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***Research Article***

# A Framework for Multiclass Classification of Eye disease Using Deep Learning

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***Abstract –*** Eye diseases must be found and treated early to prevent problems with vision and ensure the right treatment is given. A model based on deep learning and the VGG-16 structure is suggested in this study for the automatic detection of six common ophthalmic conditions: AMD, Cataract, Diabetic Retinopathy, Glaucoma, Retinal Detachment and Normal. Kaggle datasets that were made freely available were selected for this study and used in a split of 80% for training and 20% for testing. In order to match the VGG-16 model and improve image quality, we resized the images to 227×227 pixels, used ImageNet statistics for normalization and added Gaussian blur to filter out noise. The model achieved a total accuracy of 95%, macro and weighted average precision, recall and F1-scores were all recorded as 0.96 and 0.95. This confirms that the model can correctly detect a wide array of eye diseases in fundus images, suggesting it will be useful for both early screening and automatic diagnosis in ophthalmology. Although the model produced excellent results for all eye disease. This research shows that VGG-16 and other deep learning techniques can greatly benefit medical image analysis and aid doctors in making decisions about patients in ophthalmology.

*Keywords – Eye Disease, Deep Learning, VGG-16, Medical Images, AMD.*

## I. INTRODUCTION

Five major organs in the body are involved in sensing, of which the most important one is the organ of vision, which is the eyes. The eye is an important organ of vision, which has a very complicated structure. Some of the eye diseases will cause Partial or Complete vision impairment if not diagnosed in their early stages. Tackling eye disease at a very initial stage stops vision loss [1]. ED, DED including DR, DME, Gl, and Cataract are eye diseases with basic root cause caused by Diabetes. According to the statistics of European countries, the number of patients with DED was 6.4 million today, and it will increase to 8.6 million in 2050 [2]. If left untreated the various diseases may result in loss of vision and blindness of individuals between 20- 74 years of age. According to the global statistics, in the year 2015, 1.5 billion out of the 7.33 billion world population is found as visionary impaired [3].A WHO report in 2019 estimates that 2.2 billion people are affected by eye diseases [4].People in rural and remote areas are the most affected by blindness because they cannot access the right health care and eye doctors. Eye diseases can lead to blindness if not diagnosed early. Therefore, it is essential to develop an effective eye disease detection framework that can identify eye conditions early and help prevent vision loss.

Several methods have been described to address the issues related to detection of eye diseases with particular attention to the state of the art computer processing algorithms and imaging platforms. In the medical fields, various machine learning approaches have been widely employed, i.e., The Logistic Regression, Random Forest, Gradient Boosting, and Support Vector Machine algorithm for detection[5] .Besides, other numerous machine learning algorithms such as Decision Tree, Naïve Bayes, and Neural Network algorithms are used in classification[6].The model used in this study is VGG16, implemented with a deep convolutional neural network (CNN) architecture[7, 8]and Deep Learning[9].The model employed in this study is a Flower Pollination Optimized Convolutional Neural Network (FPO-CNN) for feature extraction and hyperparameters optimization. The output of the CNN is classified using a multiclass support vector machine (MSVM). Traditional machine-learning approaches struggle to handle large datasets effectively [10, 11]. [12]The models used in this study are K-Nearest Neighbors (KNN) and Random Forest (RF) for classifying glaucoma based on an optical cup and blood vessel segmentation results. Specifically, decision trees are prone to overfitting when repeatedly constructed, and large trees become difficult to interpret. Random forests require more time for training and are computationally complex. Naive Bayes can be computationally expensive, particularly for models with many variables. Support vector machines struggle with noisy datasets and selecting the right kernel function can be challenging. K-nearest neighbors are computationally intensive, and distinguishing unknown data can be costly and less efficient [13].
Eye disease may lead to blindness and is among the serious diseases that affect the eyes. Hence, its early identification and prevention is the way forward to eradicating serious loss.Vyas et al. [14] have used a convolutional neural network (CNN) based approach to diagnose dry eye disease (DED) from tear film breakup time (TBUT) videos. The method identifies DED, determines the level of severity of the disease as normal, moderate or severe and has an 83 % accuracy. Kirar et al. [15] presented glaucoma detection technique using Second-Stage Quasi-Bivariate Variational Mode Decomposition (SS-QB-VMD) to obtain fine sub-band images (SBIs) from the fundus images. Texture features extracted from SBIs were classified into different classes using a Support Vector Machine (SVM), with an accuracy of 92.67%. The approach showed a better detection accuracy compared to the existing methods and therefore useful for glaucoma diagnosis. Świerczyński et al.[16] proposed a machine learning model using Triggerfish contact lens sensor data and derived cardiac sensor attributes for glaucoma detection without intraocular pressure.nal neural network (CNN)-based approach for diagnosing dry eye disease (DED) using tear film breakup time (TBUT) videos. The method detects DED, categorizes its severity (normal, moderate, or severe), and achieves an accuracy of 83 %. Prasad et al. Prasad et al. [17] developed a DNN model for early diagnosis of Diabetic Retinopathy and Glaucoma. The model is intended to remind patients when it is time to consult with an ophthalmologist and obtained an 80% accuracy, providing a simple solution to help prevent blindness.

The key contributions of this research paper are:

- Developed a framework for multiclass classification to detect various eye diseases from fundus images.

- Tackled data imbalance challenges using image augmentation and class-weighted loss functions to improve minority class performance.

- Achieved high accuracy and strong performance metrics, outperforming baseline models and ensuring reliable, clinically usable results.

## II. MATERIALS AND METHOD

In this section, we explain how we used an eye disease dataset with healthy and sick images and methods for preprocessing such as resizing and data augmentation. Deep learning model were used to study how accurately disease classes could be distinguished.

### *A. Dataset Description*

The dataset, consisting of images from eye disease classes, downloaded from Kaggle and split into 80% for training and 20% for testing. Fig 01 shows sample image from dataset.

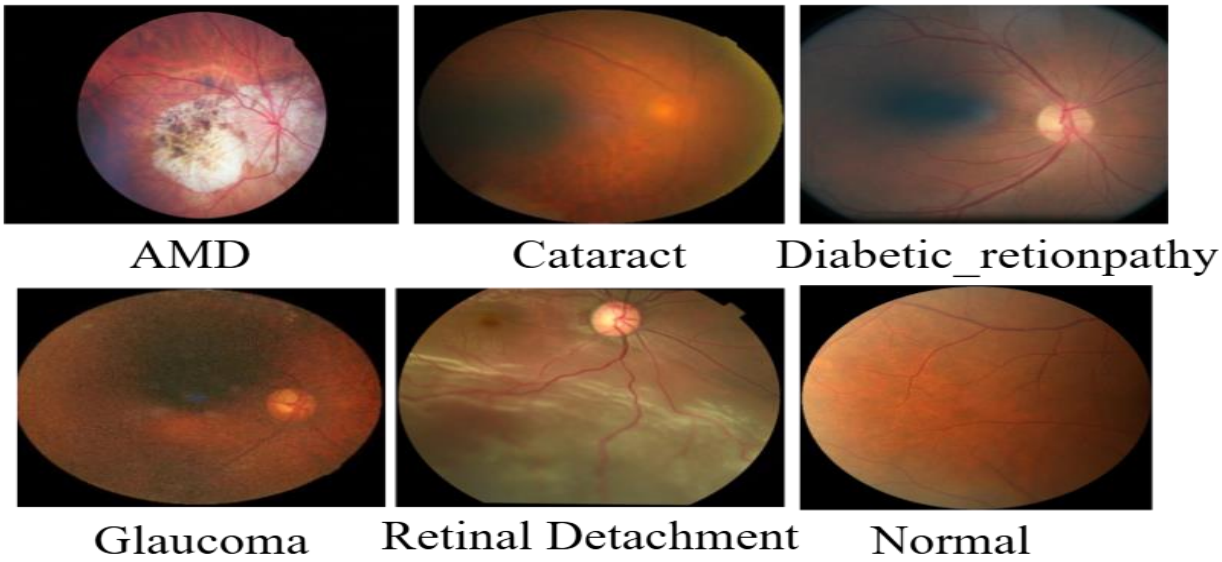


Fig.1 Sample images

### *B. Data Pre-processing*

For the eye disease dataset, techniques such as pre-processing were performed to match its data with VGG-16. All images were sized to 227×227 pixels and normalized using the average and standard deviations reported in ImageNet. Gaussian blur was also used to make the picture softer and reduce all kinds of noise. Stable training and correct classification of the images were made possible by these pre-processing steps.

### *C. Data Augmentation*

To improve the performance of the eye disease classification model, applied data augmentation techniques including random rotations, flips, brightness and contrast adjustments, as well as random cropping as showing in Fig 02 and Table 01. The addition of Gaussian noise was done to improve robustness against noisy data. By adding these augmentations, the training dataset size grew by 8% and became more diverse to aid the model generalize better in those scenarios.

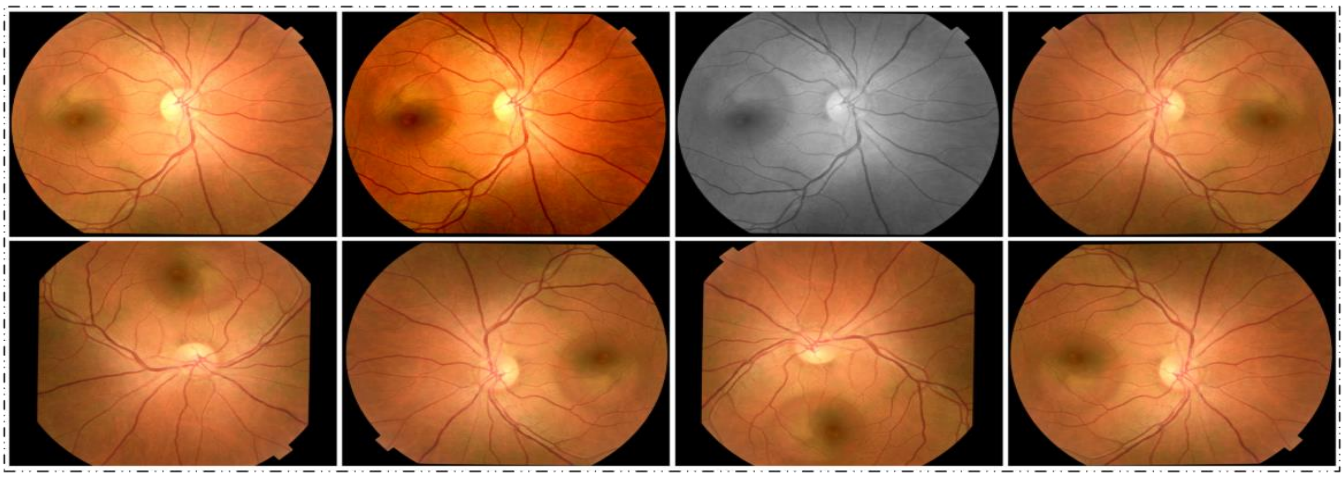

Fig. 2 Data Augmentation

Table 1. Example of a table

| Sr. No. | Disease Name | No of images | After Augmentation |
|---|---|---|---|
| 1. | AMD | 300 | 2400 |
| 2. | Cataract | 300 | 2400 |
| 3. | Diabetic_retionpathy | 300 | 2400 |
| 4. | Glaucoma | 300 | 2400 |
| 5. | Retinal Detachment | 300 | 2400 |
| 6. | Normal | 300 | 2400 |

*D. Proposed Model*

At the start, an input image measuring 227 x 227 pixels is used. Convolution and pooling operations are applied to this image to find features at several levels of detail. The first layer uses a 3x3 convolution and ReLU activation and then a max-pooling layer lowers the spatial dimensions of the feature maps. This process is done again, as the convolutional layers now find more complex features and the pooling layers reduce the size of the feature maps from 227 x 227 down to 7 x 7. At this stage, the feature maps are flattened and sent as input to the following fully connected layers. Both of the first two FC layers contain 4096 units and ReLU activation, enabling them to learn higher-level representations from the images presented to them. The model is taught to identify 6 different problems with the eye, for example Amd, Cataract, Diabetic_retionpathy, Glaucoma, Retinal detachment and normal. This architecture makes use of CNNs' ability to extract features in a hierarchy to correctly identify eye diseases seen in the input pictures.

VGG16 uses unique parameters at each layer. The convolutional layers are arranged in five groups; in the first set (Conv1), there are 2 layers of 3x3 filters and each filter has 64 which brings the total to 6,912 parameters. There are two layers in the second set (Conv2), with each layer having 3x3 filters and 128 filters in total which adds up to 147,456 parameters. The third set (Conv3) is made up of 3 layers of 3x3 filters, each with 256 filters, making a total of 884,736 parameters. It has 3 layers of 3x3 filters, each with 512 filters which adds up to 3,538,944 parameters. In total, the fifth set (Conv5) consists of 3 layers of 3x3 filters with 512 filters along which totals 7,077,888 parameters. Max-pooling layers are not parameterized, yet they condense the feature maps by shrinking their size. FC1 has 4096 neurons fully connected to the previous layer's output and totals 25,169,920 parameters; FC2 also has 4096 neurons, giving it 16,781,312 parameters; and the output layer FC3 contains 6 neurons and has 53,261 parameters. Including all these parameters, the VGG16 model possesses a total of 134,280,585. During its training

stage, the model studies these parameters to help it properly identify various eye disease issues. A diagram of the network structure of VGG-16 is available in Fig 3. The details of VGG-16 are shown in Table 2.

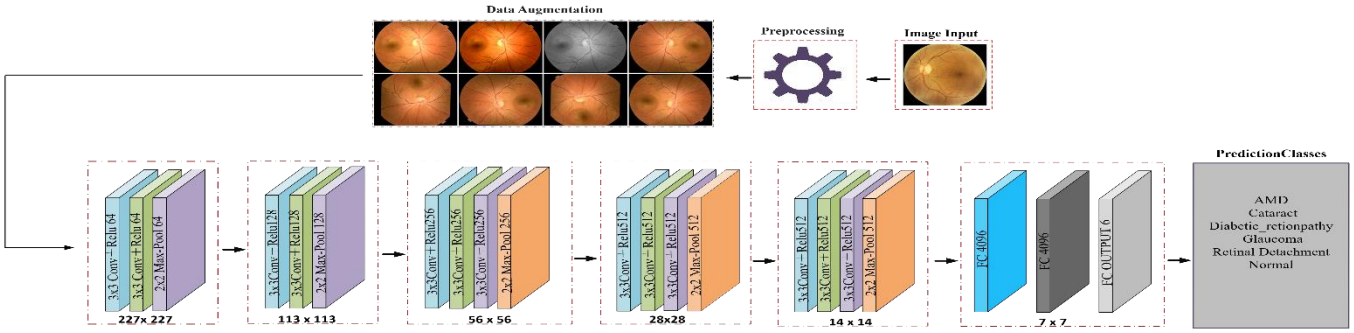


Fig. 3 Proposed Model Diagram

Table 2. Layer wise details of VGG-16 Model

| Layer | Output Size | Filter Configurations | Number of Parameters |
|---|---|---|---|
| Conv1_1 | 227 x 227 × 64 | 3 × 3, 64 | 1,792 |
| Conv1_2 | 227 × 22 × 64 | 3 × 3, 64 | 36,928 |
| Pooling1 | 113 × 113 × 64 | Max Pooling, 2 × 2, stride 2 | 0 |
| Conv2_1 | 113 × 113 × 128 | 3 × 3, 128 | 73,856 |
| Conv2_2 | 113 × 113 × 128 | 3 × 3, 128 | 147,584 |
| Pooling2 | 56 × 56 × 128 | Max Pooling, 2 × 2, stride 2 | 0 |
| Conv3_1 | 56 × 56 × 256 | 3 × 3, 256 | 295,168 |
| Conv3_2 | 56 × 56 × 256 | 3 × 3, 256 | 590,080 |
| Conv3_3 | 56 × 56 × 256 | 3 × 3, 256 | 590,080 |
| Pooling3 | 28 × 28 × 256 | Max Pooling, 2 × 2, stride 2 | 0 |
| Conv4_1 | 28 × 28 × 512 | 3 × 3, 512 | 1,180,160 |
| Conv4_2 | 28 × 28 × 512 | 3 × 3, 512 | 2,359,808 |
| Conv4_3 | 28 × 28 × 512 | 3 × 3, 512 | 2,359,808 |
| Pooling4 | 14 × 14 × 512 | Max Pooling, 2 × 2, stride 2 | 0 |
| Conv5_1 | 14 × 14 × 512 | 3 × 3, 512 | 2,359,808 |
| Conv5_2 | 14 × 14 × 512 | 3 × 3, 512 | 2,359,808 |
| Conv5_3 | 14 × 14 × 512 | 3 × 3, 512 | 2,359,808 |
| Pooling5 | 7 × 7 × 512 | Max Pooling, 2 × 2, stride 2 | 0 |
| FC1 | 1 × 1 × 4096 | Fully Connected | 102,764,544 |
| FC2 | 1 × 1 × 4096 | Fully Connected | 16,781,312 |
| FC3 | 1 × 1 × 6 | Fully Connected | 53,261 |

## III. RESULTS

The model's performance was evaluated using accuracy, precision, recall ,and F1-score for proposed model. The confusion matrix assessed class-wise distinctions, while loss and accuracy curves demonstrated the model's convergence and robustness during training and testing.

### *A. Evaluation Matrix*

We assessed our proposed model utilizing various measurements, including accuracy, precision, recall, and F1 score. The equations are presented below.

$$Accuracy = \frac{\text{True Positive+True Negative}}{\text{Total Positive+Total Negative}} \quad (1)$$

$$Percision = \frac{\text{True Positive}}{\text{True Positive+FalsePositive}} \quad (2)$$

$$Recall = \frac{\text{True Positive}}{\text{True Positive+}False\text{Negative}} \quad (3)$$

$$F1\ Score = 2\ \text{x}\ \frac{\text{PercisionRate x Recall Rate}}{\text{PercisionRate +Recall Rate}} \quad (4)$$

### B. *Proposed Model Result*

As presented in Table 03, the proposed model achieved an overall accuracy of 95%, with a macro average precision of 0.96, recall of 0.95, and F1-score of 0.95 across all eye disease classes. These results confirm the model's strong and balanced performance in handling multiclass classification tasks within the eye disease dataset.

Table 3. Overall Result of Proposed Model

| **Parameters** | **Value Obtained** |
|---|---|
| Accuracy | 0.95 |
| Precision | 0.96 |
| Recall | 0.95 |
| F1-score | 0.95 |

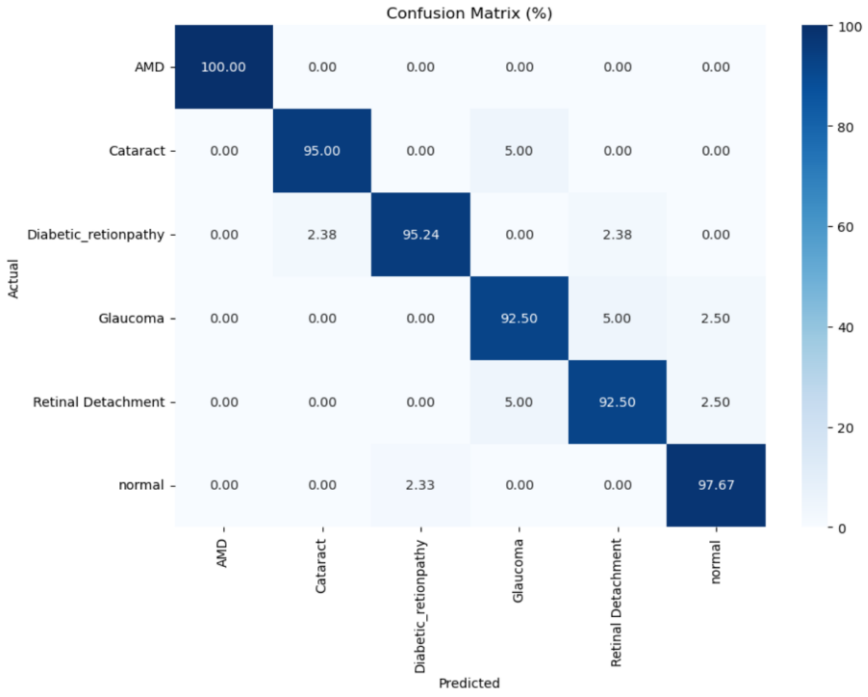


Fig. 4 Confusion Matrix

Confusion matrix for the eye disease classification model is shown in Fig 4 which describes the correspondence between the predicted and true labels for each class in detail. This visualization shows how many correctly and incorrectly classified samples there are to evaluate the model's ability to correctly identify the eight different eye disease classes.

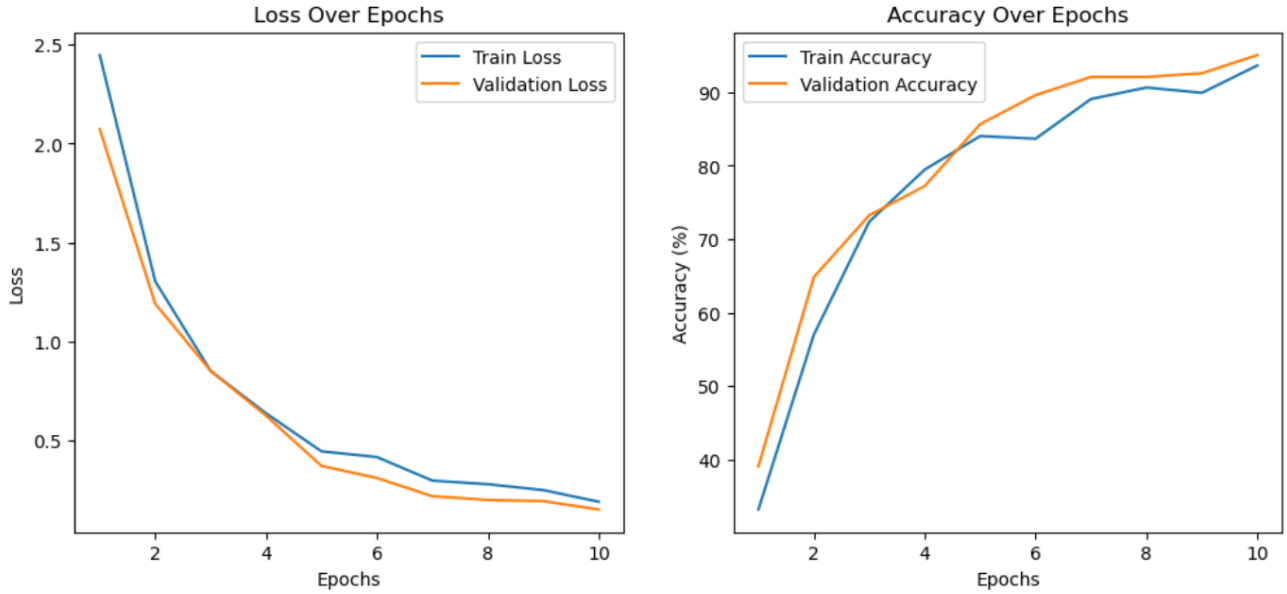


Fig. 5 Loss and Accuracy Graph

Metrics like accuracy and loss for the training process of eye disease classification model were monitored. In Fig 5 plotted the evolution of accuracy and loss through the training epochs. The accuracy curve has a good performance with the increase of training epoch in this model's ability to classify eye diseases. Like its loss curve, the model is successful in learning patterns in the dataset and minimizing errors during training phase, which is why the loss curve is a monotonic decreasing. The trends shown here indicate the robustness and reliability of the model with respect to the 6 different eye disease classes.

### C. *Evaluation with the existing state of art*

In the past years, different studies have applied machine learning and deep learning in eye disease classification, with results ranging from accurate to inaccurate. The authors[14] used a CNN to classify between three types of eye disease, achieving an accuracy rate of 83%. The author Kirar et al. [15] linking SS-QB-VMD and SVM allowed them to achieve a better accuracy of 92.67% in binary classification. Świerczyński et al.[16] also used a machine learning model with Triggerfish contact lens sensors to detect two classes, achieving an accuracy of 87%. Using a Deep Neural Network (DNN), Prasad et al. [18] could accurately identify eye diseases with an accuracy of 80%. The experiments show that eye disease detection models have progressed, yet most worked on binary classification tasks with average accuracy, showing that more work is needed for multiclass classification. Table 4 showing the comparison with existing techniques.

Table 4. Comparison with existing state of art

| Reference | Year | Model Used | No. of Classes | Accuracy |
|---|---|---|---|---|
| Vyas et al. [14] | 2024 | CNN | 03 | 83% |
| Kirar et al. [15] | 2023 | SS-QB-VMD + SVM | 02 | 92.67% |
| Świerczyńsk i et al. [16] | 2023 | ML Model Using Triggerfish Contact Lens Sensor | 02 | 0.87% |
| Prasad et al. [18] | 2019 | Deep Neural Network (DNN) | 02 | 80% |

## IV. DISCUSSION

The model suggested for eye disease classification outperformed previous research by correctly identifying six eye diseases with an accuracy of 95%. Unlike similar research from before, this study managed to solve the issue of unbalanced data and still achieved high accuracy and recall scores for every class. Using VGG-16 along with well-planned preprocessing helped to detect numerous complex features in the retina. Also, the results showed that Amd, Cataract, Diabetic_retionpathy, Glaucoma, Retinal detachment and normal classified with high reliability. This study points out that deep learning models like VGG-16 can support the development of useful, multiclass AI-based tools for eye care.

## V. CONCLUSION

VGG-16-based model was used in this study to identify six eye disease classes AMD, Cataract, Diabetic Retinopathy, Glaucoma, Retinal Detachment and Normal. Overall, the model showed an accuracy of 95%, a macro and weighted average precision of 0.96, a recall of 0.95 and an F1-score of 0.95. The outcomes highlight that the model can dependably separate various eye diseases, indicating its ability to aid in automated eye disease diagnosis. This work demonstrates that VGG-16 performs well in medical image analysis and could boost the accuracy of clinical ophthalmology applications. In order to enhance model generalization, we want to use bigger and more evenly distributed multiclass datasets in further research. Furthermore, using explainable AI methods and attention processes may improve clinician trust and interpretability.

## ACKNOWLEDGMENT

The heading of the Acknowledgment section and the References section must not be numbered.

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