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AI-BASED MEDICAL IMAGE PREDICTOR USING CONVOLUTIONAL NEURAL NETWORKS FOR MULTI-DISEASE DETECTION

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Abstract
AI is developing very fast and has really changed medical imaging, giving us new ways to be more correct and quicker at diagnosing illnesses. Looking at medical pictures like X-rays, CT scans and MRIs generally needs a specialist with lots of training, and it can take a while, which could mean a diagnosis is delayed. This is a big issue in many places, in particular if finding a skilled radiologist is hard. We've created an AI system to help doctors and other healthcare staff examine medical images. It uses a sophisticated form of learning called deep learning, and in particular, Convolutional Neural Networks (CNNs), to spot things like broken bones, pneumonia and brain tumours. It's a program you use on the internet: you upload a picture and it gives you its idea of what's wrong, and how sure it is. When we tried it out, it did a good job with all sorts of medical images, though how accurate it is affected by the image's quality and how much data it has been trained on. But even with these difficulties, it looks like a good way to help with diagnosis, not to replace doctors. In short, this shows how AI can be included in the usual way medical images are used to lessen the amount of work done by medical staff, work more quickly and give doctors more help when they are deciding on treatment.

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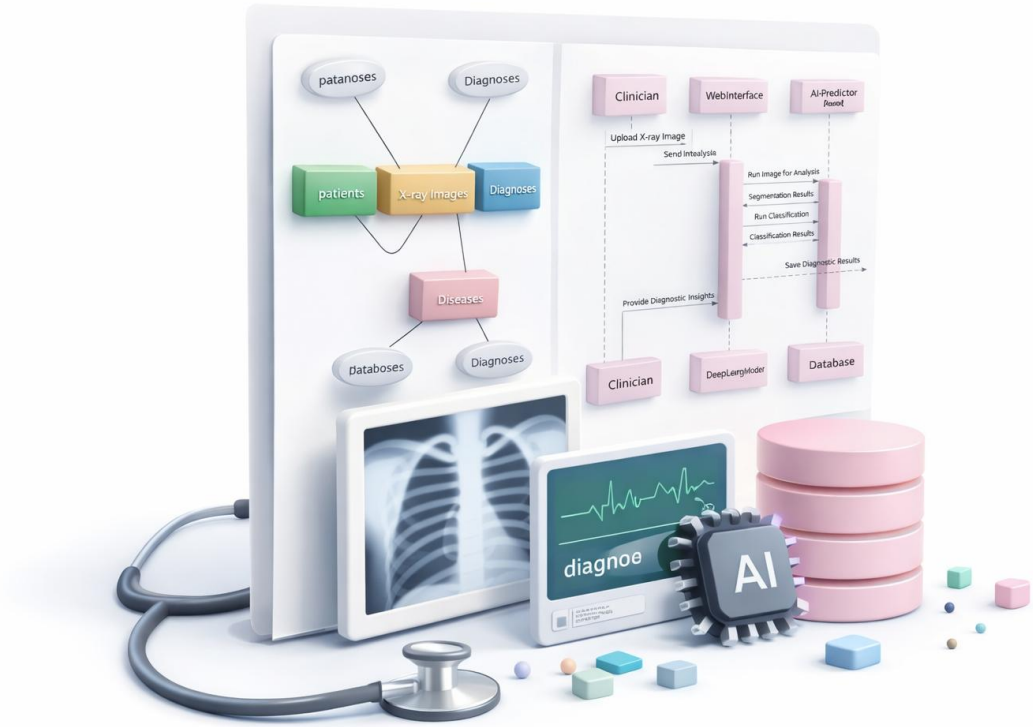

1. Introduction

AI, and particularly the more recent deep learning approaches, has improved a lot and is beginning to change how doctors do their jobs, notably when looking at medical images. X-rays, CT scans, MRIs - these all show what's going on inside of you, and discovering health issues early is very dependent on specialists interpreting these images rapidly and correctly. Unfortunately, many hospitals don't have sufficient trained radiologists, and as a result doctors often find themselves waiting longer for diagnostic results than they'd prefer. Some people have developed an AI-powered program you use on the internet to look at medical pictures. Doctors, or even other staff at the hospital, can upload the scans and the program rapidly indicates sections of the picture that appear unusual; this could be a fracture, a problem with the lungs, or something that isn't typical in the brain. This way, instead of carefully studying every single bit of detail in an image, doctors are shown the locations to concentrate on. What's good is that the AI isn't meant to be a doctor, it's more of a speedy assistant and is less prone to overlooking critical details. This means less waiting for results and better information when making patient care choices. By reducing some of the more complex parts of video review, doctors can spend more time with patients, act more quickly when something goes wrong, and generally make things easier in the hospital.

The bigger hope is that technology like this will gradually raise the level of care for everyone, not just where there are many radiologists. Looking at medical photos by hand is hard work. It takes a lot of knowledge and years of practice, and even then, you can still miss something - especially now with more scans to review. Hospitals and clinics around the world are struggling to keep up with a shortage of trained radiologists and an ever-increasing workload. All of this can mean patients wait longer for answers, doctors stretch, and sometimes details are missing. Although one may be very competent, certain changes in the scan such as a small crack in a bone or initial pneumonia symptoms are very easy to overlook particularly during a hectic day. This would result in a whole lot of pressure on the system. This is why we should have smarter tools to help us with some of the sifting. Intelligent software scanning can be used to accelerate the task, and our doctors can focus on what is important. It

can detect things which a tired eye may have overlooked and make the work of one individual a little drier. These tools are not designed to replace specialists but to support them, to pick up double-ups and help recognize trends. This lets our caregivers focus less on cross-checking every single thing and more on where they're needed most – caring for our patients.

The potential advantages of this tool developed by researchers at the University of Strathclyde and NHS Greater Glasgow and Clyde are to free up doctors' time so they can focus on the most seriously ill patients, make it easier and quicker for patients to see a Specialist if needed, almost eliminate human error in the AI's interpretations, and to get the right treatment to the right patient more quickly. The tool shows the results in an easy-to-understand manner so that doctors can immediately comprehend the situation and make decisions. It is designed to aid qualified medical practitioners by giving them an extra pair of "eyes", especially in regions where expert radiologists are scarce. There are multiple uses and examples of AI-Medical Image Predictor in the healthcare industry, the system can also be updated with information on new diseases, conditions, and medical cases to constantly improve its accuracy and efficiency. Additionally, it can be trained to focus on specific types of diseases based on the needs of the healthcare facility using it. Because it is web-based the system is deployable to a remote or resource-constrained environment where specialists' access in real time is not possible. This can be especially beneficial in the field of telemedicine giving healthcare providers the opportunity to benefit from AI-assisted analysis independent of their location.

The system can also be implemented in PACS (picture archiving and communication systems) solutions directly, providing instantaneous generation of reports in the clinically relevant format. This can save a tremendous amount of time for radiologists. The system offers a basis on which to conduct additional research on AI-based medical imaging. It can generalize to other diseases, better models, and other imaging modalities, which will lead to the innovation of this field. The technology makes it feasible to carry out extensive disease screenings in regions with limited treatment capabilities, much like how pneumonia can be detected early on in patients, thereby improving their chances of successful treatment and recovery. This system is based on deep learning principles to be specific Convolutional Neural Networks (CNNs) which are widely used for computer vision. The system utilizes trained models which take images as input and process them in terms of different layers. These layers are convolutional layers, pooling layers, and fully connected layers.

2. Literature

The latest methods have shown significant advances in medical image analysis using deep learning techniques. Deep learning covers computer vision, natural language processing, and games closely aligned with the evaluation of medical images that radically redefine how expert knowledge is modeled. It also touches on deep learning in practice and applications to computer-aided detection, quantification, and diagnosis. Modern deep learning techniques were also successful because of the pioneering efforts by scientists like Geoffrey Hinton et al., whose research took a major step forward in neural network training and allowed them to apply it to more complex tasks like medical imaging [11]. Conventionally, the process has been quite dependent on the skills of radiologists and other medical professionals who interpret images according to their anatomy and pathology understanding. But with the ongoing improvement in imaging technologies, medical data volume and complexity has grown dramatically. This has increased the time-consumption of manual analysis and in certain instances, the delays or human error. Consequently, the excitement has increased to create automated and semi-automated systems to assist in interpreting medical images and offloading healthcare professionals. [3].

Machine learning and deep learning as a subdivision of Artificial Intelligence (AI) have opened up new opportunities in the field of medical image analysis. Such techniques can be trained with huge amount of data to determine patterns and features related to certain medical conditions. In radiology, AI is utilized in some of the most important spheres: Detection: The

detection of abnormalities, lesions and unusual patterns in medical images. Classification: This is the classification of the images depending on the presence or type of disease like the difference between healthy and infected lungs. The purpose of these applications is to enhance diagnostic accuracy, decrease the time of interpretation, and improve consistency between practitioners. The AI-Medical Image Predictor fits these objectives as it is aimed at the detection of various conditions, including bone fractures, pneumonia, and brain tumors, with the use of multiple imaging modalities. [4].

A notable advancement in this domain is CheXNet, a deep learning model that achieved radiologist-level performance in detecting pneumonia from chest X-rays, demonstrating the real-world applicability of AI in clinical diagnostics [15]. Deep learning, especially deep convolutional neural networks (CNNs), which have shown promise in many image analysis tasks, have recently been applied to medical image analysis. Like natural images, medical images contain patterns and structures that vary in size and location; and medical classification and segmentation tasks associated with images are computationally complex [5]. The advancement in deep learning can be explained by some breakthroughs like AlexNet which proved the efficiency of deep Convolutional Neural Networks (CNNs) in image classification tasks in a large scale [12]. This innovation opened up the application of CNNs in medical images. Convolutional Neural Networks (CNNs) are one of the most popular deep learning architectures used for image-based tasks. CNNs are specifically used to learn spatial features in an image. These range from learning low-level features like edges to higher-level features that might relate to the anatomy of the content.

A typical CNN is comprised of the following components:

I. Convolutional layers to extract features
II. Pooling layers to reduce dimensions
III. Fully connected layers for classification.

Different architectures, AlexNet, VGG, ResNet, Inception, U-Net etc, have been used with substantial success in medical image analysis showing good results in disease detection and classification tasks. we used these well-established CNN models including the pre-trained networks for image classification to facilitate disease diagnosis. [6]. More sophisticated architectures like Residual Networks (ResNet) have also greatly enhanced training of deep neural networks by resolving the vanishing gradient issue, consequently leading to the creation of highly accurate medical image classification systems [13]. Furthermore, segmentation-based models such as U-Net have demonstrated exceptional performance in biomedical image segmentation, allowing precise localization of abnormalities in medical scans [14]. However, despite the performance gains these methods offer, the feasibility of applying them to a wide range of tasks in numerous clinical scenarios is unclear. For instance, many of these systems rely on high-resolution images, which are not universally available in clinical practice. Additionally, the large memory and compute demands of these deep learning models may limit their applicability on standard hospital workstations. Some are integrated into hospital systems such as PACS, while others are web-based tools to facilitate easier access.

The AI-Medical Image Predictor solution is designed to be more integrated and overarching, by enabling support for multiple diseases and image types of a single solution while ensuring it is user-friendly. [7]. Sometimes AI systems make difficult to understand decisions which may act as a barrier to their acceptance and trust by health care providers and patients. The transparency of the way certain AI tools are created may result in the inability to reproduce results in other situations. AI algorithms can be trained using data that inadvertently includes biases, and their use creates biased treatment decisions. Healthcare workers may be reluctant to accept AI if they think it will replace them or radically change their workflow. The rapid development of AI in healthcare has outpaced the creation of laws and regulations to ensure its safe and ethical use. AI systems learn from the data they are trained on, which can contain biases. If this data is not representative, it can lead to biased outcomes.

AI systems have to comply with existing regulations and suitably integrate with a hospital's system.

Data privacy and ownership, avoiding bias in data and algorithms, and finally, the application's role in the decision supporting process are very important ethical issues to tackle. The computational requirements associated with training and deploying deep learning models are tremendous, thus requiring a compromise to be found regarding model size and prediction performance. Many research studies have been conducted using deep learning specifically CNNs for image data analysis in the medical field. For instance, pneumonia detection has been studied using deep learning CNN models trained on large datasets like ChestXray8 and MIMIC-CXR, and CNN architectures such as ResNet and DenseNet have been applied to the task resulting satisfactory classification results.

Other studies related to image-based detection focused on both fractures in X-ray and CT images using segmentation techniques like the U-Net and detection techniques like the Faster R-CNN. Moreover, in brain tumor MRI-based studies, CNN models have been developed to segment image data using models to identify tumor boundaries and other models for classification to type the tumor.

3. METHODOLOGY

This chapter introduces the methodology that was used to develop the AI-Medical Image Predictor system. It includes the software development approach, the techniques used to ensure that the system's requirements were met, and the design artifacts employed to model the structure and function of the system. The main purpose of this chapter is to explain how the development process of the system was organized, and how the implementation was carried out in a systematic and manageable way. An SDLC model basically provides a path for efficient and robust software development. There are multiple SDLC models like Waterfall, Agile, Spiral, and Incremental SDLC. Each has its own pros and cons. For this project, we have chosen Incremental SDLC because of its flexibility to accommodate changes in requirements of the software systems.

The Incremental Model breaks the system development life cycle into small parts, where each part of the software is developed and tested during the iteration phase. Rather than creating the entire system at once, the product is delivered part by part. Its key phases will include timely completion of each component of the project. Get timely feedback of your users. Less risk as compared to larger-scale projects. Benefits here are quick response and adaptation to changes, quick response and adaptation to changes, in person discussion and feedback, driven people and their communications. self-organization and motivation of teams. These architectures are quite the right choice in the design of AI based systems since such aspects of the system as image prediction, integrating the model, improving the user interface, and so on could be created one after another. You can start a project off with the base features (image upload and prediction), then add more features (reporting, visualization) and further improvements to existing features (models). They give details on how the system interacts with the users. In the case of the AI-Medical Image Predictor system, the user is able to upload medical images, choose the models of analysis and receive the prediction. The functional requirements that are shown in Table 3.1, are bundled together in modules depending on some system behavior, meanwhile nonfunctional requirements are shown in Table 3.2.

Table 3.1: ***Functional Requirements of the System***

S.No	Functional Requirement	Description
1	User logins	Allows users to login safely
2	Role-Based Access Control	Restricts access based on user roles (Admin/User)
3	Image Upload & Preview	Enables uploading and previewing medical images
4	Model Selection	Allows users to select AI models for analysis
5	Image Preprocessing	Prepares images (resize, normalize) before prediction
6	Prediction Execution	Runs AI models to analyze images
7	Results Display	Confident predictions are shown

S.No	Functional Requirement	Description
8	Visualization	Handels higlights
9	Report Generation	Report on predictions is generated
10	Data Storage	Stores analysis results for future retrieval
11	Admin Control	Allows management of users and models
12	Error Handling	Handles invalid inputs and system errors

The individual in charge of overseeing the system and ensuring that it functions appropriately. This includes responsibilities such as:

I. Ensuring that only authorized individuals have access and grant the necessary permissions
II. Monitoring activities through logs that record all actions
III. Maintaining the AI models (developing, updating, and deploying them)

The system is intended to be used by healthcare professionals. The tasks they do are as follows:

They perform the following tasks:

i. Uploading medical images
ii. Selecting required model for analysis
iii. Viewing predictions along with confidence scores
iv. Interpreting visual outputs (heatmaps, annotations)
v. Reports generation and export
vi. Profile management

Supervisory responsibilities can be seen as three wide-ranging overall objectives. These are not viewed as a distinct compartmentalized module, but supervisory responsibilities might be conceptually viewed as Related to supervision over:

I. The use of the system.
II. The performance of the system.
III. The improvement of the system.

Table 3.2: ***Non-Functional Requirements***

S. No	Requirement	Description
1	Performance	Fast model loading and prediction time
2	Accuracy	High accuracy of predictions
3	Availability	System available 24/7
4	Security	Patients data is securely handling
5	Efficiency	Optimal use of CPU, GPU, and memory
6	Scalability	Supports multiple concurrent users

To gain a better understanding of the system several design diagrams are utilized that can assist in making the connections between different parts and the flow of data through the system more visible. Use case diagrams that is mentioned as Figure3.1, represents the interactions between users and the system.

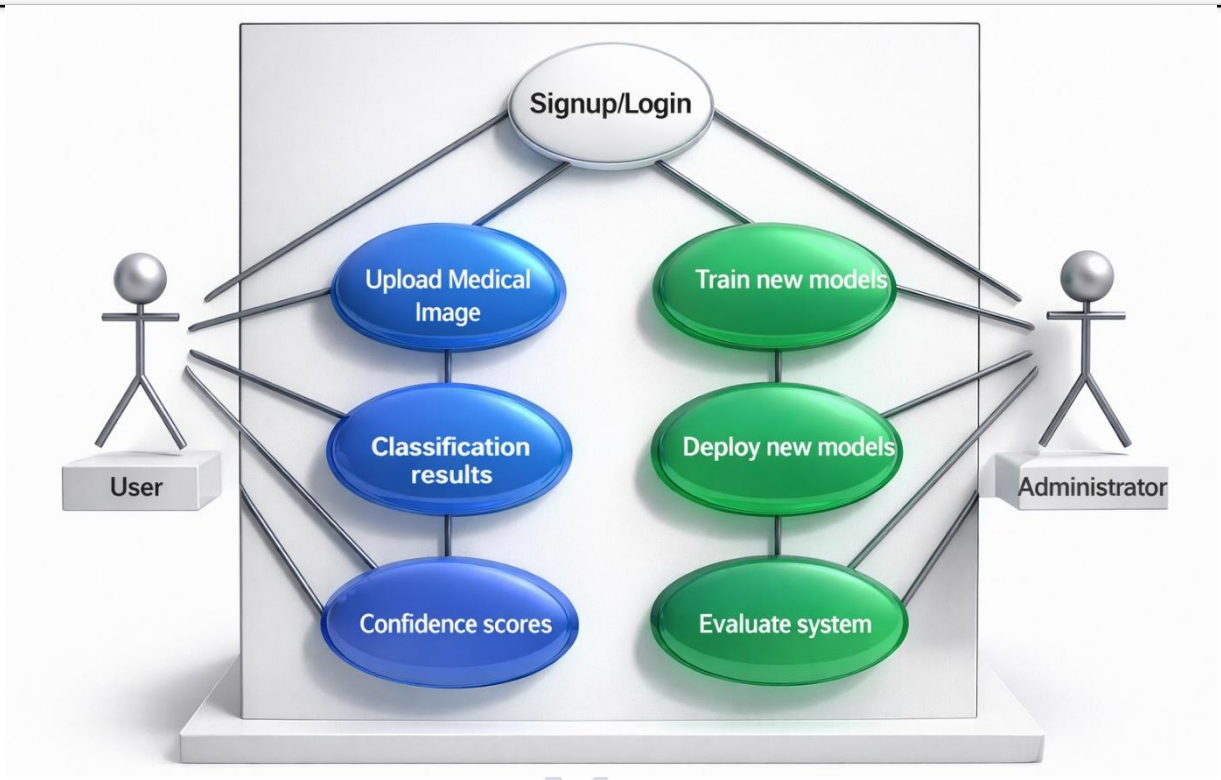

Figure 3.1: Main Use Case Diagram of the AI-Medical Image Predictor System

Administrator Use Case: Focuses on system management and model control which can be seen in Figure 3.2.

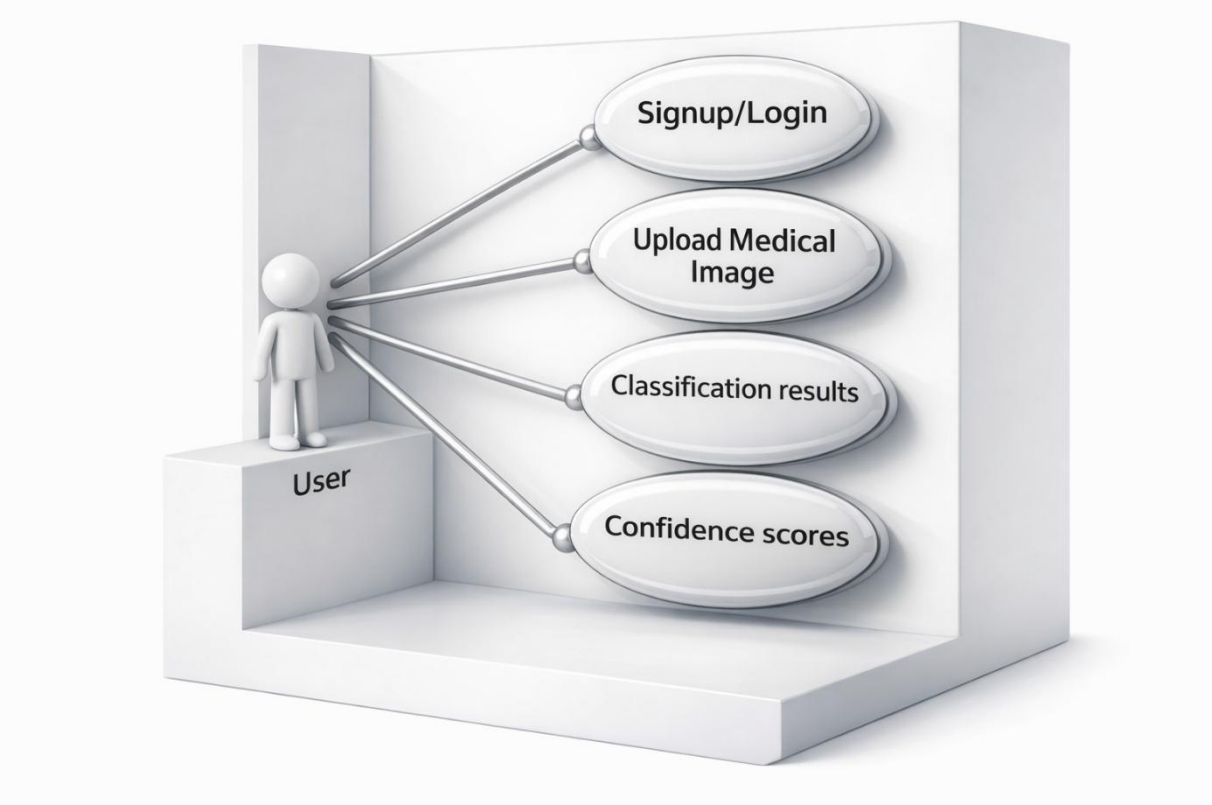

Figure 3.2: Administrator Use Case Diagram

Researcher/Developer Use Case diagram form Figure 3.3, focuses on extracting and utilizing deep learning features from the OMOP Common Data Model to integrate a variety of clinical data types including imaging data.

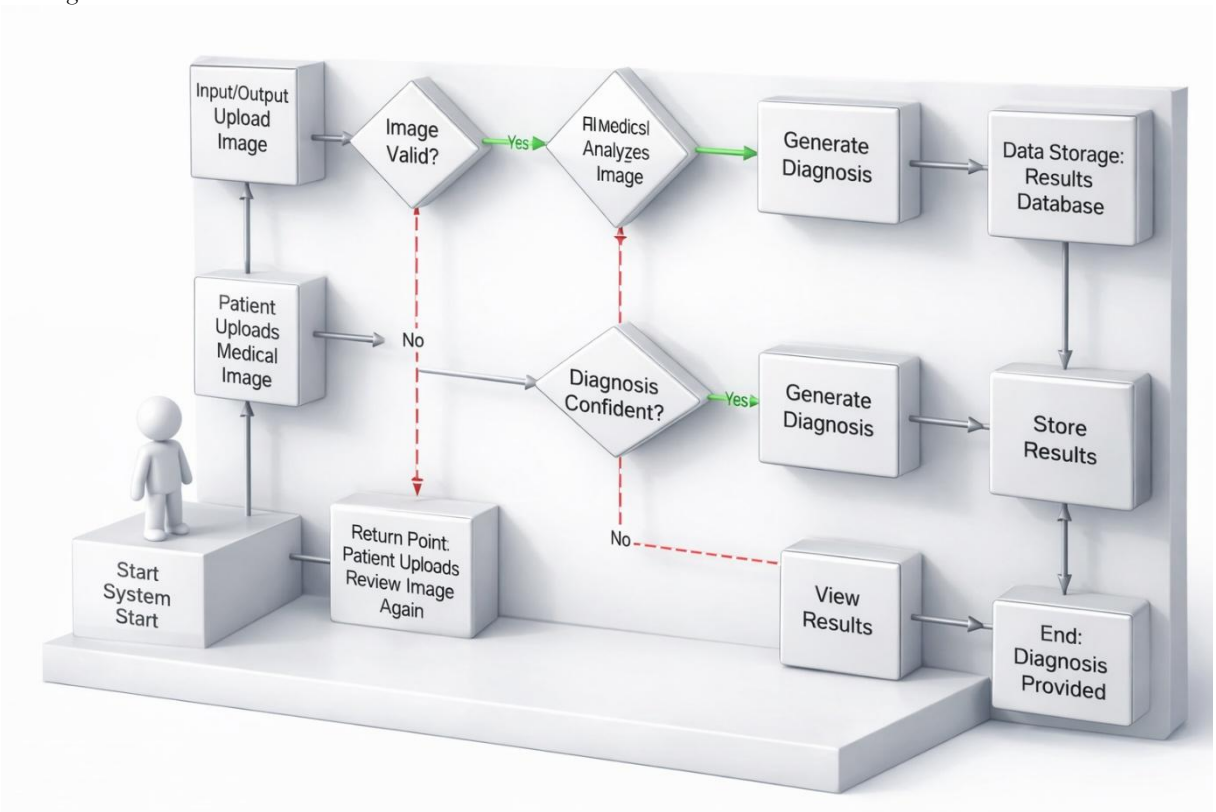

Figure 3.3: User/Clinician Use Case Diagram

The system flow diagram from Figure 3.4, depicts the entire system of medical image analysis, starting with the uploaded image to the final result generation.

The workflow includes:

a) Image upload
b) Validation
c) Preprocessing
d) Model prediction
e) Confidence evaluation
f) Storage and display of results.

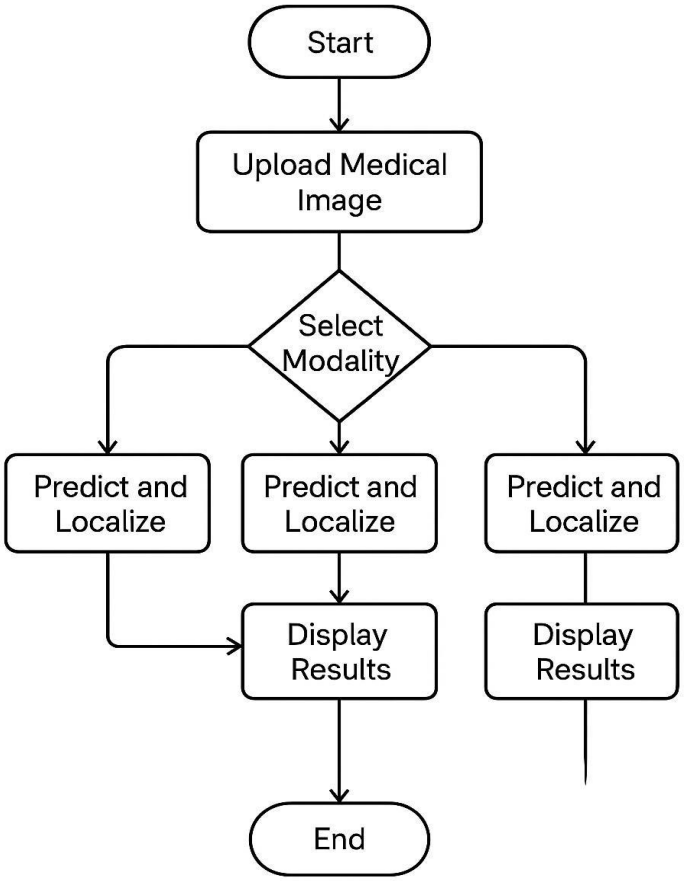

Figure 3.4: System Flow Diagram for Medical Image Analysis

Activity diagrams visualization from Figure 3.5, depicts the step-by-step workflows of the following users:

I. Administrator (user management, model management)
II. User (image upload → prediction → results)

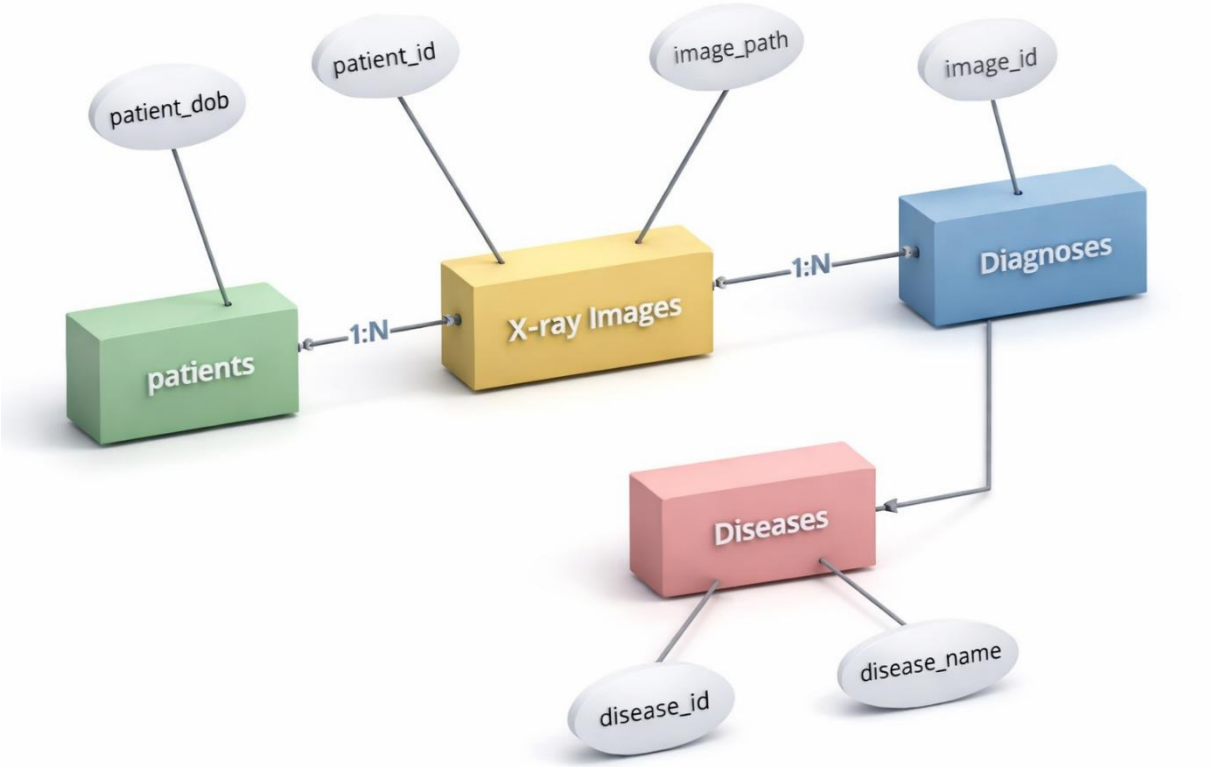

Figure. 3.5: Activity Diagram of the System Workflow

The Entity Relationship Diagram mentioned as Figure 3.6, establishes how the database is structured and how the entities of the system relate to one another. In this case, the entities are: Patients, Medical Images, Diagnoses, and Diseases.

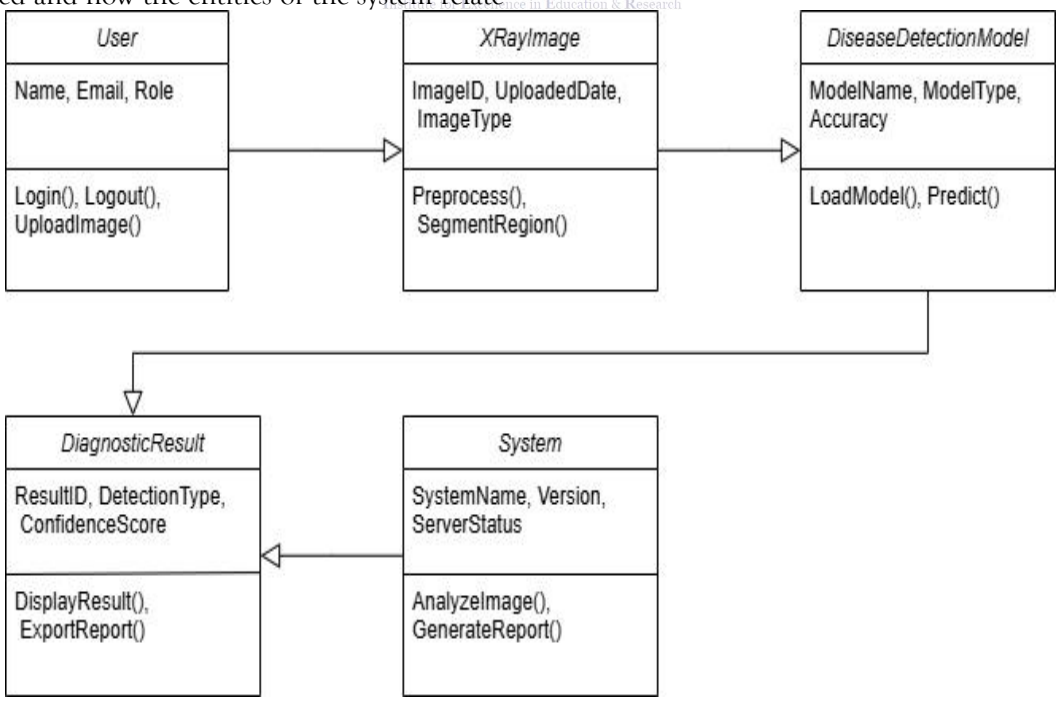

Figure 3.6: Entity Relationship Diagram (ERD)

The class diagram from Figure 3.7, shows the components of the system and their relationships as follows:

i. User
ii. Image
iii. Model
iv. Prediction result
v. System controller

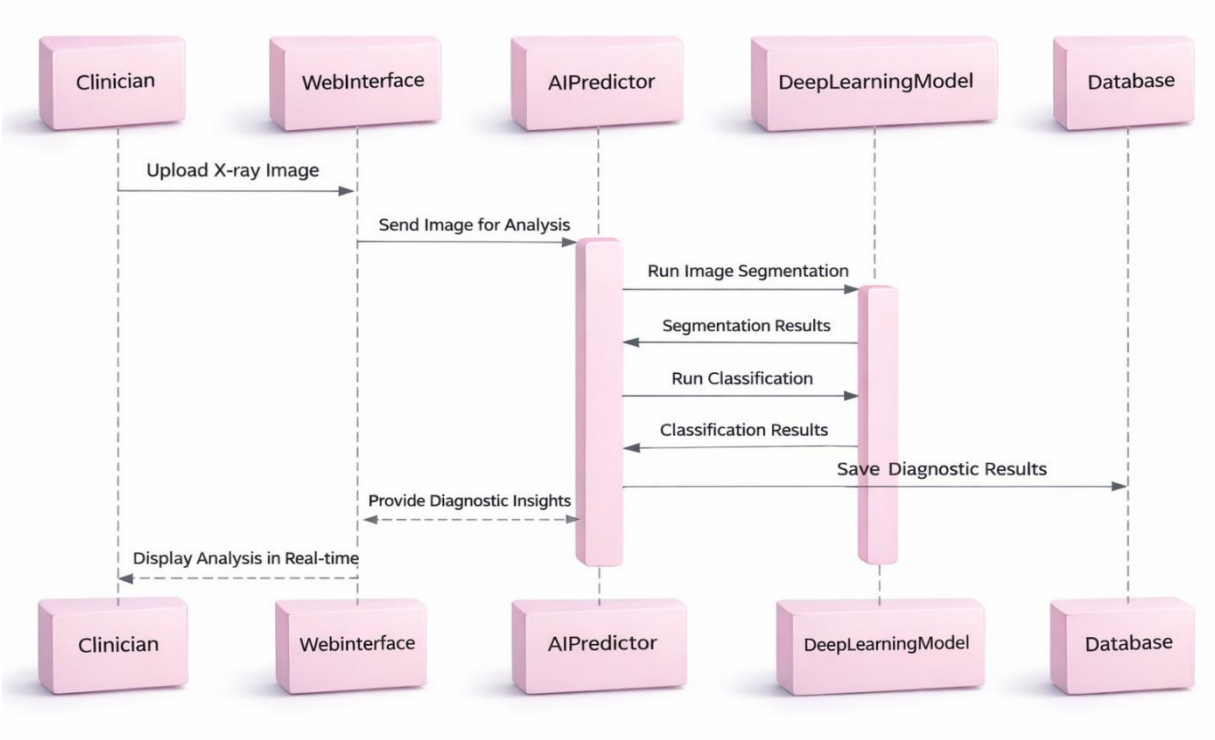

Figure 3.7: Class Diagram of the System

The user first uploads an image, then this input is processed by the system, after which the model makes a prediction based on the processed input, and finally, the results are returned and stored. This sequence is visualized in Figure 3.8.

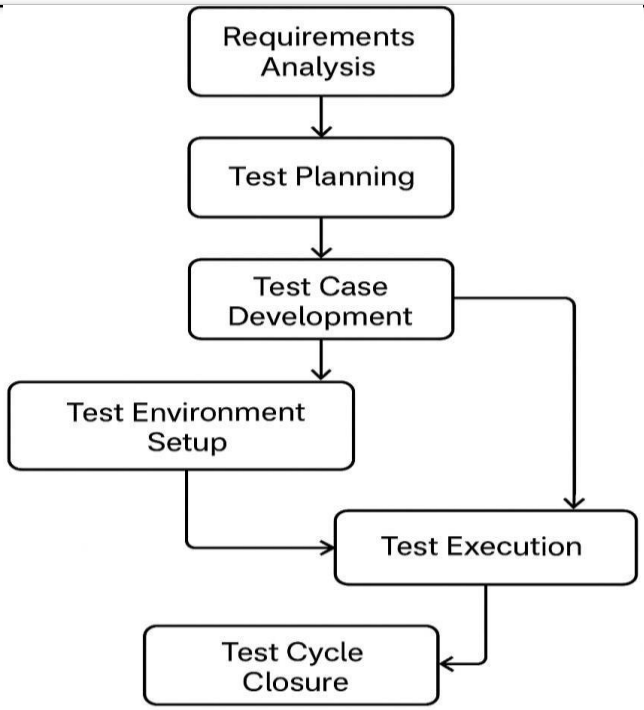

Figure 3.8: Sequence Diagram for Image Analysis Process

Testing the AI-Medical Image Predictor at various stages of development is a necessary and time-consuming activity. Testing starts at the development level with the testing of individual components and continues until the product is fixed and officially released, also known as the final version. To make sure that the system fulfills all the requirements and works as intended, it was tested extensively at unit as well as system levels. The unit was tested by testing components individually without integrating them into the system, to detect and correct errors at an early development stage. System testing, on the other hand, was performed on a complete, integrated system to evaluate its compliance with the specified requirements. The object testing is where software behavior is tested whether the software is behaving correctly or not. We conducted a trial of all system functions, including the user registration and the login page, the process of uploading images, the process of model selection and the generation of all the reports.

Testing was also done through evaluating the capability of the AI model with regard to the alignment of its prediction of reality. This is possible by computing various measures depending on the need that is to be met, sensitivity or false negative rate, specificity or false positive rate, precision, recall, etc. The testing is verified through a process where they are resized, normalized and or converted in a different format before running. We did usability testing to determine the ease of use of the system to the end-users. The following are our findings: The majority of users were able to use the system without much training. Users with no image analysis background were able to upload images and analyze them. Users were able to access the manual once they were demonstrated how to access it. We ran performance tests in order to measure how fast and responsive the system is in normal conditions. We measured these such:

I. How long does it take for the model to load?
II. How fast are those predictions made?
III. How quickly the interface responds to the us
IV. How many resources are put to used (CPU, memory, GPU)

We ran the compatibility tests to ensured that the system behaved as intended across different situations and platforms. We tested it on multiple operating systems (Windows, macOS, Linux), different web browsers (Chrome, Firefox, Safari) also including in this category mobile devices and tablets. The Load testing was done to evaluate

system behavior Inder the case of multiple users. Key findings:

i. The system maintained stable performance under moderate load
ii. No major performance degradation was observed
iii. Scalability can be improved further with enhanced infrastructure

This will make sure that all sensitive medical data will be protected. For this, we checked:

I. User authentication method
II. Multiple ways of accessing
III. Ways of Data Encryption
IV. Input validation
V. Audit logging

Installation testing ensured that the system is successfully installed on the target environment which involved: installing-testing deployment in server/cloud platforms; dependency installation checking; and system accessibility checking upon installation. The system could be successfully installed-operated with no blocking points. We developed these test cases in order to specific system functions. These test cases covered the following scenarios:

I. User registration and user logins
II. Administrator access control
III. Image upload and model selection
IV. Prediction display and visualization
V. Invalid input testing and error handling
VI. View analysis history

4. RESULTS AND DISCUSSION

This chapter will contain a detailed explanation on the revenue stream of the proposed startup. This revenue plan will describe the key sources of revenue that the proposed startup will have. It will also define the approach that the startup will be using to get revenue from the customers. In this part, we concentrate on demonstrating the system through the actual results. We present our observations from hardware and software perspectives as well as demonstrate the implemented features. While the project is mainly of a software nature, the system's performance is very much influenced by the capabilities of the hardware too. The following aspects were checked in testing. We tested how long our predictions take to generate with varying image resolutions using low, medium, and high-quality inputs. Unsurprisingly, higher-resolution images lead to longer prediction times, as do higher loads on the system. However, network latency and model design also play a role.

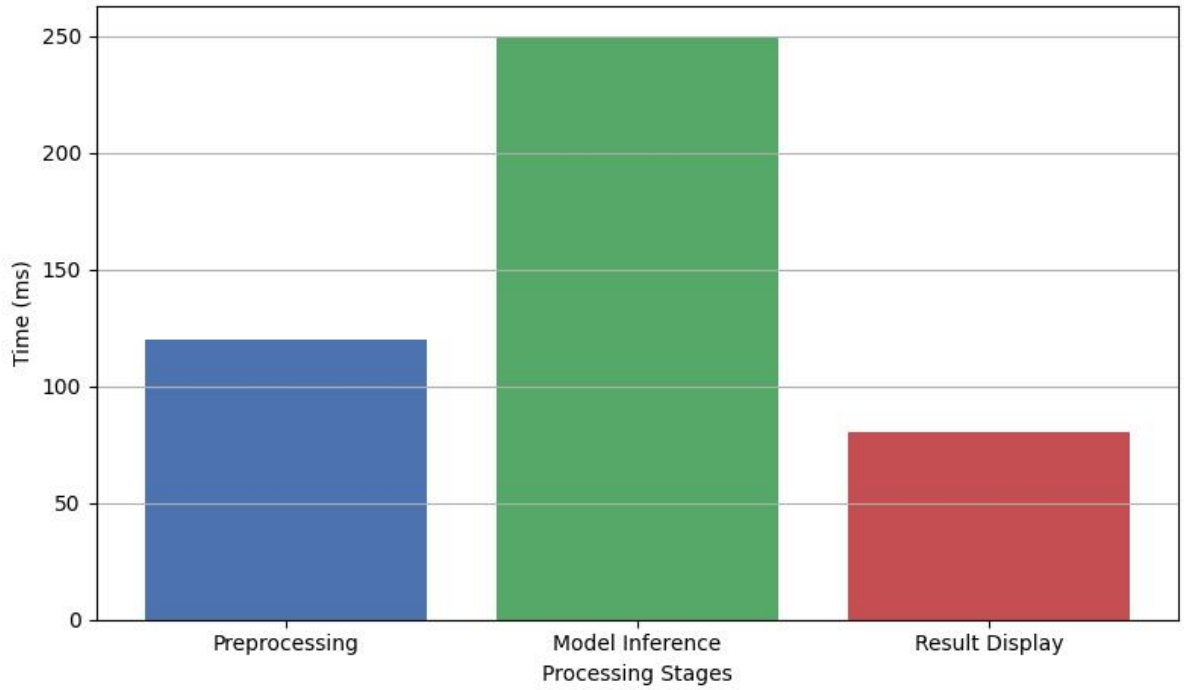

Figure 4.1: Processing Time Breakdown Across System Stages

We monitored performance of the system regarding CPU, GPU, and RAM load when preprocessing, loading the model and predictions which are presented in the Figure 4.1, and Figure 4.2. It seems that the system will be effective in normal conditions, yet, naturally, a greater load would require more computing resources.

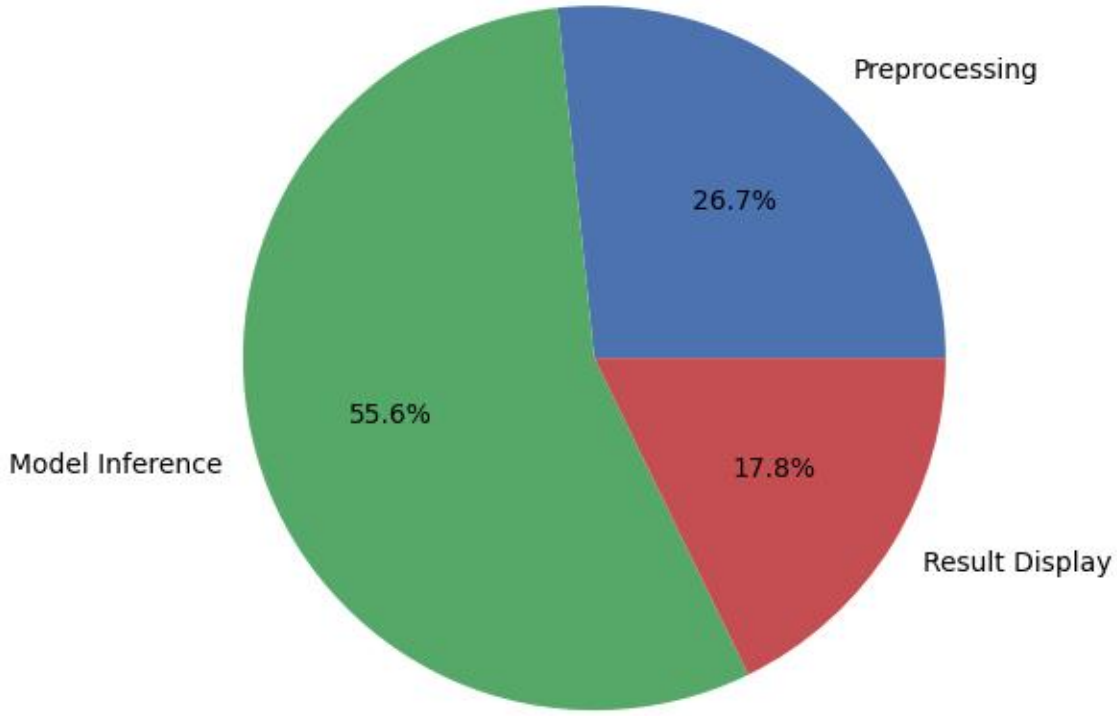

Figure 4.2: Processing Contribution by System Components

Our load testing showed that the system can handle low to moderate user load which can be seen in Figure 4.3, but that the performance would probably not remain as high as it is at low to moderate loads as shown in the Figure 4.4. This implies that in the future, cloud elasticity, and/or more efficient resource setups might be implemented to support more simultaneous users.

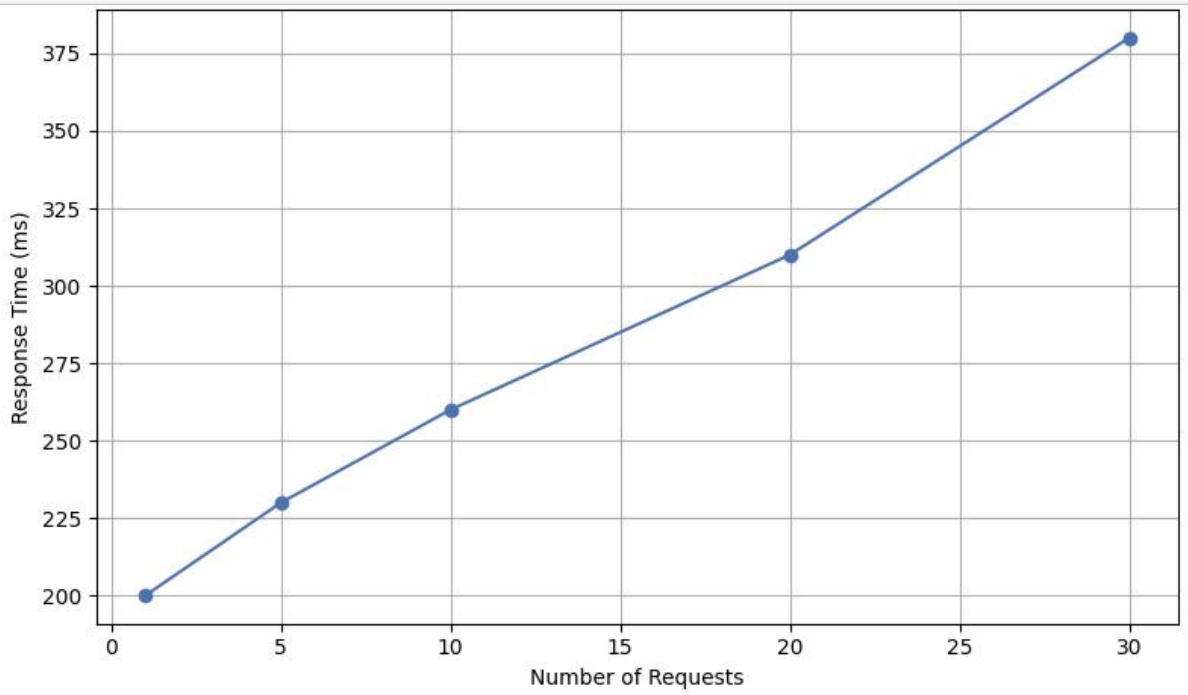

Figure 4.3: Response Time vs System Load

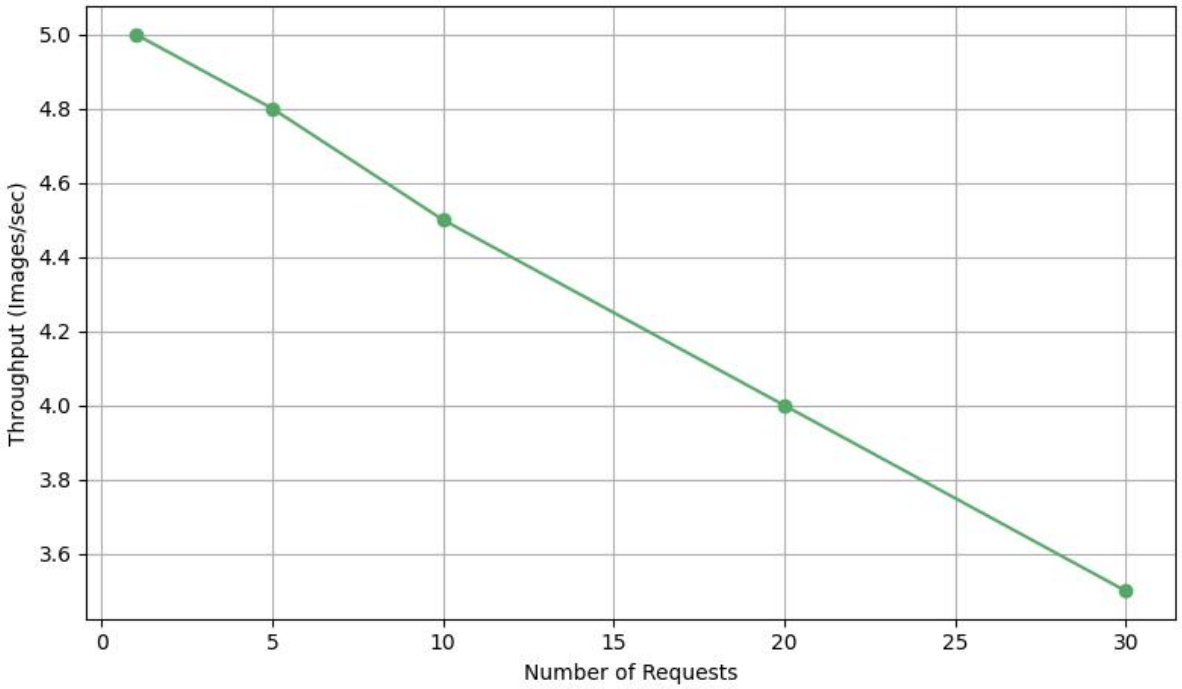

Figure 4.4: System Throughput Under Increasing Load

The software shows the easy and friendly interaction between the user and the model

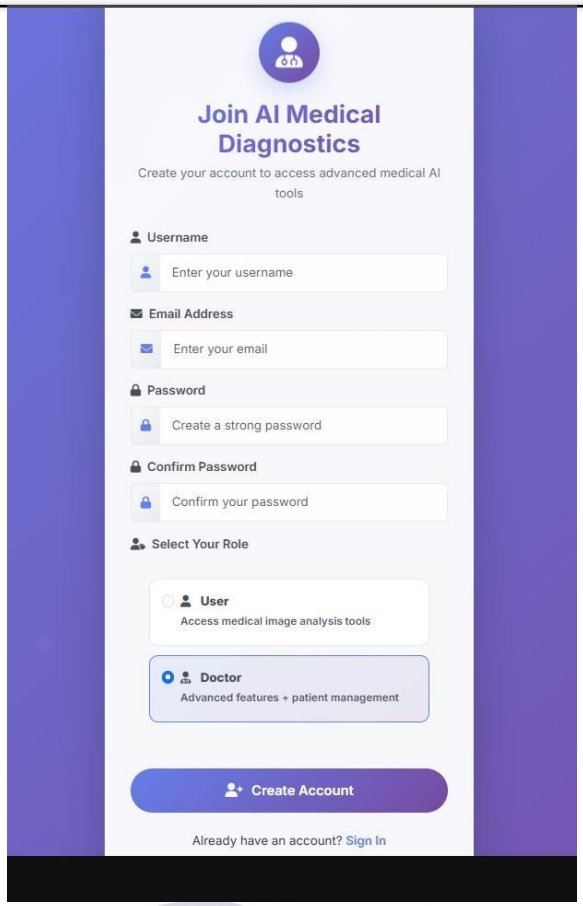

Figure 4.5: User Registration Interface

This user interface which is shown in the Figure 4.5, allows new users to sign up by providing some fundamental information such as name, email, and password.

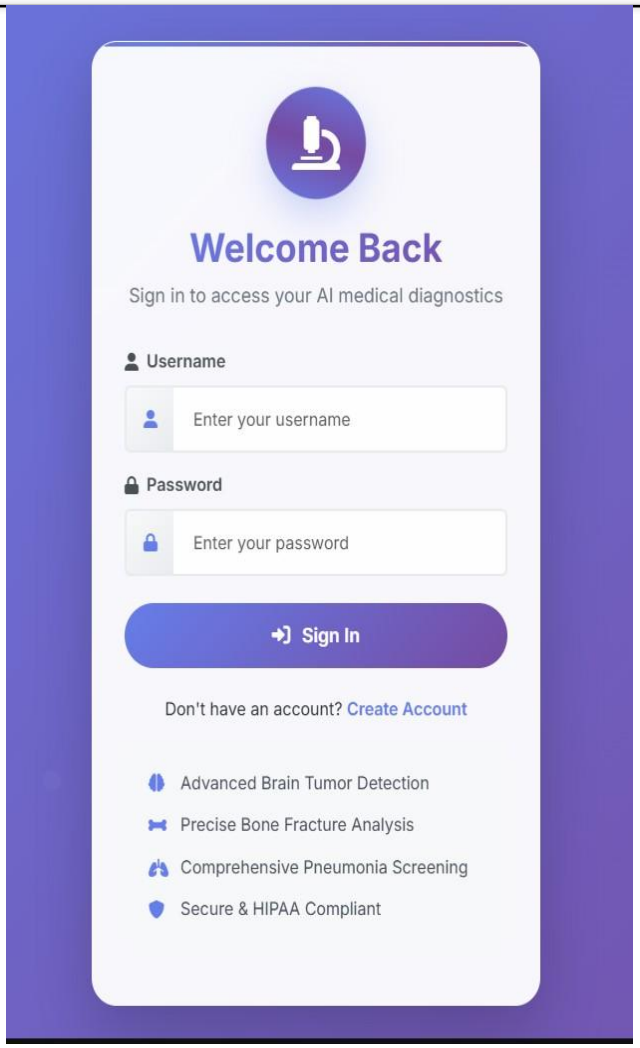

Figure 4.6: User Login Interface

In order to gain access to the system, users are required to enter their login details and upon successful authentication will be redirected to the main dashboard exactly like the Figure 4.6, presents.

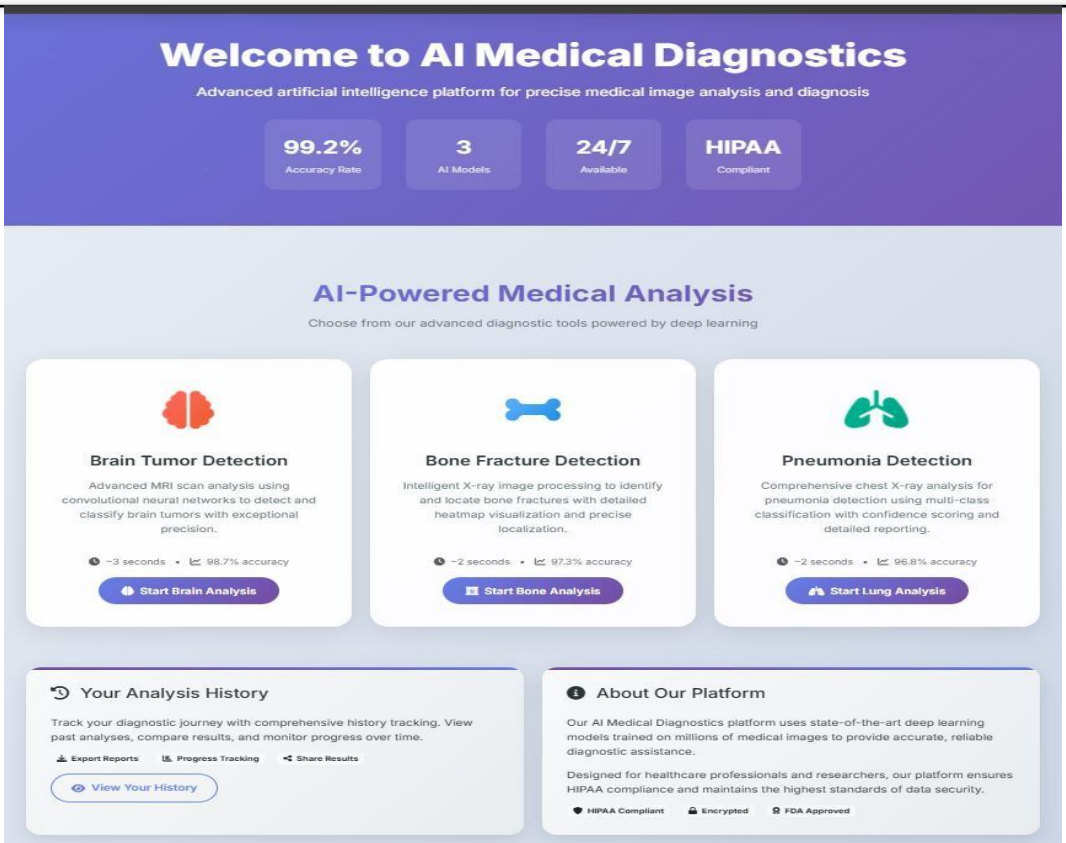

Figure 4.7: Main Dashboard Interface

The dashboard which is presented in the Figure 4.7, is the primary workspace where users can select a type of medical condition and begin the analysis.

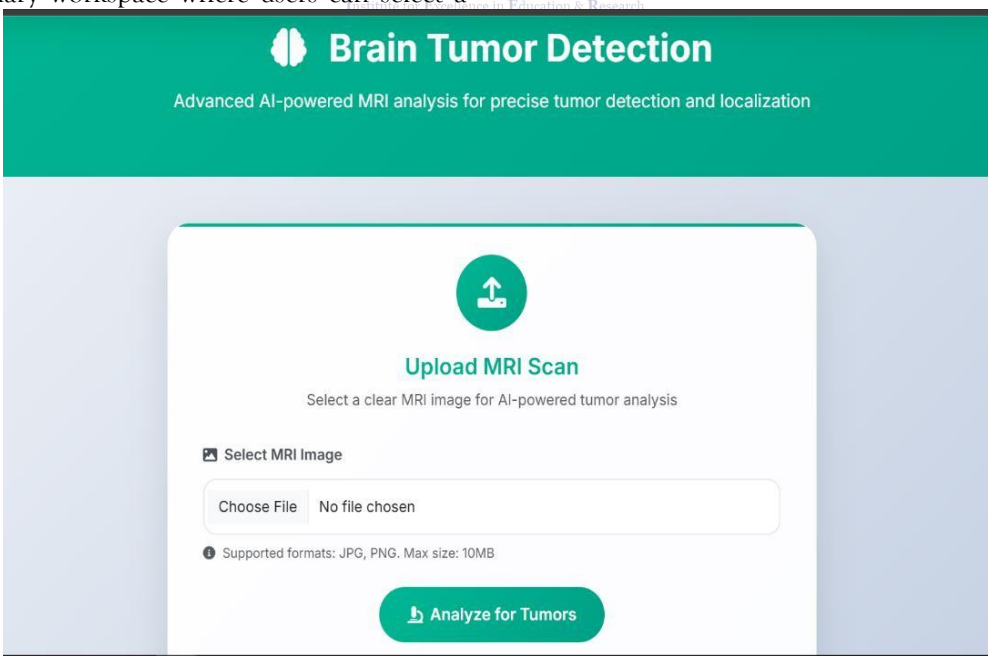

Figure 4.8: Image Classification Interface

On this page which the Figure 4.8, presents, you will be able to visualize the results of the image analysis, which include the predictions as well as the associated confidence scores.

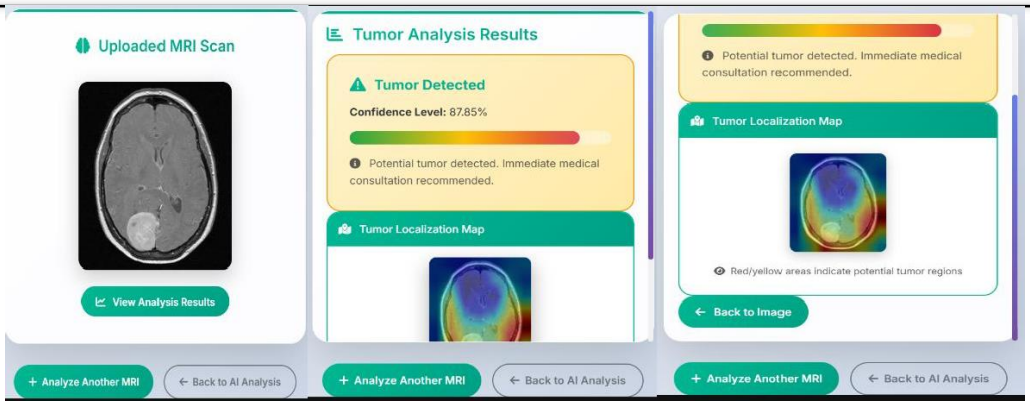

Figure 4.9: Prediction Results Interface

The final output interface shows the input analyzed images, the model predictions, and optional visualizations, such as heatmaps just like shown in the Figure 4.9.

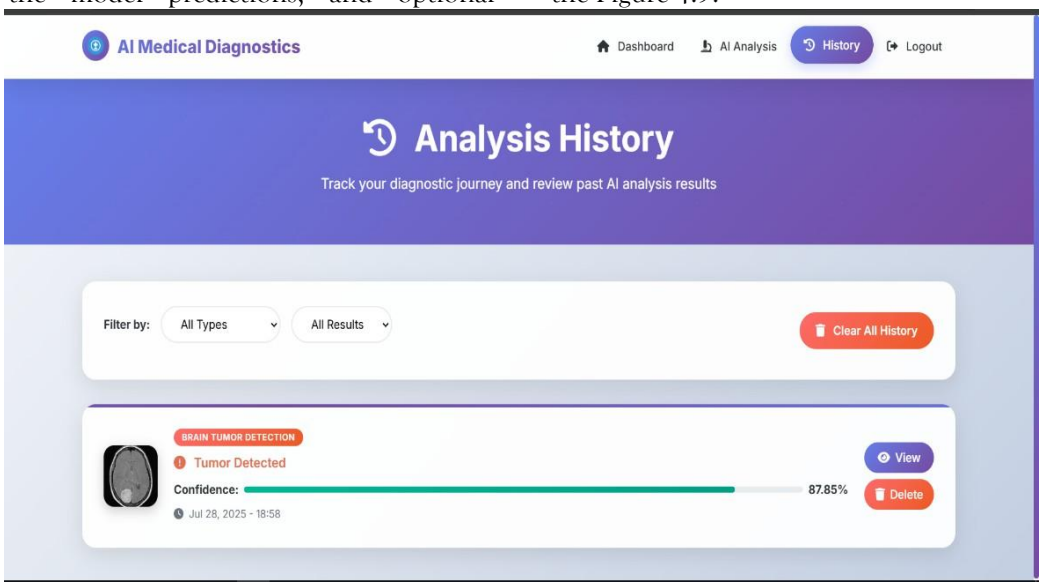

Figure 4.10: User Analysis History Interface

Historical reports are available to customers, in addition to prior forecasts and other pertinent data. This interface is presented in the Figure 4.10.

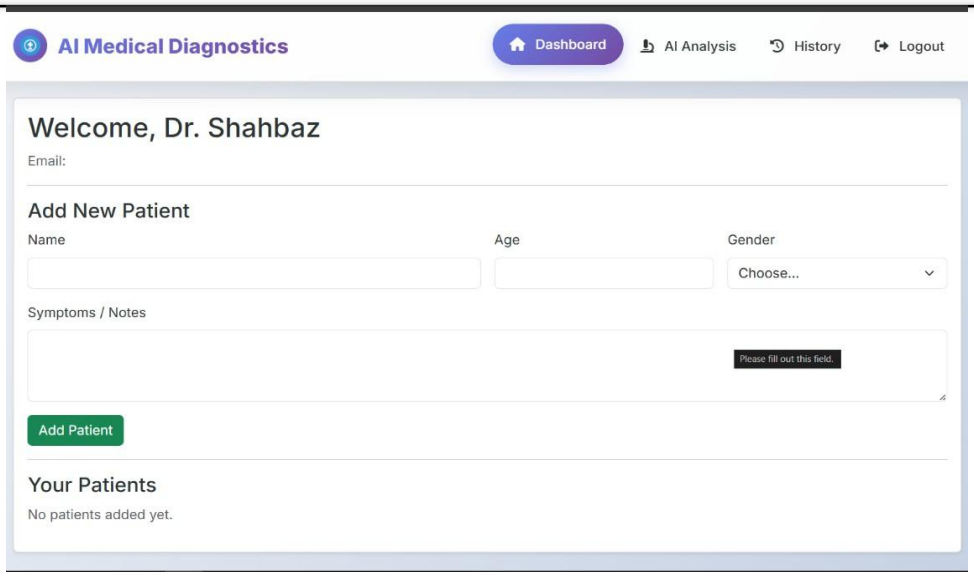

Figure 4.11: Patient Information Form Interface

Figure 4.11, presents patient information. Doctors fill out this form before conducting an examination of the patient.

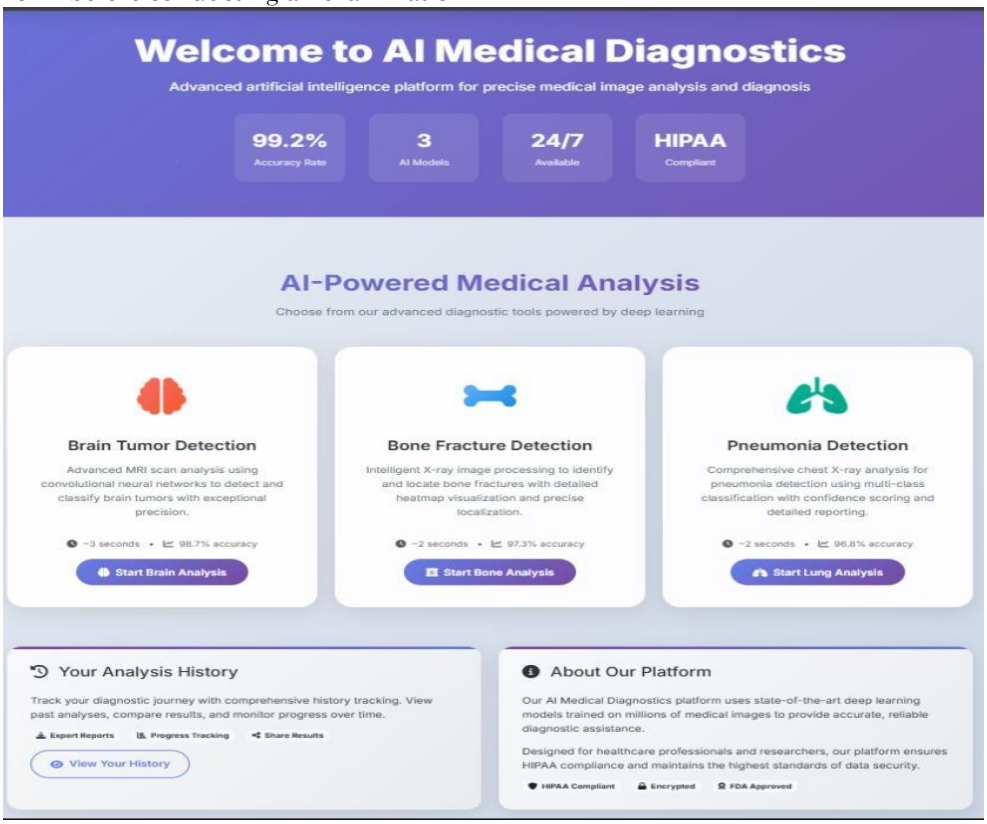

Figure 4.12: User Dashboard Interface

Figure 4.12, shows user dashboard which allows ease by starting a piece of work, and retrieving from memory a finished work, is available to the consumer meanwhile Figure 4.13, shows administrator dashboard interface.

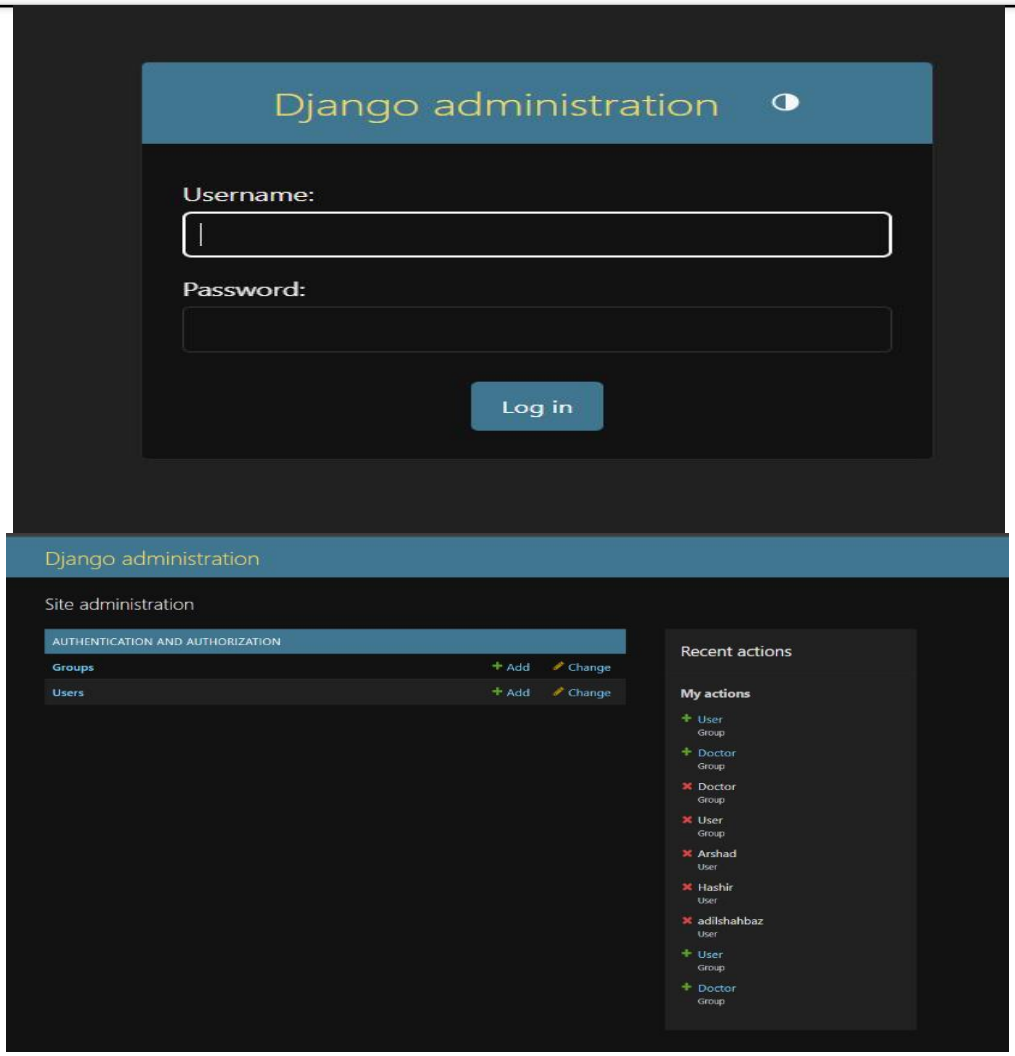

Figure 4.13: Administrator Dashboard Interface

Rephrase supports human-like rewriting of AI-created sentences. This part investigates the outcomes and the performance of the system in accordance with the original project objectives. Q. Comparison with Original goals. Q. Comparison with Initial Goals The machine fulfilled its purpose: The basic operations including uploading of pictures, choosing of models and showing of predictions worked as anticipated. Measures of performance (prediction time and responsiveness) were kept within the acceptable range. The model was highly accurate as it was able to achieve significantly close to the required threshold.

The interface was simple to use and comprehend.

Overall, the system is appropriate as a medical image analysis system to support medical professionals. While the project was overall successful, a number of limitations became apparent:

Not all intended features could be included as development time and resources were limited. Performance is inherently dependent on available hardware and concurrent system load. The quality and scope of results depend on the input data and limitations of the implemented models. The development of interfaces to applications and robotic systems presented more difficulties than expected. These limitations are typical for the development of AI-based systems and provide starting points for future work.

There are only certain diseases and imaging modalities for which most commonly used models are available. These models typically have predefined architectures, and only a limited

number of hyperparameters whose values can be modified during training. While fine-tuning some of the model's components is possible via transfer learning, the general architecture of the model must be an inherent part of the model design, and as such cannot be modified (short of using a different pre-trained model). Recommendations to enhance the system include adding more diseases to support and employing other types of medical images, better performance with a bigger and more diverse dataset, implement interpretability methods that can be used for enhancing trust in the suggested solutions, improve reporting and graphic display of results and performance measures, establish a feedback system that gathers feedback and incorporates it into the learning process. Take advantage of the improvements in AI software engineering to make the deployment, say in the cloud, effortless, better the implementation of the processing pipeline, e.g. by using containers, increase the security and compliance levels, since the system works with sensitive data.

5. CONCLUSION

The system developed offers an automatic medical image analysis system web-based, where users upload images and are given quick predictions. The system can effectively learn the discriminative features in medical images with minimal human effort by using Convolutional Neural Network (CNN) models. Its modular structure allows it to be flexible, making it easy to integrate various disease detection models and it can be easily expanded in the future. The high computational cost and long training duration of iterative model optimization is also another critical problem in deep learning based medical imaging, especially when smaller datasets or fewer pre-trained models are present. In spite of these limitations, the model has good overall performance, though some images can be dropped out because of the threshold-based filtering, and thus, the performance measures e.g. specificity (the value is 0.50) are not performed at an image level but at the level of patient.

Declarations

Ethics Approval: Neither humans nor animals are involved in this investigation. Thus, ethical approval was not necessary.

Consent to Participate: Not applicable. There are no human subjects in this study.

Consent to Publish: Not applicable: There are no human subjects in this study.

Funding: This research received no external funding.

Data Availability Statement: No data set is used in this study.

Declaration Statement: No conflicts of interest declare by the authors.

Competing Interests: The authors declare that they have not any competing interests.

Availability of Data: The datasets used or analyzed for this study are from public sources of cryptocurrency market data.

Acknowledgement: Not Applicable.

Author Contributions: Conceptualization, A.M.; methodology, F.A.; validation, M.I. and A.B.B.; formal analysis, A.B.B..; investigation, H.k.; resources, F.A.; data curation, A.M.; writing—original draft preparation F.A. and M.I.; writing—review and editing, A.B.B.; visualization, H.K..; supervision, F.A.

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