MACHINE LEARNING APPROACH TO DETECT & ANNOTATE EYE DISEASES USING RETINAL IMAGES

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Project Proposal Report

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DECLARATION

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(Ms. Devanshi Ganegoda)

ABSTRACT

This research proposal outlines a novel method for efficiently and accurately diagnosing and classifying age-related macular degeneration using a single optical coherence tomography image. Age-related macular degeneration, a common cause of vision loss and blindness in older adults worldwide, impacts millions. Current diagnostic techniques are expensive, time-consuming, and require multiple imaging tests, which inconveniences patients and delays treatment. Even though deep learning algorithms have shown promise in enhancing the speed and precision of AMD diagnosis, the current models are very costly and depend on numerous OCT images.

This study suggests a compact Deep Learning algorithm to resolve the problem, obviating the need for additional imaging studies and improving diagnostic effectiveness by precisely differentiating between wet and dry AMD from a single OCT image. The suggested technique aims to create a modal to diagnose OCT images for patients and doctors. Using a sizable dataset of OCT images, the study aims to assess the accuracy of this method and compare its efficacy to other recognized diagnostic techniques.

The clinical challenge of correctly diagnosing and managing age-related macular degeneration is significant, particularly when distinguishing between wet and dry AMD in the same patient's eye. The results of this study could improve AMD diagnosis and treatment, leading to better patient outcomes.

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LIST OF ABBREVIATIONS

Abbreviation	Description
AMD	Age-related macular degeneration
DR	Diabetic retinopathy
CNV	Choroidal neovascularization
OCT	Optical coherence tomography
DME	Diabetic macular edema
DL	Deep learning
CNN	Convolutional neural network

1. INTRODUCTION

Age-related macular degeneration and diabetic retinopathy are the most prevalent eye diseases worldwide. In Diabetic retinopathy, High blood sugar levels damage the blood vessels in the retina, resulting in vision loss or possibly blindness. It affects about one-third of all diabetics and is the leading cause of blindness in working-age adults. Age-related macular degeneration, on the other hand, is a gradual deterioration of the macula, the area of the retina's center responsible for fine detail. As the leading cause of blindness and permanent vision loss in older adults, this condition impacts millions of people worldwide.[1] Despite their part in this increase and dire risks, AMD and diabetic retinopathy may be challenging to diagnose and treat.

OCT scans, fundus photography, fluorescein angiography, and expert reviews are all standard imaging procedures used in modern diagnostic techniques for eye diseases. This procedure may increase the time and cost of disease care and delay treatment. To overcome these challenges, our research project will develop a novel method for identifying and categorizing AMD and diabetic retinopathy from OCT images and Fundus Imaging.[2] This report proposes a novel method for detecting and classifying age-related macular degeneration from OCT images.

The macula, a small, central area of the retina responsible for fine detail and delicate vision, is harmed by AMD, a chronic eye condition. Around 200 million people are typically affected by AMD, which is also the main reason for vision loss and blindness in older adults.[3]

There are two types of AMD: dry AMD and wet AMD. The most frequent condition, accounting for between 80 and 90% of all occurrences, is dry AMD.[4] It is identified by the buildup of small, yellowish deposits in the macula known as drusen, which can cause the macula to thin and deteriorate over time. Dry AMD grows slowly and typically results in only minor vision loss. However, dry AMD can progress to a more advanced form known as geographic atrophy, which can cause significant vision loss in some cases.

Wet AMD, on the other hand, is slightly more common but more severe. The development of abnormal blood vessels beneath the macula can identify it. These blood and fluid leaks can cause rapid and severe vision loss. Wet AMD can cause permanent vision loss within weeks or months if not treated immediately. Wet AMD's abnormal blood vessels are fragile and easily break, resulting in bleeding and scarring in the macula. This can result in permanent retinal damage and loss of vision. Wet AMD is frequently associated with choroidal neovascularization (CNV), a condition in which new blood vessels grow beneath the retina from the choroid layer and invade the macula [5].

Today only a few imaging procedures to diagnose AMD are OCT, fluorescein angiography, and indocyanine green angiography. OCT, a non-invasive imaging technology that uses light waves, creates high-resolution cross-sectional retina images.[2] OCT can detect and measure the retina's thickness and the presence of fluid or swelling in the macula, which are essential indicators of AMD. Unfortunately, OCT cannot independently differentiate between wet and dry AMD, so additional imaging studies are required for a proper diagnosis.

AMD must be accurately diagnosed, a complex and time-consuming process that frequently necessitates numerous visits to the ophthalmologist and various imaging tests. Patients, particularly those living in rural or remote areas with limited access to specialized medical facilities, may find this process costly, challenging, and distressing.

To overcome these challenges, researchers used DL algorithms to develop more effective and precise AMD detection techniques. DL is an AI branch that uses neural networks to sort and categorize massive amounts of data. DL algorithms have shown promising results in the field of ophthalmology, particularly in diagnosing and classifying various eye illnesses.

Nonetheless, most DL algorithms for AMD detection rely on multiple OCT images of a patient, which may pose a high cost and time constraint [3]. When diagnosing AMD, using a single OCT image can significantly reduce the cost and time required while improving the procedure's speed and precision.

This study proposes a novel method for identifying and categorizing wet and dry AMD based on a single patient's OCT image. Our approach employs a deep learning algorithm that can correctly identify the type of AMD from a single OCT image, eliminating the need for additional imaging studies and increasing the diagnostic procedure's efficacy. This research compares the effectiveness of our method to other established diagnostic techniques and assesses its accuracy using a large dataset of OCT images. Our research can improve AMD diagnosis and care, benefiting patients significantly.

1.1. Literature Survey

This section examines the methods currently used to diagnose and categorize AMD, focusing on applying DL algorithms. To accomplish this goal, a thorough search using pertinent keywords was done across numerous academic databases. This survey examines the most current methods for diagnosing and categorizing AMD, their advantages and disadvantages, and possible directions for further investigation. It does this through a systematic review of numerous research papers and articles published in the last four years. The chosen papers' methodology, dataset, performance metrics, and limitations were examined and grouped. In addition to highlighting the impressive advancements made by DL algorithms in diagnosing and classifying AMD, the survey also recognizes the difficulties and limitations of the current methods, particularly the use of multiple OCT images. This survey aims to provide insights into the current state of AMD diagnosis and classification, identify knowledge gaps, and suggest potential lines of future research by reviewing the body of existing literature on the subject.

To categorize OCT images for wet AMD, diabetic retinopathy (DR), epiretinal membranes (ERMs), and healthy eyes, Kuwayama et al. developed a CNN model. Image augmentation techniques were used during training to expand the training dataset and increase the model's generalizability [6].

The use of different CNN models, including LeNet, AlexNet, and Vgg16 architectures, for the OCT-based diagnosis of neovascularization, diabetic macular edema, drusen, and healthy retinal images was investigated by Sertkaya et al. in their study. The study found that both the Vgg16 and AlexNet architectures produced successful results and that the dropout layer structure in AlexNet significantly reduced loss. Additionally, the Vgg16 architecture achieved a classification accuracy rate of 93.01%, demonstrating successful results.[7]

Alqudah proposed an automated convolutional neural network (CNN) architecture for a multiclass classification system based on spectral-domain optical coherence tomography. AMD, CNV, DME, drusen, and normal cases were among the five types of retinal diseases that the study attempted to categorize. The researchers used a sizable dataset of 136,187 images to train and test their model to achieve this. They adjusted the CNN network structure and utilized the ADAM optimizing technique to achieve the best results. [8]

Govindaiah tested the classification of AMD using a modified sixteen-layer deep neural network. In the approach, he considered two classification schemes. The first set of classifications included No AMD, Early AMD, Intermediate AMD, and Advanced AMD. The second set of classifications included dry and wet AMD.[9]

J.H. Tan et al. proposed a fourteen-layer deep CNN with cost-effectiveness and portability for the detection of dry and wet AMD. To prevent overfitting and guarantee the accuracy of the results, blindfold and ten-fold cross-validation techniques were used to create the CNN.[10]

Arabi [4] suggested measuring the proportion of white pixels in the eye image to distinguish between dry and wet macular degeneration. However, using non-linear feature extraction from the images, Mookiah et al. [11] proposed a system for the automated detection of dry AMD.

Fundus images can be classified into normal, dry, and wet AMD classes using the Pyramid of Histogram of Oriented Gradients (PHOG) technique and non-linear features, according to a method by Acharya et al. Their approach was created to better the classification accuracy and efficiently capture the variations in the image features. [12]

Van Grinsven and colleagues developed a machine learning algorithm for identifying intermediate AMD, an early stage of AMD, by measuring drusen and classifying the disease as low-risk (no AMD or early AMD) or high-risk (AMD with advanced stages). [13]

The classification of AMD stages using OCT images is a relatively new field of study. The only research in this field used neural networks and support vector machines (SVM) to distinguish between dry and wet AMD from choroidal OCT images. [14]

Motozawa et al. compared deep-learning models without a segmentation algorithm for the binary classification problem of wet AMD and GA using transfer learning and a method of dividing an original image into three cropped images without reducing the image pixels. [15]

1.2. Research Gap

Even though AMD diagnosis and classification have been the subject of extensive research, the current diagnostic approaches are time-consuming, expensive, and frequently necessitate multiple visits to an ophthalmologist.[16] Although most current DL approaches rely on numerous OCT images of a patient, DL algorithms have shown assurance in increasing the speed and accuracy of AMD diagnosis.[3] Additionally, these DL models are considerably big and expensive computationally, which restricts their use in portable devices like smartphones and tablets.

Our proposed research aims to create a novel method for diagnosing and classifying wet and dry AMD from a single OCT image using a compact DL algorithm to overcome these limitations. We intend to enable the development of an online application that can be used to diagnose OCT images and assist physicians and patients by shrinking the size of the DL model. By reducing the need for multiple imaging tests and increasing diagnosis efficiency and accuracy, this strategy could ultimately lead to better patient outcomes.[2]

Previous research in this area has shown that it is difficult to distinguish between dry and wet AMD in the same patient's eye. It has been discovered that the algorithms created so far tend to concentrate primarily on the more prevalent disease state, causing the absence of the other state in some axes on OCT images. As a result, the lack of thorough and accurate disease diagnosis and management in these cases has been a significant clinical challenge.[1] To improve disease diagnosis and management, this research aims to create a cutting-edge algorithm that can precisely detect and classify dry and wet AMD in the same patient's eye with high precision and sensitivity.

Additionally, a substantial evaluation of our suggested method's accuracy and clinical applicability will be conducted using a sizable dataset of OCT images. The research gap we fill emphasizes our proposed study’s significance and potential influence on the diagnosis and treatment of AMD, particularly in underserved areas with limited access to specialized resources and skilled professionals. The accuracy and effectiveness of AMD diagnosis and classification could be significantly increased using our suggested method, ultimately improving patient outcomes, and lowering healthcare expenses.

Features	Our Solution	[1]	[2]	[3]
Development of a compact deep learning algorithm for diagnosing and classifying wet and dry AMD from a single OCT image	✓	✗	✗	✗
Identify and classify both Dry and Wet AMD concurrently if they are present in the same eye	✓	✗	✗	✗
Reduction of the DL model's size and complexity for use on portable devices	✓	✓	✓	✗
Robust evaluation of the accuracy and potential clinical implementation of the proposed approach on a large dataset of OCT images	✓	✓	✓	✓
Comparison of the proposed method's precision, effectiveness, and cost-effectiveness with current AMD diagnosis techniques	✓	✓	✗	✓
Develop for mobile base application	✓	✗	✓	✗

Table 1: Comparison of Former Research

1.3. Research Problem

One of the main factors contributing to vision loss and blindness in older adults is age-related macular degeneration. If untreated, the condition can have an irreversible negative impact on the macula, the central region of the retina.[17] The central region of the retina, or macula, degenerates due to the complicated disease AMD. The most prevalent form of AMD, known as dry AMD, advances slowly, whereas wet AMD, which is less common but advances more quickly, can cause severe vision loss if untreated. AMD must be identified and categorized early to be treated and managed effectively.[10]

A thorough eye exam that includes visual acuity testing, a dilated fundus examination, and imaging tests like optical coherence tomography (OCT) and fluorescein angiography are required for the most recent AMD diagnostic procedures. Although time-consuming, expensive, and requiring multiple visits to an ophthalmologist, these tests help diagnose and classify AMD. Patients in remote or underserved areas may find this particularly difficult because they have limited access to specialized equipment and qualified medical personnel. Also, multiple imaging tests can financially strain patients and healthcare systems.[5]

DL algorithms have been examined for AMD diagnosis and classification to overcome these limitations. A subset of artificial intelligence known as DL algorithms can learn by analyzing massive amounts of data without being explicitly programmed. These algorithms have demonstrated great promise for enhancing the efficacy and precision of AMD detection and classification.

Nevertheless, most currently used DL methods for diagnosing AMD rely on numerous patient OCT images. This can be time-consuming and expensive for patients who require repeated imaging tests. Additionally, these DL models' size and computational cost frequently preclude their use in portable devices like smartphones and tablets.

A compact and efficient DL-based approach is needed to accurately classify the type of AMD from a single OCT image on portable devices, which presents a significant research challenge. Developing such a strategy could significantly increase the speed and accuracy of the diagnosis process, decrease the need for multiple imaging tests, and ultimately improve patient outcomes.[2]

Our proposed study aims to develop a novel method for identifying and classifying wet and dry AMD from a single OCT image using a compact DL algorithm to address this research problem. To enhance the precision and effectiveness of our suggested strategy, we will investigate various DL architectures and methodologies. We intend to enable the development of an online application that can be used to diagnose OCT images and assist physicians and patients by decreasing the size of the DL model.[2]

We will use a sizable dataset of OCT images to assess our suggested approach's precision and clinical applicability. We will evaluate how well our proposed strategy performs compared to current DL-based and conventional AMD detection and classification approaches. We will also investigate the viability of applying our strategy to mobile devices like smartphones and tablets.

The proposed study has a sizable potential impact. Creating a quick and effective DL-based AMD diagnosis and classification method could completely change how the disease is identified and treated, especially in underserved areas. Our suggested method has the potential to significantly increase AMD diagnosis and classification efficiency and accuracy, which would ultimately result in better patient outcomes and reduced healthcare expenses.

As a result, the proposed research addresses a significant issue in AMD detection and categorization. Creating a compact and effective DL-based method for AMD detection and categorization from a single OCT image could significantly increase the speed and precision of the diagnosis procedure, lessen the requirement for various imaging tests, and eventually improve patient outcomes. Our proposed study could significantly affect AMD diagnosis and treatment, especially in economically challenged areas with limited access to specialized resources and qualified medical personnel.

2. OBJECTIVES

2.1. Main Objectives

The main goal of this proposed study is to create a novel method for differentiating between wet and dry AMD from a single OCT image and to diagnose both diseases simultaneously if the patient is undergoing both dry and wet AMD conditions in the same eye. We intend to accelerate the diagnosis process, reduce the need for various imaging tests, and ultimately enhance patient outcomes by creating a quick and accurate DL-based AMD diagnosis and classification method.

The following sub-objectives have been established to fulfill this main goal:

- The classification of AMD from a single optical coherence tomography (OCT) image should be made possible by a deep learning (DL) algorithm. This algorithm needs to be efficient and portable to be used on gadgets like smartphones and tablets.

- To create a web application that uses the DL algorithm to classify AMD and diagnose OCT images for doctors and patients. With the help of this application, healthcare efficiency should increase, and the size of the DL model needed for precise diagnoses should be reduced.

- Assessment allows organizations to develop precision of the suggested DL approach by utilizing a sizable OCT image. The objective is to give users confidence in the efficiency and dependability of the algorithm.

- To identify and categorize AMD using our proposed DL-based method and currently used DL and conventional-based approaches. The comparison will show which way is the most effective.

- To examine the viability of implementing our DL strategy on portable devices like smartphones and tablets to make AMD diagnoses accessible outside of a clinical setting. The objective is to improve accessibility and convenience for both patients and doctors.

- To create a predictive model recommending the following actions after each therapy session. Based on the patient's progress during therapy sessions, this model should enable medical professionals, trained caregivers, and family caregivers to track and monitor patient progress efficiently.

2.2. Sub Objectives

In addition to the main objectives, several specific objectives are related to implementing OCT image analysis. The following are the specific objectives:

- **Raw OCT image data conversion**: The first goal is to transform raw OCT image data into a standard digital image template that can be applied to subsequent processing and analysis. Preprocessing procedures used in this conversion process include converting the OCT image from its native color space to a standardized color space, such as RGB or grayscale, and removing image artifacts brought on by the imaging process or instrument.

- **Standardization of image size**: The sizes of the OCT images produced by various tools or operators may vary. To make it easier to compare and analyze data from multiple images, the next goal is to resize the OCT images to a standard size while maintaining key features and structures in the image.

- **Noise reduction**: Signal interference or image noise can skew or obfuscate critical details in the OCT images, which can cause distortion. The next goal is to use noise reduction techniques to remove undesirable noise and enhance the image quality.

- **Image segmentation**: The next goal is to divide the OCT image to isolate regions of interest, like the retinal layer or the optic nerve. The image segmentation algorithms can clearly distinguish the lesion area and the surrounding healthy skin, which can differentiate between various tissue types based on visual characteristics.

- **Feature detection and quantification**: The next goal is to spot and measure characteristics or abnormalities in the OCT image, like variations in the thickness or morphology of retinal layers. Techniques for automated or semi-automated image analysis can be used to complete this task.

- **Validation of analytical methods**: The goal is to use the proper quality control procedures to validate the precision and dependability of the image processing and analysis methods. The effectiveness of the methods can be evaluated using cross-validation using ground truth data or sub-variability analysis.

3. METHODOLOGY

Data gathering, preprocessing, model development, model evaluation, ethical considerations, and statistical analysis will be the main parts of the research project. Several sources, including open-access databases and exclusive ophthalmology practices, will be used to gather a sizable dataset of OCT images. The dataset will contain wet and dry AMD cases along with healthy controls. To ensure accuracy, the labels will be applied to the images following the categories they belong to.

• **Data Collection**: We will collect a large dataset of OCT images from various sources, such as public datasets and private ophthalmology clinics. Cases of wet and dry AMD, in addition to healthy controls, will make up the dataset. Expert ophthalmologists will classify the images correctly. We will anonymize the data we collect to protect our patient's privacy.

• **Data Preprocessing**: The collected OCT images will be preprocessed to improve their quality and lower noise. Standardization, normalization, and cropping will be required to extract the macular region, the main object of interest. The preprocessing stage enhances the deep learning model's performance and accuracy.

• **Model Development**: A DL model will be produced from a single OCT image to differentiate between wet and dry AMD. To learn and extract useful features from the OCT images, the model will be trained using a combination of convolutional neural networks (CNNs) and recurrent neural networks (RNNs). The proposed model's architecture will be optimized using various hyperparameter tuning techniques to achieve maximum performance. It will be contrasted with other recognized diagnostic methods to assess the efficacy and accuracy of the developed model.

• **Model Evaluation**: The performance and accuracy of the proposed model will be evaluated using a variety of metrics, including sensitivity, specificity, precision, and F1 score. A separate test dataset will determine the model's generalizability and compare its performance with other tried-and-true diagnostic methods. The model's evaluation will help decide whether it is accurate and efficient at identifying and classifying wet and dry AMD early on.

• **Ethical Considerations**: Patient confidentiality, informed consent, and data protection are just a few of the ethical principles and guidelines the study will follow. Before analysis, all data will be de-identified to protect patient privacy. All participants will provide informed consent before participating in the study, and the research team will ensure that the study does not harm the patients.

• **Statistical Analysis**: Statistical analysis will be carried out to identify significant variations between the performance of the proposed approach and that of other well-known diagnostic procedures. To do this, it will be necessary to assess the significance of the results using the proper statistical tests, such as t-tests or ANOVA. The statistical analysis will confirm the proposed deep learning model's accuracy and efficacy.

• **Limitations**: The proposed method has some drawbacks that will be discussed, along with possible workarounds or future research directions. Data subjectivity, raw data size, and computational resources are just limitations. The research team will discuss potential ways to overcome these constraints and decide on new research directions.

3.1. The System Overview Diagram

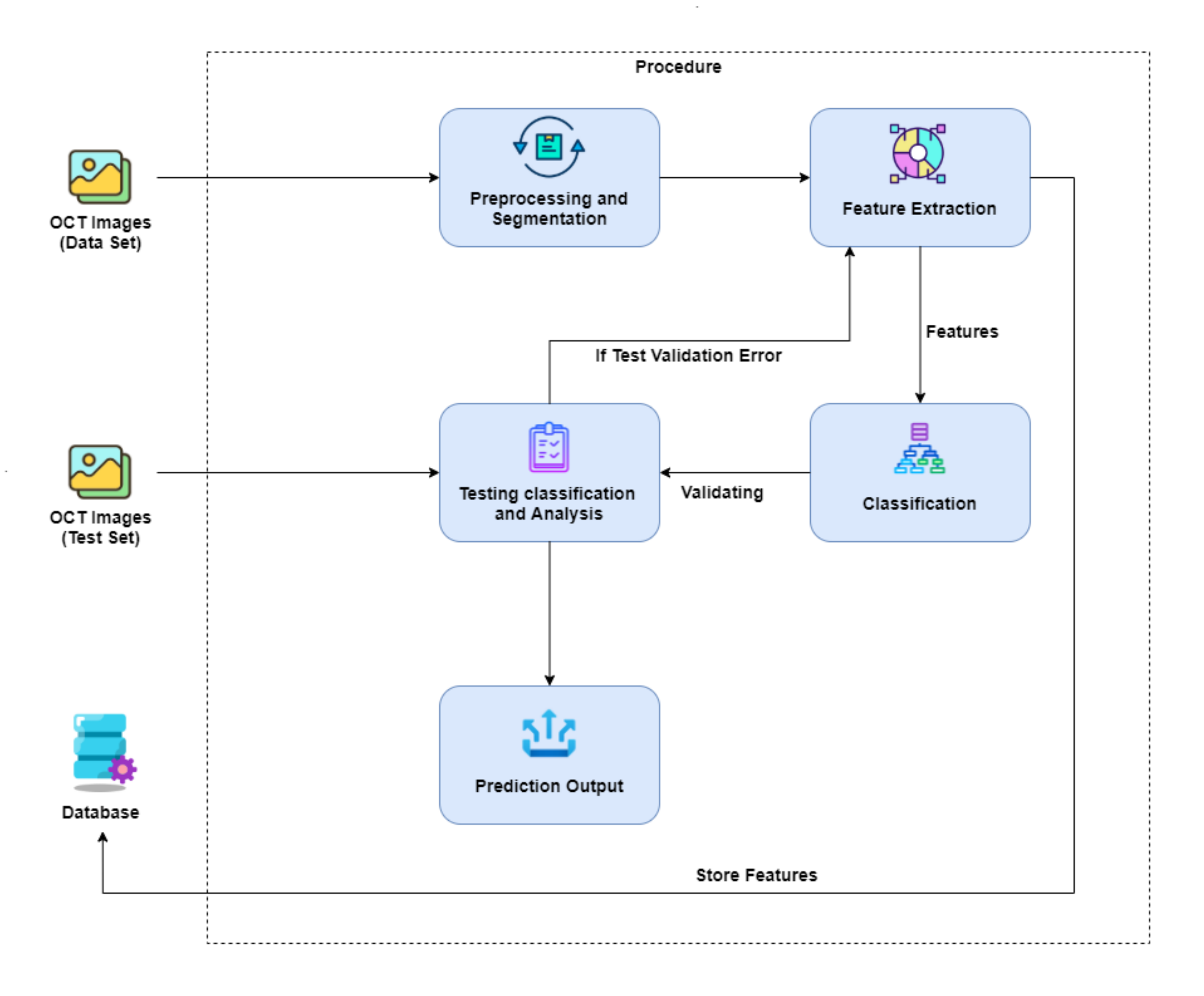

Figure 1: System Overview Diagram

The system overview diagram outlines the various steps involved in the process, the first of which is inputting OCT images into the mobile application, as shown in the system overview diagram. The images are typically obtained using optical coherence tomography (OCT), a non-invasive imaging technique that yields merged retina images. The mobile application then uploads the OCT images for analysis.

After receiving them, the system preprocesses and segments the OCT images to ensure they are ready for feature extraction. This step is crucial because it cleans the images of any objects or unwanted noise and improves the contrast in the macular area, which is the analysis's focus. Additionally, it requires figuring out the different layers of the retina in the OCT images, which is necessary for accurate feature extraction.

Advanced algorithms are used to extract key features, such as the surface area of the retina and the presence of fluid or swelling in the macula, after preprocessing and segmentation. These characteristics are obtained from the various retina layers and entered into a database for classification.

Deep learning algorithms are used in the classification process to distinguish between different AMD types based on the extracted features. Because wet and dry AMD have other treatment options and prognoses, the classification step is crucial in diagnosing AMD. To ensure the system can correctly identify the type of AMD from the extracted features, it has been trained on a sizable dataset of OCT images.

Using a test dataset of OCT images, the classification outcomes are tested in the following step of the procedure. This testing process guarantees the precision and dependability of the system's forecasts. The system is retrained with new data to enhance performance when discrepancies are discovered.

The system's last step is to produce a prediction output that, using the input OCT image, diagnoses the type of AMD. It is presented in a user-friendly interface, making it simple for medical professionals to access and interpret the output. The prediction output of the system can help medical professionals diagnose patients more accurately and quickly, potentially leading to better patient outcomes.

3.1.1 Software Solution

- **Requirement Gathering and Analysis**

The requirement gathering and analysis process aims to identify the essential requirements. The methodology will adhere to the Agile Software Development Lifecycle and require gathering system, user, and non-functional requirements from various sources.

The following resources are being utilized to gather the requirements:

- Publications on Reviewed Research: The most efficient methods, algorithms, and tools for diagnosing and classifying AMD will be identified after reviewing published research studies. The best possible solution for the suggested research will be created using the information provided.

- Reviewed Journal Publications: Comparable to research publications, ophthalmology journals will be examined to gather data on the criteria for diagnosing the disease and classifying AMD.

- Ministry of Health Guidelines: To gather crucial information on the protocols, procedures, and laws that must be followed while developing the software solution, the Ministry of Health's guidelines related to the diagnosis and treatment of AMD will be examined.

- World Health Organization (WHO) Specific suggestions: The WHO recommendations for AMD diagnosis and treatment will be reviewed to gather requirements on the most current standards and best practices for AMD diagnosis and classification.

The steps below make up the requirement gathering and analysis process:

- Identification of Stakeholders: To gather their criteria and feedback on the suggested solution, the interested parties ophthalmologists, medical professionals, researchers, and patients—will be identified.

- Collection of Requirements: The identified resources will be used to gather the requirements, including system, user, and functional requirements.

- Analysis of the Requirements: The collected requirements will be examined for gaps, contradictions, or conflicts. The study will assist in prioritizing the needs and ensuring that they satisfy the project's goals.

- Requirements Validation: The stakeholders will examine the validated requirements to ensure they meet their expectations and address their issues.

- Requirements Management: To ensure the requirements are satisfied within the estimated spending limit and timeline, the conditions will be managed throughout the project's lifecycle.

- **Feasibility Study**

  - **Schedule Feasibility**: The software solution's development must be finalized within the research project's suggested time frame. The project should be divided into minor, manageable phases with clear goals, due dates, and anticipated results. Each stage should be planned to result in the delivery of a functional prototype or software solution component. The schedule's viability should be assessed regularly to ensure the project stays on track and within the allocated timeframe.
  - **Technical Feasibility**: It is possible to implement the suggested software solution. The software should be created with suitable programming languages and software development methodologies. Large datasets of OCT images should be acceptable for the software, and it should be able to correctly identify and classify the various types of AMD. The technical viability of the software should be assessed through several experiments, simulations, and testing.
  - **Economic Feasibility**: The suggested software solution must be financially viable when considering development, testing, and maintenance costs. A cost-benefit analysis can be used to gauge the software solution's economic viability. This analysis should compare the costs of creating and maintaining the software solution to any potential benefits of the software, such as improved accuracy and quicker diagnostics.

  - **Legal and Ethical Feasibility**: The suggested software solution must be feasible in law and ethics. The software should adhere to moral and legal obligations, including patient confidentiality and privacy. The software solution must also abide by the guidelines established by regulatory bodies like the US Food and Drug Administration (FDA).

- **Design and Implementation**

Using the deep learning algorithm, the suggested program will use various technologies and libraries to accurately identify and categorize wet and dry AMD from a single OCT image. While deep learning algorithms executed in the Keras library will be used to train and deploy a predictive model that powers the core functionality of the component, React Native will be used to build the user interface for mobile applications. TensorFlow will create and deploy the deep learning model, while OpenCV will be used for computer vision tasks like image processing and feature extraction. With the help of AWS Server for scalability and high availability, MongoDB Realm will be used as the backend to store user data and enable real-time synchronization among various devices.

During the design phase, a sizable dataset of OCT images will be gathered, preprocessed to reduce noise, and improve contrast and brightness, and labeled according to whether wet or dry AMD is present. The CNN model will create the DL architecture with several layers, including fully connected, pooling, and convolutional layers. Several experiments will be conducted to optimize the hyperparameters to achieve the best performance.

After creating the architecture, the preprocessed and labeled dataset will be used to train the model. The Adam optimization algorithm with a cross-entropy loss function will be used during the training process to feed the images into the network and update the network weights to minimize the classification error. The model's performance will be assessed using a different validation dataset, with evaluation metrics such as accuracy, precision, recall, and F1-score.

The deep learning algorithm will then be integrated into software that can classify AMD as wet or dry based on a single OCT image. Ophthalmologists and other healthcare professionals can easily use the software because of its user-friendly interface.

- **Testing**

Testing is an essential step in the software development process, particularly when creating software for medical diagnosis. This study will use a thorough testing strategy to ensure the software correctly distinguishes between dry and wet AMD from a single OCT image.

The following steps will be part of our testing strategy:

- **Unit testing**: We will start with unit testing to check the functionality of distinct software components. This will entail testing each software module and function separately to detect problems before integration.
- **Integration Testing**: We will conduct integration tests after unit testing to ensure the software components function correctly. This will involve testing their interaction to ensure the modules and components interact intuitively.
- **User Acceptance Testing (UAT)**: In the final testing phase, we will conduct UAT to ensure the software satisfies end users' needs. To do this, the software will be tested on real users to see if it meets their needs, is user-friendly, and produces accurate results.

We will test the software's precision and performance using a sizable dataset of OCT images as part of our testing procedure. Furthermore, we will contrast our software's outcomes with ophthalmologists' and other widely used diagnostic methods. We will conduct additional testing to ensure the software functions appropriately if any bugs or flaws are found during testing.

- **Product Release**

We intend to make our AMD detection and classification software application available to the public through several channels after it has been developed and thoroughly tested. To make the software available to a larger audience, we will also make the application available through well-known app stores like the Google Play Store and the Apple App Store to reach a wider audience.

Users must read and accept our privacy policy, which describes how their personal information will be utilized and protected before installing and using the software. We take the privacy of our users very seriously, and our policy is set up to guarantee that their information is kept private and secure.

After accepting our privacy policy, users can sign up for the software using a legitimate email address and username. By doing so, they will have access to all the software's features and functionality, including the option to upload and examine their OCT images for AMD detection and classification.

We will offer proper assessment, user guides, and technical support via email and other communication channels to ensure users can use the software efficiently and benefit from its features.

We provide the most usable and accessible software solution possible. We will keep working to enhance its features and functionality in response to user input and ongoing research. Our software application can significantly assist patients and healthcare professionals in diagnosing and treating AMD more effectively.

4. REQUIREMENTS

4.1. Functional Requirements

- The system must distinguish between wet and dry AMD from a single OCT image.
- The system must provide precise and trustworthy results once diagnosing AMD.
- The system's accuracy and dependability must be improved by its ability to handle a sizable dataset of OCT images.
- To enable effective AMD diagnosis and treatment, the system should be able to integrate with current healthcare systems.
- The software ought to be able to produce a report that compiles the findings of the AMD analysis.

4.2. Nonfunctional Requirements

- The system must be highly secure to guarantee the privacy and security of patient data.
- To enable effective AMD diagnosis and treatment, the system must be always dependable and accessible.
- To reduce user errors, the system should be simple to use and have an intuitive interface.
- The system must be highly scalable to handle an expanding patient and data load.

4.3. User Requirements

- The system must be user-friendly and straightforward for healthcare professionals to use, and it must quickly and accurately diagnose AMD to enable early treatment and management.
- The system must be economical and accessible for all patients, especially those who live in rural or remote areas.

- The system must deliver results in real-time so that AMD can be diagnosed and treated immediately.
- The system should work with various devices like tablets and mobile phones.

4.4. System Requirements

- To ensure an accurate and dependable diagnosis of AMD, the system should be built on deep learning algorithms.
- To accurately diagnose AMD, the system must be able to handle various OCT image types.
- The system must be capable of managing multiple user requests at once.
- The system must be capable of securely storing and managing patient data.
- For real-time results, the system needs to process data quickly.

5. GANTT CHART

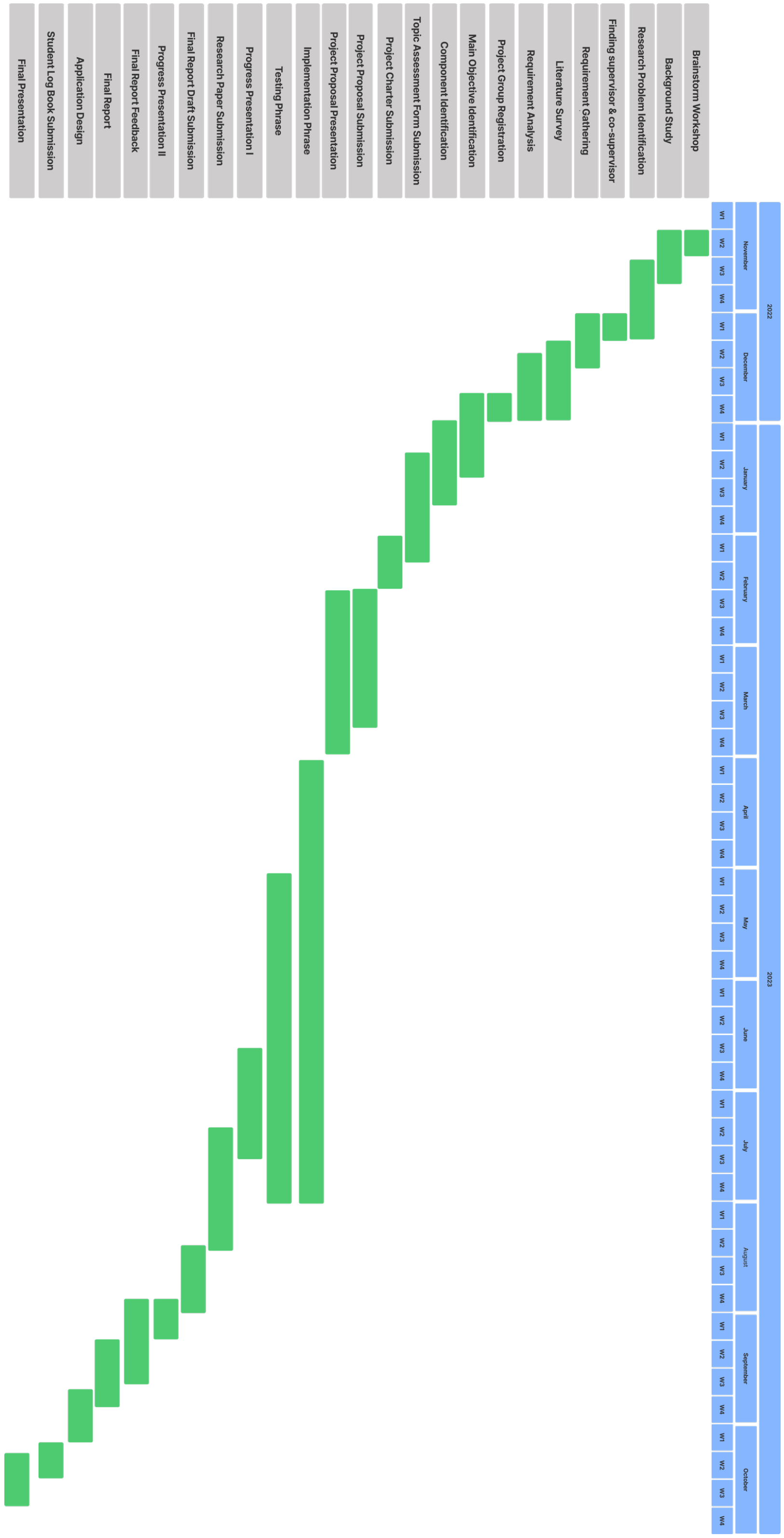

Figure 2: Gantt Chart

6. WORK BREAKDOWN STRUCTURE

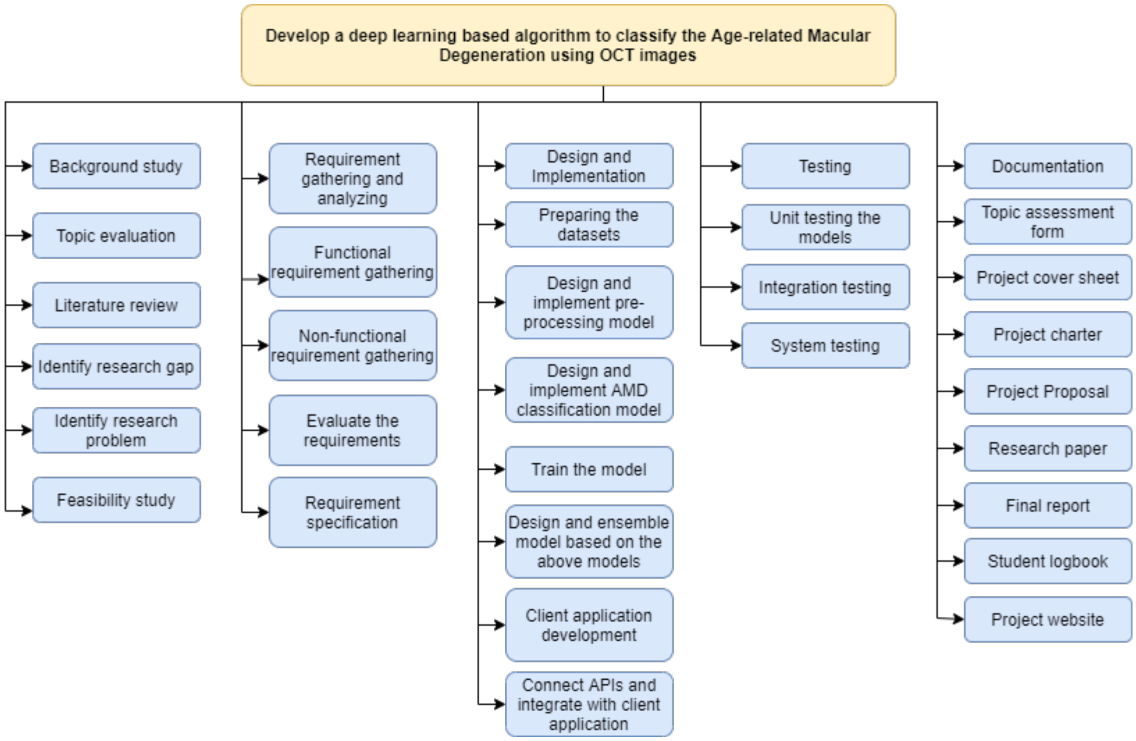

Figure 3: Work Breakdown Structure

7. BUDGET AND BUDGET JUSTIFICATION

The budget allocation for various resource types according to the requirements of the research is listed below.

Task	Cost (Rs.)
Hosting	7000
Backups	5000
Testing	2000
Marketing	5000
Other	2000
Total Cost	**21000**

Table 2 : Budget for the proposed system

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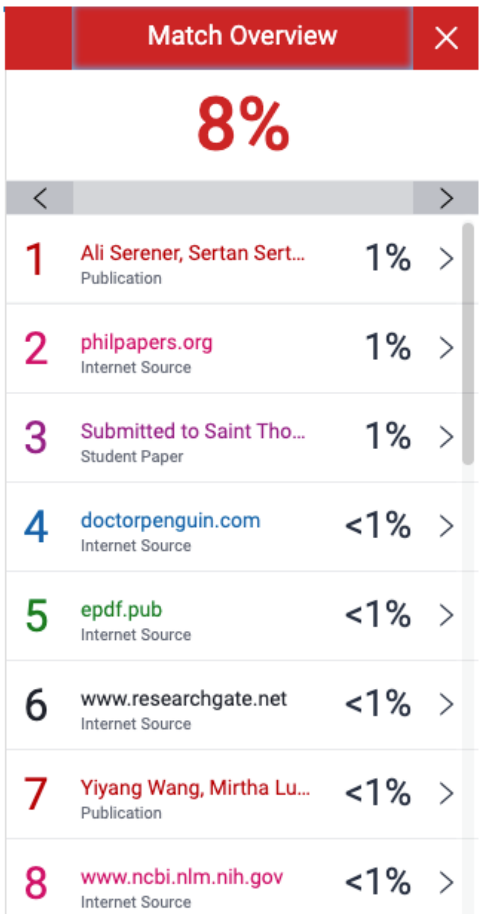
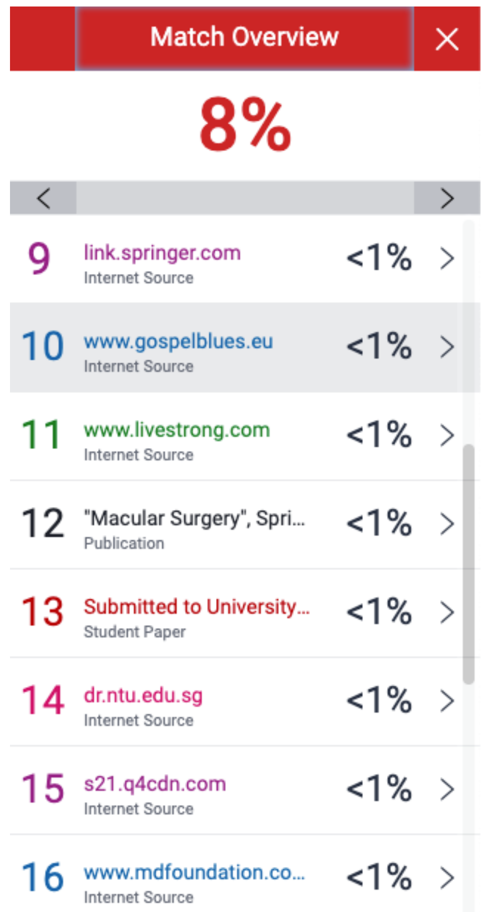
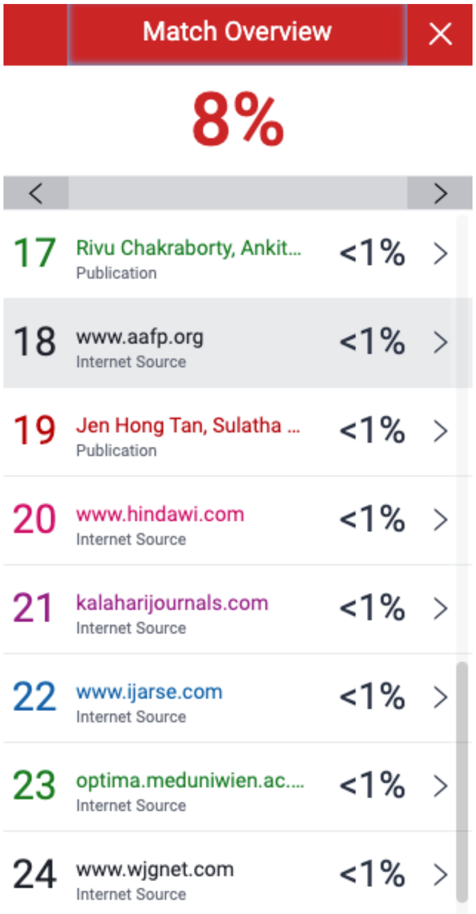
APPENDICES

Appendix A: Plagiarism Report



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