EDDNet30: A Spatial Attention and Multi-Scale Fusion Model for Enhanced Eye Disease Classification with Explainable AI

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This Report Presented in Partial Fulfillment of the Requirements for
The Degree of Masters of Science in Computer Science and Engineering

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APPROVAL

This Project titled **"EDDNet30: A Spatial Attention and Multi-Scale Fusion Model for Enhanced Eye Disease Classification with Explainable AI"**, submitted by **Showmick Guha Paul**, ID No: **242-25-003** to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfilment of the requirements for the degree of M.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on.

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DECLARATION

I hereby declare that this research has been done by me under the supervision of **Sheak Rashed Haider Noori, Professor & Head, Department of CSE,** Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

Eye illnesses are a leading global cause of blindness and vision impairment, underscoring the critical necessity for precise and timely diagnosis to avert further decline. Even though medical imaging has come a long way, it's still impossible to use fundus images to figure out what sort of retinal illness someone has since the visual indications are so complicated and hard to perceive. The goal of this work is to create and test EDDNet30, a new 30-layer deep learning model, to make it easier to tell what kind of eye disease someone has based on fundus photos. The model incorporates important architectural aspects, such as spatial attention and multi-scale fusion modules, that make it more accurate and reliable for diagnosis. To confirm the suggested model, a varied dataset of 5,531 photos, including nine main sickness types, is gathered from many sources. To improve the photographs, a lot of pre-processing methods were used, such as histogram equalization, color space conversion, and contrast change. These methods made sure that the photographs were clear and crisp. We also used image data augmentation to add more pictures to the dataset. This enabled the model learn to apply what it learned to new situations better throughout training. The spatial attention module makes the model pay greater attention to the most important parts of the visuals. The multi-scale fusion modules, on the other hand, gather and combine characteristics of different sizes, which makes it much easier to put things into categories. We compared the model against a variety of different transfer learning models to see how well it worked. The results reveal that EDDNet30 is frequently better than transfer-learning models, with an accuracy rate of 95.29% on 10% of the test data. This indicates that EDDNet30 is better at identifying the difference between eye diseases and is more reliable. We also used other explainable AI approaches like Grad-CAM, Grad-CAM++, and LIME to find and highlight the most important factors that affect the decision-making process. This made the model easier to understand. EDDNet30 might be a breakthrough advance in the automated detection of eye diseases since it makes diagnosis more accurate for use in the clinic.

Keywords: Eye disease classification, spatial attention, multi-scale fusion, explainable AI, deep learning

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CHAPTER 1

INTRODUCTION

1.1. Introduction

Eye disorders encompass a wide range of conditions that impact the eyes and may result in vision impairment or loss. This group of illnesses covers a wide range of vision problems, from mild to severe, like myopia, glaucoma, diabetic retinopathy, and age-related macular degeneration [1–5]. Ocular disorders can affect people of all ages and are a major cause of blindness around the world. The danger frequently escalates with advancing age. About 2.2 billion people around the world have some kind of vision problem or are blind. This shows how common eye illnesses are [6–9]. Finding vision problems early can cut the number of people who go blind by 80% [10]. Quick detection and precise diagnosis are important for improving patient outcomes and preventing permanent visual loss. Automated diagnostic systems, especially those that use deep learning, have been shown to be useful for making eye illness identification more accurate and useful. Recent progress in deep learning has changed the way medical imaging works, especially when it comes to analyzing fundus photos to figure out what kind of eye disease someone has.

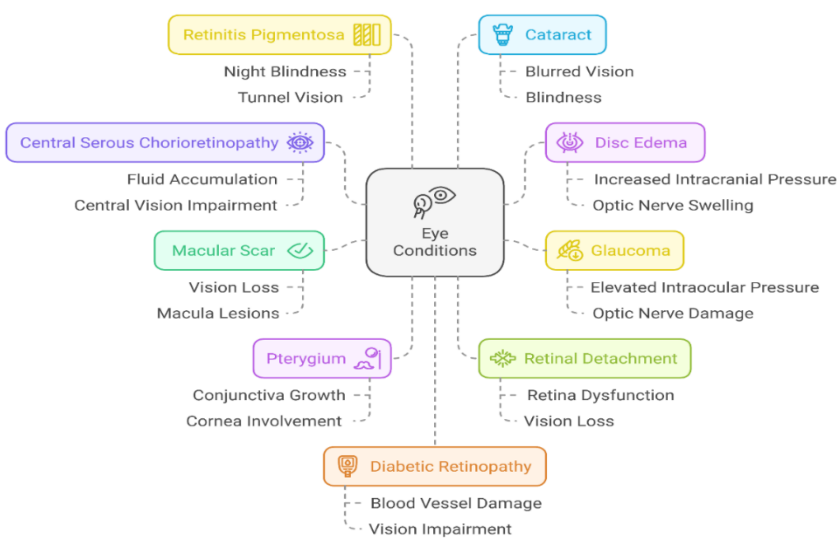

Fig. 1.1: Map diagram of key eye conditions with health issues.

Deep learning is a groundbreaking technique that has found extensive use across several domains in contemporary society. It has shown the capacity to proficiently identify diseases and perform other intricate functions [11–16]. Advanced models, including as convolutional neural networks (CNNs) and transfer learning approaches, have shown very useful in the identification of many ocular illnesses, including diabetic retinopathy, age-related macular degeneration (AMD), and glaucoma [17–21]. Using enormous datasets and sophisticated computers, these algorithms can learn about intricate patterns and properties from fundus photos. In certain situations, they may even do better than specialists. These models have performed well, but they still have a number of problems. One major issue is that they struggle with the delicate and complex characteristics in fundus pictures, such as changes in illumination, image quality, and symptoms of illness. Moreover, several modern models exhibit a deficiency in interpretability, which erodes clinicians' confidence and hinders the incorporation of these systems into clinical practice [22-24]. Because of this lack of transparency, it's extremely challenging for healthcare to use automated diagnostic technologies on a large scale. We present EDDNet30, a novel deep learning network with 30 layers that helps us better identify eye diseases using fundus pictures. This is to avoid these issues. EDDNet30 is distinct from previous approaches since it employs spatial attention processes to concentrate on regions that are important for diagnosis and multi-scale fusion modules to get both fine and coarse information. This helps understanding how complicated and subtle eye problems may be.

We also add explainable AI methods like Grad-CAM, Grad-CAM++, and LIME to the model to make it easier to understand. These strategies give visual clues about how the model makes decisions by focusing on the most significant factors that affect the expected results. This openness not only makes people trust the model more, but it also gives doctors useful information that helps them make better diagnoses and treatment plans. This study investigates nine ocular disorders in conjunction with a control group, evaluating their impact on vision and underscoring the critical significance of early detection and intervention, as depicted in Figure 1.1.

1.2. Motivation

Eye illnesses are becoming a bigger worldwide health problem that puts millions of people's vision and quality of life at risk. Early and precise diagnosis is crucial for successful treatment; yet, traditional diagnostic methods, such as manual assessment of fundus images, are labor-intensive and heavily reliant on clinical expertise. These problems show how important it is to have strong, automated, and advanced deep learning models that can make diagnoses more accurate, speed up clinical decision-making, and explain clearly how the categorization process works. These types of fresh ideas may assist patients a lot, help eye physicians make good decisions, and help more people throughout the globe see better.

1.3. Research Objectives

- To develop and validate a specialized deep learning framework, for the classification of ocular disorders using fundus images.
- To apply advanced preprocessing, spatial attention, and multi-scale fusion techniques that improve feature extraction, classification performance, and model interpretability.
- To improve diagnostic accuracy, robustness, and efficiency in ocular disease detection, thereby delivering valuable benefits to patients, ophthalmologists, and the broader healthcare community.

1.4 . Research Questions

- How can a tailored deep learning architecture incorporating spatial attention and multi-scale fusion enhance fundus image-based eye illness categorization relative to transfer learning models?

- How much do image pre-processing methods like histogram equalization, color space conversion, and contrast modification help make classification more accurate?

- How well do explainable AI methods like Grad-CAM, Grad-CAM++, and LIME help us understand how proposed model makes decisions?

1.5. Expected Output

- A high-performing deep learning model (EDDNet30) optimized for fundus image-based eye disease classification.
- Enhanced image quality through advanced preprocessing techniques such as histogram equalization, color space conversion, and contrast adjustment.
- A systematic evaluation of the effect of spatial attention and multi-scale fusion modules on classification performance.
- Superior classification accuracy (targeting ~95%+) with high precision, recall, and F1-scores across multiple eye disease categories.
- Validation of model robustness through dataset augmentation strategies and different validation schemes to ensure reliability.
- Integration of Grad-CAM, Grad-CAM++, and LIME for explainable AI, enhancing transparency in clinical decision-making.
- A framework that reduces misdiagnosis rates while maintaining high diagnostic efficiency.

1.6. Project Management and Finance

The research work doesn't get fund from any individuals or organization.

1.7. Report Layout

The study is divided into six structured sections to give a full picture of the investigation. Section 2 gives a thorough look at linked publications, giving us a better understanding of how eye diseases are now classified. Section 3 describes the proposed EDDNet30 architecture and methodology in depth, with a focus on how spatial attention and multi-scale fusion modules work together. Section 4 goes into great detail about the training tactics and evaluation procedures to show how the model was made and tested. Section 5 talks about the experimental data and how they were interpreted. It focuses on how well the model works compared to other methods. Finally, Section 6 wraps up the study by going over the main findings and talking about how they could be used in clinical settings to automatically uncover eye diseases.

CHAPTER 2
BACKGROUND

2.1. Preliminaries/Terminologies

Recent advancements in medical imaging and artificial intelligence have facilitated the creation of sophisticated algorithms for the detection and classification of eye disorders. In this context, fundus imaging is very important because it gives extensive information about the structure of the retina, including the optic disc, macula, and blood vessels. Image enhancing techniques are used to make the pictures look better and get clinically useful information, while assessment metrics like MSE, RMSE, PSNR, and SSIM are often used to check the quality of the images and the effectiveness of the preprocessing. Deep learning architectures, especially convolutional neural networks (CNNs), are now necessary for automated feature extraction. They check to see whether the categorization is right by looking for small patterns, textures, and color changes in fundus pictures. Also, explainable AI approaches like Grad-CAM, Grad-CAM++, and LIME make it simpler to grasp by presenting significant areas of the retina that change the model's predictions. This makes sure that the way computers make decisions is the same as the way doctors do. The proposed EDDNet30 framework integrates spatial attention with multi-scale fusion to enhance the accuracy, robustness, and transparency of eye disease classification.

2.2. Related Works

Eye illnesses are a key worry in healthcare since they can make vision very bad and lower quality of life in general. The best way to treat and manage these problems is to find them quickly and accurately diagnose them. In this regard, machine learning (ML) and deep learning (DL) models have surfaced as promising methodologies to aid healthcare professionals in the precise diagnosis of ocular disorders. This section will evaluate and analyze many papers on the subject, critically assessing and synthesizing existing data to provide valuable insights and context for future advancements in automated eye disease identification. Recent research has achieved significant advancements in the application of machine learning (ML) and deep learning (DL) for the diagnosis of ocular disorders from imaging modalities like as fundus photographs and optical coherence tomography (OCT) scans. Chowa et al. [25] put forward OCCT, an improved transformer-based model for classifying retinal disorders using an optical coherence tomography image. To fix the class imbalance, the study uses GAN-based data augmentation to make the dataset bigger, to 130,649 photos. An ablation study improved OCCT, which beats Vision Transformer (ViT), Swin Transformer, and CNN models including DenseNet, ResNet, and MobileNetV2 with an accuracy of 97.09%. Extensive picture preprocessing (morphological erosion, median filtering, alpha-beta correction) improves quality. The model is a strong and scalable AI method for finding retinal diseases because it is quite accurate even when it doesn't have a lot of training data.

In recent years, the merging of deep learning and machine learning has changed the way eye diseases are found and classified in a big way. The fast growth of computational models has made it possible to automatically analyze retinal fundus images and optical coherence tomography (OCT) scans. This is a promising technique to find and treat different eye problems early and correctly. These AI-driven procedures are different from previous diagnostic methods because they don't rely as much on ophthalmologists grading by hand. This makes the decision-making process much faster and supports clinical operations. A substantial corpus of literature has developed, wherein researchers have tested various model architectures, optimization methodologies, and data processing techniques to improve the accuracy and resilience of disease prediction.

Shoaib et al. [26] significantly advanced this developing domain by presenting the DiaGAN-CNN model, which integrates generative adversarial networks (GANs) for data augmentation with transfer learning methodologies employing InceptionResNet-v2 and Inception-v3. The study largely tackled the issue of restricted dataset availability, a frequent hindrance in medical imaging applications, by utilizing GANs to synthetically produce realistic samples that retained pathological features. Using this method, the DiaGAN-CNN model was able to find diabetic retinopathy (DR) and other eye problems with an amazing 98% accuracy on the ODIR dataset. This study not only showed that GAN-based augmentation can make models more generalizable, but it also showed how useful hybrid frameworks that mix standard CNNs with transfer learning backbones can be. Nonetheless, despite the highly promising results, the reliance on synthetic samples prompts inquiries regarding the representational authenticity of artificially generated images in clinical settings, indicating that meticulous assessment of GAN-generated data is essential prior to extensive implementation.

Ma et al. [27] created the Intelligent Eye Multimodal Interactive Diagnostic System (IOMIDS) because they thought diagnostic systems needed to be more interactive. IOMIDS was a new way to combine multimodal data, such as text and photos, into a chatbot-based framework. This is different from typical classification methods, which only rely on image-based prediction. This technology enabled conversational interactions between clinicians and AI, facilitating the collaborative analysis of textual symptoms and fundus images to improve diagnostic accuracy. IOMIDS demonstrated the significance of multimodality in elucidating the complexity of ocular diseases by attaining over 81% accuracy across 50 ophthalmic disorders. The performance metric was lower than that of image-only models, but the study showed that there is a trade-off between breadth and precision. It also showed that multimodal diagnostic systems can be useful as support tools in many clinical settings where detailed patient records are available along with imaging data.

Malik et al. [28] further advanced the investigation of innovative learning paradigms by introducing a Dual-Branch Semi-Supervised Learning methodology. This work recognized the difficulty posed by a lack of adequately labeled medical images, which impedes the efficacy of exclusively supervised learning systems. The dual-branch system was able to get the most information from even small sets of annotated samples by efficiently merging labeled and unlabeled fundus images. The system got 93.14% accuracy on the OIH dataset with ResNet50 as the backbone. This study underscored the unexploited potential of semi-supervised learning algorithms, especially pertinent in medical fields where the expenses and duration of expert labeling are excessively high. Even though the accuracy was a little lower than that of fully supervised transfer learning methods, the results strongly suggested that semi-supervised models could be a scalable way to deal with a lack of data, especially for rare eye disorders where labeled datasets are very hard to find.

Alongside these investigations, additional researchers have concentrated on enhancing transfer learning and hybrid feature selection methodologies to augment diagnostic precision. Kansal et al. [29] created a system that used the strengths of DenseNet201, EfficientNetB3, and InceptionResNetV2 to extract features. To improve the model's performance, scientists included a two-level feature selection technique that lets the system focus on the most discriminative retinal information. This approach achieved a validation accuracy over 98% on the ODIR dataset, setting a new benchmark for transfer learning applications in ocular diagnostics. Even though the study's approaches were quite accurate, they were mostly evaluated on one dataset, which makes me wonder how well they would work on other datasets. This is critical for utilizing AI systems in real-world eye clinics that see a lot of different kinds of patients and use a lot of different kinds of imaging instruments.

Ali et al. [30] developed the AMDNet23 framework, tailored for age-related macular degeneration (AMD). This model used both convolutional neural networks (CNNs) and long short-term memory (LSTM) networks to depict the spatial and temporal changes that transpire as retinal disease advances. When it comes to categorizing AMD, AMDNet23 had a very high accuracy rate of 96.50%. One disadvantage of this study was its dependence on a relatively small dataset, which diminished the robustness and generalizability of its conclusions. The use of LSTMs in ocular illness categorization is a notable advancement, indicating that temporal data, such as stages of disease development, may enhance spatial properties derived from CNNs.

Fahdawi et al. [31] unveiled a novel methodology with the introduction of fundus-DeepNet, a system that integrates HRNet, attention modules, and SENet blocks for the categorization of multi-label ocular disorders. Unlike binary or single-label classification methods, this system was capable of simultaneously recognizing various ocular diseases from a single fundus image, which more accurately mimics real-world clinical circumstances where comorbidities are widespread. The system achieved F1-scores and AUC values of 99% on the OIA-ODIR dataset, indicating remarkable discriminative capability. Even though the results were really good, one big problem was that they only used one dataset, which made people worry again about how well the results would hold up in the real world and in clinical settings. The study still demonstrated that architectural changes, including attention mechanisms and multi-branch networks, can significantly enhance feature learning in intricate medical imaging tasks.

Along with new models, the literature has also looked at how deep learning and standard machine learning methods compare against each other. Kaya et al. [32] performed a comparative examination of many classifiers using fundus imaging datasets. Their results showed that pre-trained InceptionV3, when used with neural networks, did better than traditional classifiers like random forests and support vector machines, getting around 91% accuracy after data augmentation. This study confirmed the emerging agreement that deep learning, especially transfer learning with pre-trained architectures, is better than regular ML models at dealing with the complex structural and textural changes that are common in fundus images.

Other specialized studies have concentrated on single-disease identification tasks exhibiting exceptionally high accuracy. Aamir et al. [33] put forward an adaptive threshold-based multi-level deep convolutional neural network (DCNN) particularly for detecting and staging glaucoma. This model reached 99.39% accuracy and had better sensitivity and specificity on a dataset of 1,338 retinal pictures. The system's adaptive thresholding made it easier to tell the difference between different stages of glaucoma, which is useful for keeping an eye on how the illness is getting worse. In a similar way, Shamsan et al. [34] showed a hybrid framework that combined CNN feature fusion with hand-crafted features, getting an AUC of 99.23% and an accuracy of 98.5%. The results indicated that integrating handcrafted features with deep learning representations can occasionally improve classification accuracy, particularly in scenarios involving tiny or significantly skewed datasets.

Wang et al. [35] made the case for custom CNN designs by using a custom 17-layer convolutional neural network to classify eye diseases. Their proprietary model was trained from scratch on a huge dataset of over 17,000 photos, unlike research that relied on transfer learning from pre-trained networks. This study, which found that well-designed domain-specific CNNs may compete with and even outperform transfer learning models, especially when big datasets are available, had an accuracy rate of 93%. The results suggested a possible compromise: transfer learning facilitates swift prototyping with considerable precision on limited datasets, whereas customized architectures would be more appropriate for extensive, domain-specific applications.

Recent studies have underscored the significance of segmentation, picture augmentation, and ensemble techniques in enhancing classification efficacy. Vadduri et al. [36] illustrated the application of sophisticated preprocessing techniques, including contrast-limited adaptive histogram equalization (CLAHE), illumination correction, and the Hough transform, to improve fundus image quality before categorization. When used with custom CNNs, these preprocessing methods made it possible to find diabetic retinopathy, glaucoma, cataracts, and normal cases with an accuracy of more than 98%. The study highlighted the significance of image quality in attaining dependable classification results, indicating that preprocessing pipelines are as essential as the learning models themselves [37].

Sikder et al. [38] investigated ensemble learning with handcrafted characteristics for the classification of diabetic retinopathy severity. Even though deep learning has been the most popular method in recent years, their system got 94.20% accuracy, showing that machine learning is still useful when it is paired with well-thought-out features. This study served as a significant reminder that traditional machine learning methods are not wholly outdated; instead, they may still yield robust and computationally efficient solutions in some clinical scenarios where computational resources are constrained or datasets are limited.

Table 2.1:

Related study summary.

Reference	Year	Sample size	Total class	Used models	Best model (accuracy)
Chowa et al. [25]	2025	130,649	4	CCT	97.09%
Shoaib et al. [26]	2024	4948	4	DiaGAN-CNN	98%
Ma et al. [27]	2025	15,640	8	Intelligent eye multimodal interactive diagnostic system	Internal: 79.6%, external: 81.1%
Malik et al. [28]	2025	4217	4	ResNet50	93.14%
Kansal et al. [29]	2025	5,000	8	BiLSTM	98%
Ali et al. [30]	2024	2000	4	AMDNet23	96.50%,
Fahdawi et al. [31]	2024	10,000	8	Fundus-DeepNet	Off-site: 92.41%, On-site: 92.66%
Kaya et al. [32]	2024	4217	4	Neural Network (NN)	90.9%
Aamir et al. [33]	2020	1338	3	multi-level DCNN	99.39%
Shamsan et al. [34]	2023	4217	4	MobileNet and handcrafted	98.5%
Wang et al. [35]	2023	5,000	8	MBSaNet	87.9%
Vadduri et al. [36]	2023	3948	4	DCNN	97%
REFUGE challenge winners [37]	2020	85,608	2	CNN	95.23%

These research jointly highlight the efficacy of CNN-based models, hybrid deep learning architectures, and multimodal approaches in the diagnosis and classification of eye disorders, as seen in table 2.1. Each method provides unique insights; nonetheless, persistent limitations remain. A lot of research still employ tiny or single datasets, which might cause overfitting and make it impossible to use the findings on other groups of individuals. Class imbalance is a common issue, especially for uncommon eye diseases, which typically messes up performance measures. Also, although if accuracy is still the most used criteria, interpretability and explain ability are often ignored, which makes it harder for doctors to trust and use the technology. The literature indicates a distinct tendency towards the amalgamation of picture improvement pipelines, multi-scale feature fusion methodologies, and explainable AI algorithms to rectify these deficiencies. New frameworks are being created with the dual goals of obtaining high accuracy and assuring transparency. This closes the gap between how well an algorithm works and how useful it is in clinical settings.

2.3. Research Gap

Even while deep learning and medical imaging for categorizing eye illnesses have made a lot of progress, there are still some important difficulties that need to be solved. Current CNN-based models often achieve high accuracy, but they struggle to maintain robustness and interpretability, which makes it hard for them to be used in clinical practice. Changes in illumination, noise, and acquisition difficulties may affect the quality of fundus images, but these differences are typically not taken into account, which renders diagnostic conclusions across various datasets wrong. Many studies also don't have extensive ablation analyses to prove that certain architectural components work, which raises questions regarding model optimization and if the results can be used in real life. Another big difficulty is that not enough people employ explainable AI approaches. These approaches are vital for creating trust in clinical settings since they indicate which parts of the retina are injured and how they affect the disease's development. These gaps show how important it is to have a personalized, clear, and performance-based framework like EDDNet30 that integrates picture improvement, multi-scale feature fusion, and explain ability to find eye diseases accurately and meaningfully in a clinical setting.

2.4. Challenges

There are a few big problems that need to be solved in order to make a good fundus image-based eye disease classification model. One big problem is that retinal images may be quite different from each other and very complicated. Changes in lighting, resolution, noise, and the instruments used to take the pictures can all have a big effect on image quality and, in turn, model performance. The high dimensionality of fundus pictures is another problem, necessitating effective feature extraction and optimization algorithms to avert overfitting while guaranteeing robust generalizability across various datasets. It is still a big problem to find a balance between high diagnostic accuracy and interpretability, as many deep learning models still work as "black boxes," which makes them hard to use in clinical settings. Robustness is further compromised by dataset-related challenges, including class imbalance and insufficient representation of uncommon eye disorders, which obstruct effective classification across all categories. Furthermore, the incorporation of explainable AI techniques that may identify abnormal retinal areas without compromising model efficiency constitutes a technological challenge. These problems highlight the need for a tailored and transparent framework, like EDDNet30, that can handle data variability, maintain accuracy, and make sure that eye disease diagnosis is clinically useful.

CHAPTER 3
RESEARCH METHODOLOGY

3.1. Proposed Methodology/Applied Mechanism

Recent progress in deep learning has changed the way medical images are processed, giving us strong tools for automatically evaluating and sorting visual data. This study utilizes a thorough approach to accurately categorize various eye diseases using deep learning methods. The basis of this approach is an organized framework called linguistic data auditing. This framework is made up of many steps that happen one after the other, beginning with carefully choosing different datasets from trustworthy sources. These datasets provide a wide spectrum of pathological eye illnesses that are necessary for accurate modeling and diagnosis. Then, a variety of preprocessing techniques were used to make the picture clearer and more uniform. The datasets were put together, and data augmentation methods and weight initialization were employed to make the training data more varied and rectify the class imbalance. Then, a custom deep-learning model was developed and trained with the objective of attaining a full and high-performing 10-class categorization. The solution uses a lot of architectural aspects, such as pre-trained models for benchmarking and a custom deep learning model called EDDNet30 (eye disease detection network) that uses new spatial attention and multiscale fusion methods. Figure 3.1 clearly displays the full procedure, from picking the data to testing the model.

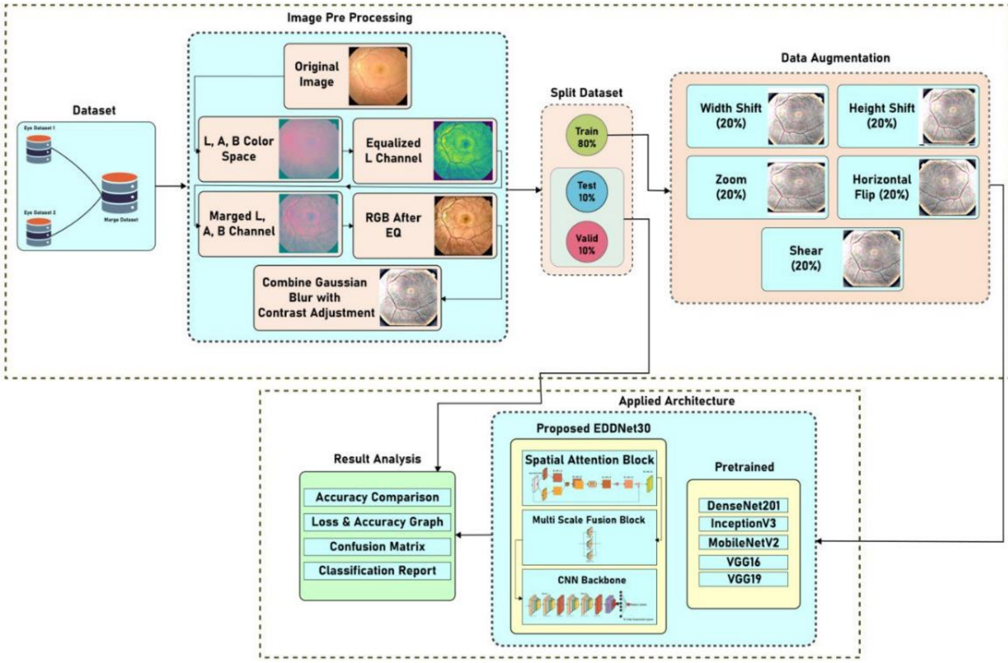

Fig. 3.1: Comprehensive workflow for eye disease detection using deep learning approaches.

3.2. Data Collection Procedure/Dataset Utilized

The dataset for this study was intentionally designed to encompass a diverse array of clinically significant eye illnesses, facilitating thorough classification and diagnostic assistance. Data was meticulously gathered from diverse repositories, each providing distinct categories of ocular disorders that encompass a wide range of pathological situations. This variety makes sure that the final dataset includes a wide range of eye disorders, which improves the model's capacity to work with different types of diagnostic categories. Table 3.1 gives a full picture of the dataset used in this investigation, including the number of photos for each of the ten types of eye illnesses.

The dataset consists of photos from two main repositories (eye dataset 1 and eye dataset 2), with each repository providing distinct categories of eye illnesses [39-40]. Figure 3.2 showed an example picture of each type of eye condition. To fix the imbalance in the datasets, different augmentation methods have been applied. This makes sure that each illness class is well-represented, which helps the model work better and more generally.

Table 3.1:

Dataset names with its count.

Dataset name	Class name	Image quantity
Eye dataset 1	Central serous chorioretinopathy - color fundus	101
	Diabetic retinopathy	1509
	Disc edema	127
	Macular scar	444
	Pterygium	17
	Retinal detachment	125
	Retinitis pigmentosa	139
	Healthy	1024
Eye dataset 2	Cataract	1038
	Glaucoma	1007
Total	**10 class**	**5531**

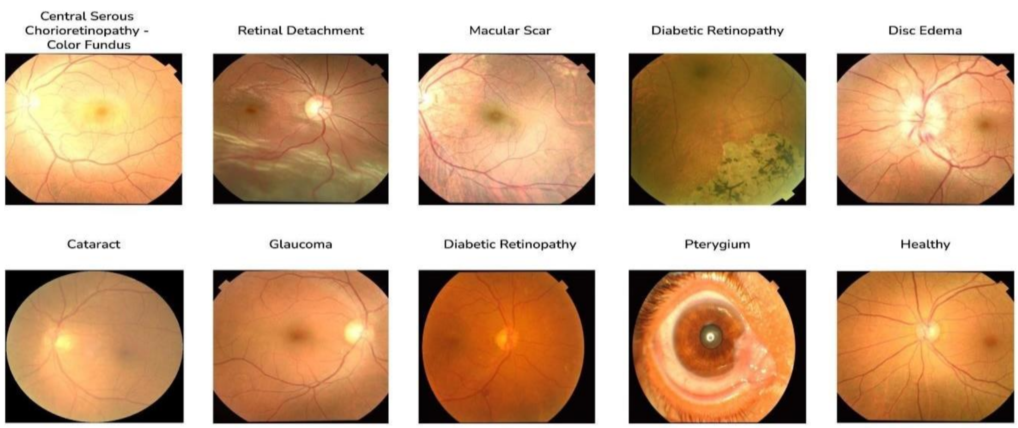

Fig. 3.2: Visual representation of eye disease classes in the dataset.

Eye diseases encompass a broad range of disorders that profoundly affect vision and general ocular health. One such illness is central serous chorioretinopathy (CSCR), which is caused by fluid building up behind the retina and causing the layers of the retina to separate in the center macular area, which is important for clear vision. Patients frequently exhibit hazy or distorted vision, central scotomas, and challenges in color discrimination. Many occurrences of CSCR go away on their own, but if they come again or last a long time without treatment, they might cause lifelong vision loss [41–43]. Disc edema, which is swelling of the optic disc where the optic nerve leaves the eye, is also quite dangerous. It is typically linked to headaches, impaired vision, and possible vision loss, and it often means that there are major neurological problems going on, like brain tumors or infections, that need to be treated right away [44–45].

Glaucoma, a primary cause of permanent blindness globally, comprises a set of disorders that progressively impair the visual nerve, frequently resulting from increased intraocular pressure. Because symptoms usually don't show up until the optic nerve is badly damaged, it's important to find them early by checking the pressure in the eye, the optic nerve, and the visual field [46–50]. Macular scars, on the other hand, are caused by a number of conditions, including age-related macular degeneration, retinal detachment, or severe inflammation. These scars hurt the macula, which is the part of the retina that controls central vision. This makes it hard to read, recognize faces, and other tasks that need detailed vision. The degree of vision impairment is predominantly influenced by the dimensions and position of the scar [51–53].

Several other eye illnesses have a direct impact on the integrity of the ocular surface or retina. Pterygium is a harmless growth of the conjunctiva that looks like a wing and grows into the cornea. It is more common in places around the equator and is generally caused by being exposed to UV light, wind, or dust for a long time. Advanced cases may result in astigmatism, visual axis obstruction, or pupil blockage, which can compromise vision [54–57]. Retinal detachment, on the other hand, is a vision-threatening disorder in which the retina separates from the tissue that supports it. This causes floaters, flashes, and shadows that look like curtains in the visual field. Permanent blindness can happen if surgery isn't done quickly. Trauma, aging, and systemic disorders such diabetic retinopathy are some of the most common risk factors [58–61]. Retinitis pigmentosa is a rare inherited retinal illness that slowly causes photoreceptor degeneration. This leads to night blindness, a progressive loss of peripheral vision, and eventually central vision impairment, which greatly lowers quality of life [62–63].

Cataracts and diabetic retinopathy (DR) are also two of the most common reasons for visual loss around the world. Cataract, mostly caused by aging, is when the natural lens becomes cloudy, which can lead to gradual vision loss and even blindness if not corrected. Trauma, long-term use of medications, and exposure to radiation are some of the other things that might cause this [64–66]. Diabetic retinopathy, or DR, is a diabetes-related problem with the blood vessels in the retina that can be either non-proliferative or proliferative. Early signs like blurred vision and floaters may show up, but the disease usually gets worse without any obvious signs, which raises the chance of serious vision loss and blindness in later stages [67–69]. These eye problems show how important it is to get diagnosed quickly, obtain the right treatment, and use innovative computer-aided systems to help doctors reduce the number of people who go blind from things that could have been avoided.

3.3. Image Pre-processing

Getting the data ready is a key part of applying deep learning to find eye problems. It ensures sure the pictures are clean, uniform, and good for training models. Figure 3.3 shows the preprocessing pipeline, which is a series of changes made to the photos that go into it to make them seem better and more consistent.

The first stage in this process is to change the format of each image to the RGB color space. This makes sure that colors look the same across all sources. This is significant because the dataset comes from different places, and each one has its own imaging settings. After that, the photos are standardized to a pixel resolution that makes sure all the inputs are the same size, which is what deep learning models need. After being resized, the photos are changed to the Lab color space. In this space, "L" stands for luminance (or grayscale intensity), and "a" and "b" stand for color dimensions. Histogram equalization, a technique that redistributes pixel intensities to make things look more contrasty, is a big enhancement that was made to the "L" channel. This change makes important visual features stand out, which helps the model find subtle patterns that are associated to different eye diseases. The logic behind histogram equalization helps make sure that the pixel intensity is spread out evenly over the image, which makes features easier to see. The equation (1), (2) governing histogram equalization, *where* σ denotes the standard deviation of the gaussian function applied during convolution.

$$L_{eq}(i) = \frac{L(i) - L_{min}}{L_{max} - L_{min}} \times 255 \quad (1)$$

$$I_{blur}(x, y) = \frac{1}{2\pi\sigma^2} exp\,(-\frac{x^2+y^2}{2\sigma^2}) \times I(x, y) \quad (2)$$

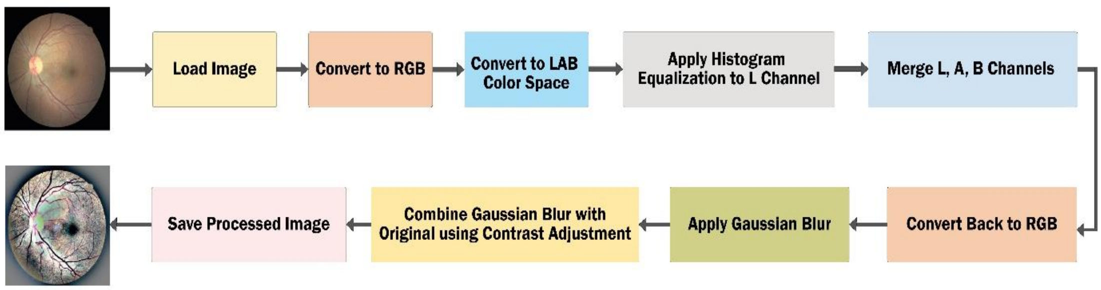

Fig. 3.3: Comprehensive preprocessing workflow for eye disease detection.

The gaussian convolution formula shows how to use gaussian blur to make the photographs even better. This stage gets the image ready for contrast adjustment by getting rid of noise and smoothing it out. The last step in improving the contrast is to combine the histogram-equalized image with the blurred image using a weighted combination. This makes the images crisper and the contrast better, which makes the important parts of the eye's anatomy easier to see.

The contrast adjustment equation is formulated as in Eq. (3) $Where\ \alpha = 4, \beta = -4\ and\ \gamma = 128$.

$$I_{final} = \alpha * I_{hist_{eq}} + \beta * I_{blur} + \gamma \quad (3)$$

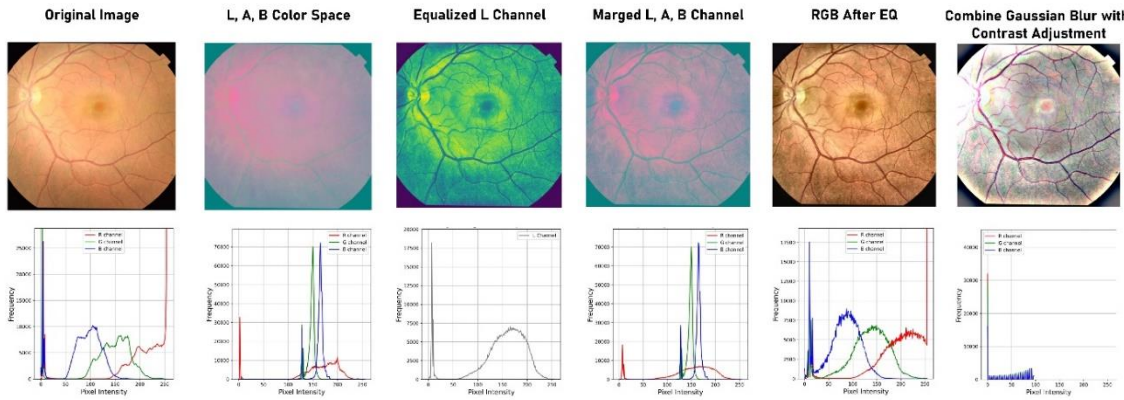

Fig. 3.4: Retinal image processing for enhanced eye disease detection.

After these changes are made, the processed photos are saved in a special folder for further use in data augmentation and model training. This methodical methodology guarantees high-quality photos, allowing the deep learning model to effectively extract distinguishing features, which is necessary for correctly identifying different eye disorders. Figure 3.4 shows a series of procedures for processing retinal images that are very important for finding eye diseases. The first picture shows the retina, with blood vessels and the optic nerve clearly visible. The next step is histogram equalization, which improves contrast by changing the distribution of pixel intensities to make smaller details, like vessels, stand out. After that, a gaussian blur is used to make the image less noisy and softer, which brings out larger structures. Finally, the processed image is the product of many changes, which probably make both big and minute elements clearer. Under the processed photos are color channel histograms (red, green, blue, and gray). These show how pixel intensity is spread out in each channel, which gives you a lot of information on the image's color composition. This image-processing method greatly improves the accuracy of diagnosing retinal disorders like diabetic retinopathy and macular degeneration by highlighting important structural features and downplaying unimportant ones. It enhances the study by offering clearer visibility of pathological alterations, hence enabling more precise and prompter identification of ocular illnesses.

3.4. Transfer Learning-Based Approach

Transfer learning is a complicated method in which a model that has already been trained on a large dataset for one purpose is adjusted on a smaller dataset for a similar job. This method dramatically improves performance by exploiting the model's ability to apply what it learned in the original task to the new task, which means that it doesn't need to be trained on the smaller, more particular dataset for a long time. By making tiny changes to these models that took use of their particular features, the system grew more accurate and dependable. This method is especially beneficial in medical imaging, because there aren't always enough datasets with labels. Transfer learning enables the model quickly find important features that are important for identifying eye problems, such blood vessel irregularities and retinal lesions. Transfer learning makes it faster and more accurate to create models. This makes it a more reliable and scalable way to find eye problems early.

3.4.1. DenseNet201

DenseNet201 is a deep learning framework based on the concept of densely interconnected convolutional networks. The DenseNet idea links layers together in a way that makes sense. The layers below feed input to the layer above, while the layers above send feature mappings to the layer below. This method fixes the problem of the vanishing gradient, making it easier to reuse features and reducing the number of parameters, which makes models that are smaller and operate better. DenseNet201 has 201 layers and is a highly deep kind that is good for applications like analyzing medical images, identifying objects, and diagnosing plant diseases since it can handle difficult picture classification and recognition tasks. DenseNet201 helps in learning, especially when you need to separate features. It is a useful tool for modern deep learning applications [70] since it can pick up on little information and is inexpensive to use.

3.4.2. InceptionV3

InceptionV3 is a very powerful deep learning architecture that is part of the Inception series. It should make it faster and more accurate to sort photos into groups. The network may collect multi-scale information by performing convolutions of various sizes at the same time in the same layer. This is feasible because of how it is set up using modules. This method lets the model get a lot of information from pictures without making the math too hard. One of the most important new elements in InceptionV3 is the use of factorized convolutions. These break up huge convolutions into smaller, more helpful steps. This strategy cuts down on the number of parameters while keeping the accuracy high, which makes InceptionV3 a powerful yet light model. InceptionV3 is a popular tool for computer vision problems. It has been used in many different fields, including as medical imaging, object recognition, and finding diseases in plants. It is a great choice for big, real-time image processing jobs that need speed and accuracy [71–72].

3.4.3. MobileNetV2

MobileNetV2 is a compact deep learning model that works well on mobile and embedded devices without losing accuracy. It builds on the success of MobileNetV1 by adding important architectural improvements including depth-wise separable convolutions and inverted residuals with linear bottlenecks. Depth-wise separable convolutions cut down on the number of parameters by splitting the usual convolution process into two parts: depth-wise convolution, which filters input channels separately, and pointwise convolution, which puts them together. The inverted residual structure makes sure that the features are first compressed (bottlenecked) and then enlarged. This makes it easier for the network to gather spatial information with fewer computations. At the bottleneck, a linear layer keeps important information from getting lost. MobileNetV2 also incorporates ReLU6 activation, which helps the model achieve a reasonable balance between speed and accuracy. MobileNetV2 is quite good at tasks like picture classification, object detection, and segmentation, especially when resources are limited [73–74].

3.4.4. VGG16

VGG16 is a basic and useful deep CNN architecture that is widely used to sort images. VGG16 has 16 weight layers. 13 of them are convolutional layers, while 3 of them are fully linked layers. The design is simple: each convolutional layer uses small 3x3 filters that become bigger as the network goes on. Max-pooling layers come after the convolutional layers. They maintain important characteristics while slowly making the spatial dimensions smaller. After the convolutional blocks, the network flattens the feature mappings into a vector and sends it through the fully connected layers. This concludes with a softmax activation that sorts everything. VGG16 is ideal for feature extraction since it employs 3x3 filters all the time and has a deep layer depth that is simple to work with. This is why it has worked well in many computer vision programs [75].

3.5. Proposed Methodology

This study introduces a novel technique using an advanced deep learning model architecture designed to improve the accuracy and robustness of eye disease detection systems. The proposed approach integrates spatial attention and multi-scale fusion blocks inside a CNN framework, particularly engineered to identify and use critical features from ocular pathology pictures that have been overlooked in previous studies [25–37]. By concentrating on the most significant areas of the photographs, this new architecture makes it simpler to discover little but crucial signs of sickness. It includes 30 layers, which means it shows the data in a highly thorough way.

Figure 3.5 depicts the structure of a deep CNN that was created specifically to discover eye problems. This structure is designed to pick up on key information in retinal pictures, which makes it possible to tell various eye diseases apart. Figure 6 shows how each layer is set up and how they work together to make the model work better and faster. The input layer of the network is set up to take photos with the shape (224, 224, 3), which is a common size for RGB images. After this, a bespoke spatial attention layer is added. This layer focuses on the most important parts of the input image by balancing the spatial relevance of distinct places. After that comes the multi-scale fusion layer, which is another

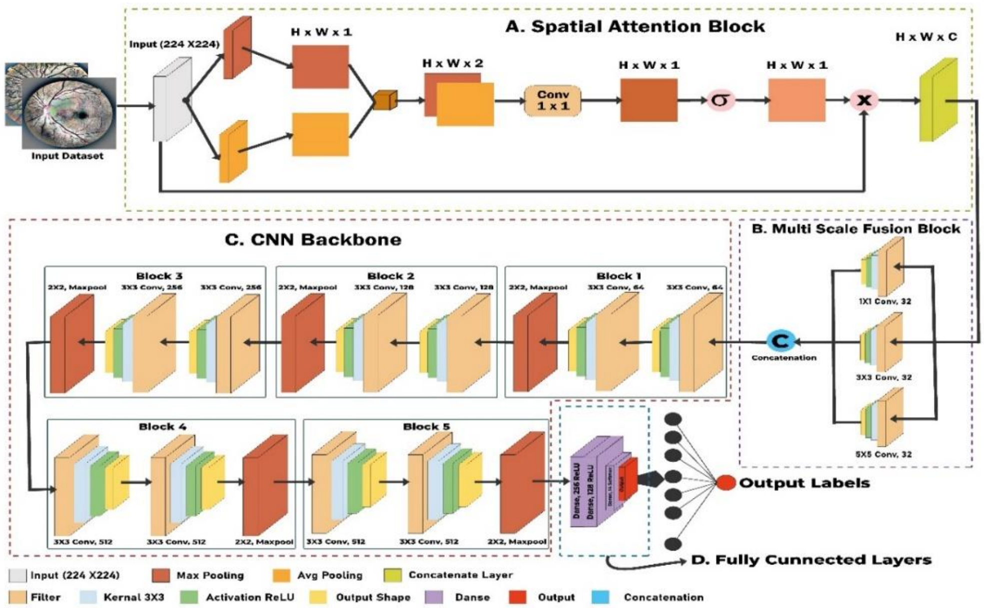

Fig. 3.5: Architecture of proposed model.

special feature that combines input from receptive fields of different sizes so that the model can see both fine and coarse details in the image.

There are six convolutional blocks in the CNN, and each one gets more complicated and deeper. There are three convolutional layers in convolution block 1, each with a different kernel size (1x1, 3x3, and 5x5). Each layer has 32 filters and uses ReLU activation. This method with many scales lets the model pick up characteristics at different levels of detail. Then, the outputs of these convolutional layers are joined together to make a single representation. The next convolution blocks use a more standard CNN method.

Convolution blocks 2 to 6 each have two to three convolutional layers, all of which use ReLU activation and have filter sizes that get bigger: 64, 128, 256, and 512, respectively. After each of these blocks, there is a MaxPooling layer with a 2x2 pool size. This reduces the spatial dimensions while keeping most of the important features.

After the convolutional layers, the model goes to a flatten layer, which turns the 2D feature mappings into a 1D vector to get it ready for the fully connected layers. The ReLU function turns on the two hidden layers that make up the fully linked (dense) layers. These layers have 256 and 128 units. These layers make the feature representations that the convolutional layers have learned even better. The output layer uses a softmax activation function with 10 units, which correspond to 10 different types of eye diseases. This makes it possible to classify more than one form of eye disease.

This advanced architecture uses spatial attention, multi-scale feature extraction, and deep convolutional layers to improve its capacity to find subtle and complicated patterns in eye illness images, making it very useful for diagnostic purposes.

3.5.1. Spatial Attention Mechanism

By focusing on important areas of input images, the spatial attention mechanism improves the performance of deep learning models [76-77]. This module has a convolutional layer with a sigmoid activation function that calculates attention weights A. This changes the contribution of each pixel in the feature maps X in real time.

Mathematically, the spatial attention embedding is computed pointwise according to equation (4).

$$A = \sigma(W_a X + b_a) \tag{4}$$

Where W_a represents the learnable weights and b_a denotes the biases of the convolutional layer. Here, σ denotes the sigmoid function applied element-wise across the spatial dimensions of X. The output A thus represents a map of weights that highlight regions of interest based on their relevance to the task at hand. The practical application of these attention weights involves performing an element-wise multiplication (Hadamard product) between A and X, resulting in equation (5).

$$Y = A \odot X \tag{5}$$

This operation effectively enhances the features associated with higher attention weights while diminishing those with lower weights. Consequently, the model becomes more proficient at identifying and emphasizing the discriminative features crucial for accurate eye disease detection.

3.5.2. Multi-Scale Fusion

The multi-scale fusion module enhances the model's ability to capture diverse and multi-level features by integrating convolutional layers with different kernel sizes: 1x1, 3x3, and 5x5. Each convolutional layer operates independently on the input feature maps X, extracting information at distinct spatial scales [78-80]. The resulting feature maps F_1, $F_{2,}$ and F_5 capture fine details, local patterns, and broader contexts respectively.

To fuse these multi-scale features effectively, the module concatenates F_1, $F_{2,}$ and F_5 along the channel axis. This concatenation process forms a fused feature map F_{fusion}, which combines information from all three convolutional paths shown in equation (6).

$$F_{fusion} = Concatenate([F_1, F_2, F_5]) \tag{6}$$

This fused representation enhances the overall feature map F_fusion by including detailed information from several geographic scales. By mixing information from multiple scales, the model understands the input data better. This helps it uncover complicated patterns and connections that are critical for correctly diagnosing eye problems. The module's design makes it more versatile and adaptive. This makes the model stronger and better at recognizing little indicators of sickness in a broad variety of medical imaging and eye care circumstances.

3.5.3. CNN Backbone

The suggested model has a lot of convolutional layers that work with max-pooling layers to reduce the amount of space. The layers are meant to get hierarchical information from the improved image input. To make the feature extraction method non-linear, convolutional layers use rectified linear unit (ReLU) activation functions.

Each convolutional layer i within the CNN backbone can be represented by equation (7).

$$F_i = ReLU(W_i \times F_{i-1} + b_i) \tag{7}$$

Where F_{i-1} represents the input feature map, W_i denotes the learnable parameters (weights) specific to the i-th convolutional layer, b_i represents the biases, * denotes the convolution operation and ReLU denotes the rectified unit activation function.

3.5.4. Fully Connected Layer

Following feature extraction, the flattened feature maps are processed through fully connected layers to perform detection. These layers facilitate learning of complex patterns in the feature representations extracted by the CNN backbone [81]. The fully connected layers are typically followed by SoftMax activation to output class probabilities. Mathematically, the computation of the output from the fully connected layers can be expressed as equation (8):

$$O = softmax(W_{fc} \times F_{fc} + b_{fc}) \tag{8}$$

Where F_{fc} denotes the flattened feature vector from the CNN backbone, W_{fc} denotes the weights of the fully connected layer, b_{fc} denotes the bias, softmax denotes the softmax activation function applied element-wise to produce class probabilities.

CHAPTER 4
EXPERIMENTAL RESULTS AND DISCUSSION

4.1. Performance Comparison

Table 4.1 compares the performance of several models based on their accuracy, precision, recall, and F1 score. VGG19 is better than VGG16 and MobileNetV2 since it has an accuracy of 84.41%, while VGG16 and MobileNetV2 have accuracies of 84.13% and 82.63%, respectively. InceptionV3 gets better, with an accuracy of 81.16% and an F1 score of 0.81. DenseNet201 is another step forward, with an accuracy of 87.50% and an F1 score of 0.87. However, EDDNet30 is by far the best, with an accuracy rate of 95.29% and almost flawless precision, recall, and F1 scores of 0.95, 0.95, and 0.95, which proves that it is the best.

Table 4.1:

Performance metrics of various models.

Models	Accuracy	Precision	Recall	F1 Score
MobileNetV2	82.63%	0.83	0.83	0.83
VGG16	84.13%	0.86	0.85	0.85
VGG19	84.41%	0.85	0.84	0.84
InceptionV3	81.16%	0.81	0.81	0.81
DenseNet201	87.50%	0.87	0.87	0.87
EDDNet30	**95.29%**	**0.95**	**0.95**	**0.95**

4.2. Effect of Preprocessing on EDDNET30

Table 4.2 shows how the EDDNet30 model works with and without preprocessing on different eye disease datasets. The results show how important preprocessing is for improving classification results. The model gets an average accuracy of 93.00% when used without preprocessing. Its precision, recall, and F1 scores are 0.90, 0.86, and 0.88, respectively. These results show that the system works well in general, but they also show that it has trouble with noisy or complex data. On the other hand, using preprocessing techniques makes the results much better. The model has an overall average accuracy of 95.29% with precision, recall, and F1 scores of 0.95 each. These improved results show how important pretreatment is for improving data quality, cutting down on noise, and making feature extraction work better, especially for difficult illness categories. The steady gains in all evaluation criteria show that preprocessing is an important step for making models more reliable, easier to understand, and more accurate at diagnosing eye diseases.

Table 4.2:

Impact of the preprocessing.

Models	Class name	Accuracy	Precession	Recall	F1 Score
EDDNet30 without pre-processing	Cataract	86.23%	0.90	0.86	0.86
	Central serous chorioretinopathy - Color Fundus	97.29%	0.95	0.97	0.96
	Diabetic retinopathy	88.24%	0.89	0.88	0.89
	Disc edema	93.96%	0.98	0.94	0.96
	Glaucoma	91.67%	0.86	0.92	0.89
	Macular scar	82.86%	0.85	0.83	0.84
	Healthy	90.14%	0.85	0.90	0.88
	Pterygium	100.00%	1.00	1.00	1.00
	Retinal detachment	98.03%	0.99	0.98	0.99
	Retinitis pigmentosa	97.22%	0.98	0.97	0.98
	Total Average	**93.00%**	**0.90**	**0.86**	**0.88**
EDDNet30 with pre-processing	Cataract	93.81%	0.89	0.93	0.91
	Central serous chorioretinopathy - Color Fundus	96.86%	0.96	0.97	0.96
	Diabetic retinopathy	87.64%	0.95	0.88	0.91
	Disc edema	99.35%	0.98	0.99	0.99
	Glaucoma	90.45%	0.94	0.90	0.92
	Macular scar	87.27%	0.89	0.87	0.88
	Healthy	95.89%	0.93	0.96	0.95
	Pterygium	100.00%	1.00	1.00	1.00
	Retinal detachment	99.27%	0.98	0.99	0.99
	Retinitis pigmentosa	99.21%	0.97	0.99	0.98
	Total Average	**95.29%**	**0.95**	**0.95**	**0.95**

4.3. Training Progress of EDDNET30

Figure 4.1(a) illustrates the training and validation loss and accuracy curves of the EDDNet30 model when evaluated on the original dataset. The model was trained with the Adamax optimizer (learning rate 0.001), a batch size of 32, and categorical crossentropy as the loss function, with accuracy used as the performance metric. Training was carried out on Kaggle using dual NVIDIA T4 GPUs (16GB each) with CUDA/cuDNN acceleration. Over 40 epochs, the training loss steadily decreased, reflecting consistent model learning, while the validation loss exhibited a similar downward trend with minor variations. Training accuracy gradually increased, stabilizing around 0.95, whereas validation accuracy plateaued near 0.90, highlighting strong generalization.

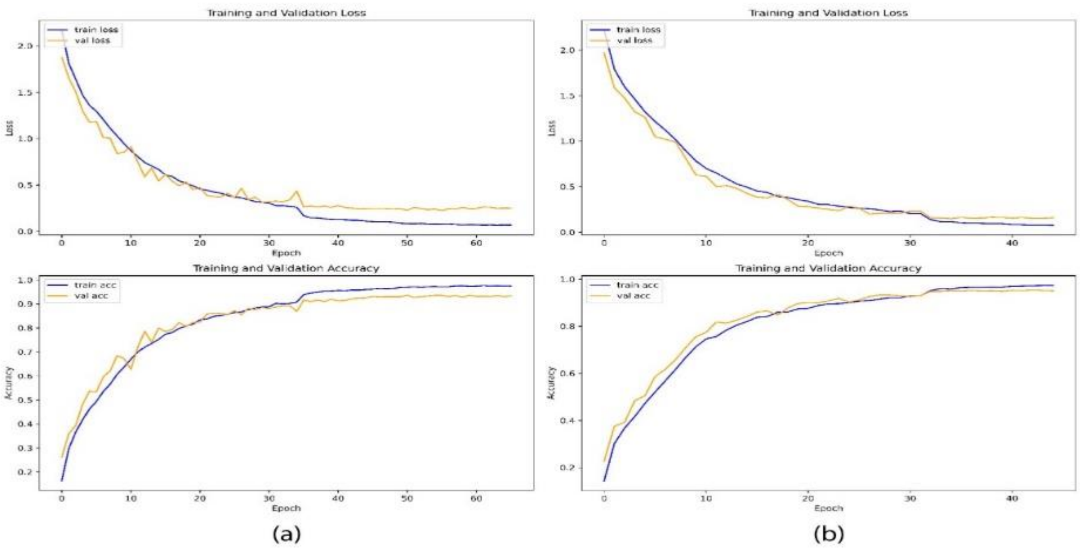

Fig. 4.1: Training and validation performance (a) original and (b) with preprocessing.

Figure 4.1(b) presents results on the pre-processed dataset, where training and validation losses both declined smoothly with negligible fluctuations. The training accuracy rose sharply, reaching close to 0.98, while validation accuracy stabilized near 0.95. The close alignment of curves confirms the absence of overfitting and demonstrates the positive effect of preprocessing on generalization and model efficacy.

Figure 4.2 provides visual outcomes of explain ability methods including Grad-CAM, Grad-CAM++, and LIME applied to various fundus images. The first column shows the original images, followed by heatmaps generated through these techniques. Grad-CAM highlights critical regions guiding model predictions, offering coarse localization of disease features. Grad-CAM++ refines this with more precise and distributed attention, particularly valuable in complex cases. LIME, in turn, provides localized, instance-specific explanations by approximating model behavior with interpretable surrogate models, allowing clinicians to identify influential retinal regions behind each prediction.

Collectively, these techniques enhance transparency and interpretability, offering deeper insights into pathological regions and strengthening clinical trust in deep learning-based eye disease diagnosis.

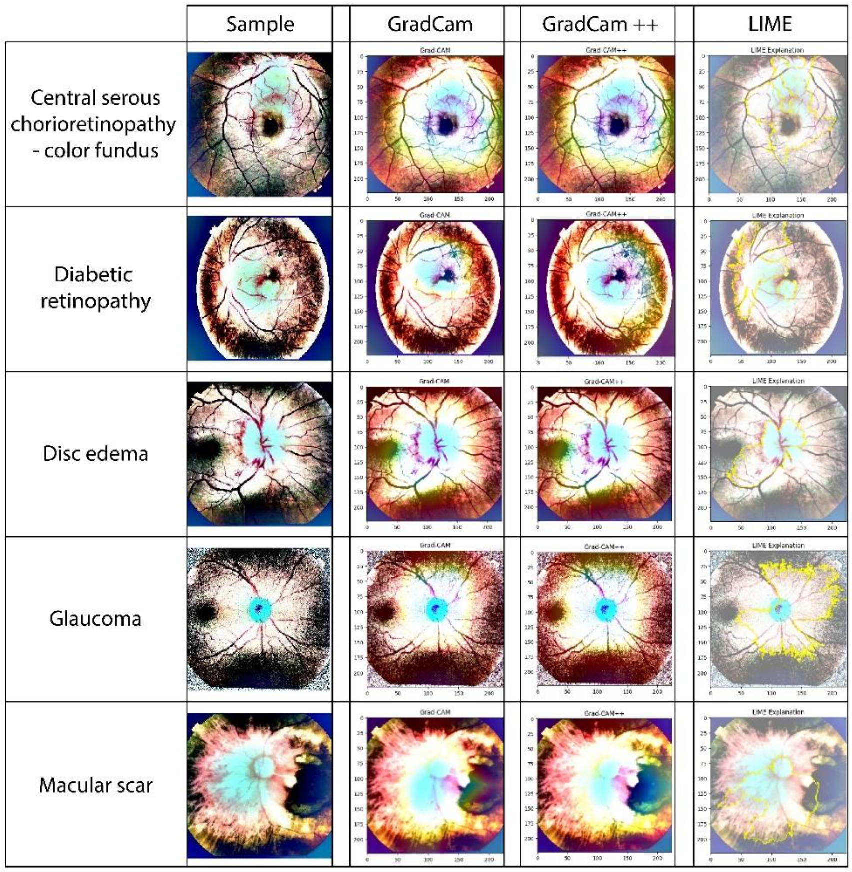

Fig. 4.2: Images result in Grad cam.

4.4. Comparative Analysis of Related Studies

This part gives a thorough comparison of the best models for classifying eye diseases, focusing on performance measures, dataset composition, and architectural trade-offs. Table 4.3 shows that many methods have promise outcomes, but when looked at as a whole, they have some big problems. For example, Ali et al. [30] got 96.50% accuracy using AMDNet23 on 2,000 fundus images, but the model only looked at age-related macular degeneration and was constrained by the size of the dataset, which made it hard to apply to other types of diseases. Kaya et al. [32] achieved 90.9% accuracy using a neural network trained on a little larger dataset, but problems like class imbalance and a tendency to overfit remained. Aamir et al. [33] achieved a remarkable 99.39% accuracy with ML-DCNN. But this was based on only 1,338 photos and didn't include a wide range of disease types, which made others wonder how well the model would work in the actual world. Shamsan et al. [34] and Wang et al. [35] advanced the limits of model accuracy, achieving 98.5% and 87.9%, respectively. Shamsan's hybrid model, on the other hand, was very hard to compute, while Wang's method, on the other hand, was less generalizable even though it used a custom CNN. Vadduri et al. [36] developed improved preprocessing and segmentation methods that enabled their DCNN model to attain 97% accuracy. The model's reliance on handcrafted features, however, hindered automation and scalability, diminishing its applicability in clinical settings.

The suggested EDDNet30 model combines the best parts of existing methods and fixes their most common problems, which is different from past attempts. It gets 95.29% accuracy on a large dataset of 5,531 fundus photos that show 10 different disease classes. This makes it much more diversified and representative than the datasets utilized in previous studies. The model passed the test with a score of 96.36%, and there is a 95% chance that the true score is between 95.61% and 97.07%. This proves that it works well with new data. The model can handle more than one kind of sickness at a time, even if there isn't enough data or the classes aren't evenly spread around. It preserves its accuracy while making the math simpler, which makes it easier to utilize in real-life healthcare situations. EDDNet30 also has a completely automated CNN architecture, so you don't have to do any human feature engineering anymore. This makes it more helpful and scalable in real time. EDDNet30's powerful architecture, focused data augmentation, and efficient feature extraction make it possible to generalize well across hard multi-class classification challenges. This gives it a better and more versatile way to automatically sort eye illnesses, with greater clinical relevance and operational efficiency.

Table 4.3:

Comparison analysis with previous studies.

Reference	Year	Sample size	Total class	Used models	Best model (accuracy)
Ali et al. [30]	2024	2000	4	AMDNet23	96.50%,
Kaya et al. [32]	2024	4217	4	Neural Network (NN)	90.9%
Aamir et al. [33]	2020	1338	3	multi-level DCNN	99.39%
REFUGE challenge winners [37]	2020	85,608	2	CNN	95.23%
Our study	2025	5531	10	EDDNet30	95.29%

CHAPTER 5
IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1. Impact on Society

The EDDNet30 model has several benefits for society when it comes to finding eye diseases, especially when it comes to making healthcare simpler to receive and having better results. By making it easier and faster to detect diseases from retinal scans, the model may decrease the period between when a disease starts and when a doctor sees it. This means obtaining treatment sooner and having a lower chance of becoming blind. It can be used in locations where there aren't many eye doctors since it is quite accurate and uses explainable AI. This will make it easier for more people to get specialized medical treatment. EDDNet30 may also help down the cost of eye disorders by cutting down on unneeded tests and helping doctors identify better, more effective methods to treat them. Once this technology is used in clinical practice, it might enable doctors create personalized treatment plans for each patient based on their specific ailment. This might aid in managing a long-term sickness and improve the patient's quality of life in general. It is also very important to use these technologies in a fair and moral way so that as many people as possible may benefit from EDDNet30 and they don't accidentally make existing health care inequities worse.

5.2. Impact on the Environment

The EDDNet30 model for finding out what sort of eye ailment someone has is like other deep learning frameworks in that it needs a lot of computing power to train and produce predictions. This might cause individuals to use more energy and have a big impact on the environment. This issue worsens when high-performance GPUs are required for extended training on large retinal datasets. But making the architecture better, fine-tuning the hyperparameters, and getting rid of extra data may all help the system consume less processing power and be more energy efficient. Putting the model on cloud infrastructures that employ renewable energy sources may also assist the environment by cutting expenses.

Along with its computing power, the clinical integration of EDDNet30 may lessen the need for costly diagnostic tests, repeated imaging, and unneeded trips to the hospital. This would indirectly cut down on emissions from moving patients and using equipment. As time goes on, EDDNet30 may become not just a powerful technique to find eye problems on a wide scale, but also an environmentally friendly way to do it. This is because deep learning algorithms and eco-friendly computing technologies are becoming better.

5.3. Ethical Aspects

When using the EDDNet30 model to categorize eye diseases, you need to think about significant moral issues including patient privacy, data security, and how accurate the algorithm is. To keep patients' trust, it is very important to protect their privacy and make sure that retinal imaging data is handled correctly. Also, doctors need to be able to look at, question, and validate the model's outputs before they utilize them to make diagnosis in real life. Dataset bias is another big problem. It might make diagnostic accuracy different for different demographic groups and make health treatment unfair. To get over these problems, EDDNet30 has to focus on fairness, accountability, and interpretability. This will make sure that its use in clinical practice is in line with ethical norms and makes patient-centered treatment easier.

5.4. Sustainability Plan

A long-term plan for the EDDNet30 model for finding eye diseases must focus on making continuing changes to the architecture and adding new data from eye imaging in order to keep it useful in the clinic. It is also vital to continuously training and supporting healthcare workers so that the model may be easily and ethically included to diagnostic procedures. To fix problems with the environment, we need to concentrate on making computers quicker and encourage the use of renewable energy sources for huge projects. Additionally, establishing strong ties with hospitals, research institutes, legislatures, insurance companies, and groups that stand out for patients will help the ecosystem persist. These kinds of partnerships not only make sure that everyone can utilize new diagnostic tools, but they also build trust, accountability, and long-term value in clinical practice.

EDDNet30 may help improve eye care and encourage ethical and long-lasting technological innovation via these programs.

CHAPTER 6
CONCLUSION AND FUTURE WORK

6.1. Summary of the Study

This study concentrated on the creation and assessment of EDDNet30, a tailored deep learning model engineered for the precise categorization of various ocular illnesses using retinal pictures. The research included spatial attention processes and multi-scale fusion blocks, which were rigorously confirmed across many ophthalmic datasets. Some of the measurements that showed how effectively EDDNet30 could tell the difference between different eye conditions were accuracy, precision, recall, and F1-score. The architecture, which was improved via extensive testing and optimization, showed that customized feature extraction and improved representation learning may improve classification. These results show that EDDNet30 might be a quick and accurate tool to diagnose eye problems, which would help doctors make better decisions and provide their patients better treatment.

6.2. Conclusions

The experiment shows how EDDNet30, a cutting-edge deep-learning model built to find eye diseases with great accuracy, may change things. EDDNet30 improves the CNN framework's ability to capture fine features and spatial correlations in ocular pictures by adding spatial attention and multi-scale fusion blocks. One of the best models for finding eye problems is EDDNet30, which has an incredible accuracy score of 95.29%. The study included a variety of performance measures, and EDDNet30 consistently came out on top when it came to demanding classification tasks. The model performs a good job at detecting the difference between different eye illness labels when you look at the results more carefully. This is very important for clinical use. The paper also speaks about how important it is to prepare data before using a model to get the best results, improve feature extraction, and cut down on noise. These findings indicate that innovative architectural designs might enhance the processing of medical pictures and automated diagnostic systems. Future study should focus on enhancing these structures, investigating other data augmentation methods, and broadening the model's applicability to various patient demographics and clinical environments. EDDNet30 has a lot of promise to help doctors make better diagnosis and provide better treatment to patients. This lets medical imaging and deep learning technology go ahead a lot more.

6.3. Implication for Further Study

The results of the EDDNet30 study provide several persuasive opportunities for more research. One key way to improve diagnosis is to combine several types of eye data, such as optical coherence tomography (OCT) and fundus photography. These could provide you more information and help you obtain a better diagnosis. Testing the model in actual clinical settings would provide substantial insights on its efficacy, usability, and areas necessitating further. It is also crucial to check how simple it is to interpret EDDNet30's predictions to make sure that its choices are in accordance with what eye doctors believe. This will help people trust the system. These new studies might help AI solutions find eye illnesses early and correctly by making them easier to understand and more reliable.

REFERENCES

[1] M. Fleckenstein, S. Schmitz-Valckenberg, and U. Chakravarthy, "Age-Related Macular Degeneration: A Review," JAMA, vol. 331, no. 2, p. 147, Jan. 2024, doi: 10.1001/jama.2023.26074.

[2] A. Cvekl and J. Vijg, "Aging of the eye: Lessons from cataracts and age-related macular degeneration," Ageing Research Reviews, vol. 99, p. 102407, Aug. 2024, doi: 10.1016/j.arr.2024.102407.

[3] Bhumika, N. S. Bora, and P. S. Bora, "Genetic Insights into Age-Related Macular Degeneration," Biomedicines, vol. 12, no. 7, p. 1479, Jul. 2024, doi: 10.3390/biomedicines12071479.

[4] G. A. Wilke and R. S. Apte, "Complement regulation in the eye: implications for age-related macular degeneration," Journal of Clinical Investigation, vol. 134, no. 9, p. e178296, May 2024, doi: 10.1172/JCI178296.

[5] S. Brodzka et al., "The Role of Glutathione in Age-Related Macular Degeneration (AMD)," IJMS, vol. 25, no. 8, p. 4158, Apr. 2024, doi: 10.3390/ijms25084158.

[6] "Vision impairment and blindness." Accessed: Jul. 8, 2025. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/blindness-and-visual-impairment

[7] "WHO launches first World report on vision." Accessed: Jul. 8, 2025. [Online]. Available: https://www.who.int/news/item/08-10-2019-who-launches-first-world-report-on-vision

[8] "One billion people have preventable eye conditions, increasingly linked to lifestyle choices: UN health agency | UN News." Accessed: Jul. 8, 2025. [Online]. Available: https://news.un.org/en/story/2019/10/1048762

[9] J. Drue, "At least 2.2 billion people have vision impairment or blindness, of which over 1 billion cases could have been prevented or have yet to be addressed," Lighthouse Guild. Accessed: Jul. 8, 2025. [Online]. Available: https://lighthouseguild.org/at-least-2-2-billion-people-have-vision-impairment-or-blindness-of-which-over-1-billion-cases-could-have-been-prevented-or-have-yet-to-be-addressed/

[10] Katy, "Understanding the Leading Causes of Blindness," Ophthalmology & Visual Sciences. Accessed: Jul. 8, 2025. [Online]. Available: https://ophthalmology.wustl.edu/understanding-the-leading-causes-of-blindness/

[11] M. Adil, A. Farouk, A. Ali, H. Song, and Z. Jin, "Securing Tomorrow of Next-Generation Technologies with Biometrics, State-of-The-Art Techniques, Open Challenges, and Future Research Directions," Computer Science Review, vol. 57, p. 100750, Aug. 2025, doi: 10.1016/j.cosrev.2025.100750.

[12] F. Naveed et al., "Sustainable AI for plant disease classification using ResNet18 in few-shot learning," Array, vol. 26, p. 100395, Jul. 2025, doi: 10.1016/j.array.2025.100395.

[13] A.-A. Al-Maari, M. Abdulnabi, Y. Nathan, A. Ali, U. Ali, and M. Khan, "Optimized Credit Card Fraud Detection Leveraging Ensemble Machine Learning Methods," Eng. Technol. Appl. Sci. Res., vol. 15, no. 3, pp. 22287–22294, Jun. 2025, doi: 10.48084/etasr.10287.

[14] R. Ullah et al., "Advancing personalized diagnosis and treatment using deep learning architecture," Front. Med., vol. 12, Mar. 2025, doi: 10.3389/fmed.2025.1545528.

[15] S. Hussain et al., "An Enhanced Random Forest (ERF)-based Machine Learning Framework for Resampling, Prediction, and Classification of Mobile Applications using Textual Features," Eng. Technol. Appl. Sci. Res., vol. 15, no. 1, pp. 19776–19781, Feb. 2025, doi: 10.48084/etasr.9148.

[16] M. Adil, A. Farouk, H. Abulkasim, A. Ali, H. Song, and Z. Jin, "NG-ICPS: Next Generation Industrial-CPS, Security Threats in the Era of Artificial Intelligence, and Open Challenges With Future Research Directions," IEEE Internet Things J., vol. 12, no. 2, pp. 1343–1367, Jan. 2025, doi: 10.1109/jiot.2024.3486659.

[17] World Health Organization, "Blindness and Vision Impairment," World Health Organization, Aug. 10, 2023. https://www.who.int/news-room/fact-sheets/detail/blindness-and-visual-impairment

[18] N. J. Shipley, “Setting Our Sights on Vision: A Rationale and Research Agenda for Integrating Eye-Tracking into Leisure Research,” Leisure Sciences, vol. 46, no. 3, pp. 274–295, Apr. 2024, doi: 10.1080/01490400.2021.1956389.

[19] F. Petrillo et al., “Understanding Acanthamoeba Keratitis: An In-Depth Review of a Sight-Threatening Eye Infection,” Microorganisms, vol. 12, no. 4, p. 758, Apr. 2024, doi: 10.3390/microorganisms12040758.

[20] J. A. Davidson, T. A. Ciulla, J. B. McGill, K. A. Kles, and P. W. Anderson, “How the diabetic eye loses vision,” Endocr, vol. 32, no. 1, pp. 107–116, Nov. 2007, doi: 10.1007/s12020-007-0040-9.

[21] K. Attebo, P. Mitchell, R. Cumming, and W. S. BMath, “Knowledge and beliefs about common eye diseases,” Australian and New Zealand Journal of Ophthalmology, vol. 25, no. 3, pp. 283–287, Aug. 1997, doi: 10.1111/j.1442-9071.1997.tb01516.x.

[22] Galloway, Nicholas R., Winfried Mawutor Kwaku Amoaku, Peter H. Galloway, Andrew C. Browning, and N. R. Galloway. Common eye diseases and their management. Springer, 1999.

[23] M. M. Abdull, C. Chandler, and C. Gilbert, “Glaucoma, ‘the silent thief of sight’: patients’ perspectives and health seeking behaviour in Bauchi, northern Nigeria,” BMC Ophthalmol, vol. 16, no. 1, p. 44, Dec. 2016, doi: 10.1186/s12886-016-0220-6.

[24] R. G. Mathew and I. E. Murdoch, “The silent enemy: a review of cataract in relation to glaucoma and trabeculectomy surgery,” British Journal of Ophthalmology, vol. 95, no. 10, pp. 1350–1354, Oct. 2011, doi: 10.1136/bjo.2010.194811.

[25] Sadia Sultana Chowa et al., “A Low Complexity Efficient Deep Learning Model for Automated Retinal Disease Diagnosis,” Journal of Healthcare Informatics Research, vol. 9, no. 1, pp. 1–40, Jan. 2025, doi: https://doi.org/10.1007/s41666-024-00182-5.

[26] M. R. Shoaib, H. M. Emara, A. S. Mubarak, O. A. Omer, F. E. Abd El-Samie, and H. Esmaiel, “Revolutionizing diabetic retinopathy diagnosis through advanced deep learning techniques: Harnessing the power of GAN model with transfer learning and the DiaGAN-CNN model,” Biomedical Signal Processing and Control, vol. 99, p. 106790, Sep. 2024, doi: https://doi.org/10.1016/j.bspc.2024.106790.

[27] R. Ma et al., "Multimodal machine learning enables AI chatbot to diagnose ophthalmic diseases and provide high-quality medical responses," npj Digital Medicine, vol. 8, no. 1, Jan. 2025, doi: https://doi.org/10.1038/s41746-025-01461-0.

[28] M. H. Malik, Z. Wan, Y. Gao, and D.-W. Ding, "Efficient diagnosis of retinal disorders using dual-branch semi-supervised learning (DB-SSL): An enhanced multi-class classification approach," Computerized Medical Imaging and Graphics, vol. 121, p. 102494, Feb. 2025, doi: https://doi.org/10.1016/j.compmedimag.2025.102494.

[29] I. Kansal, V. Khullar, P. Sharma, S. Singh, J. A. Hamid, and A. Johnson Santhosh, "Multiple model visual feature embedding and selection method for an efficient oncular disease classification," Scientific Reports, vol. 15, no. 1, Feb. 2025, doi: https://doi.org/10.1038/s41598-024-84922-y.

[30] Md. A. Ali, Md. S. Hossain, Md. K. Hossain, S. S. Sikder, S. A. Khushbu, and M. Islam, "AMDNet23: Hybrid CNN-LSTM deep learning approach with enhanced preprocessing for age-related macular degeneration (AMD) detection," Intelligent Systems with Applications, vol. 21, p. 200334, Mar. 2024, doi: 10.1016/j.iswa.2024.200334.

[31] S. Al-Fahdawi et al., "Fundus-DeepNet: Multi-label deep learning classification system for enhanced detection of multiple ocular diseases through data fusion of fundus images," Information Fusion, vol. 102, p. 102059, Feb. 2024, doi: 10.1016/j.inffus.2023.102059.

[32] İbrahim, K. A. Y. A., and İlkay ÇINAR. "Evaluation of Machine Learning and Deep Learning Approaches for Automatic Detection of Eye Diseases." *Intelligent Methods In Engineering Sciences* 3, no. 1 (2024): 37-45.doi: 10.58190/imiens.2024.85.

[33] M. Aamir et al., "An Adoptive Threshold-Based Multi-Level Deep Convolutional Neural Network for Glaucoma Eye Disease Detection and Classification," Diagnostics, vol. 10, no. 8, p. 602, Aug. 2020, doi: 10.3390/diagnostics10080602.

[34] A. Shamsan, E. M. Senan, and H. S. A. Shatnawi, "Automatic Classification of Colour Fundus Images for Prediction Eye Disease Types Based on Hybrid Features," Diagnostics, vol. 13, no. 10, p. 1706, May 2023, doi: 10.3390/diagnostics13101706.

[35] J.-Z. Wang et al., "Classification of Color Fundus Photographs Using Fusion Extracted Features and Customized CNN Models," Healthcare, vol. 11, no. 15, p. 2228, Aug. 2023, doi: 10.3390/healthcare11152228.

[36] M. Vadduri and P. Kuppusamy, "Enhancing Ocular Healthcare: Deep Learning-Based Multi-Class Diabetic Eye Disease Segmentation and Classification," IEEE Access, vol. 11, pp. 137881–137898, 2023, doi: 10.1109/ACCESS.2023.3339574.

[37] Jaemin Son et al., "REFUGE Competition Report", Accessed: Jul. 8, 2025. [Online]. Available: https://public.grand-challenge-user-content.org/f/challenge/229/020532c2-cacf-48fc-97fa-ffb625a4d82d/REFUGE-VRT.pdf

[38] N. Sikder, M. Masud, A. K. Bairagi, A. S. M. Arif, A.-A. Nahid, and H. A. Alhumyani, "Severity Classification of Diabetic Retinopathy Using an Ensemble Learning Algorithm through Analyzing Retinal Images," Symmetry, vol. 13, no. 4, p. 670, Apr. 2021, doi: 10.3390/sym13040670.

[39] T. Khatun, "Eye Disease Image Dataset." Mendeley Data, Apr. 02, 2024. doi: 10.17632/S9BFHSWZJB.1.

[40] "eye_diseases_classification,"www.kaggle.com. https://www.kaggle.com/datasets/gunavenkatdoddi/eye-diseases-classification

[41] M. Wang, I. C. Munch, P. W. Hasler, C. Prünte, and M. Larsen, "Central serous chorioretinopathy," Acta Ophthalmologica, vol. 86, no. 2, pp. 126–145, Mar. 2008, doi: 10.1111/j.1600-0420.2007.00889.x.

[42] M. Gemenetzi, G. De Salvo, and A. J. Lotery, "Central serous chorioretinopathy: an update on pathogenesis and treatment," Eye, vol. 24, no. 12, pp. 1743–1756, Dec. 2010, doi: 10.1038/eye.2010.130.

[43] R. Liegl and M. W. Ulbig, "Central Serous Chorioretinopathy," Ophthalmologica, vol. 232, no. 2, pp. 65–76, 2014, doi: 10.1159/000360014.

[44] S. Urfalioglu, "The evaluation of patients with optic disc edema: a retrospective study," North Clin Istanbul, 2020, doi: 10.14744/nci.2020.25483.

[45] Almog, Yehoshua MD; Goldstein, Michaella MD. Visual Outcome in Eyes With Asymptomatic Optic Disc Edema. Journal of Neuro-Ophthalmology 23(3):p 204-207, September 2003.

[46] Abbas, Qaisar. "Glaucoma-deep: detection of glaucoma eye disease on retinal fundus images using deep learning." International Journal of Advanced Computer Science and Applications 8, no. 6 (2017).

[47] D. A. Lee and E. J. Higginbotham, "Glaucoma and its treatment: A review," American Journal of Health-System Pharmacy, vol. 62, no. 7, pp. 691–699, Apr. 2005, doi: 10.1093/ajhp/62.7.691.

[48] L. M. Nijm, J. Schweitzer, and J. Gould Blackmore, "Glaucoma and Dry Eye Disease: Opportunity to Assess and Treat," OPTH, vol. Volume 17, pp. 3063–3076, Oct. 2023, doi: 10.2147/OPTH.S420932.

[49] B. K. Betzler, S. M. Young, and G. Sundar, "Intraocular Pressure and Glaucoma in Thyroid Eye Disease," Ophthalmic Plastic & Reconstructive Surgery, vol. 38, no. 3, pp. 219–225, May 2022, doi: 10.1097/IOP.0000000000002049.

[50] M. Aamir et al., "An Adoptive Threshold-Based Multi-Level Deep Convolutional Neural Network for Glaucoma Eye Disease Detection and Classification," Diagnostics, vol. 10, no. 8, p. 602, Aug. 2020, doi: 10.3390/diagnostics10080602.

[51] E. Daniel et al., "Risk of Scar in the Comparison of Age-related Macular Degeneration Treatments Trials," Ophthalmology, vol. 121, no. 3, pp. 656–666, Mar. 2014, doi: 10.1016/j.ophtha.2013.10.019.

[52] P. G. Christakis et al., "Incidence of Macular Atrophy after Untreated Neovascular Age-Related Macular Degeneration," Ophthalmology, vol. 127, no. 6, pp. 784–792, Jun. 2020, doi: 10.1016/j.ophtha.2019.11.016.

[53] D.-U. Bartsch, M. Intaglietta, J. F. Bille, A. W. Dreher, M. Gharib, and W. R. Freeman, "Confocal Laser Tomographic Analysis of the Retina in Eyes with Macular Hole Formation and Other Focal Macular Diseases," American Journal of Ophthalmology, vol. 108, no. 3, pp. 277–287, Sep. 1989, doi: 10.1016/0002-9394(89)90118-9.

[54] J. C. Hill and R. Maske, "Pathogenesis of pterygium," Eye, vol. 3, no. 2, pp. 218–226, Mar. 1989, doi: 10.1038/eye.1989.31.

[55] S.-M. Saw and D. Tan, "Pterygium: prevalence, demography and risk factors," Ophthalmic Epidemiology, vol. 6, no. 3, pp. 219–228, Jan. 1999, doi: 10.1076/opep.6.3.219.1504.

[56] J. Tan, U. Vollmer-Conna, L. Tat, and M. Coroneo, "Dry-Eye Disease in Recurrent Pterygium," Ophthalmic Res, vol. 61, no. 4, pp. 199–203, 2019, doi: 10.1159/000493544.

[57] T. Shahraki, A. Arabi, and S. Feizi, "Pterygium: an update on pathophysiology, clinical features, and management," Ophthalmol Eye Dis, vol. 13, p. 251584142110201, Jan. 2021, doi: 10.1177/25158414211020152.

[58] The Eye Disease Case-Control Study Group, "Risk Factors for Idiopathic Rhegmatogenous Retinal Detachment," American Journal of Epidemiology, vol. 137, no. 7, pp. 749–757, Apr. 1993, doi: 10.1093/oxfordjournals.aje.a116735.

[59] D. N. Shah et al., "Exudative Retinal Detachment in Ocular Inflammatory Diseases: Risk and Predictive Factors," American Journal of Ophthalmology, vol. 218, pp. 279–287, Oct. 2020, doi: 10.1016/j.ajo.2020.06.019.

[60] R. Amer, H. Nalcı, and N. Yalçındağ, "Exudative retinal detachment," Survey of Ophthalmology, vol. 62, no. 6, pp. 723–769, Nov. 2017, doi: 10.1016/j.survophthal.2017.05.001.

[61] H. Lewis, "Peripheral retinal degenerations and the risk of retinal detachment," American Journal of Ophthalmology, vol. 136, no. 1, pp. 155–160, Jul. 2003, doi: 10.1016/S0002-9394(03)00144-2.

[62] F. Parmeggiani, F. S. Sorrentino, D. Ponzin, V. Barbaro, S. Ferrari, and E. Di Iorio, "Retinitis Pigmentosa: Genes and Disease Mechanisms," CG, vol. 12, no. 4, pp. 238–249, Jun. 2011, doi: 10.2174/138920211795860107.

[63] C. Hamel, "Retinitis pigmentosa," Orphanet J Rare Dis, vol. 1, no. 1, p. 40, Dec. 2006, doi: 10.1186/1750-1172-1-40.

[64] K. Naderi, J. Gormley, and D. O'Brart, "Cataract surgery and dry eye disease: A review," European Journal of Ophthalmology, vol. 30, no. 5, pp. 840–855, Sep. 2020, doi: 10.1177/1120672120929958.

[65] J. R. Chang et al., "Risk Factors Associated with Incident Cataracts and Cataract Surgery in the Age-Related Eye Disease Study (AREDS)," Ophthalmology, vol. 118, no. 11, pp. 2113–2119, Nov. 2011, doi: 10.1016/j.ophtha.2011.03.032.

[66] M. Miura et al., "Prevalence and Characteristics of Dry Eye Disease After Cataract Surgery: A Systematic Review and Meta-Analysis," Ophthalmol Ther, vol. 11, no. 4, pp. 1309–1332, Aug. 2022, doi: 10.1007/s40123-022-00513-y.

[67] E. J. Sussman, "Diagnosis of Diabetic Eye Disease," JAMA, vol. 247, no. 23, p. 3231, Jun. 1982, doi: 10.1001/jama.1982.03320480047025.

[68] A. J. Barber, "A new view of diabetic retinopathy: a neurodegenerative disease of the eye," Progress in Neuro-Psychopharmacology and Biological Psychiatry, vol. 27, no. 2, pp. 283–290, Apr. 2003, doi: 10.1016/S0278-5846(03)00023-X.

[69] Krishnaiah, S., Das, T., Nirmalan, P. K., Shamanna, B. R., Nutheti, R., Rao, G. N., & Thomas, R. (2007). Risk factors for diabetic retinopathy: Findings from The Andhra Pradesh Eye Disease Study. Clinical Ophthalmology, 1(4), 475–482. https://doi.org/10.2147/opth.s12160082

[70] S. Ovreiu, E.-A. Paraschiv, and E. Ovreiu, "Deep Learning & Digital Fundus Images: Glaucoma Detection using DenseNet," in 2021 13th International Conference on Electronics, Computers and Artificial Intelligence (ECAI), Pitesti, Romania: IEEE, Jul. 2021, pp. 1–4. doi: 10.1109/ECAI52376.2021.9515188.

[71] Y. Pan et al., "Fundus image classification using Inception V3 and ResNet-50 for the early diagnostics of fundus diseases," Front. Physiol., vol. 14, p. 1126780, Feb. 2023, doi: 10.3389/fphys.2023.1126780.

[72] S. Faizal, C. A. Rajput, R. Tripathi, B. Verma, M. R. Prusty, and S. S. Korade, "Automated cataract disease detection on anterior segment eye images using adaptive thresholding and fine tuned inception-v3 model," Biomedical Signal Processing and Control, vol. 82, p. 104550, Apr. 2023, doi: 10.1016/j.bspc.2022.104550.

[73] R. Patel and A. Chaware, “Transfer Learning with Fine-Tuned MobileNetV2 for Diabetic Retinopathy,” in 2020 International Conference for Emerging Technology (INCET), Belgaum, India: IEEE, Jun. 2020, pp. 1–4. doi: 10.1109/INCET49848.2020.9154014.

[74] R. Rokhana, W. Herulambang, and R. Indraswari, “Classification of Ocular Diseases on Fundus Images Using Weighted MobileNetV2,” in 2022 International Electronics Symposium (IES), Surabaya, Indonesia: IEEE, Aug. 2022, pp. 570–575. doi: 10.1109/IES55876.2022.9888652.

[75] S. Tammina, “Transfer learning using VGG-16 with Deep Convolutional Neural Network for Classifying Images,” IJSRP, vol. 9, no. 10, p. p9420, Oct. 2019, doi: 10.29322/IJSRP.9.10.2019.p9420.

[76] M. Mateen, J. Wen, Nasrullah, S. Song, and Z. Huang, “Fundus Image Classification Using VGG-19 Architecture with PCA and SVD,” Symmetry, vol. 11, no. 1, p. 1, Dec. 2018, doi: 10.3390/sym11010001.

[77] Zhu, Xizhou, Dazhi Cheng, Zheng Zhang, Stephen Lin, and Jifeng Dai. "An empirical study of spatial attention mechanisms in deep networks." In Proceedings of the IEEE/CVF international conference on computer vision, pp. 6688-6697. 2019.

[78] V. Das, S. Dandapat, and P. K. Bora, “Multi-scale deep feature fusion for automated classification of macular pathologies from OCT images,” Biomedical Signal Processing and Control, vol. 54, p. 101605, Sep. 2019, doi: 10.1016/j.bspc.2019.101605.

[79] V. Das, S. Dandapat, and P. K. Bora, “Automated Classification of Retinal OCT Images Using a Deep Multi-Scale Fusion CNN,” IEEE Sensors J., vol. 21, no. 20, pp. 23256–23265, Oct. 2021, doi: 10.1109/JSEN.2021.3108642.

[80] R. Fan, Y. Liu, and R. Zhang, “Multi-Scale Feature Fusion with Adaptive Weighting for Diabetic Retinopathy Severity Classification,” Electronics, vol. 10, no. 12, p. 1369, Jun. 2021, doi: 10.3390/electronics10121369.

[81] P. Glaret Subin and P. Muthukannan, “Optimized convolution neural network based multiple eye disease detection,” Computers in Biology and Medicine, vol. 146, p. 105648, Jul. 2022, doi: 10.1016/j.compbiomed.2022.105648.

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