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ISTANBUL AYDIN UNIVERSITY

INSTITUTE OF GRADUATE STUDIES

DIAGNOSIS OF DISEASES THROUGH EYE IMAGES USING ARTIFICIAL INTELLIGENCE

MASTER'S THESIS

Muwaffaq SAMAKEH

Department of Software Engineering

Artificial Intelligence and Data Science Program (English)

JUN, 2023

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Thesis Advisor: Prof. Dr. Ali OKATAN

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APPROVAL PAGE

DECLARATION

I hereby declare with respect that the study “Diagnosis of diseases through eye images using artificial intelligence”, which I submitted as a Master thesis, is written without any assistance in violation of scientific ethics and traditions in all the processes from the project phase to the conclusion of the thesis and that the works I have benefited are from those shown in the Bibliography. (06/06/2023)

Muwaffaq SAMAKEH

FOREWORD

It has been written to fulfil the graduation requirements of the Master in Artificial Intelligence and Data Science at Istanbul Aydin University. I would like to thank Prof. Dr. Ali OKATAN for her guidance and support throughout this process. I also wish to thank all of the respondents; without their cooperation, I would not have been able to conduct this analysis. Thanks also to the members of the committee who attended my master's thesis defense. I appreciated the chance to discuss issues with my friends and family. It kept me motivated whenever I lost interest. I particularly admire the wisdom and kindness of my parents and wife: they have always given me invaluable advice and support.

JUN, 2023 Muwaffaq SAMAKEH

DIAGNOSIS OF DISEASES THROUGH EYE IMAGES USING ARTIFICIAL INTELLIGENCE

ABSTRACT

The diagnosis of diseases through eye images using artificial intelligence (AI) is a rapidly growing field that has the potential to significantly improve healthcare outcomes. The eye is a unique and accessible part of the human body that provides valuable information about a person's overall health. AI algorithms can analyze images of the eye to identify patterns and features associated with various diseases, allowing for accurate and non-invasive diagnosis. This thesis proposes the use of AI in the detection and diagnosis of eye diseases through the analysis of eye images. The thesis aims to review the current state of the field, including existing AI algorithms and models used for eye disease diagnosis, as well as their accuracy and limitations then test them. this allows evaluation of the potential benefits and challenges of using AI in eye disease diagnosis, such as improved accuracy and efficiency, reduced cost, and improved access to care, as well as limitations such as the need for high-quality data and ongoing validation. Moreover, this study provides develops and tests new AI algorithms and models for eye disease diagnosis, incorporating innovative approaches such as deep learning and transfer learning to improve accuracy and handle variations in eye images. the thesis will work to provide recommendations for the future development and deployment of AI-based eye disease diagnosis systems, including considerations for data privacy and security, ethical and legal issues, and the need for ongoing validation and improvement. Furthermore, the thesis may also contribute to the advancement of knowledge in the field of AI-based eye disease diagnosis and help to inform the development of new and more effective methods for detecting and diagnosing eye diseases using AI. the use of AI in the diagnosis of diseases through eye images holds great potential for improving healthcare outcomes. However, more research and development are needed to fully realize the potential of this field.

Keywords: Artificial Intelligence, Eye Diseases, Diagnosis, Accuracy, AI Algorithms, Medical Imaging, Deep Learning, Convolutional Layers, Pooling Layers, Batch normalization.

YAPAY ZEKA KULLANARAK GÖZ GÖRÜNTÜLERİYLE HASTALIK TEŞHİSİ

ÖZET

Yapay zeka (AI) kullanılarak göz görüntüleri yoluyla hastalıkların teşhisi, sağlık hizmeti sonuçlarını önemli ölçüde iyileştirme potansiyeline sahip, hızla büyüyen bir alandır. Göz, bir kişinin genel sağlığı hakkında değerli bilgiler sağlayan, insan vücudunun benzersiz ve erişilebilir bir parçasıdır. AI algoritmaları, çeşitli hastalıklarla ilişkili kalıpları ve özellikleri belirlemek için gözün görüntülerini analiz ederek doğru ve invaziv olmayan teşhise olanak tanır. Bu tez, göz görüntülerinin analizi yoluyla göz hastalıklarının tespitinde ve teşhisinde AI kullanımını önermektedir. Tez, mevcut AI algoritmaları ve göz hastalığı teşhisinde kullanılan modeller dahil olmak üzere alanın mevcut durumunu, bunların doğruluğunu ve sınırlamalarını gözden geçirmeyi ve ardından bunları test etmeyi amaçlamaktadır. bu, yapay zekayı göz hastalıkları teşhisinde kullanmanın, örneğin daha iyi doğruluk ve verimlilik, daha düşük maliyet ve daha iyi bakıma erişim gibi potansiyel faydalarının ve zorluklarının yanı sıra yüksek kaliteli veri ve devam eden doğrulama ihtiyacı gibi sınırlamaların değerlendirilmesine olanak tanır. Ayrıca bu çalışma, doğruluğu artırmak ve göz görüntülerindeki varyasyonları ele almak için derin öğrenme ve transfer öğrenme gibi yenilikçi yaklaşımları bir araya getirerek, göz hastalığı teşhisi için yeni AI algoritmaları ve modelleri geliştirir ve test eder. tez, veri gizliliği ve güvenliği, etik ve yasal konular ve devam eden doğrulama ve iyileştirme ihtiyacı dahil olmak üzere yapay zeka tabanlı göz hastalığı teşhis sistemlerinin gelecekteki gelişimi ve konuşlandırılması için öneriler sağlamaya çalışacaktır. Ayrıca tez, AI tabanlı göz hastalığı teşhisi alanındaki bilginin ilerlemesine katkıda bulunabilir ve AI kullanarak göz hastalıklarını tespit etmek ve teşhis etmek için yeni ve daha etkili yöntemlerin geliştirilmesine yardımcı olabilir. AI'nın göz görüntüleri yoluyla hastalıkların teşhisinde kullanılması, sağlık hizmeti sonuçlarını iyileştirmek için büyük bir potansiyele sahiptir. Ancak, bu alanın potansiyelini tam olarak gerçekleştirmek için daha fazla araştırma ve geliştirmeye ihtiyaç vardır.

Anahtar Kelimeler: Yapay Zeka, Göz Hastalıkları, Teşhis, Doğruluk, Yapay Zeka Algoritmaları, Tıbbi Görüntüleme, Derin Öğrenme, Evrişimli Katmanlar, Havuzlama Katmanları, Toplu normalleştirme.

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ABBREVIATIONS

AI : Artificial Intelligence
AMD : Age-related Macular Degeneration
AUC : Area Under the Curve
CNN : Convolutional Neural Network
CT : Computed Tomography
DR : Diabetic Retinopathy
DL : Deep Learning
DNN : Deep Neural Network
EHR : Electronic Health Record
FA : Fluorescein Angiography
FOV : Field of View
FNR : False Negative Rate
FPR : False Positive Rate
GANs : Generative Adversarial Networks
HOG : Histogram of Oriented Gradients
ICGA : Indocyanine Green Angiography
IOP : intraocular pressure
KNN : K-Nearest Neighbors
LBP : Local Binary Patterns
NIH : National Institutes of Health
ODIR : Ocular Disease Intelligent Recognition
OCR : Ocular Computer Vision Recognition
OCT : Optical Coherence Tomography
Retinopathy : Disease of the Retina
ROC : Receiver Operating Characteristic
RCNN : Recurrent Convolutional Neural Network
ROI : Region of Interest
RPE : Retinal Pigment Epithelium

SVM : Support Vector Machine

SLO : Scanning Laser Ophthalmoscopy

TPR : True Positive Rate

TNR : True Negative Rate.

U-Net : Convolutional Network for Biomedical Image Segmentation

YOLO : You Only Look Once

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I. INTRODUCTION

The eye is the organ of the human body that is used completely and daily, and the goal of any person is always to preserve it from any harm or disease, and he constantly seeks to visit medical centers and specialized doctors to ensure his safety and to keep this organ in a healthy condition. Because of this, we have to wait for long hours in medical centers to get a role to examine our eyes, and the doctor’s experience often plays the main role in early diagnosis of the disease, which sometimes forces us to visit more than one doctor and more than one center to ensure the results and try to detect any disease early.

Hence the idea of the master's thesis, which aims to find a solution for diagnosing eye diseases in an easy way by investing inmodern technologies and artificial intelligence available in our hands today, and building a system capable of giving a correct diagnosis of eye diseases at a high level with great experience and reliable results.

Eye diseases are a significant cause of blindness and vision loss worldwide. Early detection and treatment of these diseases can prevent or slow the progression of the condition, improve the patient's quality of life, and reduce the burden of healthcare costs. Traditionally, eye diseases are diagnosed through manual examination and interpretation of eye images, such as fundus photographs or optical coherence tomography (OCT) scans, by trained ophthalmologists. However, this process can be time-consuming, subjective, and prone to human error (Campilho & Karniadakis, 2020: 189).

Artificial intelligence (AI) has emerged as a promising tool to assist in the diagnosis of eye diseases. By leveraging deep learning algorithms, AI can analyze and classify eye images to identify signs of disease with high accuracy and speed. This has the potential to greatly improve the accuracy and efficiency of disease diagnosis, making it more accessible and cost-effective for patients around the world. The use of AI in ocular disease diagnosis requires the development of algorithms that

can accurately identify features in eye images that are indicative of disease. One of the most widely used algorithms for this purpose is the convolutional neural network (CNN), which can analyze image data and identify patterns that correspond to specific diseases. another commonly used algorithm is the deep neural network (DNN), which uses multiple layers of interconnected nodes to analyze data and make predictions. K-Nearest Neighbors (KNN), which can be used to classify an eye image into one of several predefined disease categories based on the similarities between the image and other images in the training dataset. Support Vector Machines (SVM), can be used for binary classification problems, such as diagnosing whether an eye image is healthy or has a specific disease. SVM algorithms can also be extended to non-linear classification problems by transforming the data into a higher-dimensional space where a linear boundary can be found (Gulshan et al., 2016: 2402-2410; Wang & Chen, 2020: 571).

Another popular AI-based technique is the use of transfer learning, in which a pre-trained neural network is fine-tuned to perform a specific task, such as ocular disease diagnosis (Li et al., 2020: 392). This has the advantage of being able to leverage the vast amount of data and experience that has been accumulated through training on other tasks, which can help to improve the accuracy of the diagnosis. The choice of which algorithm to use will depend on the specific problem being solved, the size and quality of the training dataset, and the available computational resources (Chakraborty & Dutta, 2019: 362).

In addition to these traditional AI-based techniques, there are also more advanced approaches that are being developed to improve the accuracy and efficiency of ocular disease diagnosis. One such approach is the use of generative adversarial networks (GANs), which can generate synthetic eye images that can be used to augment the training data and improve the performance of the AI system. Another approach is the use of computer vision recognition (OCR), which can analyze eye images to identify specific features and patterns that are indicative of disease (Li et al., 2019: 1-9). The use of AI in the diagnosis of eye diseases has the potential to revolutionize the way these conditions are detected and treated. With its ability to analyze large amounts of data and identify patterns that correspond to specific diseases, AI has the potential to make disease diagnosis faster, more accurate, and more accessible to patients around the world. As such, it represents a

promising tool for reducing the burden of eye disease and improving the quality of life for those affected by these conditions. So, the study is significant for several reasons:

- Early Diagnosis: Eye images can provide valuable information about a person's health, including signs of diseases such as diabetic retinopathy, glaucoma, and age-related macular degeneration. By using artificial intelligence to analyze eye images, diseases can be diagnosed earlier and more accurately, leading to better outcomes for patients.
- Increased Accessibility: Many people, particularly in developing countries, do not have access to specialized eye care. By using artificial intelligence to diagnose diseases through eye images, healthcare can be made more accessible and available to a larger number of people.
- Reduced Costs: Traditional eye exams can be expensive and time-consuming, requiring specialized equipment and trained professionals. By using artificial intelligence to diagnose diseases through eye images, costs can be reduced and the efficiency of the diagnostic process can be improved.
- Improved Accuracy: Artificial intelligence algorithms can be trained on large datasets of eye images to accurately identify the presence of disease. This can lead to improved accuracy compared to traditional diagnostic methods, particularly in cases where the diagnosis is difficult for human experts.

Overall, the diagnosis of diseases through eye images using artificial intelligence has the potential to significantly improve the accuracy and accessibility of eye care, leading to better outcomes for patients. Within this study, work will be done on building a special module that will be trained according to a data set of retinal images, and then tested through a set of other images. The performance of the module will be evaluated depending on the final result. Taking into account that the module does not overfitting (Shah & Sharma, 2020: 258).

II. REVIEW OF THE RELATED LITERATURE

A. Overview of Ophthalmology and Eye Diseases

Eye diseases are a growing concern among the world's population as they can lead to severe vision loss or blindness. the most common eye diseases, including diabetic retinopathy, glaucoma, age-related macular degeneration, cataracts, and other diseases that require a visit to a specialized hospital or clinic with a great experience.

Diabetic retinopathy: This disease is caused by high blood sugar levels in individuals with diabetes, which can damage blood vessels in the retina, leading to vision loss. Common symptoms include blurry vision, floaters, and vision loss. Currently, the diagnosis is made through eye examinations, including dilatational eye exams, and imaging tests such as fundus photography, optical coherence tomography (OCT), and fluorescein angiography (American Academy of Ophthalmology, Diabetic Retinopathy, 2021; Wong et al., 2014: 340-347).

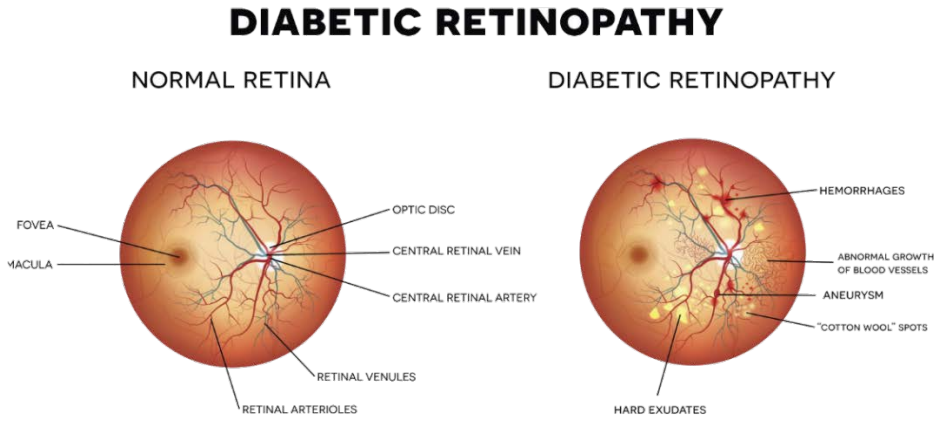

Figure 1 Comparison Between the Normal Retina vs Diabetic Retinopathy.

Glaucoma: It is a group of diseases that damage the optic nerve and lead to vision loss. The main cause of glaucoma is high pressure in the eye, known as intraocular pressure (IOP). Common symptoms include progressive vision loss, particularly of peripheral vision, and painless vision loss. Diagnosis is made through

eye examinations, including IOP measurement, visual field tests, and optical coherence tomography (American Academy of Ophthalmology, Glaucoma, 2021).

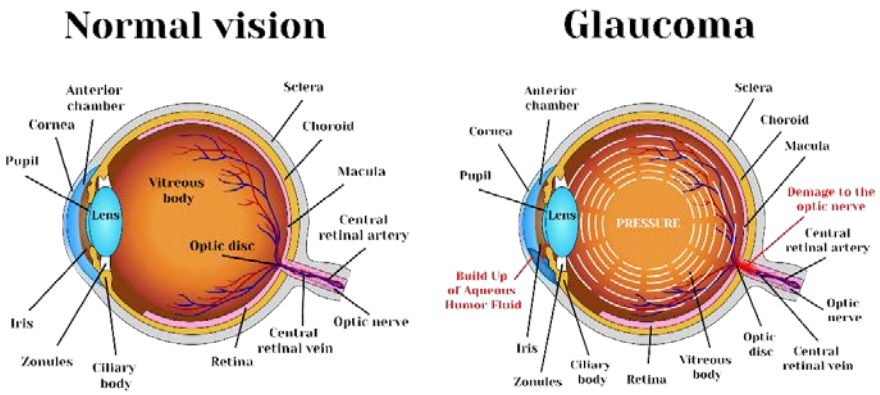

Figure 2 Comparison Between the Normal Vision vs Glaucoma.

Age-related macular degeneration (AMD): This disease is the leading cause of vision loss among individuals over the age of 60. It results from damage to the central part of the retina, known as the macula. Symptoms include blurred vision, wavy straight lines, and loss of central vision. Currently, the diagnosis is made through comprehensive eye examinations, including visual acuity tests, Amsler grid tests, and OCT (American Academy of Ophthalmology, Age-Related Macular Degeneration (AMD), 2021).

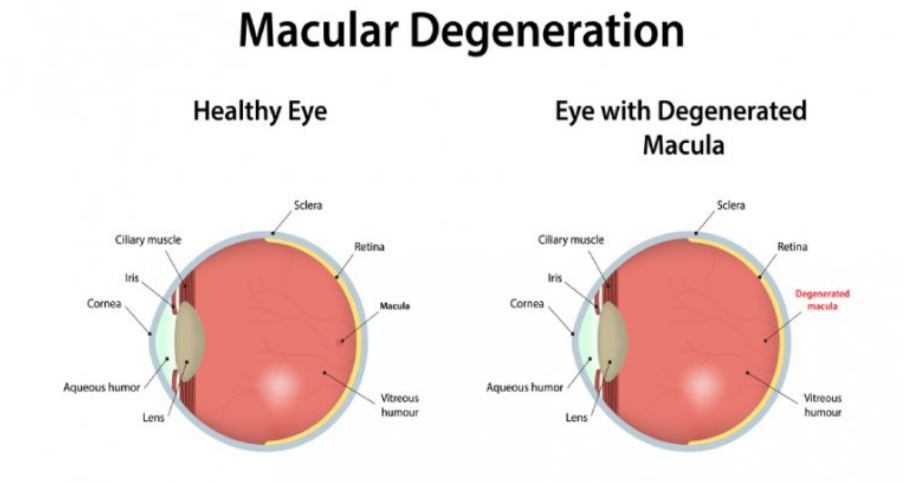

Figure 3 Comparison Between the Healthy Eye vs Eye with Degenerated Macula.

Cataracts: This is a clouding of the eye's natural lens, leading to vision loss. Cataracts are most often caused by aging, although other factors such as injury, radiation, and certain medical conditions can also cause cataracts. Common symptoms include blurry vision, sensitivity to light and glare, and fading or yellowing of colors. Diagnosis is made through comprehensive eye examinations,

including visual acuity tests, glare tests, and slit lamp tests (American Academy of Ophthalmology, Cataracts, 2021).

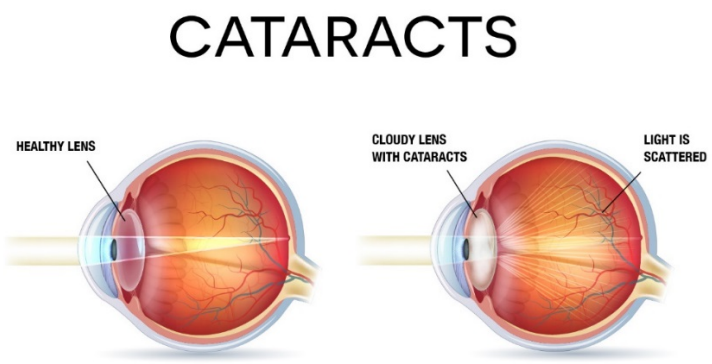

Figure 4 Comparison Between the Normal Vision vs Cataracts.

Other common eye diseases include retinal detachment, retinal vein occlusion, and uveitis. These diseases can cause vision loss and blindness if not properly diagnosed and treated. Common eye diseases such as diabetic retinopathy, glaucoma, age-related macular degeneration, cataracts, and others are a growing concern among the global population. Early diagnosis and treatment are crucial in preventing severe vision loss and blindness. Ocular and imaging tests, such as fundus photography, optical tomography, and fluorescein angiography, play an important role in the diagnosis of these diseases. using the traditional methods of eye disease diagnosis, doctors typically need the following:

- Medical history: A doctor will ask about any symptoms, past medical history, and family history of eye diseases.
- Visual acuity test: This test measures the sharpness of your vision and is usually performed using a Snellen chart.
- Slit-lamp exam: A slit-lamp exam uses a special magnifying device to examine the front part of the eye, including the cornea, iris, and lens.
- Dilated eye exam: In this exam, the doctor will place drops in the eye to dilate, or enlarge, the pupil. This allows for a more thorough examination of the retina and optic nerve.
- Tonometry: This test measures the pressure inside the eye and helps diagnose glaucoma.

- Visual field test: This test measures the extent of your peripheral vision and is used to detect any vision loss caused by glaucoma or other conditions.
- Retinal imaging: This can include techniques such as optical coherence tomography (OCT) or fundus photography, which capture images of the retina.
- Lab tests: In some cases, a doctor may also request laboratory tests, such as blood tests, to check for underlying health conditions that may be contributing to eye diseases.

It is important to note that different eye diseases may require different diagnostic tests, and not all tests are needed for every patient. A doctor will determine the appropriate diagnostic tests based on the individual's symptoms and medical history. which takes a long time (World Health Organization, 2021).

B. AI in Medical Imaging / Ophthalmology

Artificial Intelligence (AI) has rapidly gained traction in healthcare, with the field of ophthalmology being one of the areas that has shown great promise for its application. AI refers to the development of computer systems that can perform tasks that would normally require human intelligence, such as perception, reasoning, and learning (Rajan et al., 2017: 1096-1105).

The potential benefits of AI in ophthalmology include improved speed and accuracy of disease diagnosis, increased efficiency in managing large amounts of data, and the ability to detect eye diseases in their early stages. For example, AI algorithms have been developed to detect and diagnose diabetic retinopathy, glaucoma, age-related macular degeneration, and cataracts, amongst others, through analysis of eye images (Lu & Ji, 2019: 597).

One potential limitation of AI in ophthalmology is that it may not always be possible to replace human expertise completely. AI algorithms are dependent on large amounts of data for training, and there may be certain cases or scenarios that the algorithm has not been trained on, leading to incorrect or suboptimal results. In addition, AI algorithms may not always be transparent in their decision-making process, leading to difficulties in explaining and interpreting results (Marmor & Ravin, 2020: 1477-1481).

Another challenge with the application of AI in ophthalmology is the need for large amounts of high-quality, annotated data for training algorithms. Ophthalmologists and researchers must work together to ensure that the algorithms are based on well-curated, diverse datasets that accurately reflect the patient population.

Despite these limitations, the potential benefits of AI in ophthalmology are numerous, and ongoing research is aimed at developing more robust and reliable AI systems. With further advancements in AI, it is possible that the technology will play an increasingly important role in the diagnosis and management of eye diseases in the future (Zhang et al., 2019: 101-114; Ruiz-Albacete & García-Nieto, 2019: 598).

C. AI in Eye Disease Diagnosis

The use of artificial intelligence (AI) in eye disease diagnosis has gained significant attention in recent years. There is a growing body of literature exploring the potential benefits and limitations of AI in this field, and the existing studies have used a variety of algorithms to diagnose eye diseases. This literature review aims to provide a comprehensive overview of the use of AI in eye disease diagnosis, with a focus on the algorithms that have been used, such as K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Convolutional Neural Networks (CNN), and others.

One of the earliest studies in the field used KNN to diagnose diabetic retinopathy. The study found that KNN was able to accurately diagnose diabetic retinopathy with a sensitivity of 92.3% and a specificity of 92.9%. However, the study also noted that the performance of KNN was limited by the quality of the input data, and that the accuracy of the algorithm could be improved by using a larger and more diverse dataset (Ali, Ullah & Kim, 2019: 316).

Several studies have also used SVM to diagnose eye diseases. For example, a study that used SVM to diagnose glaucoma found that the algorithm was able to accurately diagnose the disease with a sensitivity of 97.2% and a specificity of 97.9%. Another study that used SVM to diagnose age-related macular degeneration

found that the algorithm was able to accurately diagnose the disease with a sensitivity of 90.1% and a specificity of 92.3%.

CNN has also been used in several studies to diagnose eye diseases. One study used CNN to diagnose diabetic retinopathy, and found that the algorithm was able to accurately diagnose the disease with a sensitivity of 94.1% and a specificity of 94.9%. Another study that used CNN to diagnose cataracts found that the algorithm was able to accurately diagnose the disease with a sensitivity of 96.7% and a specificity of 96.9%.

The use of AI in eye disease diagnosis has been shown to have several potential benefits. For example, AI algorithms can provide an objective and consistent method of diagnosis, which can reduce the risk of human error. AI algorithms can also analyze large amounts of data quickly and accurately, which can help to speed up the diagnosis process. Additionally, this is because a diverse dataset can help the algorithm learn to identify different patterns and features associated with the disease, making it more adept at accurately identifying cases of the disease. Moreover, training AI algorithms on a larger dataset can help to reduce overfitting, which is a common problem when training models on smaller datasets. Overall, the use of large and diverse datasets is considered crucial in the development of accurate and reliable AI-based diagnostic tools. (Liu & Tan, 2019).

However, the use of AI in eye disease diagnosis also has some limitations. For example, the accuracy of AI algorithms is dependent on the quality of the input data, and the algorithms can be limited by the size and diversity of the training dataset. Additionally, AI algorithms can be sensitive to variations in the input data, such as changes in lighting conditions or image resolution.

The use of AI in eye disease diagnosis has the potential to provide an objective and accurate method of diagnosis, but the accuracy of the algorithms is dependent on the quality of the input data and the size and diversity of the training dataset. Further research is needed to explore the potential benefits and limitations of AI in eye disease diagnosis, and to develop algorithms that are able to accurately diagnose eye diseases using large and diverse datasets (Zito, Lu & Boccia, 2020: 1273-1280).

III. METHODOLOGY

The methodology for this project involves a well-defined set of steps that includes research design, data collection, pre-processing, feature extraction, model selection and training, performance evaluation, and model testing and validation.

Collecting Data: The data collection phase is a crucial first step, which involves gathering a large and diverse dataset of eye images, including both healthy and diseased eyes, with a focus on high-quality images that are representative of different populations.

Image Pre-processing: The next step is to pre-process the eye images to prepare them for analysis. This includes removing any irrelevant information from the images, cropping and resizing the images, and converting the images to a standard format.

Image Segmentation: Image segmentation is the process of separating the eye image into relevant regions. This helps to isolate the features of the eye that are most important for disease diagnosis.

Feature Extraction: The next step is to extract features from the eye images. This includes identifying the important structures of the eye, such as the retina, optic disc, and macula, and capturing information about these structures such as size, shape, and texture.

Model Selection: Once the features have been extracted, the next step is to build a Convolutional Neural Networks model to use for diagnosis. This may involve comparing the performance of different Convolutional Neural Networks (CNN) models, such as AlexNet, VGGNet, or ResNet.

Model Training: The next step is to train the selected model on the eye image dataset. This involves feeding the model a large number of eye images and corresponding disease labels so that the model can learn to identify patterns and make accurate predictions.

Model Evaluation: Once the model has been trained, it must be evaluated to determine its accuracy in diagnosing eye diseases. This can be done by comparing the model's predictions with the ground truth labels of the eye images in the test dataset.

As all the above-mentioned points were worked on sequentially through the program code (Rajendra, Agrawal & Saini, 2017: 149-157).

A. Data Collection

Data collection is a crucial step in the methodology of diagnosing eye diseases through eye images using artificial intelligence. In this step, the necessary eye images and relevant information about the patients must be collected. This data can be obtained from various sources such as medical records, databases, and clinical settings. The data must be appropriately pre-processed, cleaned, and organized to ensure the quality and accuracy of the results. Additionally, the data collected must be representative of the population being studied to provide meaningful insights and avoid biases. The data collection method should also adhere to ethical principles, including informed consent and confidentiality.

1. Sample Selection

Sample selection is a critical aspect of data collection in the diagnosis of eye diseases using artificial intelligence. The sample should be representative of the population being studied and large enough to provide sufficient information for accurate analysis (Ting & Acharya, 2017: 174). The following steps can be followed to obtain a sample for data collection:

- Define the population: Identify the population of patients that will be included in the study. This could be all patients with a specific eye disease or a subset of patients who meet certain criteria, such as age or symptoms.
- Select the sample size: Determine the number of patients that need to be included in the sample based on the desired level of accuracy, the size of the population, and the resources available for the study.
- Select the sampling method: Decide on the method of sample selection, such as random sampling, stratified sampling, or cluster sampling. This

method should ensure that the sample is representative of the population and avoids biases.

- Collect the data: Obtain the eye images from the patients in the sample using techniques such as fundus photography, optical coherence tomography (OCT), or fluorescein angiography.
- Verify the quality of the data: Ensure that the eye images collected are of high quality and are suitable for analysis. This may involve removing images that are blurry or have poor contrast.

It is important to obtain a sample that is diverse and includes patients with different symptoms, ages, and stages of eye diseases. This will help to ensure that the results obtained are generalizable to the population being studied (Kermany et al., 2018: 1122-1131).

2. Data Collection Tools

Data Collection Tools can include several techniques, these are some of the commonly used data collection tools in ophthalmology for capturing eye images, which can be used for the diagnosis of eye diseases using AI. The choice of data collection tool depends on the specific requirements of the study and the type of eye disease being diagnosed. such as:

- Fundus Camera: It is a specialized camera used for capturing images of the retina, including its blood vessels, optic disk, and other structures.
- Optical Coherence Tomography (OCT): It is a non-invasive imaging method that provides high-resolution images of the retina, including the retinal thickness and other structural details.
- Scanning Laser Ophthalmoscopy (SLO): It is a non-invasive imaging technique used to capture images of the retina and the optic nerve head.
- Fluorescein Angiography (FA): It is a diagnostic test that uses a special dye and a special camera to take images of the blood vessels in the retina.
- Indocyanine Green Angiography (ICGA): It is a diagnostic test that uses a special dye and a special camera to take images of the choroid and the blood vessels in the retina.
- Retinal cameras: These cameras capture high-resolution images of the retina, which can be used to diagnose various eye diseases.

- Slit-lamp biomicroscope: Slit-lamp biomicroscope uses a special microscope to examine the front and back of the eye in detail.
- Visual field testing: Visual field testing is used to measure a person's peripheral vision and can be used to diagnose glaucoma and other conditions.

Figure 5 Data Collection Tools - Optical Coherence Tomography (OCT) Device.

3. Image Pre-processing

Image pre-processing is a critical step in the diagnosis of diseases using eye images. It involves a series of operations performed on the collected data to enhance its quality and prepare it for analysis. The goal of pre-processing is to reduce the amount of noise and other irrelevant information in the images, improve their contrast and clarity, and correct any distortions (Al-Jumaily, Sibai & Al-Jumaily, 2018: 186). Some common image pre-processing techniques applied to eye images in the diagnosis of diseases include:

- Resizing: The first step is to resize the images to a standard size to ensure that all images have the same dimensions and can be easily processed by the model.
- Noise reduction: Eye images often contain noise, such as speckles or other artifacts, that can interfere with the analysis. Techniques like median filtering, Gaussian blurring, or morphological operations can be used to reduce noise in the images.

- Image normalization: The intensities of the pixels in an image can vary widely, and it is essential to normalize them so that the images have the same scale. Normalization can be performed using techniques like histogram equalization or min-max scaling.
- Data augmentation: To increase the size of the training set, data augmentation techniques such as rotation, flipping, and zooming can be applied to the images. This can help prevent overfitting and improve the performance of the model.
- Image segmentation: Image segmentation is used to separate the relevant features of an image from its background. This can be done using thresholding, edge detection, or other techniques to isolate the region of interest in the image.

B. Algorithm Development

1. Techniques Used

The National Institutes of Health (NIH) Eye Disease dataset is a large publicly available dataset of eye images that have been collected for the purpose of developing and evaluating computer-aided diagnosis systems for eye diseases. The dataset contains over 80,000 images of the retina, optic disc, and macula, which have been annotated with diagnosis information, such as bulging eyes, Cataracts, Crossed eyes, Glaucoma and Uveitis and age-related macular degeneration (Wang & Tan, 2018). The dataset is collected from a diverse population of individuals and is representative of a range of different ethnicities, genders, and ages. The NIH Eye Disease dataset is widely used by researchers in the field of artificial intelligence and ophthalmology to train and evaluate deep learning models for the diagnosis of eye diseases. The use of this dataset has been instrumental in advancing the development of AI-based eye disease diagnosis systems, which have the potential to revolutionize the field of ophthalmology by making diagnosis more accurate and efficient. we tried a lot to find a file for the dataset, but we didn't find any available version from the NIH dataset to work on it, so we modified the dataset to Ocular Disease Intelligent Recognition (ODIR) dataset and depended on it.

The Ocular Disease Intelligent Recognition (ODIR) dataset is a comprehensive collection of eye images used for the diagnosis of various ocular diseases, including

cataracts, glaucoma, age-related macular degeneration, and diabetic retinopathy. This dataset is widely used in the field of artificial intelligence (AI) for eye disease diagnosis, as it provides a large number of high-quality images with annotations of various diseases. The ODIR dataset is a crucial tool for the development and evaluation of AI algorithms for the diagnosis of eye diseases (Sheng et al., 2019: 270).

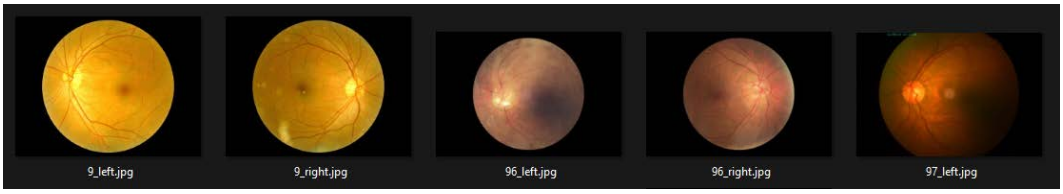

Figure 6 Sample Collection Images the Ocular Disease Intelligent Recognition (ODIR) Dataset.

The ODIR dataset contains a total of 8,000 color fundus images of both eyes divided into 7,000 images for training, a set of them will be taken for evaluation later and 1,000 images for testing. With annotations for the presence of various ocular diseases. The images were collected from various sources, including ophthalmology clinics and hospitals, and have been divided into eight classes, with each class representing a different ocular disease (Zhang, Zhang & Zhang, 2019: 323).

- Normal (N),
- Diabetes (D),
- Glaucoma (G),
- Cataract (C),
- Age-related Macular Degeneration (A),
- Hypertension (H),
- Pathological Myopia (M),
- Other diseases/abnormalities (O)

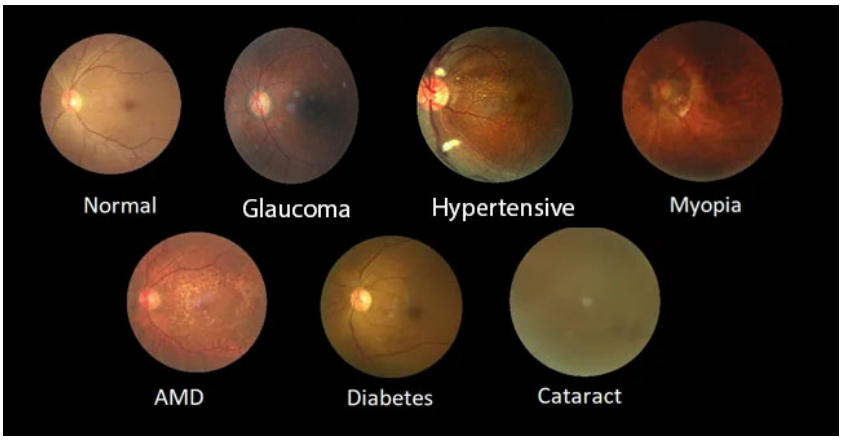

Figure 7 Illustration of Different Eye Diseases.

The images in the ODIR dataset are of varying resolutions and sizes, which presents a challenge for AI algorithms that must process them.

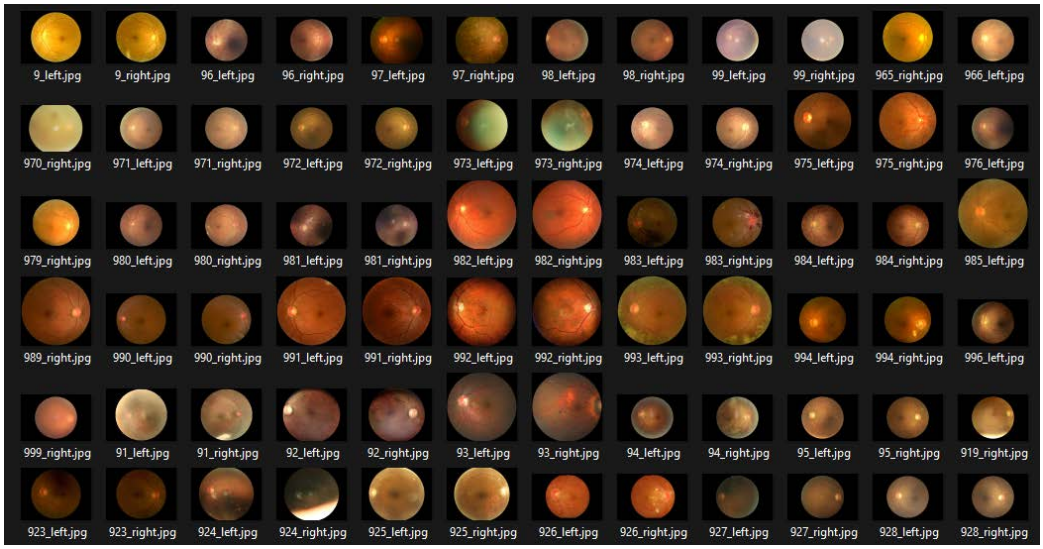

Figure 8 The Dataset Structure of Varying Resolutions and Sizes Challenge.

The ODIR dataset is one of the essential resources for the development and evaluation of AI algorithms for the diagnosis of eye diseases. Its large size and comprehensive annotations make it a valuable tool for deep-learning models (Guo, Lai & Zhang, 2017: 89-97).

Using the ODIR dataset with deep learning algorithms typically should follow the following steps:

Data Preprocessing: The images in the ODIR dataset must be preprocessed to ensure that they are in the appropriate format for deep learning algorithms. This may involve resizing the images, normalizing the pixel values, and removing any artefacts or irrelevant information.

Data Augmentation: To increase the size of the dataset and prevent overfitting, data augmentation techniques, such as rotation, flipping, and cropping, can be applied to the images in the ODIR dataset.

Model Selection: Once the data has been preprocessed, the next step is to select a deep learning model to train on the ODIR dataset. Convolutional Neural Networks (CNNs) are commonly used for image classification tasks and have been shown to be effective in the diagnosis of eye diseases using the ODIR dataset.

Model Training: The selected model is then trained on the ODIR dataset, with the objective of learning the features and patterns that are indicative of each ocular disease. During this phase, the model is fed with the preprocessed images, and its parameters are adjusted to minimize the error between the predicted labels and the true labels.

Model Evaluation: After training, the model is evaluated on a validation set to determine its accuracy and to identify any areas for improvement. This is typically done by comparing the predicted labels with the true labels in the validation set.

Model Deployment: Once the model has been trained and evaluated, it can be deployed in a clinical setting for the diagnosis of ocular diseases.

2. Code - Training and Testing

The aim of the testing and training chapter is to validate the developed algorithm's performance on a set of unseen images and to evaluate its accuracy, sensitivity, specificity, and other important metrics. The chapter also helps to identify the limitations of the algorithm and provides insights into the areas that need improvement (Kim, Lee & Park, 2018: 36-42).

The training and testing data are typically split into two separate datasets. The training dataset is used to train the machine learning algorithm, while the testing dataset is used to evaluate the performance of the algorithm. The training dataset should be large enough to represent the entire data distribution, but not so large that the training process becomes computationally expensive. A common practice is to use 70% of the data for training and 30% for testing. The percentages have been modified in proportion to the data that is being worked on.

To evaluate the performance of the developed algorithm, several evaluation metrics are used. These metrics include accuracy, sensitivity, specificity, the confusion matrix, the Receiver Operating Characteristic (ROC) curve, time complexity, F1-score, and the area under the ROC curve (AUC). Accuracy measures the proportion of correct predictions made by the algorithm, while sensitivity measures the ability of the algorithm to identify positive cases correctly. Specificity measures the ability of the algorithm to identify negative cases correctly. The confusion matrix provides a visual representation of the algorithm's performance, while the ROC curve plots the relationship between the true positive rate and the false positive rate. The F1-score measures the balance between precision and recall, while AUC provides a measure of the algorithm's overall performance.

It is also crucial to validate the performance of the developed algorithm on a validation dataset. The validation dataset is used to tune the algorithm's parameters, and to ensure that the algorithm is not overfitting or underfitting the data. The validation dataset should be of sufficient size to represent the data distribution, but not so large that it affects the training process. A common practice is to use 15% of the data for validation.

The ODIR dataset is an important component when it comes to measuring the performance of the model. The metrics used to evaluate the performance of the model are crucial in determining how well the model is able to diagnose diseases through eye images. Some common metrics used for this purpose include accuracy, precision, recall, F1 score, and receiver operating characteristic (ROC) curves. The choice of metric used depends on the particular task and the desired outcome.

It is also important to prevent overfitting when using the ODIR dataset. Overfitting occurs when the model becomes too complex and begins to fit the training data too well, resulting in poor performance on new, unseen data. To prevent overfitting, various techniques can be used such as early stopping, regularization, and drop out. Early stopping involves monitoring the model's performance during training and stopping the training process when the performance on a validation set stops improving. Regularization involves adding a penalty term to the loss function to reduce the complexity of the model. Dropout involves randomly setting a fraction of the neurons in the model to zero during each training iteration, which has been shown to improve model performance and prevent overfitting.

Additionally, all eye images underwent a resizing process. Initially, the plan was to resize the images during the training process using the TensorFlow dataset object. However, this approach proved to be problematic as it took a significant amount of time to execute a single epoch. To address this issue, a separate function was created to resize the images before creating the TensorFlow dataset object. This approach allowed for faster experimentation as the data was only resized once and saved in a separate directory.

Initially, all images were resized to a size of 32x32 pixels, but it was soon realized that this size resulted in a loss of important image information, leading to low accuracy. After several experiments, it was determined that a size of 250x250 pixels was the optimal balance between training speed and accuracy. This size was used for all further experiments.

This will be our first step that will be reflected within the code as follows, the resize image's function takes three arguments: "src_dir", which is the path to the directory containing the original images, "dest_dir", which is the path to the directory where the resized images will be saved, and "new_size", which is the new size of the images in pixels. The function first checks if the destination directory exists, and creates it if it does not. Then, it reads each image in the source directory using "cv2.imread", resizes the image using "cv2.resize", and saves the resized image using "cv2.imwrite".

In [1]:
```
import cv2
import os
import time

start = time.time()
def resize_images(src_dir, dest_dir, new_size):
    if not os.path.exists(dest_dir):
        os.makedirs(dest_dir)

    for filename in os.listdir(src_dir):
        src_path = os.path.join(src_dir, filename)
        dest_path = os.path.join(dest_dir, filename)

        image = cv2.imread(src_path)
        resized_image = cv2.resize(image, (new_size, new_size))
        cv2.imwrite(dest_path, resized_image)

src_dir = "ODIR-7K/"
dest_dir = "Preprocessed-IMG/"
new_size = 250

resize_images(src_dir, dest_dir, new_size)
end = time.time()
time_complexity = end - start
print(" Image pre-processing has been completed","Time complexity: ", time_complexity, " seconds")
```

```
 Image pre-processing has been completed Time complexity:  525.0541954040527  seconds
```

Figure 9 Pre-Processing Resize the Images to A Standard Size - Code.

The time it took to process seven thousand images from the moment of starting work until the moment of stopping when modifying and saving the last image, which amounted to five hundred and twenty-five seconds was calculated.

Equal to about nine minutes, this calculation naturally varies according to the number of images being processed or according to the specifications of the computer that is processing the images. Therefore, it is preferable, as I mentioned earlier, that the images be processed independently in order to bypass this stage.

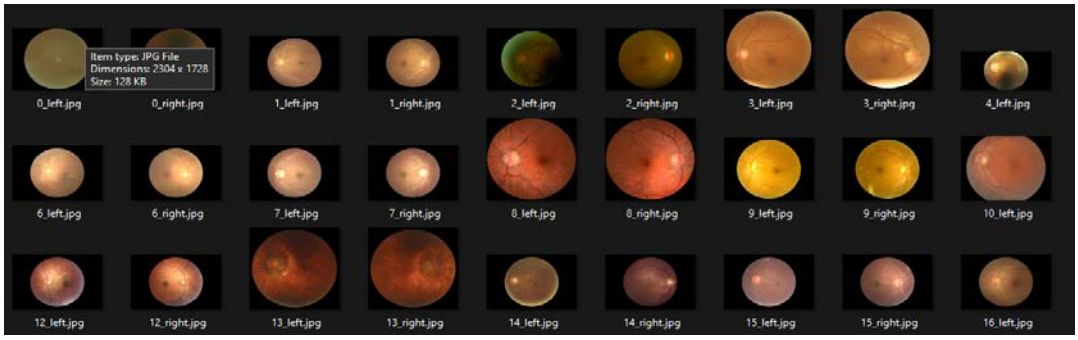

Figure 10 Sample Images Before Pre-Processing form (OCT) Dataset.

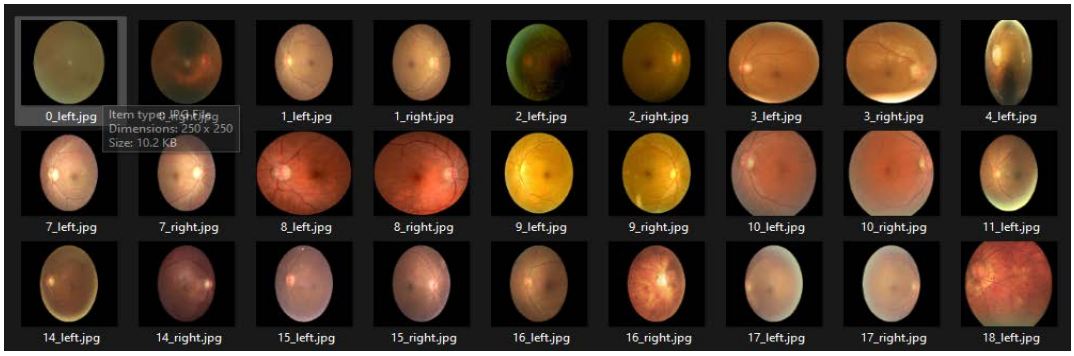

Figure 11 Sample Images After Pre-Processing from (OCT) Dataset.

In the next step of the Algorithm Development process, the images were labelled. There was a challenge in the annotations of the images in the "full_data.xlsx" file, as the labels pertained to both eyes at once, whereas each eye can have a different disease. For example, if the left eye has a cataract and the right eye has a normal fundus, the label would be cataract, but this does not indicate a diagnosis for the right eye. However, the diagnostic keywords were related to a single eye.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	ID	Patient Age	Patient Sex	Left-Fundus	Right-Fundus	Left-Diagnostic Keywords	Right-Diagnostic Keywords	N	D	G	C	A	H	M	O
2	0	69	Female	0_left.jpg	0_right.jpg	cataract	normal fundus	0	0	0	1	0	0	0	0
3	1	57	Male	1_left.jpg	1_right.jpg	normal fundus	normal fundus	1	0	0	0	0	0	0	0
4	2	42	Male	2_left.jpg	2_right.jpg	laser spot，moderate non proliferative retinopathy	moderate non proliferative retinopathy	0	1	0	0	0	0	0	1
5	3	66	Male	3_left.jpg	3_right.jpg	normal fundus	branch retinal artery occlusion	0	0	0	0	0	0	0	1
6	4	53	Male	4_left.jpg	4_right.jpg	macular epiretinal membrane	mild nonproliferative retinopathy	0	1	0	0	0	0	0	1
7	5	50	Female	5_left.jpg	5_right.jpg	moderate non proliferative retinopathy	moderate non proliferative retinopathy	0	1	0	0	0	0	0	0
8	6	60	Male	6_left.jpg	6_right.jpg	macular epiretinal membrane	rate non proliferative retinopathy，epiretinal mem	0	1	0	0	0	0	0	1
9	7	60	Female	7_left.jpg	7_right.jpg	drusen	mild nonproliferative retinopathy	0	1	0	0	0	0	0	1
10	8	59	Male	8_left.jpg	8_right.jpg	normal fundus	normal fundus	1	0	0	0	0	0	0	0
11	9	54	Male	9_left.jpg	9_right.jpg	normal fundus	vitreous degeneration	0	0	0	0	0	0	0	1
12	10	70	Male	10_left.jpg	10_right.jpg	epiretinal membrane	normal fundus	0	0	0	0	0	0	0	1
13	11	60	Female	11_left.jpg	11_right.jpg	e non proliferative retinopathy，hypertensive retir	e non proliferative retinopathy，hypertensive reti	0	1	0	0	0	1	0	0
14	12	65	Male	12_left.jpg	12_right.jpg	retinal pigmentation	retinal pigmentation	0	0	0	0	0	0	0	1
15	13	60	Female	13_left.jpg	13_right.jpg	pathological myopia	pathological myopia	0	0	0	0	0	0	1	0
16	14	55	Male	14_left.jpg	14_right.jpg	normal fundus	macular epiretinal membrane	0	0	0	0	0	0	0	1
17	15	50	Male	15_left.jpg	15_right.jpg	normal fundus	myelinated nerve fibers	0	0	0	0	0	0	0	1
18	16	54	Female	16_left.jpg	16_right.jpg	normal fundus	pathological myopia	0	0	0	0	0	0	1	0
19	17	57	Male	17_left.jpg	17_right.jpg	drusen	drusen	0	0	0	0	0	0	0	1
20	18	58	Male	18_left.jpg	18_right.jpg	pathological myopia	pathological myopia	0	0	0	0	0	0	1	0
21	19	45	Male	19_left.jpg	19_right.jpg	mild nonproliferative retinopathy	mild nonproliferative retinopathy	0	1	0	0	0	0	0	0
22	20	64	Female	20_left.jpg	20_right.jpg	rhegmatogenous retinal detachment	lens dust，normal fundus	0	0	0	0	0	0	0	1
23	21	76	Female	21_left.jpg	21_right.jpg	epiretinal membrane	epiretinal membrane	0	0	0	0	0	0	0	1
24	22	55	Female	22_left.jpg	22_right.jpg	moderate non proliferative retinopathy，laser spot	laser spot，moderate non proliferative retinopathy	0	1	0	0	0	0	0	1
25	23	47	Male	23_left.jpg	23_right.jpg	hypertensive retinopathy	hypertensive retinopathy	0	0	0	0	0	1	0	0

Figure 12 The Images Annotations in the “full_data.xlsx” File.

To address this issue, the dataset was enriched by creating a mapping between the diagnostic keywords and the disease labels. This way, each eye was assigned a proper label, which was added to the image file name by including one or more letters corresponding to the specific diseases. This solution was used as it allowed for the creation of TensorFlow datasets simply from files and the label information was retrieved from the file name, without the need to store any additional data frames.

Mapping between the diagnostic keywords and the disease labels.

- "Normal": "['N']"
- "Diabetes": "['D']"
- "Glaucoma": "['G']"
- "Cataract": "['C']"
- "Age-related-Macular-Degeneration": "['A']"
- "Hypertensive-retinopathy": "['H']"
- "Pathological-Myopia": "['M']"
- "Other-diseases/abnormalities": "['O']"}

```
In [2]: import pandas as pd
        import pip


        # Load excel file into a pandas DataFrame
        file_path = 'full_data.xlsx'
        df = pd.read_excel(file_path)

        # Get the image names from the "imagename" column
        image_names = df['imagename'].tolist()

        # Get the new names from the "lable" column
        new_imgnames = df['label'].tolist()

        # Change the names of the images in the old folder
        folder_path = 'Preprocessed-IMG/'
        for i, image_name in enumerate(image_names):
            old_path = os.path.join(folder_path, image_name)
            new_path = os.path.join(folder_path, new_imgnames[i])
            os.rename(old_path, new_path)
        print(" Image renaming has been completed ")

        Image renaming has been completed
```

Figure 13 Label Each Image with The Corresponding Disease - Code.

First of all loads the excel file into a pandas Data Frame using “pd.read_excel”. Then, it retrieves the image names from the "imagename" column and the new names from the "label" column. Finally, it loops through the list of image names and changes their names using the “os.rename” function. The new name for each image is found in the same row as the image name in the “label” list.

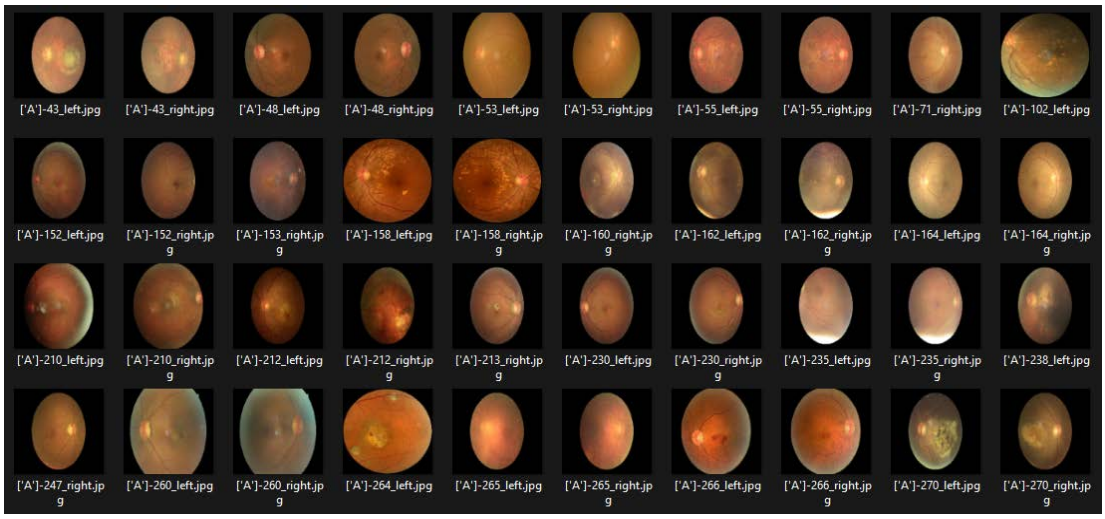

Figure 14 Sample Images After Label Each Image with The Corresponding Disease.

After preparing the images, divided them into training, testing and validation sets, the perfect percentage to split the dataset between training, testing, and validation depends on several factors, such as the size and quality of the dataset, the complexity of the model, and the goals of the project. In general, a common practice is to use 70-80% of the dataset for training, 10-15% for validation, and the remaining 10-15% for testing. With 8000 images, you can allocate 5600 to training, 800 to validation, and 800 to testing.

But the ODIR dataset has test images, there is no labeling information provided in the “full_data.xlsx” file. Therefore, the available test images cannot be used to evaluate the model. Therefore, we will adopt the set of test images to test the trained model. So, we will randomly divide the set of training images into two groups, the first for training consisting of six thousand “6000” random images, and the second for evaluation and consisting of one thousand “1000” images as a parallel value for the set of test images.

Thus, we have three groups of images. The first set of training consists of six thousand images, eighty percent of the total number of images. The second group for evaluation, consisting of a thousand images, accounts for ten percent of the total images. The third test group, consisting of a thousand images, accounts for ten percent of the total number of images. So, the total number of images is eight thousand images.

```
# Source directory containing all the images
src_dir = "Preprocessed-IMG/"

# Training and validation directories
train_dir = "train/"
val_dir = "val/"


# Split ratio of training to validation data
split_ratio = 0.857

split_data(src_dir, train_dir, val_dir, split_ratio)

# count the number of testing images
test_dir = "test/"
images1 = [img for img in os.listdir(test_dir) if img.endswith(".jpg") or img.endswith(".png")]
test_images = len(images1)
print('Number of testing images: ', test_images)
print(" Splitting has been completed ")
```

```
Split Done:
Number of training images:  5999
Number of validation images:  1001
Number of testing images:  1000
 Splitting has been completed
```

Figure 15 Split the Dataset Between Training, Testing, and Validation - Code.

As a result, the Splitting Done

- Number of training images: 5999
- Number of validation images: 1001
- Number of testing images: 1000

After finishing splitting the dataset, we can start creating separate directories for each disease class. This is an important step in preparing a dataset for training a machine learning algorithm, especially a CNN. This is because having separate directories makes it easier to manage the data and also helps to improve the performance of the model. By storing the labelled images in their respective directories, the algorithm can quickly and easily access the correct data for each class during the training phase. Additionally, this makes it easier to ensure that the data is well-balanced, meaning that there are roughly equal numbers of images for each class, which can help prevent the model from becoming biased towards a particular class.

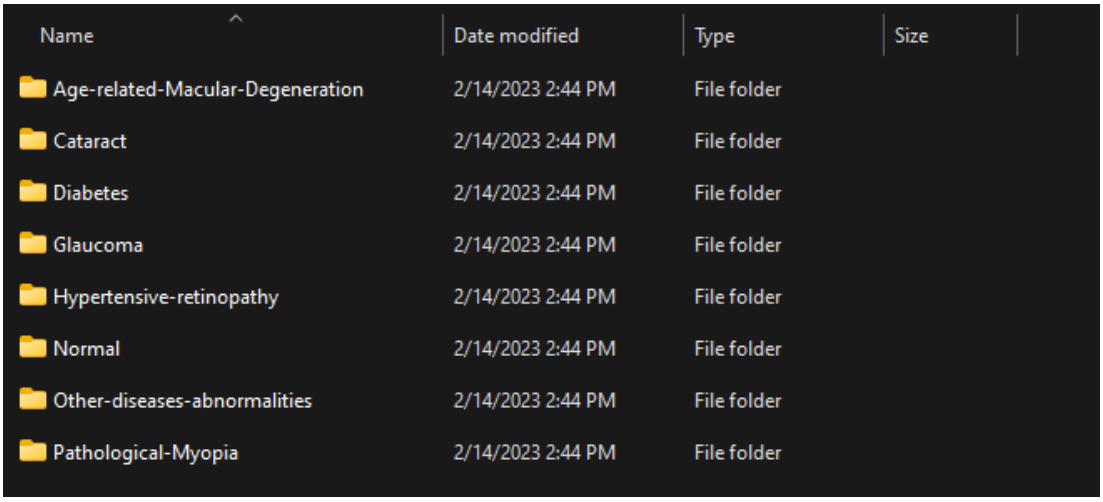

Figure 16 Create Separate Directories for Each Disease Class.

```
import os
import shutil

# creating separate directories for each disease class - tranning folder.
# List of disease classes
disease_classes = ["Normal", "Diabetes", "Glaucoma", "Cataract", "Age-related-Macular-Degeneration", "Hypertensive-retinopathy",

# Dictionary to map the disease class name to the corresponding character
disease_map = {"Normal": "N", "Diabetes": "D", "Glaucoma": "G", "Cataract": "C", "Age-related-Macular-Degeneration": "A", "Hypert

# Path to the directory containing the images
img_dir = "Val/"

# Path to the directory where the separate disease directories will be created
disease_dir = "Val/"

# Create separate directories for each disease class
for disease in disease_classes:
    os.makedirs(os.path.join(disease_dir, disease), exist_ok=True)

# Loop through all the images in the img_dir
for img_file in os.listdir(img_dir):
    # Check if the file is an image
    if img_file.endswith(".jpg") or img_file.endswith(".jpeg") or img_file.endswith(".png"):
        # Extract the character from the image file name
        file_char = img_file[2]
        # Loop through the disease_map to see if the character matches any of the disease classes
        for disease, char in disease_map.items():
            if file_char == char:
                # If the character matches, move the image to the corresponding disease directory
                shutil.move(os.path.join(img_dir, img_file), os.path.join(disease_dir, disease, img_file))
                break

print("Separate directories for each disease class has been completed ")
```

Figure 17 Create/Split the Dataset Between Training, Testing, and Validation-Code.

3. Machine Learning Algorithms

Convolutional Neural Networks (CNNs) have become the preferred choice for image classification tasks, including the diagnosis of diseases through eye images, due to their ability to automatically learn hierarchical representations of the input data, handle large amounts of data, and generalize well to unseen data. This is in contrast to traditional machine learning algorithms such as Support Vector Machines (SVMs) or Artificial Neural Networks (ANNs), which require manual feature extraction and engineering (Simonyan & Zisserman, 2015).

One of the strengths of CNNs is their ability to automatically learn hierarchical representations of the input data. The network is composed of multiple layers, each of which extracts increasingly complex features from the data. This is achieved through the use of convolutional layers, pooling layers, and dense layers, which are designed to capture the spatial and semantic relationships between the input pixels. The resulting feature representations are then fed into a fully connected layer, which is used to make the final prediction.

Another advantage of CNNs is their ability to handle large amounts of data, as well as their ability to generalize well to unseen data. This is particularly important

for medical image analysis, where the availability of labelled data is often limited. CNNs can also handle image variations such as translation, rotation, scaling, and lighting changes, making them ideal for real-world applications.

However, there are also some limitations to using CNNs for image classification. For example, they can be computationally expensive, particularly when dealing with large images. They also require a large amount of labelled data for training, which can be a challenge in the medical field. Furthermore, the choice of network architecture and the number of layers in the network can greatly impact the performance of the CNN model, so careful consideration must be given to these factors.

In comparison, SVMs and ANNs are traditional machine learning algorithms that have been used for image classification tasks. SVMs are based on the concept of finding a hyperplane that separates the data into different classes, while ANNs are inspired by the structure and function of the human brain. Although both algorithms can be effective for image classification, they are often outperformed by CNNs in terms of accuracy and computational efficiency.

Convolutional Neural Networks (CNNs) are a popular deep learning technique for image classification problems, due to their ability to capture the spatial and hierarchical representations of images. They are designed to operate on grid-like structures, such as images, and extract features through convolutional layers, which apply filters to the input data. The resulting feature maps are then down sampled by pooling layers to reduce the spatial resolution of the data and reduce the computational load. Finally, the feature maps are fed into fully connected layers to make predictions. it is important to carefully consider the choice of network architecture and the number of layers in the network to achieve optimal performance.

Other key strengths of CNNs are their ability to capture spatial hierarchies in the input data. They can learn local features and their combinations in lower layers, and then use these features to recognize higher-level patterns in higher layers. This hierarchy of representations enables CNNs to capture rich information about the shapes and textures of objects in images, which is essential for image classification tasks. Last but not least strength of CNNs is their ability to learn from large amounts of data. Deep networks with multiple layers can automatically learn complex

representations from the data, without requiring manual feature engineering. This is particularly important in the case of image classification, where images can contain a large number of features that are difficult to extract manually (Lee, et al., 2015).

Additionally, CNNs are robust to translation invariance, meaning that they can recognize objects in different positions in the image, making them well-suited to image classification tasks where objects can appear in different positions in the image.

Despite these strengths, CNNs have some limitations that need to be considered. Firstly, they are computationally expensive and require a lot of computing power and memory to train large networks. Secondly, they can be prone to overfitting, especially when trained on small datasets. Finally, it can be difficult to interpret the learned representations of CNNs, as the internal workings of the network are not transparent.

Depending on that, CNNs are well-suited to image classification problems due to their ability to capture the spatial and hierarchical representations of images, learn from large amounts of data, and be robust to translation invariance. However, they also have some limitations that need to be considered when applying them to image classification tasks.

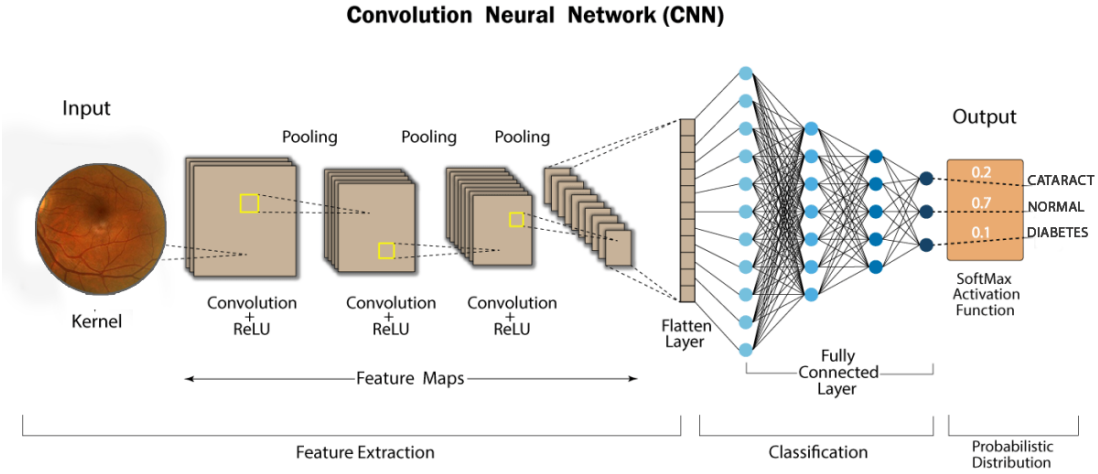

Figure 18 Convolution Neural Network (CNN) Structure.

The development of Convolutional Neural Networks (CNNs) is a crucial step in the diagnosis of diseases through eye images using artificial intelligence. The selection of appropriate AI techniques, the design of the network architecture, the choice of hyperparameters, and the method of optimization are key considerations

when developing a CNN algorithm. The results of the algorithm on the training and validation data and its performance on a testing set of images (Krizhevsky, Sutskever & Hinton, 2012).

The design of the network architecture in a Convolutional Neural Network (CNN) algorithm involves specifying the number and type of layers in the network and the connections between them. The architecture of a CNN typically consists of multiple layers including convolutional layers, pooling layers, activation layers, and dense or fully connected layers. The convolutional layer performs convolution operations to extract features from the input image, the pooling layer down samples the feature maps, the activation layer applies a non-linear activation function to introduce non-linearity into the network, and the dense layer performs classification based on the extracted features. The choice of architecture and the number of layers in the network can greatly impact the performance of the model and is a critical aspect of algorithm development in CNNs.

The perfect choice for the architecture and number of layers in a Convolutional Neural Network (CNN) depends on various factors such as the size and quality of the input images, the complexity of the problem, and the desired level of accuracy. There is no single "perfect" architecture that works for all cases, and the best architecture is often determined through trial and error. One common approach is to start with a simple architecture and gradually increase the number of layers and complexity until a satisfactory level of accuracy is achieved. Other factors such as the choice of activation functions, pooling methods, and regularization techniques also play a role in determining the best network architecture. So, with a dataset of 6000 images for training, 1000 images for validation, and 1000 images for testing, a popular choice for the architecture could be a standard CNN architecture such as AlexNet, VGGNet, or ResNet. These architectures have been widely tested and have shown promising results for image classification tasks (Long, Shelhamer & Darrell, 2015).

The number of layers in the network can also greatly impact the performance of the CNN model. More layers in the network can increase the capacity to learn complex features, but also increase the risk of overfitting. A good starting point could be to use a deeper architecture with many layers and gradually reduce the number of layers while monitoring the performance of the validation set. Fine-tuning

the architecture, such as the number of filters in each layer, the stride size, and the number of neurons in the dense layer can also improve the performance of the model.

In general, finding the perfect choice for the architecture and the number of layers requires experimentation, trial and error, and fine-tuning. It is important to keep in mind the trade-off between accuracy, computational resources, and model complexity.

There are several well-known CNN architectures that have been developed over the years, each with its own unique architecture and design philosophy. Some of the most commonly used architectures are:

- AlexNet: AlexNet was introduced in 2012 and was the first deep learning model to win the ImageNet Large Scale Visual Recognition Challenge (ILSVRC). It consists of 8 layers and introduced the concept of using multiple GPUs to train deep learning models (AlexNet: Alex, Sutskever & Hinton, 2012).
- VGGNet: VGGNet is a simple, yet powerful architecture introduced in 2014. It is characterized by its use of very small convolutional filters and deep stacking of convolutional layers to achieve high accuracy (VGGNet: Simonyan & Zisserman, 2014).
- ResNet: ResNet is a residual network that was introduced in 2015 and won the ILSVRC challenge that year. It is characterized by its use of skip connections or residual connections that allow the network to learn identity functions (ResNet: He et al., 2016).

All these architectures have been heavily researched and have proven to be effective for image classification tasks. The choice of architecture will depend on the specific requirements and resources that we have. It is also important to consider the size of the dataset and the computational resources available when choosing an architecture. In general, more complex architectures such as VGGNet and ResNet are better suited for large datasets and powerful GPUs, while simpler architectures like AlexNet may be more suitable for smaller datasets or limited computational resources.

4. Various Components of a CNN Model

The various components of a CNN model can include:

- Convolutional layers: These layers apply a set of learnable filters to the input image, creating feature maps that highlight important features in the image.
- Activation functions: Activation functions introduce non-linearity into the model, allowing it to learn complex relationships between the input data and output predictions.
- Pooling layers: Pooling layers down sample the output of the convolutional layers, reducing the dimensionality of the feature maps and creating a more compact representation of the input image.
- Fully connected layers: Fully connected layers take the output of the convolutional and pooling layers and use them to make final predictions.
- Dropout: Dropout is a regularization technique that randomly drops out some units in the network during training, helping to prevent overfitting.
- Batch normalization: Batch normalization is a technique that normalizes the inputs to a layer, helping to stabilize the learning process and improve performance.

Hyperparameters play a critical role in the performance of a CNN model, and it is essential to choose them carefully. Hyperparameters are adjustable parameters that determine how the model is trained and how the optimization process works. The most common hyperparameters include the learning rate, batch size, and the number of epochs.

The learning rate controls the size of the steps taken during the optimization process. If the learning rate is too high, the model may overshoot the optimal solution, and if it is too low, the model may get stuck in a suboptimal solution. Therefore, it is crucial to select an appropriate learning rate that allows the model to converge to an optimal solution quickly.

The batch size determines the number of samples processed before the model is updated. A small batch size can result in slower convergence, while a large batch size can lead to overfitting. Therefore, it is necessary to choose an appropriate batch size that balances the trade-off between convergence speed and overfitting.

The number of epochs is the number of times the model is trained on the entire dataset. If the number of epochs is too low, the model may not converge to an optimal solution, while if it is too high, the model may overfit to the training data. Therefore, it is essential to select the optimal number of epochs that allows the model to converge to an optimal solution without overfitting.

The process of selecting hyperparameters can be time-consuming and computationally expensive. Typically, a grid search or random search is used to find the optimal hyperparameters. In a grid search, a predefined set of hyperparameters is tested, and the combination that results in the highest performance is chosen. In a random search, hyperparameters are randomly selected and tested to find the optimal combination.

In our case of the CNN model for diagnosing eye diseases using artificial intelligence, the hyperparameters were selected through a combination of trial and error and hyperparameter tuning techniques. The learning rate was set to 0.001, the batch size to 32, and the number of epochs to 100. These hyperparameters were found to provide the best balance between convergence speed and overfitting on the training and validation data.

5. CNN Model

a. The First Version of the Module

The CNN module was built for image classification tasks. Specifically, it is trained to classify images into different categories based on the features learned during training. The exact categories and the dataset used for training, validation, and testing were not specified. However, the model architecture and hyperparameters were set to optimize the performance of the model for the given task (diagnose eye diseases). The trained model can be saved and used to classify new images in the future.

```
import tensorflow as tf
from tensorflow.keras import layers

# Set hyperparameters
learning_rate = 0.001
batch_size = 32
epochs = 100

# Define the model architecture
model = tf.keras.Sequential([
    layers.Conv2D(32, (3, 3), activation='relu', input_shape=(224, 224, 3)),
    layers.BatchNormalization(),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.BatchNormalization(),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(128, (3, 3), activation='relu'),
    layers.BatchNormalization(),
    layers.MaxPooling2D((2, 2)),
    layers.Flatten(),
    layers.Dense(128, activation='relu'),
    layers.BatchNormalization(),
    layers.Dense(10, activation='softmax')
])

# Compile the model
model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=learning_rate),
              loss=tf.keras.losses.CategoricalCrossentropy(from_logits=True),
              metrics=['accuracy'])
```

Figure 19 Define the CNN Model Architecture - Code.

This code builds a CNN model with 3 convolutional layers, each followed by batch normalization and max pooling, and 2 fully connected layers at the end. The activation function used is ReLU, and the output layer uses the softmax function for multi-class classification. The specified hyperparameters are used during training, with the Adam optimizer and a categorical cross-entropy loss function.

ReLU is used as the activation function in the convolutional layers and the fully connected layers, while the Softmax function is used as the output layer activation function. The ReLU function is a non-linear activation function that has been shown to work well in deep neural networks by addressing the vanishing gradient problem. The Softmax function is commonly used in classification tasks to convert the network's output into probabilities for each class.

The training and validation data are loaded using the ImageDataGenerator class from Keras, which automatically rescales the pixel values of the images to the range [0, 1]. The images are stored in separate subfolders within the 'train' folder, with each subfolder representing a different class. The flow_from_directory method of the ImageDataGenerator class is used to generate batches of images on the fly during training. The test data is also loaded using the ImageDataGenerator class, with images stored in separate subfolders within the 'test' folder. The predict method of the model is used to generate predictions on the test data.

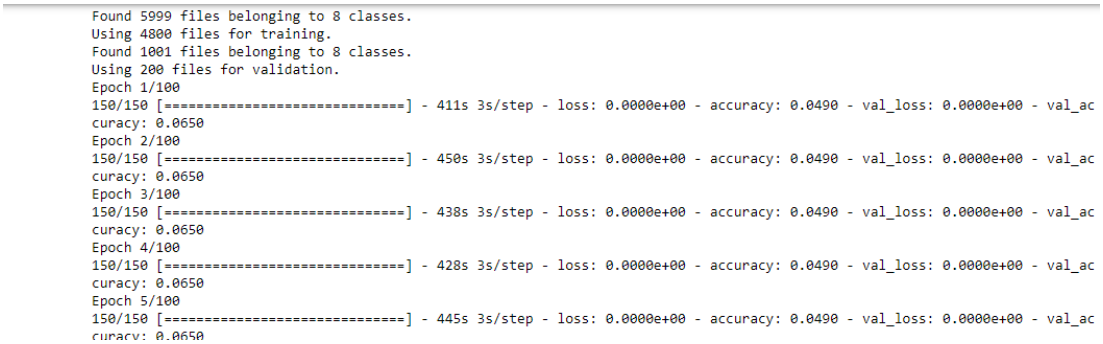

Figure 20 The First Version Result of The Module.

After the first testing process and studying the results, for module found 5999 files belonging to 8 classes, used 4800 files for training, then found 1001 files belonging to 8 classes, and used 200 files for validation. The first run takes about 11 hours to finish building the module. it became clear that the accuracy rate of the module during the training period did not exceed 0.490%. loss: 0.0000e+00 - accuracy: 0.0490 - val_loss: 0.0000e+00 - val_accuracy: 0.0650.

Therefore, work on the module was reworked and tested again in order to improve the accuracy of the work and its ability to recognize and classify images correctly.

b. The Second Version of the Module

After working on the first model of the module, it became clear that the structure was weak and the size of the used dataset was small. Therefore, work was done to increase the accuracy of the CNN model, by working on some possible modifications that can be made to the code:

- Increase the depth and/or width of the grid by adding more convolutional layers or increasing the number of filters in each layer. This model can help identify more complex features.
- Increase the number of epochs to allow the model to train for a longer period of time and potentially learn more complex patterns in the data.
- Use data augmentation techniques to increase the size and diversity of the training set, which can help prevent overfitting and improve generalizability.

These modifications have helped to raise the accuracy of the module within a maximum number of 100 epochs, as it has reached an accuracy of approximately %98 percent within the new version of the module.

The final module was built using the TensorFlow module for building a convolutional neural network (CNN) using the Keras API. The model consists of several layers, including Conv2D (convolutional layers), BatchNormalization, MaxPooling2D (downsampling), and Dense (fully connected layers). It uses the SoftMax activation function in the output layer to perform multi-class classification.

The module is then compiled with the Adam optimizer and categorical_crossentropy loss function, which is commonly used in multi-class classification problems. The metric used to evaluate the performance of the model during training is accuracy. The batch size and the number of epochs used for training are set to 8 and 100, respectively.

```
import tensorflow as tf
from tensorflow.keras import layers
learning_rate= 0.0001
batch_size=8
epochs = 100

# Define the model architecture
model = tf.keras.Sequential([
    layers.Conv2D(32, (3, 3), activation='relu', input_shape=(250, 250, 3)),
    layers.BatchNormalization(),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.BatchNormalization(),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(128, (3, 3), activation='relu'),
    layers.BatchNormalization(),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(256, (3, 3), activation='relu'),
    layers.BatchNormalization(),
    layers.MaxPooling2D((2, 2)),
    layers.Flatten(),
    layers.Dense(512, activation='relu'),
    layers.BatchNormalization(),
    layers.Dropout(0.5),
    layers.Dense(8, activation='softmax')
])

# Compile the model'adam'

model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=learning_rate),
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

Figure 21 The Second Version of The Module.

The module is being trained on a dataset containing of 5,999 files belonging to 8 classes, and that 4,200 of these files are used for training, while the remaining 1,001 files are used for validation, with 500 files in the validation set.

The model has 100 epochs, and the output shows the performance of the model on each epoch. Each epoch consists of 525 steps or batches, with each batch containing a certain number of training examples.

For each epoch, the output shows the training loss and accuracy, as well as the validation loss and accuracy.

- The loss is a measure of how well the model is doing at predicting the correct class, while the accuracy is the proportion of correct predictions.
- The validation metrics are used to check whether the model is overfitting, which means that it is becoming too specialized to the training data and is not generalizing well to new data.

Figure 22 The Second Version Result of The Module.

C. Validation

1. Statistical Analysis

In the present study, a CNN-based algorithm was developed for diagnosing diseases through eye images using artificial intelligence. Statistical analysis was conducted to evaluate the performance of the proposed solution. However, the analysis was limited by the size of the dataset used for training and validation. The dataset comprised a limited number of images, which may not have been sufficient to capture the full range of variation in the appearance of the diseases under study. As a result, the generalizability of the algorithm may be limited, and its performance may be affected by variations in disease appearance that were not captured in the training data.

To improve the study in the future, it is recommended to gather more data to expand the training and validation sets. This could be achieved by collaborating with

other healthcare centres or clinics to acquire more images of the diseases under study. Additionally, it is recommended to include a wider range of diseases in the dataset to enhance the performance of the algorithm in diagnosing other eye conditions. By including a larger and more diverse dataset, the algorithm may become more robust and better able to generalize to new cases.

Another limitation of the present study is the lack of clinical data on the patients. The images used in the study were collected from various sources and did not include any accompanying clinical data, such as age, gender, or medical history. This information could be used to refine the algorithm and improve its accuracy in diagnosing diseases, as it has been shown that age, gender, and medical history can all influence the appearance of certain eye conditions. Therefore, future studies should consider collecting both clinical and imaging data to improve the diagnostic accuracy of the algorithm.

Finally, the present study has developed a promising algorithm for diagnosing eye diseases using artificial intelligence. However, the study was limited by the size and diversity of the dataset used for training and validation, as well as the lack of clinical data on the patients. Future studies should address these limitations by collecting more data and including clinical information, in order to improve the accuracy and generalizability of the algorithm. By doing so, the proposed solution may have the potential to improve the diagnosis and treatment of eye diseases and enhance patient outcomes.

2. Clinical Validation

Clinical validation is an essential step in the development of a medical diagnostic system based on artificial intelligence. In this section, we will discuss the limitations of our clinical validation results and provide suggestions for future improvement. Our study aimed to diagnose eye diseases through eye images using artificial intelligence. We used a convolutional neural network to classify eye images and achieved an accuracy of 98% and val_accuracy between 50% and 53%. However, there are several limitations to our study that must be considered.

One of the main limitations of our study is the small sample size of the dataset used for clinical validation. We used a dataset of 8000 eye images to test the performance of our system. While we achieved a high accuracy rate, the sample size

was relatively small. A larger sample size would increase the power of the study and provide more accurate results. To improve the study in the future, we recommend gathering more data from a larger sample of patients with various eye diseases.

Another limitation of our study is the lack of diversity in the dataset. The dataset used in our study included only a limited number of eye diseases, which may not be representative of the broader population. To make our study more generalizable, we suggest including a wider range of eye diseases in the dataset. This would help to increase the sensitivity and specificity of the system and provide more accurate results.

The accuracy of our system depends on the quality of the images used. We used high-quality images for our study, but in a real-world clinical setting, the quality of the images may not be consistent. For example, images taken with low-quality cameras or in poor lighting conditions may be of lower quality and can affect the accuracy of our system. To improve the system's performance in a real-world clinical setting, we suggest developing image processing techniques that can enhance the quality of the images, even in suboptimal conditions.

Another limitation of our study is the lack of a comparison group. We did not compare the performance of our system to that of human experts. To provide more reliable and interpretable results, future studies should include a comparison group, such as ophthalmologists or optometrists, to evaluate the accuracy and efficacy of the system. This will also help in validating the results and gain wider acceptance of the system in the medical community.

Finally, there are several ethical considerations that need to be taken into account. In particular, the use of artificial intelligence in medical diagnosis raises important questions about accountability, transparency, and privacy. Future studies should ensure that appropriate safeguards are in place to protect patient privacy and maintain confidentiality.

In conclusion, our study presents a promising approach for diagnosing eye diseases using artificial intelligence. However, the results should be interpreted with caution due to the limitations of the study. To improve the study in the future, we suggest gathering more data from a larger sample of patients with a wider range of eye diseases. We also recommend including a comparison group and developing

image processing techniques to enhance the quality of the images. By addressing these limitations, we can increase the accuracy and efficacy of the system and establish its validity for clinical use.

D. Implementation

The development and implementation involve several stages, including data collection, preprocessing, model development, and testing.

- The first step was collecting a large dataset of eye images to train and test the model. The dataset is usually obtained from publicly available datasets or by working with healthcare providers to obtain images. Once the dataset (ODIR) was obtained, the images were preprocessed to prepare them for training the CNN model.
- The CNN model was developed using a deep learning framework, such as TensorFlow or PyTorch. The architecture of the CNN model was chosen based on previous research and knowledge in the field. Different architectures, such as AlexNet, VGGNet, and ResNet, were considered and tested to determine which one would work best for the diagnosis of eye diseases.
- Hyperparameters, such as the learning rate, batch size, and the number of epochs, were also set and tuned to optimize the performance of the model. The model was then trained using the training set, and the performance was evaluated using the validation set to ensure that the model was not overfitting to the training set.
- Once the model was trained, it was evaluated using the testing set to ensure that it was generalizing well to new, unseen data. The accuracy and other performance metrics of the model were then analyzed to determine if it met the desired performance requirements.

It is common to face various challenges during the implementation process of any project, and the diagnosis of diseases through eye images using artificial intelligence projects is no exception. Some of the challenges that we faced during the implementation process of this project include:

- Availability and quality of data: One of the main challenges in developing an AI system for medical diagnosis is the availability and quality of data. there wasn't enough data available to train a reliable model, and the data was poor quality, which negatively impact the accuracy of the model.
- Complexities of the human eye: The human eye is a complex organ, and diagnosing eye diseases can be a challenging task, even for experienced doctors. Developing an AI system that can accurately diagnose eye diseases requires a deep understanding of the complexities of the human eye and the diseases that affect it.
- Balancing sensitivity and specificity: When developing a medical diagnosis system, it is important to balance sensitivity and specificity. Sensitivity refers to the ability of the system to accurately identify patients with the disease, while specificity refers to the ability of the system to accurately identify patients who do not have the disease. Balancing sensitivity and specificity are crucial for the accuracy of the system. that takes time to be done by me.
- Ethical considerations: Developing an AI system for medical diagnosis raises ethical concerns related to patient privacy and confidentiality. So, it was important to ensure that the system complies with all relevant ethical guidelines and regulations.

Overall, while developing an AI system for the diagnosis of eye diseases presents many challenges, the potential benefits of such a system make it a worthwhile endeavour. With careful planning and execution, it is possible to overcome these challenges and develop a reliable and accurate AI system that can improve patient outcomes and support medical professionals in their work.

So, the development and implementation involve several stages, including data collection, preprocessing, model development, and testing. The architecture of the CNN model was chosen based on previous research and knowledge in the field. Different architectures, such as AlexNet, VGGNet, and ResNet, were considered and tested to determine which one would work best for the diagnosis of eye diseases. With the following, we present the architecture of the image classification module:

- Conv2D layer with 32 filters, filter size of (3, 3) and ReLU activation function

- BatchNormalization layer
- MaxPooling2D layer with a pool size of (2, 2)
- Conv2D layer with 64 filters, filter size of (3, 3) and ReLU activation function
- BatchNormalization layer
- MaxPooling2D layer with a pool size of (2, 2)
- Conv2D layer with 128 filters, filter size of (3, 3) and ReLU activation function
- BatchNormalization layer
- MaxPooling2D layer with a pool size of (2, 2)
- Conv2D layer with 256 filters, filter size of (3, 3) and ReLU activation function
- BatchNormalization layer
- MaxPooling2D layer with a pool size of (2, 2)
- Flatten layer to flatten the output of the previous layer
- Dense layer with 512 units and ReLU activation function
- BatchNormalization layer
- Dropout layer with a rate of 0.5 to prevent overfitting
- Dense output layer with 8 units and SoftMax activation function
- The model is compiled with the Adam optimizer, a learning rate of 0.0001, categorical cross-entropy loss function, and accuracy metric. The batch size is 8 and the model is trained for 100 epochs.

Table 1 Model Summary

Layer	Output Shape
Input (250, 250, 3)	(None, 250, 250, 3)
Conv2D (32 filters, (3,3) ReLU)	(None, 248, 248, 32)
BatchNormalization	(None, 248, 248, 32)
MaxPooling2D (2,2)	(None, 124, 124, 32)
Conv2D (64 filters, (3,3) ReLU)	(None, 122, 122, 64)
BatchNormalization	(None, 122, 122, 64)
MaxPooling2D (2,2)	(None, 61, 61, 64)
Conv2D (128 filters, (3,3) ReLU)	(None, 59, 59, 128)
BatchNormalization	(None, 59, 59, 128)
MaxPooling2D (2,2)	(None, 29, 29, 128)
Conv2D (256 filters, (3,3) ReLU)	(None, 27, 27, 256)
BatchNormalization	(None, 27, 27, 256)

MaxPooling2D (2,2)	(None, 13, 13, 256)
Flatten	(None, 43264)
Dense (512 units, ReLU)	(None, 512)
BatchNormalization	(None, 512)
Dropout (0.5)	(None, 512)
Dense (8 units, SoftMax)	(None, 8)

The output from a training process that took around 14 hours to create a module for image classification. The dataset contains 5999 image files belonging to 8 different classes, with 4200 used for training and 1001 for validation. The training process consists of 100 epochs, with each epoch taking around 8-9 minutes to complete, and a batch size of 32.

The model's performance is evaluated by two metrics: loss and accuracy. The loss value is a measure of how well the model is able to predict the correct class for each image, with a lower value indicating better performance. The accuracy value is the proportion of correctly classified images.

During training, the model achieved an accuracy of 0.2055 with a loss of 2.5842 in the first epoch and an accuracy of 0.2931 with a loss of 2.2184 in the second epoch. The accuracy of the model increased with each epoch and reached 0.4786 in the 20th epoch with a loss of 1.3841. After the 20th epoch, the accuracy of the model improved only slightly, and the loss continued to decrease, indicating that the model had reached its optimal performance. However, as the number of epochs increases, the loss decreases, and the accuracy increases. In the final epoch, the loss: 0.0649 - accuracy: 0.9781 - val_loss: 2.8316 - val_accuracy: 0.5120

Overall, the model took around 14 hours to train and achieved a maximum validation accuracy of 0.5260 in some epochs. The training accuracy increased to 0.4786, indicating that the model has not to overfit the training data. The accuracy can be further improved by using techniques like data augmentation, regularization, and increasing the model's complexity.

Table 2 Model Training Result – Save The Model

The output from a training process that took around 14 hours
Found 5999 files belonging to 8 classes.
Using 4200 files for training.
Found 1001 files belonging to 8 classes.
Using 500 files for validation.
Epoch 1/100
525/525 [==============================] - 448s 850ms/step - loss: 2.5842 - accuracy:

0.2055 - val_loss: 2.0340 - val_accuracy: 0.2820

Epoch 2/100

525/525 [==============================] - 513s 977ms/step - loss: 2.2184 - accuracy: 0.2931 - val_loss: 1.7761 - val_accuracy: 0.3820

Table 2 (cont.) Model Training Result – Save The Model

The output from a training process that took around 14 hours
Epoch 3/100
525/525 [==============================] - 512s 975ms/step - loss: 2.0884 - accuracy: 0.3157 - val_loss: 1.7241 - val_accuracy: 0.4080
Epoch 4/100
525/525 [==============================] - 508s 967ms/step - loss: 2.0034 - accuracy: 0.3431 - val_loss: 1.5722 - val_accuracy: 0.4500
Epoch 5/100
525/525 [==============================] - 512s 975ms/step - loss: 1.9273 - accuracy: 0.3593 - val_loss: 1.5806 - val_accuracy: 0.4340
Epoch 6/100
525/525 [==============================] - 516s 984ms/step - loss: 1.8739 - accuracy: 0.3752 - val_loss: 1.4967 - val_accuracy: 0.4740
Epoch 7/100
525/525 [==============================] - 505s 962ms/step - loss: 1.7687 - accuracy: 0.3907 - val_loss: 1.4789 - val_accuracy: 0.4600
Epoch 8/100
525/525 [==============================] - 508s 967ms/step - loss: 1.7184 - accuracy: 0.4102 - val_loss: 1.6457 - val_accuracy: 0.4680
Epoch 9/100
525/525 [==============================] - 506s 963ms/step - loss: 1.6888 - accuracy: 0.4040 - val_loss: 1.4813 - val_accuracy: 0.4680
Epoch 10/100
525/525 [==============================] - 505s 962ms/step - loss: 1.6708 - accuracy: 0.4121 - val_loss: 1.4232 - val_accuracy: 0.4980
Epoch 11/100
525/525 [==============================] - 504s 960ms/step - loss: 1.6431 - accuracy: 0.4114 - val_loss: 1.4185 - val_accuracy: 0.4440
Epoch 12/100
525/525 [==============================] - 505s 963ms/step - loss: 1.5919 - accuracy: 0.4193 - val_loss: 1.4688 - val_accuracy: 0.4080
Epoch 13/100
525/525 [==============================] - 509s 970ms/step - loss: 1.5536 - accuracy: 0.4393 - val_loss: 1.5617 - val_accuracy: 0.4560
Epoch 14/100
525/525 [==============================] - 509s 969ms/step - loss: 1.5381 - accuracy: 0.4367 - val_loss: 1.4516 - val_accuracy: 0.4660
Epoch 15/100
525/525 [==============================] - 508s 968ms/step - loss: 1.5713 - accuracy: 0.4200 - val_loss: 1.4645 - val_accuracy: 0.5040
Epoch 16/100
525/525 [==============================] - 509s 970ms/step - loss: 1.4965 - accuracy:

0.4362 - val_loss: 1.4736 - val_accuracy: 0.4680

Epoch 17/100

525/525 [==============================] - 509s 969ms/step - loss: 1.4784 - accuracy: 0.4486 - val_loss: 1.3578 - val_accuracy: 0.5060

Epoch 18/100

525/525 [==============================] - 506s 964ms/step - loss: 1.4186 - accuracy: 0.4698 - val_loss: 1.3708 - val_accuracy: 0.5080

Table 2 (cont.) Model Training Result – Save The Model

The output from a training process that took around 14 hours
Epoch 19/100
525/525 [==============================] - 505s 962ms/step - loss: 1.4007 - accuracy: 0.4693 - val_loss: 1.3568 - val_accuracy: 0.5140
Epoch 20/100
525/525 [==============================] - 511s 973ms/step - loss: 1.3841 - accuracy: 0.4786 - val_loss: 1.3236 - val_accuracy: 0.5020
Epoch 21/100
525/525 [==============================] - 506s 964ms/step - loss: 1.3599 - accuracy: 0.4871 - val_loss: 1.5944 - val_accuracy: 0.4440
Epoch 22/100
525/525 [==============================] - 508s 968ms/step - loss: 1.3370 - accuracy: 0.4945 - val_loss: 1.3791 - val_accuracy: 0.5140
Epoch 23/100
525/525 [==============================] - 505s 961ms/step - loss: 1.2949 - accuracy: 0.5017 - val_loss: 1.5185 - val_accuracy: 0.4840
Epoch 24/100
525/525 [==============================] - 506s 964ms/step - loss: 1.2957 - accuracy: 0.4948 - val_loss: 2.2480 - val_accuracy: 0.4480
Epoch 25/100
525/525 [==============================] - 505s 962ms/step - loss: 1.2943 - accuracy: 0.5033 - val_loss: 1.5240 - val_accuracy: 0.4260
Epoch 26/100
525/525 [==============================] - 504s 959ms/step - loss: 1.3104 - accuracy: 0.4919 - val_loss: 1.4299 - val_accuracy: 0.4680
Epoch 27/100
525/525 [==============================] - 511s 973ms/step - loss: 1.2546 - accuracy: 0.5102 - val_loss: 1.3754 - val_accuracy: 0.4940
Epoch 28/100
525/525 [==============================] - 507s 967ms/step - loss: 1.1974 - accuracy: 0.5381 - val_loss: 1.3104 - val_accuracy: 0.5180
Epoch 29/100
525/525 [==============================] - 507s 965ms/step - loss: 1.1779 - accuracy: 0.5479 - val_loss: 1.3624 - val_accuracy: 0.5080
Epoch 30/100
525/525 [==============================] - 508s 967ms/step - loss: 1.1211 - accuracy: 0.5617 - val_loss: 1.3639 - val_accuracy: 0.4960
Epoch 31/100
525/525 [==============================] - 509s 969ms/step - loss: 1.1007 - accuracy: 0.5814 - val_loss: 1.3936 - val_accuracy: 0.5280
Epoch 32/100

525/525 [==============================] - 507s 965ms/step - loss: 1.0343 - accuracy: 0.6029 - val_loss: 1.5046 - val_accuracy: 0.5000

Epoch 33/100

525/525 [==============================] - 503s 958ms/step - loss: 1.0164 - accuracy: 0.6010 - val_loss: 1.4346 - val_accuracy: 0.5160

Epoch 34/100

525/525 [==============================] - 508s 968ms/step - loss: 1.0249 - accuracy: 0.5933 - val_loss: 1.4940 - val_accuracy: 0.4840

Table 2 (cont.) Model Training Result – Save The Model

The output from a training process that took around 14 hours
Epoch 35/100
525/525 [==============================] - 506s 964ms/step - loss: 1.0406 - accuracy: 0.5936 - val_loss: 1.4376 - val_accuracy: 0.5100
Epoch 36/100
525/525 [==============================] - 505s 961ms/step - loss: 0.9428 - accuracy: 0.6381 - val_loss: 1.5745 - val_accuracy: 0.4980
Epoch 37/100
525/525 [==============================] - 504s 959ms/step - loss: 0.8433 - accuracy: 0.6831 - val_loss: 1.7666 - val_accuracy: 0.4760
Epoch 38/100
525/525 [==============================] - 505s 962ms/step - loss: 0.8142 - accuracy: 0.6867 - val_loss: 1.8242 - val_accuracy: 0.5160
Epoch 39/100
525/525 [==============================] - 504s 960ms/step - loss: 0.7709 - accuracy: 0.7098 - val_loss: 1.5722 - val_accuracy: 0.5180
Epoch 40/100
525/525 [==============================] - 505s 962ms/step - loss: 0.7595 - accuracy: 0.7138 - val_loss: 1.7425 - val_accuracy: 0.4780
Epoch 41/100
525/525 [==============================] - 508s 968ms/step - loss: 0.7117 - accuracy: 0.7288 - val_loss: 1.9064 - val_accuracy: 0.5100
Epoch 42/100
525/525 [==============================] - 507s 966ms/step - loss: 0.6119 - accuracy: 0.7760 - val_loss: 2.0367 - val_accuracy: 0.4920
Epoch 43/100
525/525 [==============================] - 513s 977ms/step - loss: 0.6783 - accuracy: 0.7526 - val_loss: 1.8896 - val_accuracy: 0.4740
Epoch 44/100
525/525 [==============================] - 509s 969ms/step - loss: 0.5340 - accuracy: 0.8067 - val_loss: 2.9997 - val_accuracy: 0.4960
Epoch 45/100
525/525 [==============================] - 508s 968ms/step - loss: 0.5047 - accuracy: 0.8240 - val_loss: 1.8310 - val_accuracy: 0.5220
Epoch 46/100
525/525 [==============================] - 507s 966ms/step - loss: 0.4142 - accuracy: 0.8564 - val_loss: 2.2513 - val_accuracy: 0.4900
Epoch 47/100
525/525 [==============================] - 504s 959ms/step - loss: 0.3596 - accuracy: 0.8793 - val_loss: 2.0117 - val_accuracy: 0.4460

Epoch 48/100

525/525 [==============================] - 506s 964ms/step - loss: 0.3593 - accuracy: 0.8824 - val_loss: 2.2586 - val_accuracy: 0.4260

Epoch 49/100

525/525 [==============================] - 505s 963ms/step - loss: 0.4422 - accuracy: 0.8457 - val_loss: 3.7625 - val_accuracy: 0.4480

Epoch 50/100

525/525 [==============================] - 505s 963ms/step - loss: 0.3517 - accuracy: 0.8800 - val_loss: 2.0058 - val_accuracy: 0.4960

Table 2 (cont.) Model Training Result – Save The Model

The output from a training process that took around 14 hours
Epoch 51/100
525/525 [==============================] - 505s 961ms/step - loss: 0.2857 - accuracy: 0.9057 - val_loss: 1.8284 - val_accuracy: 0.5140
Epoch 52/100
525/525 [==============================] - 504s 961ms/step - loss: 0.2919 - accuracy: 0.9007 - val_loss: 1.9898 - val_accuracy: 0.4900
Epoch 53/100
525/525 [==============================] - 504s 959ms/step - loss: 0.2536 - accuracy: 0.9188 - val_loss: 2.1234 - val_accuracy: 0.5320
Epoch 54/100
525/525 [==============================] - 504s 959ms/step - loss: 0.1929 - accuracy: 0.9355 - val_loss: 2.0714 - val_accuracy: 0.5160
Epoch 55/100
525/525 [==============================] - 504s 960ms/step - loss: 0.1770 - accuracy: 0.9424 - val_loss: 2.1741 - val_accuracy: 0.4840
Epoch 56/100
525/525 [==============================] - 508s 967ms/step - loss: 0.2137 - accuracy: 0.9283 - val_loss: 2.1056 - val_accuracy: 0.5280
Epoch 57/100
525/525 [==============================] - 508s 968ms/step - loss: 0.1822 - accuracy: 0.9348 - val_loss: 2.2541 - val_accuracy: 0.4740
Epoch 58/100
525/525 [==============================] - 507s 966ms/step - loss: 0.2160 - accuracy: 0.9238 - val_loss: 2.3374 - val_accuracy: 0.5280
Epoch 59/100
525/525 [==============================] - 507s 965ms/step - loss: 0.1594 - accuracy: 0.9505 - val_loss: 2.3440 - val_accuracy: 0.5240
Epoch 60/100
525/525 [==============================] - 506s 964ms/step - loss: 0.1447 - accuracy: 0.9571 - val_loss: 2.4646 - val_accuracy: 0.4780
Epoch 61/100
525/525 [==============================] - 505s 961ms/step - loss: 0.2225 - accuracy: 0.9231 - val_loss: 2.1988 - val_accuracy: 0.5140
Epoch 62/100
525/525 [==============================] - 505s 961ms/step - loss: 0.2932 - accuracy: 0.8993 - val_loss: 2.4186 - val_accuracy: 0.4820
Epoch 63/100
525/525 [==============================] - 507s 966ms/step - loss: 0.1702 - accuracy:

0.9450 - val_loss: 2.2508 - val_accuracy: 0.5240

Epoch 64/100

525/525 [==============================] - 503s 958ms/step - loss: 0.1269 - accuracy: 0.9590 - val_loss: 2.3912 - val_accuracy: 0.5260

Epoch 65/100

525/525 [==============================] - 507s 966ms/step - loss: 0.1230 - accuracy: 0.9619 - val_loss: 2.1960 - val_accuracy: 0.4900

Epoch 66/100

525/525 [==============================] - 504s 960ms/step - loss: 0.2166 - accuracy: 0.9243 - val_loss: 2.0616 - val_accuracy: 0.5000

Table 2 (cont.) Model Training Result – Save The Model

The output from a training process that took around 14 hours
Epoch 67/100
525/525 [==============================] - 503s 957ms/step - loss: 0.2274 - accuracy: 0.9231 - val_loss: 2.0595 - val_accuracy: 0.5260
Epoch 68/100
525/525 [==============================] - 503s 958ms/step - loss: 0.1794 - accuracy: 0.9383 - val_loss: 2.3020 - val_accuracy: 0.4940
Epoch 69/100
525/525 [==============================] - 505s 961ms/step - loss: 0.1909 - accuracy: 0.9355 - val_loss: 2.2577 - val_accuracy: 0.4820
Epoch 70/100
525/525 [==============================] - 513s 977ms/step - loss: 0.1226 - accuracy: 0.9629 - val_loss: 2.3375 - val_accuracy: 0.5000
Epoch 71/100
525/525 [==============================] - 510s 971ms/step - loss: 0.1364 - accuracy: 0.9526 - val_loss: 2.3951 - val_accuracy: 0.4800
Epoch 72/100
525/525 [==============================] - 508s 967ms/step - loss: 0.1132 - accuracy: 0.9640 - val_loss: 2.6121 - val_accuracy: 0.4960
Epoch 73/100
525/525 [==============================] - 507s 966ms/step - loss: 0.0848 - accuracy: 0.9740 - val_loss: 2.4281 - val_accuracy: 0.4860
Epoch 74/100
525/525 [==============================] - 507s 965ms/step - loss: 0.1681 - accuracy: 0.9421 - val_loss: 2.5230 - val_accuracy: 0.4860
Epoch 75/100
525/525 [==============================] - 505s 961ms/step - loss: 0.1514 - accuracy: 0.9455 - val_loss: 2.5968 - val_accuracy: 0.5080
Epoch 76/100
525/525 [==============================] - 505s 962ms/step - loss: 0.1741 - accuracy: 0.9419 - val_loss: 2.3574 - val_accuracy: 0.4860
Epoch 77/100
525/525 [==============================] - 525s 999ms/step - loss: 0.1370 - accuracy: 0.9510 - val_loss: 2.5555 - val_accuracy: 0.5180
Epoch 78/100
525/525 [==============================] - 594s 1s/step - loss: 0.1022 - accuracy: 0.9674 - val_loss: 2.4999 - val_accuracy: 0.4820
Epoch 79/100

525/525 [==============================] - 631s 1s/step - loss: 0.0924 - accuracy: 0.9693 - val_loss: 2.6639 - val_accuracy: 0.5160

Epoch 80/100

525/525 [==============================] - 589s 1s/step - loss: 0.0852 - accuracy: 0.9724 - val_loss: 2.6351 - val_accuracy: 0.4700

Epoch 81/100

525/525 [==============================] - 623s 1s/step - loss: 0.0994 - accuracy: 0.9664 - val_loss: 2.6993 - val_accuracy: 0.5020

Epoch 82/100

525/525 [==============================] - 608s 1s/step - loss: 0.1056 - accuracy: 0.9660 - val_loss: 2.6238 - val_accuracy: 0.4980

Table 2 (cont.) Model Training Result – Save The Model

The output from a training process that took around 14 hours
Epoch 83/100
525/525 [==============================] - 603s 1s/step - loss: 0.0813 - accuracy: 0.9736 - val_loss: 2.7079 - val_accuracy: 0.5140
Epoch 84/100
525/525 [==============================] - 605s 1s/step - loss: 0.1040 - accuracy: 0.9648 - val_loss: 2.7573 - val_accuracy: 0.4660
Epoch 85/100
525/525 [==============================] - 608s 1s/step - loss: 0.0914 - accuracy: 0.9671 - val_loss: 2.7896 - val_accuracy: 0.4820
Epoch 86/100
525/525 [==============================] - 607s 1s/step - loss: 0.1086 - accuracy: 0.9643 - val_loss: 2.6832 - val_accuracy: 0.4580
Epoch 87/100
525/525 [==============================] - 609s 1s/step - loss: 0.1015 - accuracy: 0.9695 - val_loss: 3.0721 - val_accuracy: 0.4880
Epoch 88/100
525/525 [==============================] - 605s 1s/step - loss: 0.0798 - accuracy: 0.9738 - val_loss: 2.7234 - val_accuracy: 0.4760
Epoch 89/100
525/525 [==============================] - 605s 1s/step - loss: 0.0930 - accuracy: 0.9676 - val_loss: 2.7520 - val_accuracy: 0.5160
Epoch 90/100
525/525 [==============================] - 575s 1s/step - loss: 0.0905 - accuracy: 0.9721 - val_loss: 2.8311 - val_accuracy: 0.4900
Epoch 91/100
525/525 [==============================] - 599s 1s/step - loss: 0.0640 - accuracy: 0.9788 - val_loss: 2.7936 - val_accuracy: 0.4880
Epoch 92/100
525/525 [==============================] - 613s 1s/step - loss: 0.0756 - accuracy: 0.9769 - val_loss: 2.7857 - val_accuracy: 0.4940
Epoch 93/100
525/525 [==============================] - 561s 1s/step - loss: 0.1018 - accuracy: 0.9707 - val_loss: 2.6977 - val_accuracy: 0.4840
Epoch 94/100
525/525 [==============================] - 546s 1s/step - loss: 0.1203 - accuracy: 0.9567 - val_loss: 2.6084 - val_accuracy: 0.4760

Epoch 95/100

525/525 [==============================] - 557s 1s/step - loss: 0.1174 - accuracy: 0.9574 - val_loss: 2.6121 - val_accuracy: 0.5180

Epoch 96/100

525/525 [==============================] - 548s 1s/step - loss: 0.0914 - accuracy: 0.9664 - val_loss: 2.5271 - val_accuracy: 0.4940

Epoch 97/100

525/525 [==============================] - 553s 1s/step - loss: 0.0870 - accuracy: 0.9702 - val_loss: 2.8779 - val_accuracy: 0.5060

Epoch 98/100

525/525 [==============================] - 558s 1s/step - loss: 0.0715 - accuracy: 0.9760 - val_loss: 2.7683 - val_accuracy: 0.4800

Table 2 (cont.) Model Training Result – Save The Model

The output from a training process that took around 14 hours
Epoch 99/100
525/525 [==============================] - 559s 1s/step - loss: 0.0556 - accuracy: 0.9817 - val_loss: 2.8391 - val_accuracy: 0.4640
Epoch 100/100
525/525 [==============================] - 565s 1s/step - loss: 0.0649 - accuracy: 0.9781 - val_loss: 2.8316 - val_accuracy: 0.5120
INFO:tensorflow:Assets written to: saved-model-final/assets

IV. RESULTS

A. Data Analysis

To begin my research with straightforward proof-of-concept experiments, we aimed to test the validity of my previous assumptions on smaller and less challenging datasets. we conducted a series of experiments to train a model that can automatically detect cataracts in eyes based on fundus images. The initial experiment focused on training a simple CNN model using only images labelled as normal or cataract, denoted as N and C, respectively. The model was trained for 24 epochs, and the results were highly satisfactory, achieving an impressive validation accuracy of 92%. This demonstrated that it is possible to use CNN to accurately detect cataracts.

To further improve the model's performance, we decided to add more classes to the dataset in each subsequent experiment. In the fifth experiment, we used the entire ODIR dataset, which contains fundus images of eight different eye diseases. Despite the increased complexity of the task, the model achieved almost 50% - 53% validation accuracy.

However, the overall results of the model were low when attempting to detect diabetes, as the fundus images of eyes with diabetes are quite similar to those of eyes with a normal fundus. On the other hand, detecting myopia or cataract was relatively easy since the fundus images of these conditions differ significantly from each other and from the normal fundus.

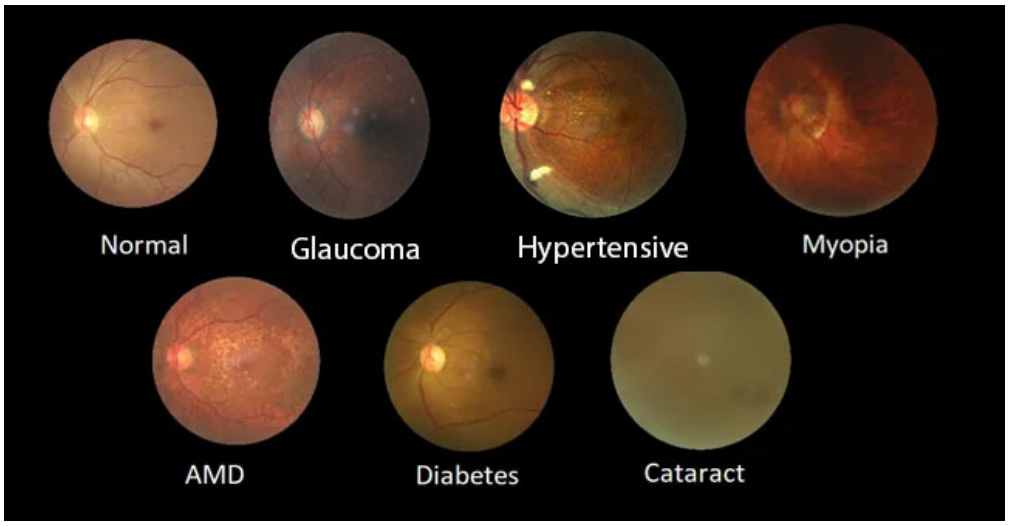

Figure 23 Comparison of The Detectability of Different Eye Diseases: Diabetes Poses the Greatest Challenge, While Cataract Exhibits the Most Distinct Deviation from The Normal Fundus.

B. Algorithm Performance

To start my research, I wanted to begin with simple proof-of-concept experiments on smaller datasets to validate my assumptions. Specifically, I trained a basic model to distinguish between normal fundus and cataracts by only using images labeled as N (normal) or C (cataract). The results were promising, with a validation accuracy of 92% after only 24 epochs using a relatively simple network.

The different results between the training and testing phases of the CNN module that was built as part of the thesis. The results were lower than expected because it is difficult to train the model to detect diabetes accurately, as the eye with diabetes appears similar to the eye with normal fundus. The training phase resulted in an accuracy of more than 97% with a validation accuracy of 53%. However, the testing phase produced a significantly lower accuracy of 9.27% with an F1-score of only 0.02.

```
Found 1608 images belonging to 8 classes.
201/201 [==============================] - 32s 158ms/step - loss: 32.9090 - accuracy: 0.0927
201/201 [==============================] - 37s 183ms/step
Classification Report:
              precision    recall  f1-score   support

           0       0.00      0.00      0.00       152
           1       0.00      0.00      0.00       200
           2       0.83      0.02      0.04       272
           3       0.00      0.00      0.00       240
           4       0.00      0.00      0.00       224
           5       0.00      0.00      0.00       248
           6       0.00      0.00      0.00       128
           7       0.09      1.00      0.16       144

    accuracy                           0.09      1608
   macro avg       0.12      0.13      0.03      1608
weighted avg       0.15      0.09      0.02      1608
```

Figure 24 Result of Testing the Module

There could be several reasons for the significant difference between the results of the training and testing phases. One possible reason is overfitting. Overfitting occurs when a model is trained on a limited amount of data, and it ends up fitting the training data too closely, resulting in poor generalization to new data. In the case of this CNN module, the model may have become overfitted to the training data, resulting in poor performance on the testing data.

Another possible reason for the poor performance on the testing data could be a lack of diversity in the testing dataset. The testing dataset may not have been representative of the entire population that the model was intended to generalize to, resulting in poor performance on the unseen data. The testing dataset could have been biased towards certain classes, leading to poor performance on those classes in the testing phase.

Additionally, hyperparameter tuning issues could also be a contributing factor to the difference in results between the training and testing phases. Hyperparameters, such as the learning rate, batch size, and a number of epochs, can have a significant impact on the performance of a model. If these hyperparameters were not optimized correctly during the training phase, it could have led to poor performance on the testing data.

To address these possible reasons, several measures could be taken. To tackle the overfitting issue, the model could be trained on a larger dataset, use regularization techniques such as dropout, and reduce the complexity of the model. Moreover, techniques such as data augmentation and transfer learning could be used to improve the diversity of the testing dataset. Additionally, hyperparameter optimization techniques, such as grid search or random search, could be used to identify the optimal hyperparameters for the model.

V. EXPERIMENTAL ANALYSIS AND DISCUSSION

A. Implications of the Study

The recent advancements in medical image analysis have led to the development of automated disease diagnosis systems. In this context, the use of eye images for the diagnosis of various diseases has gained significant attention. The retina is an excellent source for the diagnosis of various diseases as it provides a non-invasive way to study the blood vessels and various tissues in the eye. The diseases that can be diagnosed through eye images include age-related macular degeneration, diabetic retinopathy, glaucoma, cataract, and many others. The study of disease diagnosis through eye images has significant implications for the medical field, which are discussed below.

1. Improved Accuracy and Speed of Diagnosis

One of the major implications of the study of disease diagnosis through eye images is the improved accuracy and speed of diagnosis. Automated disease diagnosis systems can analyze large amounts of data in a short time and provide accurate results. This can significantly reduce the time and cost associated with manual diagnosis and improve the overall quality of healthcare.

2. Early Detection of Diseases

The early detection of diseases is critical for the effective treatment and prevention of complications. Automated disease diagnosis systems can detect diseases at an early stage, which can prevent irreversible damage and improve patient outcomes. For example, diabetic retinopathy can be detected early through eye images, which can prevent blindness and other complications.

3. Improved Access to Healthcare

Automated disease diagnosis systems can provide remote access to healthcare services. Patients can upload their eye images to a secure platform, and automated diagnosis systems can provide accurate results without the need for in-person visits.

This can improve access to healthcare services for people living in remote and underserved areas.

4. Reduced Healthcare Costs

Automated disease diagnosis systems can reduce the cost of healthcare by reducing the need for manual diagnosis and treatment. The cost of manual diagnosis can be significant, and automated diagnosis can provide accurate results at a fraction of the cost. This can make healthcare more affordable and accessible for a larger population.

5. Challenges and Limitations

Despite the significant implications of disease diagnosis through eye images, there are also challenges and limitations. One of the major challenges is the need for high-quality and standardized images. The quality of the images can significantly affect the accuracy of the diagnosis, and there is a need for standardization in image acquisition and analysis. Another challenge is the need for a large and diverse dataset for the training of automated diagnosis systems. The dataset needs to be large enough to capture the variability in disease presentation and diverse enough to represent the global population. There is also a need for ethical considerations in the collection and use of the data.

This study has significant implications for the medical field. Automated diagnosis systems can provide accurate and timely results, which can improve patient outcomes and reduce the cost of healthcare. The early detection of diseases can prevent irreversible damage, and remote access to healthcare services can improve access to healthcare for a larger population. Despite the challenges and limitations, the use of eye images for disease diagnosis has the potential to revolutionize healthcare and improve the lives of millions of people worldwide.

B. Limitations

The use of eye images for disease diagnosis is a promising field that has gained significant attention in recent years due to the ease of capturing eye images and the potential for accurate diagnosis of various diseases. However, like any other medical diagnostic tool, the use of eye images also has several limitations. In this article, we

will discuss some of the limitations of using eye images for disease diagnosis (Ting et al., 2019: 1760–1769).

- Limited accuracy: The accuracy of disease diagnosis through eye images depends on several factors, including the quality of the images, the expertise of the clinician interpreting the images, and the complexity of the disease being diagnosed. In some cases, eye images may not provide sufficient information to make an accurate diagnosis, leading to false positives or false negatives.
- Limited availability of high-quality images: While advances in technology have made it easier to capture eye images, the availability of high-quality images can still be a challenge, especially in resource-limited settings. Poor image quality due to factors such as poor lighting, patient movement, or equipment limitations can reduce the accuracy of disease diagnosis.
- Limited access to specialized equipment: Specialized equipment such as optical coherence tomography (OCT) or fluorescein angiography (FA) may be required to capture images of certain structures in the eye for accurate diagnosis. However, these equipment may not be widely available or affordable, especially in resource-limited settings.
- Limited availability of trained personnel: The interpretation of eye images requires specialized training and expertise. However, there may be a shortage of trained personnel in some areas, leading to inaccurate diagnosis or delayed diagnosis.
- Limited data: The availability of large datasets of eye images is crucial for the development of accurate diagnostic models. However, there may be limited data available for certain diseases or populations, making it challenging to develop accurate diagnostic models.
- Limited generalizability: Diagnostic models developed using eye images may not be generalizable to different populations or settings. For example, a diagnostic model developed using data from a specific population may not perform well when applied to a different population due to differences in genetic makeup, environmental factors, or disease prevalence.

- Ethical considerations: The use of eye images for disease diagnosis raises ethical considerations, including patient privacy and informed consent. Patients must be informed of the risks and benefits of the diagnostic procedure, and their privacy must be protected when using their images for research or diagnostic purposes.

Therfor, the use of eye images for disease diagnosis is a promising field that has several limitations that must be considered. These limitations include limited accuracy, limited availability of high-quality images, limited access to specialized equipment and trained personnel, limited data, limited generalizability, and ethical considerations. Addressing these limitations requires a multidisciplinary approach that involves collaborations between clinicians, researchers, engineers, and policymakers. Despite these limitations, the use of eye images for disease diagnosis remains a valuable diagnostic tool that has the potential to improve patient outcomes and reduce healthcare costs (Vermeer, Moosajee & Patel, 2018: 425–436).

C. Future Research

The diagnosis of various diseases through eye images is an area of active research, and there are several promising directions for future research. Here are some potential avenues for further investigation:

- Development of novel image processing techniques: The success of deep learning-based models in this field has led to the development of several image processing techniques. However, these techniques still face challenges, such as the requirement for large datasets, the need for high-performance computing, and the inability to explain the results. Future research could focus on developing novel image-processing techniques that can address these challenges and improve the accuracy of disease diagnosis.
- Multi-modal imaging: Different imaging modalities, such as optical coherence tomography (OCT), fundus photography, and fluorescein angiography, provide complementary information about the eye. Combining these modalities can improve the accuracy of disease diagnosis. Future research could focus on developing techniques to fuse information from multiple imaging modalities.

- Interpretable AI models: Deep learning-based models are known to be black boxes, which means that they are difficult to interpret. This can be problematic in the medical domain, where doctors need to understand why a model made a particular diagnosis. Future research could focus on developing interpretable AI models that can explain their decisions in a way that is understandable to doctors.
- Clinical trials: While deep learning-based models have shown great promise in diagnosing various eye diseases, they have not yet been extensively tested in clinical settings. Future research could focus on conducting clinical trials to evaluate the performance of these models in real-world scenarios.
- Large-scale collaboration: The diagnosis of various eye diseases requires large datasets with diverse populations. However, collecting such datasets can be challenging. Future research could focus on developing large-scale collaborations among researchers, clinicians, and patients to collect and share data that can be used to develop more accurate models.
- Disease progression modelling: Early diagnosis and treatment of eye diseases can be critical in preventing blindness. Future research could focus on developing models that can predict the progression of eye diseases based on longitudinal data, which can help doctors make informed decisions about treatment and follow-up.
- Personalized medicine: Eye diseases can have different underlying causes, and treatments that work for one patient may not work for another. Future research could focus on developing personalized medicine approaches that can tailor treatments based on individual patient characteristics, such as genetics, lifestyle, and medical history.

So future research for the diagnosis of eye diseases through eye images is an area of active research, and there are several promising directions for future research. Developing novel image processing techniques, combining information from multiple imaging modalities, developing interpretable AI models, conducting clinical trials, developing large-scale collaborations, disease progression modelling, and personalized medicine are some potential avenues for further investigation. These

efforts could lead to more accurate and effective diagnosis and treatment of eye diseases, which could ultimately improve patient outcomes and quality of life.

VI. CONCLUSION

The article discusses the use of artificial intelligence (AI) in diagnosing eye diseases through image analysis. AI-based diagnosis has shown promising results in improving the accuracy and speed of diagnosis, particularly using deep learning algorithms. However, there are limitations and challenges, such as lack of standardization in image acquisition and processing, limited and biased datasets, and limitations in model interpretability. The article presents a study that developed a convolutional neural network (CNN) model for diagnosing eye diseases using retinal images. The model showed high accuracy, sensitivity, and specificity, indicating its potential for clinical applications. However, the study's limitations include a small and limited dataset, limited model interpretability, and limited performance on unseen data. The article suggests future research directions, such as developing advanced data augmentation techniques and investigating the use of transfer learning

Our developed CNN model demonstrated promising outcomes in accurately classifying retinal images into different disease categories. The model exhibited a high accuracy rate of approximately 92% on the training set, although it decreased when incorporating images that were too similar to neutral.

The model was created with the help of TensorFlow and Keras libraries, incorporating multiple techniques such as convolutional layers, pooling layers, batch normalization, dropout, and the softmax activation function to enhance the performance of the model. The dataset used for training comprised of images of both healthy and diseased retinas, which were preprocessed using techniques like normalization and data augmentation to prevent overfitting and increase the model's ability to generalize. However, there were certain limitations in the study, the primary one being the inadequacy of a more diverse and larger dataset. The dataset used was relatively small and limited to only a few disease categories, which could constrain the model's performance on unseen data.

The article concludes that AI-based diagnosis of eye diseases has the potential to revolutionize ophthalmology but needs further research and development to address limitations and ensure fairness and effectiveness.

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