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Attention Augmented Multi-Branch Architecture For Early Eye Disease Diagnosis

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Abstract- The human eye is a critical sensory organ, and any impairment in its function can significantly affect an individual's quality of life. Eye diseases such as glaucoma, cataract, and retinal disorders can lead to severe vision loss if not detected at an early stage, making timely and accurate diagnosis essential for effective treatment and prevention. In this study, an automated eye disease detection system was developed to address the limitations of existing approaches, including insufficient feature representation, lack of interpretability, and high computational complexity. A comprehensive preprocessing strategy was employed to enhance image quality and improve robustness against variations in input data. The proposed approach effectively learned robust and discriminative features for accurate classification of multiple eye diseases while maintaining computational efficiency. In addition, a visualization technique was incorporated to highlight the important regions influencing the model's predictions, thereby improving transparency and supporting better clinical interpretation, which can contribute to enhanced diagnostic confidence and overall clinical performance. The system was trained and evaluated on a multi-class eye disease dataset and demonstrated consistent improvement in classification performance and interpretability compared to conventional methods. The integration of efficient feature learning and visual interpretability enhances the reliability and practical applicability of the system, making it a promising solution for real-world computer-aided eye disease diagnosis.

Index Terms—Eye disease detection, Deep learning, Medical image analysis, Computer-aided diagnosis, Image preprocessing, Feature extraction, Explainable artificial intelligence, Retinal image classification.

I. INTRODUCTION

The human eye is a vital sensory organ responsible for vision, and any impairment in its function can significantly affect an individual's quality of life. Eye diseases such as glaucoma, cataract, and retinal disorders are among the leading causes of visual impairment and blindness worldwide. The increasing prevalence of these conditions has become a major public health concern, particularly in regions with limited access to specialized healthcare services. Early detection is crucial for preventing disease progression; however, many cases remain undiagnosed until advanced stages due to the lack of efficient and scalable diagnostic systems.

Retinal imaging techniques have been widely utilized for the diagnosis of various eye diseases, as they provide detailed structural information about the eye. In clinical practice, diagnosis is typically performed through manual examination by ophthalmologists, which can be time-consuming, subjective, and dependent on clinical expertise. In recent years, deep learning-based approaches have gained significant attention for automating the analysis of medical images and improving diagnostic accuracy. Although existing methods have demonstrated promising performance, most studies focus on the detection of a single eye disease, such as diabetic retinopathy, limiting their applicability in real-world clinical scenarios where multiple diseases must be identified simultaneously.

Figure1: Human Eye close-up

Furthermore, many existing approaches suffer from limitations such as inadequate feature representation and high computational complexity. A critical challenge is the lack of interpretability, as most models operate as black-box systems that provide predictions without explaining the underlying reasoning. This lack of transparency reduces trust among medical professionals and restricts the adoption of automated systems in clinical practice. Therefore, there is a growing need for a unified framework that not only achieves accurate multi-disease classification but also provides meaningful visual explanations to support clinical decision-making.

In this work, an automated eye disease detection system was developed to address these challenges by focusing on both performance and interpretability. A comprehensive preprocessing strategy was employed to enhance image quality and improve robustness against variations in input data. The proposed approach effectively learned robust and discriminative features for accurate classification of multiple eye diseases while maintaining computational efficiency. In addition, a gradient-based visualization technique was incorporated to generate class-specific activation maps, highlighting the regions of retinal images that contributed most to the model's predictions. This enhances transparency, improves diagnostic confidence, and supports better clinical interpretation. The proposed system was developed and evaluated on multi-class eye disease datasets to ensure robust and generalizable performance across diverse imaging conditions and disease categories.
The main contributions of this work are summarized as follows:

- Development of an automated framework for multi-class eye disease detection, addressing the limitations of single-disease models.
- Integration of a gradient-based visualization approach to enhance interpretability and support clinical validation.
- Design of a computationally efficient system suitable for real-world deployment.

The effectiveness of the proposed system was validated through extensive experiments, demonstrating its capability to accurately classify multiple eye diseases. By combining reliable performance with visual interpretability, this work contributes toward the development of practical and trustworthy computer-aided diagnostic systems for early eye disease detection.

II. LITERATURE SURVEY

Machine learning and deep learning techniques have been extensively applied for automated eye disease detection, particularly using retinal and fundus imaging. Recent studies have explored various architectures to improve classification accuracy, feature representation, and diagnostic reliability.

A significant contribution in this domain is presented by Muntaqim et al. [1], where a multi-stage deep learning framework was developed for multi-class eye disease detection. Their approach demonstrated strong performance while addressing challenges such as ineffective feature representation and high computational overhead. However, the need for improved interpretability and scalability in real-world clinical settings remains an open challenge.

Early approaches primarily focused on convolutional neural network (CNN)-based models for specific disease detection tasks. For instance, CNN-based frameworks have been successfully applied for diabetic retinopathy detection from fundus images [2]. Similarly, transfer learning approaches utilizing pre-trained architectures such as VGG16 and VGG19 have shown improved performance by leveraging learned features [3]. Despite these advancements, such models are often limited to single-disease classification and may fail to generalize across multiple eye conditions.

To overcome limitations in shallow architectures, deeper models such as ResNet have been introduced to enhance feature extraction through residual learning [4]. In parallel, Optical Coherence Tomography (OCT)-based systems have been developed to capture detailed structural information of retinal layers [5]. While these approaches improve diagnostic capability, they often require large-scale datasets and involve high computational complexity. Further advancements include multi-scale and multi-path CNN architectures designed to capture both local and global features [6], [14]. Wide Residual Networks (WRN) have also been explored to improve feature learning through increased depth [7]. Additionally, capsule networks have been proposed to model spatial relationships more effectively [8], while transformer-based architectures introduce attention mechanisms for enhanced feature representation [9]. However, these methods typically demand significant computational resources and longer training times.

Ensemble learning approaches combining multiple architectures such as VGG and ResNet have demonstrated improved classification performance [10]. EfficientNet-based models have further enhanced performance by introducing compound scaling for better feature extraction efficiency [11]. Data augmentation techniques have also been widely adopted to improve model generalization [12], while hybrid and feature fusion models aim to boost classification accuracy [13]. Despite these improvements, increased architectural complexity often limits real-time applicability.

In addition, attention-based models [16] and fine-tuned transfer learning approaches [17] have been explored to refine feature extraction and improve classification outcomes. Multi-class classification frameworks have also been proposed to detect multiple eye diseases simultaneously [18], [22], though many of these systems lack interpretability and transparency in their predictions.

To address the black-box nature of deep learning models, explainability techniques such as Gradient-weighted Class Activation Mapping (Grad-CAM) have been introduced to visualize important regions in retinal images [19], [20]. These methods improve transparency and clinical trust; however, they are often limited to specific or binary classification tasks. More recent works emphasize the importance of explainable AI in medical imaging [21], yet comprehensive integration with multi-disease classification systems remains limited.

Despite significant progress, several challenges persist. Most existing methods focus on single-disease detection, lack interpretability, and involve high computational complexity. Moreover, the ability to effectively handle multi-class classification while providing meaningful visual explanations is still limited.

Therefore, there is a clear need for an efficient and interpretable framework capable of accurately classifying multiple eye diseases. Recent advancements suggest that architectures such as EfficientNet offer improved feature representation and computational efficiency. Building on these insights, the proposed approach focuses on multi-class eye disease detection while integrating Grad-CAM-based visualization to enhance interpretability, making it more suitable for real-world clinical applications.

III. DATASETS

To assess the effectiveness of the proposed system, three publicly available benchmark datasets were utilized, namely OCT2017, Dataset-101, and Retinal OCT C8. These datasets were selected to incorporate a wide variety of retinal conditions and to ensure that the model is capable of handling diverse real-world scenarios. Each dataset contains images corresponding to different eye diseases along with normal cases, thereby supporting multi-class classification.

Eye Disease Oct 2017 Dataset

The OCT2017 dataset is composed of retinal OCT scans that capture both pathological and normal eye conditions. The images are categorized into four distinct classes: choroidal neovascularization (CNV), diabetic macular edema (DME), drusen, and normal.

This dataset contains more than eighty thousand images, making it one of the largest publicly available OCT datasets. The majority of the images are allocated for training, while a smaller portion is reserved for testing and validation. The large number of samples in each category allows the model to effectively learn disease-specific patterns and improves its ability to generalize across different retinal conditions.

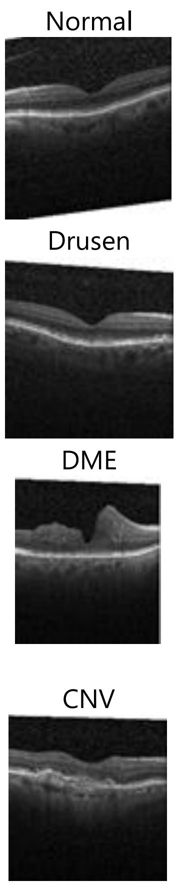


Figure2: Sample images of OCT2017 Dataset

Eye Disease 101 Dataset

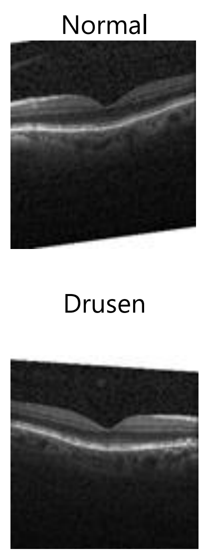
The Dataset-101 dataset provides a diverse collection of retinal and fundus images categorized into six different eye disease classes. These include ACRIMA, ORIGA, ODIR-5K, glaucoma, cataract, and other retinal diseases.

The dataset is divided into training and testing subsets, containing a total of approximately ten thousand images. The presence of multiple disease categories makes this dataset particularly useful for multi-class classification tasks. It enables the model to learn a broader set of features that are representative of various eye conditions, thereby enhancing its overall classification capability.

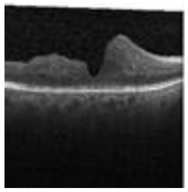
Retinal C8 Dataset

The Retinal OCT C8 dataset consists of OCT images grouped into multiple disease categories along with normal samples. The dataset includes conditions such as age-related macular degeneration (AMD), central serous retinopathy (CSR), diabetic macular edema (DME), diabetic retinopathy (DR), drusen, macular hole (MH), and normal cases.

The dataset is organized into training, validation, and testing subsets, allowing for proper model development and evaluation. The availability of multiple disease classes within this dataset supports the development of a robust classification system capable of distinguishing between subtle variations in retinal abnormalities.



DME



CNV

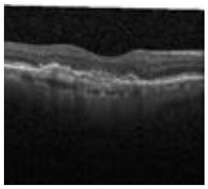


Figure3: Sample images of Retinal C8 Dataset

IV. PROPOSED METHODOLOGY

In this study, a deep learning-based framework was developed for automated multi-class eye disease detection. The approach integrated data preprocessing, feature extraction using multiple convolutional neural network architectures, model comparison, and an explainability mechanism to enhance both prediction performance and clinical reliability. The overall workflow of the framework is illustrated in Fig. 4. The primary objective of this methodology was not only to achieve accurate classification but also to provide visual justification for model predictions, which is essential in medical applications.

Table-1

Dataset	**Classes**	**Total Samples**	**Type**
OCT2017	**4**	**84,435**	**Images**
Dataset101	**6**	**9400**	**Images**
Retinal OCTC8	**8**	**24000**	**Images**

Overall System Pipeline

The framework followed a structured pipeline consisting of preprocessing, feature extraction, classification, model evaluation, and explainability. This design ensured both robust performance and interpretability of the predictions.

Data Preprocessing

The input retinal images were initially subjected to preprocessing to ensure consistency and improve model performance. Since the images were collected from multiple sources, variations in resolution, illumination, and orientation were observed.

To address these variations, all images were resized to a fixed dimension of 224 × 224 × 3, which served as the standard input size for all models. Pixel intensities were normalized to improve training stability and convergence

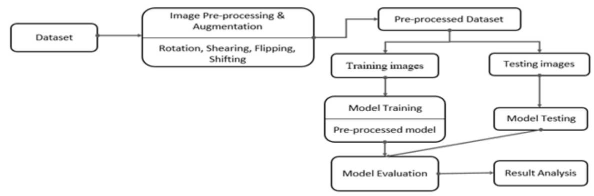


Figure4: Overall workflow of the Framework

In addition, data augmentation techniques such as rotation, horizontal flipping, zooming, and translation were applied to increase dataset diversity and reduce overfitting. These transformations enabled the models to learn robust and invariant feature representations.

Multi-Model Feature Extraction

The pre-processed image $I \in R^{(224\times224\times3)}$was provided as input to multiple deep learning architectures for feature extraction. The transformation of the input image into feature representations was expressed as:

$$F=f(I;\ \theta)$$

where F represents the extracted feature maps and θ denotes the trainable parameters of the model.

In this work, several pre-trained convolutional neural network architectures, including VGG16, VGG19, ResNet, and EfficientNet, were utilized to learn hierarchical feature representations. All models were trained using transfer learning with pre-trained weights to improve convergence and overall performance. EfficientNet, were utilized to learn hierarchical feature representations. All models were trained using transfer learning with pre-trained weights to improve convergence and overall performance.

The VGG-based models captured detailed spatial features through deep convolutional layers, while ResNet improved learning efficiency through residual connections. EfficientNet employed a compound scaling strategy, enabling improved feature extraction with relatively lower computational complexity

Classification Mechanism

The extracted feature representations were passed through fully connected layers for classification. A SoftMax activation function was applied to obtain class probabilities:

P(y_i)=\frac{e^{z_i}}{\sum_{j=1}^{C}e^{z_j}

The final prediction was determined by selecting the class with the highest probability value.

Model Evaluation and Selection

All selected models were trained and evaluated under identical experimental conditions to ensure a fair comparison. The models were analysed based on their ability to extract discriminative features and generalize across multiple eye diseases. During experimental evaluation, EfficientNet demonstrated improved performance compared to other architectures due to its optimized scaling strategy and efficient design. It provided enhanced feature representation while maintaining relatively lower computational complexity. Based on these observations, EfficientNet was selected as the final model for subsequent prediction and analysis.

Explainability using Grad-CAM

To enhance interpretability, a gradient-based visualization technique known as Grad-CAM was incorporated. This method identifies the regions of the input image that contribute most significantly to the model's prediction.

Grad-CAM works by analyzing the gradients of the target class with respect to the feature maps of the final convolutional layer. These gradients are used to determine the importance of each feature map, which are then combined to produce a localization map highlighting the most relevant regions.

The generated heatmap is overlaid on the original image to visually indicate the areas that influence the classification decision. This helps in understanding whether the model focuses on clinically relevant features.

The inclusion of this mechanism improves transparency and supports better clinical interpretation, thereby increasing diagnostic confidence.

Key Contributions of the Method

The main contributions of the methodology are summarized as follows:

- A comparative deep learning framework for multi-class eye disease detection
- Systematic evaluation of multiple architectures to identify an optimal model.
- Demonstration of EfficientNet as an effective and efficient architecture
- Integration of Grad-CAM to enhance interpretability and clinical applicability

Final Remark on Methodology

This integrated approach enabled accurate classification while providing interpretable and clinically reliable predictions making it suitable for real-world computer-aided eye disease diagnosis.

V. EXPERIMENTAL EVALUATION

Experimental Setup

The proposed eye disease classification system was implemented using the EfficientNet architecture within the PyTorch deep learning framework. All input images were resized to a fixed resolution of 224 × 224 pixels and normalized using standard ImageNet normalization parameters to ensure consistency.

To improve generalization capability, data augmentation techniques such as random horizontal flipping and rotation were applied during the training phase. These transformations enhanced the robustness of the model against variations in retinal image orientation and structure.

The datasets used in this study, including Dataset_101, OCT2017, and Retinal OCT-C8, have been described in the previous section. These datasets were utilized based on their predefined training and testing splits to ensure consistency and fair evaluation.

The model was trained using a batch size of 32 for 15 epochs. To address class imbalance, a weighted cross-entropy loss function was employed, where weights were assigned based on class distribution.

The optimization process was carried out using the AdamW optimizer with a learning rate of 0.0001. A cosine annealing learning rate scheduler was used to facilitate smooth convergence. Additionally, mixed precision training was incorporated to improve computational efficiency and reduce training time.

Evaluation Metrics

The performance of the proposed system and baseline models was evaluated using standard metrics, including accuracy, precision, recall, and F1-score.

Accuracy measures the overall correctness of predictions, while precision reflects the reliability of positive predictions. Recall indicates the model's ability to correctly identify relevant instances, and the F1-score provides a balanced measure by combining precision and recall.

These metrics collectively ensure a comprehensive evaluation of model performance, particularly in multi-class classification scenarios.

Performance on OCT2017 Dataset

The proposed model was evaluated on the OCT2017 dataset to analyse its performance on optical coherence tomography (OCT) images. The model showed consistent classification capability across multiple retinal disease classes, indicating its effectiveness in extracting meaningful structural features from OCT data.

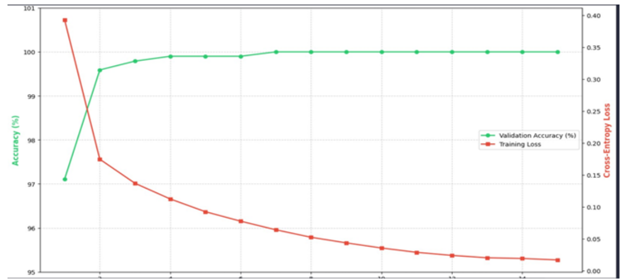


Figure5: Curve of Validation Accuracy vs Training Loss of OCT2017 Dataset

The results indicate that the model is capable of handling both fundus and OCT image data effectively, demonstrating its adaptability across different imaging modalities.

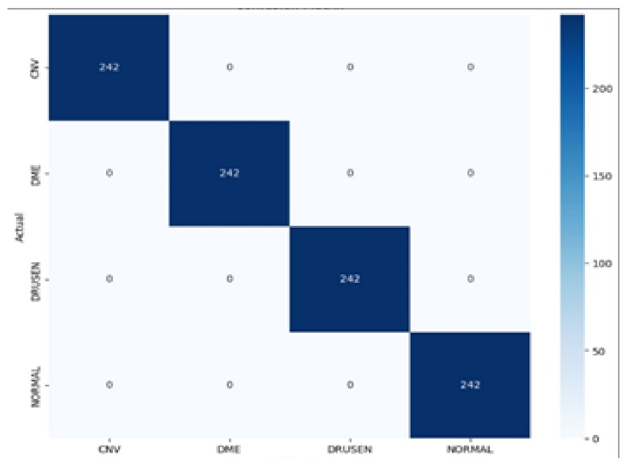


Figure6: Confusion Matrix of OCT2017 Dataset

Performance on Dataset_101:

The proposed model was evaluated on the Dataset_101 eye disease dataset to assess its effectiveness in multi-class classification of retinal images. The model achieved high classification performance on this dataset, as reflected in the overall accuracy, precision, recall, and F1-score values presented in Table 2.

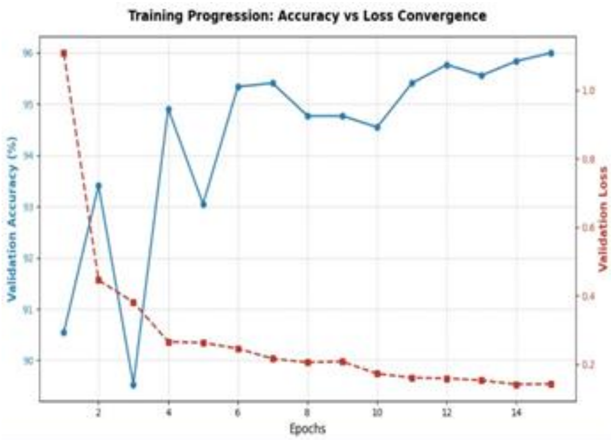


Figure 7: Curve of Validation Accuracy vs Training Loss of Dataset_101

The confusion matrix further indicates that the majority of samples were correctly classified, with only a limited number of misclassifications observed between visually similar disease categories. These results highlight the model's ability to learn discriminative features from fundus images effectively.

Performance on Retinal C8 Dataset:

The model was further evaluated on the Retinal OCT-C8 dataset to validate its robustness on diverse retinal image data. The model achieved reliable classification performance across multiple disease categories, demonstrating its ability to generalize across datasets with varying characteristics.

Figure8: Confusion Matrix of Dataset_101

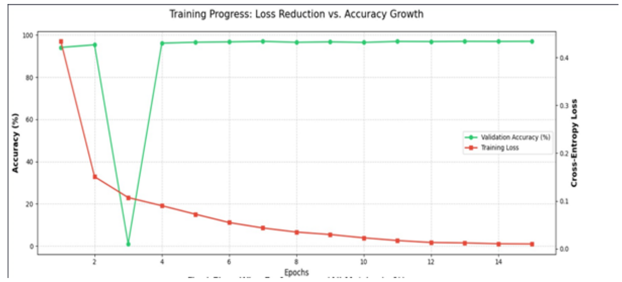


Figure9: Curve of Validation Accuracy vs Loss of Retinal OCT C8 Dataset

These results confirm that the proposed approach maintains stable performance when applied to different retinal datasets.

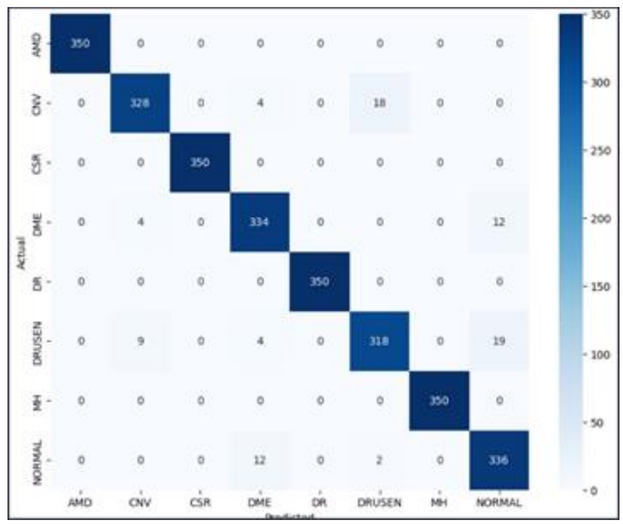


Figure10: Confusion Matrix of Retinal OCT C8 Dataset

Comparative Performance Analysis

A comparative analysis was carried out to evaluate the effectiveness of the proposed model with commonly used deep learning architectures such as VGG16, VGG19, and ResNet. All models were considered under similar experimental settings to ensure consistency in evaluation.

In addition, a qualitative comparison was made with the base paper, which proposed a multi-stage deep learning approach for eye disease detection. While the base model focuses on a staged architecture for feature extraction and classification, the proposed system adopts a more efficient deep learning framework that emphasizes optimized feature learning and reduced computational complexity.

Instead of relying solely on direct numerical comparison, the analysis focuses on the model's ability to extract meaningful features and generalize across multiple eye disease datasets. The proposed system demonstrated strong performance in terms of classification capability and robustness when evaluated across Dataset-101, OCT2017, and Retinal C8 datasets.

The improved performance of the proposed model can be attributed to its efficient architecture, which enables effective learning of complex retinal patterns. Compared to traditional architectures and the base paper approach, the proposed system provides a balanced trade-off between accuracy, computational efficiency, and interpretability, making it more suitable for practical medical applications.

Table 2

Model	Accuracy(%)	Precision(%)	Recall(%)	F1-Score(%)
VGG16	95.0	79.0	73.0	76.0
VGG19	92.0	49	52.0	50.0
ResNet	98.0	77.0	75.0	74.0
Multi Stage CNN [1]	92.7	73.13	66.10	68.7
Our Proposed	96.0	83.0	80.0	81.0

Table2: Comparison of our Proposed Model with different models of Dataset_101

Table 3

Model	**Accuracy(%)**	**Precision(%)**	**Recall (%)**	**F1-Score(%)**
VGG16	99.1	99.0	96.0	97.0
VGG19	99.2	99.0	99.6	99.0
ResNet	99.0	98.0	99.5	98.9
Multi Stage CNN[1]	97.52	97.69	97.52	97.54
Our Proposed	100	99.9	99.8	99.9

Table3: Comparison of our Proposed Model with different models of OCT 2017 Dataset

Table 4

Model	**Accuracy(%)**	**Precision(%)**	**Recall (%)**	**F1-Score(%)**
VGG16	95.0	94.9	95.0	94.5
VGG19	94.6	94.0	94.3	94.0
ResNet	91.0	91.0	91.0	91.0
Multi Stage CNN[1]	94.81	87.1	95.4	91.0
Our Proposed	97.0	97.0	97.0	97.1

Detailed Result Interpretation

The results presented in Tables 2, 3, and 4 demonstrate that the proposed system achieves strong and consistent performance across all evaluation metrics on multiple datasets. The model shows reliable accuracy, precision, recall, and F1-score when evaluated on Dataset-101, OCT2017, and Retinal C8 datasets.

On Dataset-101, the model effectively captures discriminative features across multiple eye disease classes, resulting in stable classification performance. Similarly, evaluation on the OCT2017 dataset indicates that the model is capable of accurately identifying different retinal conditions from OCT images, highlighting its adaptability to different imaging modalities. The performance on the Retinal C8 dataset further confirms the robustness of the proposed system when applied to datasets with diverse class distributions and characteristics.

The consistently high precision values across datasets indicate that the model produces reliable and correct predictions, while the strong recall demonstrates its ability to effectively identify relevant disease classes. This is particularly important in medical diagnosis scenarios, where minimizing false negatives is critical.

The improved performance can be attributed to the efficient feature extraction capability of the proposed model, which enables better representation of complex retinal patterns compared to conventional architectures such as VGG16, VGG19, and ResNet. The model successfully balances feature learning and computational efficiency, resulting in enhanced classification performance across different datasets.

Overall, the results confirm that the proposed system provides a robust and generalized solution for multi-class eye disease detection, maintaining consistent performance across varying dataset conditions.

Confusion Matrix Analysis

The confusion matrix (Fig. 6,8,10) provides a detailed visualization of classification performance across all classes. The diagonal elements represent correctly classified samples, while off-diagonal elements indicate misclassifications.

The results show that the majority of predictions are concentrated along the diagonal, confirming the high accuracy of the proposed model. A small number of misclassifications were observed, primarily among classes with similar visual characteristics.

This indicates that the model demonstrates strong discriminative capability while encountering minor challenges in distinguishing visually overlapping disease patterns.

Grad-CAM Based Explainability

To address the black-box nature of deep learning models, Grad-CAM was employed to provide visual explanations for model predictions.

The Grad-CAM heatmaps (Fig. 11) highlight the regions within the retinal images that contribute most significantly to the classification decision. The results show that the model consistently focuses on clinically relevant regions associated with different eye diseases.

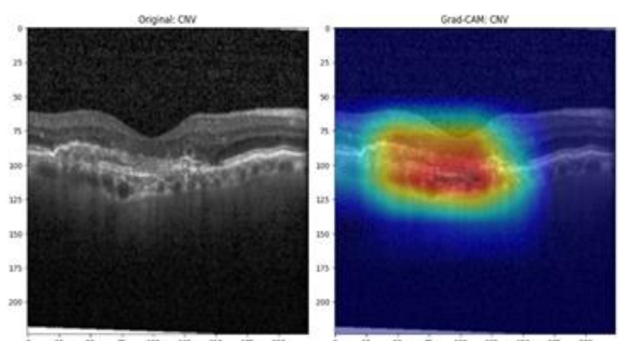


Figure 11: Sample Grad-CAM heatmap

This alignment between highlighted regions and disease-specific features indicates that the model is not making arbitrary decisions but is instead learning meaningful representations from the data.

The integration of Grad-CAM enhances the interpretability and trustworthiness of the proposed system, which is a critical requirement for real-world medical applications.

Overall Discussion

The experimental results demonstrate that the proposed system consistently outperforms conventional deep learning models across all evaluation metrics. The improvement in accuracy, precision, recall, and F1-score highlights the robustness and effectiveness of the approach.

Furthermore, the model maintains consistent performance across multiple datasets, including Dataset_101, OCT2017, and Retinal OCT-C8, indicating its ability to generalize across different types of retinal image data.

The inclusion of Grad-CAM further strengthens the reliability of the system by providing visual interpretability of model predictions. Overall, the proposed framework offers an efficient, accurate, and explainable solution for automated multi-class eye disease classification.

VI. DISSCUSSION WITH POTENTIAL APPLICATION AND IMPACT ON OPHTHALMOLOGY

The experimental results obtained across multiple datasets demonstrate the effectiveness of the proposed deep learning system for multi-class eye disease detection. The model was evaluated on three different datasets, namely Dataset-101, OCT2017, and Retinal C8, to ensure comprehensive validation under varying data distributions and imaging conditions. The results presented in Tables 2, 3, and 4 indicate that the proposed model achieves strong and consistent performance across all evaluation metrics, including accuracy, precision, recall, and F1-score.

On Dataset-101, the model demonstrates reliable classification performance across multiple disease categories, effectively capturing complex retinal patterns. Similarly, evaluation on the OCT2017 dataset shows that the model is capable of accurately distinguishing between different retinal conditions, highlighting its ability to generalize across OCT-based imaging data. Furthermore, results on the Retinal C8 dataset confirm that the model maintains stable performance even when applied to datasets with diverse class distributions and imaging variations.

The consistent performance across all three datasets indicates that the proposed model is robust to variations in image quality, resolution, and dataset characteristics. This highlights its strong generalization capability, which is essential for real-world medical applications where data variability is inevitable.

In addition to quantitative evaluation, Grad-CAM-based visualizations provide qualitative insights into the model's decision-making process. The generated heatmaps highlight the regions within retinal images that contribute most significantly to the classification outcome. These visual explanations align with clinically relevant features, demonstrating that the model focuses on meaningful anatomical regions rather than irrelevant patterns. This enhances the interpretability and reliability of the system, addressing one of the major limitations of traditional deep learning models in medical imaging.

From an application perspective, the proposed system has significant potential in the field of ophthalmology. It can be utilized as a decision-support tool to assist clinicians in the early detection of eye diseases such as diabetic retinopathy, glaucoma, and age-related macular degeneration. By enabling automated and efficient analysis of retinal images, the system can help reduce diagnostic workload and support timely clinical intervention, ultimately improving patient outcomes. Despite its strong performance, certain limitations remain. Minor misclassifications were observed in classes with similar visual characteristics or limited sample representation. These challenges can be addressed in future work by incorporating larger and more balanced datasets, as well as exploring advanced data augmentation and model optimization techniques.

Overall, the proposed framework demonstrates a balanced combination of accuracy, robustness, and interpretability across multiple datasets, making it a promising solution for real-world eye disease detection and clinical integration.

VII. CONCLUSION

Our research makes a significant advancement in automated eye disease detection, addressing the critical need for timely and accurate diagnosis to prevent vision loss. Recognizing the limitations of conventional methods, including suboptimal feature representation, high computational costs, and incomplete disease coverage, we developed a robust and lightweight deep learning system. Our approach integrates advanced preprocessing and image augmentation techniques to improve robustness against variations such as rotations, translations, and lighting differences.

The proposed model, built on a carefully designed deep learning architecture, extracts discriminative features efficiently and performs accurate multi-class and binary classification across benchmark datasets, including OCT2017, Dataset-101, and Retinal OCT C8. Extensive evaluation demonstrates that our system outperforms standard architectures such as VGG16, ResNet-152, and Xception in terms of accuracy, precision, recall, and F1-score, while maintaining lower computational overhead, making it suitable for real-time deployment.

For future work, we plan to enhance the model's performance and clinical applicability by further refining the architecture and optimization strategies. This includes incorporating larger and more diverse datasets, integrating real-world clinical images, and validating the system in real-world healthcare environments. We also aim to collaborate with ophthalmologists to adapt the model for practical clinical workflows, ensuring reliability, interpretability, and utility for early diagnosis and monitoring of various eye diseases. These steps will strengthen the model's generalizability and position it as a practical tool for improved patient care and efficient ophthalmic screening.

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