

**COMSATS University Islamabad,**

**Abbottabad Campus**

***Automated Retinopathy Diagnosis and result interpretation using Explainable AI (XAI)***

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***Bachelor of Science in Computer Science (2020-2024)***

**The candidate confirms that the work submitted is their own and appropriate  
 credit has been given where reference has been made to the work of others**.

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**COMSATS University, Islamabad,**

**Abbottabad Campus**

***Automated Retinopathy Diagnosis and result interpretation using Explainable AI (XAI)***

**A project presented to**

**COMSATS Institute of Information Technology, Islamabad, Abbottabad**

**In partial fulfillment**

**of the requirement for the degree of**

***Bachelor of Science in Computer Science (2020-2024)***

***By***

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Talal Khan Muhammad Taha Malik

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Abdul Mohiz Khan Tareen

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**CERTIFICATE OF APPROVAL**

It is to certify that the final year project of BS (CS) “Automated Retinopathy Diagnosis and result interpretation using Explainable AI (XAI)” was developed by   
**Muhammad Taha Malik (CIIT/FA20-BCS-015/ATD)** , **Abdul Mohiz Khan Tareen (CIIT/FA20-BCS-001/ATD)** and **Talal Khan (CIIT/FA20-BCS-029/ATD)** under the supervision of **Dr. Sardar Khaliq Uz Zaman** and that in his opinion; it is fully adequate, in scope and quality for the degree of Bachelors of Science in Computer Sciences.

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**Supervisor**

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**External Examiner**

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**Head of Department**

**(Department of Computer Science)**

**EXECUTIVE SUMMARY**

This project's goal is the development of an innovative machine learning-based system aimed at automating the detection of retinopathy from retinal images, while at the same time enhancing interpretability through Explainable AI (XAI) techniques. Retinopathy, a severe ocular condition associated with hypertensive and diabetic patients, requires early detection for timely intervention and prevention of irreversible vision impairment. Our primary objective is to train a robust and accurate machine learning model which can process retinal images, classifying different stages of retinopathy, and aid healthcare professionals in making informed decisions. Key tasks include diverse dataset collection, model and training, comprehensive model evaluation, and user-friendly interface development. Furthermore, we intend to integrate XAI techniques such as trainable attention, CAM, Guided Grad-CAM, Grad-CAM++, and multiple Instance Learning to provide good understanding into the model's decision-making process. This project represents a critical step toward improving the early diagnosis of retinopathy and ensuring transparent and interpretable AI-driven healthcare solutions.

**ACKNOWLEDGEMENT**

All praise is to Almighty Allah who bestowed upon us a minute portion of His boundless knowledge by virtue of which we were able to accomplish this challenging task.

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Talal Khan Muhammad Taha Malik

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**ABBREVIATIONS**

|  |  |
| --- | --- |
| SRS | Software Require Specification |
| PC | Personal Computer |
| DFD | Data Flow Diagram |
| SDD | Software Design Description |

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# Introduction

Retinopathy is a condition that causes vision impairment.   Diabetic retinopathy can cause the blood vessels in the retina to swell and rapture or cause new abnormal blood vessel growth on the surface of retina. Hypertensive retinopathy can narrow the blood vessels in the retina due to high blood pressure.

Hence therefore resulting in total blindness. Anyone with high blood pressure or who has diabetes is susceptible to the condition of retinopathy. This disease can potentially infect the body's neurological system, with very fatal results.  However, this illness can be cured with the right treatment and early diagnosis. Previously, ophthalmologists had to spend a lot of time manually diagnosing and classifying the severity of this condition, but with the help of our project, we can automate the process. Our project will incorporate machine learning model for detecting the severity of retinopathy and explainable AI, which will make it easier for us to comprehend how our model arrived at this decision. Our project will produce results quickly and accurately, saving time. The field of medicine will benefit greatly from this research.

## Brief

The An automated retinopathy diagnostic system based on XAI is being developed within this

project. The main goal of our project is to create a machine learning model that can

correctly detect and differentiate retinopathy from retinal images. We executed our model

development in Python programming language using efficient net architecture and TensorFlow library. From a methodological standpoint, use case analysis was utilized to pinpoint the functionalities and requirements of the system to approach it from a user’s point of view. Furthermore, it reports on early detection for retinopathy and how our system can enhance health outcomes. Moreover, it looks into making AI transparent by integrating XAI techniques that will be used to interpret models meant for medical diagnoses. Our project targets at coming up with an advanced AI technology solution for diagnosing retinopathy that is reliable, exposed and easy-to-use.

## Relevance to Course Module

The present project we have done on the Explainable AI (XAI) techniques for automated retinopathy diagnosis is closely related to some courses we took during our Bachelor of Computer Science (BCS) programme.

***Machine Learning:*** The core algorithm for retinopathy detection that we developed was based on the concepts learned in machine learning courses. These involve knowing different types of models, approaches to train them, and evaluation techniques.

***Artificial Intelligence:*** Artificial intelligence has been employed in our project based mainly on overfitting, underfitting as well as regularization. Through our understanding of AI, we managed to improve the ability of the model to generalize its decision-making processes

***Database Systems:*** A system that stores and retrieves user’s data. Our knowledge in database systems helped us design an effective data storage and retrieval mechanism including data integrity and security.

***Software Engineering:*** Principles from software engineering were followed throughout the development life cycle of our project. These involved requirements gathering, system design, implementation, testing, deployment stages in order to ensure a robust and maintainable software system is created.

## Project Background

The project involves the application of Explainable AI (XAI) in automated retinopathy diagnosis. Retinopathy is a retinal disorder that is usually caused by diabetes and hypertension. It can lead to loss of sight if it is not diagnosed and treated in its early stages.

Our idea concerns the creation of an automatic system that will analyse retinal images for indications or lack thereof, as to whether they show presence any other form of retinopathy development at all or its severity. The aim of this practical application is to enable medical professionals in timely finding about patient’s health complications.

The system incorporates Explainable AI (XAI) techniques that make possible transparency and understanding of how the AI model arrives at certain conclusions. This means that physicians can know what makes the essence of those findings and trust them.

In general, our research work involves the use of machine learning, and artificial intelligence (AI) technologies to automate retinopathy diagnosis which would otherwise result in life-long vision impairment.

## Literature Review

This review covers literature on automated retinopathy diagnosis using Explainable AI (XAI), and interpretation which includes among others issues related to optical coherence tomography image analysis, deep learning-based detection models for diabetic eye diseases, automatic screening for DR with deep learning algorithms. Let me illustrate some key points mentioned:

**Retinal Imaging Technologies:** Retinal Imaging Technologies: This review discusses the current state of retinal imaging techniques like fundus photography and optical coherence tomography (OCT) and how useful they are in getting detailed pictures of the retina which can aid in diagnosing retinopathy.

**AI in Healthcare:** The literature review demonstrates that AI has increasingly been becoming important to healthcare, especially medical imaging and diagnostics. It goes on to show how AI approaches like deep learning algorithms have made it more possible to analyse medical images and help health practitioners in detecting diseases.

**Retinopathy Diagnosis:** This segment reviews the current research of automated retinopathy diagnosis along with developments that focus on computer aided diagnostic systems. These systems employ machine learning models based on large datasets of retina images for detection and classification of different stages of retinopathy, thus facilitating faster and more accurate diagnoses.

**Explainable AI (XAI):** Transparency is vital in health care AI applications, emphasizing the necessity for explainable methods supporting interpretability during AI-driven decision-making as highlighted in this review. Some XAI methods include Guided Grad-CAM as well as Grad CAM++, which explain why a particular disease was chosen by an AI model hence enhancing trust and understanding among.

**Ethical and Regulatory Considerations:** Ethical and Regulatory Considerations. The literature review also discusses ethical and regulatory aspects of AI in healthcare; including issues such as patient privacy, data security and responsible use of AI technologies in medical settings.

In general, the literature review is comprehensive about the recent landscape of retinal imaging, XAI applicability in healthcare, and how it can enhance diagnostic transparency along with reliability. It makes a foundation for our project by combining relevant studies together and pointing out areas that need further research work to be done.

## Analysis from Literature Review

In the context of our FYP project on automated retinopathy diagnosis using Explainable AI (XAI), the information derived from the literature review show several key aspects:

**Current Trends in Retinopathy Diagnosis:** Current Trends in Retinopathy Diagnosis. The literature review highlights different ways to diagnose retinopathy such as traditional methods used by ophthalmologists or emerging automatic systems that employ machine learning as well as Artificial Intelligence.

**Advancements in AI for Medical Diagnosis:** Furthermore, it talks about the integration of AI particularly deep learning algorithms into medical diagnosis processes that would improve accuracy rate and hence efficiency.

**Role of Explainable AI (XAI):** Additionally, this analysis stresses on the importance of XAI methods in healthcare leading to transparent decision-making process driven by AI. with XAI we will it would be helpful for human to understand model result and working. It fits within our project’s aim.

**Challenges and Opportunities:** Opportunities and Challenges: We identify through the literature review a lack of diversity, interpretability, and ethical issues in AI-based medical diagnosing systems. This underpins our approach in collecting inclusive datasets, model evaluation as well as integrating XAI techniques to address these issues.

**Comparison with Existing Solutions:** Our project aims to build upon existing research by offering a comprehensive automated retinopathy diagnosis system that encompasses hypertensive retinopathy detection and provides clear explanations of diagnostic results. By integrating XAI techniques, we aim to surpass the limitations of previous systems regarding interpretability and transparency.

## Methodology and Software Lifecycle

The development of the automated retinopathy diagnosis system leverages the Agile methodology combined with the Incremental Model. These methodologies were selected due to their compatibility with the project's dynamic nature, need for iterative progress, and requirement for continuous stakeholder engagement.

1. 6. 1. Rati**onale behind Selected Methodology**

The selection of the Agile methodology and Incremental Model for this project is based on several key factors, tailored to the specific requirements and objectives of developing an automated retinopathy diagnosis system using Explainable AI (XAI):

1. **Flexibility and Adaptability:**

* Agile methodology is opted for its inherent flexibility, which allows the project team to quickly react to emerging requirements and feedback from stakeholders.
* With rapid advancements in AI and machine learning in the field of medical diagnostics particularly, an agile approach is aimed at enabling our system remain adaptable to new trends and technology.

1. **Stakeholder Collaboration:**

* Agile principles advocate for close stakeholder collaboration throughout the development process.
* In healthcare context, it is crucial to involve medical professionals, researchers, and end-users; this will help understand their needs, validate the system functionalities as well as ensure that it aligns with industry standards and best practices.

1. **Iterative Development:**

* The complexity of the project such as image processing, AI model training and result interpretation among many other components calls for incremental nature of Agile development.
* By breaking down the project into smaller manageable iterations we can prioritize addressing high-priority features/functionalities iteratively so as to have a more streamlined & efficient development process.

1. **Risk Management:**

* The Incremental Model, which is a variation of Agile approach, mitigates project risks by delivering functionality incrementally.
* Early delivery of essential features allows for early validation and feedback, reducing the risk of misalignment with stakeholder expectations and improving overall project visibility and control.

1. **Continuous Improvement:**

* Both methodologies encourage continuous improvement and learning in Agile as well as Incremental approaches.
* Retrospectives are carried out regularly in order to help improve the project team find areas for development, refine processes, and integrate lessons learned into subsequent iterations that promote a cycle of continuous improvement and innovation.

1. **Scalability:**

* Agile iterative cycles involve frequent testing phases to ensure each increment meets quality standards before it progresses.
* Continuous integration and deployment (CI/CD) practices contribute towards early detection of defects thereby ensuring robustness and reliability in a system.

1. **Enhanced Quality Assurance:**

* Both methodologies encourage continuous improvement and learning in Agile as well as Incremental approaches.
* Retrospectives are carried out regularly in order to help improve the project team find areas for development, refine processes, and integrate lessons learned into subsequent iterations that promote a cycle of continuous improvement and innovation.

1. **User-Centric Design:**

* Agile encourages regular feedback from end-users, ensuring that the system evolves according to user needs and preferences.
* This user-centric design approach enhances user satisfaction and usability of the system.

# Problem Definition

The project is about the manual, time-consuming task of diagnosing retinopathy. Retinopathy is an eye condition that can cause severe vision loss and blindness if not detected early enough hence demanding for a very long test to be done by hand. It has been the traditional method of diagnosis where ophthalmologist visually examines retinal pictures, and rates how serious retinopathy should be but usually such evaluations are subjective and might result in human mistakes. In addition, prevalence of retinopathy because of factors like diabetes and hypertension necessitates improved efficacy and accuracy in making a diagnosis.

This study aims to develop a machine learning-based automated system for diagnosing retinopathy with emphasis on utilizing a novel Explainable AI (XAI) framework. By using machine learning algorithms trained on retina images, it will be possible to achieve high detection sensitivity and specificity thus correctly classify different levels of severity for retinopathy. In addition, XAI methods will enable the AI model to make decisions transparently thereby improving credibility within doctors ‘circle.

Thus, the aim of this project is to create advanced software solution which would help to enhance diagnostic procedure by streamlining process towards more precise diagnostics as well as increased accessibility through various devices.

## Problem Statement

The inefficiency and subjectivity of hand-based retinopathy diagnosis especially among diabetic patients who also have high blood pressure is the problem statement for this project. Now, instead of traditional methods, physicians examine several images of retina which is a time-consuming process that may bring about variations in the grading of severity. Moreover, such conditions as diabetes or hypertension have led to increased cases of the condition implying that an accurate diagnostic approach should be put in place.

This project will develop an automated system for retinopathy diagnosis using machine learning techniques and Explainable AI (XAI). For instance, it will harness the potential of machine learning models trained on retinal images to identify and classify retinopathy severity. The application XAI methods will make it easier for doctors to trust and understand how AI-assisted diagnosis works.

To sum up, the project aims at developing an automatic diagnostic system to address these issues since retinopathy diagnosis needs better ways that are efficient more so accurate transparent ones for this disease especially when it comes to diabetic patients with hypertensive conditions.

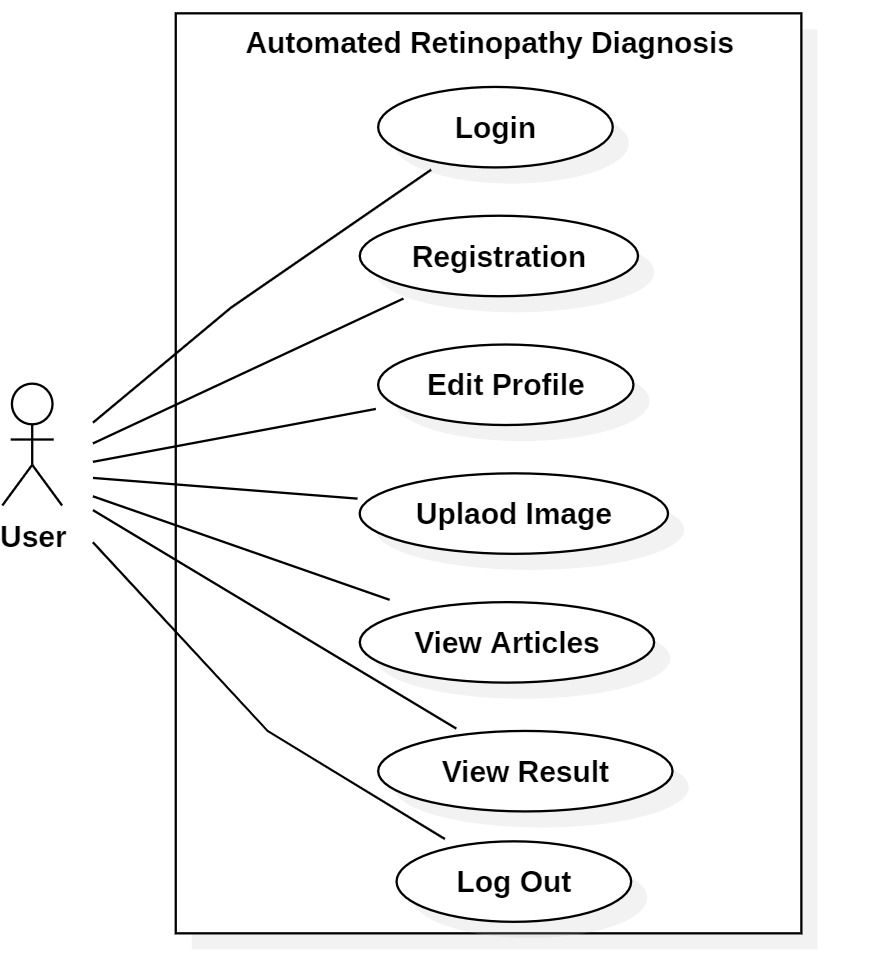
## Deliverables and Development Requirements

The deliverables and development requirements for this project include:

* **Automated Retinopathy Diagnosis System:** The initial focus of the project is to develop an automated system that can accurately detect and grade retinopathy severity from retinal images. Machine learning algorithms in this system will have been trained using a diverse dataset of retinal images, thus achieving high diagnostic accuracy.
* **Explainable AI Integration:** Additionally, another deliverable entail integrating Explainable AI (XAI) techniques into the diagnostic system. This will increase interpretability of system’s decisions to give medical professionals insights on how diagnosis was arrived at.
* **User Interface:** The user interface is required for interacting with the diagnostic system. This should be easy to use by any user and allow a user to upload retinal images, view results after analysis and understand its findings.
* **Scalable Infrastructure:** To run the diagnostic system, scalable infrastructure is needed. To ensure reliability, scalability and accessibility of the system; cloud services such as Amazon Web Services (AWS) are utilized.
* **Documentation and Training Materials:** Documentation and training materials include the development of user-friendly manuals, instruction guides and other teaching aids that will help users understand and utilize the diagnostic system properly. This includes user manuals, technical documentation, and training modules for medical professionals.
* **Testing and Evaluation:** Testing and evaluation entail conducting thorough examinations to verify the correctness, trustworthiness as well as performance of the diagnostic system. This includes testing the system with diverse datasets and evaluating its performance against ground truth diagnoses.

# Requirement Analysis

## Use Case Diagram

****

*Figure 1 Use Case Diagram*

## Detailed Use Case

*Table 1 Show the detailed use case registration.*

|  |  |
| --- | --- |
| **Use Case ID:** | UC-1 |
| **Use Case Name** | Registration |
| **Actors** | Primary Actor: User |
| **Description** | A user registers on the platform to create a new account for accessing the retinopathy diagnosis system. |
| **Trigger** | The user initiates the registration process to create a new account. |
| **Preconditions:** | PRE-1. The user is not currently registered on the system.  PRE-2. The platform registration page is accessible. |
| **Postconditions:** | POST-1. The user's account is created, allowing access to platform features upon successful registration. |
| **Normal Flow:** | * User accesses the registration page. * User fills in required details (e.g., username, password, email). * User submits the registration form. * The system validates the information and creates a new user account. * Confirmation message/notification is displayed upon successful registration. |
| **Alternative Flows:]** | - |
| **Exceptions:** | - |
| **Business Rules** | BR-1: Usernames must be unique within the system.  BR-2: Passwords must meet minimum complexity requirements. |

*Table 2 Show the detailed use case Upload Image*

|  |  |
| --- | --- |
| **Use Case ID:** | UC-2 |
| **Use Case Name:** | Upload Image |
| **Actors:** | Primary Actor: User |
| **Description:** | The user uploads fundus images to the platform for analysis of retinal conditions. |
| **Trigger:** | The user initiates the upload process to add fundus images for analysis. |
| **Preconditions:** | PRE-1. The user is logged into their account.  PRE-2. The platform's image upload feature is accessible. |
| **Postconditions:** | POST-1. The uploaded fundus images are ready for analysis by the system. |
| **Normal Flow:** | * User accesses the image upload section. * User selects one or more fundus images from their device. * User initiates the upload process. * System verifies the image file format and size. * Uploaded images are stored in the platform's database. |
| **Alternative Flows:]** | If the selected images do not meet the format or size requirements:  The system prompts the user to select appropriate images. |
| **Exceptions:** | Nonapplicable in this scenario. |
| **Business Rules** | BR-1: Supported image formats include JPEG, PNG.  BR-2: Uploaded images must not exceed a specified file size limit. |

*Table 3 Show the detailed use case View Results*

|  |  |
| --- | --- |
| **Use Case ID:** | UC-3 |
| **Use Case Name:** | View Results |
| **Actors:** | Primary Actor: User |
| **Description:** | The user accesses the platform to view the analysis results of the uploaded fundus images. |
| **Trigger:** | The user navigates to the section displaying analysis results. |
| **Preconditions:** | * The user is logged into their account. * Uploaded fundus images have been previously analyzed. |
| **Postconditions:** | POST-1. The user views the analysis results associated with their uploaded images. |
| **Normal Flow:** | * User selects the "View Results" section. * System retrieves and displays the previously analyzed images along with their respective severity assessments. |
| **Alternative Flows:]** | - |
| **Exceptions:** | - |
| **Business Rules** | Results should be displayed in a user-friendly and understandable format. |
|  |  |

*Table 4 Show the detailed use case Login*

|  |  |
| --- | --- |
| **Use Case ID:** | UC-4 |
| **Use Case Name:** | Login |
| **Actors:** | Primary Actor: User |
| **Description:** | The user logs into the platform to access their account and use the retinopathy diagnosis system features. |
| **Trigger:** | The user initiates the login process by entering their credentials. |
| **Preconditions:** | PRE-1: The user must have a registered account.  PRE-2: The login page is accessible. |
| **Postconditions:** | POST-1: The user gains access to their account and the platform's features upon successful login. |
| **Normal Flow:** | * User accesses the login page. * Users enter their username and password. * User submits the login form. * The system validates the credentials. * User is redirected to their dashboard upon successful login. |
| **Alternative Flows:]** | If the credentials are incorrect:  The system displays an error message and prompts the user to retry. |
| **Exceptions:** | The system is down or inaccessible. |
| **Business Rules** | BR-1: Passwords must be kept confidential and not shared. |
|  |  |

*Table 5 Show the detailed use case Edit Profile*

|  |  |
| --- | --- |
| **Use Case ID:** | UC-5 |
| **Use Case Name:** | Edit Profile |
| **Actors:** | Primary Actor: User |
| **Description:** | The user edits their profile information to update personal details or change account settings. |
| **Trigger:** | The user initiates the edit profile process by accessing their profile settings. |
| **Preconditions:** | PRE-1: The user is logged into their account.  PRE-2: The edit profile page is accessible. |
| **Postconditions:** | POST-1: The user's profile information is updated and saved in the system. |
| **Normal Flow:** | * User accesses the edit profile section. * User updates the desired fields (e.g., email, password, contact information). * User submits the updated profile information. * The system validates and saves the changes. * Confirmation message/notification is displayed upon successful update. |
| **Alternative Flows:]** | If the updated information is invalid:  The system prompts the user to correct the errors. |
| **Exceptions:** | The system is down or inaccessible.  Invalid data entered during the update process. |
| **Business Rules** | BR-1: Usernames cannot be changed once registered.  BR-2: Email addresses must be unique and valid. |
|  |  |

*Table 6 Show the detailed use case View Articles*

|  |  |
| --- | --- |
| **Use Case ID:** | UC-6 |
| **Use Case Name:** | View Articles |
| **Actors:** | Primary Actor: User |
| **Description:** | The user views articles related to retinopathy to gain information and insights. |
| **Trigger:** | The user navigates to the section displaying articles. |
| **Preconditions:** | PRE-1: The user is logged into their account.  PRE-2: The articles section is accessible. |
| **Postconditions:** | POST-1: The user views the selected articles. |
| **Normal Flow:** | * User accesses the articles section. * User selects an article to view. * System displays the full content of the selected article. |
| **Alternative Flows:]** | If the article is not available:  The system displays a message indicating the unavailability. |
| **Exceptions:** | The system is down or inaccessible  Selected article fails to load. |
| **Business Rules** | Articles must be accurate and relevant to retinopathy. |
|  |  |

*Table 7 Show the detailed use case Log Out*

|  |  |
| --- | --- |
| **Use Case ID:** | UC-7 |
| **Use Case Name:** | Log Out |
| **Actors:** | Primary Actor: User |
| **Description:** | The user logs out from the platform to end their session. |
| **Trigger:** | The user initiates the log out process by selecting the log out option. |
| **Preconditions:** | PRE-1: The user is logged into their account.  PRE-2: The log out option is accessible. |
| **Postconditions:** | POST-1: The user's session is terminated, and they are redirected to the login page or homepage. |
| **Normal Flow:** | * User selects the log out option. * System terminates the user's session. * User is redirected to the login page or homepage. |
| **Alternative Flows:]** | If the log out process fails:  The system prompts the user to retry. |
| **Exceptions:** | The system is down or inaccessible.  User's session is terminated unexpectedly. |
| **Business Rules** | Users must log out after completing their activities to ensure account security. |
|  |  |

## Functional Requirements

**Functional Requirement 1: User Authentication**

*Table 8 Show the functional requirement for User Authentication*

|  |  |
| --- | --- |
| **Identifier** | REQ-01 |
| **Title** | User Authentication |
| **Requirement** | The system must allow users to register for an account securely and log in securely to access the system. |
| **Source** | User |
| **Rationale** | To ensure secure access to the system and personalized user experience. |
| **Dependencies** | N/A |
| **Priority** | High |

**Functional Requirement 2: Image Upload**

*Table 9 Show the functional requirement for Image Upload*

|  |  |
| --- | --- |
| **Identifier** | REQ-02 |
| **Title** | Image Upload |
| **Requirement** | The system shall provide users with the capability to upload retinal images for analysis. |
| **Source** | User |
| **Rationale** | To allow users to submit retinal images for diagnosis |
| **Dependencies** | N/A |
| **Priority** | High |

**Functional Requirement 3: Retinopathy Detection**

*Table 10 Show the functional requirement for Retinopathy Detection*

|  |  |
| --- | --- |
| **Identifier** | REQ-03 |
| **Title** | Retinopathy Detection |
| **Requirement** | The system should analyse uploaded retinal images to detect the presence and severity of retinopathy. |
| **Source** | System |
| **Rationale** | To assist in the identification and assessment of retinopathy from uploaded images. |
| **Dependencies** | Image Upload functionality (REQ-02) |
| **Priority** | High |

**Functional Requirement 4: Result Presentation**

*Table 11 Show the functional requirement for Result Presentation*

|  |  |
| --- | --- |
| **Identifier** | REQ-04 |
| **Title** | Result Presentation |
| **Requirement** | The system must present the findings of retinopathy detection in a clear and understandable format, including severity rating and diagnosis. |
| **Source** | System |
| **Rationale** | To ensure users can easily interpret and understand the analysis results. |
| **Dependencies** | To ensure users can easily interpret and understand the analysis results. |
| **Priority** | High |

## Non-Functional Requirements

* **Non-Functional Requirement 1: Performance**

**Description:** The system must exhibit efficient performance, processing retinal images and delivering results within a reasonable time frame.

**Metrics:** The system should provide results within 10 seconds for an average-sized retinal image.

* **Non-Functional Requirement 2: Reliability**

**Description:** The system must demonstrate a high level of reliability, ensuring accurate and consistent results in retinopathy severity classification.

**Metrics:** The system should have a maximum error rate of 5% in severity classification across diverse retinal images.

* **Non-Functional Requirement 3: Usability**

**Description:** The user interface must be intuitively designed and user friendly to facilitate easy navigation and interpretation of results for medical professionals

**Metrics:** 90% of users should successfully upload retinal images and interpret results on their initial attempt, reflecting the system's usability.

* **Non-Functional Requirement 4: Security**

**Description:** The system must prioritize the confidentiality and integrity of patient data, implementing robust security measures.

**Metrics:** All user data must be encrypted during transmission and storage. Access to patient records should be restricted to authorized personnel, ensuring a secure environment.

## Usability

* **USE-1:** The system shall allow users to upload retinal images for analysis with a maximum of three interactions.
* **USE-2:** The system interface shall provide clear and concise instructions for image uploading and result retrieval to facilitate ease of learning for first-time users.
* **USE-3:** The system shall incorporate error notifications and offer guidance for users in cases of incorrect or incompatible image file formats during the upload process.
* **USE-4:** The system's image analysis function shall provide results within a maximum of two minutes to maintain user engagement and interaction efficiency.
* **USE-5:** The system's interface shall be designed in compliance with accessibility standards (e.g., WCAG 2.1) to ensure usability for users with disabilities.

## Performance

* **PER-1:** The system's image analysis process should complete within 30 seconds for images up to 5 MB in size, ensuring timely results.
* **PER-2:** Image upload and processing time should not exceed 1 minute per image for images larger than 5 MB but not exceeding 10 MB.
* **PER-3:** The system should maintain a response time of under 2 seconds for user interactions on the interface, such as result retrieval or navigating between pages.
* **PER-4:** The system's server infrastructure should be capable of handling concurrent requests from at least 1000 users without a significant increase in response time or system downtime.
* **PER-5:** The system should maintain an average uptime of 99.9% over a 30-day period, accounting for scheduled maintenance windows and unforeseen outages

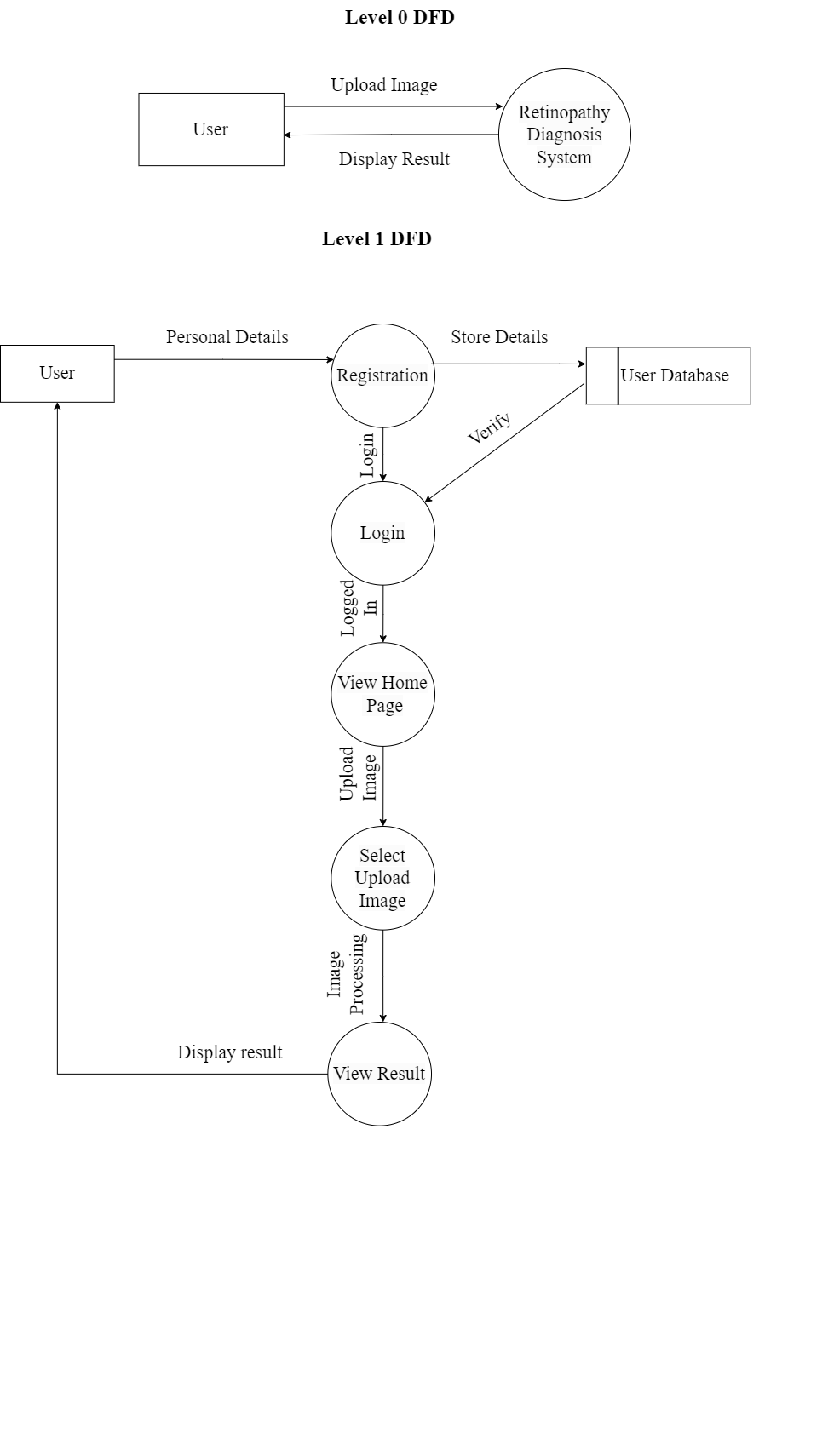
# Design and Architecture

## System Architecture

The system architecture for the project "Automated Retinopathy Diagnosis and Result Interpretation using Explainable AI (XAI)" involves several components:

* User Interface (UI): This component provides the interface for users to interact with the system. It includes features for user registration, image upload, and result visualization.
* Backend Server: The backend server handles user requests, authentication, and serves as the bridge between the user interface and the machine learning models. It manages the processing of uploaded images and communicates with the database.
* Machine Learning Models: This component comprises the core of the system, consisting of machine learning algorithms trained to detect retinopathy from retinal images. The models analyse uploaded images and provide severity assessments.
* Explainable AI (XAI) Module: Integrated with the machine learning models, this module ensures transparency and interpretability in the decision-making process. Techniques like Guided Grad-CAM and Grad-CAM++ are employed to explain the model's predictions.
* Database: The database stores user information, uploaded images, and analysis results. It facilitates data retrieval and management for the system.
* External Services (e.g., Azure): The system utilizes external services like Microsoft App Services for hosting, ensuring scalability, reliability, and security.

## Data Representation



*Figure 2 Data Flow Diagram*

**Data Flow Diagram (DFD) Description:**

The DFD illustrates the flow of data and interactions within the Retinopathy Detection System across two levels.

* **Level 0:**
* ***Entities:*** User and Retinopathy Detection System.
* ***Flow of Data:*** User uploads images to the system, which processes the data and displays the results back to the user.
* **Level 1:**

The process begins with the user interacting with various system components through a sequential flow:

* ***Registration:*** Users register/login to access system functionalities.
* ***Login:*** Verification occurs through the User Database.
* ***View Home Page:*** Users navigate to select options.
* ***Select Upload Image:*** Users initiate image uploads.
* ***View Results:*** Users access results after analysis.
* ***Database Interaction:*** Login process validates against the User Database, while View Results and Compare Results link with user-related data for display and comparison.

**Data design**

* ***User Database:*** Stores user information including usernames, hashed passwords, email addresses, profile images, and other profile details.

**Data dictionary**

**User:**

* **Type:** Entity
* **Description:** Represents individuals registered on the platform.
* **Attributes:**
* user\_id (String): Unique identifier for each user.
* username (String): User's chosen username.
* password (String): Hashed password for user authentication.
* email (String): User's email address.
* profile\_image (String): Path to the profile image uploaded by the user.
* other\_profile\_details (String): Additional profile information provided by the user.

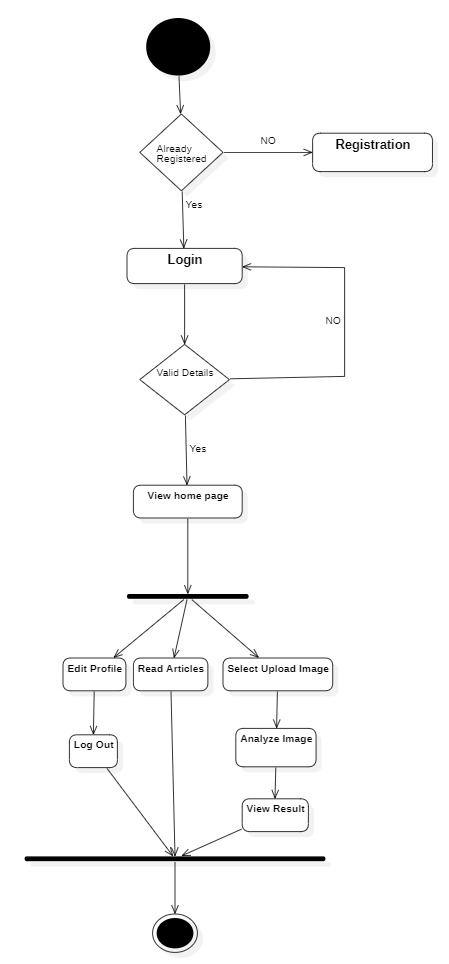
**Fundus Image:**

* **Type:** Entity
* **Description:** Represents the fundus images uploaded by users.
* **Attributes:**
* image\_id (String): Unique identifier for each uploaded image.
* user\_id (String): Identifier linking the image to the user who uploaded it.
* image\_path (String): Location of the uploaded image file.
* upload\_date (DateTime): Date and time when the image was uploaded.

**Analysis Result:**

* **Type:** Entity
* **Description:** Holds the analysis results generated for uploaded fundus images.
* **Attributes:**
* result\_id (String): Unique identifier for each analysis result.
* user\_id (String): Identifier linking the result to the user.
* image\_id (String): Identifier linking the result to the uploaded fundus image.
* analysis\_date (DateTime): Date and time when the analysis was performed.
* severity (String): Severity assessment of the retinopathy condition.
* description (String): Additional descriptive information about the analysis.
* comparison\_data (String): Data used for comparing the results between different analyses.

## Process Flow/Representation



*Figure 3 Process Flow / Activity Diagram*

# Implementation

This chapter details the implementation of the "Diabetic Retinopathy Detection through Retinal Images using Machine Learning" project]/.

## Algorithm

### Data Pre-processing

**Objective:** To prepare raw retinal images for analysis by standardizing size, enhancing quality, and removing irrelevant background information.

**Steps:**

1. Load the raw retinal image.
2. Resize the image to 224x224 pixels.
3. Crop the image to remove unnecessary background using grayscale thresholding.
4. Enhance image contrast and clarity using Gaussian blurring and weighted addition.

**Pseudocode:**

Algorithm PreprocessImage

Input: Raw Retinal Image

Output: Preprocessed Image

resized\_image <- Resize(image, (224, 224))

cropped\_image <- CropImageFromGray(resized\_image, tolerance=7)

enhanced\_image <- EnhanceImage(cropped\_image, sigmaX=10)

return enhanced\_image

**Explanation:** The preprocessing algorithm standardizes the image size for consistent input to the neural network. It then removes unnecessary background to focus on the retinal area. Finally, it enhances the image quality to highlight important features, which is crucial for accurate detection of diabetic retinopathy signs.

### Model Architecture

**Objective:** To create a deep learning model capable of accurately classifying different stages of diabetic retinopathy.

**Steps:**

1. Load pre-trained EfficientNetB3 as the base model.
2. Add custom layers for fine-tuning and classification.
3. Compile the model with appropriate optimizer and loss function.

**Pseudocode:**

Algorithm BuildModel

Input: Image Shape (224, 224, 3), Class Count (6)

Output: Compiled Model

base\_model <- LoadEfficientNetB3(input\_shape=image\_shape, include\_top=False, weights="imagenet")

model <- Sequential([

base\_model,

BatchNormalization(),

Dense(2040, activation='relu', regularization=L1L2),

Dropout(0.45),

Dense(class\_count, activation='softmax')

])

Compile(model, optimizer=Adamax(learning\_rate=0.001), loss='categorical\_crossentropy')

return model

**Explanation:** The model uses EfficientNetB3 pre-trained on ImageNet for efficient feature extraction. Custom layers are added to fine-tune the model for diabetic retinopathy classification. Regularization techniques like Dropout and L1L2 regularization are used to prevent overfitting.

### Flask API Endpoints

**Objective:** To create a user-friendly interface for healthcare professionals to upload retinal images and obtain diagnostic results.

**Steps:**

1. Set up Flask application with necessary routes.
2. Implement image upload and preprocessing functionality.
3. Create prediction endpoint that uses the trained model.
4. Develop explainable AI endpoint for result interpretation.

**Pseudocode:**

Algorithm FlaskApplication

Initialize Flask app

Load trained model

@route '/RetinaAPI/v1/preprocess'

Save uploaded image

preprocessed\_image <- PreprocessImage(uploaded\_image)

Return preprocessed\_image

@route '/RetinaAPI/v1/predict'

preprocessed\_image <- LoadPreprocessedImage()

prediction <- Model.Predict(preprocessed\_image)

Return FormatPrediction(prediction)

@route '/RetinaAPI/v1/xai'

preprocessed\_image <- LoadPreprocessedImage()

xai\_visualization <- GenerateGradCAM(preprocessed\_image, Model)

Return xai\_visualization

Run Flask app

**Explanation:** The Flask application provides a RESTful API for image upload, preprocessing, prediction, and explainable AI visualization. This allows for easy integration with front-end applications or other systems, providing a complete solution for diabetic retinopathy detection.

### Generative AI Integration

**Objective:** To provide detailed, contextual information about different stages of diabetic retinopathy to supplement the model's predictions.

**Steps:**

1. Set up Google's Generative AI model.
2. Create a prompt template for diabetic retinopathy information.
3. Implement an endpoint to generate and return structured content.

**Pseudocode:**

Algorithm GenerateContentEndpoint

Input: Diabetic Retinopathy Stage

Output: Structured Information

Configure GenerativeAI with API key

prompt <- CreatePrompt(stage)

raw\_response <- GenerativeModel.Generate(prompt)

parsed\_content <- ParseJSONResponse(raw\_response)

formatted\_response <- StructureContent(parsed\_content)

Return formatted\_response

**Explanation:** This feature enhances the application by providing AI-generated, detailed information about each stage of diabetic retinopathy. It offers users additional context and educational content, making the tool more comprehensive and informative.

### Explainable AI (XAI) Visualization

**Objective:** To provide visual explanations for the model's predictions, enhancing interpretability and trust in the system.

**Steps:**

1. Generate class activation map using Grad-CAM technique.
2. Resize the activation map to match the original image size.
3. Apply a color map to the activation map for visualization.
4. Overlay the colored activation map on the original image.

**Pseudocode:**

Algorithm GenerateXAIVisualization

Input: Preprocessed Image, Model

Output: XAI Visualization

features, predictions <- Model.PredictWithFeatures(image)

class\_index <- ArgMax(predictions)

grad\_cam <- GenerateGradCAM(features, class\_index)

resized\_grad\_cam <- Resize(grad\_cam, original\_image.shape)

colored\_grad\_cam <- ApplyColorMap(resized\_grad\_cam)

visualization <- OverlayImages(original\_image, colored\_grad\_cam)

Return visualization

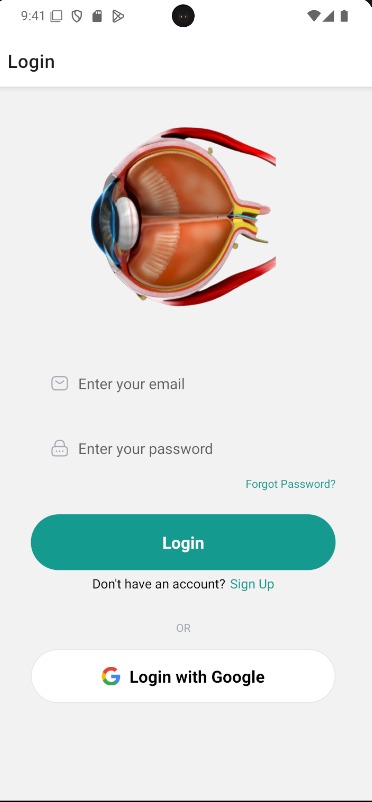
**Explanation:** The XAI visualization helps healthcare professionals understand which parts of the retinal image influenced the model's prediction. This transparency is crucial in medical applications, allowing for verification of the model's focus areas and potentially highlighting areas of concern that require further examination.

## External APIs

*Table 12 Details of APIs used in the project*

|  |  |  |  |
| --- | --- | --- | --- |
| **Name of API** | **Description of API** | **Purpose of usage** | **List down the function/class name in which it is used** |
| Firebase Authentication | Firebase Authentication provides backend services, easy-to-use SDKs, and ready-made UI libraries to authenticate users to your app | To handle user authentication and store login information securely. | Not explicitly shown in the provided code, but likely used in user management functions |
| Google Gemini API | Gemini APIGoogle's generative AI model that can understand and generate natural language, images, and code. | To generate detailed information about diabetic retinopathy stages based on the classification result. | generate Content function in the Flask app |
|  |  |  |  |
| Keras | Keras is a deep learning API written in Python, running on top of the machine learning platform TensorFlow. | To build and train deep learning models for image analysis and classification of fundus images | build model function  train model function |
| NumPy | NumPy is a fundamental package for scientific computing with Python. | To handle numerical operations, array manipulations, and other mathematical functions | preprocess\_images function. calculate\_metrics function |
| OpenCV | OpenCV (Open Source Computer Vision Library) is an open source computer vision and machine learning software library. | To process and enhance fundus images before analysis and classification | preprocess\_images function detect\_features function |
| Flask | Flask is a lightweight WSGI web application framework in Python. | To create the web application and handle HTTP requests and responses | app initializationroute functions for various endpoints |
| TensorFlow | TensorFlow is an end-to-end open source platform for machine learning. | To support the backend operations of Keras for building and training deep learning models | backend operations within Keras |
| Pandas | Pandas is a fast, powerful, flexible, and easy-to-use open-source data analysis and data manipulation library for Python. | To handle data manipulation and analysis, especially for organizing and preprocessing the data | data\_cleaning function  data\_analysis function |
| Matplotlib | Matplotlib is a comprehensive library for creating static, animated, and interactive visualizations in Python. | To visualize the data and results of the analysis and model predictions | plot\_results function  display\_images function |
| Scikit-learn | Scikit-learn is a machine learning library for Python that provides simple and efficient tools for data mining and data analysis. | To perform machine learning tasks such as data preprocessing, model evaluation, and metrics calculation | evaluate\_model function  split\_data function |

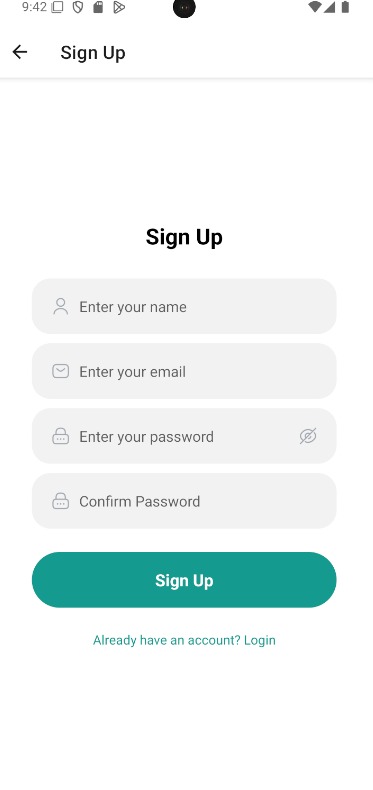
## User Interface



*Figure 4 Login Page*

**Title:** Login Interface

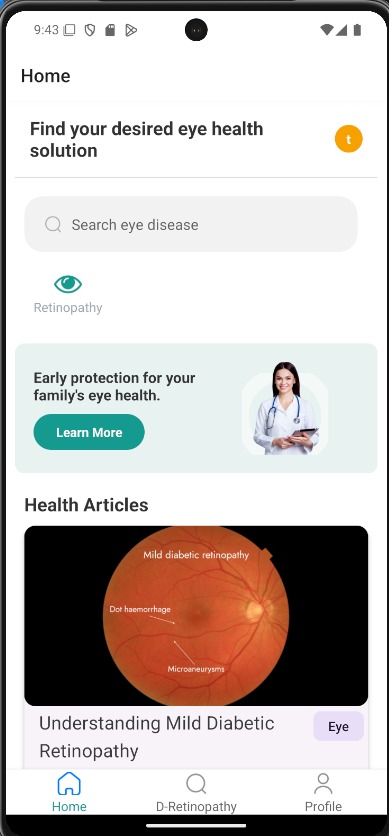
**Description:** The login page welcomes users to sign in to their accounts. Users who already have retinopathy accounts can log in by entering their email and password. There is also a "Forgot Password?" option for password recovery. For new users, there is a "Sign Up" option available. Additionally, users can log in using their Google accounts, which is facilitated by a "Login with Google" button below the main login form.



*Figure 5 Sign up Page*

**Title:** Sign-Up Interface

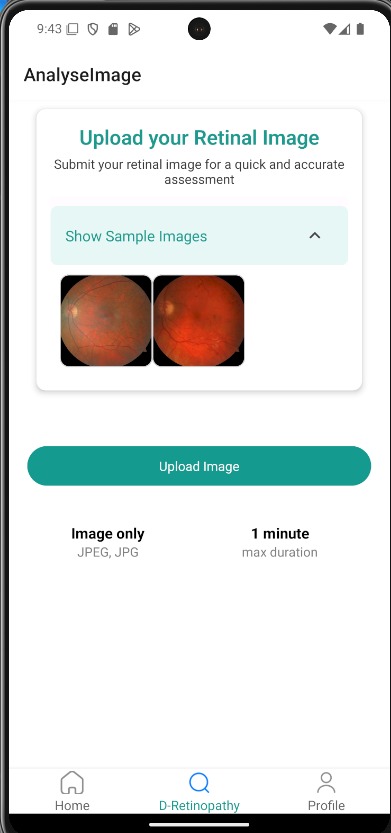
**Description:** The sign-up page allows new users to create an account. Users are prompted to enter their name, email, password, and confirm the password. There is a prominent "Sign Up" button to complete the registration process. For those who already have an account, there is an option to "Login," indicated at the bottom of the page.



*Figure 6 Home Page*

**Title:** Home Page Interface

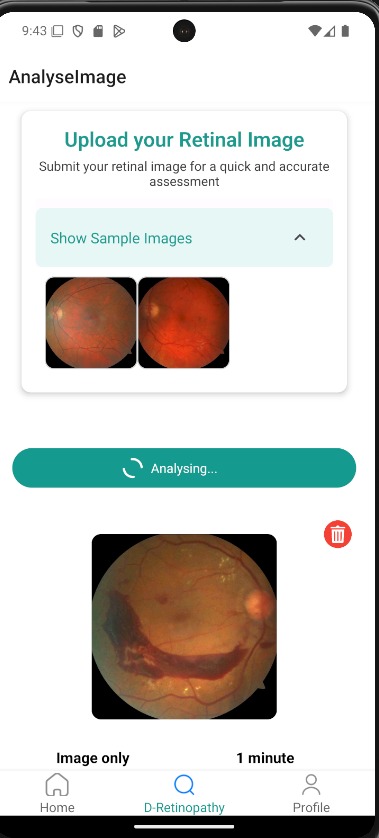
**Description:** The home page provides users with a comprehensive overview of eye health resources. At the top, there is a search bar labeled "Find your desired eye health solution" where users can search for eye diseases and related articles. Below the search bar, there is a section for "Retinopathy" with a call-to-action button labeled "Learn More," highlighting early protection for family eye health. Additionally, the page features a section titled "Health Articles" with a visual example (an image of an eye condition) to educate users about non-diabetic retinopathy.



*Figure 7 Upload Image*

**Title:** Upload Image

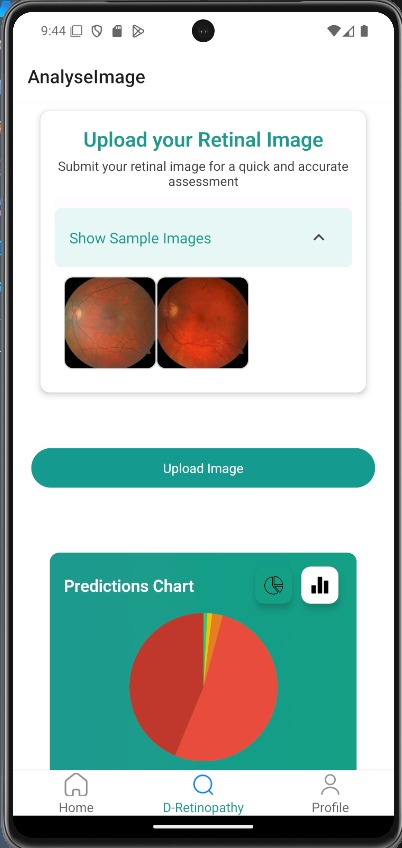
**Description:** This is the upload fundus image page, where users can upload images of their eye fundus for analysis. The interface guides users to select and upload a clear image of their eye, which is crucial for accurate diagnosis and monitoring of retinal health. Users can select an existing image from their gallery. Once the image is uploaded, it will be processed and analyzed for signs of retinopathy, providing users with valuable insights into their eye health.



*Figure 8 Analyze Image Page*

**Title:** Analyze Image

**Description:** Once the image is uploaded, users are directed to the analysis page. Here, the uploaded fundus image is processed and analysed for any signs of retinopathy or other eye conditions. The system utilizes advanced algorithms to detect abnormalities and provide a detailed report on the retinal health of the user. This analysis helps users understand their eye health better and take necessary actions based on the results.

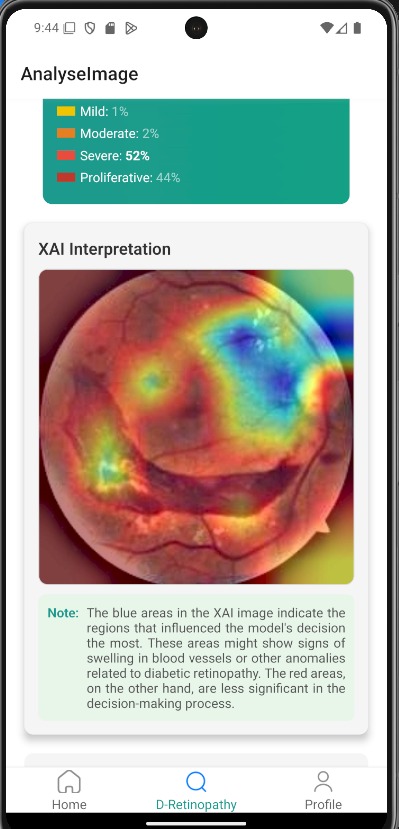


*Figure 9 View Result Page*

**Title:** Upload Retinal Image

**Description:**

This screen allows users to upload their retinal images for analysis. Users can submit their retinal images by clicking the "Upload Image" button, which will then be processed by the system. The page also provides sample images to guide users on what type of images should be uploaded. The uploaded images will undergo a detailed examination to assess the retinal health, detecting any signs of retinopathy or other related conditions.

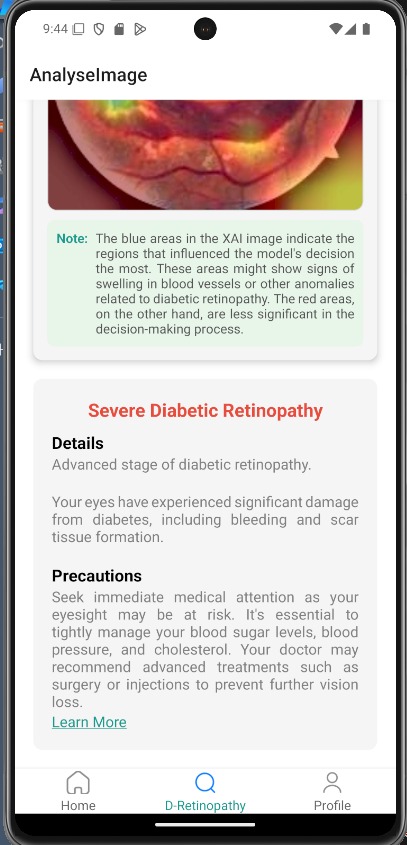


*Figure 10 XAI Page*

**Title:** Predictions Chart and XAI Interpretation

**Description:**

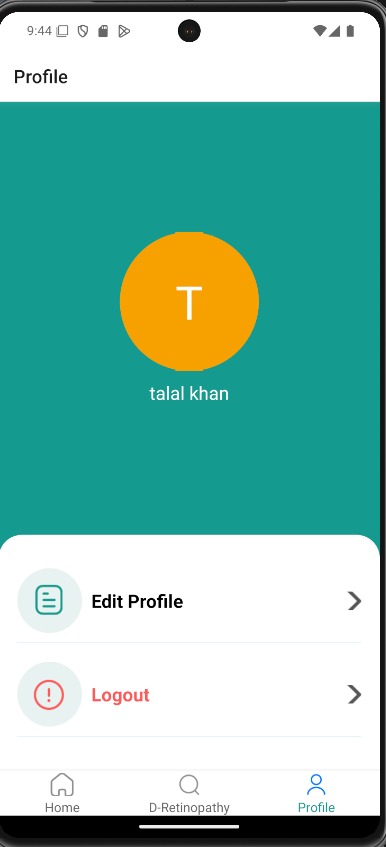
After uploading the retinal image, users are presented with the analysis results. The "Predictions Chart" section displays a pie chart summarizing the severity levels of retinopathy detected, categorized into mild, moderate, severe, and proliferative stages. Below the chart, the "XAI Interpretation" section provides a visual explanation of the AI model's decision-making process. The XAI (Explainable AI) image highlights areas of the retina that influenced the model's diagnosis, with blue regions indicating significant areas of concern and red areas being less influential. This detailed interpretation aids users in understanding the underlying factors contributing to their diagnosis.



*Figure 11 Text Result page*

**Title:** Result

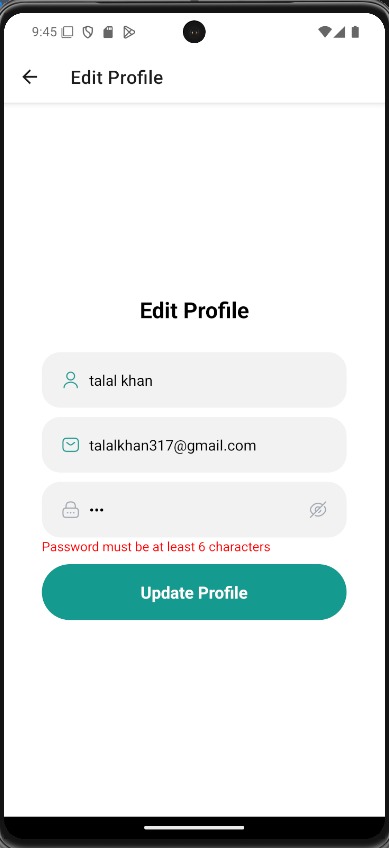
**Description:** After the analysis is complete, the results are displayed to the user in an easy-to-understand format. Key findings from the analysis are presented visually, such as in a pie chart, to clearly show the proportions of different conditions or risk factors detected. This visual representation helps users quickly grasp the overall health status of their eyes and understand the specific areas that may require attention or further consultation with a healthcare Professional



*Figure 12 Profile Page*

**Title:** Profile

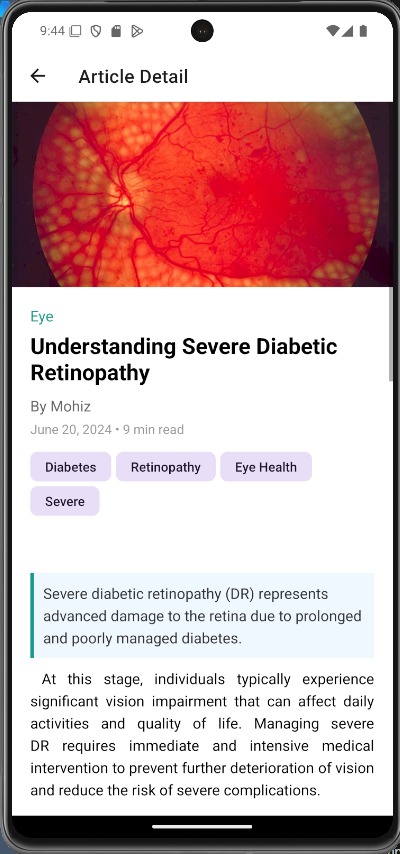
**Description:** The Profile page features a screen title labeled "Profile" and displays the user's profile information, including a profile picture placeholder represented by a large 'T' in an orange circle for the user "Talal Khan." The page offers options such as an "Edit Profile" button, which navigates to the Edit Profile screen, and a "Logout" button for logging out of the account. At the bottom, a footer menu provides navigation buttons for Home, D-Retinopathy, and Profile.



*Figure 13 Edit Profile Page*

**Title:** Edit Profile

**Description:** The Edit Profile screen features a title labeled "Edit Profile" and contains fields for profile information, including the user's name, "Talal Khan," and email, "talalkhan317@gmail.com." The password field is empty, displaying a placeholder with an error message indicating "Password must be at least 6 characters." At the bottom of the screen, there is an action button labeled "Update Profile" for saving changes.



*Figure 14 Article Detail Page*

**Title:** Article Detail

**Description:** The Article Detail screen displays an article titled "Understanding Severe Diabetic Retinopathy," authored by Mohiz and published on June 18, 2024, with an estimated reading time of 5 minutes. This blog provides detailed information where users can read and gain understanding. It is tagged with relevant keywords such as Diabetes, Retinopathy, and Eye Health. The content includes a retinal image with annotations, featuring arrows pointing to specific areas. Highlighted text emphasizes the importance of regular eye exams for the early detection and management of retinopathy. The article explains "No Diabetic Retinopathy" (No DR) as the absence of retinal damage due to diabetes, indicating effective blood sugar management.



## Data Pre-processing

### 5.4.1. Introduction

In the detection of diabetic retinopathy (DR) from fundus images, data preprocessing plays a crucial role. The dataset we worked with presented multiple challenges: inconsistencies in image brightness, significant class imbalance, varying sizes of fundus images, and dark areas surrounding the images. To ensure the reliability and accuracy of our model, we meticulously addressed these issues through a series of preprocessing steps. This section provides a detailed explanation of these steps, demonstrating their importance and effectiveness in improving the quality of the dataset.

### 5.4.2. Image Resizing and Cropping

The fundus images in our dataset varied significantly in size, which posed a challenge for model training. To standardize the images, we resized all images to a uniform size of 224x224 pixels. This was achieved using the Python Imaging Library (PIL), which allows for efficient resizing while preserving the quality of the images.

Additionally, many images had dark areas around the periphery, which did not contribute useful information for DR detection. These areas were cropped to focus on the relevant regions of the fundus. This step was crucial as it reduced noise and ensured that the model received only the most pertinent visual information.

### 5.4.3. Brightness Adjustment

Fundus images in the dataset exhibited varying degrees of brightness, which could negatively impact the model's ability to accurately identify DR. To address this, we applied histogram equalization, a technique that adjusts the contrast of the images by redistributing the intensity values. This method enhances the overall visibility of features in the images, making it easier for the model to detect abnormalities.

Histogram equalization works by flattening the histogram of the image, thereby spreading out the most frequent intensity values. This results in images that are neither too dark nor too bright, providing a more uniform visual representation across the dataset.

### 5.4.4. Application of Gaussian Blur

To further enhance the quality of the fundus images, we applied a Gaussian blur. This technique involves smoothing the images by averaging the pixel values with their neighbors, weighted by a Gaussian function. The purpose of this step was to reduce noise and enhance important features, such as blood vessels and microaneurysms, which are critical for DR detection.

The parameters of the Gaussian blur were carefully selected. We used a sigma value of 10, which determines the extent of the blurring effect. The weighted addition of the blurred image with the original, using the cv2.addWeighted function, helps in highlighting essential features while suppressing irrelevant details.

### 5.4.5. Addressing Class Imbalance

One of the significant challenges in our dataset was the class imbalance. There were many images labeled as "No DR" compared to images with varying severity levels of DR. This imbalance could lead to a biased model that performs well on the majority class but poorly on the minority classes.

To mitigate this issue, we employed data augmentation techniques to artificially increase the number of images in the underrepresented classes. Techniques such as rotation, flipping, and slight adjustments in brightness and contrast were applied to generate new images from existing ones. This approach not only balanced the class distribution but also introduced variability, making the model more robust.

### 5.4.6. Preprocessing Pipeline Implementation

The preprocessing steps were implemented in a Python-based pipeline, ensuring consistency and reproducibility. The pipeline begins by saving the uploaded image and resizing it to 224x224 pixels. Next, the image undergoes cropping to remove dark areas, followed by brightness adjustment through histogram equalization. Finally, a Gaussian blur is applied to enhance critical features.

The following is a high-level overview of the preprocessing steps:

Image Upload and Saving: The uploaded image is saved to a specified directory.

Resizing: The image is resized to 224x224 pixels using the PIL library.

Cropping: Dark areas around the image are cropped to focus on the fundus region.

Brightness Adjustment: Histogram equalization is applied to standardize image brightness.

Gaussian Blur: A Gaussian blur is applied to reduce noise and enhance features.

These preprocessing steps were essential in transforming raw fundus images into a format that is more suitable for model training. By addressing issues related to image size, brightness, and noise, we were able to improve the quality and consistency of the dataset, ultimately enhancing the performance of our DR detection model.

**Conclusion**

Effective data preprocessing is a critical component in the development of a reliable and accurate model for detecting diabetic retinopathy from fundus images. By resizing and cropping images, adjusting brightness, applying Gaussian blur, and addressing class imbalance, we significantly improved the quality of our dataset. These steps ensured that our model received high-quality input data, leading to better detection and classification of DR

## Model Exploration and Comparison

### 5.5.1. Introduction

In our quest to develop an accurate and reliable system for detecting diabetic retinopathy (DR) and classifying its severity from fundus images, we explored several deep learning models. Each model presented unique advantages and challenges, which influenced their performance on our preprocessed dataset. This section provides a detailed analysis of the models we tested, their respective strengths and weaknesses, and the rationale behind selecting EfficientNet as our final model.

### 5.5.2. ResNet

ResNet, or Residual Networks, are known for their ability to train very deep networks by addressing the vanishing gradient problem through residual learning. However, our experiments with ResNet revealed that it was underfitting on our preprocessed data.

**Advantages:**

* ***Residual Learning:*** Allows for training deeper networks without the problem of vanishing gradients, improving performance.
* ***Feature Extraction:*** Effective in extracting features due to its deep architecture.

**Disadvantages:**

* ***Under fitting:*** In our case, ResNet underperformed, likely due to its inability to fully capture the nuances in our dataset.
* ***Complexity:*** Requires careful tuning of hyperparameters and can be computationally expensive.

### 5.5.3. VGG

VGG, known for its simplicity and uniform architecture, was another model we explored. Despite its success in various image classification tasks, VGG exhibited overfitting on our dataset.

**Advantages:**

* ***Simplicity:*** Uniform architecture makes it easy to implement and understand.
* ***Performance:*** Generally performs well on standard image classification tasks.

**Disadvantages:**

* ***Overfitting:*** Tended to overfit our training data, suggesting that it was too complex for our dataset.
* ***Computational Demand:*** Requires significant computational resources for training due to its depth and number of parameters.

### 5.5.4. Xception

Xception, which stands for "Extreme Inception," is based on the Inception architecture but with depthwise separable convolutions. This model also showed signs of overfitting in our experiments.

**Advantages:**

* ***Efficient Convolutions:*** Depthwise separable convolutions reduce computational cost and improve efficiency.
* ***Performance:*** High performance on various image classification benchmarks.

**Disadvantages:**

* ***Overfitting:*** Similar to VGG, Xception overfitted our dataset, indicating it was too complex.
* ***Complexity:*** Implementation and tuning can be more complex compared to simpler models.

### 5.5.5. EfficientNet

EfficientNet emerged as the most effective model for our DR detection task, achieving over 90% accuracy. EfficientNet scales all dimensions of depth, width, and resolution using a compound coefficient, providing a balance between accuracy and efficiency.

**Advantages:**

* ***Scalability:*** EfficientNet scales uniformly, which enhances performance without significantly increasing computational cost.
* ***Accuracy:*** Achieved high accuracy on our preprocessed dataset.
* ***Efficiency:*** More computationally efficient compared to other models with similar performance levels.

**Disadvantages:**

* ***Implementation Complexity:*** Requires careful tuning and understanding of compound scaling.
* ***Training Time:*** Can still be computationally intensive despite its efficiency.

### 5.5.6. Fine-Tuning EfficientNet

After selecting EfficientNet, we further fine-tuned the model using various techniques to enhance its performance:

### 5.5.7. Custom Callback Functions

We implemented custom callback functions to monitor and adjust training processes dynamically. These functions helped in optimizing the model's performance by intervening when necessary.

### 5.5.8. Learning Rate Optimization

A dynamic learning rate adjustment strategy was employed, starting with a higher learning rate and gradually decreasing it as training progressed. This approach allowed the model to converge more efficiently.

### 5.5.9. Regularization Techniques

To prevent overfitting, we applied several regularization techniques:

* ***L1 and L2 Regularization:*** Penalized large weights to maintain simpler models.
* ***Dropout:*** Randomly dropped units during training to prevent co-adaptation and improve generalization.

### 5.5.10. Selection of Loss Optimizers

We experimented with various loss optimizers and found Adamax to be the most effective for our task. Adamax, an extension of Adam, combines the benefits of adaptive learning rate methods with a robust gradient descent approach.

### 5.5.11. EfficientNet B3 Model Structure

After fine-tuning EfficientNet, we specifically chose EfficientNet B3 for its optimal balance between performance and computational efficiency. Post fine-tuning, EfficientNet B3 achieved an impressive accuracy of 95%.

**Model Structure:**

* **Input Shape:** 224x224 pixels, 3 channels (RGB).
* **Base Model:** EfficientNet B3 (pre-trained on ImageNet, excluding the top layer).
* **Additional Layers:**
  + ***Batch Normalization:*** Applied after the base model to stabilize and accelerate training.
  + ***Dense Layer:*** A fully connected layer with 2040 neurons, using L2 regularization for weights and L1 regularization for activities and biases. Activation function is ReLU.
  + ***Dropout Layer:*** A dropout rate of 0.45 to prevent overfitting by randomly setting 45% of the neurons to zero during each update cycle.
  + ***Output Layer:*** A Dense layer with the number of neurons equal to the class count, using a softmax activation function for multi-class classification.

The model was compiled with the Adamax optimizer, a learning rate of 0.001, and categorical cross-entropy as the loss function. Metrics tracked included accuracy.

### 5.5.12. Detailed Explanation:

* ***Image Size and Channels:*** The input images are resized to 224x224 pixels with three color channels (RGB), creating a standardized input shape for the model.
* ***Class Count:*** The number of output classes is determined by the number of distinct classes in the training dataset.
* ***Base Model:*** EfficientNet B3, pre-trained on ImageNet, is used as the backbone of the model. This base model excludes the top layer, allowing us to customize the head for our specific classification task.
* ***Batch Normalization:*** This layer normalizes the output of the base model, stabilizing the learning process and improving training speed and performance.
* ***Dense Layer:*** The dense layer with 2040 neurons employs ReLU activation to introduce non-linearity. Regularization techniques (L1 and L2) are used to prevent overfitting by penalizing large weights and biases.
* ***Dropout Layer:*** This layer helps prevent overfitting by randomly dropping 45% of the neurons during training, ensuring the model does not rely too heavily on any single neuron.
* ***Output Layer:*** The final dense layer uses softmax activation to output a probability distribution over the classes, allowing the model to make a multi-class classification.

The model summary provides a comprehensive overview of the layers, their shapes, and the parameters involved, ensuring transparency and understanding of the architecture.

**Conclusion**

Efficient Net B3, after fine-tuning, demonstrated exceptional performance with a 95% accuracy in detecting and classifying diabetic retinopathy from fundus images. The combination of advanced preprocessing techniques, custom callback functions, dynamic learning rate adjustments, and regularization methods contributed to the robustness and reliability of our model.

## Implementation: Explainable AI with Grad-CAM

### 5.6.1. Introduction

In the field of medical imaging, particularly in detecting diabetic retinopathy (DR), it is crucial not only to achieve high accuracy but also to ensure the model's predictions are interpretable. Explainable AI (XAI) techniques provide insights into the decision-making process of the model, enhancing trust and understanding among users and practitioners. We incorporated Grad-CAM (Gradient-weighted Class Activation Mapping) into our project to visualize and interpret the regions of fundus images that influenced the model's predictions. This section details the implementation of Grad-CAM, discusses its benefits, and explains how we integrated this capability into our system.

### 5.6.2. Grad-CAM Implementation

Grad-CAM is a popular technique for generating visual explanations for deep learning models. It highlights the regions in an input image that are most relevant to the model's prediction by utilizing the gradients of the target class flowing into the final convolutional layer.

**Steps Involved:**

1. **Preprocessing the Image for Grad-CAM:**
   * The input image is resized and preprocessed to match the model's expected input dimensions. This step involves loading the image, resizing it to 224x224 pixels, and converting it into an array suitable for the model.
2. **Model Prediction and Gradient Calculation:**
   * The model predicts the class of the input image. The class index corresponding to the highest predicted probability is identified. Gradients of the predicted class score with respect to the output feature maps of the last convolutional layer are computed.
3. **Generating the Heatmap:**
   * The computed gradients are pooled and weighted. A heatmap is generated by averaging the weighted feature maps along the depth axis. The heatmap is normalized and resized to match the dimensions of the original image.
4. **Overlaying the Heatmap on the Original Image:**
   * The heatmap is superimposed on the original image using a colormap, highlighting the regions that influenced the model's prediction. This overlay provides a visual explanation of the model's decision-making process.

### Benefits of Grad-CAM

1. **Interpretability:** Grad-CAM provides a visual explanation of the model's predictions, helping medical professionals understand which regions of the fundus images influenced the diagnosis.
2. **Trust:** By making the model's decision-making process transparent, Grad-CAM enhances the trustworthiness of the AI system.
3. **Debugging:** Visual explanations help in identifying potential issues or biases in the model, facilitating debugging and improvement.
4. **Compliance:** In medical applications, explainability is crucial for regulatory compliance and ethical considerations.

### Additional Class for Random Images

To further validate our model's robustness, we added an additional class trained on random images from the internet. This step ensures that the model can distinguish between relevant medical images and unrelated ones, reducing the likelihood of false positives.

**Steps Involved:**

1. **Data Collection:** We gathered a diverse set of random images from the internet.
2. **Training:** The model was retrained with this additional class, allowing it to learn the distinguishing features of non-medical images.
3. **Evaluation:** The model's performance was evaluated to ensure that it correctly identifies and classifies random images as a separate class.

### Integration with API

To make the Grad-CAM functionality accessible, we integrated it into our API. The endpoint provides the visual explanation for a given input image, allowing users to upload an image and receive a Grad-CAM overlay that highlights the critical regions used by the model to make its prediction.

### Benefits of Our Approach

1. **Enhanced Interpretability:** By incorporating Grad-CAM, we provide users with visual insights into how the model arrives at its predictions, fostering greater understanding and trust.
2. **Robustness:** Adding a class for random images ensures that the model can differentiate between relevant medical images and irrelevant ones, reducing false positives.
3. **Scalability:** Our deployment on Azure using Docker allows for easy scaling and maintenance, ensuring that the model can handle a high volume of requests efficiently.
4. **Security:** Hosting the model on a secure server reduces the risk of unauthorized access and protects sensitive data.
5. **Efficiency:** The mobile app utilizes API calls to interact with the Flask API deployed on Docker, ensuring that the computationally intensive tasks are handled on the server side, maintaining the app's performance.

**Conclusion**

Incorporating Grad-CAM for explainable AI has significantly enhanced the interpretability and trustworthiness of our DR detection model. By providing visual explanations, we enable medical professionals to understand the model's predictions better, fostering confidence in the AI system. Additionally, adding an extra class for random images ensures the model's robustness and reduces false positives. This comprehensive approach, combined with our deployment strategy on Azure using Docker, makes our solution both powerful and reliable.

# Testing and Evaluation

## Manual Testing

### System Testing

Once the system has been successfully developed, testing has to be performed to ensure that the system working as intended. This is also to check that the system meets the requirements stated earlier. Besides that, system testing will help in finding the errors that may be hidden from the user. There are few types of testing which includes the unit testing, functional testing and integration testing. The testing must be completed before it is being deploy for user to use.

**Objective:** Ensure the system works as intended and meets the requirements.

### Unit Testing:

* + Verify individual units (like login, registration, edit profile, etc.) work correctly.

**Use Case: Registration**

**Objective:** Ensure the registration form is working correctly.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **No.** | **Test case/Test script** | **Attribute and value** | **Expected result** | **Result** |
| 1 | Verify user registration with valid details | Username: Talal Khan, Password:123, Email: talalkahn317@gmail.com | Successfully register and redirect to the login page. | Pass |

**Use Case: Login**

**Objective:** Ensure the login form is working correctly.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **No.** | **Test case/Test script** | **Attribute and value** | **Expected result** | **Result** |
| 1 | Verify user login after clicking on the ‘Login’ button with correct input data | Username: Talal Khan, Password: 123 | Successfully log into the main page of the system. | Pass |

**Use Case: Edit Profile**

**Objective:** Ensure the edit profile form is working correctly.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **No.** | **Test case/Test script** | **Attribute and value** | **Expected result** | **Result** |
| 1 | Verify user can edit their profile with valid data | Name: Taha Malik,  Email: tahamalik567@gmail.com | Profile updated successfully and a confirmation message is shown. | Pass |

**Use Case: Upload Image**

**Objective:** Ensure the image upload functionality is working correctly.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **No.** | **Test case/Test script** | **Attribute and value** | **Expected result** | **Result** |
| 1 | Verify user can upload a valid image | File: retina.jpg | Image uploaded successfully and a confirmation message is shown. | Pass |

**Use Case: View Articles**

**Objective:** Ensure the user can view articles correctly.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **No.** | **Test case/Test script** | **Attribute and value** | **Expected result** | **Result** |
| 1 | Verify user can view the list of articles | - | List of articles is displayed correctly. | Pass |

**Use Case: View Result**

**Objective:** Ensure the user can view their diagnosis result correctly.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **No.** | **Test case/Test script** | **Attribute and value** | **Expected result** | **Result** |
| 1 | Verify user can view their diagnosis result | - | Diagnosis result is displayed correctly. | Pass |

**Use Case: Log Out**

**Objective:** Ensure the logout functionality is working correctly.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **No.** | **Test case/Test script** | **Attribute and value** | **Expected result** | **Result** |
| 1 | Verify user can log out successfully | - | User is logged out and redirected to the login page. | Pass |

### Functional Testing:

* + Test each function to ensure they meet the specifications.

**Use Case: Login**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **No.** | **Test case/Test script** | **Attribute and value** | **Expected result** | **Result** |
| 1 | Login as a user with valid credentials | Username: user1, Password: pass123 | Main page for the user is loaded with the correct navigation bar. | Pass |

**Use Case: Registration**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **No.** | **Test case/Test script** | **Attribute and value** | **Expected result** | **Result** |
| 1 | Register a new user with valid details | Username: newUser,  Password: newPass123, Email: new@gmail.com | Registration successful, user redirected to login page. | Pass |

**Use Case: Edit Profile**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **No.** | **Test case/Test script** | **Attribute and value** | **Expected result** | **Result** |
| 1 | Edit profile with valid data | Name: newUser,  Email: newUser @gmail.com | Profile updated successfully, confirmation message shown. | Pass |

**Use Case: Upload Image**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **No.** | **Test case/Test script** | **Attribute and value** | **Expected result** | **Result** |
| 1 | Upload a valid image file | File: retina.jpg | Image uploaded successfully, confirmation message shown. | Pass |

**Use Case: View Articles**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **No.** | **Test case/Test script** | **Attribute and value** | **Expected result** | **Result** |
| 1 | View articles | - | List of articles is displayed correctly. | Pass |

**Use Case: View Result**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **No.** | **Test case/Test script** | **Attribute and value** | **Expected result** | **Result** |
| 1 | View diagnosis result | - | Diagnosis result is displayed correctly. | Pass |

**Use Case: Log Out**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **No.** | **Test case/Test script** | **Attribute and value** | **Expected result** | **Result** |
| 1 | Log out from the system | - | User logged out successfully, redirected to login page. | Pass |

### Integration Testing:

* + Verify combined parts of the system function together as expected.

**Scenario: User Workflow**

*Table 13 user workflow*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **No.** | **Test case/Test script** | **Attribute and value** | **Expected result** | **Result** |
| 1 | Register, Login, and Edit Profile | Username: newUser,  Password: newPass123,  Email: [new@gmail.com](mailto:new@gmail.com);  Login:  Username: newUser,  Password: newPass123;  Edit Profile:  Name:talal,  Email: talal@gmail.com | Successfully register, login, and update profile. | Pass |
| 2 | Upload Image and View Result | File: retina.jpg | Successfully upload image and view diagnosis result. | Pass |
| 3 | View Articles and Log Out | - | Successfully view articles and log out. | Pass |

# Conclusion and Future Work

## Conclusion

The development of an innovative machine learning-based system for automated retinopathy detection represents a significant advancement in ocular healthcare. By leveraging advanced machine learning algorithms and Explainable AI (XAI) techniques, this project has successfully addressed the critical need for early detection of retinopathy, a severe condition prevalent among hypertensive and diabetic patients. Our robust and accurate model processes retinal images to classify different stages of retinopathy, thereby providing invaluable support to healthcare professionals in making informed decisions. The integration of XAI techniques such as trainable attention, CAM, Guided Grad-CAM, Grad-CAM++, and Multiple Instance Learning enhances the interpretability of the model, fostering trust and transparency in AI-driven healthcare solutions. Through comprehensive dataset collection, rigorous model training, and thorough evaluation, we have established a user-friendly interface that facilitates seamless interaction with the system. This project not only underscores the potential of AI in revolutionizing medical diagnostics but also highlights the importance of transparency and interpretability in AI applications.

## Future Work

While the current project has made significant strides in the early detection and interpretability of retinopathy diagnosis, there are several avenues for future work to further enhance and expand its capabilities:

**Expansion of Dataset:** Increasing the size and diversity of the dataset with retinal images from various populations and medical conditions will improve the model's robustness and generalizability. Collaborating with international medical institutions can help in acquiring a more comprehensive dataset.

**Integration with Electronic Health Records (EHRs):** Integrating the system with EHRs can provide a more holistic view of a patient's health, allowing for personalized diagnosis and treatment plans. This integration can also facilitate longitudinal studies to monitor disease progression.

**Real-time Processing and Deployment:** Enhancing the system to support real-time image processing and deploying it in clinical settings will be crucial for practical applications. This involves optimizing the model for speed and ensuring it meets regulatory standards for medical devices.

**Multi-modal Data Integration:** Incorporating additional data modalities, such as patient history, genetic information, and other diagnostic images, can improve the accuracy and comprehensiveness of the diagnosis.

**Patient and Clinician Feedback Loop:** Establishing a feedback loop where patients and clinicians can provide input on the system's performance and usability will help in continuously refining and improving the interface and functionality.

**Continuous Learning and Adaptation:** Implementing mechanisms for continuous learning where the model can be updated with new data and feedback will ensure that the system remains current with the latest medical knowledge and practices.

**Exploration of Other Medical Applications:** Extending the framework to detect other ocular diseases or even other types of medical conditions using similar techniques can broaden the impact of this technology.

**Regulatory Approval and Ethical Considerations:** Working towards obtaining regulatory approval for clinical use and addressing ethical considerations related to AI in healthcare will be essential for the widespread adoption of this technology.

By pursuing these future directions, we can further enhance the efficacy, reliability, and adoption of AI-driven solutions in healthcare, ultimately contributing to better patient outcomes and advancing the field of medical diagnostics.

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