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RESEARCH PAPER

Deep Learning-Powered AI System for Automated Detection of Common Ocular Diseases from Medical Images

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***Abstract*—Glaucoma, cataracts, diabetic retinopathy, and age-related macular degeneration are among the most common eye disorders globally, although numerous others can also lead to vision loss or impairment. Despite its critical importance, early detection is difficult to achieve because of the sensitivity of the symptoms and the need for skilled interpretation of medical pictures. Using fundus images from the ODIR dataset, this work suggests an AI system powered by deep learning for automated identification of common eye illnesses. A multi-class classification utilizing a fine-tuned VGG-16 convolutional neural network is part of the technique, along with data augmentation to rectify class imbalance and preprocessing methods like CLAHE and Gaussian denoising. The model achieved impressive classification performance, with a recall of 90.00%, an F1-score of 92.00%, a precision of 94.00%, and an accuracy of 98.27%. Examining the suggested model in comparison to DenseNet121, CNN, and VGG-16 + CNN reveals that it offers a better equilibrium between recall and precision. In terms of scalable and dependable eye disease screening, these findings validate the efficacy and therapeutic promise of the suggested method. In addition to highlighting the significance of deep learning integration in medical imaging workflows, the paper proposes future improvements that involve attention mechanisms and ensemble learning to increase sensitivity.**

Keywords*—Fundus Images, Deep Learning, VGG-16, Data Augmentation. Artificial Intelligence (AI), Automated Detection, Ocular Diseases, Retinal Image Classification, Convolutional Neural Networks (CNN), Fundus Photography.

I. INTRODUCTION

Numerous eye illnesses, including cataracts, AMD, glaucoma, DR, myopia, and hypertension-related eye problems, are common and, if unchecked, can cause significant vision loss or even blindness [1][2]. These conditions are particularly concerning in diabetic patients, as they are linked to a higher risk of mortality from ischemic heart disease [3]. Despite their clinical significance, early detection remains challenging due to the subtle or asymptomatic nature of early-stage symptoms.

One common non-invasive imaging method for checking the retina for disease symptoms is fundus photography. Though effective, traditional diagnostic methods are heavily dependent on expert interpretation—an approach that is inherently subjective, labor-intensive, and difficult to scale [4][5]. Glaucoma, cataracts, diabetic retinopathy (DR), and age-related macular degeneration (AMD) are among the most prevalent eye diseases and conditions. When doctors look at the macula, optic disc, and retinal blood vessels, they can discover glaucoma [6][7]. However, this manual approach limits efficiency and consistency in large-scale screening scenarios.

Automating medical diagnoses is one area where artificial intelligence (AI) shows promise [8][9], thanks to the fast development of healthcare technology [10]. Applications in radiology and imaging have demonstrated AI's potential to detect diseases earlier and uncover previously unnoticed pathologies [11][12]. However, many current AI systems remain task-specific and dependent on manually labelled input data, limiting their effectiveness in real-world clinical environments [13].

Deep learning (DL), a subset of AI, offers a compelling solution by learning directly from large volumes of medical images [14]. bypassing the need for handcrafted features or manual segmentation. The development of computer-aided diagnosis (CAD) systems for fundus image analysis is particularly well-suited to DL-based models because to their outstanding performance in computer vision tasks [15][16][17]. These models streamline disease detection processes and improve diagnostic accuracy by automatically extracting complex visual features.

A. Motivation and Contribution

Globally, ocular diseases account for a disproportionate share of cases of blindness and visual impairment. It is crucial to discover these diseases early on in order to treat them effectively and prevent irreparable damage. Manual inspection of fundus pictures is one example of a classic diagnostic procedure; nevertheless, it is subjective, takes a lot of time, and needs professional interpretation, all of which affect its scalability in real-world clinical environments. An exciting possibility to create automated systems for early, accurate, and efficient detection of eye diseases has arisen thanks to the growing availability of medical imaging data and developments in deep learning. This study was motivated by the demand to construct a model based on deep learning that is durable, interpretable, and scalable. The goal is to let doctors examine fundus photos for several ocular illnesses at once, making diagnostics more accessible and lowering clinical workload. The study's main findings are these:

- The ODIR dataset was used to develop a DL-based AI system that could multi-classify eight different types of ocular diseases using a fine-tuned VGG-16 model.

- Applying cutting-edge pre-processing techniques, like CLAHE for contrast enhancement and Gaussian denoising for image quality standards.
- Improvements in model generalizability to under-represented illness classes and correction of class imbalance through the use of targeted data augmentation techniques.
- A number of performance indicators, including recall, accuracy, precision, F1-score, and confusion matrix, show that the model outperforms its rivals, DenseNet121 and CNN.
- The proposed model's exceptional performance and practical application in diagnostic procedures set it apart from state-of-the-art models.

B. Novelty and Justification

A custom-built pre-processing and augmentation pipeline for multi-class eye illness identification utilizing fundus pictures is integrated with a fine-tuned VGG-16 deep learning architecture; this is the unique aspect of this work. Unlike prior approaches that focus on binary or limited disease classification, this study addresses eight distinct ocular conditions within a single unified framework while mitigating class imbalance through targeted data augmentation. Use of VGG-16 is warranted due to its shown efficacy in medical picture classification and its capacity to derive abundant hierarchical features with comparatively modest computational burden. By combining robust image pre-processing, balanced dataset preparation, and a well-optimized CNN model, this study offers a scalable, accurate, and clinically relevant solution for automated ocular disease screening, demonstrating its potential for real-world implementation in teleophthalmology and point-of-care diagnostics.

C. Structure of the Paper

The paper is structured in the following way: In Section II, look at how deep learning has been used to catch eye diseases. Section III details the technique that has been suggested, which encompasses the dataset, pre-processing, and model creation. The experimental findings and analysis of performance are presented in Section IV. Section V wraps up the research and makes recommendations for moving forward.

II. Literature Review

This section presents the literature review on ocular disease detection, highlighting recent trends, key findings, advantages, and future research directions. Table I summarizes these aspects, providing an overview of the methodologies and outcomes discussed. The reviewed studies that contribute to the ongoing advancements in ocular disease detection using intelligent systems are shown below:

Kaleel and Rajakumari (2025) built a hybrid DL model that uses the Vision Transformer and Convolutional Neural Networks to detect eye disorders in fundus images. The model improved medical image analysis and interpretability by highlighting significant regions impacting classification decisions. Four datasets were used, with the model achieving 87.25% training and 83.70% validation accuracy on the ODIR-5K dataset [18].

Chen et al. (2024) presented to enhance YOLOv5's automated diagnosis of ocular surface disorders. The CBAM attention module was introduced in the feature extraction stage of YOLOv5, and C3 module was improved to CBAMC3 module, which enhanced the feature extraction capability and made the backbone network more focused on the lesion area of the eye surface. subsequently, the BiFPN module was added to the neck network to boost feature fusion and increase the accuracy of illness identification in pictures of the eye's surface. The findings of the experiments demonstrate that their suggested technique achieves a 97.9% success rate in detecting ocular surface disorders on the test set. This allows for the automated identification and localization of these diseases, and it also has strong auxiliary diagnostic significance [19].

Li et al. (2024) provided an imaging system that is augmented with deep learning to automatically evaluate these three representative OSDs in a trustworthy and objective manner. In their all-inclusive pipeline, use processing methods that are developed from RGB and dual-mode infrared (IR) images. It measures OSDs accurately and consistently using a multi-stage deep learning algorithm. Class classification accuracy was 96.2% and SCH area identification was 0.956 (F1 score = 0.980), yielding an impressive 98.7% accuracy for the suggested strategy. Their approach can detect MGD, a common cause of dry eyes, at an early stage. With an 87.1% success rate and an F1 score of 0.781, it detects gland morphological anomalies by quantitatively analyzing the meibomian gland area ratio [20].

Fauzi, Ismail and Ahmedy (2024) a model CNN with 600 eye images to identify glaucoma and diabetic retinopathy. The entire process of training the model was carried out using a supervised learning method. The model's accuracy was improved using many picture enhancement approaches. The outcome demonstrates that, after classification's evaluation, the model managed to obtain 97% accuracy value [21].

Mostafa et al. (2023) use the ODIR dataset to fine-tune the suggested model and run comprehensive tests to determine the optimal training hyperparameters. Using the ODIR dataset, the results show that the suggested method achieves a recall of 97:99%-100% and a precision of 96-100% for binary classification [22].

Singh et al. (2022) provided a method for automated OD diagnosis that involved a two-stage detection process. This feature extraction process makes advantage of the Mobile Net architecture, which is well-suited to those who use smartphones or iPhones but do not have access to personal computers at home. By comparison to competing architectures like VGG and RESNET, this one is lightning fast. By validating its predictions with data from more than 1500 patients, the network achieved an accuracy of 95.68% after training on 3500 patients' records [23].

TABLE I. Automated Ocular Disease Detection: A Review of Current Deep Learning Methods

References	Methodology	Results Analysis	Advantages	Limitations	Future Work
Kaleel & Rajakumari (2025)	Hybrid CNN + ViT with Grad-CAM on four datasets (ODIR-5K, ODIR, Salem, RDC)	Accuracy: up to 97%, Validation Loss: as low as 0.252	Combines local (CNN) and global (ViT) features; interpretable via Grad-CAM	Training and validation gaps; limited dataset diversity	Apply on real-world hospital datasets for generalizability

Chen et al. (2024)	Modified YOLOv5 with CBAM-C3 and BiFPN modules for feature enhancement	mAP: 97.9% on ocular surface diseases	Accurate and efficient detection with localization; lightweight model	Model may focus only on surface-level abnormalities	Extend model to broader ocular datasets including fundus images
Li et al. (2024)	Multi-stage DL model using RGB & IR images for assessing MGD and OSDs	Accuracy: 98.7% (classification), 88.1% (gland detection); F1 up to 0.980	Dual-mode imaging; interpretable metrics; suitable for dry eye diagnosis	Gland detection F1 still below 0.8	Improve MG region identification using hybrid CNN-transformers
Fauzi, Ismail & Ahmedy (2024)	CNN model on 600 images; augmentation techniques applied	Accuracy: 97% on glaucoma and DR	Simple and effective CNN model; data augmentation helps performance	Small dataset size; binary classification focus	Expand to multiclass classification with larger datasets
Mostafa et al. (2023)	Binary classification on ODIR dataset with optimized hyperparameters	Accuracy: 98–100%, Recall: 97.99–100%, Precision: 96–100%	Strong binary classifier; high metric values	Lacks class diversity; binary-only detection	Develop a robust multi-class framework using same pipeline
Singh et al. (2022)	MobileNet for on-device OD detection (trained on 5000+ samples)	Accuracy: 95.68%	Efficient for mobile deployment; lightweight	May lacks robustness across high-resolution datasets	Improve sensitivity and integrate explainability features

A. Research Gap

Despite advancements in ocular disease detection using CNNs, Vision Transformers, and hybrid models, key challenges persist. Many studies focus on binary or limited multi-class classification with high accuracy on curated datasets like ODIR or RDC but lack generalizability to diverse clinical environments. Interpretability methods such as Grad-CAM remain underutilized, and explainability across all disease classes is often insufficient. Moreover, limited attention is given to lightweight model deployment for mobile or edge devices, crucial for remote care. Standardized evaluation frameworks are also missing, hindering fair comparison. These gaps highlight the need for robust, explainable, and deployable models for real-world clinical use.

III. Methodology

Data collecting, preprocessing, augmentation, feature selection, model training, and performance evaluation are the steps in Figure 1, that make up the suggested pipeline for medical condition categorization based on fundus images of the eye. Obtain the ODIR dataset (5,000 fundus pictures labelled with 8 diseases) and look at it; pay close attention to the dataset's apparent class imbalance. The photos are adjusted in size, tagged pixel-by-pixel, contrast-boosted with CLAHE, and denoised with a Gaussian distribution to guarantee uniform quality before processing. Because there is a correlation between class inequality and the use of data augmentation techniques like flipping, rotating, and color modifications, samples from minority classes are artificially enhanced. The dataset is split as follows: 80% goes to training, 10% to validation, and 10% to testing. For each of the eight illness categories, a VGG-16 CNN model is used for categorization, and it has been fine-tuned using a SoftMax output layer. The model's performance may be assessed using metrics including recall, accuracy, precision, F1-score, and confusion matrix, which can guarantee the objective and reliable diagnosis of all eye illnesses.

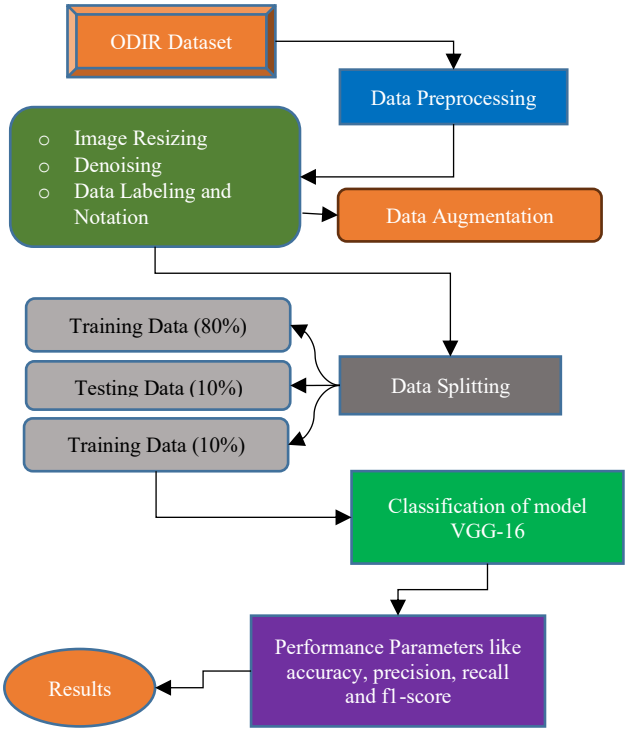

Fig. 1. Flowchart for Ocular disease image classification using deep learning models

A. Data Collection

This work makes use of the ODIR dataset. When it comes to detecting eye illnesses using many classes, no public dataset comes close to it. Fundus photos were gathered from multiple hospitals in China and utilized to create this dataset by Shang gong Medical Technology Co., Ltd. This collection's fundus images are organized according to 8 different types of eye diseases. D, cataract, glaucoma, myopia, hypertension, age-related muscle degeneration, abnormalities/illnesses, and abnormalities/diseases are among the many illnesses and conditions that fall under these several groups. There are two subsets to this dataset: training and testing. There are 5,000 color fundus images (CFPs) in the training set. It has the capability to train on around 3,500 examples and test on the rest. Figure 2 displays a few images taken from the ODIR dataset.

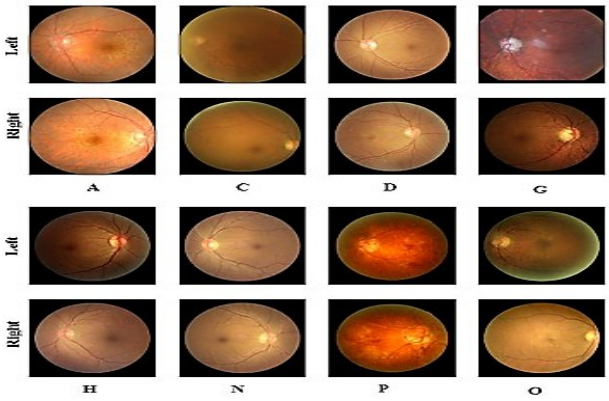

Fig. 2. Sample images of ODIR dataset

Figure 2 displays the fundus images of the left and right eyes retrieved from the ODIR dataset. Various eye disorders and conditions are depicted in these images. Some of these eye conditions include high blood pressure, cataracts, diabetes retinopathy, myopia, normal and age-related macular degeneration, and hypertension.

TABLE II. DISTRIBUTION OF THE IMAGES ACROSS CLASSES IN ODIR DATASET

No.	Labels	Training Cases	Off-Sie Training Cases	On-Sie Training Cases	All Cases
1	N	1135	161	324	1620
2	D	1131	162	323	1616
3	G	207	30	58	307
4	C	211	32	64	243
5	A	171	25	47	295
6	H	94	14	30	138
7	M	177	23	49	249
8	O	944	134	268	1346

Table II presents the distribution of images across eight ocular disease classes in the ODIR dataset, revealing a significant class imbalance. The Normal (N) and Diabetic Retinopathy (D) classes are the most prevalent, with 1,620 and 1,616 cases, respectively, followed by the Others (O) category with 1,346 instances. In contrast, Hypertension (H) and Age-related Macular Degeneration (A) are underrepresented, with only 138 and 295 cases. Glaucoma (G), Cataract (C), and Myopia (M) demonstrate moderate representation of the case numbers 307, 243, and 249, respectively. The significance of using efficient data balancing strategies to guarantee accurate and equitable model performance for all illness classes is highlighted by this imbalance.

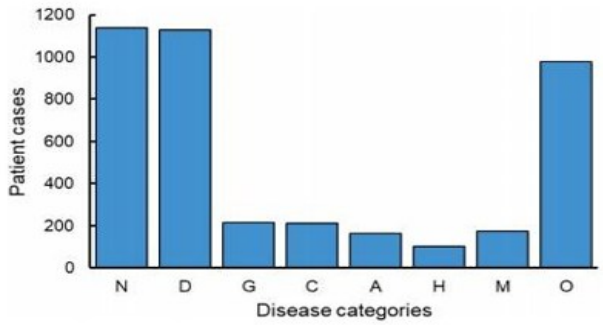

Fig. 3. Data distribution of into ocular disease classes

Figure 3 illustrates the distribution of patient cases across various ocular disease categories in the dataset, highlighting a pronounced class imbalance. The Normal (N) and Diabetic Retinopathy (D) classes each account for over 1,100 cases, followed by the Others (O) category with approximately 950 cases. The groups with the fewest cases are hypertension (H), age-related macular degeneration (A), cataract (C), glaucoma (G), and myopia (M), with most classes having between 150 and 250 cases. This imbalance emphasizes the need for appropriate data balancing techniques during model training to mitigate bias and ensure reliable performance across all disease categories.

B. Data Preprocessing

The data preprocessing phase includes essential steps such as image resizing, labeling, denoising, and enhancement to ensure optimal model input quality. All preprocessing steps—resizing, annotation, CLAHE enhancement, and Gaussian filtering are briefly described below to standardize and refine the retinal images for accurate classification. The preprocessing steps are listed below:

- **Image Resizing:** Standard image dimensions are 128×128 pixels. Resizing the input images is crucial for conserving space and memory and lowering training time, even if using the original sizes for learning can be more advantageous.
- **Data Labelling and Annotation:** Label the retinal images with pixel-level annotations to designate which pixels correspond to retinal blood vessels and those that do not. This labelling process serves as the reference data for training and evaluation. Utilize image annotation tools or engage experts to guarantee precise labelling, acknowledging the intricacies of retinal vascular structures [24].
- **Denoising:** The additional black pixels surrounding the retina are cut out of the photographs. After that, the photos are enhanced using the CLAHE approach. CLAHE enhances border and regional information, brightens fundus photos, and successfully improves low contrast medical images [25]. With an 8x8 tile size and a Clipping Limit of 5.0, CLAHE is applied to the L channel of the eye photos for improved contrast. It is possible for the CLAHE method to introduce picture noise. According to Eequation (1), it can get rid of it by using the Gaussian filter.

$$G_f(a,b) = Ae^{\frac{-(a-\lambda_a)^2}{2\beta_a^2}+\frac{-(b-\lambda_b)^2}{2\beta_b^2}} \quad (1)$$

λ and A stand for the mean and amplitude, respectively, while β denotes the standard deviation for variables a and b. Figure 4 displays the outcomes of the CLAHE and Gaussian filters applied on the photographs.

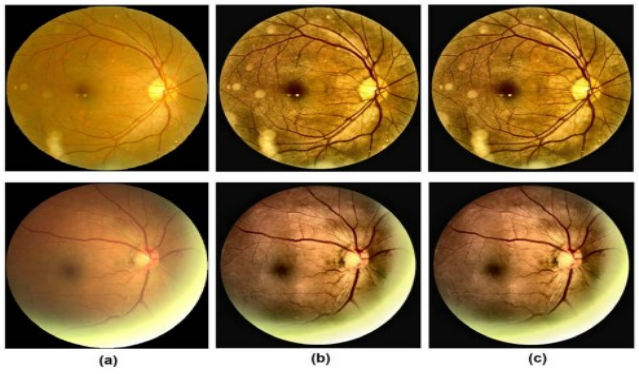

Fig. 4. The ODIR dataset's example images before processing, labelled as (a) normal, (b) CLAHE, and (c) Gaussian filter.

C. Data Augmentation

Data augmentation strategies were used to alleviate class imbalance and boost model generalization for under-represented ocular illness classes. utilized basic changes that kept the labels intact, such turning the image horizontally and vertically, rotating it, and adjusting the brightness, saturation, and hue. These augmentations ensured each disease class had sufficient representation, reducing overfitting and supporting robust training.

D. Data Splitting

An 80:10:10 ratio was employed to partition the dataset, with 80% going into training the VGG-16 model, 10% into validation to track learning progress, and 10% into testing to assess generalization. A stratified sampling strategy was employed to maintain balanced class distribution across all subsets, ensuring robust and reliable performance assessment of the ocular disease classification model.

E. Proposed VGG-16 Model for Image Classification

The CNN architecture utilized for picture classification is VGG-16. This idea originated with Oxford University's Visual Geometry Group [26]. The code for VGG-16 is easy to comprehend and implement since the network is basic and has a consistent topology across all nodes. Several convolutional layers and a down sampling layer (max-pooling) are included in each block of this model's convolutional architecture. The model has 13 convolutional layers, 3 of which are completely linked, with ReLU activation functions and max-pooling procedures interspersed to introduce non-linearity and spatial down-sampling, respectively.

To carry out a multi-class classification, the last fully connected layer of VGG-16 is adjusted to give probability scores of individual classes of ocular diseases by employing SoftMax activation function, which is represented as Equation (2):

$$\mathrm{P}(\mathrm{y}=\mathrm{j}|\mathrm{x}) = \frac{\mathrm{e}^{\mathrm{z_j}}}{\sum_{\mathrm{k}=1}^{\mathrm{K}} \mathrm{e}^{\mathrm{z_k}}} \quad (2)$$

In Equation (2) $\mathrm{P}(\mathrm{y}=\mathrm{j}|\mathrm{x})$ is predicted probability that input image x is in the class j and z_j is the logit parameter of the class jj. The denominator sums the exponentials of all logits across K classes. For the ODIR dataset, K=8, representing the eight ocular disease categories.

F. Performance Metrics

Accuracy, precision, and the model's capacity to handle class imbalance are some of the basic performance measures used to assess the suggested ocular illness categorization model [27]. A key tool in this evaluation is the confusion matrix, which summarizes correct and incorrect predictions across all classes. The model's performance is assessed using this two-dimensional grid, which displays both the actual and projected labels. Critical metrics like F1-score, recall, and accuracy can be derived from it. Listed below are some key concepts:

- The classification method accurately predicted a favorable outcome in cases when there were true positives.
- False positives, in which the algorithm incorrectly anticipated a negative result as a positive one, are one indicator of algorithm accuracy.
- True Negatives are examples of when the algorithm correctly foretold a negative result.
- False Negatives are situations in which the algorithm incorrectly labelled positive results as negative.

1) Accuracy

This technique takes a look at the overall number of forecasts and compares it to the sum of all the predictions, positive and negative, in order to get the accuracy rate [28]. The reliability of the model provides a comprehensive assessment of its predictive power. Equation (3) provides an example of how it is represented:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

2) Precision

Precision is a measure of accuracy that is defined as the ratio of the number of positive forecasts to the number of accurate predictions. The precision of the model is a measure of how well it predicts favorable outcomes. The statistical equations of precision is reproduced in Equation (4):

$$Precision = \frac{TP}{TP+FR} \quad (4)$$

3) Recall

The actual positives divided by the genuine positives is the formula. The sensitivity (also known as recall) of the model indicates how well it can predict positive classes. Here is the recall formula in Equation (5):

$$Recall = \frac{TP}{TP+FN} \times 100 \quad (5)$$

4) F1 Score

Precision and memorization are both stabilized by it. When a middle ground between accuracy and recall is required, the F1 score, which is a harmonic average of the two, can be useful. Equation (6) provides the mathematical expression of f1-sore:

$$F1-\text{score} = \frac{2.\text{TP}}{2.TP+FP+FN} \quad (6)$$

IV. Result Analysis and Discussion

This sections show the outcomes of using the deep learning approach to find real-life eye diseases on the ODIR dataset. In order to evaluate the suggested models' ability to classify images, numerous crucial performance indicators were used, such as F1-score, recall, accuracy, and precision. Python language was used in establishing the experiments on a Jupiter Notebook environment in Google Collab. Kera's, TensorFlow, NumPy, Pandas, Seaborn, and Matplotlib libraries were used to develop models, manage data and make visualizations. It was introduced on a hardware environment with an NVIDIA RTX 3060 GPU and 12oming VRAM and 32 Gb of RAM, which is sufficient to train and assess the suggested model of VGG-16 properly. The subsequent paragraphs explain the performance results of the suggested VGG-16 design on ocular diseases detection.

TABLE III. Performance of VGG-16 model for ocular disease detection by using ODIR dataset

Measure	VGG-16 MODEL
Accuracy	98.27
Precision	94.00
Recall	90.00
F1-score	92.00

The evaluation of the VGG-16 model's performance for eye illness diagnosis using the ODIR dataset is presented in Table III. This model is exceptionally strong in classification, with a 98.27% accuracy rate, a 94.00% precision rate, a 90.00% recall rate, and an F1-score of 92.00%. Since the model can accurately identify positive examples while minimizing erroneous ones, these metrics indicate that the model is very balanced in terms of trade-off. The consistency between numerical values and their visual representation further validates the model's dependability and efficacy in medical image-based diagnosis of ocular disorders.

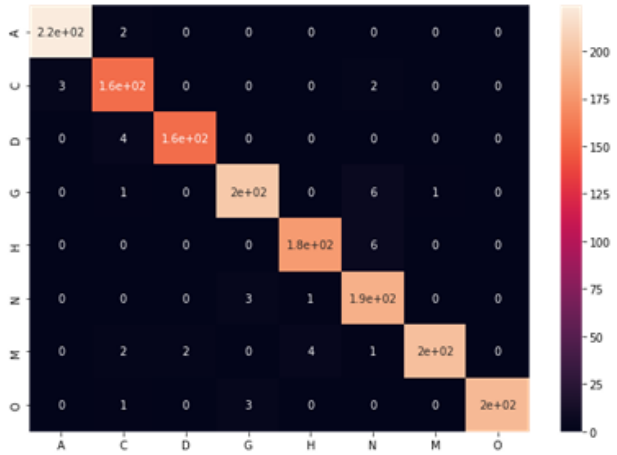

Fig. 5. VGG 16 model Confusion matrix of ODIR dataset

Figure 5 displays the VGG-16 model's confusion matrix for eye disease identification. It clearly shows how the model classifies diseases into 8 different groups. The diagonal-dominance of the matrix is quite immense where correctly classified instances are noted to be 220 under class A, 160 under class C, 160 under class O, 200 under class G, 180 under class H, 190 under class N, 200 under class M and 200 under class O. This means there is a low misclassification among classes since very few off-diagonal values were obtained limiting them to a value of 1-4. This numerical ranking indicates high discriminative power, robustness, and performance characteristics of the model to solve multi-classification analysis of ocular diseases of a complex nature.

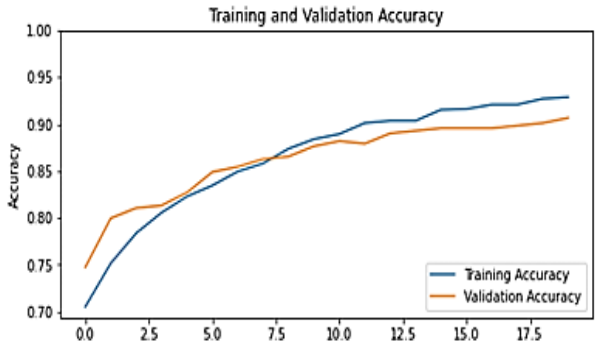

Fig. 6. Training and Validation Curve of VGG-16 model

Figure 6 shows the VGG-16 model's accuracy curve for detecting eye diseases throughout numerous epochs, both during training and validation. There is a noticeable upward trend in the training and validation accuracy, which begins at 0.72 and 0.76 epochs, respectively, and ends at 0.94 and 0.92 epochs, respectively. The similarity of the two curves shows good generalization performance. This shows that the model isn't getting too accustomed to the input data and is able to successfully train and generalize to new data sets.

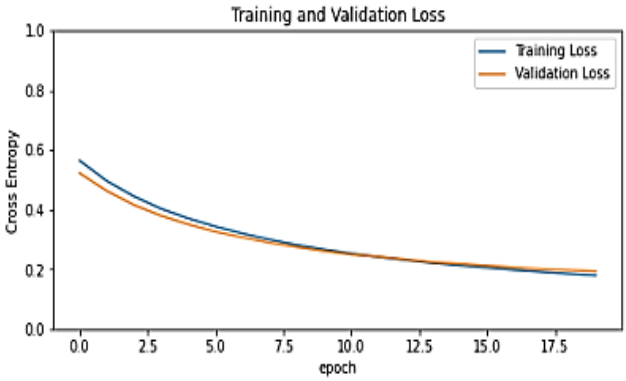

Fig. 7. Training and Validation Loss curve proposed VGG-16 model

Figure 7 shows the training and the validation loss curves on oversight of the proposed VGG-16 model through subsequent epochs, on the task of ocular disease detection. These two curves also exhibit a steady and smooth decease as the training loss is going down by approx. 0.58 to 0.18 and the validation loss is also going down by approx. 0.52 to 0.17. The fact that the two curves go close to each other and have a similar path shows that the model has been generalized well with less evidence of overfitting. This trend towards low values of loss implies the stable learning dynamics and the successful optimization of the cross-entropy loss function, which confirms high levels of stability and reliability of the model when using it to classify medical images.

A. Comparative Discussion

In this section, a comparative analysis of ocular disease detection on ODIR dataset is provided in detail using image classification models. The proposed VGG-16 model is compared to existing architecture, such as DenseNet121 [26], a typical CNN [25] and a hybrid VGG-16 + CNN model [27]. Table IV compares the most important performance indicators, such as recall, accuracy, precision, and F1-score. The overall effectiveness of each model in addressing the class imbalance problem and successfully identifying many types of eye disorders is provided by these evaluators. The review demonstrates the competitive aspect of the proposed VGG-16 model, especially resulting in a high level of balance between the accuracy and recall of the results, which is of the essence to reliable and generalizable classification to real-world clinical practice.

TABLE IV. THE COMPARISON OF VGG-16 WITH CURRENT MODELS OF THE OCULAR DISEASE DETECTION

Measures	Proposed VGG-16	DenseNet121	CNN	VGG-16 + CNN
Accuracy	98.27	96.20	93.81	96.00
Precision	94.00	98.00	91.63	98.00
Recall	90.00	96.00	85.77	96.00
F1-score	92.00	97.00	89.51	97.00

The comparative performance analysis between the proposed VGG-16 model and existing architectures—DenseNet121, CNN, and a hybrid VGG-16 + CNN are shown in Table IV, demonstrates the superior classification effectiveness of the future approach for ocular disease detection. The proposed model, VGG-16 achieves 98.27 accuracy which is higher than CNN (93.81%), DenseNet121 (96.20%) and VGG-16 + CNN (96.00%). Although the precision, recall, and thus performance of DenseNet121 and

the hybrid model are higher (98.00% precision and 96.00% recall), the proposed model performs better since it has a more balanced performance leading to a 92.00% F1-score value. These findings indicate its capabilities to have consistent precision and recall and are therefore stable in the reduction of false positives and false negatives in many types of ocular diseases.

The VGG-16 model proposed has several features, which make it more reliable to be used in clinical practices; one is that the model provides a high accuracy rate and a balanced metric performance. It is strong in that it utilizes deep feature extraction yet keeping the computations efficient. The relatively reduced recall over some of the other models may however indicate that there is a possibility of improvement on sensitivity on minority or complex cases. Further developments can be aimed at adding attention mechanism or ensemble approaches to better fine-tune the detection performance and better generalize to broader ocular datasets. Top of Form, Bottom of Form.

V. Conclusion and Future Work

Ocular diseases can be defined as a wide array of health conditions in which the eye and its integrity are affected, thus, causing a person to experience visual impairment or even blindness in case it is left undiscovered at the initial stages. Common instances of conventional eye diseases are glaucoma, age-related macular degeneration, diabetic retinopathy, and cataracts. In order to prevent permanent blindness and cure the disease quickly, a timely and accurate diagnosis is crucial. This study presents a DL system with a hierarchical architecture for automated early diagnosis of ocular disorders utilizing the ODIR fundus picture dataset. The methodology incorporates key stages such as standardized image preprocessing, comprising resizing, CLAHE-based contrast enhancement, and Gaussian filtering to ensure clarity and consistency of visual data. Flipping, rotating, and varying colors were some of the augmentation techniques used to fix the obvious class disparity. With an impressive 94.00% precision, 98.27% accuracy, 90.00% recall, and 92.00% F1-score, the suggested VGG-16 architecture modified for multiclass classification using a SoftMax output performed admirably. Comparative evaluation with established models such as DenseNet121, CNN, and VGG-16 + CNN highlights the superior balance of accuracy and consistency demonstrated by the proposed model, reinforcing its robustness in ocular image classification. Future work will focus on enhancing model sensitivity by integrating attention mechanisms like SE blocks or Vision Transformers. Ensemble learning techniques will be explored to improve generalization. Additionally, cross-dataset validation will be conducted to ensure robustness across diverse image sources. Incorporating interpretability tools such as Grad-CAM will also help increase clinical transparency and support real-world deployment in ophthalmic diagnostics.

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