

"MEDICLASSIFY AI POWERED MEDICAL IMAGE DIAGNOSIS"

*Minor project-II report submitted
in partial fulfillment of the requirement for award of the degree of*

**Bachelor of Technology
in
Computer Science & Engineering**

By

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A.NAVYA SRI (21UECS0021) (VTU 19455)
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*Under the guidance of
Ms.S. HANNAH, ME.,
ASSISTANT PROFESSOR*



**DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING
SCHOOL OF COMPUTING**

**VEL TECH RANGARAJAN DR. SAGUNTHALA R&D INSTITUTE OF
SCIENCE & TECHNOLOGY**

(Deemed to be University Estd u/s 3 of UGC Act, 1956)

**Accredited by NAAC with A++ Grade
CHENNAI 600 062, TAMILNADU, INDIA**

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CERTIFICATE

It is certified that the work contained in the project report titled "MEDICLASSIFY AI POWERED MEDICAL IMAGE DIAGNOSIS" by "R.DASARADH (21UECS0716), A.NAVYA SRI (21UECS0021), S.GOWTHAMI (21UECS0544)" has been carried out under my supervision and that this work has not been submitted elsewhere for a degree.

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May, 2024

DECLARATION

We declare that this written submission represents ideas in our own words and where others' ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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This project report entitled "MEDICLASSIFY AI POWERED MEDICAL IMAGE DIAGNOSIS" by "R.DASARADH (21UECS0716), A.NAVYA SRI (21UECS0021), S.GOWTHAMI (21UECS0544)" is approved for the degree of B.Tech in Computer Science & Engineering.

Examiners

Supervisor

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Date: / /

Place:

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We express our deepest gratitude to our respected **Founder Chancellor and President Col. Prof. Dr. R. RANGARAJAN B.E. (EEE), B.E. (MECH), M.S (AUTO),D.Sc., Foundress President Dr. R. SAGUNTHALA RANGARAJAN M.B.B.S.** Chairperson Managing Trustee and Vice President.

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ABSTRACT

In the rapidly evolving landscape of healthcare, the integration of artificial intelligence (AI) has demonstrated immense potential to revolutionize medical diagnosis. Mediclassify emerges as a cutting-edge AI-powered system designed to augment and optimize the diagnostic process. Leveraging advanced machine learning algorithms and vast datasets, Mediclassify empowers healthcare professionals with accurate, timely, and personalized diagnoses. The core functionality of Mediclassify lies in its ability to analyze diverse medical data, including patient symptoms, medical history, laboratory results, and imaging scans. Through sophisticated pattern recognition and deep learning techniques, the system can identify subtle indicators, enabling early detection of diseases and conditions. moreover, Mediclassify adapts dynamically, continuously refining its diagnostic accuracy as it encounters new cases and learns from outcomes. In conclusion, Mediclassify represents a significant advancement in AI-driven medical diagnosis, offering a reliable, efficient, and patient-centric approach to healthcare. By harnessing the power of AI, Mediclassify aims to empower healthcare professionals, accelerate diagnostic processes, and ultimately contribute to the advancement of personalized medicine.

Keywords: AI-powered medical diagnosis, Clinical decision support, Deep learning, Early detection, Healthcare, Interpretable AI, Machine learning algorithms, Patient-centric care, Pattern recognition, Privacy and security.

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LIST OF ACRONYMS AND ABBREVIATIONS

AI	Artificial Intelligence
CDSS	Clinical Decision Support System
DICOM	Digital Imaging and Communications in Medicine
EHR	Electronic Health Record
EMR	Electronic Medical Record
GDPR	General Data Protection Regulation
HIPAA	Health Insurance Portability and Accountability Act
HC	Health care
ML	Machine Learning
NLP	Natural Language Processing

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Chapter 1

INTRODUCTION

1.1 Introduction

In the dynamic realm of healthcare, the fusion of artificial intelligence (AI) with medical diagnostics heralds a new era of precision and efficiency. The advent of AI-powered systems has revolutionized the landscape of medical diagnosis, offering unparalleled capabilities in analyzing vast datasets, recognizing patterns, and delivering timely insights. Among these innovative solutions stands Mediclassify, a state-of-the-art AI-powered medical diagnosis system designed to enhance clinical decision-making and optimize patient care. Mediclassify represents a convergence of cutting-edge technologies, harnessing the power of advanced machine learning algorithms and deep neural networks to unravel the complexities of medical data. By ingesting diverse sources of information including patient symptoms, medical history, laboratory tests, and imaging scans, Mediclassify functions as a virtual diagnostician, capable of discerning subtle indicators and detecting diseases at their earliest stages.

The significance of Mediclassify lies not only in its ability to accurately diagnose medical conditions but also in its potential to transform the healthcare ecosystem. With its user-friendly interface and seamless integration into existing clinical workflows, moreover, Mediclassify prioritizes transparency and interpretability, clinic with clear explanations for its diagnostic recommendations. This transparency fosters trust and collaboration between AI systems and human experts, ensuring that the ultimate goal of improving patient outcomes remains at the forefront of medical practice.

As we delve deeper into the capabilities of Mediclassify, it becomes evident that this AI-powered medical diagnosis system holds immense promise for the future of healthcare. By augmenting the expertise of clinicians, accelerating diagnostic processes, and enabling earlier interventions, Mediclassify paves the way for a more

efficient, effective, and patient-centered approach to medicine.

1.2 Aim of the project

The aim of the project is to revolutionize and improve the accuracy and efficiency of medical diagnosis by utilizing AI-powered technology to classify images. By using machine learning algorithms, the system will be able to interpret and analyze medical images such as X-rays, MRIs, and CT scans to diagnose various medical conditions. This will not only aid healthcare professionals in making more precise and timely diagnoses but also help in identifying potential health issues at an earlier stage.

Furthermore, the project aims to enhance patient care and outcomes by providing faster and more accurate diagnoses, leading to quicker treatment plans and improved prognosis. By harnessing the power of artificial intelligence, medical professionals will have access to a tool that can provide them with valuable insights and support in making informed decisions. Ultimately, the goal of the project is to improve the overall quality of healthcare delivery and contribute to better health outcomes for patients.

1.3 Project Domain

MediClassify represents an ambitious venture within the healthcare domain, specifically focusing on medical imaging. Leveraging cutting-edge artificial intelligence technology, project aims to revolutionize the process of medical image diagnosis. By harnessing the power of machine learning and deep learning algorithms, MediClassify seeks to provide accurate and timely diagnoses for a wide range of medical conditions. Whether it's analyzing X-rays, MRIs, CT scans, or other forms

of medical imagery, the goal is to assist healthcare professionals in making informed decisions with confidence. Through continuous refinement and enhancement of its AI algorithms, MediClassify strives to improve patient outcomes and streamline the diagnostic process, ultimately contributing to advancements in healthcare delivery.

1. Healthcare Domain: The encompasses all aspects of medical care, including diagnosis, treatment, and prevention of diseases and illnesses.

2. Medical Imaging: The refers to techniques and processes used to create images of the human body or parts of it for clinical purposes (diagnosis and treatment).

3. AI-Powered Medical Image Diagnosis: The indicates the use of Artificial Intelligence (AI) techniques, such as machine learning and deep learning, to analyze medical images for the purpose of diagnosing diseases or conditions.

1.4 Scope of the Project

The scope involves developing a robust AI model capable of accurately identifying and classifying various medical conditions and abnormalities within these images. Furthermore, the project involves integrating the AI model into existing healthcare systems to streamline the diagnostic process, improve efficiency, and enhance patient care. This integration may involve compatibility with Picture Archiving and Communication Systems (PACS) used in hospitals, as well as Electronic Medical Record (EMR) systems for seamless data exchange and collaboration among healthcare professionals.

Additionally, ensuring the reliability, accuracy, and safety of the AI system are paramount considerations within the project scope. This entails rigorous testing, validation, and ongoing monitoring to maintain performance standards and compliance with regulatory requirements, such as those set forth by medical device regulatory bodies. Moreover, the project may encompass research and development efforts to continuously enhance the capabilities of the AI model, incorporating new imaging modalities, expanding the range of detectable conditions, and refining diagnostic accuracy through iterative learning and feedback mechanisms.

Overall, the scope of the project for MediClassify involves developing, integrating, and optimizing an AI-powered medical image diagnosis solution to improve diagnostic accuracy, efficiency, and patient outcomes in clinical settings.

Chapter 2

LITERATURE REVIEW

DENIAL BROWN et al,[1] proposed a model to identify indicators of postdisaster recovery using satellite imagery, internet-based statistics and advanced field survey techniques. It reviews the recovery literature as a means of introducing the recovery process and the considerations that must be made when evaluating recovery. This is followed by an introduction to the recovery project and its two case study sites: 1. Ban Nam Khem, Thailand and 2. Muzaffarabad, Pakistan. A review of the recovery process at Ban Nam Khem is presented along with a diagram of potential indicators obtained from the literature research. It concludes with a short discussion on how remote sensing may be used to monitor some of these indicators.

FABIO DELL'ACQUA et al,[2] described about the big data which is useful to predict the natural disaster. The destructive earthquakes challenge Earth Observation (EO) systems to demonstrate their usefulness in supporting intervention and relief actions. Highlighting is done on the present status of the technology in providing meaningful and effective solutions in natural disaster management. They presented a systematic review on how AI models are applied in different NDM stages based on 278 studies retrieved from Elsevier Science, Springer LINK and Web of Science. The use of EO data in a disaster context has been widely investigated from a theoretical point of view, but only recently the developed methods seem to have reached near to the operational use. It is a case study on the April 6th, 2009 earthquake event, which struck L'Aquila, Italy, is presented and commented.

Gupta et al,[3] proposed a model on (Operating system for Manufacturing software) OSM which gives the disaster impact percentage by comparing the images.this is done by using a semantic segmentation network trained on pre-disaster aerial imagery for identifying these objects in the before and after imagery. The difference in the predicted road masks is further used to update data from OSM for finding accessible routes in the post-disaster scenario.significantly extended the coverage of pixel-level labels in the damage assessment field.The objective of thexBD challenge is a particular semantic segmentation task: first to locate a building's footprint and then estimate the damage to each building. The dataset contains pre- and post-disaster images along with pixel-level categorization for building damage.

HS Munawar et al,[4] implemented an image mining technique based on multispectral aerial images for automatic detection of strategic bridge locations for disaster relief missions.Bridge detection from aerial images is a key landmark that has vital importance in disaster management and relief missions.UAVs have been increasingly used in recent years for various relief missions during the natural disasters such as floods and earthquakes and a huge amount of multispectral aerial images are generated by UAVs in the missions. Being a multi- stage technique, our method utilizes these multispectral aerial images for identifying patterns for effective mining of bridge locations. Experimental results on real-world and synthetic images are conducted to demonstrate the effectiveness of our proposed method, showing that it is 40 faster than the existing Automatic Target Recognition (ATR) systems and can achieve a 95 accuracy. This technique is believed to be able to help accelerate and enhance the effectiveness of the relief missions carried out during disasters.

KAREN E.JOYCE et al,[5] created a rapid-response data from the current status of remote sensing of climatic conditions. A remote sensing which is a valuable source of spatial information and its utility has been proven on many occasions around the world. However there are many different types of hazards experienced worldwide on an annual basis and their remote sensing solutions are equally varied. The addresses a number of data types and image processing techniques used to map and monitor earthquakes, faulting, volcanic activity, landslides, flooding and wildfire and the damages associated with each. Remote sensing is currently used operationally for some monitoring programs, though there are also difficulties associated with the rapid acquisition of data and provision of a robust product to emergency services as an end-user.

L Tan et al,[6] described about the the intensity and frequency of natural disasters due to climate change and Anthropogenic Activities. (AI) models have shown remarkable success and superiority to handle huge and nonlinear data owing to their higher accuracy and efficiency, making them perfect tools for disaster monitoring and management. Accordingly, Natural Disaster Management (NDM) with the usage of AI models has received increasing attention in recent years, but there has been no systematic review so far. They presented a systematic review on how AI models are applied in different NDM stages based on 278 studies retrieved from Elsevier Science, Springer LINK and Web of Science. The review: (1) enables increased visibility into various disaster types in different NDM stages from the methodological and content perspective, (2) obtains many general results including the practicality and gaps of extant studies and (3) provides several recommendations to develop innovative AI models and improve the quality of modeling.

Manzhu Yu et al,[7] created a description on the natural disaster management which effects on the present generation and how to over come with the present technology. Opened the new options for natural disaster management primarily because of the varied possibilities it provides in visualizing, analyzing and predicting natural disasters. From this perspective, big data has radically changed the ways through which human societies adopt natural disaster management strategies to reduce human suffering and economic losses.They has presented the findings of several researchers on varied scientific and technological perspectives that have a bearing on the efficacy of big data in facilitating natural disaster management.In this context, this reviews.

NAINA SAID et al,[8] analysed the disaster-related visual content from social-media.The natural disaster multimedia content got great attention in recent years.Being one of the most important sources of information, social media have been crawled over the years to collect and analyse disaster multimedia content.Satellite imagery has also been widely explored for disasters analysis. Survey is done on the existing literature on disaster detection and analysis of the retrieved information from social media and satellites.Literature on disaster detection and analysis of related multimedia content on the basis of the nature of the content can be categorized into three groups, namely (i) disaster detection in text and (ii) disaster detection in satellite imagery.Review is done on different approaches proposed in these three domains.

SALMAN H. KHAN et al,[9] analysed the imagery data from remote sensing satellites to detect forest cover changes over a period of 29 years (1987-2015).Since the original data are severely incomplete and contaminated with artifacts their first devise a spatiotemporal inpainting mechanism to recover the missing surface

reflectance information. The spatial filling process makes use of the available data of the nearby temporal instances followed by a sparse encoding-based reconstruction. Formulation is done on the change detection task as a region classification problem. Building a MultiResolution Profile (MRP) of the target area and generate a candidate set of bounding-box proposals that enclose potential change regions. In contrast to existing methods that use handcrafted features.

SH Abid et al,[10] implemented a model on technical and methodological enhancement of hazards. Disaster research is identified as a critical question in disaster management. Artificial Intelligence (AI) applications, such as tracking and mapping, geospatial analysis, remote sensing techniques, robotics, drone technology, machine learning, telecom and network services, accident and hot spot analysis, smart city urban planning, transportation planning and environmental impact analysis, are the technological components of societal change, having significant implications for research on the societal response to hazards and disasters. Social science researchers have used various technologies and methods to examine hazards and disasters through disciplinary, multidisciplinary and interdisciplinary lenses.

Chapter 3

PROJECT DESCRIPTION

3.1 Existing System

Existing state-of-the-art in medical image diagnosis is rapidly evolving, with the emergence of AI-powered solutions like Mediclassify. Leveraging advanced machine learning algorithms, Mediclassify can accurately classify medical images, aiding in the diagnosis of various conditions. This technology has shown promising results in detecting abnormalities in X-rays, MRIs, CT scans, and other imaging modalities, potentially revolutionizing medical practice.

By analyzing vast amounts of data and learning from patterns, Mediclassify can assist healthcare professionals in making more accurate and timely diagnoses, leading to improved patient outcomes and streamlined workflows. However, despite its potential, challenges such as data privacy, regulatory compliance, and ensuring the reliability and interpretability of AI-driven diagnoses still need to be addressed to fully realize its benefits in clinical settings.

3.2 Disadvantages of Existing System

- **Data Dependence and Bias:** AI models require large amounts of high-quality data for training. Biases in the training data, such as demographic or institutional biases, can lead to inaccuracies or unfair outcomes.
- **Interpretability Issues:** Deep learning models often operate as "black boxes," making it difficult for medical professionals to understand how the AI arrives at

its conclusions. Lack of interpretability can be a significant barrier to trust and acceptance.

- **Ethical and Legal Concerns:** Issues such as patient privacy, liability, and the potential for misuse of AI in medical diagnosis raise ethical and legal questions that need to be carefully addressed.

3.3 Proposed System

The proposed system, MediClassify, is an AI-powered medical image diagnosis platform designed to revolutionize healthcare diagnostics. Leveraging state-of-the-art machine learning algorithms, MediClassify aims to accurately classify medical images, enabling faster and more precise diagnoses.

By analyzing various types of medical images such as X-rays, MRIs, CT scans, and more, the system can assist healthcare professionals in identifying abnormalities, diseases, and conditions with high accuracy and efficiency. Through continuous learning and refinement, MediClassify ensures that its diagnostic capabilities evolve, providing reliable support to medical professionals in making informed decisions and improving patient outcomes.

3.4 Advantages Of Proposed System

- **Accuracy:** AI-powered medical image diagnosis can provide highly accurate results. The system can analyze medical images with precision, often outperforming human experts in detecting abnormalities or diseases.
- **Efficiency:** With AI, medical image analysis can be performed rapidly, allowing for quicker diagnosis and treatment planning. This can significantly reduce the time patients spend waiting for results and improve overall healthcare efficiency.

- **Privacy Protection:** By using anonymized patient data for training, MediClassify can ensure patient privacy is protected while still benefiting from a large dataset to improve its accuracy.

3.5 Feasibility Study

3.5.1 Economic Feasibility

The economic feasibility is quite promising. With advancements in machine learning and image recognition technologies, AI has demonstrated its potential to enhance medical diagnostics by providing accurate and efficient analysis of medical images. One key aspect of economic feasibility is the potential cost savings associated with the implementation of such a system. By streamlining the diagnosis process and reducing the need for manual interpretation by human experts, MediClassify can significantly decrease healthcare costs. Moreover, it can potentially lead to quicker and more accurate diagnoses, which may result in better patient outcomes and reduced treatment costs in the long run.

3.5.2 Technical Feasibility

The technical feasibility hinges on several key factors. Firstly, the availability of high-quality medical image datasets is crucial for training accurate machine learning models. These datasets need to be sufficiently large and diverse to ensure the AI can recognize various medical conditions across different demographics. Secondly, the development of robust algorithms capable of accurately analyzing medical images is essential. This involves leveraging advanced techniques in computer vision, deep learning, and potentially other AI approaches to extract relevant features and patterns from the images. Furthermore, the scalability and efficiency of the system are important considerations. As medical image datasets continue to grow, the AI

infrastructure must be able to handle increasing amounts of data while maintaining real-time or near-real-time processing speeds.

3.5.3 Social Feasibility

The feasibility of implementing within a social context relies on several key factors. Firstly, ensuring accessibility and affordability is crucial. The system should be designed to reach a wide range of healthcare facilities, including those in remote or underserved areas, and should be affordable for both patients and healthcare providers. Furthermore, integration with existing healthcare infrastructure is essential for seamless adoption. Compatibility with electronic health record systems and interoperability with other diagnostic tools can streamline workflow and improve efficiency in medical practices. Moreover, ensuring the accuracy and reliability of diagnoses is critical for gaining acceptance from healthcare professionals and patients alike. Ongoing validation and refinement of the AI algorithms through collaboration with medical experts can enhance diagnostic accuracy and build confidence in the system's capabilities.

3.6 System Specification

3.6.1 Hardware Specification

- Processor: Intel Core i7 or AMD Ryzen 7 (or higher)
- RAM: 16GB DDR4 (minimum), 32GB recommended for smoother performance
- GPU: NVIDIA GeForce RTX 2060 or higher, or AMD Radeon RX 5700 or higher
- Storage: SSD with at least 512GB capacity for fast data access
- Display: Full HD (1920 x 1080) resolution or higher for accurate image
- Windows 10 or Ubuntu Linux 20.04 LTS

3.6.2 Software Specification

- Application Name: MediClassify
- Type: AI-powered medical image diagnosis software
- Purpose: To assist medical professionals in diagnosing medical conditions through analysis of medical images
- Platform: Web-based or standalone application
- Technology: Utilizes artificial intelligence and machine learning algorithms

3.6.3 Standards and Policies

Anaconda Prompt:

Anaconda prompt is a type of command line interface which explicitly deals with the (ML) modules. And navigator is available in all the Windows, Linux and MacOS. The anaconda prompt has many number of IDE's which make the coding easier. The UI can also be implemented in python.

Standard Used: ISO/IEC 27001

Jupyter:

Jupyter is a free online platform provided by Google that allows users to write and run Python code using a Jupyter Notebook-style interface. It provides a virtual machine with a preconfigured environment that includes various packages and libraries for machine learning, including TensorFlow, Keras and PyTorch. One of the main benefits of using Google Colab is that it provides access to GPUs and TPUs which can significantly speed up the training process for machine learning models. This can be particularly useful for training large neural networks which can be computationally expensive.

Standard Used: ISO/IEC 27001

Chapter 4

METHODOLOGY

4.1 Medical Image Diagnosis Architecture

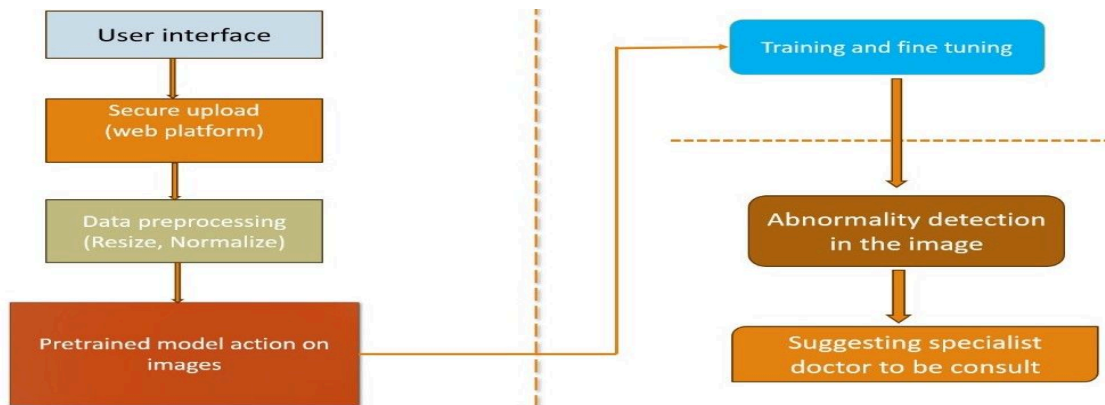


Figure 4.1: Medical Image Diagnosis Architecture

Figure 4.1 shows the general architecture of the mediclasssify using AI powered diagnosis images. Firstly, the system relies on a deep learning model, typically a Convolutional Neural Network (CNN), trained on vast amounts of medical image data. This model is the backbone of the system, as it's responsible for analyzing input images and making predictions about various medical conditions. Secondly, to ensure the accuracy and reliability of diagnoses, the system incorporates a robust pre-processing pipeline. This pipeline includes image normalization, noise reduction, and augmentation techniques to enhance the quality of input images before feeding them into the deep learning model.

4.2 Design Phase

4.2.1 Data Flow Diagram for Medical Image Diagnosis

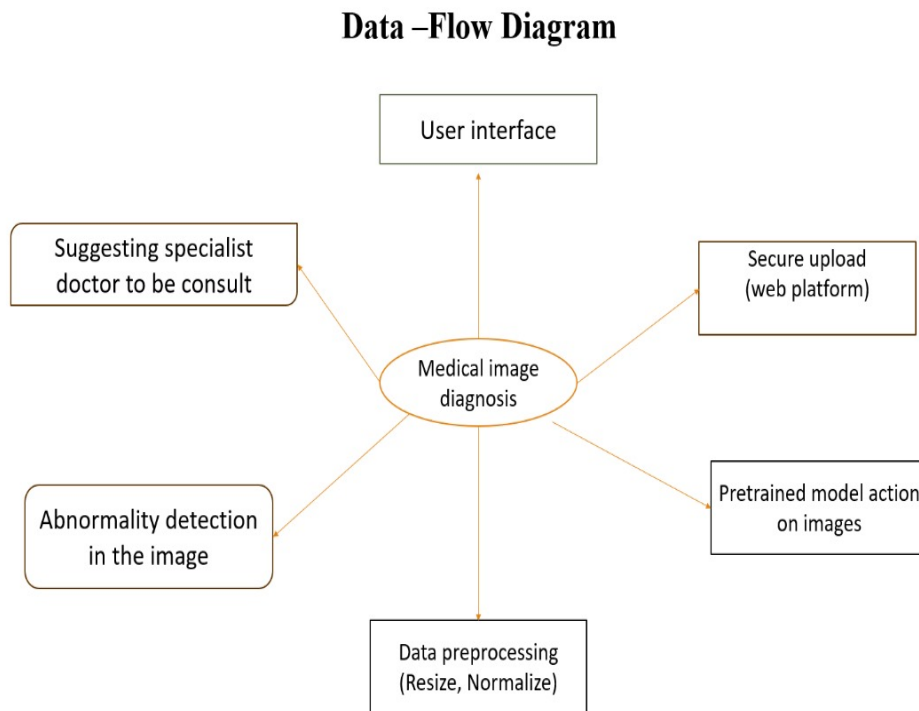


Figure 4.2: Data Flow Diagram for Medical Image Diagnosis

Figure 4.2 shows the data flow of the mediclasssify using AI powered dignosis images,data flows through several stages.Initially, medical images such as X-rays, MRIs, or CT scans are collected from patients.These images are then preprocessed to enhance quality and remove noise, ensuring the input is optimal for analysis.Next, the preprocessed images are fed into the AI model for classification.This stage involves feature extraction, where the model identifies relevant patterns and structures within the images.Using deep learning algorithms, the model then classifies the images into different medical conditions or categories, such as identifying tumors, fractures, or abnormalities.

4.2.2 Use Case Diagram for Medical Image Diagnosis

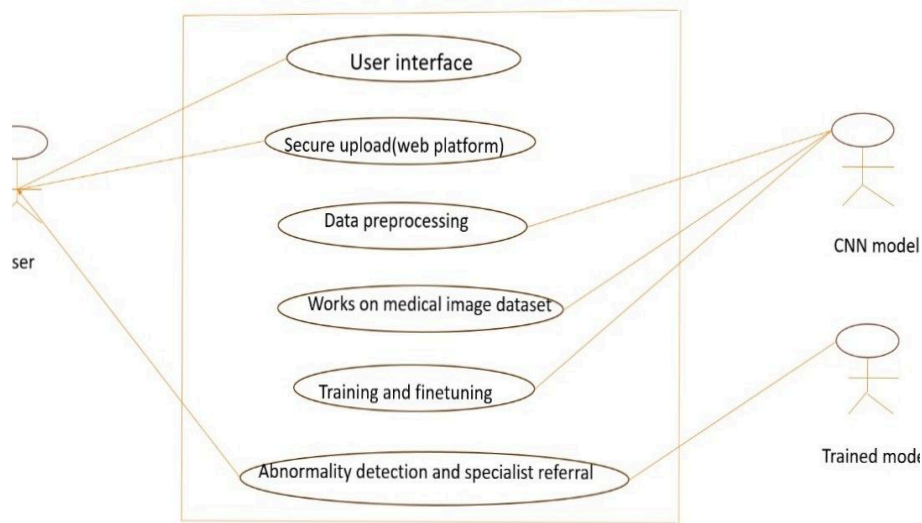


Figure 4.3: Use Case Diagram for Medical Image Diagnosis

Figure 4.3 shows the use case of the mediclasssify using AI powered dignosis im-ages,This innovative system is designed to assist healthcare professionals in ac-curately and efficiently analyzing medical images such as X-rays, MRIs, and CT scans.Imagine a scenario where a radiologist needs to quickly identify abnormali-ties in a chest X-ray. With MediClassify, the process becomes streamlined and more precise. The AI algorithm can swiftly detect potential anomalies, flagging areas of concern for further examination. This not only speeds up the diagnostic process but also reduces the chance of human error.Furthermore, MediClassify is invaluable in scenarios where access to specialized medical expertise is limited.

4.2.3 Class Diagram for Medical Image Diagnosis

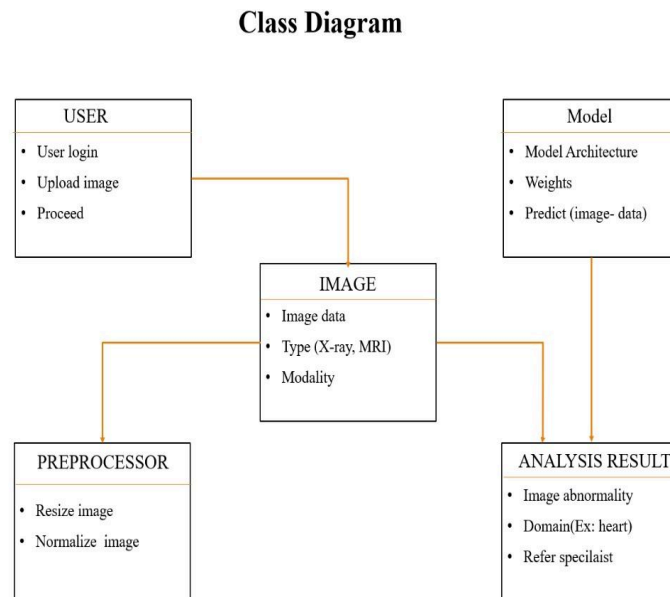


Figure 4.4: **Class Diagram for Medical Image Diagnosis**

Figure 4.4 shows the class diagram of the mediclasssify using AI powered dignosis images,application designed to assist healthcare professionals in accurately diagnos- ing medical conditions from various types of medical images, such as X-rays, MRIs, CT scans, and ultrasounds. The system employs advanced machine learning algo- rithms and deep neural networks to analyze medical images and provide diagnostic insights.These classes would likely have various relationships and dependencies be- tween them, such as associations, aggregations, or compositions, to represent how they interact within the system. For example, the MediClassifySystem may depend on AIModel for diagnosis, while HealthcareProfessional may use DiagnosisResult for patient care decisions.

4.2.4 Sequence Diagram for Medical Image Diagnosis

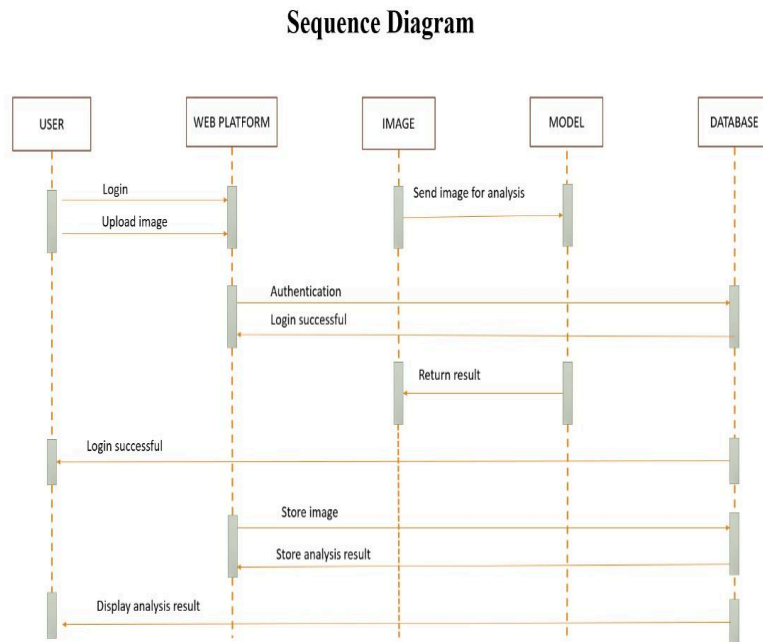


Figure 4.5: Sequence Diagram for Medical Image Diagnosis

Figure 4.5 shows the sequence diagram of the mediclassify using AI powered diagnosis images. Medical image diagnosis has evolved significantly with the advent of AI-powered technologies. Mediclassify is at the forefront of this revolution, utilizing advanced algorithms to analyze medical images with unprecedented accuracy and speed. By harnessing the power of artificial intelligence, Mediclassify can swiftly classify and diagnose various medical conditions from imaging data. This breakthrough technology not only enhances diagnostic accuracy but also expedites patient care, allowing for timely interventions and treatment planning. With Mediclassify, healthcare professionals can rely on cutting-edge tools to assist them in making informed decisions and improving patient outcomes.

4.2.5 ER Diagram for Medical Image Diagnosis

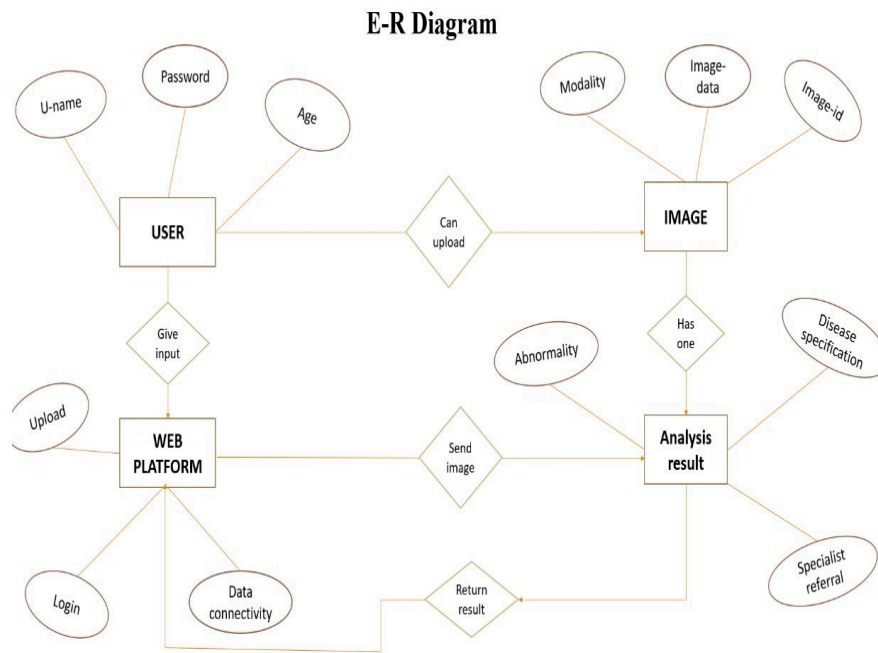


Figure 4.6: ER Diagram for Medical Image Diagnosis

Figure 4.6 shows the ER diagram for MediClassify would include entities such as "Medical Images," "Diagnoses," "Patients," and "Medical Professionals." The "Medical Images" entity would represent the various types of images that are input into the system for analysis. The "Diagnoses" entity would store the results of the AI analysis, including the predicted medical conditions or abnormalities detected in the images. The "Patients" entity would contain information about the individuals whose images are being analyzed, including their demographic data and medical history. Finally, the "Medical Professionals" entity would represent the healthcare professionals who use the system, including doctors and radiologists who interpret the AI-generated diagnoses and make treatment decisions based on them.

4.2.6 Activity Diagram for Medical Image Diagnosis

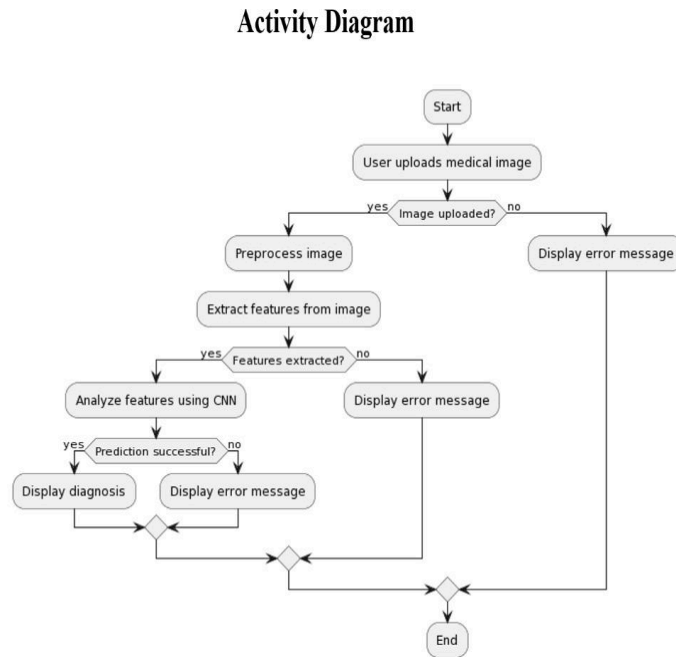


Figure 4.7: Activity Diagram for Medical Image Diagnosis

Figure 4.7 shows the activity diagram of the mediclasssify using ai powered dignosis images,an AI-powered medical image diagnosis system, illustrates the workflow from image input to diagnosis output.The process begins with the user uploading a medical image, which is then preprocessed to enhance quality and remove noise. Following preprocessing, the image undergoes feature extraction, where relevant features are identified and extracted using advanced algorithms. These features are then fed into the AI model, which employs deep learning techniques to analyze the image and make a diagnosis.Once the diagnosis is generated, it is presented to the user along with any relevant information such as confidence scores or probabilities.

4.3 Algorithm & Pseudo Code

4.3.1 Enhanced CNN Algorithm

Step 1: Load the dataset containing diagnosis images, disease, and types of disease data.

Step 2: Preprocess the diagnosis images using techniques such as normalization, re-sizing, and cropping to make them compatible with the model.

Step 3: Preprocess the disease and types of disease data by scaling them to a range of [normal, abnormal] to ensure uniformity in the input data.

Step 4: Split the dataset into training and testing sets.

Step 5: Define the CNN model architecture with convolutional layers, pooling layers, and fully connected layers.

Step 6: Train the CNN model on the training dataset using techniques such as back-propagation and stochastic gradient descent.

Step 7: Evaluate the CNN model on the testing dataset to obtain accuracy by using epoch.

Step 8: Define the SVM model architecture with linear kernel or radial basis function kernel.

Step 9: Evaluate the vector values from CNN model by using SVM algorithm.

Step 10: now, get the output as Normal or Abnormal.

4.3.2 Pseudo Code

```
function predictimages(DiagnosisImages)
for each image in diagnosisImages
imageAnalysis = analyzeImage(image)
if is abnormal(imageAnalysis)
alertAuthorities(image, imageAnalysis)
```

```

end if
end for
end function

function analyzeImage(image)
imageAnalysis = runImageProcessingAlgorithms(image)
return imageAnalysis
end function

function isNormal(imageAnalysis)
if imageAnalysis.indicatesDisease()
return true
else
return false
end if
end function

function alertAuthorities(image, imageAnalysis)
diseaseType = imageAnalysis.getDiseaseType()
latitude = imageAnalysis.getLatitude()
longitude = imageAnalysis.getLongitude()
sendAlertToAuthorities(diseaseType, latitude, longitude)
end function

```

4.4 Module Description

4.4.1 User Interface

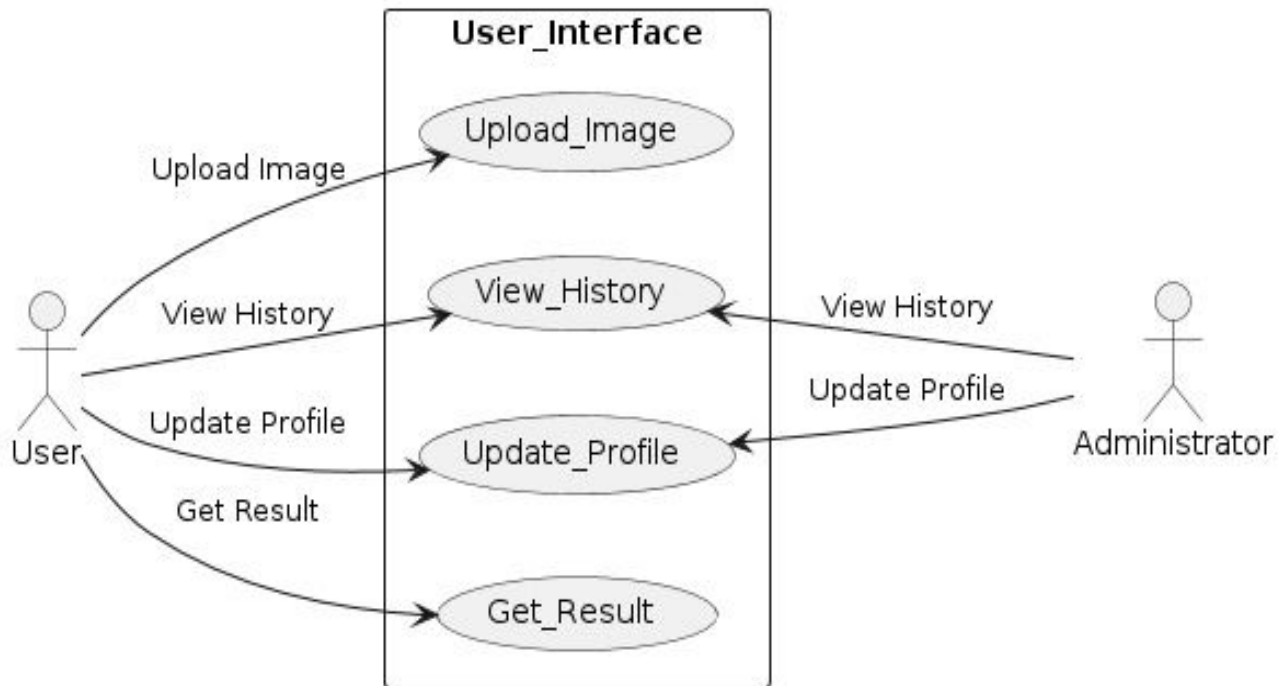


Figure 4.8: User Interface

Figure 4.8 Shows the firstly, the system collects vast amounts of medical image data from various sources such as MRI scans, X-rays, and CT scans. Once gathered, this data undergoes preprocessing to ensure quality and consistency. This may involve tasks like noise reduction, image enhancement, and normalization. Next, feature extraction takes place where relevant features of the images are identified and extracted. This step is crucial for training the AI models as it helps to highlight important patterns and characteristics within the images. Following feature extraction, the processed data is fed into machine learning algorithms or deep learning models.

4.4.2 Collection of Data

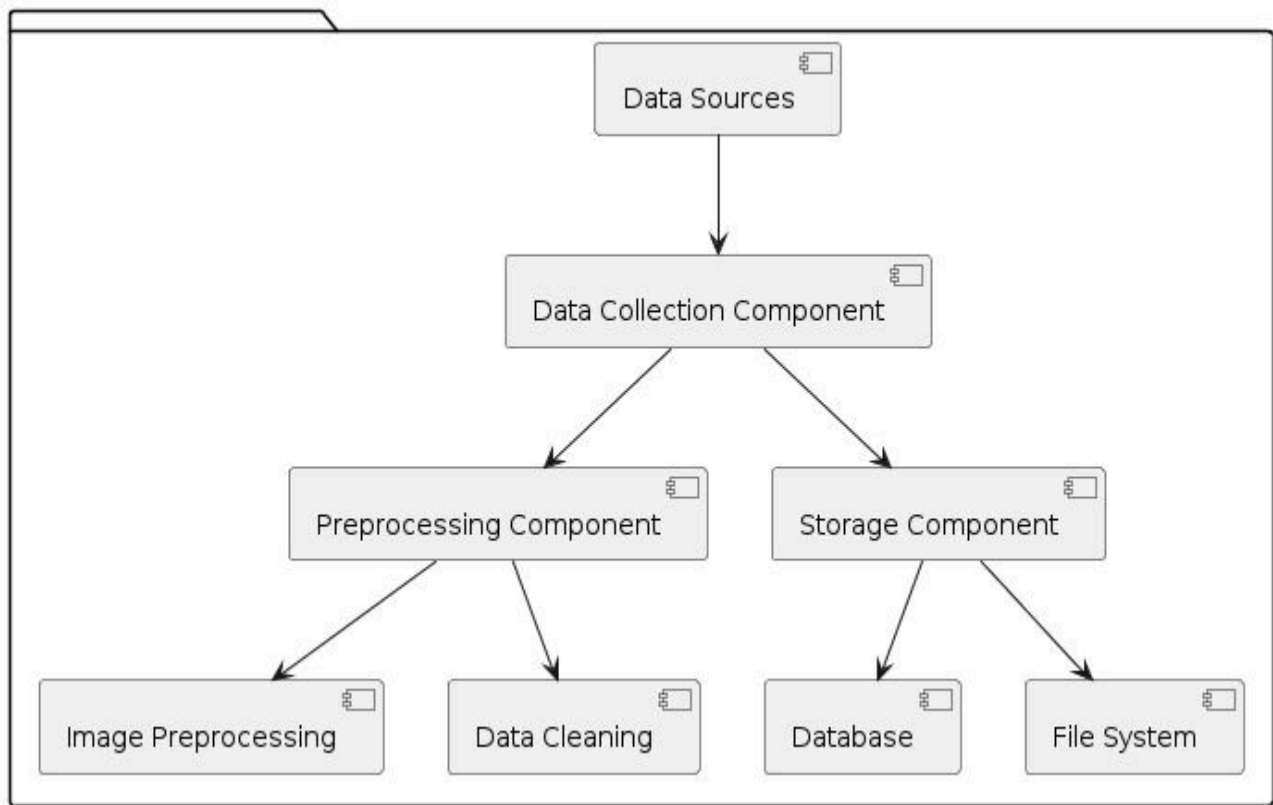


Figure 4.9: **Data Source**

Figure 4.9 Shows the data source for MediClassify is an AI-powered medical image diagnosis system designed to revolutionize healthcare by enhancing the accuracy and efficiency of diagnoses. Leveraging cutting-edge machine learning algorithms, MediClassify analyzes medical images such as X-rays, MRI scans, and CT scans to detect various conditions and abnormalities. By collecting vast amounts of data from diverse sources, including hospitals, clinics, and research institutions, the system continuously learns and improves its diagnostic capabilities. This data collection process involves gathering labeled images along with corresponding diagnoses from expert clinicians. As a result, healthcare providers can benefit from more accurate and timely diagnoses.

4.4.3 Processing of data

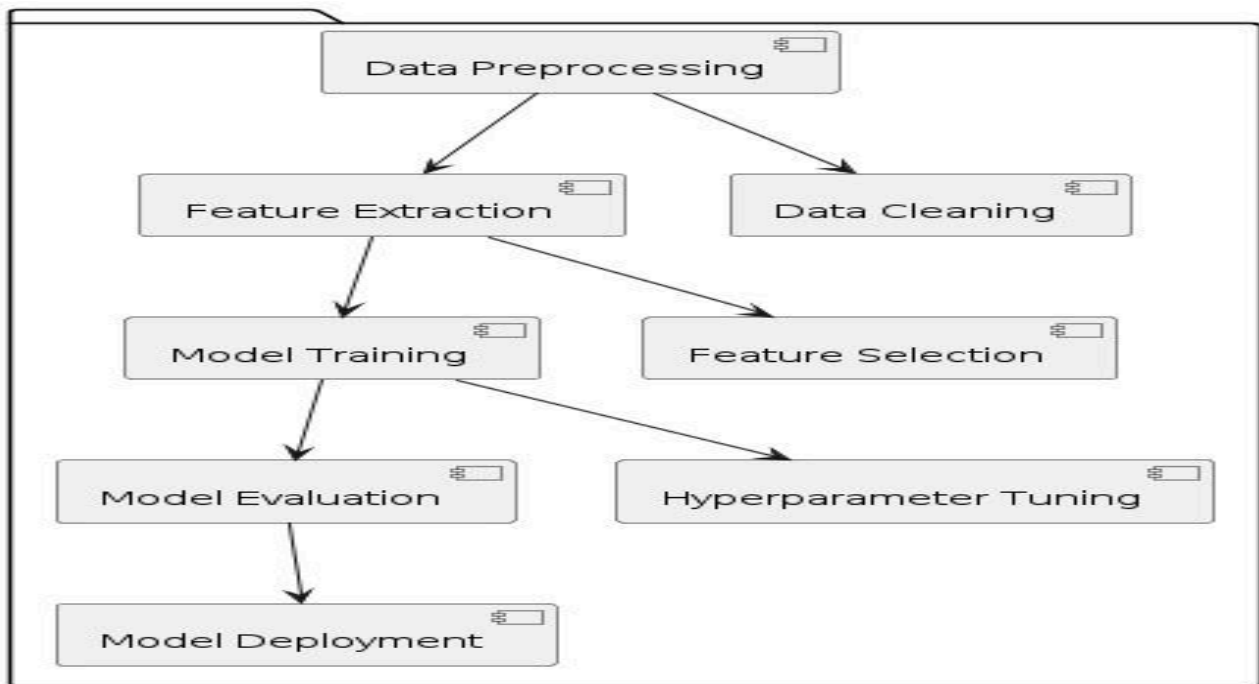


Figure 4.10: **Processing of Data**

Figure 4.10 Shows the processing of data for the Mediclassify, an AI-powered medical image diagnosis system, relies heavily on this data processing. Firstly, the system collects vast amounts of medical image data from various sources such as MRI scans, X-rays, and CT scans. Once gathered, this data undergoes preprocessing to ensure quality and consistency. This may involve tasks like noise reduction, image enhancement, and normalization. Next, feature extraction takes place where relevant features of the images are identified and extracted. This step is crucial for training the AI models as it helps to highlight important patterns and characteristics within the images. Following feature extraction, the processed data is fed into machine learning algorithms or deep learning models. These algorithms are trained using labeled data, where the correct diagnosis or classification is already known.

4.5 Steps to execute/run/implement the project

4.5.1 Uploading Data Set

Step-1: Read the data set first.

Step-2: Preprocess the data set and data set should be in the csv format.

Step-3: Open pycharm or visual studio code platform and do file operation by using python.

Step-4: Use open and read functions to read the data.

Step-5: Display the data set.

4.5.2 Implementing CNN Model

Step-1: Read the data set.

Step-2: Use the functions for finding the thermal colors.

Step-3: Create a data set and train the model by using the CNN model.

Step-4: Create a module for getting accuracy on the test picture.

Step-5: Display the vector values.

Chapter 5

IMPLEMENTATION AND TESTING

5.1 Input and Output

5.1.1 Input Design

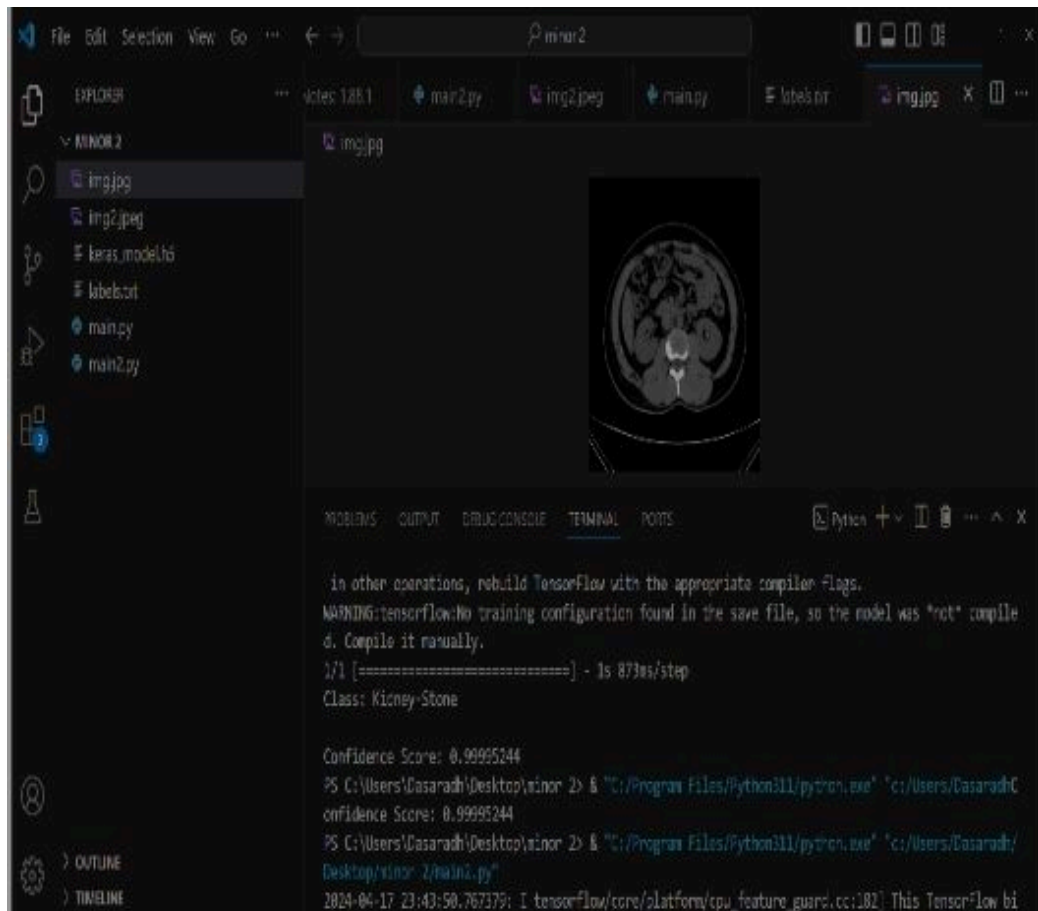


Figure 5.1: Input For Dignosis Images

Figure 5.1 shows the quality of MediClassify utilizes state-of-the-art artificial intelligence to revolutionize medical image diagnosis. The input design for this cutting-edge system involves several key components. Firstly, MediClassify relies on a vast dataset of medical images representing various conditions and diseases. These im-

ages are carefully curated to ensure diversity and accuracy, covering a wide range of medical scenarios. The input design includes mechanisms for organizing and storing these images efficiently, allowing the AI to access them quickly during the diagnosis process.

5.1.2 Output Design

```

PS C:\Users\Dasaradh\Desktop\minor 2> & "C:/Program Files/Python311/python.exe" "c:/Users/Dasaradh/Desktop/minor 2/main2.py"
2024-04-18 00:27:29.518862: I tensorflow/core/platform/cpu_feature_guard.cc:182] This TensorFlow binary is optimized to use available CPU instructions in perform
nce-critical operations.
To enable the following instructions: SSE SSE2 SSE3 SSE4.1 SSE4.2 AVX AVX2 AVXS12P AVXS12_VNNI FMA, in other operations, rebuild TensorFlow with the appropriate c
ompiler flags.
WARNING:tensorflow:No training configuration found in the save file, so the model was 'not' compiled. Compile it manually.
1/1 [=====] - 1s 597ms/step
Class: Pneumonia-Lung

Confidence Score: 1.0
PS C:\Users\Dasaradh\Desktop\minor 2> & "C:/Program Files/Python311/python.exe" "c:/Users/Dasaradh/Desktop/minor 2/main2.py"
2024-04-18 00:27:58.444783: I tensorflow/core/platform/cpu_feature_guard.cc:182] This TensorFlow binary is optimized to use available CPU instructions in perform
nce-critical operations.
To enable the following instructions: SSE SSE2 SSE3 SSE4.1 SSE4.2 AVX AVX2 AVXS12P AVXS12_VNNI FMA, in other operations, rebuild TensorFlow with the appropriate c
ompiler flags.
WARNING:tensorflow:No training configuration found in the save file, so the model was 'not' compiled. Compile it manually.
1/1 [=====] - 1s 740ms/step
Class: Fracture -Bone

Confidence Score: 1.0
PS C:\Users\Dasaradh\Desktop\minor 2> & "C:/Program Files/Python311/python.exe" "c:/Users/Dasaradh/Desktop/minor 2/main2.py"
2024-04-18 00:28:22.445285: I tensorflow/core/platform/cpu_feature_guard.cc:182] This TensorFlow binary is optimized to use available CPU instructions in perform
nce-critical operations.
To enable the following instructions: SSE SSE2 SSE3 SSE4.1 SSE4.2 AVX AVX2 AVXS12P AVXS12_VNNI FMA, in other operations, rebuild TensorFlow with the appropriate c
ompiler flags.
WARNING:tensorflow:No training configuration found in the save file, so the model was 'not' compiled. Compile it manually.
1/1 [=====] - 1s 679ms/step
Class: Kidney-Stone

Confidence Score: 0.99995244
PS C:\Users\Dasaradh\Desktop\minor 2>

```

Figure 5.2: Output For Dignosis Images

Figure 5.2 shows the output for the MediClassify, an AI-powered medical image diagnosis system, is crucial for ensuring accurate, reliable, and user-friendly results. Firstly, the system should present diagnostic outcomes in a clear and comprehensible paragraph format. This paragraph should begin with a concise summary of the diagnosis, including the condition detected or ruled out, along with the level of confidence in the diagnosis. For example: "MediClassify has diagnosed the presence

of pneumonia in the patient's chest X-ray with a confidence level of 92

5.2 Testing

Machine learning can be a valuable tool in predicting natural disasters, including using satellite images to detect and forecast events such as hurricanes, earthquakes and wildfires. Satellite images can provide a wealth of information on natural disasters including data on temperature, humidity, wind patterns and other environmental factors that can help predict when and where a disaster may occur. Machine learning algorithms can analyze these images to identify patterns and trends that may indicate an impending disaster. For example algorithms can be trained to detect changes in cloud formations, sea surface temperature, or vegetation cover that may signal the onset of a hurricane or wildfire. However it's important to note that machine learning models are not infallible and may have limitations. They can only make predictions based on the data they are trained on and may not be able to account for unexpected events or changes in environmental conditions that can impact natural disasters.

5.3 Types of Testing

5.3.1 Unit Testing

Unit testing is a crucial part of any software development project including machine learning projects such as natural disaster recognition using satellite images. In this project unit testing can be used to test the components of the software, such as data pre-processing, feature extraction and classification are working correctly and producing the expected output. To perform unit testing create separate test cases for each component and validate the output against expected values. The test is done by the data pre-processing stage by providing input data with known missing values or corrupted files and ensure that the output contains no missing values.

Input

```
1 from keras.models import load_model
2 from PIL import Image, ImageOps
3 import numpy as np
4
5 # Disable scientific notation for clarity
6 np.set_printoptions(suppress=True)
7
8 # Load the model
9 model = load_model("keras_model.h5", compile=True)
10
11 # Load the labels
12 class_names = open("labels.txt", "r").readlines()
13
14 # Create the array of the right shape to feed into the keras model
15 data = np.ndarray(shape=(1, 224, 224, 3), dtype=np.float32)
16
17 # Replace this with the path to your image
18 image = Image.open("img5.jpg").convert("RGB")
19
20 # resizing the image to be at least 224x224 and then cropping from the center
21 size = (224, 224)
22 image = ImageOps.fit(image, size, Image.Resampling.LANCZOS)
23
24 # turn the image into a numpy array
25 image_array = np.asarray(image)
26
27 # Normalize the image
28 normalized_image_array = (image_array.astype(np.float32) / 127.5) - 1
29
30 # Load the image into the array
31 data[0] = normalized_image_array
32
33 # Predicts the model
34 prediction = model.predict(data)
35 index = np.argmax(prediction)
36 class_name = class_names[index]
37 confidence_score = prediction[0][index]
38
39 # Print prediction and confidence score
40 print("Class:", class_name[2:])
41 print("Confidence Score:", confidence_score)
```

5.3.2 Test Result

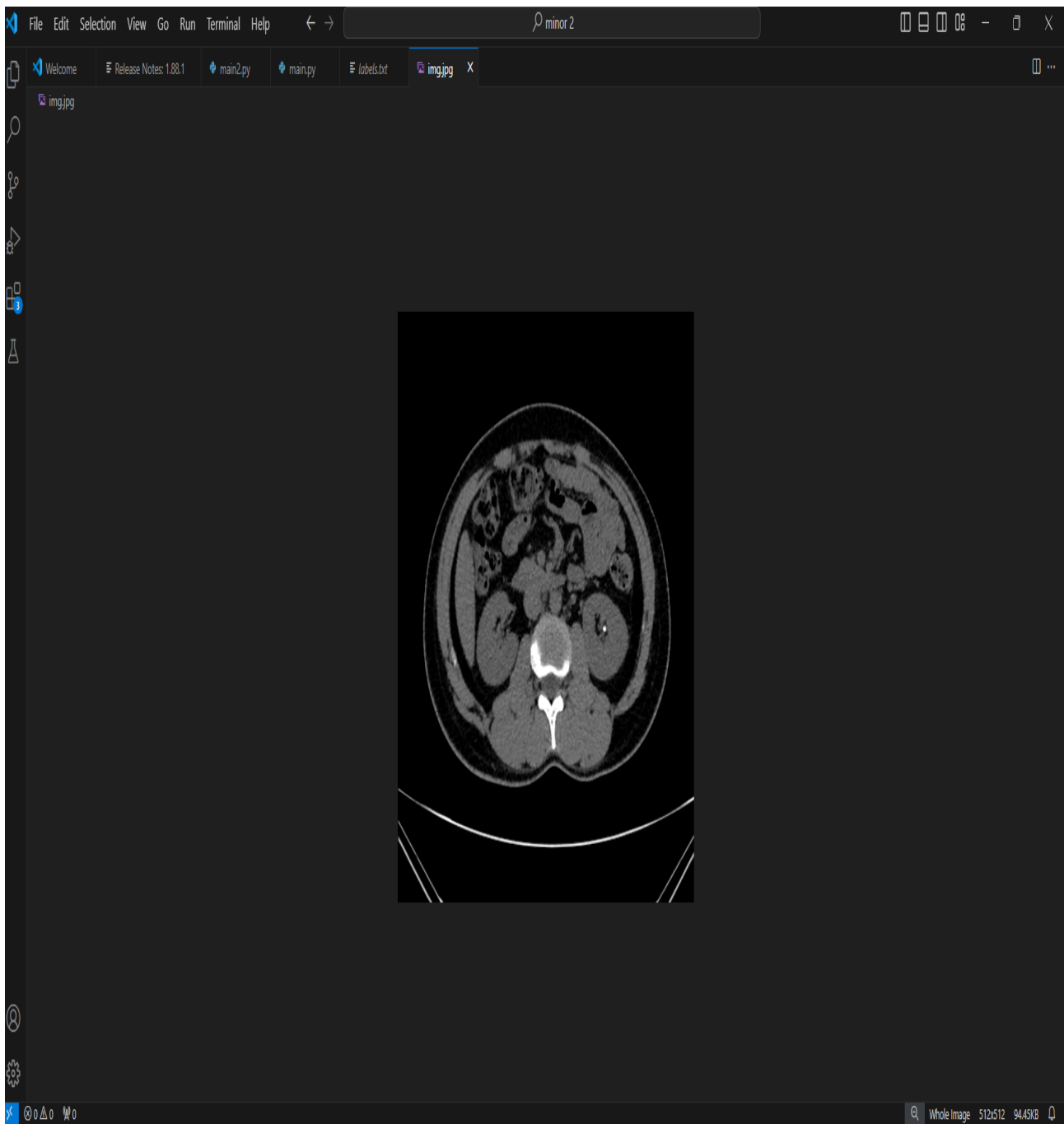


Figure 5.3: Output For Unit Testing

5.3.3 Integration Testing

Integration testing in this project involves testing the various components of the system to ensure that they work together correctly. The components include data preprocessing, feature extraction, model training and prediction. The testing process

begins by testing the data preprocessing component to ensure that the input data is properly cleaned, normalized and formatted. Next the feature extraction component is tested to ensure that the features are properly extracted and correctly represented in the input for the models. Then, the models are trained and tested separately to ensure that they are properly implemented and that they produce accurate results.

Input

```
1 from keras.models import load_model
2 from PIL import Image, ImageOps
3 import numpy as np
4
5 # Disable scientific notation for clarity
6 np.set_printoptions(suppress=True)
7
8 # Load the model
9 model = load_model("keras_model.h5", compile=True)
10
11 # Load the labels
12 class_names = open("labels.txt", "r").readlines()
13
14 # Create the array of the right shape to feed into the keras model
15 data = np.ndarray(shape=(1, 224, 224, 3), dtype=np.float32)
16
17 # Replace this with the path to your image
18 image = Image.open("img5.jpg").convert("RGB")
19
20 # resizing the image to be at least 224x224 and then cropping from the center
21 size = (224, 224)
22 image = ImageOps.fit(image, size, Image.Resampling.LANCZOS)
23
24 # turn the image into a numpy array
25 image_array = np.asarray(image)
26
27 # Normalize the image
28 normalized_image_array = (image_array.astype(np.float32) / 127.5) - 1
29
30 # Load the image into the array
31 data[0] = normalized_image_array
32
33 # Predicts the model
34 prediction = model.predict(data)
35 index = np.argmax(prediction)
36 class_name = class_names[index]
```

```

37 confidence_score = prediction[0][index]
38
39 # Print prediction and confidence score
40 print("Class:", class_name[2:])
41 print("Confidence Score:", confidence_score)

```

5.3.4 Test Result

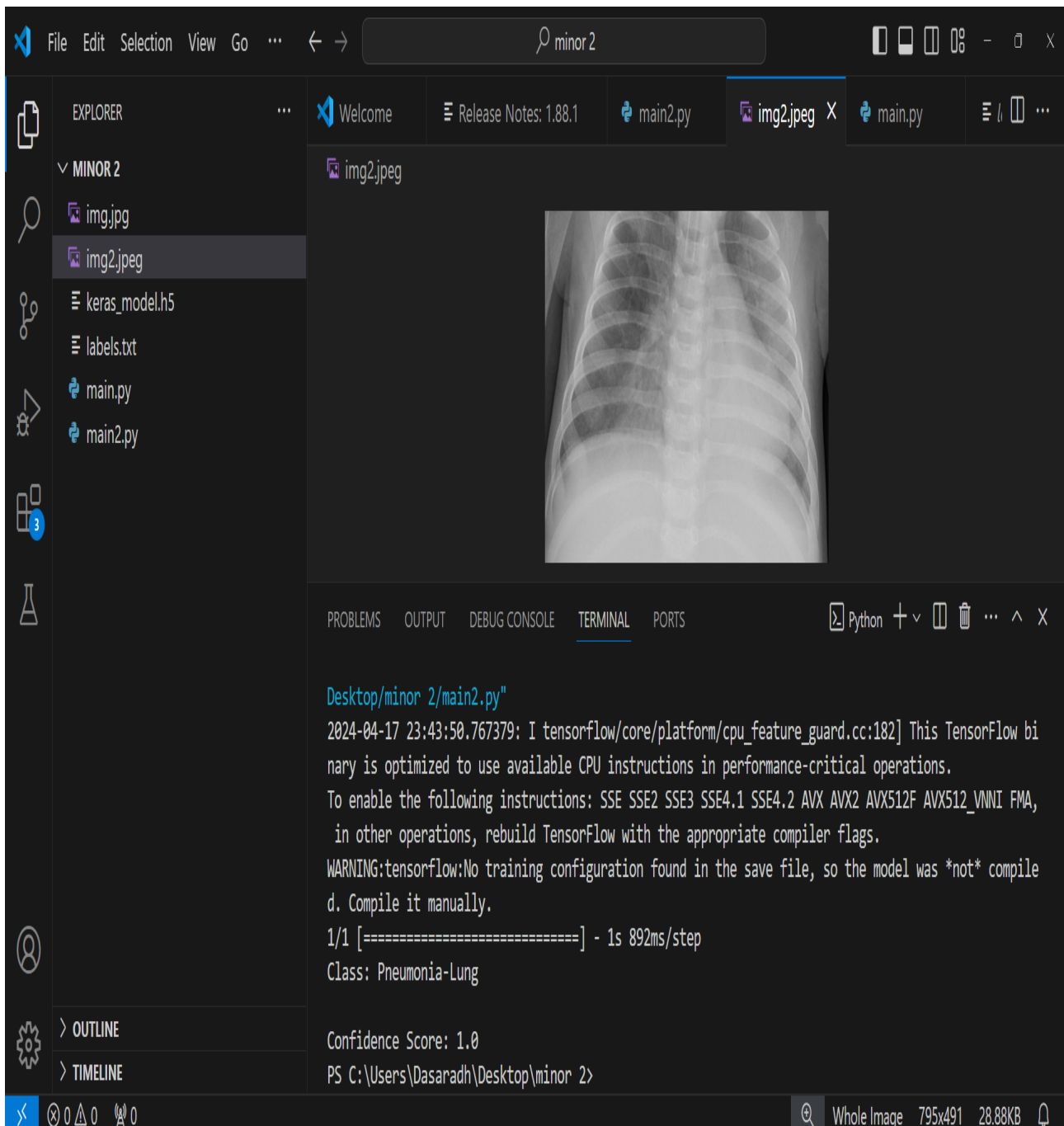


Figure 5.4: Output For Integration Testing

5.3.5 System Testing

System testing for the project would involve testing the entire system as a whole ensuring that all components work together seamlessly to achieve the desired functionality. In the case of natural disaster recognition system testing would involve testing the end-to-end workflow of the system including input data processing, feature extraction, model training, prediction and output generation. The system should be tested with various types of input data to ensure that it can handle different scenarios and produce accurate results. Additionally performance metrics such as accuracy, precision, recall and F1-score should be evaluated to ensure that the system meets the desired levels of accuracy and reliability. System testing would also involve testing the system's scribbled and performance under different loads and stresses to ensure that it can handle the expected volumes of data and user traffic.

Input

```
1 from keras.models import load_model
2 from PIL import Image, ImageOps
3 import numpy as np
4
5 # Disable scientific notation for clarity
6 np.set_printoptions(suppress=True)
7
8 # Load the model
9 model = load_model("keras_model.h5", compile=True)
10
11 # Load the labels
12 class_names = open("labels.txt", "r").readlines()
13
14 # Create the array of the right shape to feed into the keras model
15 data = np.ndarray(shape=(1, 224, 224, 3), dtype=np.float32)
16
17 # Replace this with the path to your image
18 image = Image.open("img5.jpg").convert("RGB")
19
20 # resizing the image to be at least 224x224 and then cropping from the center
21 size = (224, 224)
22 image = ImageOps.fit(image, size, Image.Resampling.LANCZOS)
23
24 # turn the image into a numpy array
```

```
25 image_array = np.asarray(image)
26
27 # Normalize the image
28 normalized_image_array = (image_array.astype(np.float32) / 127.5) - 1
29
30 # Load the image into the array
31 data[0] = normalized_image_array
32
33 # Predicts the model
34 prediction = model.predict(data)
35 index = np.argmax(prediction)
36 class_name = class_names[index]
37 confidence_score = prediction[0][index]
38
39 # Print prediction and confidence score
40 print("Class:", class_name[2:])
41 print("Confidence Score:", confidence_score)
```


5.3.6 Test Result

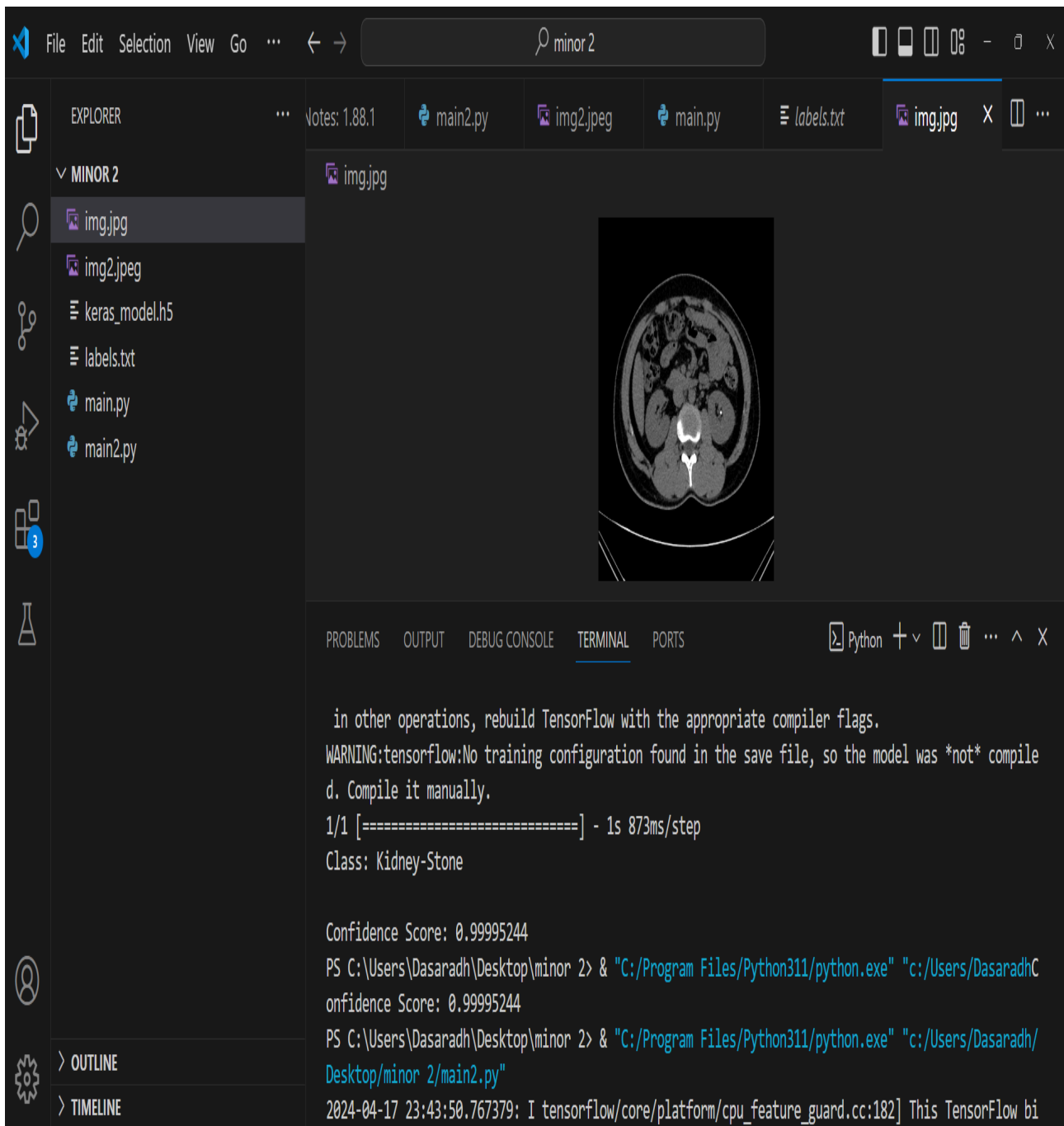


Figure 5.5: Output For System Testing

Figure 5.5 shows the Furthermore, the project to enhance patient care and outcomes by providing faster and more accurate diagnoses, leading to quicker treatment plans and improved prognosis. Ultimately, the goal of the project is to improve the overall quality of healthcare delivery and contribute to better health outcomes for patients.

Chapter 6

RESULTS AND DISCUSSIONS

6.1 Efficiency of the Proposed System

The proposed system, MediClassify, leverages AI-powered medical image diagnosis to enhance the efficiency and accuracy of medical diagnostics. By utilizing advanced machine learning algorithms, MediClassify can rapidly analyze medical images such as X-rays, MRIs, and CT scans, providing timely and accurate assessments of various conditions.

This streamlined approach reduces the time needed for manual analysis and interpretation, allowing healthcare professionals to focus more on patient care. Additionally, the system's ability to quickly identify patterns and abnormalities can lead to earlier detection of diseases, potentially improving patient outcomes and reducing healthcare costs. Overall, the efficiency gains offered by MediClassify have the potential to revolutionize medical imaging diagnostics, making it an invaluable tool in modern healthcare settings.

6.2 Comparison of Existing and Proposed System

Existing system:

Existing systems for mediclassify utilize AI-powered medical image diagnosis to assist healthcare professionals in accurately interpreting medical images such as X-rays, MRI scans, and CT scans. These systems employ deep learning algorithms trained on vast amounts of annotated medical image data to detect abnormalities, diseases, and conditions. Through pattern recognition and analysis, these AI systems

can provide valuable insights, aiding in the early detection, diagnosis, and treatment planning of various medical conditions. Moreover, they can help reduce the workload of radiologists and improve overall diagnostic accuracy and efficiency, potentially leading to better patient outcomes.

Proposed system:

MediClassify is an innovative AI-powered system designed to revolutionize medical image diagnosis. Leveraging advanced machine learning algorithms, it accurately analyzes medical images such as X-rays, MRIs, and CT scans to assist healthcare professionals in diagnosing various conditions. By combining deep learning techniques with vast medical knowledge, the system can swiftly detect anomalies, lesions, and other indicators of diseases with high precision.

One of the key strengths of MediClassify is its ability to handle a wide range of medical imaging modalities, making it versatile across different specialties and medical scenarios. Whether it's identifying tumors, fractures, or abnormalities in organs, the system provides reliable assistance to radiologists and clinicians, helping them make faster and more accurate diagnoses.

6.3 Sample Code

```
1 from keras.models import load_model
2 from PIL import Image, ImageOps
3 import numpy as np
4
5 # Disable scientific notation for clarity
6 np.set_printoptions(suppress=True)
7
8 # Load the model
9 model = load_model("keras_model.h5", compile=True)
10
11 # Load the labels
12 class_names = open("labels.txt", "r").readlines()
13
14 # Create the array of the right shape to feed into the keras model
15 data = np.ndarray(shape=(1, 224, 224, 3), dtype=np.float32)
16
```

```

17 # Replace this with the path to your image
18 image = Image.open("img5.jpg").convert("RGB")
19
20 # resizing the image to be at least 224x224 and then cropping from the center
21 size = (224, 224)
22 image = ImageOps.fit(image, size, Image.Resampling.LANCZOS)
23
24 # turn the image into a numpy array
25 image_array = np.asarray(image)
26
27 # Normalize the image
28 normalized_image_array = (image_array.astype(np.float32) / 127.5) - 1
29
30 # Load the image into the array
31 data[0] = normalized_image_array
32
33 # Predicts the model
34 prediction = model.predict(data)
35 index = np.argmax(prediction)
36 class_name = class_names[index]
37 confidence_score = prediction[0][index]
38
39 # Print prediction and confidence score
40 print("Class:", class_name[2:])
41 print("Confidence Score:", confidence_score)

```

Output

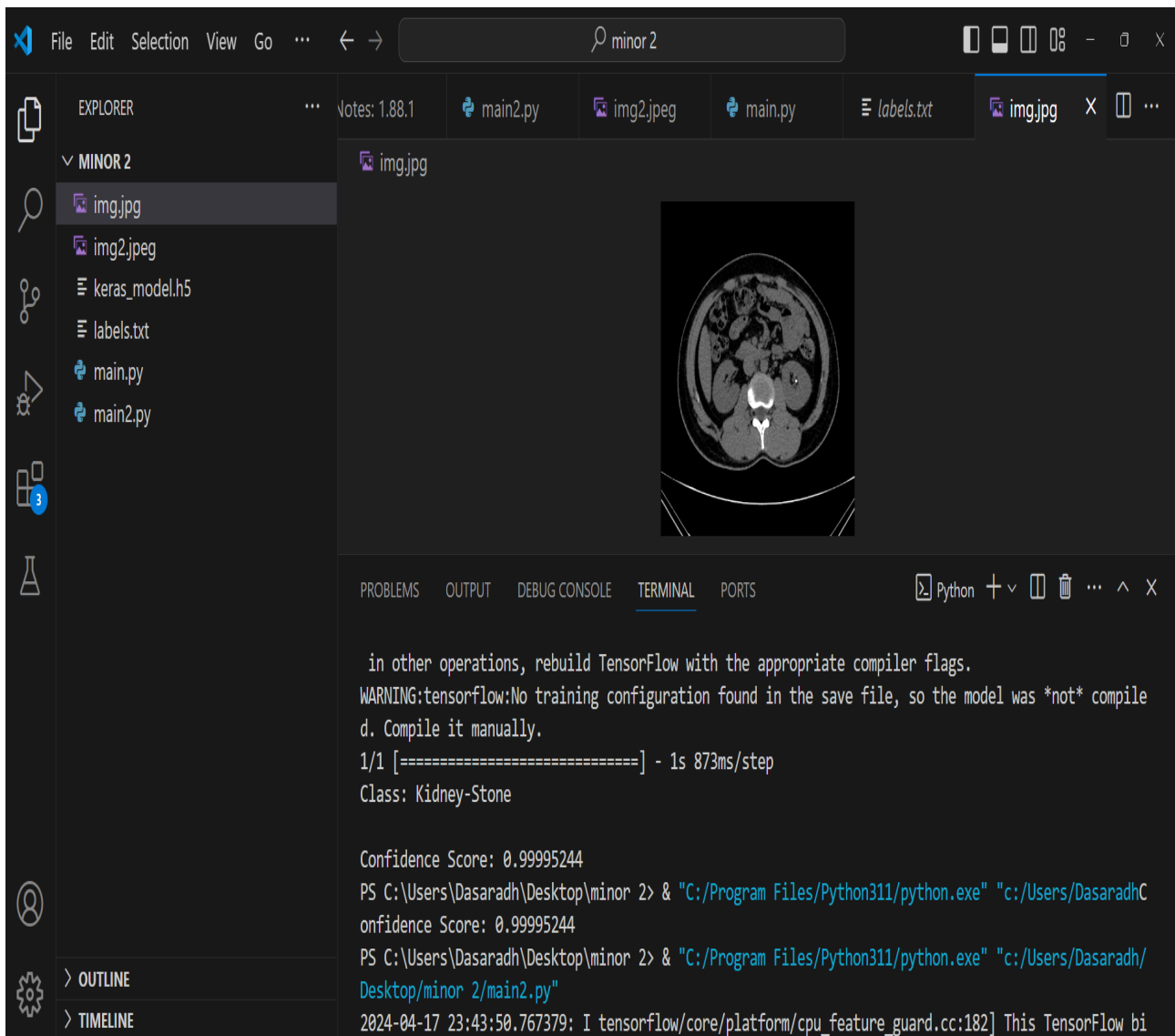


Figure 6.1: **Output For Kidney Stone**

Figure 6.1 shows the project involves testing the various components of the system to ensure that they work together correctly. The components include data preprocessing, feature extraction, model training and prediction. The testing process begins by testing the data preprocessing component to ensure that the input data is properly cleaned, normalized and formatted. Next the feature extraction component is tested to ensure that the features are properly extracted and correctly represented in the input for the models.

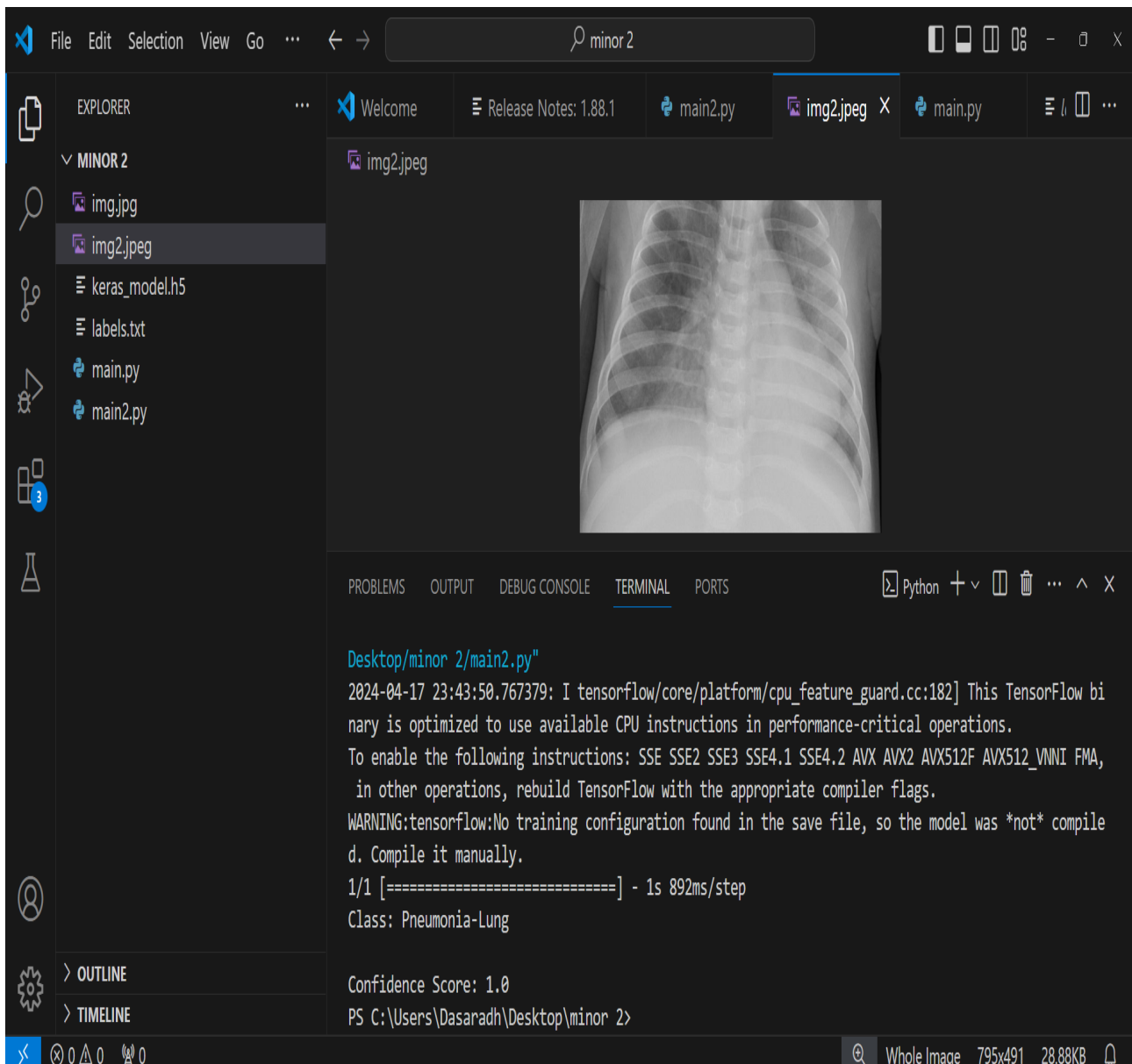


Figure 6.2: **Output For Pneumonia Images**

Figure 6.2 shows the project involves testing the various components of the system to ensure that they work together correctly. The components include data preprocessing, feature extraction, model training and prediction. The testing process begins by testing the data preprocessing component to ensure that the input data is properly cleaned, normalized and formatted. Next the feature extraction component is tested to ensure that the features are properly extracted and correctly represented in the input for the models.

Chapter 7

CONCLUSION AND FUTURE ENHANCEMENTS

7.1 Conclusion

The algorithms used in this work are CNN and SVM was successful in predicting the place that are in difficult condition with normal images. The performance of the models was evaluated based on various metrics like accuracy, precision, recall and F1-score, which indicates that the proposed model is effective in identifying disease area. The data pre-processing techniques such as image normalization, data augmentation and feature extraction were applied to improve the performance of the model. The thermal images, disease and type of disease were used as input features for the model, which were effective in predicting disease-prone areas.

The proposed system can be used by government authorities and hospitals management organizations for timely disease warning and response. However, there are some limitations to the project, such as the availability and quality of diagnosis images, which can affect the accuracy of the model. Overall, the project provides a promising approach to predicting disease using machine learning techniques and can be further improved by incorporating more features and refining the models.

7.2 Future Enhancements

In the future, MediClassify, our AI-powered medical image diagnosis system, will undergo significant enhancements aimed at improving accuracy, efficiency, and user

experience. One key enhancement will involve leveraging advanced deep learning techniques to further refine the system's ability to detect and classify various medical conditions from imaging data. Additionally, we plan to integrate real-time feedback mechanisms that allow healthcare providers to provide input and validation on diagnoses, helping to continuously improve the system's performance and adaptability to new cases.

Furthermore, we aim to enhance the interpretability of the system by incorporating features that provide insights into the decision-making process, allowing clinicians to better understand how the AI arrives at its conclusions. This will foster trust and acceptance of AI-based diagnoses within the medical community.

Another crucial aspect of our future enhancements involves expanding the range of medical conditions that the system can accurately identify. By continually training the AI on diverse datasets and incorporating insights from medical experts, we aim to broaden its diagnostic capabilities to cover a wider spectrum of diseases and abnormalities.

Moreover, we plan to optimize the deployment of MediClassify in various healthcare settings, ensuring seamless integration with existing medical infrastructure and workflows. This includes developing user-friendly interfaces tailored to different user roles, from radiologists to general practitioners, making it easier for them to access and interpret diagnostic results.

Chapter 8

PLAGIARISM REPORT



Chapter 9



SOURCE CODE & POSTER PRESENTATION

9.1 Source Code

```
1 from keras.models import load_model
2 from PIL import Image, ImageOps
3 import numpy as np
4
5 # Disable scientific notation for clarity
6 np.set_printoptions(suppress=True)
7
8 # Load the model
9 model = load_model("keras_model.h5", compile=True)
10
11 # Load the labels
12 class_names = open("labels.txt", "r").readlines()
13
14 # Create the array of the right shape to feed into the keras model
15 data = np.ndarray(shape=(1, 224, 224, 3), dtype=np.float32)
16
17 # Replace this with the path to your image
18 image = Image.open("img5.jpg").convert("RGB")
19
20 # resizing the image to be at least 224x224 and then cropping from the center
21 size = (224, 224)
22 image = ImageOps.fit(image, size, Image.Resampling.LANCZOS)
23
24 # turn the image into a numpy array
25 image_array = np.asarray(image)
26
27 # Normalize the image
28 normalized_image_array = (image_array.astype(np.float32) / 127.5) - 1
29
30 # Load the image into the array
31 data[0] = normalized_image_array
32
33 # Predicts the model
34 prediction = model.predict(data)
35 index = np.argmax(prediction)
```

```
36 class_name = class_names[index]
37 confidence_score = prediction[0][index]
38
39 # Print prediction and confidence score
40 print("Class:", class_name[2:])
41 print("Confidence Score:", confidence_score)
```

9.2 Poster Presentation

MEDI CLASSIFY: AI POWERED MEDICAL IMAGE DIAGNOSIS

Department of Computer Science & Engineering
School of Computing
10214CS602- MINOR PROJECT-II
WINTER SEMESTER 2023-2024

ABSTRACT

Our project aims to develop an innovative deep learning-based system for automated medical image classification, focusing on fractures, kidney stones, and pneumonia. Leveraging convolutional neural networks (CNNs) and a user-friendly web interface, our system enables seamless image analysis and diagnosis, enhancing accessibility for healthcare providers and patients. Through meticulous data collection and model training, our system demonstrates promising performance in accurately identifying medical conditions, with potential implications for early disease detection and patient management.

INTRODUCTION

Our project focuses on the development of an innovative system for automated medical image classification, aimed at assisting healthcare professionals in timely diagnosis and treatment planning. Leveraging state-of-the-art deep learning techniques, our system analyzes radiological images to classify three major diagnostic categories: fractures, kidney stones, and pneumonia. By harnessing the power of convolutional neural networks (CNNs) and integrating them into a user-friendly web interface, we aim to enhance accessibility and streamline the diagnostic process. Through meticulous data collection, preprocessing, and model training, our project endeavors to provide accurate and efficient medical image analysis, ultimately contributing to improved patient care and outcomes.

METHODOLOGIES

- 1.Data Collection and Preprocessing:** We collect a diverse dataset of medical images, including fractures, kidney stones, and pneumonia cases. The images are meticulously preprocessed to ensure
- 2.Model Architecture Design:** We design a convolutional neural network (CNN) architecture tailored to the task of medical image classification. The architecture consists of multiple layers for feature extraction and classification.
- 3.Model Training and Evaluation:** The CNN model is trained on the preprocessed dataset using standard deep learning techniques. We split the dataset into training and validation sets to assess model performance. Various evaluation metrics are employed to measure the model's accuracy and generalization capability.
- 4.Integration into Web Interface:** Once the model is trained and evaluated, we integrate it into a user-friendly web interface. It provides a good user interface through web platform

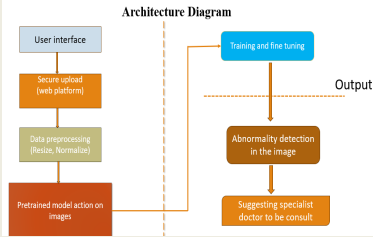
RESULTS

Our project successfully developed a deep learning-based system for automated medical image classification, focusing on fractures, kidney stones, and pneumonia. Leveraging convolutional neural networks (CNNs) and a diverse dataset of radiological images, our system demonstrated promising performance in accurately identifying medical conditions. Through meticulous data collection, preprocessing, and model training, we achieved high accuracy rates in classification tasks, empowering healthcare professionals with efficient tools for early disease detection and patient management.

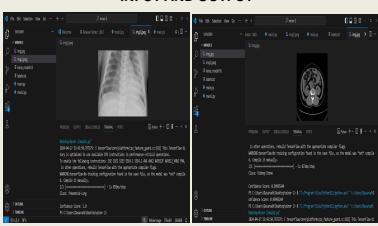
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ARCHITECTURE DIAGRAM



INPUT AND OUTPUT



CONCLUSIONS

In this project, we successfully developed a deep learning-based system for automated medical image classification, focusing on fractures, kidney stones, and pneumonia. Through meticulous data collection, preprocessing, and model training, our system demonstrates promising performance in accurately identifying medical conditions from radiological images. The integration of the model into a user-friendly web interface enhances accessibility for healthcare providers and patients, facilitating timely diagnosis and treatment planning. Our work lays a solid foundation for future advancements in automated medical diagnosis systems, with the potential to improve patient outcomes and revolutionize healthcare delivery.

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