A Deep Learning-driven Approach for Early Detection of Ocular Abnormalities Using MobileNet and EfficientNet

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“In the name of Allah, the most Beneficent, the most Merciful"

Glory be to **Allah Almighty**, the Creator and Sustainer of the Universe, the Omnipotent and the Omnipresent. There is nothing I could have accomplished without His guidance and blessings. I dedicate this thesis to my **teachers and my parents**, who supported me each step of the way.

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ABSTRACT

Keyword: Eye Diseases, Deep learning MobileNet, EfficientNet, Multiple eye disease, Diabetic retinopathy, hypertensive retinopathy, glaucoma, cataract

Diabetic retinopathy, hypertensive retinopathy, glaucoma, and cataract are well-established eye diseases resulting from elevated blood pressure, increased blood glucose levels, and heightened eye pressure. Symptoms typically manifest at later stages, encompassing phenomena such as AV (arteriovenous) nicking, constricted veins in the optic nerve, cotton wool patches and blood accumulation in the optic nerve. These pathologies can progress to severe complications, including retinal artery occlusion, optic nerve damage, and the potential for irreversible vision impairment. The integration of artificial intelligence (AI) and deep learning models offers a promising prospect for early disease detection. This study utilizes datasets sourced from reputable internet platforms to introduce a novel methodology called CAD-EYE designed for the classification of diabetic retinopathy, hypertensive retinopathy, glaucoma, and cataract. CAD-EYE employs MobileNet and EfficientNet models, with a particular emphasis on feature fusion to enhance overall performance of the diagnostic system. The system has been trained on **65,871** digital fundus images sourced from diverse datasets.

In a comparative analysis, CAD-EYE outperforms state-of-the-art models such as CNN+LSTM, ResNet, GoogleNet, VGGNet, InceptionV3, and Xception in terms of classification accuracy. These findings underscore the efficacy of CAD-EYE as an adept diagnostic tool, designed not to replace optometrists but to complement the efforts of healthcare professionals by providing valuable assistance in the early identification of ocular pathologies.

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List of Abbreviations and Acronyms

Convolutional Neural Network	CNN
Machine Learning	ML
Deep Learning	DL
Hypertensive Retinopathy	HR
Diabetic Retinopathy	DR
Rectified Linear Unit	RELU
Extreme Gradient Boosting	XGBoost
Eye Disease Classification	EDC
Neural Search Architecture Network	NASNet

Chapter 1

Introduction

The eye holds a pivotal role among the important organs essential for daily functioning. Conditions impacting the eye possess the capacity to inflict irreversible harm to the retina, potentially resulting in visual impairment or complete blindness. These ocular disorders present challenges to fundamental activities such as reading, driving, recognizing faces, and navigating one's surroundings. Consequently, visual impairment exerts a substantial influence on an individual's overall quality of life. Globally, a minimum of 2.2 billion struggle with various forms of visual impairment, with a concerning aspect being that at least one billion of these cases could have been prevented or have not received adequate treatment. The socio-economic ramifications of vision impairment are profound, with an estimated annual cost of USD 411 billion globally, imposing a considerable economic burden on societies worldwide. Unfortunately, statistics highlight a substantial disparity in treatment access. Globally, only 36% of individuals experiencing vision impairment from refractive errors and a mere 17% of those affected by cataracts have undergone necessary and suitable treatments. These small percentages prove the pressing requirement for enhanced global initiatives aimed at addressing and preventing visual impairments, with a focus on the potential positive impact on both society and the economy [1].

The recognition and examination of ocular pathologies are intricately linked to the utilization of fundoscopy, a diagnostic technique that allows for a detailed examination of eye images. In medical terms, Fundoscopy, is a non-invasive process used to assess the inner structures of the eye. This includes the retina, blood vessels inside the eyes, head of the optic nerve and to a extent, the structure of choroid as well. This examination presents an inspection of all the components of eyes as mentioned before. This kind of inspection is otherwise carried out by medical professionals such as ophthalmologists. Other specialists who deal with such inspections include neurologists, internists and/ or pediatricians. Its primary purpose lies in the diagnosis and monitoring of different kinds of eye conditions. Some of these conditions include diabetic retinopathy, macular degeneration, retinal hemorrhages, glaucoma and papilledema [6].

During the fundoscopic examination, in order to dilate the pupil of patient, parasympatholytic eye drops are frequently administered (the drops are topical and short-acting). Following this, an ophthalmoscope, a specialized optical device, is employed to illuminate the retina through the pupil. This illumination enables the formation of retinal image. This kind of image is visible through the pupil, offering valuable insights into overall eye health. It also indicates if there are any abnormalities or diseases present [6]. The images obtained from fundoscopy, documenting any observed changes in the eye or abnormalities, can also be captured during the examination. To obtain these images, a device called ophthalmoscope is used, along with this device, a camera is attached which focuses on the retina or other eye structures [7]. The fundoscopic pictures thus gathered form an important source of information for the creation of artificially intelligent systems. These systems are intended to help the diagnosis of different ailments of eye and then to treat them. For the purpose of research, several well-known public datasets such as MESSIDOR and EyePACS have been used by researchers working in the field of Machine Learning (ML). Other similar datasets include DRIVE & E-optha [8–11]. Computer systems can be made to acquire the capability to recognize and scrutinize patterns associated with distinct eye conditions through the integration of AI algorithms with datasets of fundoscopic images. The AI systems thus formed have the potential to help professionals in the medical field to diagnose and treat eye diseases with enhanced accuracy. This, ultimately helps conserve time and moreover improves access to care. Moreover, these systems can make the treatment procedures more standardized. They can also help to develop personalized plans for treatment.

1.1 Medical Background of Diseases

Despite Subsequent paragraphs delve into a comprehensive exploration of the diseases elucidated in this research paper, namely diabetic retinopathy, hypertensive retinopathy, glaucoma and cataract; unraveling their intricate mechanisms and elucidating their profound impacts on vision impairment.

Glaucoma, a sight-threatening condition, can lead to vision loss and blindness if left untreated or inadequately managed. Globally, glaucoma is regarded as one of the primary causes of irreversible blindness and ultimately it leads to a diminished quality of life [17]. Early identification and detection of glaucoma plays a crucial role in preventing irreversible vision loss, as the condition can lead to permanent visual impairment. Traditional methods for glaucoma detection have often shown limited accuracy [2]. However, a novel approach has been developed, enabling faster and more effective disease detection by analyzing the characteristics of the optic disc in retinal images. An essential factor in glaucoma is intraocular pressure (IOP), analogous to blood pressure but specific to eye pressure can be used for classification of this issue. Elevated IOP can cause damage to the optic nerve, resulting in symptoms such as blurred vision and eventual blindness over time [3-5]. Manual analysis of eye images is time-consuming and subject to variations in accuracy based on the examiner's expertise, highlighting the necessity for automated methods in glaucoma detection. These days, automated computerized retinal image analysis has become a useful screening technique for detecting a range of eye conditions and hazards. Glaucoma manifests in two primary types: first category is that of open-angle glaucoma (also known as chronic glaucoma) and the second category is that of closed-angle glaucoma (also known as acute glaucoma), both of which can increase intraocular pressure. Notably, during the early stages of glaucoma, patients often do not exhibit noticeable visual signs or symptoms, posing a challenge to early detection.

Detecting glaucoma at its early stages is crucial to prevent progression to irreversible blindness. In recent years, digital retinal images have emerged as a valuable tool for conducting glaucoma screenings. Various techniques and procedures have been developed to identify retinal abnormalities associated with glaucoma, enabling early detection and intervention for this vision-threatening condition. The integration of machine learning (ML) and artificial intelligence (AI) techniques into telemedicine screening programs holds the potential to further enhance diagnostic accuracy, increase detection rates, and improve overall program efficiency. This advancement is essential for identification of cases involving glaucoma. Moreover, it also helps manage such cases. Many researchers working on glaucoma detection have faced challenges related to datasets. This includes datasets being not large enough. Moreover in several cases, images are taken from private sources, therefore, they often lack the actual changes in images observed in real-time. This further leads to limited robustness of the systems. In addition to that the generalizability of models is also affected [26-27].

A common complication related to diabetes, called diabetic retinopathy, affects the eyes. It stands as a leading reason that leads to loss of vision particularly, in age groups of in middle-aged and elderly individuals. It poses a significant global public health concern [12]. In the United States, the estimated prevalence of diabetic retinopathy and vision-threatening diabetic retinopathy (VTDR) among adults with diabetes is 28.5% and 4.4%, respectively [13]. Projections suggest that in around 10 years, the prevalence figures of diabetic retinopathy will reach around 160.50 million and those of vision threatening diabetic retinopathy will reach around 44.82 million. The estimates also indicate that the populations most affected by these diseases would include those of Middle East and North Africa. Other regions include the Western Pacific areas [14]. Diabetic retinopathy is diagnosed by identifying specific characteristics of the retina. These features include microaneurysms, exudates and hemorrhages. Clinical classification includes various types of DR including mild DR, moderate DR, proliferative DR and severe non-proliferative DR.[12].

Efficient screening of these kind of complications and furthermore, timely treatment can lead to reduce blindness. This has been proven in countries with substantial services, one example of which is United Kingdom [15]. By using the photos of the retina, screening of diabetic retinopathy is done. Furthermore, manual interpretation, is also widely and it has shown superior performance in certain cases compared to in-person dilated eye exams [16]. However, many low- and middle-income countries face challenges in implementing systematic diabetic retinopathy screening programs due to the lack of well-established primary care infrastructure. Consequently, there is a critical need for customized and cost-effective plans particularly aimed to address; first screening and then treatment for a considerable portion of the population suffering from diabetes [15]. Deep learning (DL), has the capability to automatically learn important image features when it is aided by a consolidated dataset including labeled examples [10]. DL has exhibited profound results in the automated image analysis of fundus photographs, achieving high sensitivity and specificity. The integration of deep neural networks into the screening process using images of retina can significantly improve the identification of diabetic retinopathy and other risk factors with exceptional accuracy and reliability [15].

Another type of eye disease which is quite commonly widespread all around the world is hypertensive retinopathy (HR). It is caused by hypertension, the cause of which is increased vascular resistance [59]. Several human tissues are damaged by this ailment, including those of the eyes, and the heart [60]. Apart from these health issues, hypertensive retinopathy (HR) is one of the most prominent causes of cardiovascular disease. Moreover, it ultimately leads to mortality [61]. As indicated by the name, Hypertensive retinopathy is an anomaly of the retina which occurs due to hypertension. Several significant signs are depicted because of HR-related retinal irregularities such as the development of arteriolar narrowing and retinal hemorrhage. Some other indicators include arteriovenous nicking, cotton wool spots, microaneurysms and papilledema. In some extreme cases, macular edema and/ or optic disc, can also be observed

[62]. In order to ensure timely medical intervention for the sake of avoiding greater damage, early diagnosis of hypertensive retinopathy is essential [63].

Yet another commonly prevalent eye disease called cataract is also associated with lens of the eye and it leads to the patients finding it difficult to see. Potential causes of cataract include either the lens's hydration (fluid increase) or the denaturation of proteins in the lens. In general, cataract is a disease that attacks the elderly, but in several cases, issues such as congenital abnormalities can be the cause. Similarly, eye diseases can also cause cataracts. Some such eye diseases that trigger the ailment of cataract include glaucoma, ablation, uveitis, retinitis pigmentosa, and other intraocular disorders [65]. Cataract can be categorized into several types based on its stage: these categories include incipient cataract, intumescent cataract, immature cataract, mature cataract, hyper-mature cataract, and morgagnian cataract.

Quality of life of patients suffering from cataract is impacted. The impact includes the productivity of patients as well as their mobility. Situation like these results in a decrease in quality of life of such people [66]. Cataracts can be anticipated by early detection when the eye begins to experience disturbances. At present several methods are used ophthalmologists to diagnose the presence of cataracts. These tests include visual acuity tests, retina exams and slit-lamp tests. Another such test is the applanation tonometry. These methods are also not adequate enough for timely detection of cataract owing to two reasons; first, the time duration needed for detection and secondly, the limited stages of cataracts that can be identified. Therefore, the need for developing a cataract identification system based on image processing through automated process such as AI/ DL arises.

It is imperative to develop a model capable of effectively handling images acquired under various environmental conditions. This is to ensure that the limitations of existing techniques and systems are addressed. This research focuses on not only enhancing the robustness of machine learning-based classification of retinal images, but also to increase the generalizability.

In order to complete this aim, Large-Scale Dataset, consisting of approximately 65000 diverse images, has been used. Additionally, a machine learning model, though highly complex but capable of efficiently processing such huge chunk of data has been developed. The combination formed by using this diverse dataset along with a robust model is intended to improve the performance and significantly alleviate the reliability classification system for retinal images.

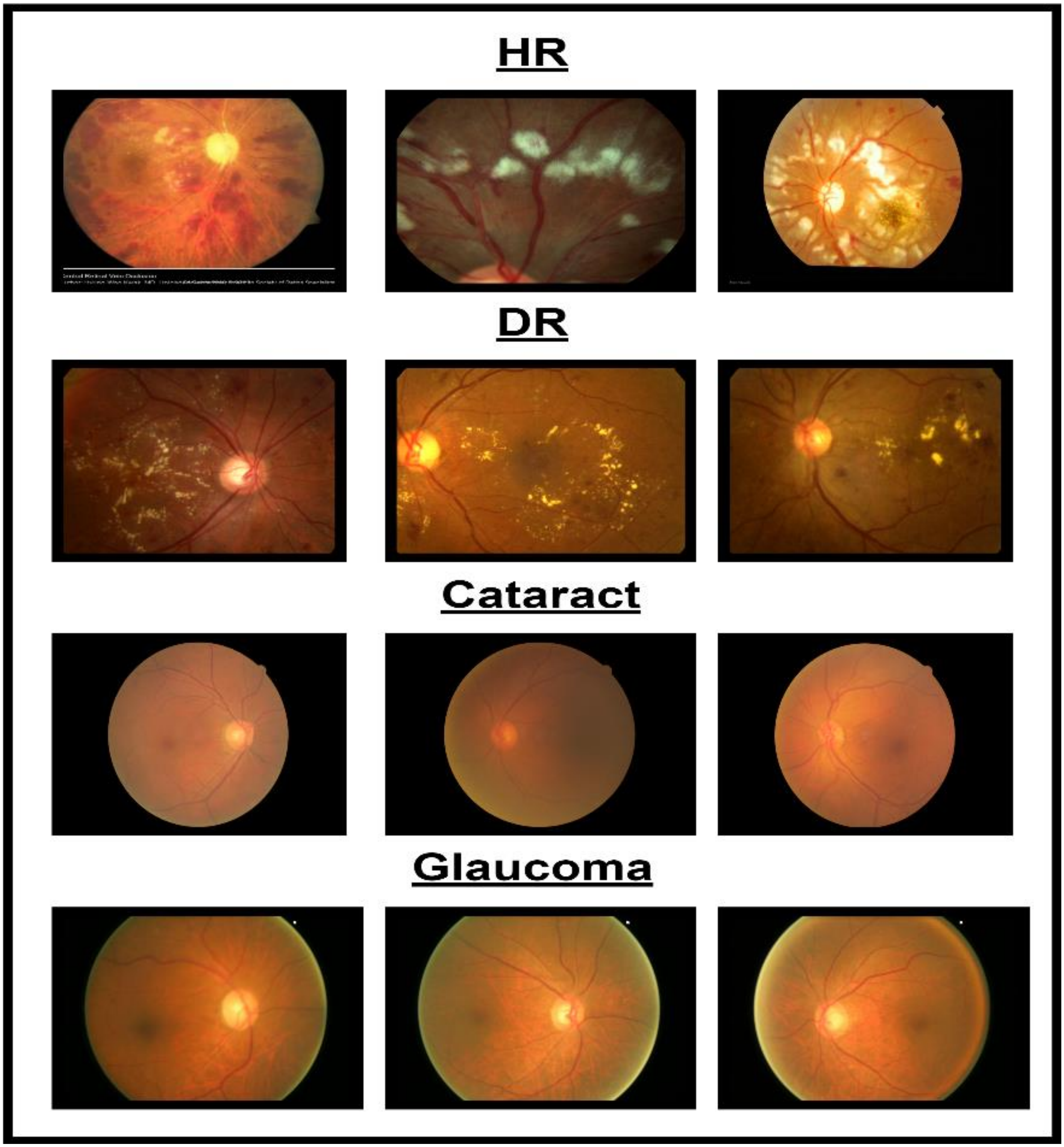

Figure.1.1: Illustration of Eye Diseases

1.2 Research Motivation

Despite advancements in diverse methodologies for diagnosing eye disorders including diabetic retinopathy, hypertensive retinopathy, glaucoma, and cataract, from images, considerable challenges persist. Figure 1.1 displays images depicting various eye disorders.

- Despite the application of advanced image processing technologies during and after image acquisition, accurately delineating distinctive eye features in images related to normal cases, diabetic retinopathy, hypertensive retinopathy, glaucoma, and cataract poses a significant challenge. The intricacies involved in precisely identifying and further extracting features related to eye disorders contribute to the complexity of this task.
- Datasets available publicly encompass a diverse range of images related to normal cases, diabetic retinopathy, hypertensive retinopathy, glaucoma, and cataract, however they often lack comprehensive professional medical annotations. Consequently, computerized systems encounter difficulties in precisely diagnosing the symptoms associated with specific disorders.

This research has a dual objective. Firstly, it aims to construct a comprehensive dataset for the classification of normal, diabetic retinopathy, hypertensive retinopathy, glaucoma, and cataract eye disorders. Secondly, it aims to bring forth a deep learning (DL) model that can autonomously classify images of eye diseases. To achieve this, a multilayered system has been employed to create the CAD-EYE system. Through rigorous training, this CAD-EYE system becomes proficient in reliably recognizing eye-associated disorders, including anatomical component identification, across diverse images. The significance of this work lies in the fact that it suggests an innovative system for categorization of eye diseases, potentially offering real-world applications in medical diagnosis.

1.3 Research Contribution

Within the framework of research, a novel deep learning (DL) model has been introduced to tackle the challenge of identifying various eye diseases. Furthermore, new dataset—a meticulously curated collection sourced from reputable internet resources and complemented by some private datasets from previous studies, is also presented. Significant contributions of the research are highlighted as follows:

- Substantial dataset consisting of 65 thousand photos sourced from reputable internet platforms and supplemented by private datasets from previous studies, has been compiled. This extensive dataset is crucial in ensuring that the trained model attains considerably high classification accuracy.
- During construction of the CAD-EYE system, the study has utilized two models; namely MobileNet and EfficientNet, employing a technique called feature-fusion. This approach has led to the development of a multi-layered architecture that proved adept at effectively addressing the classification challenge.
- The system design of the CAD-EYE model integrates additional layers for the identification of ocular diseases. The purpose of using CNN model is to extract attributes associated with eye disorders, and these features are subsequently enhanced through the feature fusion approach.
- The classification approach proposed in this study for eye disorders relies on deep features and color space phases, constituting the core of the methodology. An attempt to establish a computerized technique that surpasses existing methods in the detection of normal, diabetic retinopathy, hypertensive retinopathy, glaucoma, and cataract has been made, as illustrated in **Figure 1**.
- Our system has exhibited superior performance compared to the approaches proposed previously, achieving accuracy of 98%, which is considerably higher.

1.4 Outline Report

This research report has been organized in a way that **section 2** encompasses the literature review, covering relevant research work done in our domain, **section 3** outlines the method to be employed. **Section 4** presents the architecture that has been used, whereas **section 5** highlights the experimental outcomes. In **section 6**, our findings are compared with those of contemporary studies already conducted in the field. **Section 7** conducts a comprehensive examination of the research findings. Finally, **Section 8** presents the study's conclusions.

Chapter 2

Literature Review

Numerous research studies have explored the identification of eye diseases, employing diverse methodologies and technologies crucial for enhancing the precision and efficiency of disease diagnosis in the field of ophthalmology. In this context, we provide an overview of notable studies. There has been emphasis on applying artificial intelligence techniques in healthcare systems, particularly for fast diagnosis [39]. Several machine learning algorithms such as Decision Tree and Random Forest have been made use of for this purpose. Similarly, other such algorithms include Neural Networks and Naïve Bayes. The models were trained with varied data, including patient information, age, disease history, and clinical observations. Notably, the Random Forest and Decision Tree algorithms demonstrated exceptional accuracy rates, surpassing 90% when compared to alternative approaches. Venturing beyond algorithmic approaches, Gelder et al. [40] delved into the realm of human clinical trials and explored the potential of retinal pigment epithelium (RPE) transplantation. Their study scrutinized the advancements in retinal regenerative medicine over the past decade, shedding light on human clinical trials related to RPE transplantation. The application of deep learning (DL) in ophthalmology, has facilitated the identification of conditions such as glaucoma-like disc, macular edema and age-related macular degeneration. The fields of ophthalmology where DL has been used include fundus pictures, visual fields and optical coherence tomography. DL in ocular imaging and telemedicine allows several steps to be conducted in an improved manner. The areas of application include screening and identification. Consequently, the stage of monitoring patients in primary care is also affected for such systems in community settings [34-35]. However, the use of DL in ophthalmology comes with its own set of concerns, including aspects related to clinical implementation as well as technically ensuring that everything runs smoothly. Other similar challenges include conveying the findings of algorithm, considerations related to legality of processes and finally difficulties in convincing people to adopt artificially intelligent algorithms. These individuals range from doctors and physicians to patients.

The fundamental layer of a CNN architecture is the convolutional layer. Its main task is to perform the extraction of features from images given to it as input. For the purpose of generating diverse feature outputs, multiple convolution kernel filters are employed by the convolution layer. Next comes the layer that plays a role in reducing the dimensionality of extracted features and compressing data to avoid overfitting. This layer is called the pooling layer, also known by the name of down-sampling layer and it works to make better the fault tolerance of the model being developed. The final results of the object classification task are generated by a layer called the fully connected dense layer. In this layer, image classification is carried out by amalgamation of the feature data from each neuron as acquired from the convolution layer. In order to have an optimal performance, with the exception of the final layer that deals with the weights allotted, other layers of a CNN model/ architecture are calibrated as not-trainable. Typically, there are three prominent layers of a CNN architecture. The convolutional layer, which serves to extract features from images provided to it, employs multiple convolution kernel filters to produce diverse image feature results.

A prevalent aspect in current literature often involves the extraction of blood vessels or the segmented identification of lesions. The intricacy of framework design is further heightened by the diverse instruments and strategies employed for these purposes [28-29]. The present system employs an algorithm based on Convolutional Neural Network to recognize various stages and types of glaucoma. In their research, Linglin Zhanga highlighted that in the developed world, cataracts, emerge as one of the most prevalent causes of blindness and accounts for more than half of all cases. Timely identification and treatment of cataract can alleviate the botheration caused to patient and moreover can help to avoid blindness . However, identification of cataract in clinical settings require the expertise of eye doctors who are adequately qualified. This kind of situation has the potential to make early ramification a challenging process due to invisible costs. Based on the recent study on automated identification of cataract based on fundus images, a predefined set of features is utilized, which can possibly lead to inaccurate results. This is due to redundancy and/ or noisy representation [30]. Ele. Daniel Shu Wei Ting et al., emphasizes that deep learning has fostered prominent consideration in recent years, hence enhancing the artificially intelligent systems [31]. Researchers have found applications of deep learning in several fields such as speech recognition and natural language processing. Similarly, image recognition is another area impacted by it however, the healthcare industry has only recently started to witness its impacts [32-33].

In a recent study, it has been indicated that diabetic retinopathy, a common complication caused by diabetes leads to retinal lesions which impair vision [36]. DR, if not detected early, can lead to vision loss. It is highlighted that unfortunately, there is no way to ensure that diabetic retinopathy does not occur and treatments can only sustain eyesight. Manual diagnosis of DR retina fundus photographs by ophthalmologists is expensive, time-consuming, and prone to errors. Deep learning, particularly convolutional neural networks, has shown enhanced performance in the categorization and interpretation of medical images, offering a promising avenue for the diagnosis of DR and other medical conditions [36-37].

Study presented in [38] examines and discusses the latest methodologies and techniques being used to detect diabetic retinopathy and further classify its types by making use of color fundus images through deep learning. The analysis also includes an assessment of datasets specific to DR in color fundus retinas. Additionally, certain complex challenges have been identified, calling for further research. The proposed approach significantly enhances the detection of the disc and cup. It is based on super-pixel classification. However, the model exhibits a bias that causes it to understate large cups whereas the small ones are overvalued. The techniques used typically depend on the differences found regarding the cup and the neuro-retinal rim. This is essential for the computation of cup-to-disc ratio (CDR). It is a complex task which is affected by the contrast observed and can become difficult in case of minimal contrast. Regarding glaucoma detection, the traditional method involved analyzing pressure inside the eye also known as the intraocular pressure or the IOP. In one of the previous studies, features have been computed through the image, by making use of the characteristics. These features help to create a binary distinction as to whether the subject has glaucoma or is healthy.

This study presented a comprehensive overview of the dynamic landscape of regenerative and restorative medicine for various eye diseases, emphasizing the potential for future advancements in disease diagnosis and treatment. Another compelling investigation conducted by Abbas [41] concentrated on the development of automated computer-aided diagnostic (CAD) systems for glaucoma detection. To achieve this, the study employed Convolutional Neural Networks (CNN) architecture to extract crucial features from retinal images. The primary objective was to discern between glaucoma and non-glaucoma retinal fundus images, utilizing a dataset comprising 1200 retinal images. Impressively, the model achieved an average accuracy (ACC) of 99%, showcasing its potential to enhance glaucoma diagnosis. In the domain of feature extraction, Jain et al. [42] aimed to differentiate individuals with retinal problems from those without such issues. They accomplished this task through the analysis of retinal images, utilizing a model trained on datasets containing both patient and normal individual retinal fundus images.

The outcomes revealed remarkable accuracy (ACC) rates ranging from 96.5% to 99.7%, underscoring the effectiveness of their approach. Metin et al. [43] addressed the critical concern of retinal diseases, particularly emphasizing the significance of early diagnosis. To address this challenge, they utilized machine learning and deep learning methodologies, incorporating CNN-based ResNet50 and MobileNetV2 models. These models were employed for the classification of retinal diseases, yielding promising results. The models achieved average macro ACC values ranging from approximately 81% to 94%, along with an average F1 score of 0.96 for normal retinas, further emphasizing the potential of AI-driven solutions in early disease detection. Shifting the focus to diabetic eye disease (DED), Rarki et al. [44] applied CNN methods for the detection of retinal eye diseases in multiclass scenarios. Their study covered various classes of DED, and the model underwent testing using a diverse dataset of retinal fundus images, meticulously assessed by an ophthalmologist. The overall accuracy (ACC) reached 81.33%, accompanied by 100% sensitivity and 100% specificity for multiclass classification, showcasing the potential of CNNs in detecting a range of diabetic eye diseases.

Umer et al. [45] investigated the application of Optical Coherence Tomography (OCT) in automating the detection and classification of retinal eye diseases. Currently, ophthalmologists rely on manually examining OCT images, a process prone to inaccuracies and subjectivity. To address this, the study introduced various methods to automate disease detection, utilizing a dataset comprising of four-class retinal eye disease images. Modified versions of two models; first namely AlexNet and second namely ResNet-50 models were employed to extract feature vectors. The method proposed for detecting retinal diseases achieved an impressive overall average accuracy index (ACC) of over 99.95%, highlighting the potential for precise disease diagnosis.

Gargeya et al. [46] addressed the automatic diagnosis of diabetic retinopathy (DR) using image processing techniques and CNN models. Their study involved a substantial dataset comprising 75,137 publicly available retinal fundus images from diabetic patients. The assessment of model performance utilized the area under the receiver operating characteristic curve (AUC) as a metric, employing 5-fold cross-validation. Notably, the model achieved a 97% AUC, along with 94% sensitivity and 98% specificity for DR diagnosis, highlighting its effectiveness in automated disease diagnosis. In summary, these studies collectively showcase diverse approaches and technologies in the field of ophthalmology for detecting and diagnosing a wide spectrum of eye diseases. They underscore the potential of artificial intelligence, deep learning, and automated diagnostic systems in enhancing accuracy, objectivity, and efficiency in disease diagnosis, ultimately benefiting patients and healthcare practitioners alike.

The authors tackle the crucial challenge of detecting and classifying Diabetic Retinopathy (DR), a significant concern for diabetic patients vulnerable to severe visual impairment. They introduce an innovative automated system named DR-NASNet, which employs advanced techniques, including preprocessing methods such as Ben Graham and CLAHE, data augmentation to address class imbalance. Moreover, it involves integration of dense blocks within the NAS-Net architecture. The consequent system not only attains remarkable state-of-the-art results with high accuracy but also maintains a compact model size and lower complexity. Through the utilization of combined datasets and a linear SVM classifier, DR-NASNet proficiently categorizes DR images into five severity levels. This breakthrough holds the promise of providing valuable support to ophthalmologists, offering an efficient tool for the early classification of DR, thereby assisting in its timely management and potentially preventing vision loss in diabetic patients [47].

There are studies that marks a notable advancement in the early detection and management of Hypertensive Retinopathy (HR). Optometrists who are the clinical experts for eye related diseases, use image recognition technology for the retinal fundus images to ascertain the presence of ocular ailments related to hypertensive retinopathy. These procedures offer both a non-restrictive solution as well as a cost-effective way forward. The foremost advantage achieved through the use of detection systems that are automated is to help in the process of image evaluation/ assessment that is done by optometrists. This in turn ensures an important step for recognizing and consequently, treating the presence of hypertensive retinopathy [64].

The introduction of the Incept-HR methodology, coupled with the creation of the Pak-HR dataset, underscores the potential of AI and deep learning in the healthcare domain. Incept-HR demonstrates its efficacy through impressive performance, deeming it a valuable tool that can be used for diagnosis. It is essential to state that the proposed system is designed as a supplementary tool for healthcare professionals, augmenting their capacity to promptly identify HR. Furthermore, Incept-HR's outperformance of established models like VGG19 and VGG16 suggests its potential to elevate HR detection and contribute to enhanced patient care. This research signifies a step forward in achieving more effective screening, early intervention, and improved healthcare for individuals at risk of HR due to hypertension [48].

"Mobile-HR" introduces a novel diagnostic system for Hypertensive Retinopathy (HR) based on the MobileNet architecture, optimized through transfer learning. HR is a significant eye disease characterized by alterations in retinal arteries due to elevated blood pressure, resulting in various visual symptoms. Traditionally, ophthalmologists diagnose HR by analyzing fundus images, emphasizing the importance of early detection to prevent vision loss. Prior computer-aided diagnostic (CADx) systems encountered challenges like hyperparameter tuning, class imbalance, and overfitting. Mobile-HR addresses these issues by incorporating dense blocks, employing transfer learning, and applying data augmentation. Experimental results showcase its effectiveness, positioning Mobile-HR as a promising tool for HR diagnosis. These findings open up new possibilities for enhancing HR detection and patient care, offering potential benefits for both ophthalmologists and patients [49].

The classification and investigation of cataracts necessitate a comprehensive understanding of their diverse manifestations within the eye lens. Both subjective observation and objective measurement techniques continue to be widely employed in this field. Notably, techniques such as Scheimpflug slit image analysis, among the latter, offer a more precise means of identifying early transparency breakdowns. Objective approaches are pivotal in epidemiological research as they facilitate the accurate monitoring of risk variables, including UV-B radiation exposure, and their potential role in cataract development. This significance arises from the fact that age-related changes in lens transparency occur before apparent opacifications. Longitudinal cohort studies, involving repeated examinations, are imperative for gaining deeper insights into the multifactorial processes associated with cataracts. Subjective evaluations alone may fall short in detecting minor changes in transparency. In summary, objective techniques for categorizing cataracts are indispensable for advancing our understanding of this vision-impairing disorder and the linked risk factors [50].

A substantial contributor to visual impairment and a critical public health issue, cataracts are addressed through an automated identification method utilizing retinal image categorization rooted in computer science. Recognizing the crucial role of early diagnosis in preventing blindness, the approach involves employing deep learning networks to extract distinctive features from fundus images, coupled with preprocessing using the maximum entropy approach. Subsequently, the automated identification of four classes of cataract photos—normal, mild, medium, and severe—is carried out using conventional classification techniques, specifically SVM and Softmax. Noteworthy in the findings is emphasis on the aspect that features obtained through deep learning and categorized by Softmax exhibit superior accuracy. The overarching objective is to enhance the prospects for timely intervention and improved visual outcomes by advancing the early detection of cataracts through the fusion of computer science and medical imaging [51].

For a detailed overview of research findings related to the identification and categorization of eye illnesses, refer to Table 2.1

Table 2.1. Comparison and Analysis of Present Studies

Title	**Methodology**	**Data Information**	**Models**

Classification of retinal images with deep learning for early detection of diabetic retinopathy disease [27]	Classification was made by Convolutional Neural Network which is a deep learning algorithm	MESSIDOR, DIARETDB, STARE	CNN
Deep Learning Method for the detection of Diabetic Retinopathy [28]	Deep Learning Approach is applied in which the processed image is fed into a Convolutional Neural Network to predict whether the patient is diabetic or not	High-Resolution Fundus (HRF)	CNN
Diabetic retinopathy detection using soft computing techniques [29]	Gray level co-occurrence matrices (GLCM), Classifiers such as Support Vector Machine (SVM), Random Forests, Gradient boost, AdaBoost, Gaussian Naive Bayes	MESSIDOR	GLCM
Disc-Aware Ensemble Network for Glaucoma	Disc-aware ensemble network	SCES, SINDI	CNN

Screening from Fundus Image [33]			
Detection and classification of diabetic retinopathy using retinal images [35]	Random Forests technique based on the area and perimeter of the blood vessels and hemorrhages	STARE	Filters and Random Forests
Weakly-supervised localization of diabetic retinopathy lesions in retinal fundus images [37]	CNN architecture	DiaretDB1	CNN
Glaucoma-Deep: Detection of Glaucoma Eye Disease on Retinal Fundus Images using Deep Learning [40]	Convolutional neural network (CNN) and deep-belief network (DBN)	DRIONS-DB, sjchoi86-HRF	CNN
Convolutional Neural Network for Multi-class Classification of Diabetic Eye Disease [43]	Multi- class DED, automated classification framework	MESSIDOR	CNN
A deep feature fusion and selection-based retinal eye disease	Selection based retinal disease detection,	-	AlexNet, ResNet50

detection from OCT images [44]	Modified-Alexnet and ResNet-50		
DR-NASNet: Automated System to Detect and Classify Diabetic Retinopathy Severity Using Improved Pretrained NASNet Model [45]	Detection and classification of severity of DR using an improved version of NASNet Model that has been pre-trained	APTOS-2019, PAK-DR(Private)	NASNet
FAS-Incept-HR: a fully automated system based on optimized inception model for hypertensive retinopathy classification[46]	Automated early detection of this illness can be aided by AI and deep learning models.	PAK-HR (Private)	InceptionV3
Mobile-HR: An Ophthalmologic-Based Classification System for Diagnosis of Hypertensive Retinopathy Using Optimized MobileNet Architecture [47]	MobileNet architecture to optimize the diagnosis of HR disease using dense blocks	PAK-HR (Private), DRIVE, DiaRetDB0	MobileNet

Chapter 3

Materials and Methods

In our research, we present a novel framework named CAD-EYE, combining the strengths of EfficientNet and MobileNet. CAD-EYE approach is used to categorize images of eye diseases, discerning between diabetic retinopathy, hypertensive retinopathy, glaucoma, cataract -related issues and normal cases. Within the CAD-EYE system, the feature fusion methodology of EfficientNet and MobileNet is utilized to extract valuable features, employing transfer learning for training on eye-related abnormalities. The CAD-EYE system incorporates essential mechanisms for detecting images depicting eye diseases and recognizing the mentioned issues. The different phases of the system are depicted through a flow chart in Figure 3.1. Features obtained from EfficientNet and MobileNet are amalgamated and the model parameters undergo continuous refinement throughout the training period.

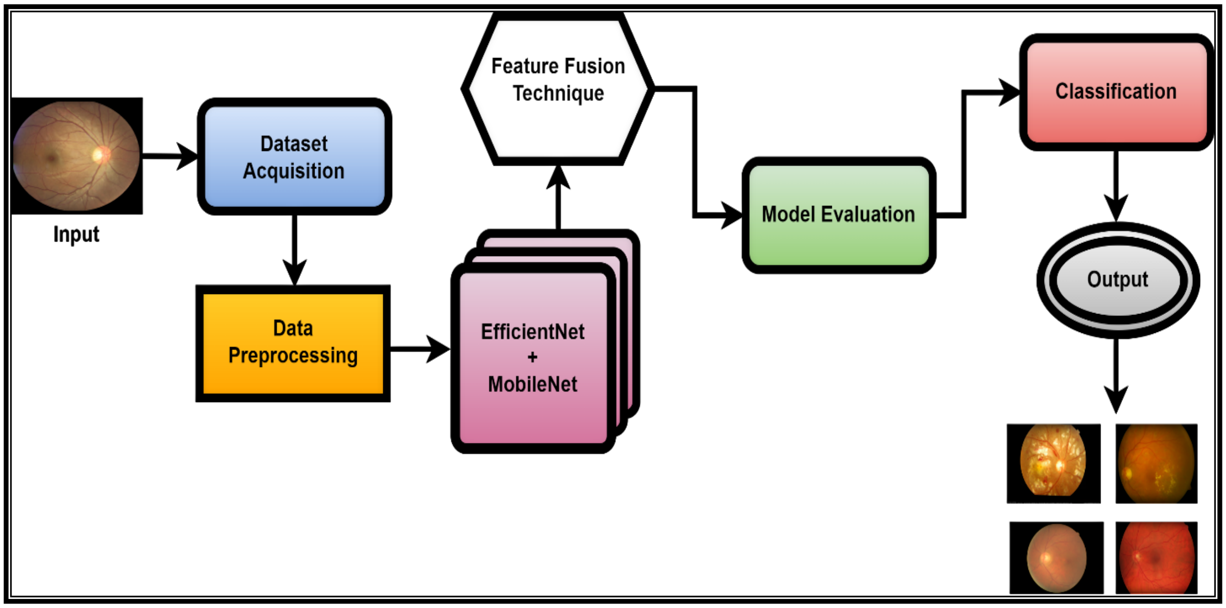

Figure 3.1: Systematic flow chart of CAD-EYE model for identification of eye diseases

The creation of the CAD-EYE model marks an advancement in the field of deep learning as well as computer vision. Two well-established deep learning models, EfficientNet & MobileNet, are made use of, culminating in a unique hybrid model with the potential to surpass its predecessors. By combining the effective feature extraction of EfficientNet with the strong training stability and transferability of MobileNet, this paradigm shows potential of improved performance on variety datasets. Notably, its adaptability to distinct domains stands out as a distinctive feature, achieved through the deliberate integration of intricate components.

The incorporation of the "EfficientNet and MobileNet feature fusion technique" has stood out as an innovative and notable contribution with regards to solutions based on deep learning. This approach is highly favored in diverse computer vision tasks, effectively blending the strengths of EfficientNet and MobileNet. Key attributes include commendable interpretability, minimal resource utilization, and demonstrated real-world efficacy. Moreover, this methodology aims to improve not only efficiency but also the performance within the realm of computer vision. The training process that the model undergoes, utilizes a designated dataset and incorporates techniques like feature fusion from EfficientNet and MobileNet to enhance the model's performance and versatility.

Tailoring tasks to specific requirements becomes particularly valuable when generic models encounter challenges in achieving optimal performance. An outstanding feature of the innovative model under study, which combines EfficientNet and MobileNet architectures, lies in its extensive empirical validation.

This hybrid model demonstrates high efficiency with regards to utilization of resources, rendering it well-suited for deployment in environments where resources are restrained; this includes edge devices, for which memory constraints as well as computational constraints are critical considerations. Apart from enhanced efficiency, the model ensures greater standards of interpretability, a crucial aspect in industries like healthcare and autonomous driving. The elucidation of the decision-making process, achieved through the integration of thick blocks from EfficientNet and MobileNet components, proves pivotal for applications where trust and safety are paramount concerns.

3.1 Data Acquisition and Pre-Processing

The CAD-EYE model underwent training and evaluation using the Multiple-EYE dataset, which comprises 65,871 photos. These images were gathered from both private and public sources, including reputable eye facilities in different countries and well-known internet platforms. Prior to data sharing, explicit consent was obtained from patients and physicians, with a commitment to maintaining confidentiality by providing the data anonymously without revealing any clinical details. This approach ensured accessibility for research purposes while safeguarding patient data. The Multiple-EYE dataset, compiled from various sources, includes eye fundus images related to diverse eye conditions such as diabetic retinopathy, hypertensive retinopathy, glaucoma, cataract, and normal images. A meticulous curation process was undertaken by qualified ophthalmologists in the training dataset, who discerned normal and eye disease photos to establish a standardized dataset. The expertise of these ophthalmologists, well-versed in detecting eye-related traits, played a pivotal role in this manual curation process. To enhance the interpretability and explainability of the CAD-EYE model, the HISTOMSR pre-processing approach has been employed. HISTOMSR's ability to generate clear heatmaps highlighting essential areas in an image, along with its user-friendly nature and suitability for object localization, positions it as a valuable tool for understanding the decision-making process of the model. The selection of HISTOMSR approach aligns with the goals of this research. The incorporation of HISTOMSR approach reflects ongoing efforts that aim to improve the reliability of models based on DL, fostering their accessibility and trustworthiness in diverse applications, as illustrated in Figure 3.2.

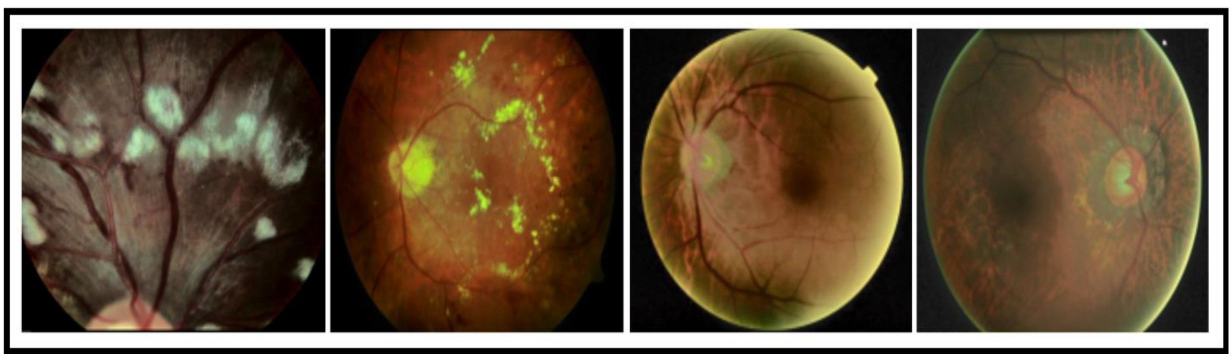

Figure 3.2: Results of Image Preprocessing technique HISTOMSR

Figure 1.1 shows a representation of a meticulous examination of 65,871 eye photographs. Table 3.1 provides a breakdown of the datasets utilized to formulate the set of fundus images for training and testing. All experiment images were uniformly downsized to 700×600 pixels and processed to generate binary labels. The complete dataset comprises of 65,871 photos, with 9,393 utilized for system evaluation. To ensure impartiality, the dataset has been initially categorized into different classes, with an aim to balance the overall number of photos for each class. Prior to input into an algorithm tailored specifically for the CAD-EYE model, photos have undergone pre-processing involving resizing to 700×600 pixels. Standardization has also been applied to minimize variation between data points. The CAD-EYE system has been trained and evaluated using data from Multiple-EYE, wherein resolution of each image is 1125×1264 pixels.

Table 3.1. Dataset of Eye diseases for the CAD-EYE framework

Ref	Dataset Used	Normal Eye	DR	HR	Glaucoma	Cataract	Total
[53]	Eyepacs, Aptos, Messidor	23,125	23,125	-	-	-	46,250
[54]	Eye disease dataset	-	-	-	50	100	150
[55]	Eye Diseases Classification	250	250	-	250	250	1000
[56]	Dataset for different eye disease	1,637	-	-	1,637	1,637	4,101
[57]	DiaRetDB1	100	100	-	-	-	200
Private	PAK-HR	3,000	-	3,000	-	-	6,000
Private	DR-Insight	1,000	-	4,000	-	-	5000
Private	Imam-HR	1,130	-	2,040	-	-	3,170
		30,242	**23,475**	**9,040**	**1,937**	**1,987**	**65,871**

The images, sourced from various sources, were resized to a standard dimension of 700×600 pixels for the purpose of simplification and standardization of the dataset. Additionally, seasoned pulmonologists played a crucial role in generating both eye disease and non-eye disease data during the dataset construction process for accurate ground truth evaluation. To enhance image features and eliminate interference, the Grad-Cam technique has been applied to preprocess the images, as depicted in Figure 3.2. Employing Grad-Cam on eye fundus images facilitated the identification of key regions in detecting the presence of eye diseases. This technique aided in recognizing distinctive characteristics that significantly made an impact on the predictions made by CNN, for the diagnosis of diabetic retinopathy, hypertensive retinopathy, glaucoma and cataract images.

3.2 Data Augmentation

The dataset table clearly indicates an uneven distribution of data, potentially leading to bias in favor of a particular class during the process of training the model. Rather than acquiring additional data, this challenge can be addressed through a method known as "data augmentation”. Data augmentation deliberately generates additional data points from existing ones, thereby enhancing the diversity of dataset. This approach is instrumental in making the performance of system better as well as preventing overfitting in it. During the process of training, images can be enhanced using the approach known as AutoAugment. Alongside data augmentation technique, other techniques may be applied to solve the data balancing problem. These techniques include resampling methods like oversampling and under sampling. Also, other ensemble methods including bagging and/or boosting may also be used. Moreover, GAN which is a data generation technique may also be used. Each of these techniques has its own advantages and can be tuned to the specific dataset used. These techniques are critical for achieving robust and generalized machine learning models with high accuracy. Each of these approaches offers unique advantages and can be tailored to the specific characteristics of the dataset and the objectives of the machine learning task. Employing these advanced approaches to tackle imbalance of classes is crucial in order to achieve enhanced accuracy, as well as more robust and equitable models of machine learning.

A widely used approach which is also effective for resolving imbalance class problem, is that of Data Augmentation. First off, data augmentation is a simple procedure that doesn't require a lot of changes to the hyperparameters or model architecture. It entails applying different transformations, including rotation, flipping, cropping, or noise introduction, to existing data in order to create new training samples. This creates an artificially larger minority class, which helps to achieve a more even distribution of classes. It uses existing data to create new instances that can aid the model for generalizing. This strategy is essential for enhancing and maintaining the model's functionality while preventing overfitting. For our research, we detail the AutoAugment transformation policy, and construct a set of procedures for transformation that includes resizing the pictures, flipping the images horizontally and then applying a policy of AutoAugment. During this process, training images are taken in from dataset organized in a directory structure under the './dataset/train' folder. ImageFolder class from Torchvision dataset helps apply the AutoAugment transformation to each image. Training a DL model on a dataset that has been customized, involves making use of augmented photos provided by the DataLoader in batches. This is done to enhance performance and generalization. While recognizing the challenge of imbalanced class is important and highlights a persistent issue in machine learning, it doesn't offer a comprehensive solution beyond the use of data augmentation strategies. Exploring better and more efficient approaches for dealing with this issue is crucial in order to achieve more effective, robust and consistent outcomes. The overall procedure of data augmentation is explained as follows:

Table 3.2. Steps for Data Augmentation

Step No	Process
1	Importing torch, torchvision & albumentation (all the necessary libraries required).
2	Defining the function $get\_autoaugment\_transform()$ to construct the channel for AutoAugment transformation. AutoAugment policy and other image transformations are defined through Albumentations. The resulting channel resizes images, by horizontal flips, and normalizing the values of pixel.
3	Carrying out following actions related to the dataset: **a.** Load custom dataset from torchvision.datasets. using ImageFolder **b.** Apply onto the dataset, the AutoAugment transformation, which has been previously defined
4	Creating a class to handle batching and shuffling of dataset through the course of training process. This will be created through DataLoader using torch.utils.data.DataLoader.
5	Defining a simple CNN model class SimpleCNN using nn.Module. Pertinent loss function and optimizer are prepared for training the model. Hyperparameters like, the number of training epochs, batch size and learning are also defined Examples of loss function include CrossEntropyLoss and example of optimizer include SGD or Adam
6	Training of model using specified epochs by repeatedly executing following steps: a. Call $model.train()$. in order to set the model to training mode b. Obtain batches of augmented images as well as the labels corresponding to them. This will be done by looping through the DataLoader

	c. Forward pass is implemented on the model. d. Defined loss function is used to calculate the difference between expected outputs and ground truth label e. Backward pass is implemented to compute gradients of the model's parameters with respect to the loss. f. Parameters of the model are updated through computed gradients as well as the chosen optimizer
7	Model becomes ready for inference and evaluation once the training is complete, (on new data)

Chapter 4

Proposed Architecture

The comprehensive model structure seamlessly integrates the distinctive capabilities of MobileNetV2 and EfficientNet through a meticulous feature fusion process, ultimately leading to a final layer compatible with an XGBoost classifier for image classification. This innovative approach involves leveraging the pre-trained convolutional neural networks, MobileNetV2 and EfficientNet, each renowned for its specific architectural strengths. The fusion methodology, facilitated by global average pooling and concatenation, strategically captures and harmonizes spatial information from both architectures. Subsequent dense layers further refine the feature space, extracting nuanced relationships. The final architectural element introduces an XGBoost classifier, extending the model's versatility beyond the neural network domain. This hybrid architecture, combining deep learning with gradient boosting, offers a sophisticated ensemble approach for image classification tasks, leveraging the strengths of both paradigms to achieve enhanced predictive performance. The model is poised not only to benefit from the hierarchical feature extraction capabilities of deep neural networks but also to capitalize on the interpretability and ensemble learning process of XGBoost, ensuring robust and accurate classification outcomes as illustrated in Figure 4.1.

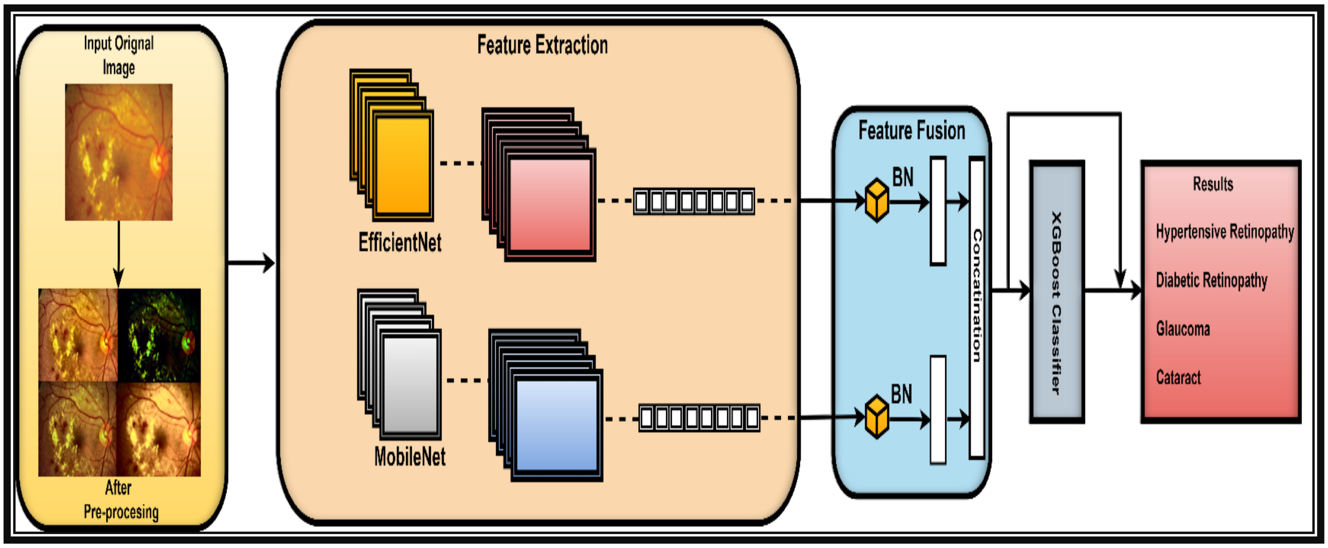

Figure 4.1: Proposed Architecture of CAD-Eye System12

Let M represent the MobileNetV2 model, and E represent the EfficientNet model.

$$MobileNetV2\ features: X_M = M(Input) \tag{4.1}$$

$$EfficientNetB0\ features: X_E = E(Input) \tag{4.2}$$

Set all layers of both models as non-trainable.

$$X_M^{frozen} = Freeze(X_M) \tag{4.3}$$

$$X_E^{frozen} = Freeze(X_E) \tag{4.4}$$

Let GlobalAveragePooling2D (·) GlobalAveragePooling2D(·) represent the global average pooling operation, and Dense (·) Dense(·) represent a dense layer.

$$X_M^{Pooled} = GlobalAveragePooling2D\left(X_M^{frozen}\right) \quad (4.5)$$

$$X_E^{Pooled} = GlobalAveragePooling2D\left(X_E^{frozen}\right) \quad (4.6)$$

$$X_{Concat} = Concatenate\left(X_M^{Pooled}, X_E^{Pooled}\right) \quad (4.7)$$

$$X_{dense1} = Dense(128, activation = 'relu')(X_{Concat}) \quad (4.8)$$

$$X_{dense2} = Dense(num_{classes}, activation = 'softmax')(X_{dense1}) \quad (4.9)$$

$$fusion_{model} = Model(inputs = [M.input, E.input], outputs = X_{dense2}) \quad (4.10)$$

$$fusion_{model}.compile\left(optimizer = 'adam', loss = 'categorical_{crossentropy}', metrics = ['accuracy']\right) \quad (4.11)$$

$$fusion\_model.fit([train_{generator}.next(\quad)[0], train_{generator}.next(\quad)[0]. train_{generator}.next(\quad)[1], epochs = 10, validation\_data = ([test\_generator.next()[0], test\_generator.next()[0]], test\_generator.next()[1]) \quad (4.12)$$

The proposed model architecture initiates with the extraction of features from input images through the pre-trained MobileNetV2 (M) and EfficientNet (E) models, represented by Equations (4.1) and (4.2) respectively. Following this, all layers of both models are rendered non-trainable to preserve their learned weights (Equations 4.3 and 4.4). Subsequently, global average pooling is applied to the frozen features, producing X_M^{Pooled} and X_E^{Pooled} (Equations 4.5 and 4.6). These pooled features are then concatenated, forming X_{Concat} (Equation 4.7). The concatenated features are subjected to dense layers with rectified linear unit (ReLU) activation, resulting in X_{dense1} and X_{dense2} (Equations 4.8 and 4.9). Finally, the fusion model is defined with two inputs (from MobileNetV2 and EfficientNet) and one X_{dense2} , denoted by Equation (4.10). Subsequent to model definition, the architecture is compiled using the Adam optimizer, categorical cross entropy loss, and accuracy as the monitoring metric (Equation 4.11). The training phase, Equation (4.12), involves fitting the fusion model to the training dataset utilizing data generators for a specified number of epochs, thus culminating in a meticulously crafted model capable of leveraging the complementary strengths of both MobileNetV2 and EfficientNet for image classification tasks. Figures 4.2, 4.3, 4.4 and 4.5 show the visual results of the predicted CAD-EYE system. Process to carry out feature map extraction using CAD-EYE model, is enumerated in Table 4.1.

Table 4.1. CAD-EYE feature map extraction method

Step No	Operations	Explanation
1	Load Pre-trained Models	$X_M = M(Input)$ Extract features using MobileNetV2. $X_E = E(Input)$ Extract features using EfficientNetB0.
2	Freeze Layers	$X_M^{frozen} = Freeze(X_M)$ Set MobileNetV2 layers as non-trainable. $X_E^{frozen} = Freeze(X_E)$ Set EfficientNetB0 layers as non-trainable.
3	Global Average Pooling	$X_M^{Pooled} = GlobalAveragePooling2D\left(X_M^{frozen}\right)$ Apply global average pooling to MobileNetV2 features. $X_E^{Pooled} = GlobalAveragePooling2D\left(X_E^{frozen}\right)$ Apply global average pooling to EfficientNetB0 features.

4	Concatenation	$X_{Concat} = Concatenate\left(X_M^{Pooled}, X_E^{Pooled}\right)$ Concatenate pooled features.
5	Dense Layers	$X_{dense1} = Dense(128, activation = 'relu')(X_{Concat})$ Apply dense layer with ReLU activation. $X_{dense2} = Dense(num_{classes}, activation = 'softmax')(X_{dense1})$ Final dense layer for classification.
6	Fusion Model Definition	$fusion_{model} = Model(inputs = [M.input, E.input], outputs = X_{dense2})$ Compile with Adam optimizer.
7	Compile the Model	$fusion\_model.compile(optimizer = 'adam', loss = 'categorical\_crossentropy', metrics = ['accuracy'])$. Compile with Adam optimizer.
8	Train the Model	$fusion\_model.fit([train\_generator.next()[0], train\_gene$ $10, validation\_data = ([test\_generator.next()[0], test\_generator.next()[0]], tes$ Train using data generators.

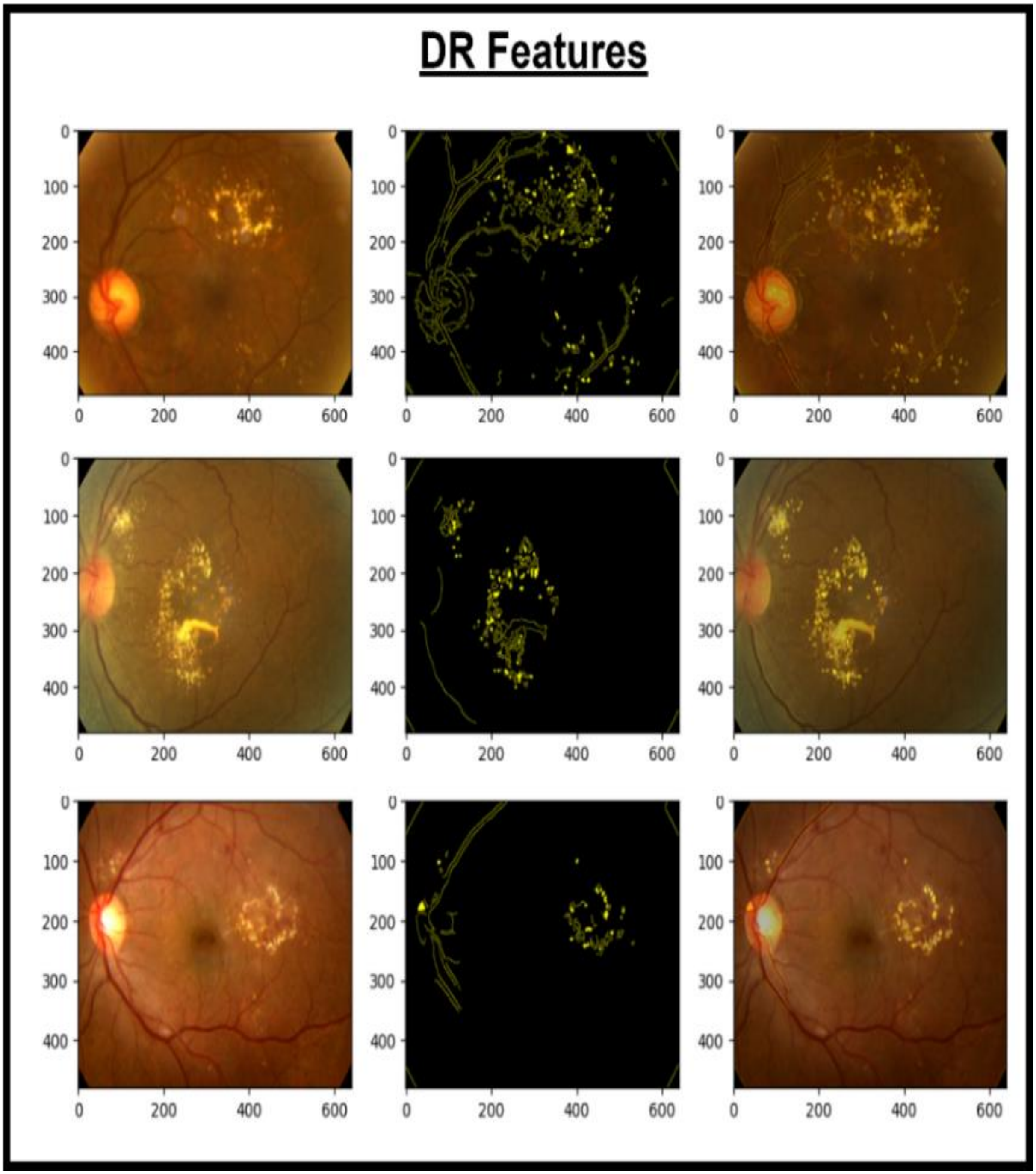

Figure 4.2: Results produced by the CAD-EYE architecture for DR

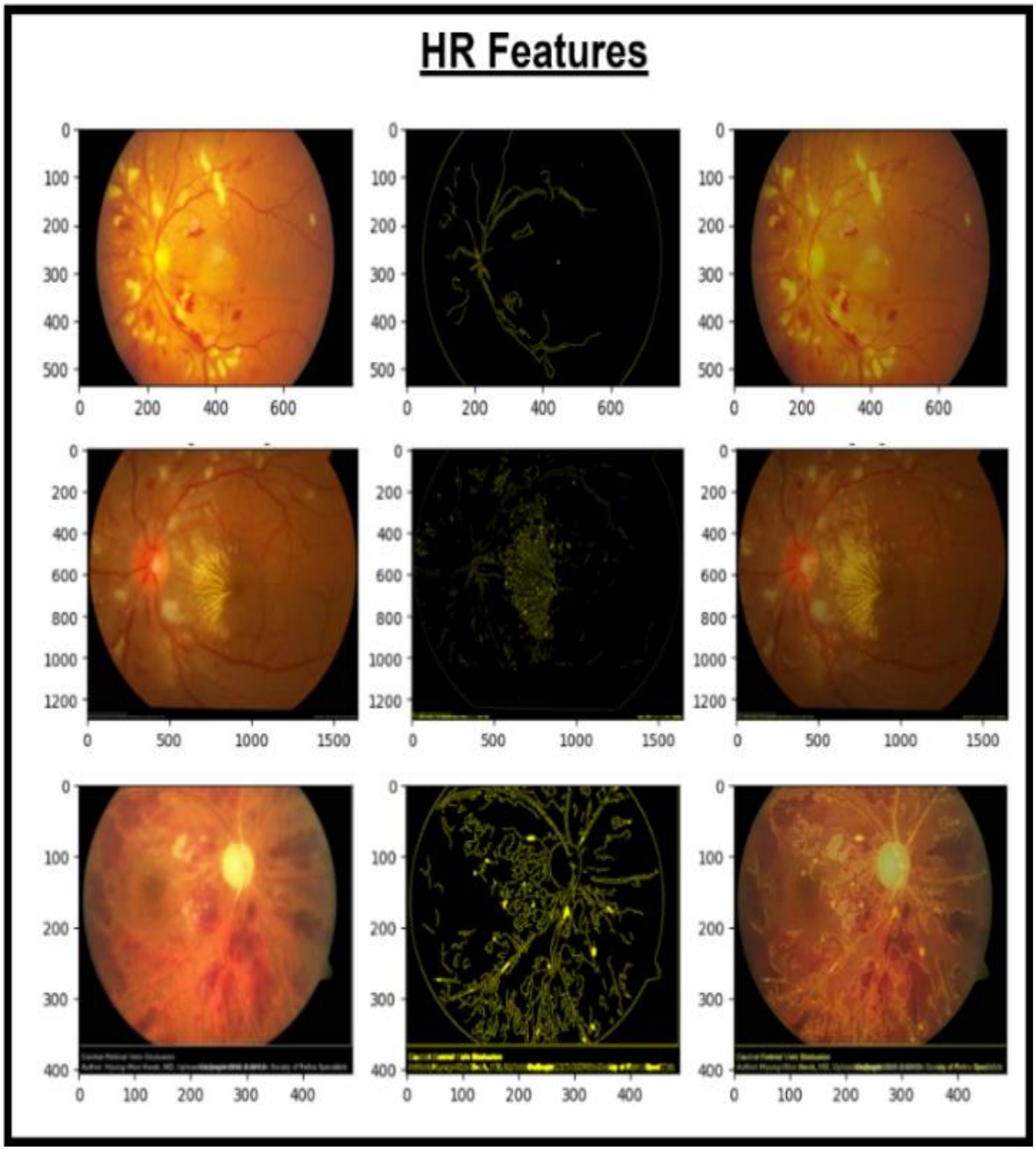

Figure 4.3: Results produced by the CAD-EYE architecture for HR

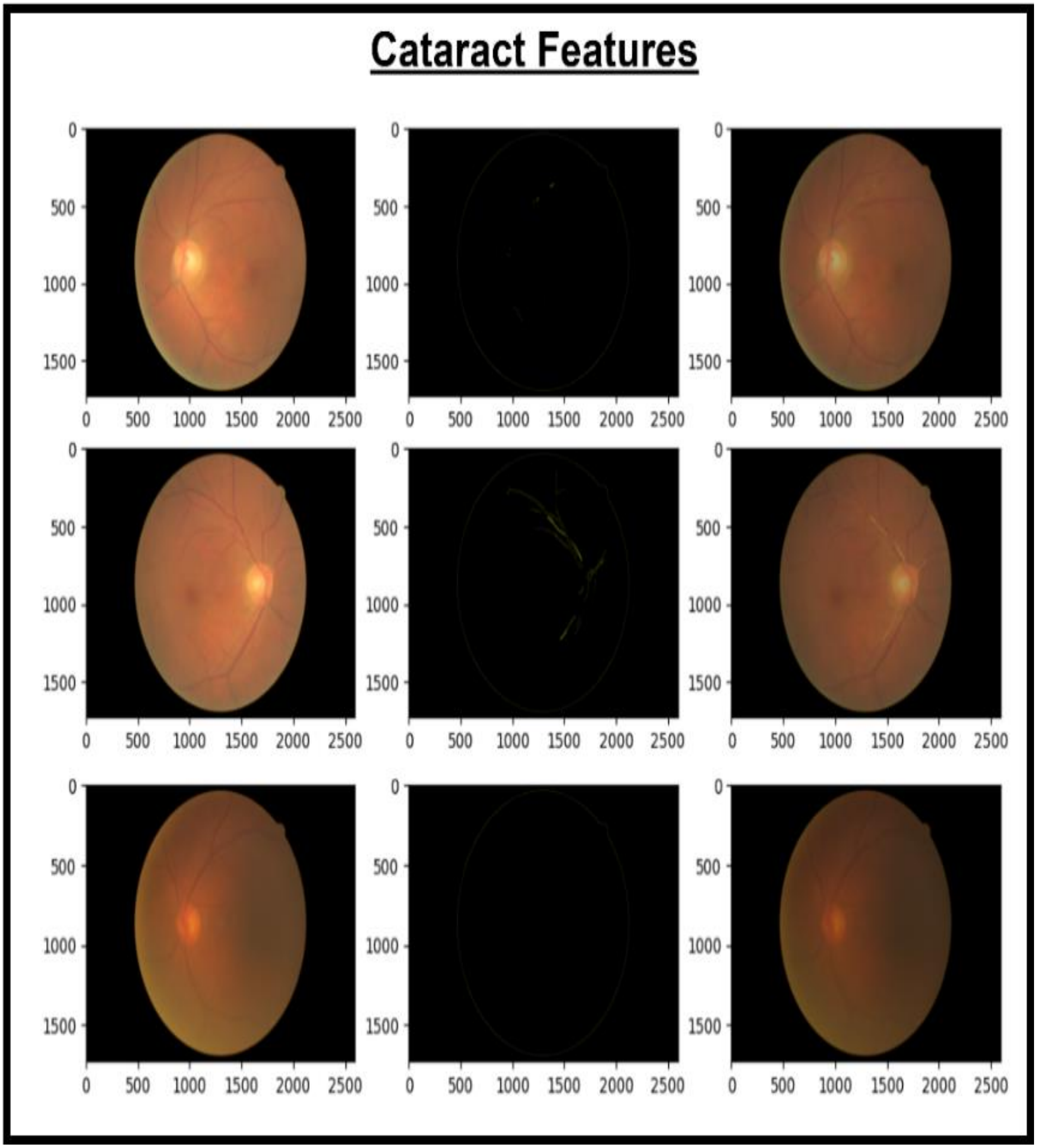

Figure 4.4: Results produced by the CAD-EYE architecture for Cataract

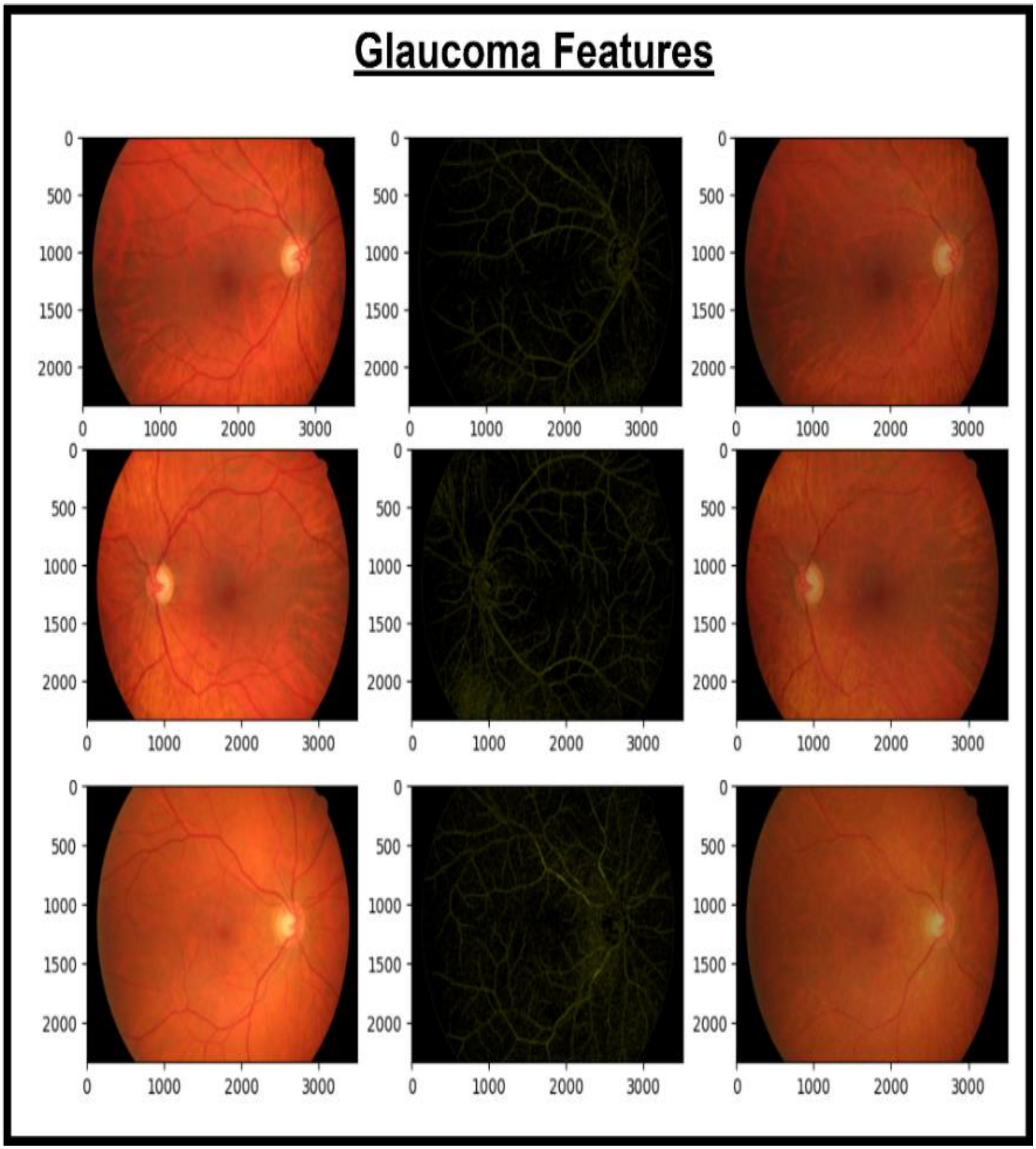

Figure 4.5: Results produced by the CAD-EYE architecture for Glaucoma

4.1 Recognition of Eye Diseases

In an effort to automate the challenging process of diagnosing eye conditions using fundus photos, our novel fusion system, aptly named CAD-EYE-Fusion, ingeniously combines the influential features of MobileNetV2 and EfficientNetB0. Illustrated in Figure 4.1, this innovative architecture seamlessly amalgamates features from both models through a strategic fusion mechanism, integrating layers such as Global Average Pooling, Dense, and Batch Normalization. Intricately woven skip connections expedite the learning process within the network. The holistic CAD-EYE-Fusion system leverages the combined feature representation to significantly enhance image classification performance for eye diseases. The architecture boasts multiple dense blocks, constructed with depth wise convolutional layers. One of these layers is the ReLU activation layer. Similarly, other layers include the max pooling and the batch normalization layers. The skip connections within these dense blocks facilitate efficient training and connectivity. Comprising a total of three dense blocks, our model ensures consistency in input and output sizes, enabling effective feature learning. The final classification output is obtained through an additional layer that tailors the categorization process, including layers such as Dense and Batch Normalization, maintaining 850 nerve cells for optimal performance. Batch normalization layers are seamlessly integrated into CAD-EYE-Fusion as a preprocessing step, contributing to improved training and convergence of the model. The detailed incorporation of batch normalization is provided in Table 4.2, emphasizing its significance in the comprehensive fusion system designed for robust eye disease classification from medical images.

$$B = \{ X_{1 \ldots\ldots m}\}, \gamma, \beta \tag{4.13}$$

$$\{y_i = BN_{\gamma\beta}(X_i)\} \tag{4.14}$$

$$\mu_B \leftarrow \frac{1}{m}\sum_{i=1}^{m} Xi \tag{4.15}$$

$$\sigma_B \leftarrow \frac{1}{m}\sum_{i=1}^{m} Xi - \mu_B \tag{4.16}$$

$$X_i \leftarrow \frac{X_i - \mu_B}{\sigma_B^2 + \epsilon} \tag{4.17}$$

$$y_i \leftarrow YX_i + \beta = BN_{\gamma\beta}(X_i) \tag{4.18}$$

Table 4.2. Symbol Table

Symbol	**Values/ Meaning**
$\boldsymbol{B}$	Batch
$\boldsymbol{x}$	Batch minimum activating value
$\boldsymbol{\epsilon}$	Constant used for numerical stability
$\boldsymbol{\mu_B}$	Mean of the mini-batch
$\boldsymbol{\gamma}$	Learning variable
$\boldsymbol{\sigma_B^2}$	Variance of the mini-batch
$\boldsymbol{\beta}$	Learning variable

4.2 XGBoost Classifier

In our research, we have also explored the efficacy of the XGBoost algorithm for the task of recognizing features associated with diabetic retinopathy, hypertensive retinopathy, glaucoma and cataract. The algorithm, outlined in detail as Algorithm 1, employs a gradient boosting framework with decision trees as base learners. XGBoost is particularly well-suited for binary classification tasks, and we have configured it with hyperparameters such as the learning rate

(η), regularization term (λ), and the number of trees (T). For the feature extraction process in the realm of computer vision, we adopted Depthwise Conv2D, providing a more specialized convolutional operation. This alteration aimed to enhance the model's ability to discern intricate patterns in retinal images. The training process involves iteratively constructing decision trees and updating the model based on the calculated gradients (gi) and Hessians (hi) for each training sample. During the training of the XGBoost model, the prediction of the t-th tree is sequentially incorporated into the ensemble, guided by the learning rate and the weights determined by the optimization process. The final prediction for a testing sample is the sum of predictions from all trees in the ensemble, resulting in a robust recognition model. Mathematically, the XGBoost algorithm optimizes an objective function that balances a loss term and a regularization term. The output for a testing sample ($Atest$) is computed as the sum of the predictions from each tree, weighted by the learning rate and tree weights. This ensemble approach allows XGBoost to find out the complex relationships in the data and also to generate a reliable recognition outcome for the classification of diabetic retinopathy, hypertensive retinopathy, glaucoma and cataract samples. Proposed XGBoost classifier is explained in Table 4.3.

Table 4.3. Proposed XGBoost classifier

Step No	Description	Input	Output
1	Initialize XGBoost model	-	XGBoost model with hyperparameters (η, λ, T)
2	Train XGBoost model on normal and abnormal samples	Training data: $X = \{(x_1, a_1), (x_2, a_2), \dots, (x_m, a_m)\}$	Trained XGBoost model

		Labels: $a = \{0,1\}$	
3	Use Depthwise Conv2D instead of Conv2D	Feature map $x = \{a_1, a_2, a_3, \dots, a_n\}$	Modified feature map
4	Build classifier based on XGBoost. • Train XGBoost model. • Generate ensemble of trees • Training data: X, Labels: a	Trained XGBoost model Ensemble of decision trees	
5	Allocate class label for testing samples	Testing data: $x = \{x_{test1}, x_{test2}, x_{test3}, \dots, x_{testk}\}$	Predicted class labels for X_{test}
6	Recognition of four types of diseases in retinal image samples	Predicted class labels	Recognition results for diabetic retinopathy, hypertensive retinopathy, glaucoma, cataract samples

Chapter 5

Results

A dataset comprising of 65,871 fundus images, encompassing high-resolution normal, diabetic retinopathy, hypertensive retinopathy, glaucoma and cataract images has been utilized to train the CAD-EYE model. These images were sourced from various reliable online platforms. For feature extraction and classification activities, all **65,871** images were resized to 700 x 600 pixels. The CAD-EYE system has been trained for a total of 100 epochs. The optimal model has been identified in the 30th epoch, leading to achieving an f1-score of 0.97. Statistical analysis has determined the metrics such as the values for accuracy/ ACC, sensitivity/ SE and specificity/ SP for the proposed CAD-EYE system, which have further been compared with those of other systems. The development of the CAD-EYE architecture has been conducted on a machine equipped with an HP-i7 CPU. Other technical specifications include the CPU having 8 cores. Storage capacities include 32 GB of RAM. Moreover, for graphics processing, a 2 GB Gigabyte NVIDIA GPU has been used. The operating system used for building and developing this system was Windows 11 Professional 64-bit.

5.1 Test 1

For the purpose of assessing the performance of DL models against CAD-EYE system, a test was conducted. It is worth mentioning that an equal number of epochs were employed for training each DL model. Table 5.1 presents the comparative results of the CAD-EYE system and other models in terms of sensitivity, area under the curve/ AUC, specificity and accuracy. Results acquired indicate that CAD-EYE system outperforms several other types of deep learning models, depicting a far better outcome. Figure 5.1 visually depicts the comparison between various deep learning models including CAD-EYE.

Table 5.1. Comparison of various deep learning models including CAD-Eye

Models	**Sensitivity**	**Specificity**	**Accuracy**
VGG19	75	77	79.2
InceptionV3	80.1	81.5	82.4
Xception	79.2	80.4	83.8
VGG16	72	76	78.6
ResNet50	82.5	84.9	86.7
MobileNet	83.6	84.7	87.5
CAD-EYE	**95.2**	**96.7**	**97.7**

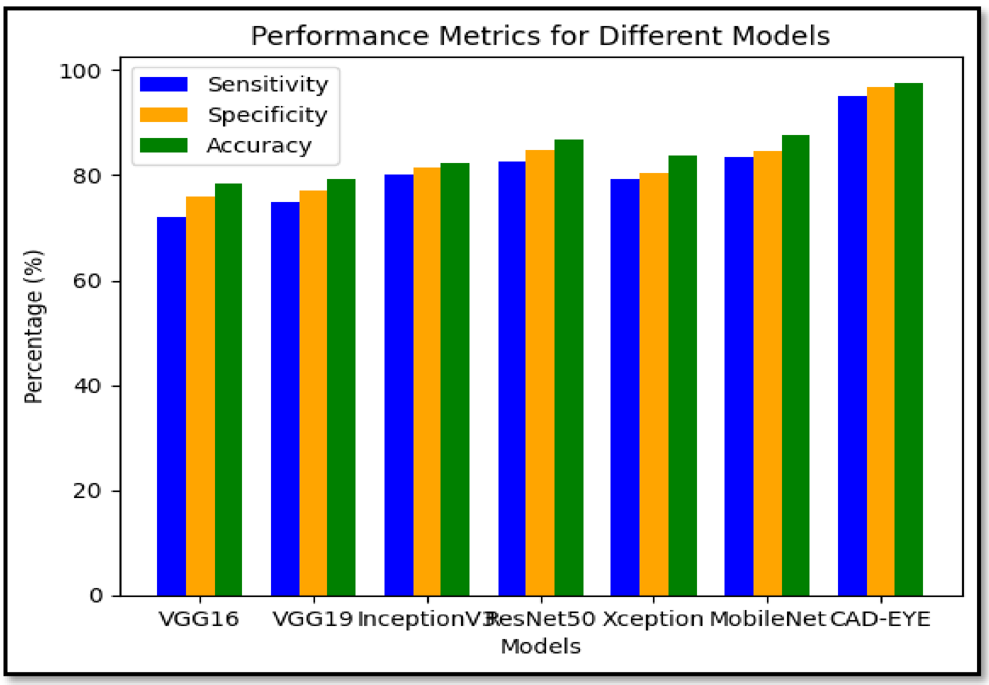

Figure 5.1: Comparison between different DL models & CAD-Eye

5.2 Test 2

To evaluate the effectiveness of our proposed CAD-EYE approach, we utilized the dataset of **65,871** fundus images obtained from different reputable sources. Initially, we employed the datasets to assess the performance of the model on both the training dataset as well as the validation datasets and to evaluate the function used for loss. A visual representation of the accuracies (training and validation) of the CAD-EYE model, is presented in Figures 5.2 and 5.3. The results unequivocally demonstrate the high efficacy of our model.

Figure 5.2: Results of accuracy and loss for training and validation of proposed model

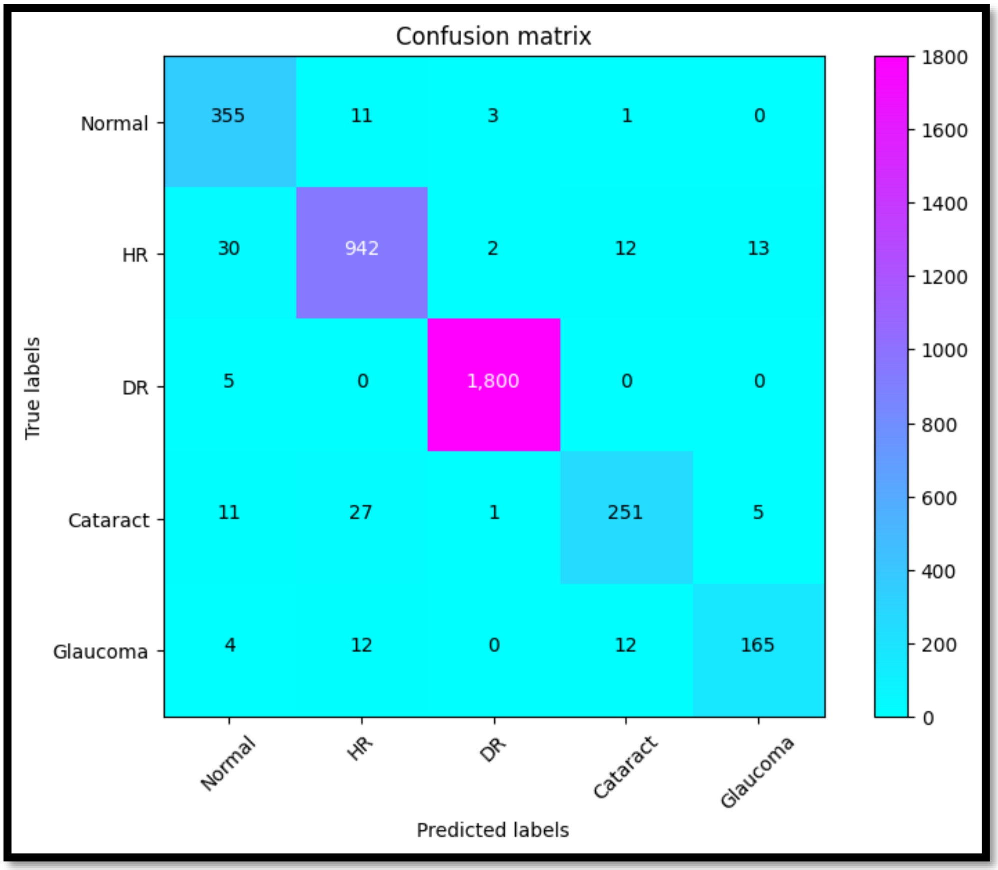

Figure 5.3: Confusion matrix for CAD-EYE

5.3 Test 3

Lastly, we have assessed the efficacy of our proposed CAD-EYE system using the EDC dataset [55]. Initially, we examined the loss function. Subsequently, we appraised the model's performance with EDC dataset. After training on this dataset, the accuracies achieved by the CAD-EYE model, are visually presented as per Figure 5.4. The results demonstrate the remarkable effectiveness of our model in both training and validation scenarios. Furthermore, as outlined in Table 5.2, by utilizing the EDC dataset, we achieved a notable accuracy of 99% on both the training and validation sets.

Table 5.2. Performance Assessment of EDC Dataset

Dataset	**Sensitivity**	**Specificity**	**F1-Score**	**Recall**	**Accuracy**
EDC [55]	99.50	99.68	99.95	99.98	1.0

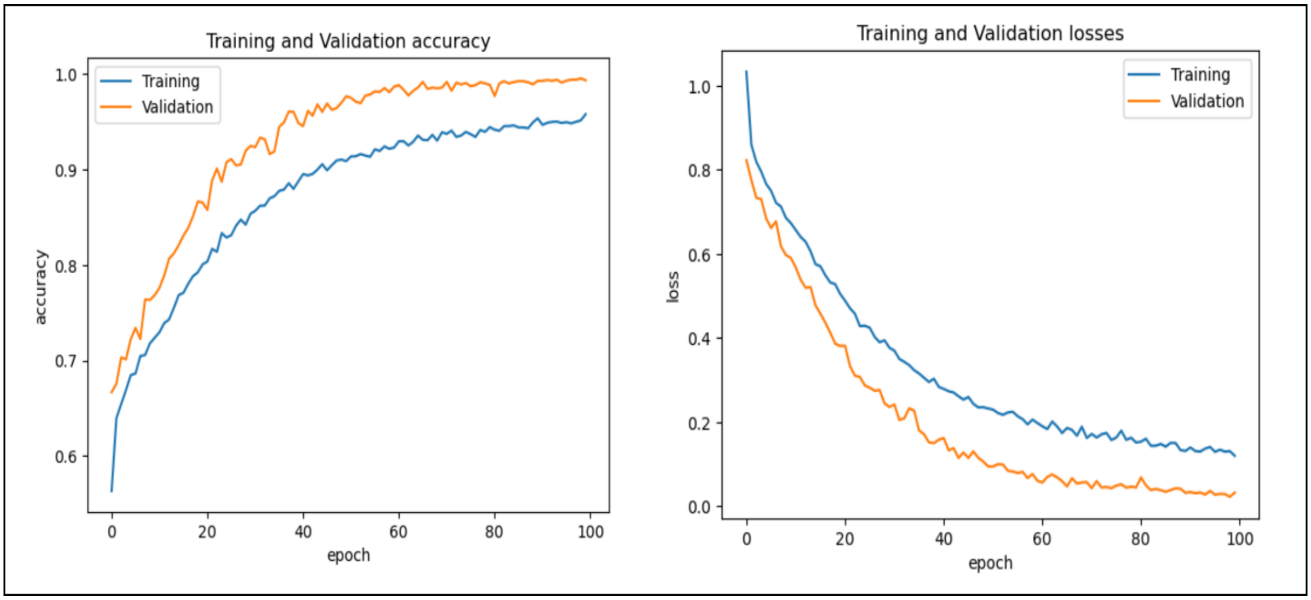

Figure 5.4: Results of accuracy and loss for training and validation of proposed model through EDC Dataset

Chapter 6

State of the art Comparison

There is only a limited number of studies that have explored the application of deep learning techniques for identifying eye diseases in retinal images. Among these, the EDC research [58] stands out for utilizing deep learning with a small dataset to detect normal, cataract, glaucoma, and diabetic retinopathy in retinal images. The latest deep learning model addressing normal, cataract, glaucoma, and diabetic retinopathy detection is referred to as EDC [58].

Table 6.1. Superior Performance of CAD-EYE than EDC [58]

Dataset	**Sensitivity (SE)**	**Specificity (SP)**	**F1-Score**	**Recall**	**Accuracy**
EDC Model [58]	98.7	96.3	98.7	98.7	99.4
CAD-EYE	99.50	99.68	99.95	99.98	1.0

The CAD-EYE system we developed has demonstrated outstanding outcomes, achieving values of 99.50%, 99.68%, 99.98%, 99.95%, 99.98%, and 1.0 for SE, SP, F1-Score, Recall, and ACC, respectively. In EDC [58], it is noted that a very limited set of input fundus images for training, resulting in high precision and accuracy has been utilized. However, it is crucial to mention that the EDC dataset lacked approval from expert optometrists. In our case, the CAD-EYE system underwent testing and training on a dataset of 65,871 images, which received validation from expert optometrists. Consequently, we achieved a classification accuracy of 98%, representing a substantial improvement over the current state-of-the-art work.

Chapter 7

Summary of Research Work

The eye is a vital organ of human body and holds paramount significance in facilitating an individual's professional and daily activities. Various maladies can impact ocular functionality, underscoring the critical importance of early detection for effective intervention. This study introduces a classification system designed to discern and categorize four distinct eye diseases: diabetic retinopathy, hypertensive retinopathy glaucoma, and cataract. The proposed system employs innovative approaches to achieve a unified model capable of classifying diverse ocular conditions within the provided categories. The incorporation of novel ideas is deemed essential to realize the objective of disease classification through a singular model in this research endeavor. First an innovative image processing algorithm is proposed. The novel method is called HISTOMSR method. This image processing algorithm focuses on areas that are crucial for classification. Second, a feature fusion between the features extracted from state-of-art models (MobileNet, EfficientNet) is proposed. Also, a dataset is created that combines different datasets collected from online sources. This step is necessary since the model will be trained on classifying four different diseases.

The proposed model is experimented through three different experiments to prove its superior performance. The aim of first experiment has been to compare the performance of the model in comparison to other state-of-art models. These models include VGG16, VGG19, ResNet, Xception, InceptionV3 and MobileNet. Outcome generated shows the superior performance of our model in comparison to these models. The results indicate that CAD-EYE was able to achieve 97% accuracy which is higher than the best state-of-art model by 10%. The second experiment conducted in this research is to test our proposed model using a dataset created by combining images from different online sources. The dataset contains 65,871 fundus images. The dataset contains high-resolution normal, diabetic retinopathy, hypertensive retinopathy, glaucoma and cataract eye disease images. The presented results show the ability of the proposed models to achieve accuracies higher than 95%. The third experiment conducted in this research is aimed to test our proposed model against the EDC (Kaggle's eye disease classification) dataset. It is noted that EDC dataset contains a very limited set of input fundus images for training. Moreover, it is important to mention that EDC dataset lacks approval from expert optometrists. Our collected dataset for CAD-EYE system consists of 65,871 images which received validation from expert optometrists. The experiment is necessary to evaluate the model against similar work from literature.

A state-of-art comparison with a similar work from literature shows the better performance of the proposed system. The proposed system has been able to achieve accuracies higher than the reported accuracies in literature.

In conclusion the classification approach proposed in this study for eye disorders relies on features extraction and features fusion as a core of the methodology. This represents a pioneer attempt to establish a computerized technique that surpasses existing methods in the detection of normal, diabetic retinopathy, hypertensive retinopathy, glaucoma and cataract eye diseases.

Chapter 8

Conclusion

Millions of individuals worldwide are affected by eye diseases such as diabetic retinopathy, hypertensive retinopathy, glaucoma and cataract. Early detection is pivotal for preventing the progression of these diseases. For the purpose of our research, we have proposed a completely automated system for carrying out first the detection and then the classification of diabetic retinopathy, hypertensive retinopathy, glaucoma and cataract. Innovative preprocessing stages have been used. Furthermore, deep learning models have been utilized to achieve accuracy which is optimal. Newly introduced HISTOMSR image preprocessing technique is employed to reduce noise, highlight lesions, and enhance the classification performance of these diseases. This novel image processing approach focuses on crucial areas in affected images, aiding in their identification. Additionally, we propose a feature fusion between the features extracted from state-of-art models (MobileNet, EfficientNet). The model is thoroughly evaluated using a diverse dataset, comprising of data from various sources. Comparative analysis with state-of-the-art models in the literature reveals the superior performance of our proposed methodology. An examination of their strengths and limitations proves the effectiveness of our approach over other models. In order to validate the efficacy of the proposed method, further evaluation on a large, diverse dataset, encompassing a significant number of prospective disease instances, is essential. Future research may explore the analysis of new datasets using NASNet or MobileNet. Moreover, other augmentation techniques may also be utilized. This method can be used as an automatic prescreening tool for disease recognition. However, future developments may incorporate knowledge-based information to extend the CAD-EYE model, providing insights into issues related to dynamic blood glucose levels. Moreover, addressing quality of images can become a focus of further research to ascertain a better, more efficient system, which can be further utilized in various clinical settings.

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