, and cataract eye diseases.

7. Conclusion

The proposed VGG19 model is not only accurate but also accessible. This means it can be easily implemented in various healthcare settings, from large hospitals to smaller clinics, ensuring that more patients benefit from advanced diagnostic technology. The layers of the proposed VGG19 model are effective at capturing intricate patterns in retinal fundus images that may not be easily discernible to the naked eye or traditional analysis methods. The proposed VGG19 model achieved a high accuracy of 94%, demonstrating its effectiveness in capturing relevant features for distinguishing between diabetic retinopathy, glaucoma, and cataract eye diseases. This study presents a successful application of the Visual Geometry Group 19 model for eye disease classification and detection.

In the future, we can develop a web-based application on top of the current VGG19 model to predict eye diseases by uploading user retinal fundus images to an online platform. Future research should focus on larger and more diverse datasets, as well as investigate the model's performance.

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