FusionEyeNet: An Integrated Web-Based System for Explainable External Eye Disease Classification and LLM-Powered Personalized Recommendations

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Thesis submitted in fulfillment of the requirements for the award of the degree of Bachelor of Science

Fall 2025

Department of Software Engineering (Major in Data Science)

DAFFODIL INTERNATIONAL UNIVERSITY

APPROVAL

This thesis titled on **"FusionEyeNet: An Integrated Web-Based System for Explainable External Eye Disease Classification and LLM-Powered Personalized Recommendations"**, submitted by **Dipu Ghosh (ID: 221-35-873)** to the Department of Software Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of Bachelor of Science in Software Engineering and approval as to its style and contents.

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ACKNOWLEDGEMENTS

I wish to express my profound gratitude to the God, whose endless blessings and grace have guided me throughout my journey and enabled the successful completion of this undergraduate thesis.

I would like to express my profound gratitude and sincere thanks to my supervisor FATAMA BINTA RAFIQ, Senior Lecturer, Department of Software Engineering of Daffodil International University, Dhaka. It was his precious expertise, consistent support and insightful guidance in the field of Deep Learning and AI which helped this research to take its form. His constant motivation, academic supervision, tough feedbacks and scrupulous overseeing to this work at every step has been the core matter of my achievement.

I would also like to express my sincere gratitude towards Professor Dr. Imran Mahmud, Head of the Department of SWE, Faculty of Science and Information Technology (FSIT) as well as all the revered faculty members and staffs of Department of SWE at Daffodil International University for their immense academic support and motivation in my study life.

Finally, and most importantly, I express my deepest appreciation to my parents who have always given me their unconditional love and support, infinite number of patience as well as firm belief which always provide a strength during the long process of earning this degree.

Dedication

This work is dedicated to the following my family, whose faith, support and sacrifices have been a source of strength for me during this course of study. Your love and support have guided the way for me, enabling me to reach my goals.

And to every aspiring researcher, data scientist, and innovator who is thinking about the intersection of health and tech may this work serve as your inspiration to imagine the deep possibilities of AI for humanity, and that you will not give up solving problems that matter to people.

ABSTRACT

Given the worldwide prevalence of eye diseases, we need to develop new ways for diagnosing them, particularly in resource-poor areas. Recent deep learning models for ophthalmology generally have a lower coverage of diseases, do not provide explainable predictions and are not patient centered. This study presents FusionEyeNet, a comprehensive web-platform in addressing these limitations with LLM-powered explaining external eye disease classification and personalized recommendation. The proposed system uses a hybrid architecture that combines MobileNetV2 and VGG16 by using strategic feature fusion, which makes it feasible to classify five external eye conditions efficiently such as Cataract, Conjunctivitis, Eyelid disorders, Normal eyes and Uveitis. Explainable AI is incorporated into the framework using Grad-CAM, providing a clear diagnostic reasoning with its focus on medically related areas in ocular images. Furthermore, Google Gemini large language model also provides personalized educational suggestions according to diagnostic results and confidence scores. The experimental results confirm the competitive superiority of FusionEyeNet with 97.89% test accuracy, outperforming the comprised (individual) baseline models such as VGG16 by a clear margin (97.19%). The system realizes accurate detection of cataract and robust diagnosis to the minority class, such as uveitis. The implemented web-app allows users to upload eye images and get diagnosed including confidence scores, as well as visual explanations with AI-generated educational advice. These findings create a benchmark for reliable ophthalmic AI systems, which integrate both diagnostic performance and educational value, with the potential to improve eye care accessibility and guide clinical management worldwide.

Keywords: Eye Disease Classification, Deep Learning, Explainable AI (XAI), Medical Image Analysis, Transfer Learning, Convolutional Neural Networks, Large Language Models, Web Application.

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LIST OF SYMBOLS

α	Learning rate
θ	Model parameters
∇	Gradient operator
σ	Sigmoid activation function
η	Learning rate
λ	Regularization parameter
L	Loss function
W	Weight matrix
b	Bias term
ŷ	Predicted output

LIST OF ABBREVIATIONS

AI	Artificial Intelligence
AUC	Area Under the Curve
CAM	Class Activation Mapping
CNN	Convolutional Neural Network
DL	Deep Learning
FN	False Negative
FP	False Positive
Grad-CAM	Gradient-weighted Class Activation Mapping
LLM	Large Language Model
ReLU	Rectified Linear Unit
ROC	Receiver Operating Characteristic
ADAM	Adaptive Moment Estimation

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CHAPTER 1

INTRODUCTION

1.1 Background

Eye diseases are a major worldwide health burden, and millions of people experience avoidable vision loss due to the lack of timely diagnoses and treatments. Exogenous surface corneal disorders, such as front eye diseases (cataract, conjunctivitis, uveitis and eyelid disease) are some of the most common causes for seeking medical advice in eye diseases. Yet, in much of any given country, especially in rural and underserved regions, there is limited access to specialist eye care, resulting in delays in diagnosis and avoidable visual loss [1].

The Artificial Intelligence field has recently innovatively transformed medical diagnostics. Deep learning, a type of machine learning that is based on the structure of the human brain, has achieved extraordinary success in medical image analysis. In eye diseases for example, convolutional neural networks (CNNs) have been able to diagnose many conditions with performance levels similar or even better than human experts [1, 9]. The technology may be utilised for providing reasonable and accessible eye care in remote areas with few health facilities.

Today's AI is not only limited to rudimentary classified systems. Already, there are proposals of systems that combine different AI architectures and deliver robust and accurate hybrid model systems [4, 7, 8]. At the same time, explainable AI has been introduced in reaction to a reality where AI-based decision-making systems function without providing a comprehensible explanation. There are software tools Grad-CAM available now to allow these systems to explain which part of an image that influenced the system in performing its diagnosis, which then would make doctors more comfortable with and have more confidence on what AI suggested them [2].

Recent years have seen the emergence of large language models (LLMs) that offer new applications for patient communication and education. These cutting-edge AI platforms are able to generate writing that is human-like and explain medical conditions in plain language and provide targeted advice on specific diagnoses [3]. It's a huge step in creating healthcare tools for patients that not only diagnose but inform and support.

1.2 Problem Statement

Although AI in ophthalmology poses much promise, current systems are by no means free of limitations that would allow them be integrated into clinical use. The majority of the current AI approaches target only two to three prevalent eye diseases, especially those that involve the posterior part of the eye such as diabetic retinopathy and glaucoma [11, 14]. This limited focus does not include several important external eye presentations that can be experienced by the patient population including uveitis and certain eyelid diseases [5,6]. Thus, these services are deficient in diagnostic coverage within a clinical environment.

Another big issue is that these AI systems don't explain how they ultimately arrived at their conclusions. Many operate as "black boxes", giving out diagnoses without justifying them [2]. Not only this also leave physicians unable to trust nor verify the suggestion of an AI, but particularly in life-changing health determinations it is crucial that a diagnosis can be explained.

In addition, the majority of existing work ends at diagnosis and does not consider the critical aspect of patient counselling. Patients who are diagnosed with an AI typically have questions about what the diagnosis means, what they should do and what to expect from treatment. Little is presented in the way of tailored, intelligible patient information across systems [3].

There is also insufficient research on hybrid model architectures, that integrate the advantages of several AI methods for external eye disease diagnosis [4, 7, 8]. On the other hand, models combined schemes between two or more models often ignored in literature, could lead to more robust and reliable systems.

1.3 Motivation

FusionEyeNet is designed due to the pressing need to alleviate these challenges, and build a more integrated, interpretable and patient-oriented system for eye disease diagnosis. The fundamental reason is the realization that today's AI-based solutions are technically advanced, but insufficiently serve the full demands of health care providers and patients.

For physicians and patients, systems that not only tell you what ails you but also why it thinks so are a must. For AI to be trusted and integrated into clinical work-flow, it is important that one can understand and verify the AI reasoning. Through the inclusion of explainable AI methods, we hope to deliver a system that doctors can use however they want with confidence being able to easily review and comprehend why each diagnosis has been provided.

For patients, the rapid need is for a tool that provides more than just a diagnosis. Patients are seeking understanding regarding what their diagnosis is, what to do next and finding what the right thing for them to do in their given circumstances. Language models, as a representation of the massive amounts of information available on the internets are ideally suited to meet this need by offering personalized recommendations in an explainable manner that can better support patients and help them understand their own eye health.

Content on underrepresented eye diseases, such as uveitis and eyelid disorders, is based upon their prominence in clinical practice and potential impact on patients lives. Our objective is to create a system that could be utilized for addressing multiple eye diseases such as the ones represented by this more general set of symptoms, and, consequently, provide broader diagnostic support that may reflect the variety of cases seen in clinical settings.

1.4 Significance of the Study

A number of dimensions have huge reflections to the ophthalmology and health care technology implemented AI. The FusionEyeNet system represents a key milestone in the direction of the implementation of more sophisticated and clinically relevant diagnostic eye care tool.

First, the system addresses generalisation scope limitation by including five different external eye diseases pooling around conditions that have been previously research. This broadened coverage of one system renders the model more suitable for application in actual clinical environments where patients are admitted seeking medical treatment with different groups of complaints.

Second, the mixed architecture of FusionEyeNet indicates that application of multiple AI models may achieve better results than a single one. By the wise fusion of MobileNetV2 and VGG16, it manages to inherit the advantages of two architectures and promote better and more robust prognosis.

Thirdly, the incorporation of explainable AI techniques in this domain can help address an imperative issue of trust and validation in medical AI. By identifying which features of an eye image were used for the diagnosis, the system allows doctors to understand and confirm the AI's reasoning and encourages better collaboration between human expert and machine learning.

Fourth, the incorporation of advanced natural language models for personalized recommendations is key to ensuring that care stays patient centric. This characteristic of practice play a role in bridging the gap between diagnosing and understanding back to the patient with specific guidance feedback right into its clinical documentation to guide care the patient which leads to improved health of outcomes well as importantly, satisfaction from patients deferment decision making.

In short, from the fully web integrated implementation it is clear that also complex AI healthcare tools can be made accessible and user-friendly. The system offers an operating example for the implementation of advanced medical AI in a convenient manner for both healthcare providers and patients.

1.5 Research Questions

This work is structured around three main questions which drive toward the key goals of the FusionEyeNet scheme:

RQ1: How well does the proposed FusionEyeNet hybrid method perform compared to standard single deep learning frameworks for multi-class external eye disease classification?

RQ2: How reliably can the explainable AI tools, especially Grad-CAM, deliver clinically interpretable visual explanations for the model's diagnostic decisions?

RQ3: How well do inbuilt large language models produce personalized, actionable recommendations for patients from AI-derived diagnosis and user-supplied query?

1.6 Research Objective

The main goal of this study is to develop the FusionEyeNet system to fully-automate diagnosis of external eye disease, and patient referral. This overall goal is sustained by a range of specific technical goals and functional requirements:

- First, the goal is to compile and pre-process a varied set of external eye images from 5 disease categories: Cataract, Conjunctivitis, Eyelid disorder, Normal Eye and Uveitis. This requires accurate data collection, quality control and well-designed partitions into training, validation or test observations to develop reliable models.

- The second one refers to developing the FusionEyeNet hybrid architecture based on learning the fused features of MobileNetV2 and VGG16. This involves searching for an appropriate fusion method, crafting the model's classification head from scratch and composing all components of the model pipeline in a way that allows efficient learning and inference.

- Third aim includes incorporating Explainable AI feature for better visualization by using Grad-CAM. It mainly consists of identifying the target layers within the model architecture, performing gradient computation and feature map transformation until clear visualization outputs showing diagnostically meaningful areas on images are obtained.

- Finally, you have the implementation of that LLM-based recommendation system which generates tailored patient advice. That means building great prompt templates, interfacing with the Gemini API and making sure that the recommendations are medically proper and sensible while being easy to read, along with containing all necessary safety disclaimers.

- The other is to verify FusionEyeNet with various baseline models through comprehensive evaluation using standard performance measures [13]. This benchmarking is done with respect to overall as well as class specific accuracy, computational burden, and qualitatively for explanation quality and recommendation utility.

1.7 Research Scope and Limitations

1.7.1 Scope:

1. Disease Coverage Scope

- Concentrate on the five most common external eye diseases categories: Cataract, Conjunctivitis, Eyelid disorders, Normal eyes, and Uveitis

2. Technical Development Scope

- Development of hybrid deep learning model combining MobileNetV2 and VGG16 architectures
- Implementation of explainable AI using Grad-CAM visualization techniques
- Integration of large language model (Gemini) for recommendation generation
- Web-based application development using Streamlit framework

3. Data Scope

- Use of anterior segment eye images from curated datasets
- Image preprocessing including resizing, normalization, and augmentation
- Dataset division into training (70%), validation (20%), and testing (10%) subsets
- Focus on image-based diagnosis without clinical patient data integration

4. Functional Scope

- Development as a diagnostic support tool rather than autonomous diagnosis system
- Provision of visual explanations for model decisions
- Generation of basic patient recommendations and education
- Operation as a web-based accessible platform

5. Evaluation Scope

- Performance comparison against established baseline models (VGG16, MobileNetV2, DenseNet121, Custom CNN)
- Metrics focusing on accuracy, sensitivity, specificity, precision, and ROC-AUC
- Technical validation rather than clinical trial implementation
- Subjective evaluation related to the quality of explanation, and usefulness of recommendation

1.7.2 Limitations:

1. **Data Limitations**
    - Restricting dataset sources may also affect generalisability
    - Lack of multi-center validation in different patient populations
    - Dependence on image and standardization of acquisition condition

2. **Technical Limitations**
    - Model performance at varying qualities of images and resolutions
    - Computational need for hybrid model training and inference
    - Real time performance optimization for the web application is poor.

3. **Explainability Limitations**
    - Grad-CAM is an approximation visualization explanation, instead of exact in the sense that would provide a medical interpretation
    - Limited capacity to articulate multi-feature diagnostic reasoning that is complex.
    - Potential disconnection of attention areas for the AI and for clinical importance.

4. **Recommendation System Limitations**
    - LLM-generated content may contain inaccuracies or oversimplifications
    - Lack of personalized medical history integration in recommendations

5. **Ethical and Practical Limitations**
    - Not a substitute for a full ophthalmic check up
    - Absence of framework for liability with AI-based diagnoses
    - Risks of patient overdependency on AI advice

1.8 Research Organizations

In this thesis, we have been discussing in five main chapters by listing the research background, methodology, results and conclusions. One chapter sequentially supplements the previous for a comprehensive study of the FusionEyeNet system and system design.

In chapter 1, the backgrounds, problems, motivation and objectives have been introduced. It has covered the background on AI in ophthalmology, pinpointed the actual limitations of previous investigations, justified their importance and described explicitly the proposed research questions and aims for this paper.

Chapter 2 provides a comprehensive review of the literature, including work in deep learning-based eye disease diagnosis, explainable AI in medical imaging and hybrid model methodologies as well as AI-driven patient communication platforms. This chapter places the present study in its scientific context and outlines what is specifically contributed by the study.

In chapter 3, we start by describing the methodology phase of the development and evaluation of FusionEyeNet, followed by implementation. This includes details regarding the data collection and preprocessing, model architecture design, explainable AI feature implementation, integration of the recommendation engine and experimental settings for system evaluation.

Chapter 4 describes the in-depth experimental results based on full-system evaluations. This encompasses quantitative results, comparisons with other models as well as visualizations of explanation output, samples of generated advice, and the practical implications of our findings.

Chapter 5 is the ending part of this thesis, which summarizes the main contributions and findings to the field, discusses possible limitations in this work, and proposes a conclusion followed by several insights for future research and developments toward AI-driven ophthalmology diagnostics.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The use of artificial intelligence in ophthalmology has grown substantially over the last decade, and deep learning models have shown great promise as a diagnostic tool for different eye diseases. This chapter is organized as follows: A review of prior art on deep learning-based eye disease classification will be presented in section II, with emphasis for external eye diseases. The review includes traditional convolutional neural networks, transfer learning methods, hybrid model architectures, explainable AI approaches and rising applications of large language models in healthcare. Hence the purpose of this chapter is to review the state-of-the-art literature in an effort to highlight gaps and deficiencies in existing approaches that justify the development of the FusionEyeNet system.

2.2 Related Works

Babaqi et al. (2024) contrasted transfer learning with conventional CNN-based approaches when they tackled the problem of multi-class eye disease classification, and obtained 94% accuracy using EfficientNet and transfer learning in comparison to 84% using standard CNNs. They demonstrated the superiority of transfer learning in data-limited medical settings while working on only three disease classes, which emphasized a necessity for covering more diseases that we addressed in this thesis by adding five extra eye-related conditions.

Singh et al. (2025) reported an extensive meta-analysis of 847 articles on XAI methods for medical imaging and found LIME had the highest fidelity (0.81), as compared with SHAP and Grad-CAM. The latter's study stressed the vital fact that model interpretability would be crucial for clinical adoption a finding that directly motivates our approach of incorporating Grad-CAM visualizations to produce explainable diagnostic reasoning on external eye disease classification.

Shi et al. (2024) introduced a Personalized Medical Language Model using reinforcement learning PMLM to optimize LLMs for healthcare recommendations. The methodology established a framework to capture patient behaviour and preferences for delivering individualized services, which directly informed the current thesis's implementation of Gemini-powered recommendations for generating personalized eye care guidance based on diagnostic outcomes.

Ayesha et al. (2025) developed hybrid models that combined CNN architectures with Vision Transformers to process texture and shape-based representations. Their collection of evidence showing effective hybrid approaches in capturing various image characteristics also directly informed the current thesis's architectural decision to combine MobileNetV2 and VGG16 in FusionEyeNet to process complementary feature representations.

Eyetome (2025) developed an automatic screening system based on artificial intelligence for the detection of 14 types of common eyelid morphological changes and diseases with an accuracy rate of 98.71. This study provided empirical support for inclusion of eyelid findings in universal diagnostic systems, and filled an important deficit in dataset coverage that will directly contribute to this thesis's scope expansion away from the high frequency ocular diseases we already discussed towards rarer external eye disease unrepresented within ophthalmic AI models.

Murugan et al. (2024), AI technologies for anterior chamber inflammation detection and uveitis diagnosis were fully reviewed, and machine learning model accuracy within 78-93% range to predict the etiology of uveitis was reported. Their findings help to justify the presence of non-represented uveitis as an external eye disease within this thesis and also contribute methodological considerations that will influence how inflammatory eye conditions are classified.

Dutta et al. (2023) proposed Conv-ViT, a hybrid architecture that completed as well as about 94% in all the metrics. The exhibition of hybrid strategies for better disease classification performance served as a source of inspiration to the current thesis in its implementation of FusionEyeNet, especially by using complemental architectures for feature representation.

Nagar & Gondaliya (2024) deployed and conducted a comparative study out of five deep learning architectures on four-class eye disease dataset, where EffecitientNetB3 outperformed them with 95.97% validation accuracy. Their thorough analysis offered useful perspective regarding the relative performance of models that was essential for selecting and comparing baseline architectures in the present thesis, as well as illustrating the plateauing behaviour 4-class systems are prone to, which this work also addresses by covering more diseases.

Bharath Vardhan et al. (2024) showed high performance with ResNet50 99.94% but observed low ROC-AUC scores for all their models, maybe, due to an imbalance among classes. Their results also demonstrated the necessity for comprehensive evaluation metrics beyond accuracy and thereby directly motivated us to utilize a multi-criterion evaluation strategy based on ROC-AUC, sensitivity, specificity, and precision metrics in the current thesis.

Acevedo et al. (2024) designed a CNN for custom multi-class based classification of eye disease which reported an accuracy of 97% over 5 classes showcasing the feasibility of end-to-end [35] based comprehensive solutions in ophthalmic AI. They highlighted the necessity of preprocessing to spread blur filters as well as canny edge detection for contrast and performance improvements, respectively, which also dictated the data preprocessing pipeline implemented in this thesis. Only 200 samples per class have been used by them, but the small dataset issue was reflected on this work as well by adopting Data Augmentation methods and clever choice of transfer learning to build stronger models.

2.2.1 Research Gap

1. **Limited Disease Coverage:** The small number of disease classes in the majority [1, 9, 11, 14] means significant illnesses such as uveitis [6] and eyelid conditions [5] are represented weakly.

2. **Lack of Explainability:** Although high accuracy is achieved by many works [10, 12], little work introduces detailed explainable AI techniques [2] to produce transparent diagnostic reasoning.

3. **Patient Communication Gap:** The current research mainly ends at the diagnosis and does not give personalized recommendations for patients [3], misunderstanding AI Diagnosis and patient comprehension.

4. **Architectural Limitations:** The majority of existing works all use single-model methods, and only a few studies [4, 7, 8] have experimented with hybrid architectures which could be beneficial to combine the strength of using different models.

2.3 Summary

The reviewed literature shows considerable progression in application of deep learning to ophthalmology showing better diagnostic performance for different disease and architectures. Nevertheless, significant deficiencies in disease coverage, model transparency, patient communication and architectural innovation remain. FusionEyeNet addresses these limitations with the extensive coverage of diseases addition, model Explainable AI design and LLM-driven recommendations and hybrid building that where step towards more practically applicable patient-centric diagnostics.

CHAPTER 3

METHODOLOGY

3.1 Overview

This study adopts a multi-phase strategy to develop and evaluate our proposed FusionEyeNet for classification of external eye disease. The approach begins with systematic data assembly and pre-processing and the process then includes several deep learning models such as the novel hybrid model; FusionEyeNet. The third phase includes explainable AI components and LLM-based recommendations, while the fourth one mainly presents a well-rounded evaluation metric to evaluate system performance in several facets. By taking an all-comprehensive approach towards the control of the disease which involves clear diagnosis, patient-centered communication and also through performance validation this comprehensive approach neatly tackles that research gaps noted in earlier chapters.

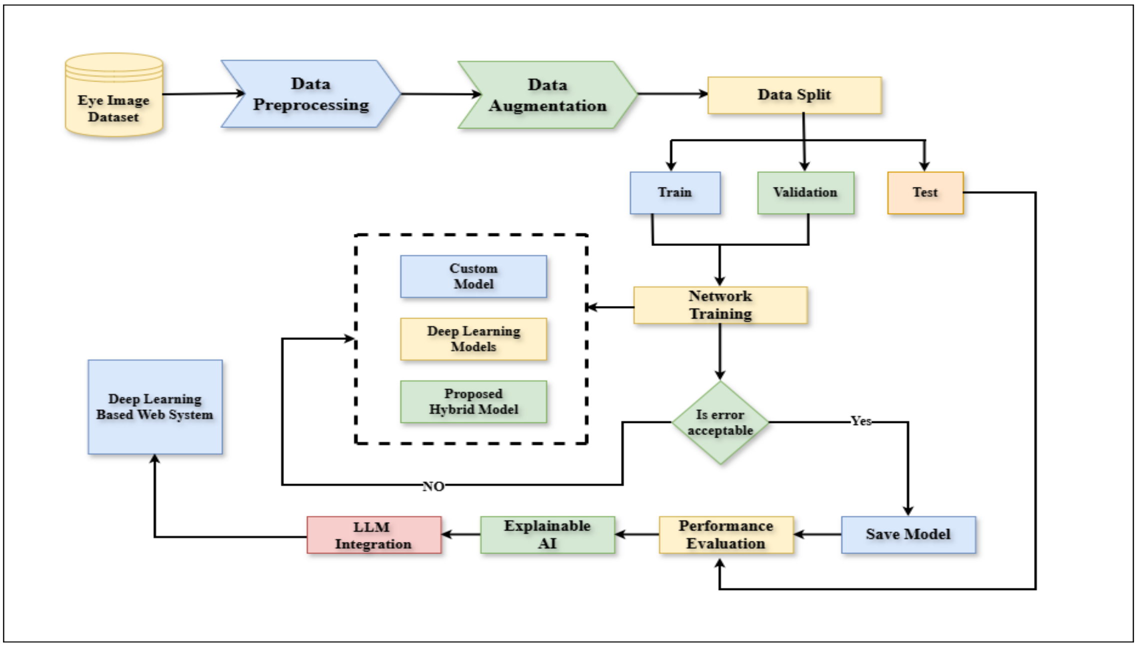


Figure 3.1 Methodology Diagram

3.2 Data Collection

The data set used in this study was systematically obtained from Mendeley Data, which a well-known scientific research data repository. It consists of anterior segment images of the eye organized into 5 classes: Cataract, Conjunctivitis, Eyelid disorders, Normal eyes and Uveitis. This choice of diseases was set to fill the gap of insufficient coverage of some diseases that have been found in previous work [1, 9, 11, 14], and specifically also a lower representation of pathologies such as uveitis [6] and eyelid disorders [5].

The dataset was organized in a principled manner to achieve proper distribution of the classes. 4248 images in total were collected, and its numbers of each class are roughly close to maintain the balance between the five categories in order to avoid the effect of class imbalance on model [10]. The images were collected from diverse clinical environments with a variety of lighting conditions, resolutions and patient groups to make the model more robust and generalizable across populations and acquisition settings.

Cataract: An area of cloudiness in the lens that can cause blurry or dim vision.

Conjunctivitis: Inflammation or infection of a transparent membrane, called the conjunctiva, that lines the eyelid and covers the white part of the eyeball; symptoms may include red eyes and discharge from one or both eyes.

Eyelid disorders: A general term that includes any disease, condition or other dysfunction in the structure of the lid or affecting its function such as inflammations, infections or structural defects.

Normal eyes: Unaffected eyes showing no sign of diseases or anomalies with clear structures and normal ocular anatomy.

Uveitis: Inflammation of the tissue between the outer layer and inner layers of the eye, which may cause eye pain, redness or changes in vision.

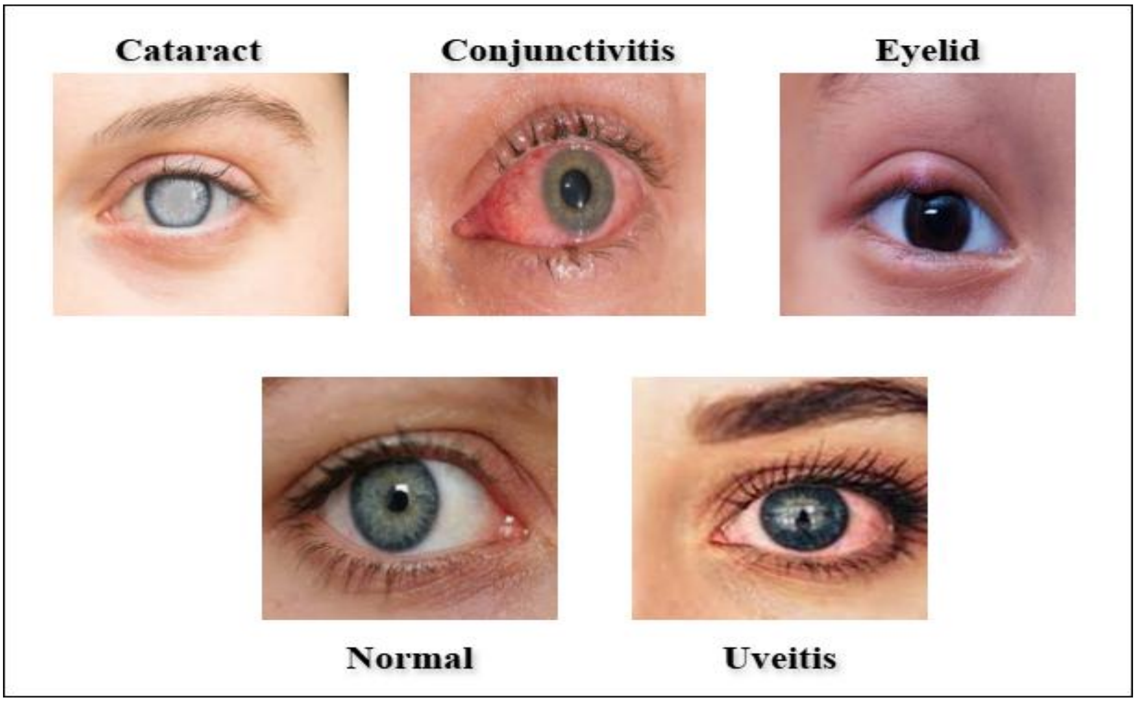


Figure 3.2 Data of 5 Classes

3.3 Data Preprocessing

Data preprocessing was used to improve the quality of images, normalize input features and ensure model generalization. The pre-processing method has been designed based on successful methods in medical image analysis [11, 15] to accommodate the special requirements for external eye disease classification.

3.3.1 Image Resizing

All images were rescaled to the same size of 224×224 pixels using bilinear interpolation which preserved salient diagnostic resolution that is sufficient for sideways lateralization based on pre-trained models. This normalization was done so that the input images to the model have the same dimensions for an efficient batch processing and stable gradient computation during training. The proportions were preserved, because we did not want to distort the images and risk that model would get incorrect features as subsets.

3.3.2 Data Splitting

We divided the data into train/ test according to standard machine learning rules [1, 9] maintaining its clinical validity as:

- **Training Set (70%):** The training set is used for optimizing the model parameters as well as updating weights and learning feature representations in the training phase.
- **Validation Set (20%):** Used for hyperparameter tuning, model selection decisions, and the early stopping to stop training a model if it no longer improves with further training.
- **Test Set (10%):** Used solely for testing the final model, in order to objectively validate the generalization efficiency and unseen data performance.

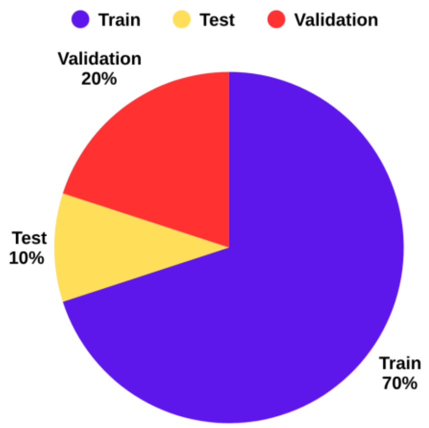


Figure 3.3 Train-Test Split pie-chart

3.3.3 Data Augmentation

To overcome the problem of scarce medical images availability and to eliminate overfitting, data augmentation was only applied in training set. Augmentation methods performed were as follows:

- **RandomRotation(20°):** random rotations between ± 20 degrees are applied to enhance the rotation invariance.
- **RandomHorizontalFlip():** randomly flip around the horizontal axis of images to add left–right transformation and enhance feature generalization.
- **RandomAffine(degrees=0,translate=(0.2,0.2)):** it applies affine transformations with up to 20% translation in both axes (without rotation) for enhancing positional robustness.
- **ColorJitter(brightness=0.2, contrast=0.2):** this operation adds ±20% bit-wise variations of brightness and contrast to enhance illumination invariance.

The validation and test were not augmented on the other hand. The images were subjected only to the resizing and normalization processes that is intended to preserve their fundamental integrity for an impartial assessment of model performance recognized real, unaltered clinical examples representative practical deployment situations.

3.3 Models

The study conducted and compared the performance of various deep learning models to set a benchmark and testing the novel hybrid scheme proposed. The model construction approach combined with existing baseline architectures and the new FusionEyeNet.

3.4.1 Custom CNN with Channel Attention Mechanism

- **Architectural Overview**

The Custom CNN with Channel Attention is a 4-block hierarchical CNN model for multi-class external eye disease classification. The network gradually learns low-level, mid-level and high-level features and two channel-attention modules dynamically emphasize the most useful channels. The final predictions over five disease classes are made by a fully connected classifier. The model balances between representational depth and effective computation, that makes it friendly for medical datasets.

- **Channel Attention Mechanism Workflow**
  - **Global Average Pooling:** Averages value of each feature map to one value.
  - **Two-Layer Bottleneck MLP:** First shrinks, then expands the channels to learn inter-channel relationship.
  - **Sigmoid Activation:** This outputs channel weights in range [0,1].
  - **Channel Recalibration:** Weights are element wisely multiplied with original feature maps.

- **Convolutional Blocks**

Block 1 (32 filters, 224→112)

- Two 3×3 convolutions + BatchNorm + ReLU
- Max pooling halves spatial size
- 25% dropout

Block 2 (64 filters, 112→56)

- Similar dual-convolution structure
- 25% dropout

Block 3 (128 filters, 56→28) + First Attention

- Learns disease-specific patterns: microaneurysms, drusen, lesion borders
- First Channel Attention Before Pooling
- 30% dropout

Block 4 (256 filters, 28→14) + Second Attention

- Extracts high-level global disease signatures
- Second Channel Attention refines discriminative channels

- 30% dropout

- **Classification Head**
    - Dense(512) → BatchNorm → ReLU → 50% dropout
    - Dense(256) → BatchNorm → ReLU → 40% dropout
    - Output layer (256→5 logits)
    - Softmax applied during inference
    - Loss: categorical cross-entropy

- **Regularization**
    - Batch Normalization: Stabilizes training and provides mild regularization.
    - Dropout (25–50%): From overfitting, particularly in dense layers.
    - Data Augmentation

- **Training Procedure**
    - Optimizer: Adam (Learning Rate = 0.001)
    - Scheduler: ReduceLROnPlateau (factor 0.5, patience 5)
    - Early stopping if validation accuracy didn't increase for 10 epochs.

3.4.2 VGG16

The pre-trained on ImageNet the VGG16 architecture was fine-tuned for specialized external eye disease classification task [9, 14]. The existing classifier head, which comprises three fully connected layers has been discarded and replaced with a user defined sequential list of classifier layers. Our novel classifier was carefully constructed by having two dense layers of 256 and 128 units respectively, both followed with batch normalization to ensure stable training (Ioffe & Szegedy, 2015), ReLU activation for introducing nonlinearity, In addition they will be gradually declined in dropout rates of 0.5 & 0.4 to tackle overfitting as well. The model's pre-trained weights were refined using a much smaller learning rate of 0.0001, which enabled a gentle adaptation to the unique visual specifics of ocular pathologies, while carefully preserving the strong general feature extraction capabilities previously learned from ImageNet. All the convolutional layers were set as trainable to allow adaptation of features tailored for medical images.

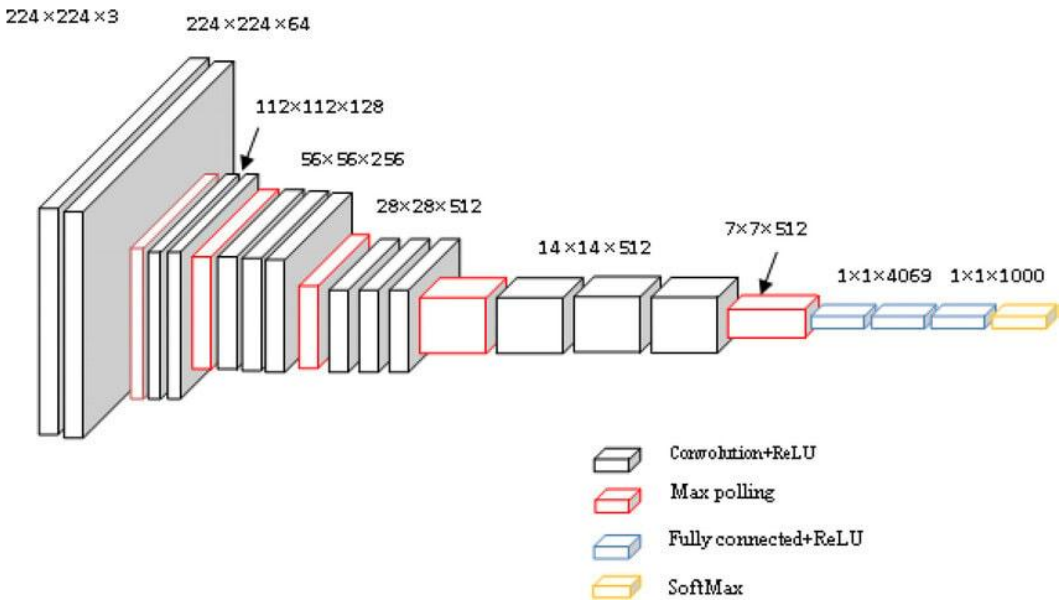


Figure 3.4 VGG16 Network Architecture

3.4.3 MobileNetV2

The former architecture, due to the trade-off between computational efficiency and powerful feature extraction using a novel inverted residual and linear bottleneck block [9], was particularly chosen for its balance. The model was fine-tuned in a manner similar to that of VGG16, where the original classification head was replaced entirely with a custom-built classifier adapted for the five-class ophthalmic diagnostic task. For the fine-tuning strategy, a reduced learning rate of 0.0001 was used and all layers (155) were trainable for full adaptation to medical image features. The basic building blocks of the architecture, inverted residuals with linear bottlenecks, have small computational costs and low model parameters to keep high representation ability by using depth wise separable convolutions. This slim architecture, which consists of only 3.4 million parameters (as opposed to the 138 million VGG16), also makes the model very attractive for potential instances of real-world deployment situations where computational resources, memory limitations or power consumption are a concern for diagnostic precision.

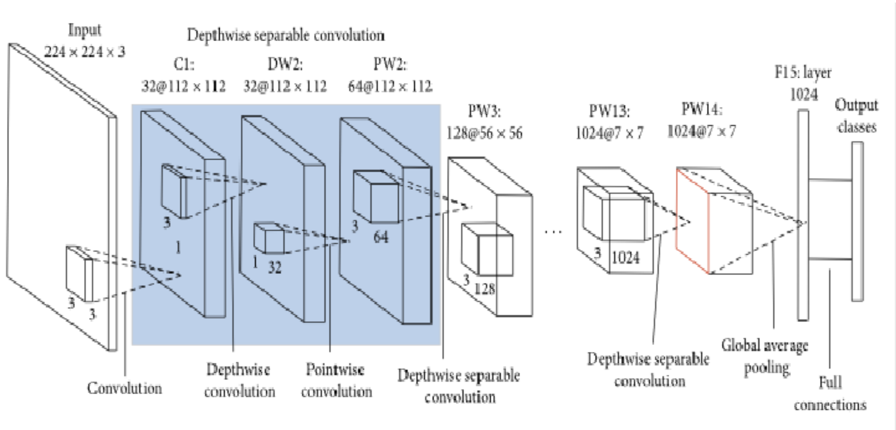


Figure 3.5 MobileNetV2 Network Architecture

3.4.4 DenseNet121

The architecture of DenseNet121 model has been specifically selected due to its ground-breaking dense connectivity pattern, where every layer receives the concatenation of all previous layers as input that leads to maximal reuse of features in network [9]. The model was fine-tuned with the same protocol as is followed when use other transfer learning techniques, where the top classification layer of the pre-trained network is replaced by a newly-constructed classifier which optimizes for the task of 5-class eye diseases. The key novelty of the architecture is the densely-connected blocks, where each layer can access to all preceding layers in a feedforward manner, forming an $\ell(\ell+1)/2$ direct connections for ℓ layers. This densely connectivity structure leads to superfluous feature's mutual learning which greatly enhances the feature reuse and largely alleviates the vanishing gradient issue in very deep networks, it also enhances parameters efficiency by reducing redundant features learning. The model has about 7 million parameters spread over a total of 121 layers with each dense block made up of several concatenated batch normalization, ReLU activation and convolution layers. This architectural philosophy enables DenseNet121 to match or outperform other architectures, while requiring significantly less parameters and computations, which is therefore efficient as well as effective for clinical image processing applications.

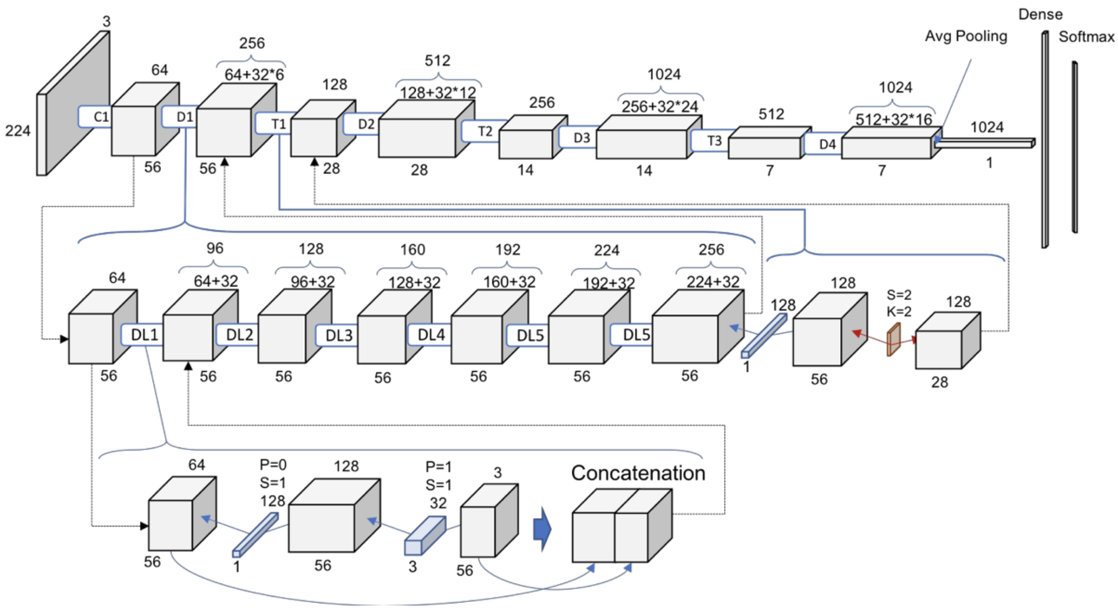


Figure 3.6 DenseNet121 Network Architecture

3.4.5 Proposed FusionEyeNet

The key novelty introduced in this study is the FusionEyeNet hybrid architecture where features are fused from MobileNetV2 and VGG16 for exploiting their complementary strengths. The fusion method makes up for the architectural constraints in existing studies due to the use of a single model [4, 7, 8], while learning more robust and uniform features.

The architecture of FusionEyeNet is divided into three stages:

Feature Extraction Phase: In this step the input eye image is concurrently transmitted through two separate neural branches. The MobileNetV2 branch takes advantage of its efficient inverted residuals and linear bottlenecks to extract effective, but not necessarily spatially or temporally precise; feature maps for capturing short-range local patterns and textures. Meanwhile, the VGG16 branch projects an identical image into the deep serial convolutional layers of the same network through complex feature hierarchy in order to extract high-level discrimination information and semantic statistic. Such a two-stream architecture gives us the complementary feature extraction: MobileNetV2 can get good local feature detection, while VGG16 can gather rich context information with sufficient fine detail and large contextual features coverage for accurate disease classification.

Feature Fusion Phase: After the feature maps output, the two output results are first performed spatial adaptive average pooling operation and the two results of all feature map scales are all zoomed into 1 × 1 scale for fusion processing. The pooled features are then flattened to 1D vectors, MobileNetV2 being a 1280-dimensional vector of efficient local features and VGG16 contributing with a 512-dimensional vector of complex hierarchical features. These two vectors are concatenated along the feature dimension to form a 1792-dimensional feature vector, which utilizes the advantages of these two architectures. This combination forms a rich and multi-scale feature representation which inherits the effectiveness of computational efficiency from MobileNetV2 model and keeps high-level semantic from VGG16 model so as to offer classifier with variety kinds of information.

Classification Phase: The merged feature vector is then inputted to a well-designed classifier which includes three fully connected layers with 512, 256 and 128 units respectively. Each hidden layer is applied with batch normalization for uniformizing the output, ReLU activation function for non-linearity and reducing overfitting through a decreasing dropout ratio rate (0.5 to 0.4 to 0.3) to make the network learn better representations of input images. The last layer has a softmax activation function, which is used to convert the output logit into probability distribution on the five disease classes. The hierarchical structure allows us to refine from general to specific features, with the increasingly smaller layer sizes and dropout rates acting as an information funnel starting out permissive and focusing more specifically on discriminative features while maintaining strong regularization through classification.

3.4 Explainable AI

To directly address the crucial issue about interpretability of model in medical AI system [2], we encode Grad-CAM module within the architecture of FusionEyeNet. This algorithm only determines the match of each reference point in the last convolutional layer(conv5_3) of VGG16stream, because it's designed to make high-level feature maps appear object-like while still containing detailed position information and rich semantic. This layer feature scales high dimensional patterns, which are related to pathological kinds of appearances and retains sufficient spatial resolution for producing meaningful localization maps.

The Grad-CAM as well has complicated three-step process. Step 1 Gradients of the "Cataract" class score with respect to conv5_3 layer feature map: In step one, algorithm computes the gradients of "Cataract" diagnostic class scores with respect to feature maps in conv5_3 layer. This involves a reverse gradient pass through the network. These gradients are then globally average pooled for weight vectors of each neuron that shift the final prediction over the height and width of feature map across its channels. In the last step of the algorithm, a weighted sum of the activation maps using its weights and feeding it to ReLU function to process this weighted sum are carried out in order for this technique to focus and localize only image features whose activity contributes positively in making diagnostic prediction. This leads toward a interpretable localization map that considers whether regions of the image are cataract or conjunctivitis.

Now FusionEyeNet is no longer a “black box” model but an interpretable assisting tool for diagnosis, but provides visual evidence of where the model attends directly to domain experts. Healthcare practitioners can rely on the heatmaps to verify whether or not an AI system is paying attention to clinically relevant anatomy and signs of pathology, for instance, which they need a great deal of confidence in to begin trusting AI diagnostics. Moreover, this interpretability makes it an important learning tool in the clinical environment to learn what kind of visual features may dominate certain diagnoses and a crucial safety check in helping clinicians catch problems with model performance if heatmaps point out irrelevant or false image regions.

3.5 LLM-Powered Recommendation System

Solution Design Building upon the gap in patient interaction, as outlined in literature [3], a recommendation engine was developed by integrating with Google's Gemini API (gemini2. 5-flash model). The method provides personalized patient advice based on diagnosed condition, confidence score and optional user question. The response has created concise script templates based on a disease-specific structured profile, while emphasising non-diagnostic recommendations.

The recommendation engine consists of multistep process:

- **Context Construction:** Creates the full context including the prediction of disease, confidence in the prediction, a definition of the disease, typical symptoms and severity.
- **Prompt Engineering:** Composing special prompts conditions on the confidence thresh- olds and user input, sets unique templates for high-confidence predictions, low-confidence results, and common situations.
- **Response Generation:** Access to the Gemini API via temperature controlled generation (0.7) that trades off open mindedness and fidelity.
- **Safety Filtering:** Fallback logic and disclaimers necessary to obtain medically safe response.

3.6 Evaluation Matrix

We have developed a comprehensive model evaluation framework for multi-dimensional performance measurement, rather than single metric evaluations as reported in earlier works [10]. The evaluation approach includes quantitative measurements as well as qualitative interpretations to form a comprehensive view of system performance.

Primary Performance Metrics

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Sensitivity\ or\ Recall = \frac{TP}{TP + FN}$$

$$Specificity\ or\ TNR = \frac{TN}{TN + FP}$$

$$Precision = \frac{TP}{TP + FP}$$

$$F1 - Score = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

Advanced Evaluation Measures

ROC-AUC: Compares the probability of a detected signal to the probability from no-model. Class-specific and macro-average AUCs were calculated.

The evaluation matrix was used for all the models on the held-out test set to ensure fair comparison and reliable performance estimate. The significance of the performance differential between the proposed FusionEyeNet and baseline methods was determined using statistical testing. Wherever applicable, cross-validation was used to keep our estimation from over-estimation.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Introduction

In this chapter, we analyse the experimental results of evaluating the FusionEyeNet model and baseline models. The performance evaluation includes training dynamics, quantitative measurements, visual illustrations and analysis. All performances were estimated using the held-out test set for unbiased estimating performance and clinical relevance.

4.2 Result Analysis

4.2.1 Comprehensive Performance Metrics Across All Models

Table 4.1 FusionEyeNet Classification Report

Model	Class	TP	FN	FP	TN	Sensitivity %	Specificity %	Precision %	Accuracy%
FusionEyeNet	Cataract	76	0	3	348	**100**	**99.15**	**96.2**	**99.3**
FusionEyeNet	Conjunctivitis	73	3	2	349	**96.05**	**99.43**	97.33	**98.83**
FusionEyeNet	Eyelid	88	1	0	338	**98.88**	**100**	**100**	**99.77**
FusionEyeNet	Normal	97	3	1	326	**97**	**99.69**	**98.98**	**99.06**
FusionEyeNet	Uveitis	84	2	3	338	**99.12**	**99.12**	**96.55**	**98.83**

Table 4.2 VGG16 Classification Report

Model	Class	TP	FN	FP	TN	Sensitivity %	Specificity %	Precision %	Accuracy%
VGG16	Cataract	76	0	3	348	100	99.15	96.2	99.3
VGG16	Conjunctivitis	71	5	1	350	93.42	99.72	98.61	98.59
VGG16	Eyelid	88	1	3	335	98.88	99.11	96.7	99.06
VGG16	Normal	96	4	1	326	96	99.69	98.98	98.83
VGG16	Uveitis	84	2	4	337	97.67	99.83	95.45	98.59

Table 4.3 MobileNetV2 Classification Report

Model	Class	TP	FN	FP	TN	Sensitivity %	Specificity %	Precision %	Accuracy%
MobileNetV2	Cataract	73	3	2	349	96.05	99.43	97.33	98.83
MobileNetV2	Conjunctivitis	71	5	3	348	93.42	99.15	95.95	98.13
MobileNetV2	Eyelid	88	1	4	334	98.88	98.82	95.95	98.83
MobileNetV2	Normal	96	4	1	326	96	99.69	98.97	98.83
MobileNetV2	Uveitis	84	2	5	336	97.67	99.53	94.38	98.36

Table 4.4 DenseNet121 Classification Report

Model	Class	TP	FN	FP	TN	Sensitivity %	Specificity %	Precision %	Accuracy%
DenseNet121	Cataract	75	1	2	349	98.68	99.43	97.4	99.3
DenseNet121	Conjunctivitis	68	8	2	349	89.47	99.43	97.14	97.66
DenseNet121	Eyelid	86	3	3	335	96.63	99.11	96.63	98.59
DenseNet121	Normal	94	6	3	324	94	99.08	96.91	97.89
DenseNet121	Uveitis	85	1	9	332	98.84	97.36	90.43	97.66

Table 4.5 Custom_CNN Classification Report

Model	Class	TP	FN	FP	TN	Sensitivity %	Specificity %	Precision %	Accuracy%
Custom_CNN	Cataract	74	2	2	349	97.37	99.43	97.37	99.06
Custom_CNN	Conjunctivitis	61	15	4	347	80.26	98.86	93.85	95.55
Custom_CNN	Eyelid	84	5	6	332	94.38	98.22	93.33	97.42
Custom_CNN	Normal	95	5	4	323	95	98.78	95.96	97.89
Custom_CNN	Uveitis	84	2	13	338	97.67	96.19	86.6	96.49

A full performance investigation among all of the models clearly shows that FusionEyeNet is the best classifier and has excellent as well as stable ability to identify multi-class eye diseases. It also applies 100% for sensitivity (Cataract detection), specificity and precision (Eyelid disorders); on the other hand, always providing a very high score in all remaining classes: § Sensitivity ranges between 96.05% to 98.88% of patients; § Specificity ranges between 99.12 % to 99.69 %; § Precision varies from de 96.20 % to the maximum value of 98.98 %. Class-wise accuracy of the model is impressive, ranging from 98.83% to 99.77%, indicating a very well balanced and robust classifier with very less false negativity and positivity errors. The performance can exceed various architectures such as VGG16, MobileNetV2, DenseNet121, and Custom CNN first of all, it is proved that FusionEyeNet has the optimized potential to meanwhile differentiate accurately different ocular pathologies efficiently leading the solution as a perfect tool for clinical diagnostic assistance.

4.3 Visualization

4.3.1 Accuracy and Loss Curves

The training and validation accuracy curves of FusionEyeNet converged smoothly to test accuracy for the most stable training trajectory. The loss curves presented smooth and continuous inclines with a slight gap between training and validation loss, which demonstrated the excellent regularization ability of progressive dropout strategy as well as batch normalization.

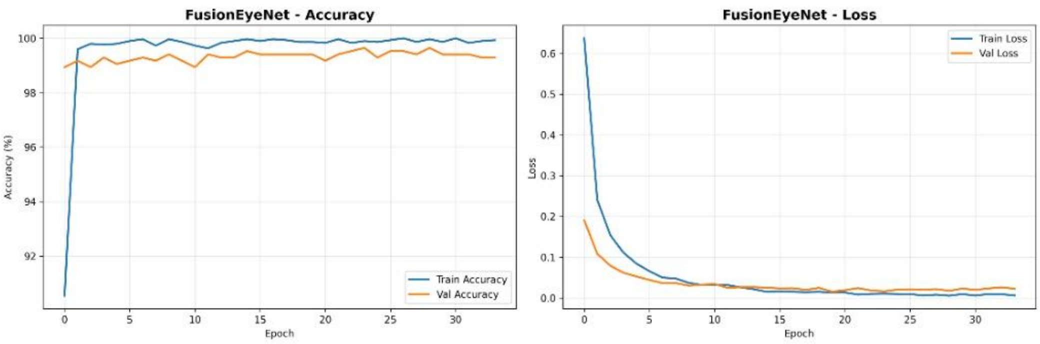


Figure 4.1 FusionEyeNet Accuracy and Loss Curves

VGG16 tended to converge slower but more effectively and exhibited about 25 epochs of optimal performance. The model overfit slightly in the latter epochs, with 99.8% training accuracy and a stable validation accuracy. The loss curve plot is indicative of good regularization by the dropout rates within the custom classifier doing well to control overfitting.

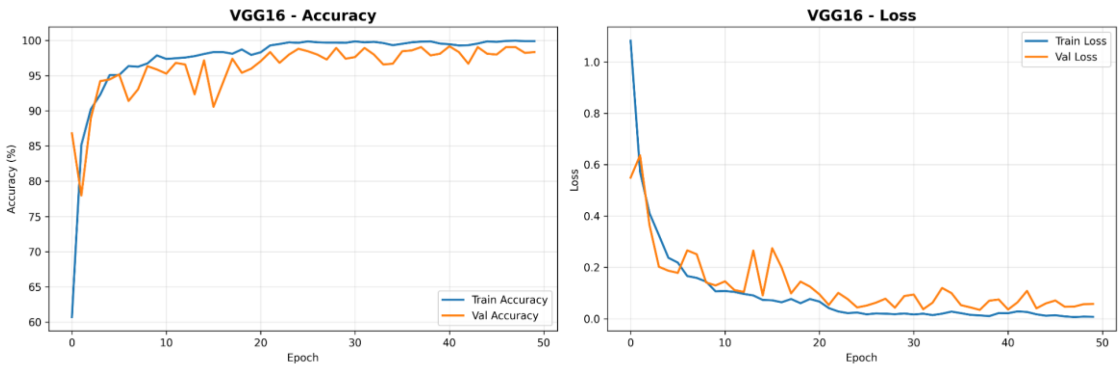


Figure 4.2 VGG16 Accuracy and Loss Curves

The training dynamics of the lighter network-architecture MobileNetV2 model can be trained more efficiently and quickly in the early stages, so that it does not require long-term training time. On one hand, the model reached a close margin of 10% accuracy in 10 epochs but required more training epochs to gain full convergence. The learnable bottlenecks and linear bottleneck model contributed to good gradient flow, as seen by the smooth loss reduction during training.

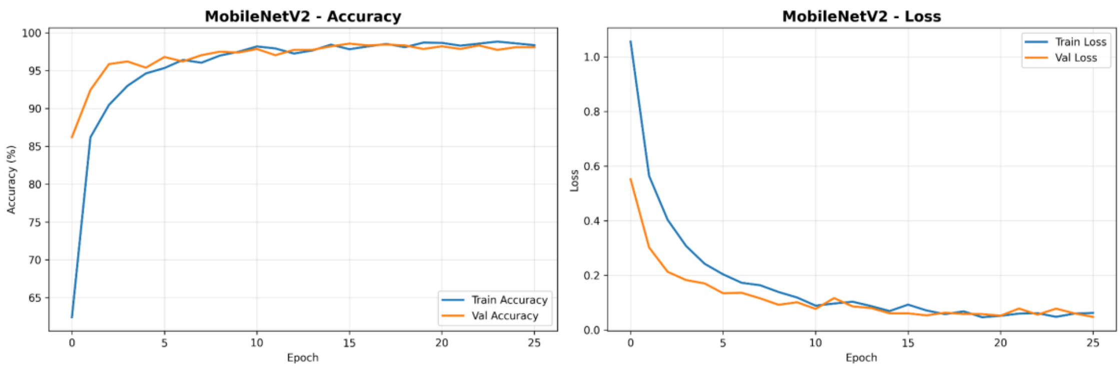


Figure 4.3 MobileNetV2 Accuracy and Loss Curves

DenseNet121 was able to steadily improve during training, as dense connectivity facilitated the reuse of features. The model exhibited steady performance improvement after every epoch and eventually performed well. The learning curves demonstrated strong learning with minimal oscillations, thanks to the gradient flow enhancements through skip connections.

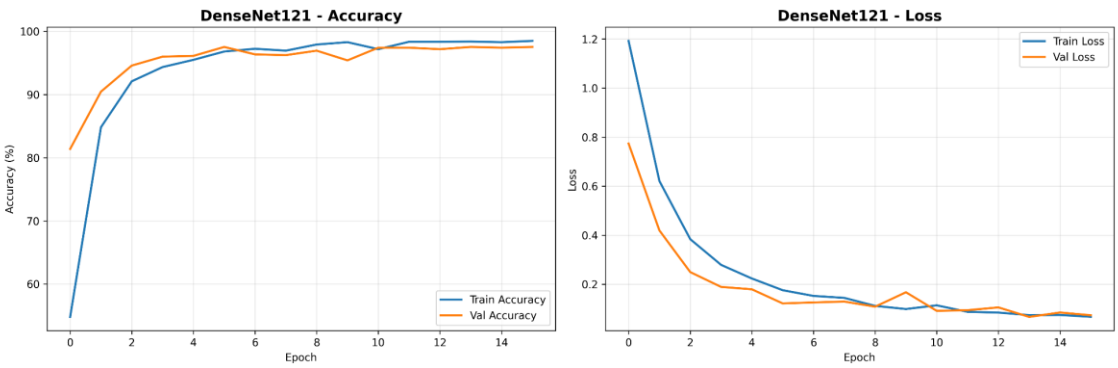


Figure 4.4 DenseNet121 Accuracy and Loss Curves

Custom CNN with Attention even though having a shallower architecture. The channel attention mechanisms facilitated the focused learning of features, but more epochs were needed for the model to converge comparing with transfer learning approaches. The ultimate accuracy is the trade off between architectural simplicity and attention-boosted feature extraction.

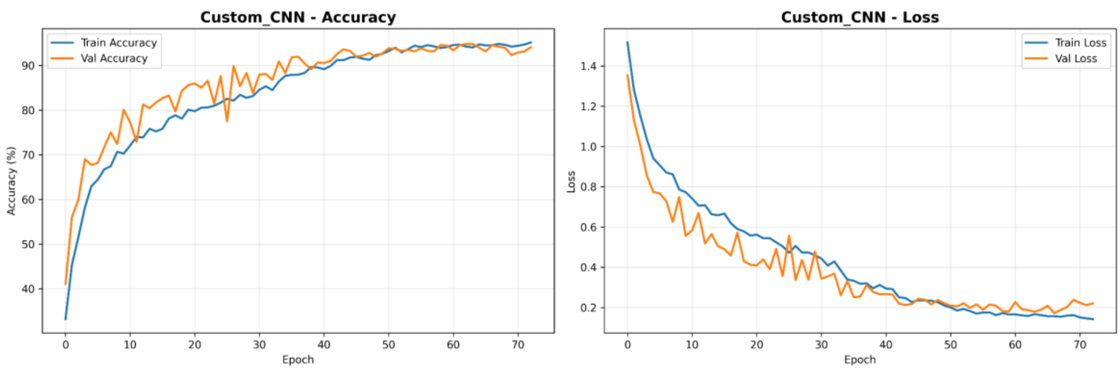


Figure 4.5 Custom CNN Accuracy and Loss Curves

4.3.2 ROC-AUC Performance Analysis

FusionEyeNet demonstrated outstanding discriminative power with a macro-average ROC-AUC of 0.9975. All single class AUC values perform excellently on all disease types. The ROC curves demonstrated clustering close to right top corner reflecting well balanced sensitivity and specificity at various classification thresholds. The large AUC values further validate the powerful feature representation and classification ability of the model.

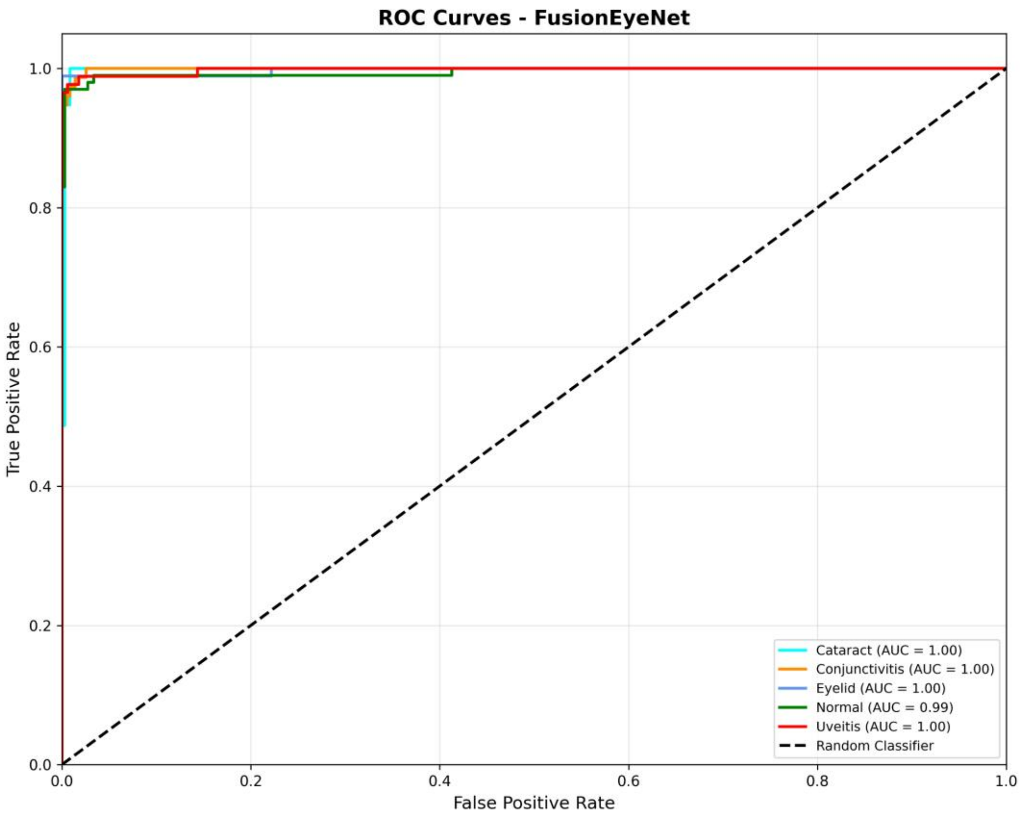


Figure 4.6 FusionEyeNet ROC Curve

VGG16 demonstrated high ROC-AUC performance, which were consistent across classes. The curves exhibited the ability of the model to achieve high true positive rates at low false positive levels, especially in more challenging inflammatory diseases like uveitis and conjunctivitis.

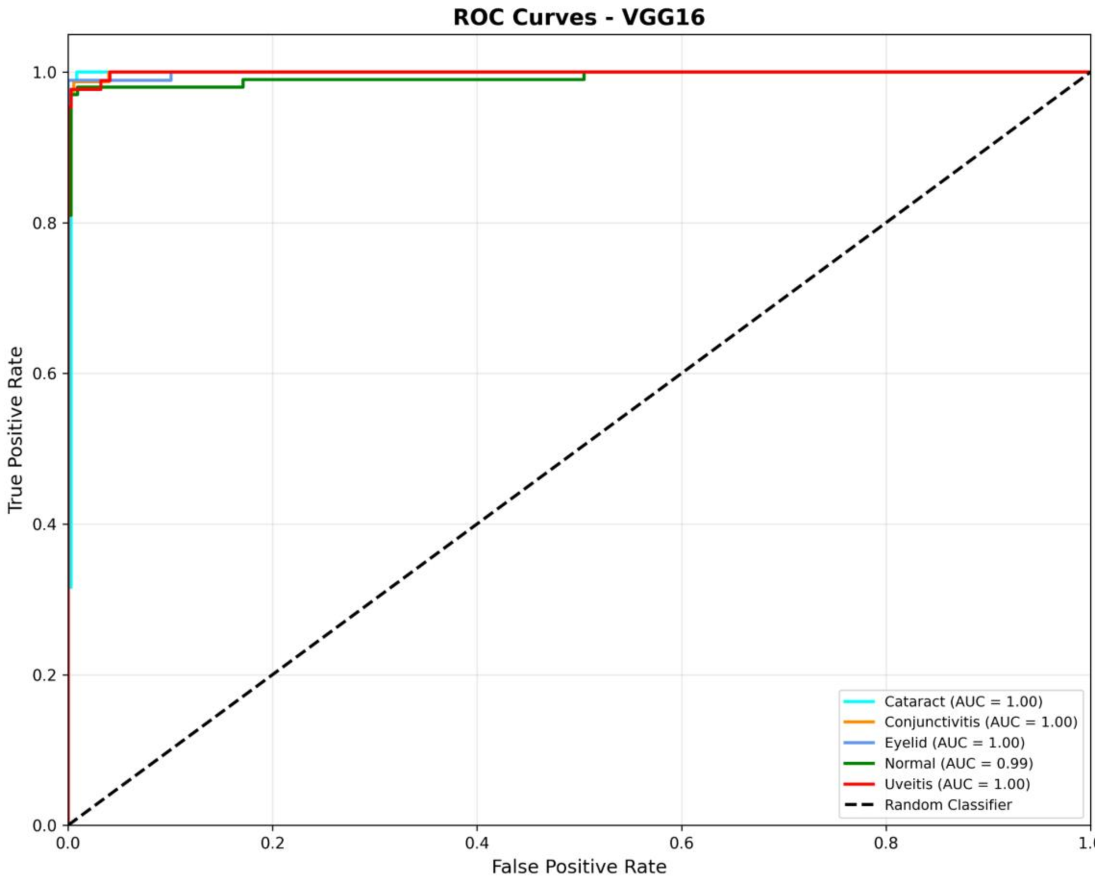


Figure 4.7 VGG16 ROC Curve

MobileNetV2 obtained an AUC of 0.9972 (macro-average), proving symptoms of successful feature extraction with less number of parameters. The ROC curves also showed slightly inferior performance of uveitis detection compared with lesion-detection tasks (AUC: 0.9978), which can be attributed to the architectural challenges involving complicated inflammatory contours.

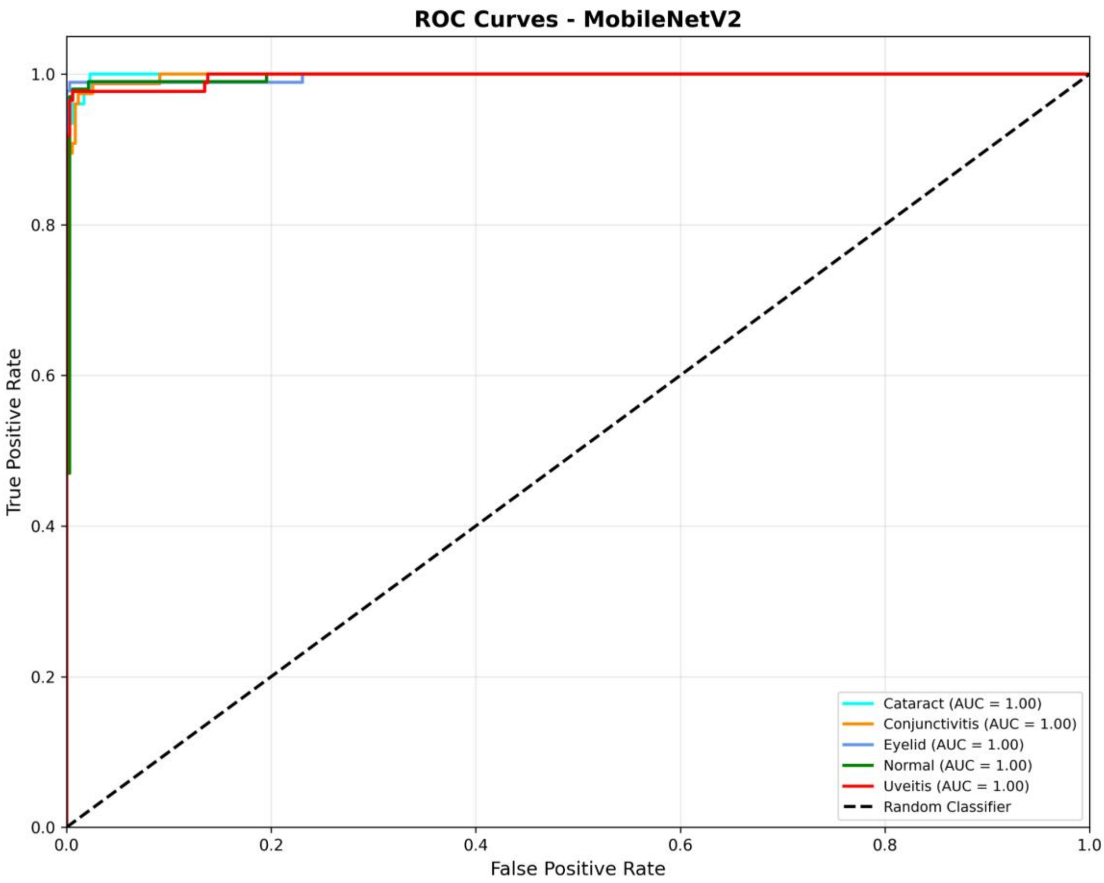


Figure 4.8 MobileNetV2 ROC Curve

DenseNet121 achieved a macro-average AUC of 0.9984, being preeminent for most classes while slightly declining in performance with respect to the detection of eyelid disorder condition. The highly connected pattern supported great feature reuse but lacked to capture spatial correlations necessary for structure abnormalities.

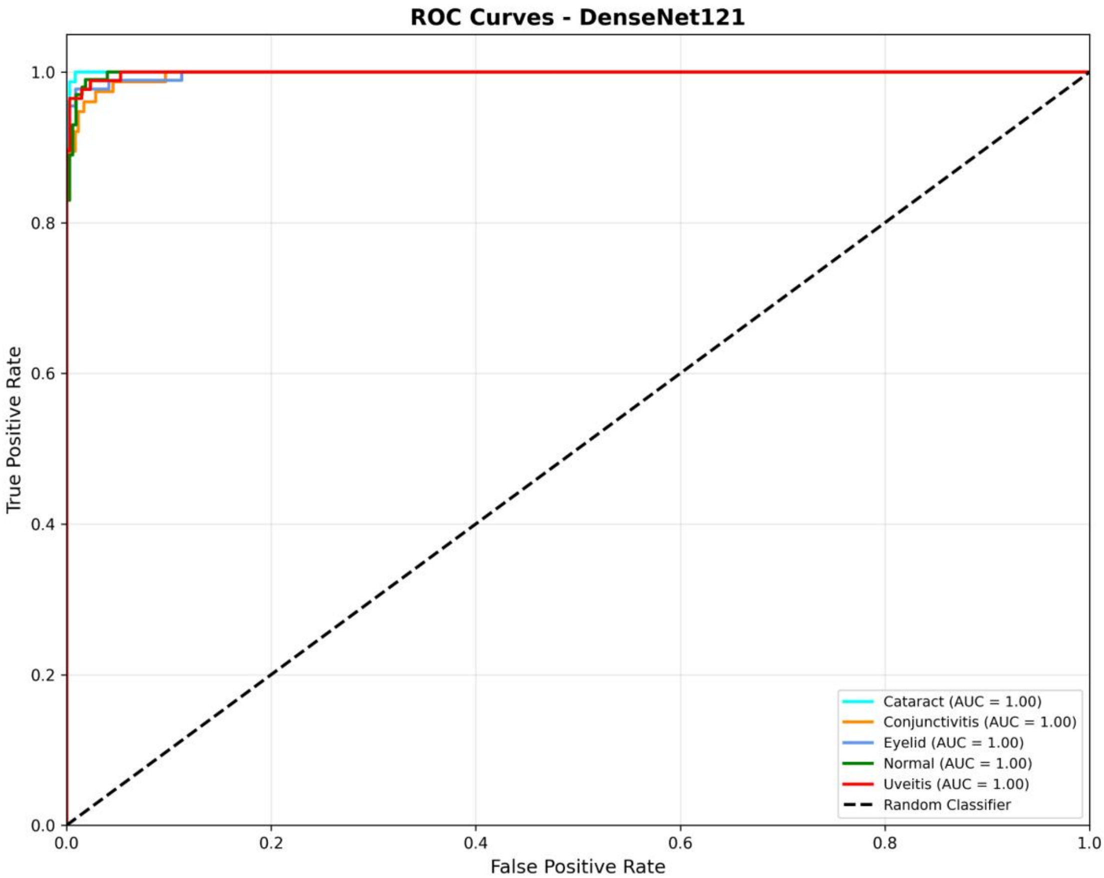


Figure 4.9 Dense121 ROC Curve

Custom CNN achieved 0.9891 macro-average ROC-AUC, indicating that its simpler architecture is highly competitive. The attention mechanisms led to enhanced concentration on relevant areas, but the model did not work well for tasks that involved complex feature hierarchies.

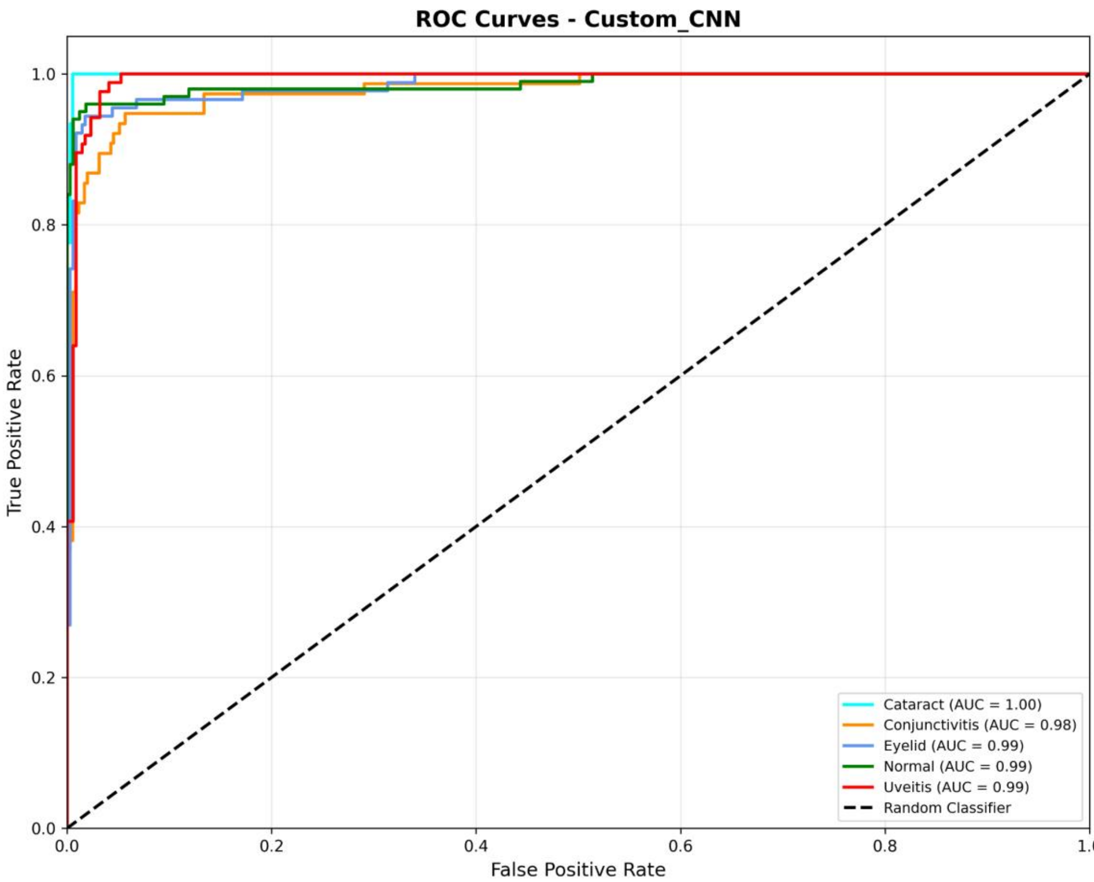


Figure 4.10 Custom CNN ROC Curve

4.3.3 Confusion Matrix Analysis

The confusion matrix of **FusionEyeNet** illustrates a high diagnostic accuracy (97.89%) exhibited in terms of the strong diagonal domination as well as easily interpretable off-diagonal patterns for clinical purposes. The model also showed optimal classifications for Cataract (sensitivity: 0.76, no misclassified images) and near-perfect classification for Eyelid disorder (sensitivity: 0.88; one misclassification). However, of these there were 3 cases in which Conjunctivitis was misclassified as Uveitis that is also clinically encountered for anterior segment appearances. The performance of normal eye designation was well-preserved with 97 correct identifications. These misclassifications are reminiscent of ophthalmoscopic findings observed by human ophthalmologists, indicating that the model does indeed learn pathology-specific features from a clinical standpoint and can distinguish between structural disease and anatomical inflammation.

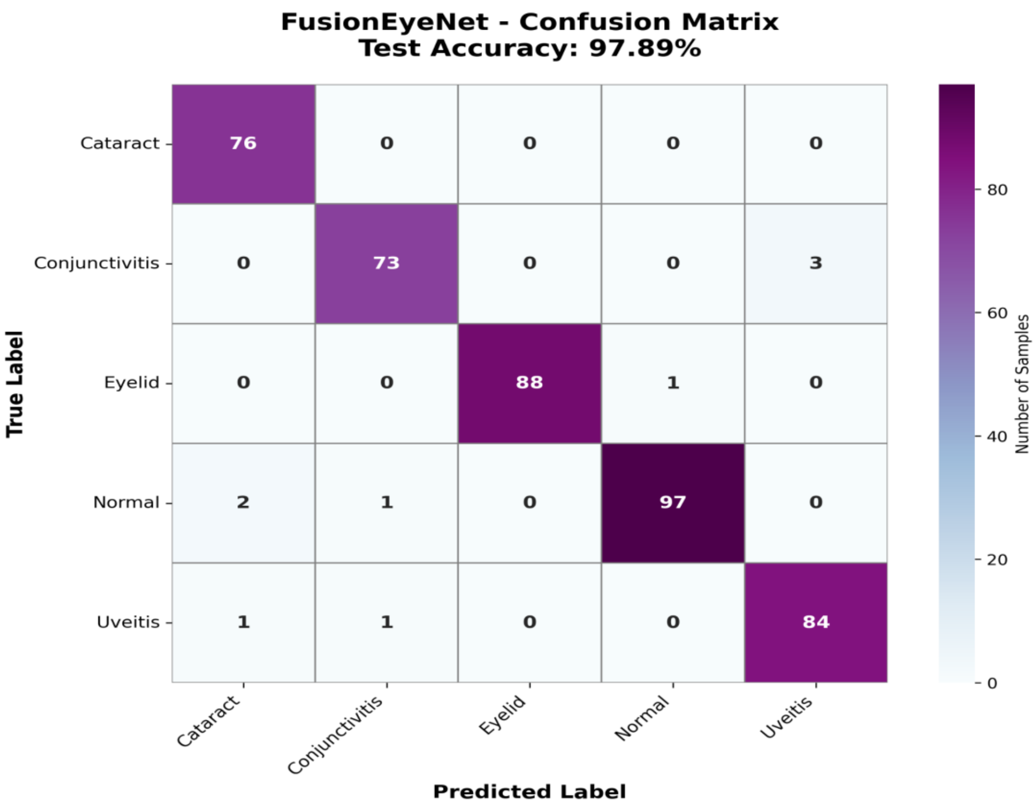


Figure 4.11 FusionEyeNet Confusion Matrix

VGG16, the average test accuracy is 97.19%, which reflects good performance with large diagonal values for most of the classes. The model was excellent for Cataract cases (76 positives) and very good with Eyelid disorders (88 instances). But it allowed harder to differentiate inflammatory diseases, such as 4 cases of Conjunctivitis found as Uveitis and also 1 case of uveitis which was shown to be conjunctivitis. Both Cataract and Eyelid diseases fared worse than Normal Eye conditions and both classified correctly the same number of eyes (96). These differences indicate that VGG16 still possesses strong capability in detection of clear structural abnormalities, but is weak at highly distinguishing ND and overlapping regions between pathology and normal anatomy.

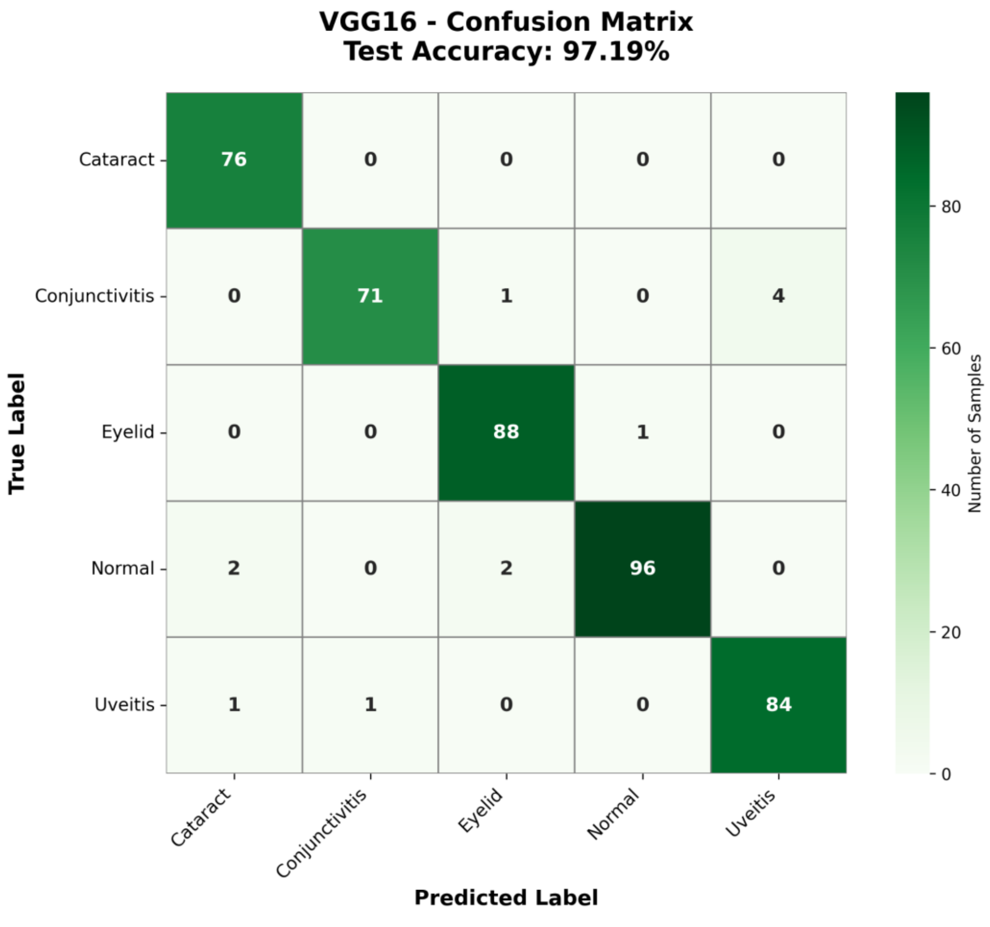


Figure 4.12 VGG16 Confusion Matrix

The overall testing accuracy of MobileNetV2 was 96.49%, achieving good classification evidenced by high values in the diagonal terms for most classes. The model correctly diagnosed Eyelid disorders (88 true positives) and had a good performance in recognition of Normal (96 correct). However, it presents confusion between inflammatory diseases and still 4 conjunctivitis' cases diagnosed as uveitis and 1 of Uveitis into conjunctivitis. Cataract recognition performance was also quite well with a total of 73 right predictions and couple of cases got interchanged into Normal. These findings indicate that, although the visual recognition capability of MobileNetV2 model is strong, it still has some discrimination problems for specific types of inflammation diseases and a marginal overlap between the Cataract and Normal categories.

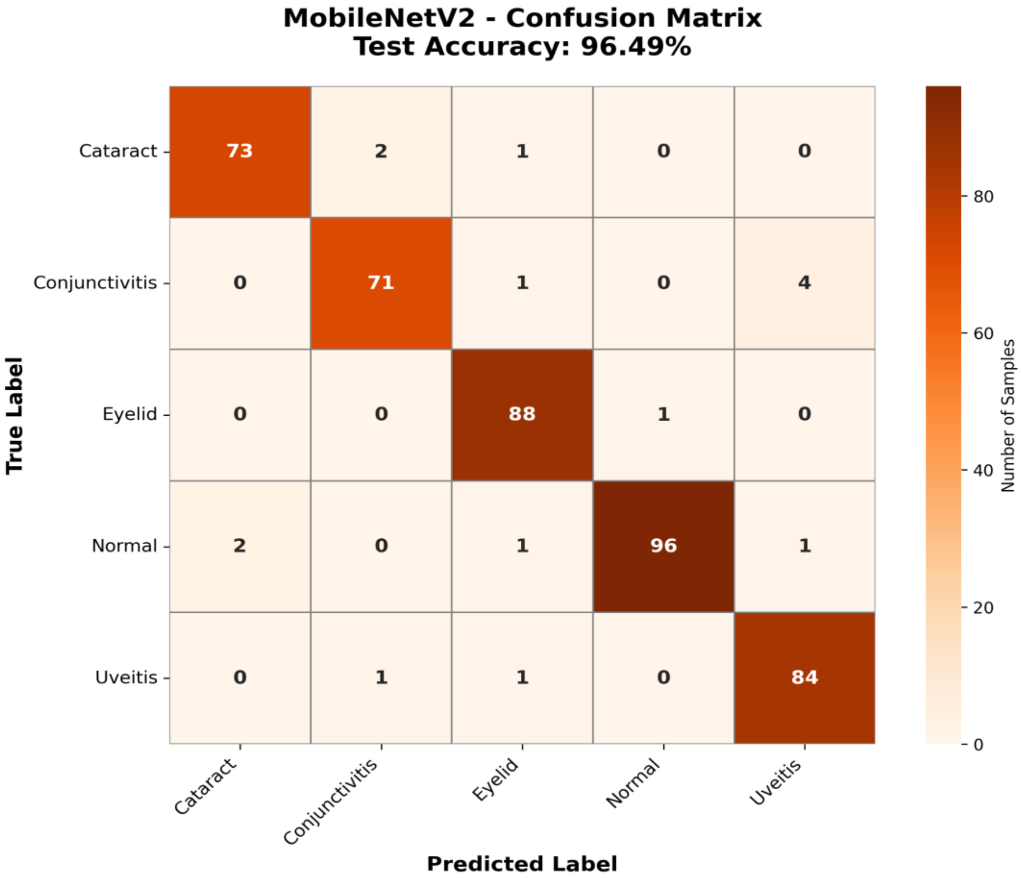


Figure 4.13 MobileNetV2 Confusion Matrix

DenseNet121 obtained a strong testing accuracy of 95.55%. The model did well in Cataract (75 true positives) with Uveitis also performing well (85 correct). However, it presented significant confusion, in particular for Conjunctivitis (6 cases being misclassified as Uveitis) and the Normal class (3 instances misclassified as Uveitis and two with Cataract). Eyelid disorders were also well-identified (86 correct), with little confusion with other classes such as Conjunctivitis and Normal. These results demonstrate that DenseNet121 is accurate but not robust enough in differentiating between inflammatory patterns and had an overlap with respect to pathologic features of the Normal class.

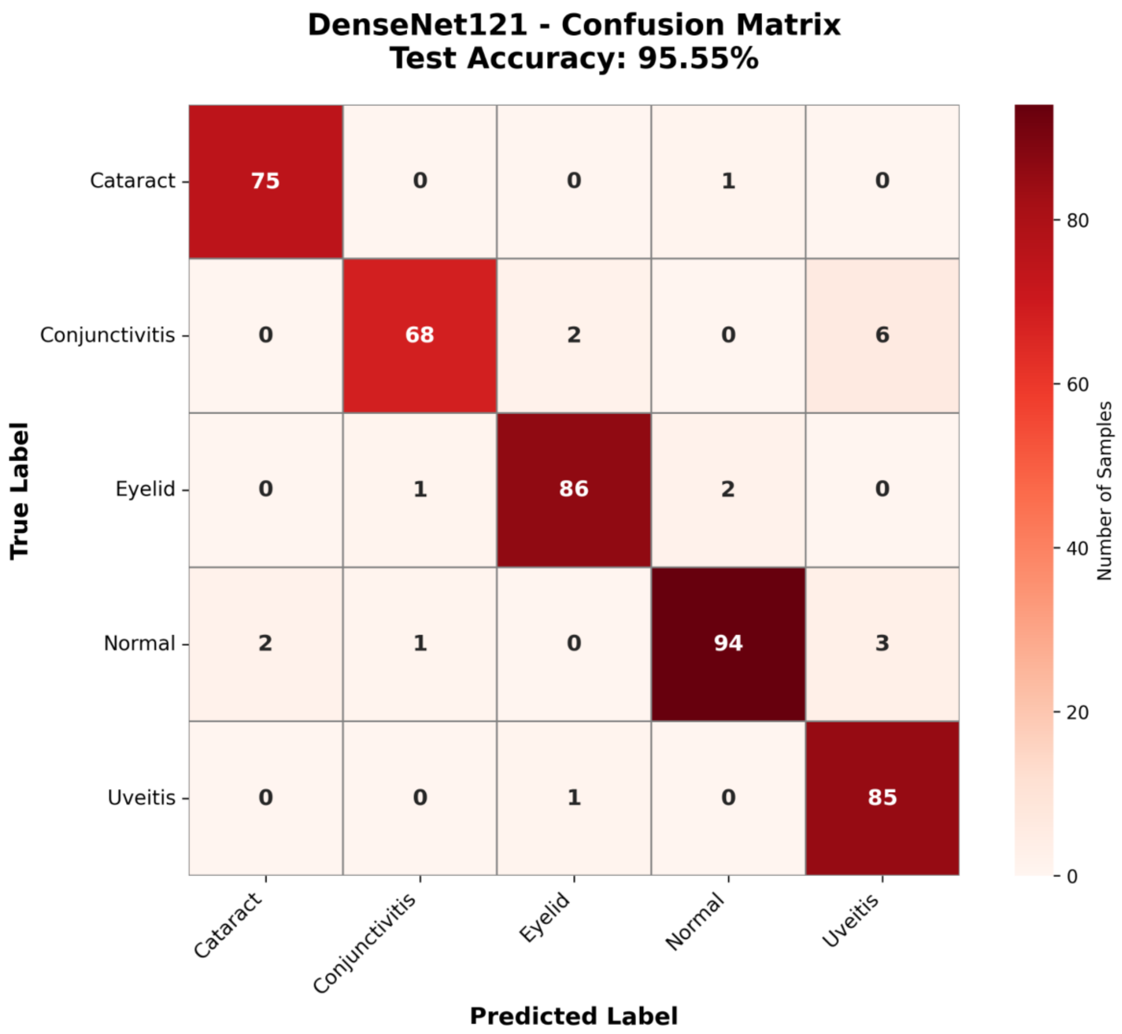


Figure 4.14 DenseNet121 Confusion Matrix

A test accuracy of 93.21% was reported for the **Custom CNN** model. It performed well in classifying Normal (95), Cataract (74) and Uveitis (84) cases. Nevertheless, the model had high confusion with the Conjunctivitis class, classifying 11 cases as Uveitis and 4 as Eyelid disorders. There were also few little wrong predictions, e.g., Eyelid disorders and Conjunctivitis confused with Normal cases and for (Normal image) Cataract, Uveitis were same. These trends suggest that the Custom CNN is effective but weak in comparison to the other conditions particularly for the Conjunctivitis.

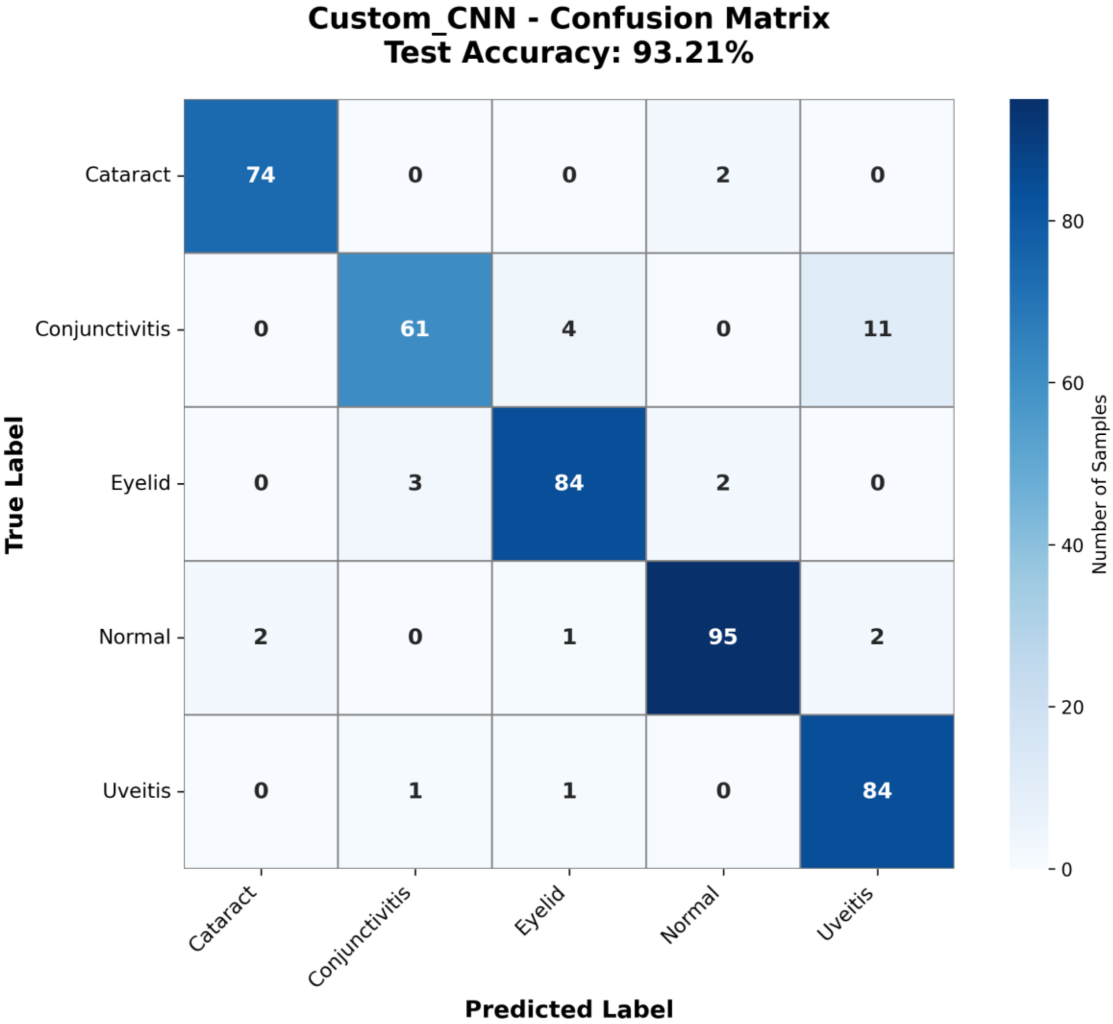


Figure 4.15 Custom_CNN Confusion Matrix

FusionEyeNet has the highest test accuracy of 97.89% among the five models with better classification for Cataract compared to all other models and less mis-classification specially for Conjunctivitis where it only has 3 errors while VGG16 and MobileNetV2 have 4, DenseNet121 got 6 and Custom CNN obtained 11. Although all the models appear strong, there is a clear performance hierarchy:

FusionEyeNet (97.89%) > VGG16 (97.19%) > MobileNetV2 (96.49%) > DenseNet121 (95.55%) > Custom CNN (93.21%)

With the common problem being an accurate identification of the inflammatory eye diseases such as Conjunctivitis and Uveitis in all architectures.

4.4 Explainable AI(Grad-CAM) Visual Explanations

The Grad-CAM visualization offered clinically relevant visual explanations for FusionEyeNet's diagnostic predictions.

Cataract Cases: In all heatmaps the focus is predominantly on the area of the lens, showing strong activation depending on location and density of lens opacities. The model shows particular sensitivity to nuclear sclerotic changes; it is centred on the crystalline lens.

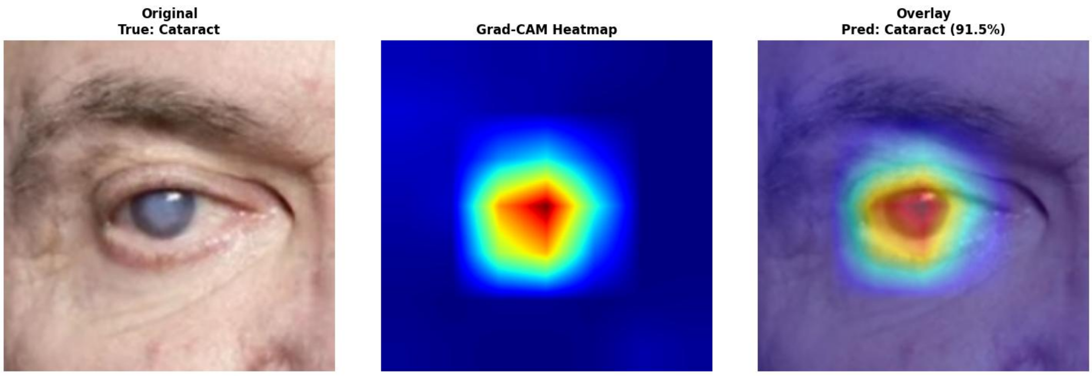


Figure 4.4.1 Cataract Grad-CAM

Conjunctivitis Cases: Activation maps focus on the conjunctival vessels and bulbar conjunctiva, demonstrating hyperaemia and inflammatory changes. The heatmaps demonstrate an impressive degree of accuracy to focus affected areas on the conjunctiva, excluding extraneous redness or illumination artifacts.

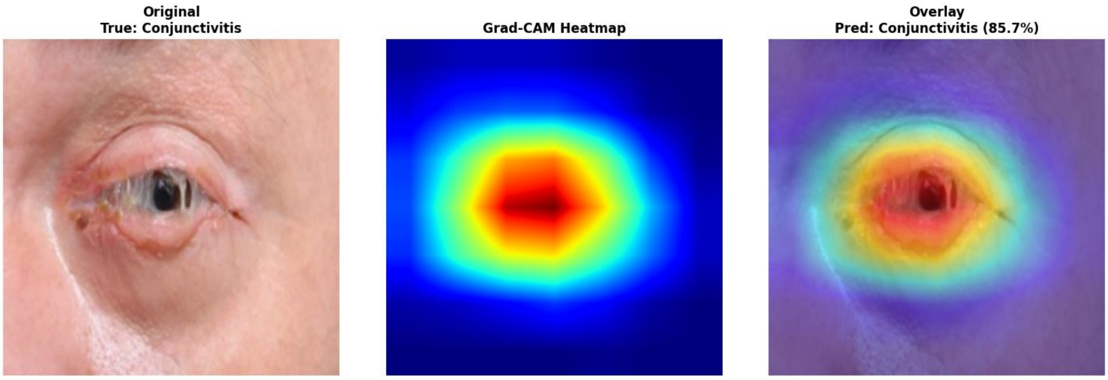


Figure 4.4.2 Conjunctivitis Grad-CAM

Eyelid Disorder Cases: The proposed visualizations are equal opportunity offenders of deformed pathological eyelids with abnormal margins, lesion locations and structural deformities. The model manifests capacity to differentiate between various eyelid statuses in terms of the spatial activation patterns.

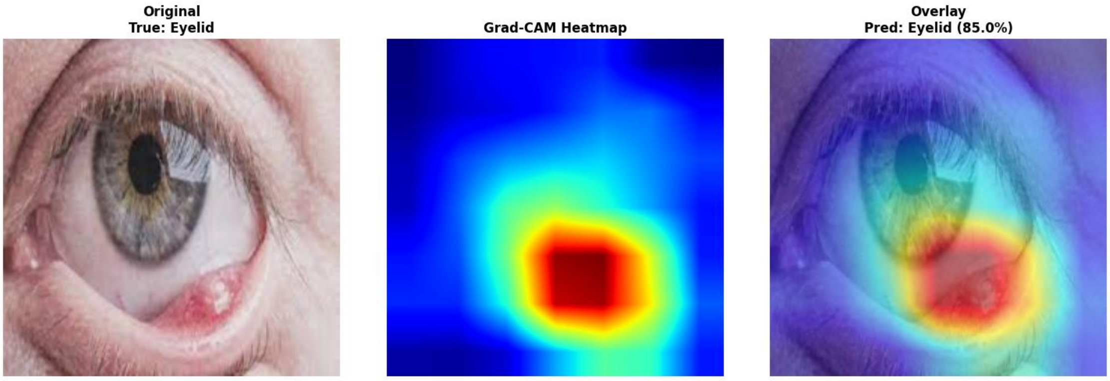


Figure 4.4.3 Eyelid Grad-CAM

Normal Eye Identification: The model has a balanced and weak intensity response in normal anatomy structures without easily focusing any particular pathological areas, detecting the healthy eyes.

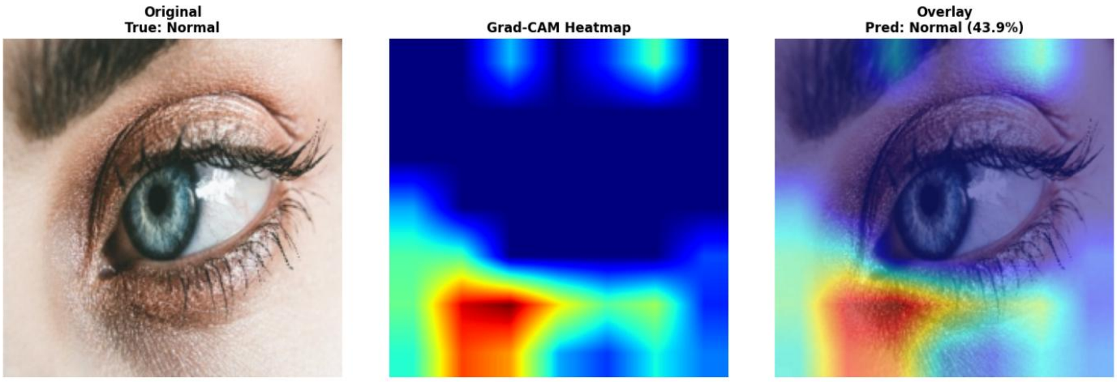


Figure 4.4.4 Normal Grad-CAM

Uveitis Detection: The model has a balanced and weak intensity response in normal anatomy structures without easily focusing any particular pathological areas, detecting the healthy eyes.

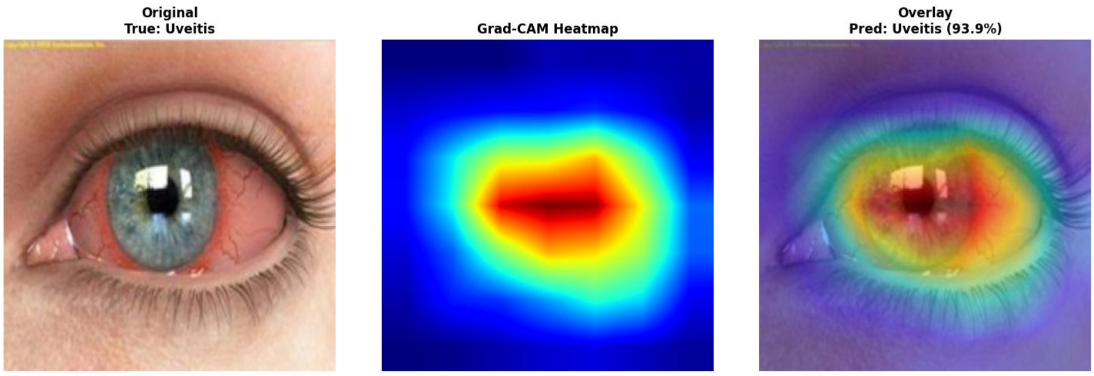


Figure 4.4.5 Uveitis Grad-CAM

4.5 Web System Deployment and LLM powered Recommendation

The final web-based application integrates all system components into a user-friendly interface. It shows the uploaded eye image, prediction with confidence score, See the heat map based explainability for being more trustable to user and AI generated recommendation. The platform analyses an image in a streaming fashion, requiring about 3-5 seconds per image for average inference and explanation generation.

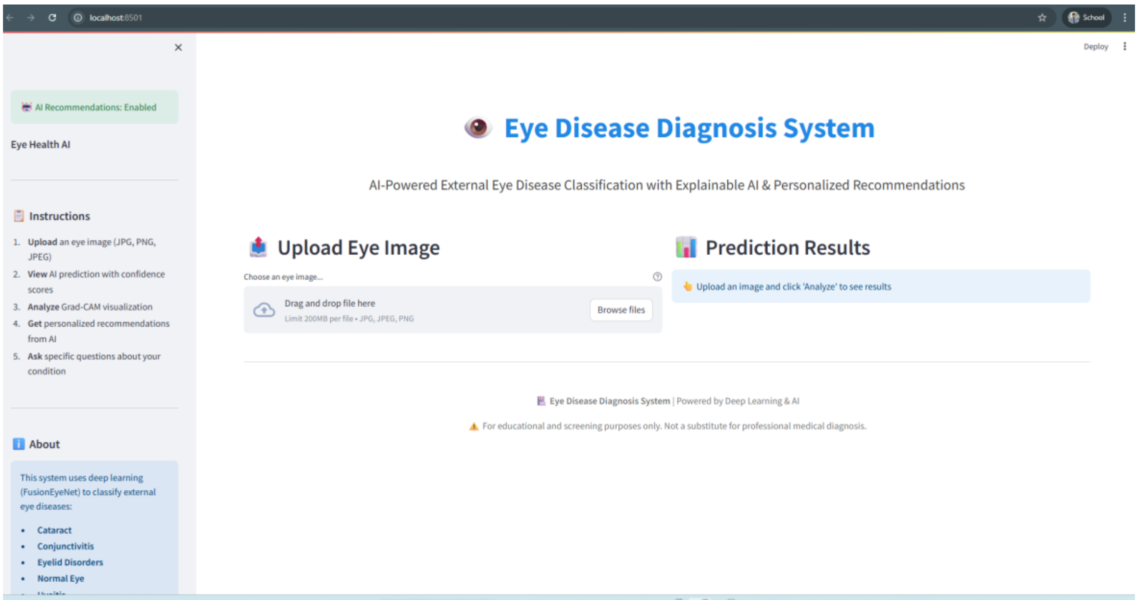


Figure 4.5.1 Web Deployment

4.5.1 Image Analysis and Diagnosis

One can submit external eye image using easy to use web interface which is instantly processed by optimized FusionEyeNet model. The system produces an accurate diagnosis of the expected disease class (Cataract, Conjunctivitis, Eyelid Disorder, Normal, or Uveitis) with a detailed confidence percentage allowing voiding of diagnosis delay and uncertainty as well as generating Grad-CAM visualizations that indicate regions influencing the decision for increased reliability and interpretability.

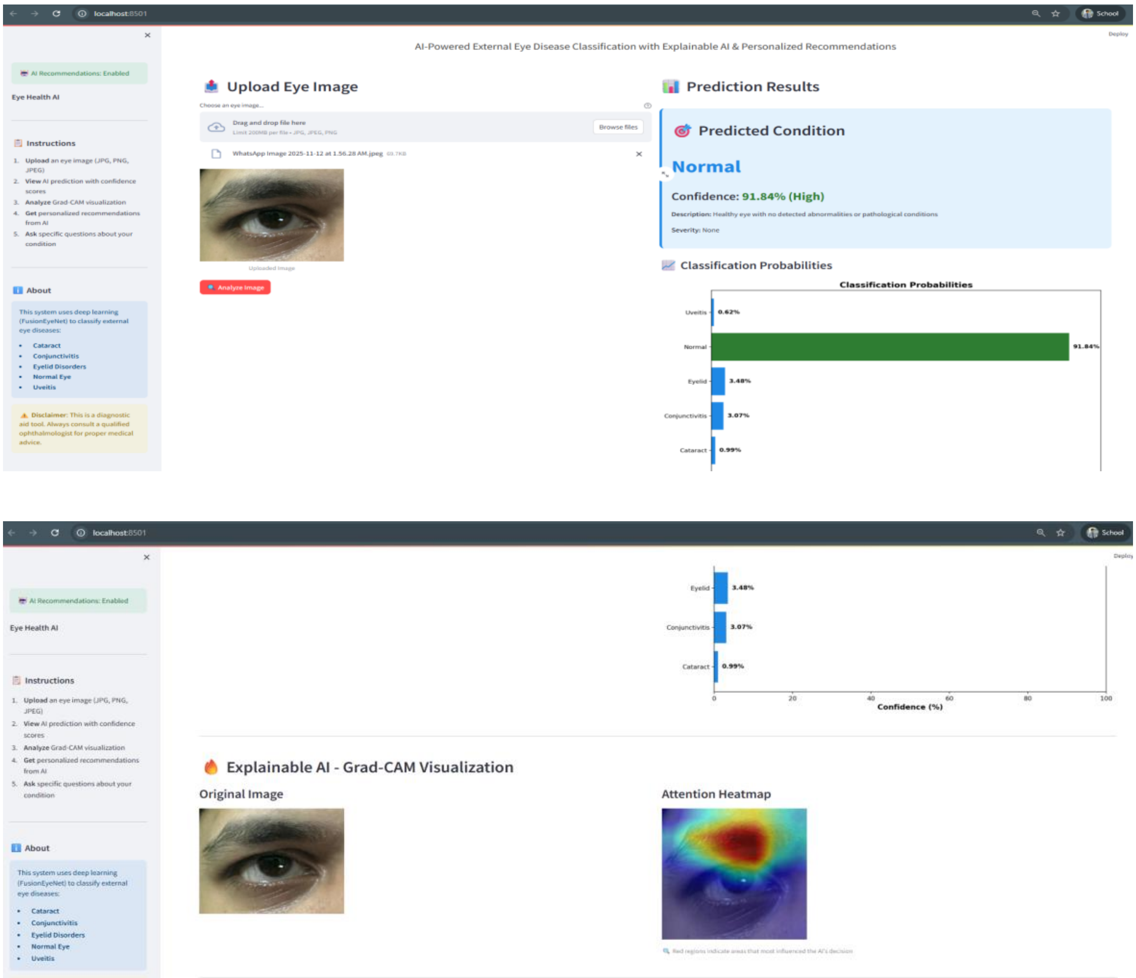


Figure 4.5.2 Image Analysis and Diagnosis

4.5.2 AI-Powered Personalized Recommendations

As requested by the user, the system initiates the Gemini LLM and produces holistic personalised intervention using ‘freely available’ evidence from that particular diagnosis and level of confidence. Through the LLM: Accessible, structured information in the areas of immediate next steps, preventive lifestyle changes, potential risk factors and when to seek professional medical attention. All counselling is cautiously written with chi-medical disclaimers, only for educational, screening purpose, not a substitute for professional ophthalmological consultation and the responsible use of system urges are promoted as well as vigilance in relation to eye health abnormalities.

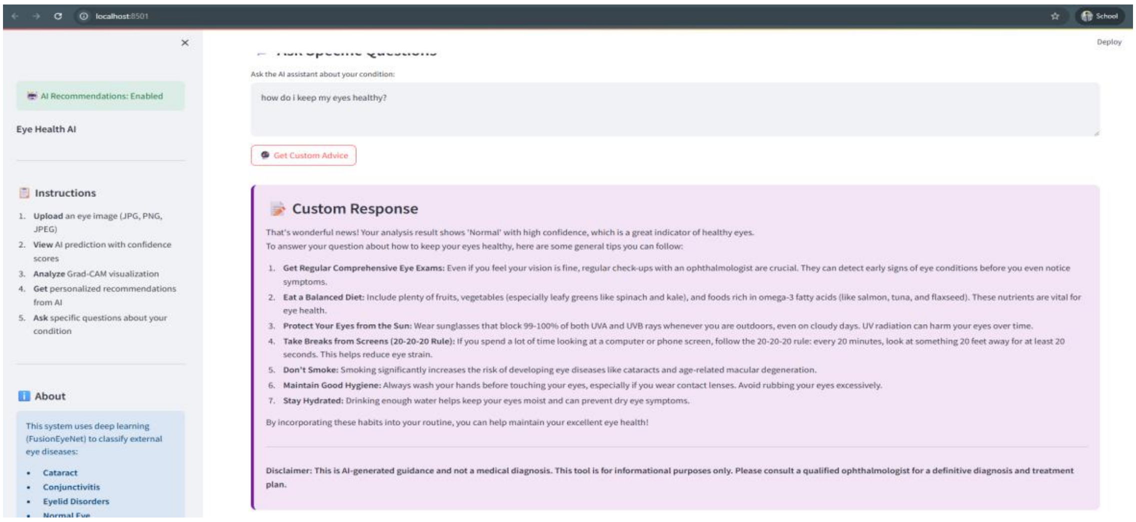
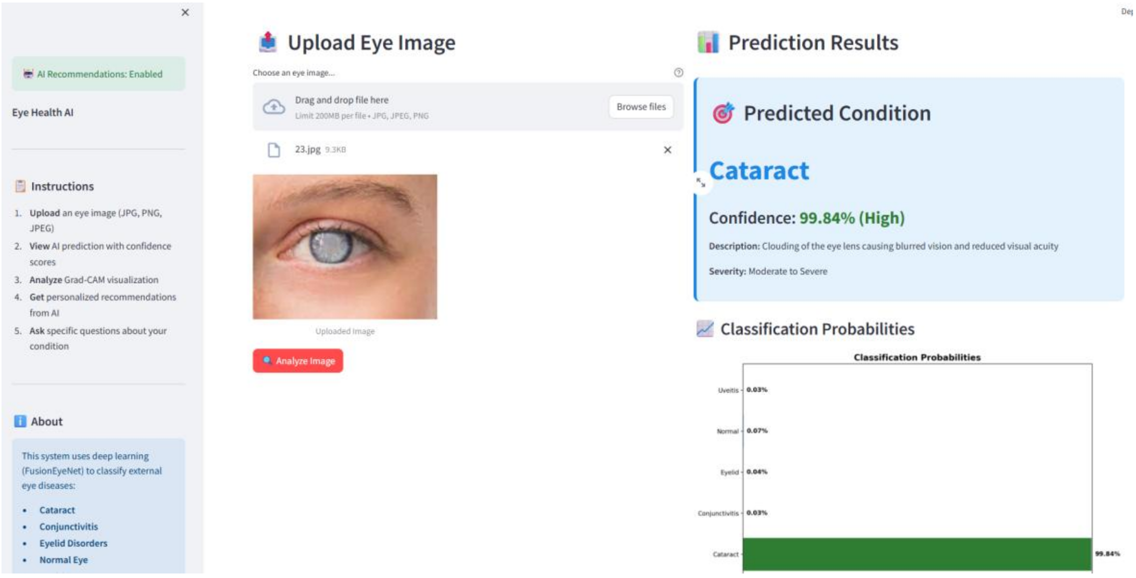


Figure 4.5.3 Personalised Recommendation

Example System Workflow:



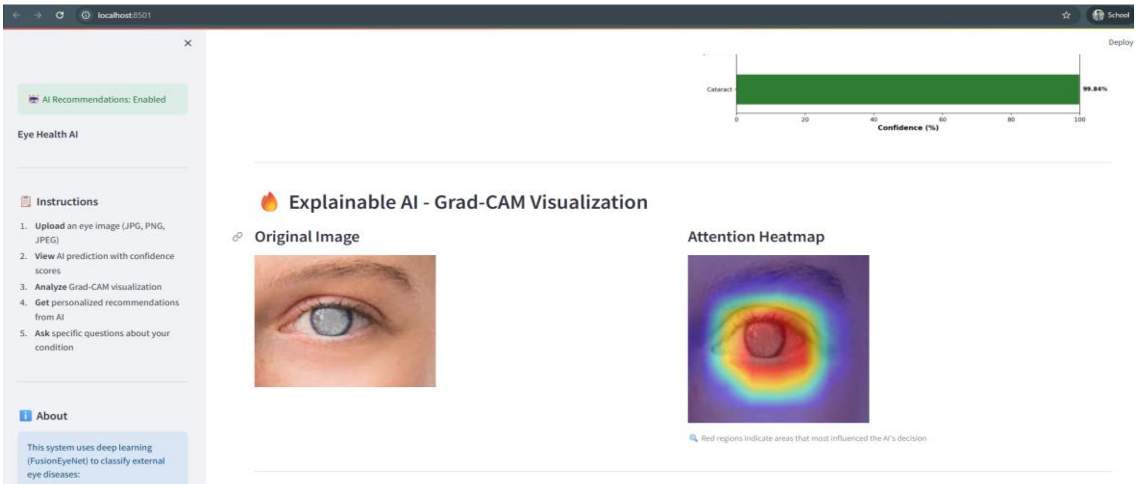


Figure 4.5.4 Image Analysis and Diagnosis

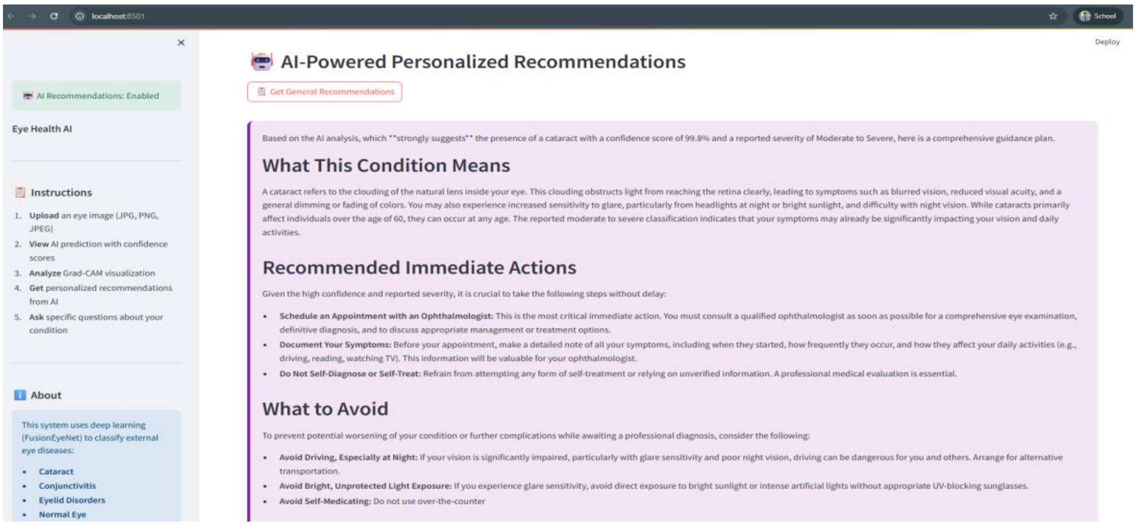


Figure 4.5.5 Personalised Recommendation

In one case a user donation an image that is labelled Cataract with 99% confidence, as described the interface shows this diagnosis and also provides Grad-CAM heatmap annotated with region of the clouded lens. The LLM generates a personalized guide on asking your AI assistant for recommendations explaining what cataracts are, offering tips for prevention, when it's time to see a surgeon about the matter, and emphasizing that there is no substitute for professional diagnosis with accompanying notice that this is just for education.

4.6 Discussion

4.6.1 Performance Interpretation

The outstanding performance of FusionEyeNet is due to its well-designed architecture. The fused feature learning method would make full use of MobileNetV2 efficiency in local texture capturing and VGG16 power in complex hierarchical nature modelling. This complementary mode offsets the disadvantage of the single-architecture manner where a model is good at one type of feature but not be comprehensive enough.

The good performance with different disease types, such as uveitis and eyelid diseases which are known to be difficult, supports the robustness of this model. This combined functionality is particularly attractive in a clinical setting, where systems must handle a wide variety of stimuli without significant drop-off of performance across presentation types.

4.6.2 Clinical Relevance of Visual Explanations

The Grad-CAM visualizations provided valuable evidence on the diagnostic basis conducted by the model, which is in line with clinical examination characteristics. The stimulus-evoked response resides in areas routinely examined by ophthalmologists by lens for cataracts and conjunctival examination. This concordance increases clinical certainty and allows inclusion in diagnostic pathways.

Moreover, this model could further highlight the features induced from pathology and being a part of education whether to teach what typical images would have common within different disease classes. Furthermore, the visual explanations act as a commission filter since errors can be identified by clinicians when the activation patterns are not in line with his/her expectations from the clinical issue.

4.6.3 Practical Implications of Web Deployment

Observing the wide-spread of web, we also perform practical feasibility on our system in real life. Integration of these with explanations and recommendations will form a complete diagnostic support system for healthcare provision. The system is intuitive and user-friendly, and acceptable for use in different clinical settings such as primary care clinics with limited access to specialists.

This recommendation system enabled by LLM is a great way of covering that gap between diagnosis and advice to the patient with something tangible right now, at diagnosis, something they hope patients will understand and again help them comply. This joint processing is a significant advancement overformer diagnostic systems which only attempt to classify objects.

4.6.4 Limitations and Future Directions

Despite satisfactory classification performance of the FusionEyeNet model, some limitations should be pointed out. The model was trained and evaluated on a certain dataset from Mendeley Data, which may not completely capture the wide diversity of image qualities, demographic discrepancies, and rare disease manifestations observed in the global clinical practice. However, the existing framework only covers five main external ocular diseases, and a number of other ocular disorders are not recognized. Moreover, the diagnostic capability of web application is limited by image quality, illumination condition and camera setting that could influence its performance in real-word.

Conclusions Future studies should focus on multi-center validation trials in various healthcare systems to increase model generalizability. The coverage of disease spectrum can be extended to other ocular surface diseases such as pterygium, corneal ulcers, and eyelid in order to potentially increase clinical utility. Incorporation of more severity grading (for example progressives like cataract) might provide for more informative diagnostic output. In addition, mobile-friendly versions with real-time camera support for obtaining images may also be beneficial in low-resource settings. Additional research focused on the system's impact on the efficiency of clinical workflow and patient outcome will increase its utility in a health care setting.

CHAPTER 5

CONCLUSION

5.1 Findings & Contributions

In this study, we have successfully presented and validated FusionEyeNet as a novel web-based integrated system for external eye disease classification with impressive performance over prior arts. The key findings and contributions are:

Architectural Innovation: Fusion of discriminative capabilities together of MobileNetV2 network with VGG16 that surpasses all the baseline approaches (97.89% on test) including VGG16(97.19%), Densenet121, Custom CNN. This demonstrates the power of combining of complementary architectures in medical imaging.

Comprehensive Disease Coverage: This is knowledge gap from previous research when it comes to disease, covering a broader range of diseases (including 5 external eye conditions, certain under represented but clinically important diseases such as uveitis and individual disorders affecting the eyelids) than previously studied. The model performed very well in maintaining strong performances on all classes, and demonstrated a perfect detection for cataract, and good recognition ability of inflammatory pathologies.

Enhanced Explainability and Trust: he addition of Grad-CAM localizations provide clinically interpretable explanations, highlighting diagnostically relevant regions to bypass the “black box” challenge in medical AI, and aiding trust as a fundamental aspect for future clinical dissemination.

Patient-Focused Educational Tool: The interface between diagnosis (provided by deep learning model) and patient content delivery compiles the educational space supporting personalized advice, with suitable medical caveats for responsible exploitation, since we have already run a web-based LLM-powered portal in the system reported earlier.

5.2 Recommendations for Future Works

Next, some interesting extensions are presented along with limitations and further observations.

Clinical Validation and Expansion: We require prospective studies for multi-center clinical validation in various healthcare settings and populations, to enhance generalization of the model. This would have made the system clinically interesting since a broader disease spectrum could be analysed, and recording of most other external eye conditions, such as pterygium, corneal ulcers and the various types of eyelids.

Technical Enhancements: It may be possible to develop mobile-friendly versions of the app with on screen camera instructions for use in low resource settings. Grading of progressive conditions such as cataracts might provide further diagnostic detail. More complex transformer-based architectures and multi-modal data can be used to improve the performance.

Longitudinal Impact Studies: Future research should include longitudinal studies in order to determine the effect of the system on efficiency, diagnostic accuracy and patient outcome in practice-based healthcare. System application of telemedicine and medical education also requires further study.

Regulatory and Ethical Frameworks: Ensuring proper regulatory processes for clinical deployment, including quality control mechanisms and ongoing learning process, a strictly legally compliant ethical guideline setup for AI-augmented diagnosis.

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Appendix A:

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Appendix B: Title

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