AUTOMATED DETECTION OF KIDNEY STONES IN COMPUTER TOMOGRAPHY (CT) IMAGES USING CONVOLUTIONAL NEURAL NETWORKS (CNN)

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APPROVAL PAGE

This research, titled "**AUTOMATED DETECTION OF KIDNEY STONES IN COMPUTER TOMOGRAPHY (CT) IMAGES USING CONVOLUTIONAL NEURAL NETWORKS (CNN)**," has been assessed and approved by the Department of Computer Science and Mathematics Committees in the Faculty of Natural Sciences and Environmental Studies, Godfrey Okoye University, Enugu, Nigeria.

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CERTIFICATION

I certify that I completed the research included therein and that it was primarily based on my observations and investigation. Consequently, I will fully accept the University's decision if I am found to have cheated on the assignment.

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DEDICATION

This project, titled "Automated Detection of Kidney Stones In Computer Tomography (CT) Images Using Convolutional Neural Networks (CNN)," is dedicated to Almighty God and to my parents, Mr and Mrs Ucheatu.

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I express my profound gratitude to God Almighty for His kindness and fortitude along this journey, without whom this significant work would not have been achieved.

My heartfelt gratitude goes to my loving and caring parents, Mr and Mrs Ucheatu, for their endless support in every way.

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Abstract

Renal calculi are one of the most frequently encountered urological diseases that have to be properly diagnosed in order to prevent complications. It is widely believed that Computer Tomography (CT) imaging represents an efficient way to diagnose renal calculi but the interpretation of CT scans may be a time-consuming process and is subject to certain human errors. The main purpose of this work is to create an automated system of diagnosing kidney stones using Computed Tomography (CT) images and the technique of Convolutional Neural Networks (CNN). A set of kidney CT images that are available in public domain was divided into two groups, namely "Stone" and "Non-Stone"Image pre-processing steps, like resizing, normalization, grayscale conversion, and data augmentation, have been applied to enhance the model performance. An automatic framework of CNN is proposed to extract important features from CT images and classify them accordingly. The results obtained by the model include an accuracy of 52.6%, a recall of 87.6%, a precision of 17.4%, and F1 score of 0.29, based on the confusion matrix with 241 true positives, 1,069 true negatives, 34 false negatives, and 1,144 false positives from a test set of 2,488 CT images. The model has been designed to be applicable in practice and implemented through web-based application with Flask technology and role-based access, where radiographers are able to upload images, get their prediction and patient's information immediately. The application of deep learning is discussed in the paper, with the particular focus on the role that can be played by CNN-based deep learning approach in terms of improving early diagnosis, simplifying the process of diagnosis and providing health care services in resource-limited settings.

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CHAPTER ONE
INTRODUCTION

1.1 Introduction

Kidney Stone remains a public health challenge, as many people develop this disease regardless of their age and geographical locations around the world (Stamatelou & Goldfarb, 2023). Calculi develop in the kidneys through crystallization due to several causative factors, including poor diet, inadequate consumption of water, genetic factors, and medical conditions such as hyperparathyroidism or gout. Renal calculi present as symptoms, from asymptomatic presentations to renal colic that can be a painful situation in which one experiences a severe pain sensation. Other common presentations are hematuria, infection in the urinary tract system, and vomiting. Without proper diagnosis or late diagnosis, an individual suffering from this disease could end up with kidney failure.

Because of the increased number of kidney stones due to alterations in the lifestyles, diet, and metabolic diseases, the need for accurate and efficient diagnosis is higher than ever. In fact, several studies have been conducted in recent years and have indicated that there has been an increase in the frequency of stones in people who take a lot of proteins, salts, and oxalates in their diets. The current trend of obesity and diabetes mellitus, which can cause insulin resistance, has also played a significant role in causing stones due to alterations in the pH level of urine and urinary calcium excretion.

Computerized Tomography (CT) has emerged as one of the most preferred options as far as detecting kidney stones is concerned because of its high sensitivity and ability to visualize the presence of the calcified structures within the urinary tract (Aiumtrakul et al., 2024). There are several advantages offered by non-contrast computed tomography (CT) over other imaging techniques such as ultrasound and plain radiography. The first advantage is the high sensitivity of CT to all stone types irrespective of their composition. This includes even uric acid stones that are non-radio-opaque (do not show up in an X-ray). The second advantage is the fact that CT provides accurate anatomical localization and thereby stones can be localized in renal parenchyma, calyces, pelvis and ureter. The third advantage of CT is that it can help identify secondary signs of obstruction like perinephric stranding or hydronephrosis. CT capitalizes well on high absorption capacity of minerals like calcium to X-rays, resulting in high intensity signals within soft tissues.

However, the conventional method of diagnosis depends highly on the radiologist's capability to go through the images obtained from the CT scan. Typically, the CT scan of the abdomen may generate numerous images that have to be scanned. In addition, the radiologist will have to go through the images one after another and distinguish the hyper dense foci, which may be suggestive of stones. The process is a very long and tedious one and requires lots of attention.

A single radiologist may have to read tens of CT scans each day in high volume clinical situations, causing the radiologist to become fatigued and thereby compromising diagnostic accuracy. However, even with optimal conditions there is inter-observer variability, which can lead to some confusion about the presence or significance of small stones or atypical stones.

This can be effective, but it typically takes a long time, is costly, and involves human error, particularly when working on a large scale in clinical environments, where fatigue and pressure to work may lead to substandard diagnosis (Bruno et al., 2025). Manual CT interpretation directly and immediately contributes to delayed turnaround for interpretation reports, resulting in delayed diagnosis and treatment decisions that can include pain management, antibiotic treatment if the patient has an active infection, or surgical intervention. As far as the economic impact is concerned, it can be quite expensive to hire any specialist radiologist to conduct routine stone detection activities within the healthcare systems that are based upon the fee-for-service or resource-based reimbursement methods. Furthermore, there are costs associated with both diagnostic mistakes—falsely negative for missing stones and diagnostic mistakes—falsely positive for unnecessary procedures—that are also significant and add to the economic inefficiency of manual-only workflows.

Moreover, the great majority of healthcare facilities located in remote areas and lacking proper resources does not have access to trained radiologists and thus cannot offer diagnosis in time, which makes things worse for their patients. The proportion between radiologists and population in low and middle income countries is abnormally low, with more specialists concentrated in urban tertiary hospitals. Clinics in rural areas may lack imaging interpretation altogether, with their patients having to travel long distances or to wait for consultants to interpret the image. Even if CT scanners can be acquired or provided through the programs offered by governmental agencies, they will not be utilized as long as there are no qualified people who could interpret the image. Patients in such regions have to endure a lengthy diagnostic process, resulting in growth, obstruction and/or damage of kidneys due to the presence of small stones before the beginning of the treatment. Such need was partially resolved through the use of telemedicine, but the problem with access to an expert human interpreter persists.

New developments in AI technology and more specifically in deep learning can provide answers to these problems (Zuhair et al., 2024). CNN models have proved to be efficient in providing the required capabilities of analysis of medical images such as disease detection and classification. Deep learning models learn features directly from the images whereas in conventional machine learning algorithms features have to be manually engineered by domain specialists designing descriptors for shape, texture, and intensity. The concept of end-to-end learning has led to a revolution in computer vision across various industries including radiology. The concept of using AI in detection of kidney stones is the use of CNN models trained on large volumes of labeled data sets of CT scans that represent the patterns of kidney stones rather than design rules about how kidney stones look.

Convolutional Neural Networks possess the capability of self-learning hierarchical structures from the imaging data, making it possible for them to extract features that may not be easily visible by the naked eye (Mienye et al., 2025). Due to the aforementioned characteristics, CNN models appear to be suitable candidates for the automated detection of small kidney stones in CT scans. The layers of CNN models work in a manner that is analogous to that of human visual information processing – whereas lower layers perceive edges, corners, and contrast in the images, middle layers learn the textures based on such features, and higher layers encode the objects based on such information (for instance, kidney stones or/and their particular features). Thus, CNN models allow the detection of small stones (<2 mm), average volume stone sizes, and stones located next to areas with similar densities (blood vessels, for example). Moreover, CNNs can distinguish the most commonly occurring non-stone objects.

AI-based automated detection systems can serve as effective decision-making support systems for medical professionals (Sarvamangala and Kulkarni, 2022). Such systems can help achieve faster initial screening, reduce the workload of the diagnostic process, standardize it, and increase access to high-quality medical services in general and in needed regions. Using a typical workflow for a clinical setting, one could use an AI system as the first reader, marking those images suspected of having abnormalities for later radiologists' analysis, while automatically clearing all the normal ones. This way, specialists would be able to analyze only complex or unclear images, decreasing the risk of burnout and job satisfaction among medical professionals. In addition, using AI-based analysis, the same algorithmic analysis will be done for all scans, eliminating daily human variability from the analysis process. In under-resourced areas, lacking radiologists, such systems can be used to inform non-specialist medical professionals about triaging patients, or enable remotely located specialist experts to focus on the most critical cases.

It should be mentioned that significantly, one needs to understand that the tools will supplement the clinical skills rather than replace them since they allow for accurate prediction in radiologists (Fahim et al., 2025). The suggested research is based on the task of automatic detection of kidney stones in CT scan images by using Convolutional Neural Networks. In the research, the technology of transfer learning and a public dataset of CT kidney will be used as the basis for creating a robust binary classification model which will be able to distinguish between normal kidney images and those that have stones. The suggested solution intends to make contribution to improving the efficiency of the diagnosis process and minimizing the possible errors made in clinical decision making about the presence of kidney stones. Such contribution is necessary both ethically and practically, as the AI algorithm may produce both false-positive and false-negative results and does not have the clinical context known to a human physician.The appropriate strategy should be the one where both work in tandem and the artificial intelligence system uses its ability to give prompt and accurate predictions, whereas the radiologists use their decision-making process on complicated cases. It is without a doubt the only strategy that will guarantee success in diagnosing kidney stones throughout the world.

1.2 Statement of the Problem

Kidney stone disease is common and extremely painful. Undiagnosed cases are at risk of contracting infections, total blockage of the kidney tract, or causing permanent damage to the kidneys.

1. The Manpower Limitation: Currently, CT scanning is the most efficient tool in stone detection; however, it is still done manually. It takes a long time to do, costs a lot, and requires a large amount of mental effort from radiologists.

2. The Error Factor: In high patient turnover settings, radiologists are likely to be fatigued by the number of patients they have to examine, which causes errors in their diagnoses.

3. The Urban-Rural Divide: In areas where there aren't enough radiologists, patients' chances of developing severe diseases increase, especially in rural or poorly equipped areas..

4 Insufficient use of existing tech: Although AI is promising, many current technologies are heavy (needs a lot of computation), not well generalised (does not work across different hospitals) and too complicated to use in real life clinical settings.

5. The Urgent Need: The need is for a system that is easy to use and based on CNN (Convolutional Neural Network), a CNN-based technique. This will serve as a “second set of eyes” that can eliminate human error and help patients get the necessary fast and life-saving decisions, anywhere they are.

1.3 Aim of the study

The objective of this project is to develop an automatic detection system that will detect the presence of kidney stones in CT images as either “Kidney Stone” or “No Kidney Stone”.

Objectives of the Study

In order to accomplish this objective, the following are the objectives of this study:

1. Get a set of pre-processed CT images of the abdomen that are labelled as having a presence of kidneys with/without kidney stones.
2. Preprocess the data set by resizing the images followed by normalizing the pixels and dividing it into train, test, and validation sets.
3. Implementation of the CNN model using transfer learning.
4. Development of a user-friendly web interface using the Flask framework.
5. Performance Evaluation of the model through Accuracy, Precision, Recall, F1-Score and Confusion Matrix.

1.5 **Significance of the Study**

Significance of the Study to the Following Groups

1. Patients: Quick Services and Better Outcomes

- Quick Diagnosis: Helps avoid problems like kidney damage and helps prevent conditions like kidney failure.

- Equal Treatment: Makes sure patients from remote areas get equally good quality scans like those living in urban areas, using an easily available web interface.

2. Radiologists: Helps Avoid Burnout and More Accurate Diagnostics

- Expert Opinion: Acts as a second opinion to help locate any missed stones because of exhaustion or too many scans.

- Saves Effort: Provides automated scans, allowing doctors to focus on more critical cases.

3. Healthcare Providers: Saves Money and is Scalable

- Saves Time: Allows performing more scans per unit time, hence reducing the cost of diagnostics.

Telemedicine Ready: Being a web-based tool means it can be used remotely to help clinics that don't have a specialist on-site.

4. The Research Community: Future-Proofing Medicine

- **Proven Tech:** Demonstrates how Transfer Learning can be used specifically for urology.
- **Versatility:** Provides a template for building similar AI tools to detect other diseases in the future.

1.5 Scope of this study

The paper proposes automatic kidney stones detection in 2D images obtained from CT scanning with CNNs. It does not consider any other diseases of the kidneys, including cysts or tumors, and considers only the classification into healthy and unhealthy tissues, the latter being the presence of kidney stones. Pre-processing includes resizing and normalization based on a pre-labeled database collected from Kaggle for obtaining accurate results.

The transfer learning process is key to this project as the process of pre-training enables the use of pre-trained neural network for the diagnostic purpose. One of the items which will be used as proof of concept prototype is the website created using Flask technology. The user will have the ability to upload the scan image and obtain instant information regarding whether there are any kidney stones present or absent from the scan image. The website will not enable localization or the computation of sizes.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

The current level of automation in detecting kidney stones will be considered in this chapter. This chapter is aimed at discussing the relationship between clinical necessity and innovation technologies in detecting kidney stones. It starts with providing an overview of kidney stone, considering its causes and incidence rates, after which it explains why CT images can be regarded as the gold standard of this condition. An overview of image processing techniques, including edge detection, will be provided and it will be noted that this method is inadequate due to a lack of accuracy and scale.

2.2 Theoretical Background

In this study, the integration between medical pathology and the deep learning method is used to automate kidney stone detection in computed tomography (CT) images. Kidney stone occurs medically due to the formation of mineralized calculi by the deposition of crystallizing minerals such as calcium oxalate in urine. Such stones are calcified, making them bright and clearly defined regions in non-contrast CT scans that represent the golden standard in diagnosis. However, kidney stone detection is sometimes difficult, particularly during early-stage development or when the stone burden is too great and small calculi cannot be detected visually.

In addressing this issue, CNN technology is used. CNNs enable automatic feature detection and identification from the input image by carrying out multiple levels of convolutions and activations on raw pixels, rather than relying on handcrafted features, as is typically done in the case of traditional machine learning. In the current study, transfer learning is applied. Here, fine-tuned versions of powerful pre-existing models such as VGG16 or ResNet, which have performed well on various visual recognition tasks, are used. By combining these algorithms with radiological knowledge, this project seeks to merge the theory and practice of radiology with computational methods.

2.3 Conceptual framework

The study combines clinical information about kidney stone with the concepts of deep learning and computer vision to allow the automatic and effective detection of kidney stones using Computer Tomography (CT) scans. It is based on the medical information that the kidney stone is the result of crystallization and coagulation of mineral deposits in the kidneys and urinary tract. The high radiodensity of these calculi gives them visibility as they present as bright and well-defined spots on CT scans (González-Enguita and García-Giménez, 2024). The use of these radiological features is a good basis for the computational analysis and automatic detection. For this system, the input data in the system are the images produced by CT scan. To enhance the quality of the image and ensure it is suitable for the deep learning models, image preprocessing techniques like resizing, normalization, and noise reduction are applied to the input image.The input image is first preprocessed using techniques such as resizing, normalization, and noise reduction to make it suitable for the deep learning models. It is also possible to use data augmentation techniques to enhance the generalization of models and possible fluctuations in imaging conditions. The images are then fed to a Post Processing using Convolutional Neural Network (CNN) which automatically identifies features and classifies them (Omoniyi et al., 2025). CNNs learn the hierarchical spatial (intensity, edge, textural) features of kidney stones via convolutional and pooling layers, without having to be programmed to include them manually. Pre-trained architectures like VGG16 or ResNet are used to perform transfer learning to use learned visual representations and enhance the classification of small medical datasets (Babu et al., 2025). Labelled CT images are used in the training of the CNN to tell the difference between the normal kidneys and those that have stones. Some of the common diagnostic metrics used to assess model performance and evaluate its reliability and clinical relevance are: accuracy, precision, recall, F1-score, and confusion matrix (Nisha et al., 2024). The trained model produced by the framework is then deployed in a web application using the Flask framework and uploads of images are allowed and predictions are done in real-time. The conceptual framework shows how the clinical knowledge, clinical computed tomography (CT) information, and deep learning can be used together to facilitate effective, predictive, and scalable kidney stone detection for clinical use as a decision support tool.

2.3.1 Overview of Kidney Stones(Nephrolithiasis)

Nephrolithiasis or kidney stones are crystalline materials that are deposited in solid form in the kidneys due to the deposition of minerals and salts that are caused by the presence of the urine. They are a prevalent condition of the urinary system in many countries around the world and occur in millions of people across all ages and geographic locations (Stamatelou & Goldfarb, 2023). As a result, this high global prevalence implies that there is a significant resource allocation required for the diagnosis, management and prevention of stone disease in health care systems in almost all countries. It impacts on patients' lives and is a heavy economic burden when it comes to ED attendance, surgical procedures and work productivity losses.

Kidney stones have been on the rise particularly in developed countries, and this increase has been attributed to changes in lifestyle, nutrition, and the growing prevalence of metabolic diseases such as obesity and diabetes(Pricop et al., 2024). The high protein, sodium, and oxalate food consumption of western diet, and inadequate fluid intake, provide an environment for urates to crystallise. In terms of sex distribution, male are more affected than female who have seen a reduction in the gender gap over the last few decades. It is found more commonly in the age group 30 to 50 years, but can occur at any age, even childhood and late adulthood.

Kidney stone formation is a complex process and for this purpose intrinsic and extrinsic factors are important. Intrinsic factors are genetic predispositions, metabolic abnormalities (hypercalciuria, hyperoxaluria, and hyperuricosuria), and structural differences in the urinary tract that can allow for urine stasis and/or urinary tract infections (Ferraro et al., 2023). v Calcium oxalate stones are the most common type of these, representing about 70-80% of all stones. This is their predominance due to the high level of oxalate in common food and the tendency of calcium to precipitate at high levels of supersaturation in the urine.

Some types of stones are only linked to underlying metabolic or infectious illnesses. For instance, uric acid stones are commonly linked with hyperuricemia and gout, and struvite stones are associated with urinary tract infections (UTIs) that are caused by urease-producing bacteria, like Proteus, and Klebsiella (Tamborino et al., 2024).

The incidence of kidney stones is quite different among various global populations, ranging from 1% to 15% depending on geographic location, diet, and access to health care facilities (Stamatelou and Goldfarb, 2023). The prevalence rate is said to be low in Nigeria and other African countries compared with those in the western countries, but is increasing with the urbanisation of the population, change in diet (with consumption of processed foods and less of traditional high fluid diets) and lack of public awareness on preventive nutrition. This increase indicates that the burden of kidney stone in Africa needs to be increased in healthcare systems in the near future.

A past history of kidney stone increases the risk of a new stone formation within 5 years, and 50% of patients have a high risk of recurrence (Mbadiwe et al., 2025). These are the high rates of recurrence, which require long-term follow up and lifestyle changes in patients. The clinical picture of kidney stones may vary widely from a totally asymptomatic course (during which stones are only detected by chance) to a sudden onset of intense back or abdominal pain (renal colic), to microscopic blood in the urine (hematuria), to nausea and vomiting, to obstruction of the urinary tract, which may manifest as anuria or difficulty voiding.

If not detected or treated in time, kidney stones can cause some serious complications. Complications can include urinary tract infection (UTI) that can progress to pyelonephritis (kidney swelling) or urosepsis (bloodstream infection), hydronephrosis (kidney swelling caused by urine retention), chronic kidney disease due to long-term back-up, and irreversible kidney damage in more severe cases (Leslie et al., 2024). The prevention of these complications and better patient care are thus very important, and they are best achieved through the early detection and proper management of the disease.

Early diagnosis of the condition is hence extremely important, and it will make the treatment of patients much more effective and facilitate effective diagnostic techniques (Sun et al., 2025). It should be noted that there are limitations when it comes to conventional tests like ultrasound and plain radiography, and CT scans (the current gold standard method) require an experienced person to interpret the results. In this regard, there is a need for modern technologies that can provide quick, accurate, and simple diagnostic procedures.

There are many factors that contribute to the development of kidney stones, as well as different types of this disease. The identification of these facts is essential for providing patients with efficient diagnostic techniques and treatment procedures. Nowadays, these methods are mostly based on the use of various advanced imaging methods and automated tests (Bargagli et al., 2025). Thus, the use of AI algorithms based on CNN models seems like a promising way of coping with the requirements of diagnosing this ancient, yet widespread, disease.

2.3.2 Medical Imaging Techniques for Kidney Stone Detection

Medical Imaging has an important place in the diagnosis and treatment of kidney stones by providing a non-invasive technique to image the urinary system. Common imaging techniques include ultrasonography, X-rays, Magnetic Resonance Imaging (MRI), and Computerized Tomography (CT), each with their own strengths and weaknesses for imaging stones of varying size and composition. Of them, CT is regarded as the gold standard because it is highly sensitive, specific, and has a high capability of localizing stones precisely. This part of the paper discusses these methods and explains why CT is preferable.

1. **Ultrasound (US):** Ultrasound is a radiation-free, non-invasive procedure that is normally employed in the detection of kidney and bladder stones. It is non-invasive, common and is appropriate in preliminary screening. Its usefulness is, however, reduced by its poor sensitivity towards small stones, specifically those less than 5 mm and difficulty in visualization of the presence of the stones in the ureters, which can result in missed diagnoses (Benn & Leslie, 2025).

2. **X-ray (KUB – Kidney, Ureter, and Bladder):** X-ray KUB is a rapid and widely available imaging technique, which has been successful in the detection of radiopaque stones, especially calcium based calculi. It offers a general diagnosis of the presence of one or more stones by giving a plain projection of the urinary tract in 2D (Choi et al., 2021). Nevertheless, it is not sensitive to radiolucent stones, including uric acid stones, and can be less accurate in the detection of smaller or overlapping stones, which decreases the diagnostic accuracy.

3. **Magnetic Resonance Imaging (MRI):** Magnetic Resonance imaging (MRI) is a radiation-free modal which gives great contrast of the soft tissues. Yet, its application in the detection of kidney stones is minimal as it has low imaging qualities of calcified structures. MRI is not normally a primary diagnostic tool in nephrolithiasis, but that is used as an alternative

to CT or X-ray when it is contraindicated, e.g., in pregnant patients or where a reduced radiation dose should be applied (Ghadimi & Thomas, 2025).

4. **Computer Tomography (CT):** Computer Tomography (CT) is the gold standard method of kidney stone detection as it has high sensitivity and specific capacity to detect any type and size of kidney stones. It is accurate in localization of the anatomies, three dimensional imaging and is able to detect stones that ultrasound or X-ray fails to recognize. CT is primarily helpful in emergency cases wherein it aids in the correct diagnosis and prompt clinical treatment.

2.3.3 Traditional Image Processing Approaches for Kidney Stone Detection

Prior to the development of deep learning alongside the more sophisticated artificial intelligence tools, kidney stone detection was mainly based on more traditional image processing tools that were applied to medical images including X-rays, ultrasound, and CT scans. These methods incorporated manually written algorithms to extract certain features of images to determine whether there are stones. The principle idea was to improve image quality, showcase pertinent structures, and mark the calculi against tissues surrounding them depending on the intensity, form, or consistency differences.

1. **Thresholding**, One of the first methods that were used in the detection of kidney stones is which uses the pixels in an image divided by the intensity. Kidney stones are brighter than the surrounding tissues in the X-ray or CT images because they are composed of calcified material. The thresholding methods utilise this difference to segment possible stone regions (Cui et al., 2021). Although it is simple and computationally efficient, thresholding is prone to changes in image quality, noise and overlapping structures in anatomy, which can cause false positive or missed detections.

2. **Edge detection** identifying the boundaries of stones by detecting sudden changes in pixel intensity was also widely used using techniques including the Sobel, Canny or Laplacian operator. Edge-based methods could also be utilized to generate the outline of the stone and thus provide information regarding its size and localization (Amer and Abushaala, 2015). The problem with such methods is that they are prone to the effects of noise and often require additional processing for false edge detection elimination purposes.

3. Image segmentation methods also played an important role in the traditional approach to image analysis. Methods such as region growing, clustering (e.g., k-means), active contour model (snakes) were utilized to divide the picture into three parts – the stone itself, the kidney, and its surroundings. Segmentation could assist in localizing the stone and determining its properties in greater detail. However, effective segmentation is often dependent upon parameter adjustment, high-resolution pictures, and manual interaction.
4. As in the previous case, this step also relied upon the handcrafted feature extraction approach. Features such as intensity, shape, texture, and geometric properties were programmed to characterize kidney stones. Machine learning classifiers (e.g. SVMs, Decision Trees, or k-NNs) were then used with such characteristics to classify the area in question as either normal or abnormal. Despite their effectiveness in laboratory environments, such methods failed to work properly in conditions involving imaging variation, stone size, and localization.

2.3.4 Deep Learning-Based Approaches for Kidney Stone Detection

It is important to mention deep learning, which has emerged as a breakthrough tool in enabling the automated detection of kidney stones from medical imagery, particularly CT scans, due to its ability to automatically detect the features hierarchy-wise from data, without going through the feature extraction step. The most common deep learning tool used for this task is the Convolutional Neural Networks (CNNs). As opposed to classical machine learning models, CNNs are also able to automatically detect relevant features by using convolution, pooling and non-linear activation layers, which allows it to be used to classify complex or even noisy images.

1. **Convolutional Neural Networks (CNNs):** CNNs consist of convolutional layers which detect edges, shapes and texture, followed by the pooling layers which decrease the dimensionality without losing important information (Mienye et al., 2025). The final node of the network has fully connected layers that classify according to categories like: No Kidney Stone, or Kidney Stone. CNNs have been shown to be incredibly accurate, typically over 85% with regard to determining presence of kidney stones based on CT scans, and can be trained well across a wide range of data.

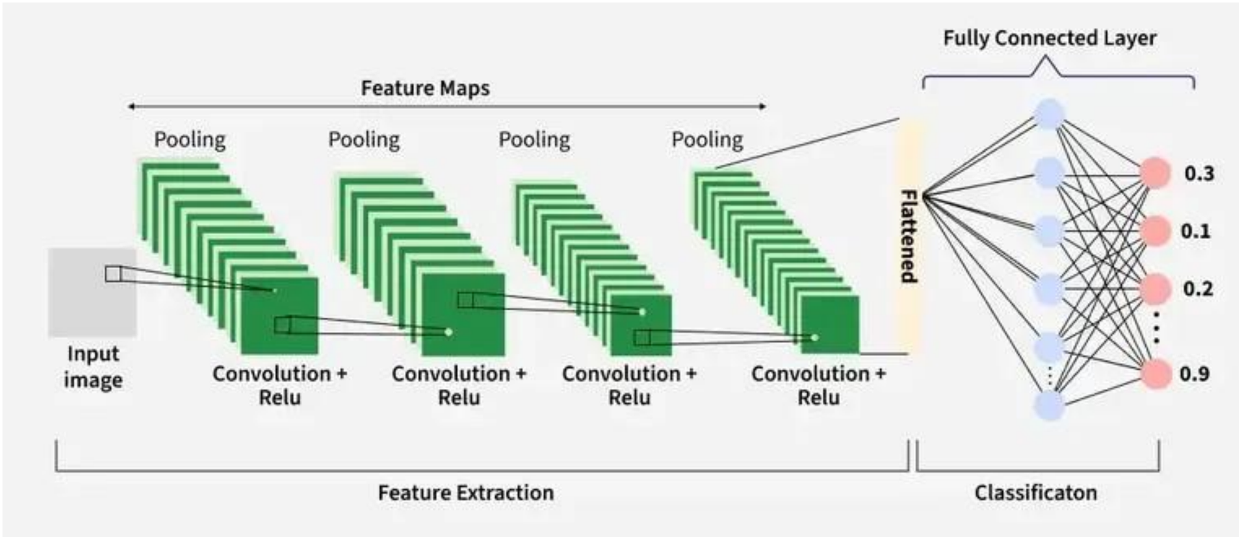

Figure 2.1: Architecture of the CNN Algorithm

2. **Transfer Learning:** Commonly used pre-trained CNN designs, including VGG16, resnet, or inception are used to enhance kidney stone dataset performance. Transfer learning exploits the experience gained on large-scale images, making it less desirable to have large amounts of medical imaging data, and it converges more quickly and is more accurate. With careful training of these models using kidney CT images, the network can be tailored to the visual features that it had learned previously to deal with the particular task of stone detection.

3. **Hybrid CNN Approaches:** Other studies use CNNs with the conventional image processing methods in order to perform better feature representations. As an example, CNN can be enhanced with preprocessing such as contrast enhancement or kidney segmentation to concentrate on areas of interest, lessening the amount of false positives generated by the surrounding tissues (Buriboev et al., 2025).

4. **Performance and Evaluation:** Kidney stone detection deep learning models are assessed with the measures of accuracy, precision, recall, F1-score, and area under the ROC curve. It has been demonstrated that the high-performance CNNs are more effective than the traditional machine learning methods when applied to process variable-size, location, and CT imaging protocols of stone.

2.4 Review of Related Literature

The previous works on automated kidney stone detection using medical imaging and machine learning algorithms is reviewed. Research has been carried out since the early days of image processing and classic classifiers, all the way to the sophisticated state of the art deep learning models, namely Convolutional Neural Networks (CNNs). The review highlights the strategies, data, results of performance and restrictions, and identifies gaps in existing strategies. It provides a base for a new system of kidney stone effective, efficient and accessible detection based on CNN in CT images.

According to Elton et al. (2022) created a deep learning model to detect and segregate kidney stones and compute their volumes on non-contrast CT images. The technique employed in the study was a Convolutional Neural Network (CNN) that was used to locate and quantify the stones, thereby helping the stones to be anatomically classified. The approach proved sensitive and specific, compared to the conventional manual processes, and at the same time, less time-consuming in the process of interpretation. Handling tiny stones and the variance in scanning techniques posed some challenges. It is evident that the use of deep learning models in the analysis of kidney stones, particularly the CNN-based approaches, has proven to be reliable, thus forming a strong foundation for CT-based automatic and clinically egoistic kidney stone analysis.

In Bouzon et al. (2023), an automatic kidney stone detector was created by making use of a simple CNN with a view to being used in resource-limited settings. The objective of the study was to come up with a high-performance kidney stone detector using a CNN on coronal CT images. The CNN model performed well when it comes to identifying stones of different sizes and positions. The disadvantages were that on smaller and medium-sized stones, the performance was not great and the stones overlapped. This study highlights the promise of low-complexity deep learning models to provide easy, fast, and efficient kidney stone detection, especially in low-computational environments.

Almuayqil et al. (2024) proposed a more complex system based on a CNN which is used for automated diagnosis of kidney stone disease (KSD) in CT images. The model consists of 8 convolutional layers, 3 pooling layers and well developed fully connected layers to successfully extract hierarchical image features with less overfitting using fewer filter size. It also uses Grad CAM to emphasize image regions that affect predictions to enhance clinical interpretability. The performance metrics for KidneyNet were tested on a multi class CT kidney data set and yielded significantly high metrics with accuracy of 99.88%, sensitivity of 99.76 and F1 score of 99.67; compared to other comparative deep learning models. The paper demonstrates that CNNs can be effectively employed to automatically detect kidney disease in medical images with high accuracy and reliability.

Chan et al. (2020) gave an overview of deep learning applications in computer aided detection (CAD) of medical imaging. The authors explained the revolution of the conventional CAD system by introducing convolutional neural networks (CNNs) and other deep learning systems for automatic learning of features, enhancing lesion discovery, and reducing false positives in various modalities including CT, MRI, and X ray. On the contrary, these studies have emphasized practical application in lung nodules and breast cancers and highlighted improved performance compared to traditional techniques. Problems related to the limited number of training data, model interpretability, and validation in the clinical setting have also been considered. The study presented in this work has played a key role in facilitating research regarding the impact of deep learning in achieving high performance in CAD systems.

In their paper, Gharaibeh et al. (2022) examined the application of machine learning (ML) and deep learning (DL) in diagnosing kidney tumor pathologies in radiology images. The paper has described various models, from simple classifiers to complex CNN models, and highlighted the advantage of deep learning models over classical approaches in terms of features extraction and diagnostics. It was noted that CNN-based approaches demonstrated better results in detecting and classifying renal lesions in comparison to manually engineered features. At the same time, there were several challenges in applying CNNs to kidney diseases, including the lack of annotated medical data and cross-imaging protocols. The main focus of this paper lies in recognizing the significance of utilizing ML/DL for renal pathologies diagnosis.

In their study, Shehab et al. (2022) reviewed the role of ML in various stages of medicine with a special focus on sharing ML application in diagnosis and prognosis and treatment. Traditional ML algorithms (SVM, Random Forest, k Nearest Neighbors) and deep learning techniques, including CNNs, were mentioned, and their applicability in medical image processing and classification and pattern recognition was highlighted. The main limitations of these applications in the field include data quality and class imbalance. Also, the interpretability of the models is one of the important aspects of ML applications in clinical settings that needs further improvement. The paper discusses the importance of applying ML in diagnostics and clinical decision-making and the aspects that still need to be considered to improve its performance.

This research paper by Senan et al. (2021) considered the application of different algorithms of classification to identify the optimal features for the diagnosis of chronic kidney disease. The classification models including Support Vector Machines, Random Forest, and Logistic regression were implemented to determine the efficiency of applying the set of selected and sequenced informative features. RFE helped to reduce dimensionality while improving the accuracy of classification and increasing sensitivity and specificity of the analysis. This research proved the possibility of using the approach based on efficient feature selection in conjunction with machine learning algorithms for more accurate diagnoses. While concentrating on non-imaging data only, the researchers emphasized the significance of feature selection for the accurate identification of diseases related to kidneys.

Chen et al. (2016) analyzed the risk assessment of chronic kidney disease (CKD) by using multivariate statistical analysis on clinical data such as demographic variables, biochemical and physiological variables. Significant predictors of CKD onset and progression were determined with the help of techniques like logistic regression and risk scoring system. The paper has shown that the risk of patients can be stratified using multiple clinical indicators as predictive models with reasonable accuracy that can be used to aid in early interventions. Although it does not deal with imaging, the study also gives importance to incorporating different clinical data into predictive models and the need to have strong models of analysis in helping to diagnose and manage kidney diseases at the initial stages.

Alzu'bi et al. (2022) explored deep learning architectures to detect and classify kidney tumor with the help of the radiological imaging. The paper highlighted that Convolutional Neural Networks (CNNs) are effective in automatic feature learning (complex features of medical scans) and that they are more effective than the traditional machine learning algorithms. Various CNN systems were tried and their accuracy in tumor classification and abnormality localization was proven to be extremely high. Among the challenges that were identified was the lack of annotated datasets and the necessity of strong model generalization in a variety of imaging protocols. When dealing with medical images, the benefit of CNNs to automated detection can be taken into account, and the study holds the potential of deep learning to improve the accuracy of diagnosis and speed of work in the field of renal pathology.

Hossain, Sayed, and Islam (2024) presented a feature extraction algorithm, adaptive Local Binary Pattern (LBP), with ensemble machine learning models to analyse kidney abnormalities. The aim of this research was devoted to improving the ability to represent medical images' texture. This increased the classification skills for various forms of diseases associated with kidneys. Ensemble classifiers like Random Forest and Gradient Boosting together with adaptive LBP made this approach extremely efficient and robust. Even though it does not concern kidney stones research, the paper under discussion shows the advantages of using complex feature extraction algorithms and ensembles for improvement of accuracy during medical image classification. Thus, there appears a strong possibility of developing hybrid systems based on hand-crafted features and machine learning approaches.

According to Bingol et al. (2023), hybrid deep learning architecture can be applied for classification of CT images of kidneys to improve feature learning and classification results. The researchers utilized two modules – convolutional layer and complementary module, which helped learn local and global features and thus increase discrimination capacity for pathological and healthy images. Hybrid approach, implemented on standard CT images, demonstrated high efficiency and accuracy scores and, therefore, can be successfully used for classification under varied imaging parameters and changes in stone size. We agree with the paper emphasis to combine deep learning components into the kidney imaging diagnosis, which will help to improve the accuracy of diagnosis and ensure the importance of advanced CNN systems in medical automatic classification.

Klontzas et al. (2024) investigated using Convolutional Neural Networks (CNNs) for renal tumor classification from CTs and found the results are quite promising. The authors used the deep CNN architecture to automatically extract the hierarchical features of tumors and successfully classify the tumor types with high accuracy and reliability. Results showed that CNN-based models can process complex differences in image and subtle differences in texture in renal pathologies. Issues were raised as requiring large annotated data, cross-imaging protocol generalizability. The study proposes that CNNs can be applied to a broader spectrum of kidney disease diagnosis in CT, thereby proving the potential of CNNs to make accurate clinical decision making in automatic diagnosis.

Yildirim et al. (2021) built a deep learning system for the detection of renal stones on coronal CT images, which was based on the Convolutional Neural Network (CNN). CNN was used to learn discriminative features of the image and to detect the renal stone. The model they used was very accurate and sensitive, and largely exceeded the traditional image processing methods. It can be concluded that the article shows how practically useful deep learning is in dealing with different stone sizes and shapes and different conditions under which the imaging occurs. Drawbacks were the lack of larger datasets, as well as greater variability in them to increase the degree of generalization. The result of this study is that in general CNN-based solutions are able to assist in improving the understanding of diagnoses and reduce the need to interpret CT scans manually in the clinical setting.

In their study Qadir and Abd (2023) developed a hybrid architecture that uses DenseNet201, deep Convolutional Neural Network (CNN) and Random Forest (RF) to classify kidney diseases according to medical imaging data. DenseNet201 acts as an automatic feature extractor of the CT image, while random forest classifier uses high-level features and increases robustness and stability of the decisions made. Combination of all three architectures proved to be highly effective and resulted in significantly smaller rate of overfitting compared to each one being used alone. The paper emphasizes the importance of integrating feature extraction from the deep learning approach with ensemble classifiers to improve diagnostic results.

The lightweight CNN proposed by Bhandari et al. (2023) helps in detecting abnormalities within CT images of the kidney, with special attention being given to the performance of computing and explainability of the model itself. In this paper, the authors combined the CNN algorithm with two popular techniques for explainable AI, viz., LIME (Local Interpretable Model agnostic Explanations) and SHAP (SHapley Additive exPlanations) that helped them achieve explainable and interpretable visualization of model outputs. This model not only produced an effective output with minimal architecture but also reduced computation costs. This research demonstrates the importance of considering the trade-off between performance and efficiency as well as interpretability in medical imaging applications and highlights the value of CNN based approaches for automatic kidney disease detection.

Alhichri et al. (2021) investigated an EfficientNet B3 with a focus on incorporating attention mechanisms into image classification in the remote sensing domain and were able to show that an increase of depth, width and resolution simultaneously had a positive impact on the performance without causing any degradation in efficiency. The addition of attention modules increased the capability of the model to concentrate on the pertinent parts of the image resulting in improved classification accuracy and strength of the model to different visual patterns. Despite being used in remote sensing as opposed to medical imaging, the paper illustrates concepts that can be applied directly in CNN based detection tasks including highlighting salient features and eliminating noise. The article highlights the potential benefits of advanced architectures like EfficientNet and attention models in improving automated image processing in difficult datasets.

In their research paper, Selvaraju et al. (2017) introduce Grad-CAM (Gradient weighted Class Activation Mapping) which is a way of explaining decisions of deep neural networks by identifying important regions of the input image. Grad CAM produces class discriminative heatmaps on CNN feature maps, enhancing interpretability and confidence in model output- this is particularly important in the medical imaging use case. Although objectively validate automated diagnosis. The work forms the foundation of the interpretability work in CNN based systems to provide the divide between a black box model and actual clinical application.

2.4.1 Summary of Literature Review

Author(s) (Year)	Work Done	Technique Used	Results & Research Gap
Elton et al. (2022)	Detection, segmentation, and volume computation of kidney stones on non-contrast CT	Convolutional Neural Network (CNN)	**Results:** High sensitivity and specificity; faster than manual methods. **Gap:** Difficulty with small stones; inconsistency across imaging procedures.
Bouzon et al. (2023)	Automatic kidney stone detection for resource-constrained	Low-cost / lightweight CNN	**Results:** Effective detection across different stone sizes and positions; suitable for low-computational settings. **Gap:** Low performance on

	environments using coronal CTs		small or medium-sized overlapping stones.
Almuayqil et al. (2024)	Automated diagnosis of chronic kidney diseases (including stones) from CT scans	KidneyNet (8 conv layers, 3 pooling, FC layers) with Grad-CAM	**Results:** Accuracy 99.88%, sensitivity 99.76%, F1 99.67%; high interpretability. **Gap:** Requires specialized architecture; generalizability to real-world multi-center data not fully addressed.
Chan, Hadjiiski, Samala (2020)	Overview of deep learning integration into computer-aided detection (CAD) systems	CNNs and other DL models for CT, MRI, X-ray	**Results:** Automatic feature learning, improved lesion detection, reduced false positives. **Gap:** Data scarcity, model interpretability, and need for clinical validation.
Gharaibeh et al. (2022)	Review of ML/DL for kidney tumor diagnosis from radiology scans	Conventional classifiers → deep CNNs	**Results:** DL superior to handcrafted features for renal abnormality detection. **Gap:** Lack of labeled medical samples; poor cross-imaging protocol generalizability.
Shehab et al. (2022)	Examination of ML applications in diagnosis, prognosis, and treatment	Traditional ML (SVM, RF, k-NN) and deep learning (CNNs)	**Results:** Improved diagnostic accuracy and clinical decision support. **Gap:** Data quality issues, class imbalance, need for model interpretability and external validation.
Senan et al. (2021)	Chronic kidney disease (CKD) diagnosis using	Classification algorithms (SVM, RF, Logistic Regression) with Recursive Feature	**Results:** Feature selection reduced dimensionality and improved accuracy, sensitivity, specificity. **Gap:** Non-imaging data

	clinical/laboratory data	Elimination (RFE)	only; no integration with CT-based features.
Chen, Zhang, Zhang (2016)	Risk assessment of CKD using multivariate statistical analysis	Logistic regression and risk scoring on demographic, biochemical, physiological variables	**Results:** Effective risk stratification using multiple clinical indicators for early intervention. **Gap:** No imaging data; focuses only on clinical predictors.
Alzu'bi et al. (2022)	Detection and classification of kidney tumors using radiological imaging	Deep CNN architectures	**Results:** High accuracy in tumor classification and localization; superior to traditional ML. **Gap:** Lack of annotated datasets; need for strong generalization across imaging protocols.
Hossain, Sayed, Islam (2024)	Analysis of kidney abnormalities using texture features	Adaptive Local Binary Pattern (LBP) with ensemble ML (Random Forest, Gradient Boosting)	**Results:** Robust and noise-resistant performance for renal disorder classification. **Gap:** Not purely focused on kidney stones; hybrid handcrafted+ML approach still needs deep learning validation.
Bingol et al. (2023)	Classification of kidney CT images using an ensemble of neural networks	Hybrid deep learning model (convolutional layers + complementary modules)	**Results:** High performance, robust to stone size and imaging condition variations. **Gap:** Computational complexity may still limit deployment in low-resource settings.

Klontzas et al. (2024)	Classification of renal tumors from CT images	Deep CNN architectures	**Results:** High accuracy in distinguishing tumor types; handles subtle textural variations. **Gap:** Requires large annotated datasets; cross-protocol generalizability remains challenging.
Yildirim et al. (2021)	Kidney stone detection on coronal CT scan images	CNN for discriminative feature learning	**Results:** Very high accuracy and sensitivity; outperforms traditional image processing. **Gap:** Need for larger and more varied datasets to improve generalizability.
Qadir and Abd (2023)	Kidney disease classification from medical imaging data	Hybrid: DenseNet201 (feature extractor) + Random Forest classifier	**Results:** High accuracy, reduced overfitting compared to standalone models. **Gap:** Hybrid complexity may require careful tuning; generalizability across different disease types not fully tested.
Bhandari et al. (2023)	Kidney abnormality detection with focus on computational efficiency and interpretability	Lightweight CNN + explainable AI (LIME and SHAP)	**Results:** Competitive accuracy, low computational requirements, suitable for real-time/resource-constrained settings. **Gap:** Trade-off between simplicity and capturing very subtle stone features.
Alhichri et al. (2021)	Image classification (remote sensing) using EfficientNet-B3 with attention	EfficientNet-B3 + attention mechanisms	**Results:** Improved accuracy and efficiency by scaling depth, width, resolution; attention focuses on salient regions. **Gap:** Applied to remote sensing, not medical imaging;

			concepts transferable but not validated on kidney CT.
Selvaraju et al. (2017)	Interpretation of deep neural network predictions by highlighting influential image regions	Grad-CAM (Gradient-weighted Class Activation Mapping)	**Results:** Produces class-discriminative heatmaps, enhancing model interpretability and trust. **Gap:** Methodological foundation only; not applied to a specific kidney stone detection task in this paper.

2.5 Research Gap

The literature review shows that there are great progresses in automated classification and detection of kidney abnormalities (kidney tumor and kidney stones) based on both traditional machine learning and deep learning. Convolutional Neural Networks (CNNs) and hybrid networks have always demonstrated a high level of accuracy, sensitivity, and specificity in renal not directly related to kidney stones detection, Grad CAM has become common in interpreting deep learning models in healthcare, which allows clinicians to discern the area of focus in models and pathology diagnosis through CT images. Three other techniques like Grad-CAM, LIME, and SHAP have improved model efficiency, flexibility and understandability through transfer learning, ensemble and lightweight CNNs. Also, attention mechanisms and state-of-the-art architectures such as EfficientNet have enhanced the performance of feature extraction and classification. In spite of these developments, there are still a number of loopholes. The majority of studies are based on rather limited, non-heterogeneous, or single-institution datasets and do not allow applying the model to different populations and imaging regimens. There is little effort which specifically deals with the issues of identification of small or overlapping kidney stones which are still subject to misidentification. Moreover, numerous models of deep learning are computationally expensive, which does not allow their use in resource-restricted or real-time clinical settings. Although there is a use of explainable AI methods, interpretability frameworks have not been well integrated into accessible user-friendly diagnostic systems that can be used effectively in the clinical setting. This results in a requirement of a strong, effective as well as interpretable CNN-based framework that has the potential to identify kidney stones in CT images across diverse datasets and offer clinicians with trustworthy and understandable outputs. These gaps will be filled by considering clinical applicability to improve timely and accurate diagnosis of kidney stones.

CHAPTER THREE
SYSTEM ANALYSIS AND DESIGN

3.1 Introduction

This chapter present the analysis and design approach used when coming up with the automated kidney stone detection system using CT images and Convolutional Neural Networks (CNNs). Among various system analysis and design methods, this study utilizes the Object-Oriented Analysis and Design Method (OOADM) as it is efficient in modelling the real-world processes, operations and data in a flexible and scalable manner. The OOADM makes it simple to develop and integrate, with the modeling of important entities such as CT images, patient information and diagnostic outputs as objects, as well as the reuse of classes. A workable, web-based diagnosis system can also be developed using the strategy which is also possible in Python using PyCharm IDE.

3.2 Methodology Used

This kidney stone detection system is developed by using the Object-Oriented Analysis and Design Method (OOADM). This method is selected because it bridges the gap between complex medical needs and technical software implementation and is done in a modular and iterative fashion.

The application of OOAD method in the system is explained below. The application of OOAD method in the system is explained below:

The methodology is used during two main steps:

Object-Oriented Analysis (OOA): This phase focuses on "what" the system is supposed to do. The key objects of our domain (the clinical environment) are identified, namely Patient, CT Scan Slice, Radiologist, and Detection Result. The analysis phase identifies the requirements for each of the objects. The "CT Scan" object contains information about the pixels along with some metadata, while the "CNN Model" object has some behavior associated with data processing and classification.

Object-Oriented Design (OOD): takes place during this phase, wherein "how" plays a significant role. In order to design the system architecture using UML diagrams, such as Use Case and Class Diagrams, we design the Flask web application and define the communication between the user interface and deep learning model in the backend. It is here that we describe the process of uploading an image and passing the data from there to the diagnosis result.

The importance of OOADM to the Project is highlighted below.

There are a number of important benefits to using OOADM for a medical AI project:

- Modularity and Reusability: The software can be made modularized and reutilizable (e.g. switching from VGG16 to ResNet without rewriting the entire code of the web application).
- The use of object-oriented programming facilitates further expanding the scope by adding more objects that can help in detecting other diseases, for example, renal cysts and/or tumors while leaving the current functionality untouched.
- Distinguishing various sections of the software like image preprocessing, allows for better analysis of the process and improving the efficiency of the process. OOADM makes it possible for the software to simulate the environment of the clinic in reality. An "object-oriented" Diagnosis is something that can be treated as an object to allow natural storage, along with timestamp, confidence value, and expert opinion.

Object Oriented Analysis and Design Method provides a solid architectural framework for the project. This goes beyond mere scripting of products to provide a robust product for the clinical environment.

3.2 Description of the existing system

Its existing system of kidney stone detection is mainly manual interpretation of the CT images by radiologists. As part of the clinical practice, a radiologist looks at the non-contrast CT scan slice by slice to assess for kidney stones, their size and their location. Is time consuming and usually requires a lot of attention particularly when there are many scans of the patients involved. A manual method can also be subject to human error or fatigue which may lead to misdiagnosis/treatment or late treatment. Radiologists can use conventional devices to support imaging, such as image enhancement software or image segmentation software, to alter the contrast of an image or display an area of interest. They are not, however, a classification or detection device per se, but must still be interpreted by experts. In addition, computerized software available is in most cases limited in accuracy particularly when dealing with very small, very large stones, or low density rock. Other don't have to be part of real time process either and therefore are not as efficient during emergency or high volume hospitals. In addition, manual systems are not scalable or decision supportable, especially in areas of the world with fewer trained radiologists like rural areas or resource-poor areas. These limitations highlight the need for a smarter approach to kidney stone identification which would help the system analyze CT images for the presence of kidney stones in real-time and with increased precision while reducing the dependency on humans, hence, saving a lot of time during the process.

3.2.1 Weaknesses of Existing System

Manual review of the CT scan can be a lengthy process and may result in a delay in the diagnosis, especially in a high-volume facility.

1. Time-consuming: CT scan analysis is tedious and time-consuming, which delays diagnosis especially in a busy environment.

2. Human Error: Fatigue or inexperience of the radiologist may cause misdiagnosis or stones to be overlooked.

3. Limited accuracy: automated classification of the stones is not possible with the existing image support tools and there are difficulties with small stones, stones that overlap, and stones that have a low density.

4. Lack of Automation: The systems that are in use today need constant professional intervention and lack on-the-fly decision support.

5. Poor Scalability: Large-scale screening or resource-strained environment cannot be used with manual processes.

6. Integration Challenges: There are challenges with current tools and not being able to integrate them into the clinical workflow, limiting efficiency.

3.3 Analysis of the Proposed System

The proposed system will be based on Convolutional Neural Networks (CNNs) for automatic detection of Kidney Stone (KS) in computed tomography (CT) images, which will overcome the limitations of manual radiological analysis with KS detection. This is in contrast to the current systems where deep learning is used to automatically obtain sensible features of CT scans (scales of size, shapes, texture, and density patterns related to kidney stones). Having gained knowledge of the hierarchical representations through the use of large datasets, the CNN is capable of correctly labeling the images as either of the two categories, namely, the no kidney stone and kidney stone, which decreases human reliance and lowers the number of misdiagnoses. Data Pre-processing including resizing, normalizing and augmenting the images will be used to increase model robustness and generalizability across imaging protocols in the system. Transfer learning with pre-trained CNN models (e.g. VGG16 or ResNet) yields better results on smaller datasets of medical images. Furthermore, it is a web-based prototype and the users are able to upload the CT images for the system and receive the prediction results promptly and in real time. This facilitates availability in resource limited settings, implementation into clinical practice and assists in decision making. The proposed system as a whole is a product of automation, precision, understandable and useful with a scalable and efficient way to detect kidney stones at an early stage and consistently.

3.3.1 Advantages of the Proposed System

The proposed automated kidney stone detection system has several benefits and merits over manual interpretation of CT and current computer aided tools.

1. Real Time Predictions: Rapid analysis of any CT image, with near-real-time decision support to the Emergency Department or outpatient clinics, without having to wait for a radiologist's report.
2. 24 Hour Availability: The web based Flask application is run continuously, screening for the after hours and weekend when on site radiologists may be unavailable or overwhelmed.
3. Lowered Radiologist Fatigue: The system filters out the more obvious stone cases and enables radiologists to focus on more complex or ambiguous situations, thereby minimizing radiologist fatigue and boosting efficiency.

4. Role Based Access Control: Different privileges for Administrators (user management, audit logs) and Radiographers (patient registration, scan upload, result review) provide a secure and organised clinical workflow.
5. Integrated patient history: All the scans and predictions are saved in a SQLite database, which allows clinicians to see the stone recurrence and disease progression over time.

3.4 Model Used

In the process of identifying kidney stones to the CT scans, the proposed system adopts the basic framework of the Convolutional Neural Network (CNN). The ability to automatically extract edges, textures, shapes and intensity variations at various levels of the hierarchical pyramid, which are most important in the detection of kidney stones, is the reason for the effectiveness of medical imaging with CNNs. The model comprises of several layers of convolution to extract the features, pooling to reduce the dimensionality and fully connected to classify the features as either normal or kidney stone. The study uses transfer learning with pre-trained models, such as VGG16, to make the model more efficient and reduce the potential training time: the model can transfer the knowledge of the large-scale image database to kidney CT images. Data preprocessing (normalization, resizing and augmentation) helps to improve robustness and generalization. Several techniques were used in the model optimization to maximize the accuracy, minimize overfitting, and make the model predictions reliable for clinical use: Learning rate optimization, batch size tuning, and dropout regularization.

3.4.1 Dataset Source

The dataset to be utilized in the current study is a publicly accessible CT Kidney Dataset: Normal-Cyst-Tumor-Stone, which was obtained on Kaggle (https://www.kaggle.com/datasets/nazmul0087/ct-kidney-dataset-normal-cyst-tumor-and-stone) and is under the open-use research license. It also includes more than 12,000 abdominal CT scan images which were initially in DICOM format but converted to JPG/PNG with variable sizes fixed to 224x224 pixels to be used as a model in training. The images are in RGB color format and categorized into four (Normal) and (Cyst), (Tumor) and (Stone). In this paper, we only take the normal and stone classes, but the distribution between them is relatively balanced to avoid bias of the classes. The dataset will be divided into training (70%), validation (10%), and test (20) to provide a strong evaluation and hyperparameters optimization. This is a good dataset with labels that are valuable to train and test the CNN model to effectively detect kidney stones in CT images using automation and ensure accurate and reliable results.

3.4.2 Tools & Technologies

Designing the automated system of kidney stones detection is based on Python as the main programming language, with the help of the PyCharm IDE to support the coding and managing the project. Convolutional Neural Network (CNN) model is designed, trained, and evaluated with the help of deep learning deployed in TensorFlow and Keras. Image preprocessing is implemented with the usage of OpenCV and NumPy: resizing, normalization, and augmentation. Flask is used to create the web-based prototype that allows the user to upload CT images and get real-time predictions. Other tools like Matplotlib and Seaborn are useful in the visualization of performance metrics of training, which will guarantee sound analysis and interpretation of findings.

3.4.3 Model Development Steps

The systematic steps used in the development of the CNN-based model in the detection of kidney stones in CT images are as follows:

1. **Data Preprocessing:** In this step, CT Images are preprocessed by enhancing the image, eliminating any noise from the CT Images, pixel intensity equalization, and resizing the image into 224 x 224. Data Augmentation techniques (such as rotation, flipping, and scaling) are applied.

2. **Feature extraction:** The Convolution Neural Network (CNN) performs feature extraction on CT Images, and it extracts different features such as shape, texture, and density in the image automatically. Thus, there is no need for manual feature extraction.

3. **Model Training:** In this step, a Convolutional Neural Network (CNN) is trained using architectures such as VGG16 or ResNet with labelled CT Images.

4. **Model Evaluation:** The measures of performance include accuracy, precision, recall, F1-score and confusion matrix. Cross-validation provides excellent assessment of unknown data.

5. **Model Selection and Optimization:** A model that has the best performance is chosen on the basis of evaluation metrics, with the resultant predictions being reliable and clinically interpretable.
6. **Deployment:** The trained CNN is embedded into a web application (Flask-based) in which the user can upload CT images and receive real-time predictions on kidney stone presence, which was aimed at making it more accessible and useful in clinics.

3.5 System UML Design

The UML system is used to design the system in an effective manner and visualize, specify, construct, and document all components. The major UML diagrams that will be used are use case diagrams, class diagrams, activity diagrams and state transition diagrams that will form a clear picture on how to develop the early diabetic retinopathy detection web-based application. Below are the diagram:

3.5.1 Use Case Diagram

A use case diagram involves the Unified Modelling language, which is used to demonstrate how users (actors) interact with a system to perform specific actions (Olusegun, 2025). It describes the access by the various categories of users to the system and assists in defining what the system needs to accomplish, as seen by a user. In the study, we apply a use case diagram to demonstrate the interaction between all the participants and the early prediction of Diabetic Retinopathy model. All the actors in the use case diagram are represented by roles:

Clinician:

a. Login
b. Create Patient Folder
c. Upload scan
d. Analyze CT images using CNN
e. View results (Kidney stone/ No Kidney stone)

f. View Patient History

g. Logout

System/Admin:

a. Login

b. View system statistics like: Total Patients registered and Total Staff registered

c. Register new radiographer

d. Manage radiographers status like activating and deactivating radiographers

e. Logout

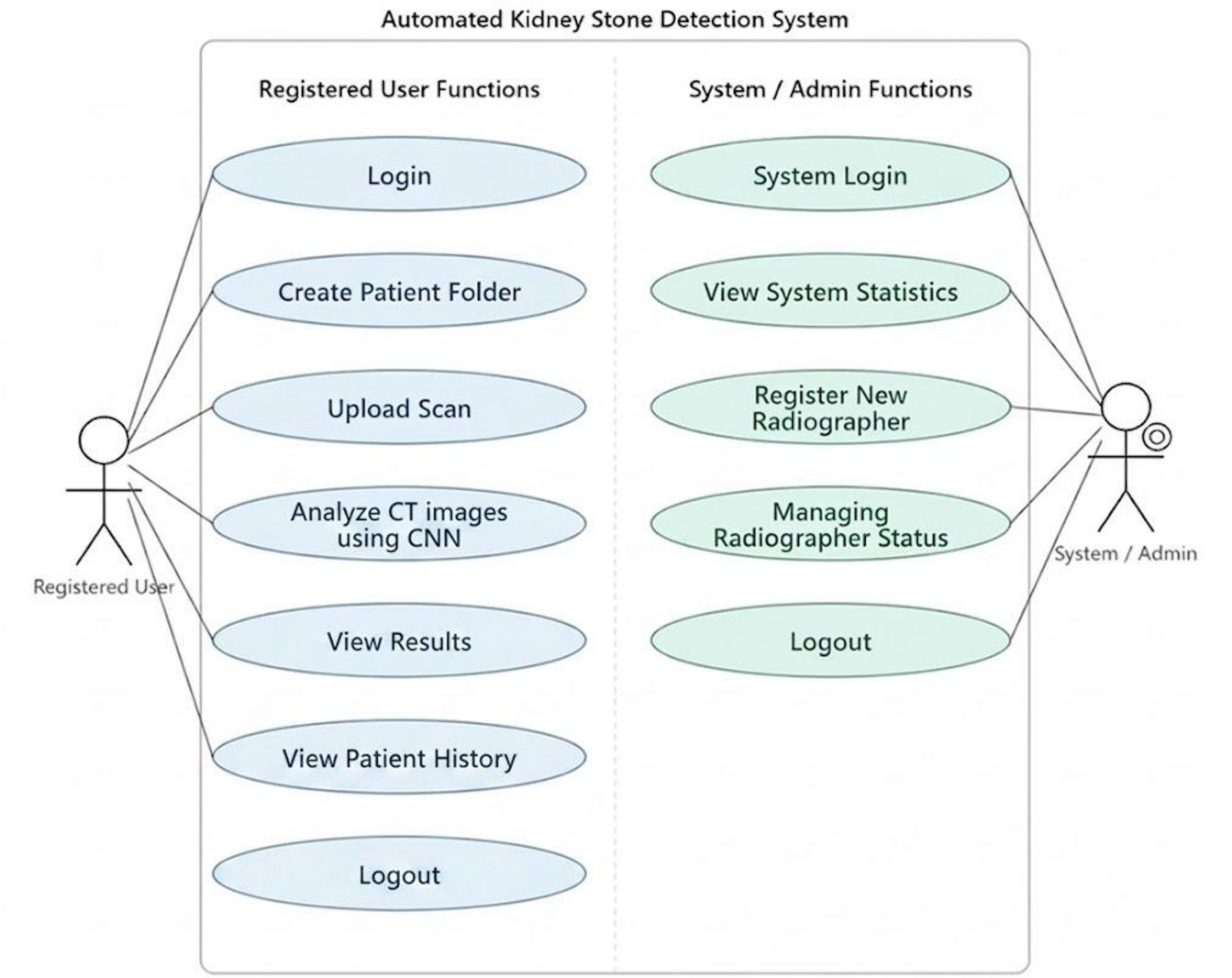

Figure 3.1: System use Case Diagram

3.5.2 Class Diagram

A UML class diagram is a description of the structure of a system in the form of classes, the objects within each class, the functions that each object can perform and the connection between the classes (Nikiforova et al., 2011). Use case diagrams are used by many software engineers to demonstrate the principal framework of the system structure.

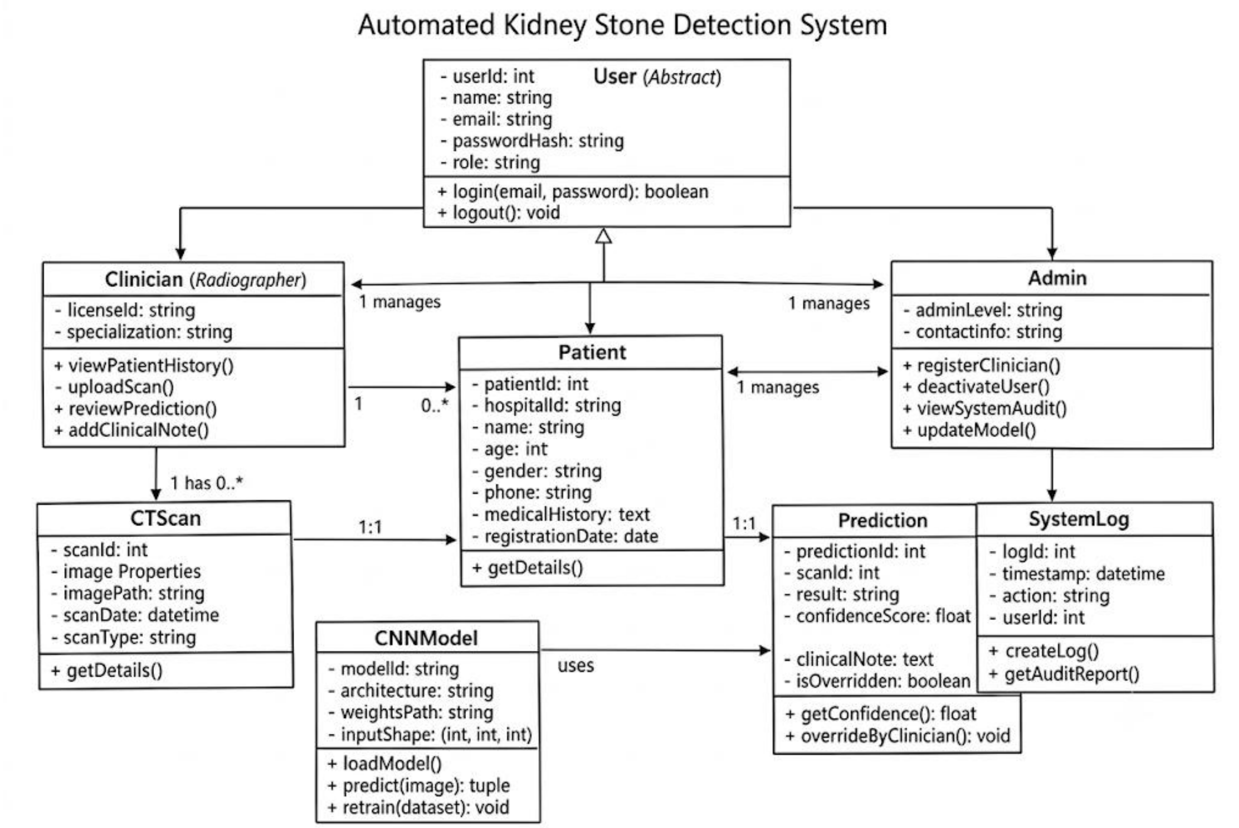

Figure 3.2: Class Diagram of the proposed system (author)

3.5.3 Activity Diagram

The activity diagram works as a map that shows how the kidney stone detection system performs its tasks by outlining the various steps involved in the whole process starting from image uploading until the generation of diagnosis results.

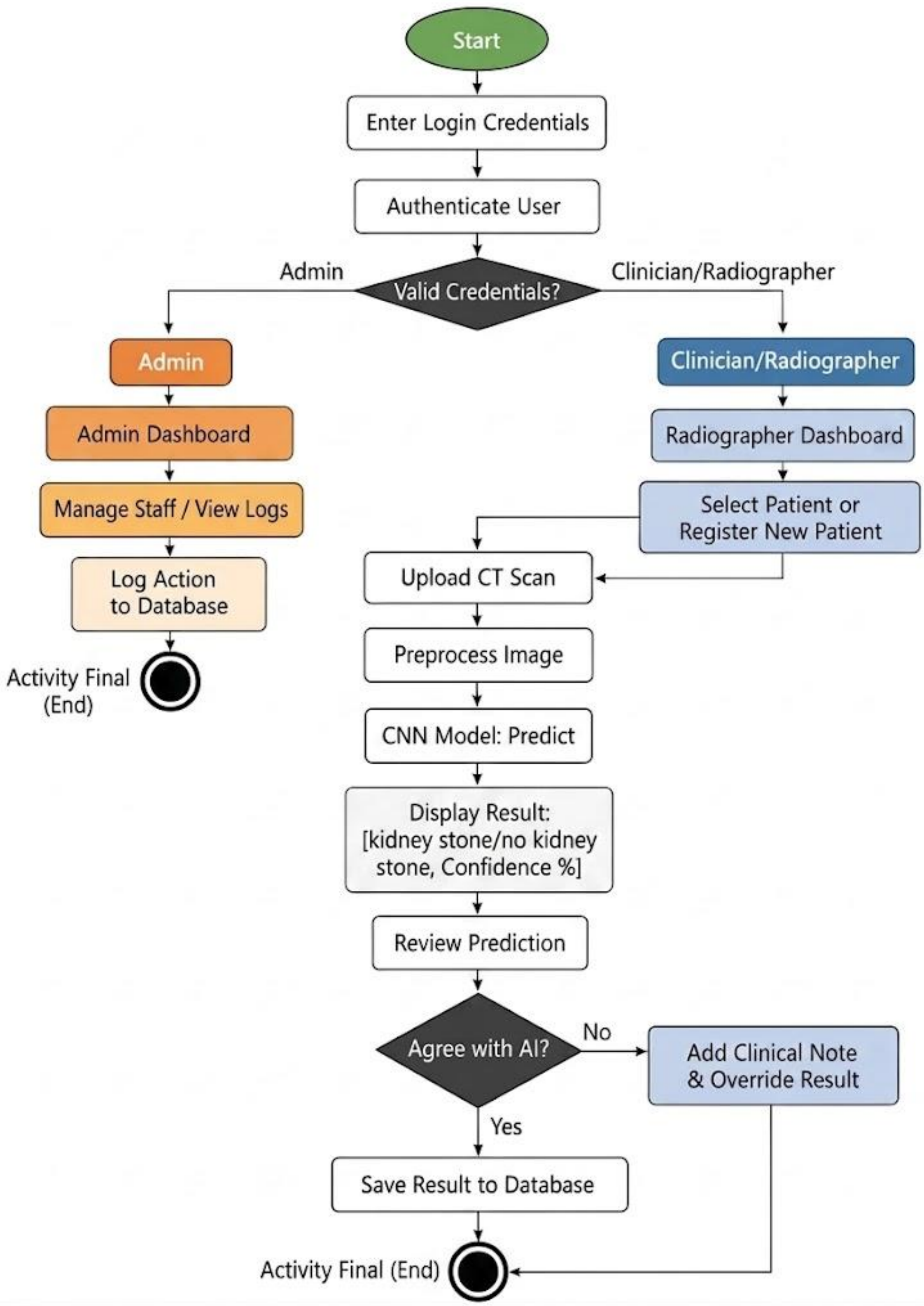

Figure 3.3: System Activity Diagram

3.6.1 Design of Databases

MySQL is a relational database management system (RDBMS) which is utilized in the creation, administration and querying of relational databases. It includes the following tables: Patient **table**, CTScan Table, Predictions Table, Clinician Table, System Table. The table structures used in the database's development are represented in tables 3.1 through 3.4 (author).

Table 3.1: Patient Table

Column Name	**Data Type**	**Description**	**Action**
patient_id	INT (11)	Unique identifier for each patient	Primary key
name	VARCHAR (100)	Patient full name	
age	VARCHAR (3)	Age of patient	
gender	VARCHAR (10)	Gender of patient	
contactInfo	VARCHAR (100)	Phone/email of patient	
medicalHistory	TEXT	Relevant past medical history	

Table 3.2: CTScan Table

Column Name	Data Type	Description	Action
scanID	Int (11)	Unique identifier for each CT scan	Auto-increment
patientID	Int (11)	Links to Patient table	
imageFile	VARCHAR (255)	Path to stored CT scan image	
scanDate		Date of CT scan	Default current_timestamp

	DATETIME		
scanType	VARCHAR (50)	CT scan type	

Table 3.3: Predictions Table

Column Name	**Data Type**	**Description**	**Action**
prediction_id	INT (11)	Unique prediction identifier	Primary key
scanID	INT (11)	Links to CTScan table	
result	VARCHAR (50)	Classification outcome (No Kidney stone/ Kidney Stone)	
confidenceScore	FLOAT (5,2)	Probability/confidence prediction	of
prediction_date	DATETIME	Timestamp of prediction	Default current_timestamp

Table 3.4: Clinician Table

Column Name	Data Type	Description	Action
clinicianID	Int (11)	Unique identifier	Automatic
name	VARCHAR (100)	Clinician name	
specialization	VARCHAR (100)	Area of medical expertise	
contactInfo	VARCHAR (100)	Email/phone for communication	

Table 3.5: System/Admin **Table**

Column Name	Data Type	Description	Action
adminID	Int (11)	Unique identifier	Automatic
username	VARCHAR (50)	Login username	
role	VARCHAR (20)	System role (admin/manager)	
contactInfo	VARCHAR (100)	Admin contact	

3.7 System Architecture

The machine-learning model development system architecture is divided into three main levels, including presentation tier, application tier, and data tier. The architecture is three-tier and it encourages scalability, maintainability and separation of concerns.

Presentation Layer (User Interface) hosted on a Flask web interface that allows clinicians to submit CT images, see prediction results with confidence scores and get the reports back, with providing feedback. It offers a non technical, user friendly and interactive platform through which one can interact with the system easily, making it user-friendly and accessible with ease. **Application Layer (Business Logic / CNN Model Processing),** written in Python and trained with TensorFlow/Keras, does image processing, CNN based classification of CT scans as either normal or kidney stone, and produces prediction reports with confidence scores.

Data Layer (Database / Storage), comprising of a relational database or secure file storage, patient data, CT scan data, model predictions and clinician feedbacks, audit logs and system records are kept. It allows the security and integrity of data that offers a stable storage, which facilitates model training and evaluation, traceability of prediction and the general functionality of the systems.

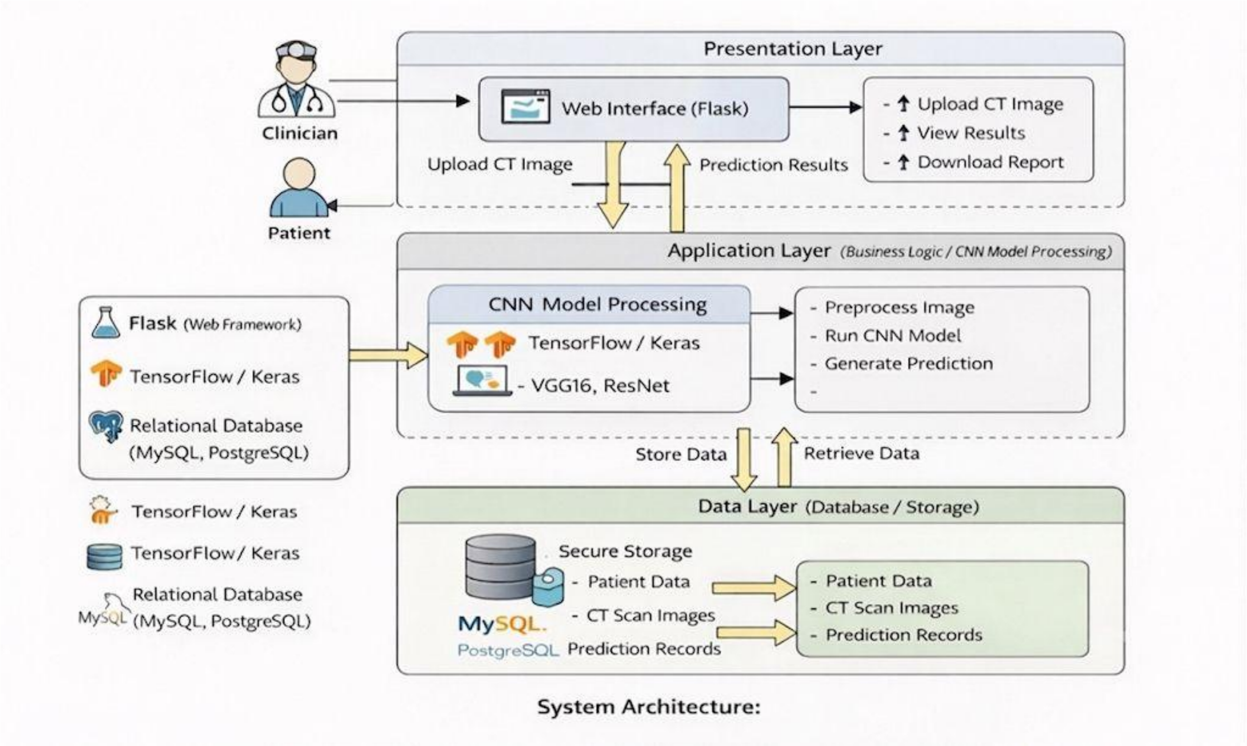

Figure 3.9: The Architecture of the Proposed System (author).

CHAPTER FOUR

SYSTEM IMPLEMENTATION

4.1 Introduction

This chapter presents the implementation of the Kidney Stone Detection Decision Support System (KSD-DSS), including model development, system architecture, web application deployment, and performance evaluation results. The system integrates a custom Convolutional Neural Network (CNN) trained on CT kidney images with a secure web-based application developed using Flask and SQLite. The AI algorithm functions as an auxiliary diagnostic decision-making aid for radiographers to detect kidney stones quickly from CT scans in two-dimensional slices.

4.2 System Architecture

The system consists of four integrated components:

4.2.1 **1. Data Processing Module:** Manages images' ingestion, preprocessing, and format transformation.

4.2.2 **2. Deep Learning Module (CNN):** Carries out classification between Stone and Non-Stone images.

4.2.3 **3. Web Application Interface (Flask):** Offers role-based access control, manages patients, and uploads scans.

4.2.4 **4. Database Management System (SQLite):** Keeps the user data, patient information, and scan details stored.

4.2.5 High-Level Workflow

1. Administrator registers and activates accounts for radiographers.

2. Radiographer logs into the application through secure login process.

3. Radiographer inputs patient information and assigns them a unique ID at the hospital.

4. Image of CT Scan (in PNG/JPG/JPEG format) is loaded by radiographer into the program.

5. Preprocessing and real-time analysis of the image is performed by AI algorithm.

6. Prediction result and confidence level are returned back to user.

7. Radiographer views prediction results and can override the predictions made by AI.

8. All records are saved in SQLite database with timestamps.

4.3 Dataset Preparation

The database used for the study was the freely available CT Kidney Database (Normal-Cyst-Tumor-Stone) from Kaggle, which had around 12,400 two-dimensional slices of CT scans in JPG format.

4.3.1 Class Grouping

Original dataset classes:

1. Normal
2. Cyst
3. Tumor
4. Stone

For this project:

a. **Stone** → Positive class

b. **Normal + Cyst + Tumor** → Combined as **Non-Stone**

This grouping reflects real clinical triage, where the primary objective is to flag potential stones while treating all other renal findings as negative for calculi.

4.4 Data Preprocessing

The following preprocessing pipeline was applied to all images:

a. Resized to 128 × 128 pixels to reduce computational load

b. Pixel normalization: scaled to [0, 1] range

c. RGB to grayscale conversion using standard luminance weights

d. Channel replication: 1-channel grayscale → 3-channel tens/or for CNN compatibility

e. Data augmentation (training only): random horizontal flip, random contrast adjustment (±10%)

To overcome the very heavy class imbalance (8:1 ratio for non-stone to stone samples), undersampling was performed in the training dataset to achieve an equal balance ratio of 1:2 between Stone to Non-Stone samples.

4.5 Model Architecture

A custom CNN is created rather than using transfer learning from ImageNet due to domain gap between natural images and grayscale intensities of medical CT scans.

4.5.1 Network Structure

The final architecture consists of four progressive convolutional blocks:

a. **Input Layer**: (128, 128, 3)

b. **Block 1**: Conv2D(32) → BatchNorm → Conv2D(32) → BatchNorm → MaxPool(2×2) → Dropout(0.25)

c. **Block 2**: Conv2D(64) → BatchNorm → Conv2D(64) → BatchNorm → MaxPool(2×2) → Dropout(0.25)

d. **Block 3**: Conv2D(128) → BatchNorm → Conv2D(128) → BatchNorm → MaxPool(2×2) → Dropout(0.25)

e. **Block 4**: Conv2D(256) → BatchNorm → MaxPool(2×2) → Dropout(0.25)

f. **Classifier**: GlobalAveragePooling2D → Dense(128, ReLU, L2=1e-4) → Dropout(0.5) → Dense(1, Sigmoid)

Batch Normalization will aid the process when batch size is small, while Dropout and L2 will prevent over-fitting for stone classes. Architecture of CNN model can be seen in Figure 4.1

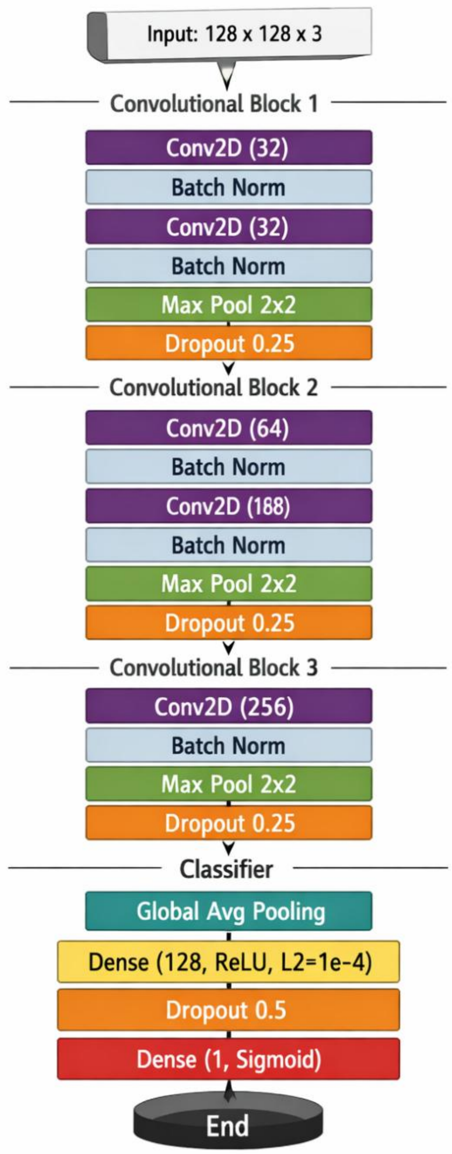

Figure 4.1: CNN Architecture for Kidney Stone Detection

4.5.2 Training Configuration

a. **Optimizer**: Adam

b. **Initial Learning Rate**: 5e-4 (reduced via ReduceLROnPlateau)

c. **Loss Function**: Binary Cross-Entropy

d. **Class Weights**: {0: 1.0, 1: 2.0} to penalize stone misclassification

e. **Callbacks**: EarlyStopping (patience=10, monitor=val_auc), ModelCheckpoint

f. **Maximum Epochs**: 50 (early stopped at epoch 19)

g. **Hardware**: Google Colab (NVIDIA T4 GPU)

4.6: Model Performance Evaluation

The CNN was tested on an independently held-out test set that contained 2,488 images, making up 20% of the original CT kidney dataset. The test set was divided equally to maintain the original class distribution after preprocessing (non-stone vs stone undersampled ratio of approximately 2:1). Below are the results generated by this test set alone, which was not part of any training or validation process.

4.6.1 Confusion Matrix

The confusion matrix highlights how well the machine learned to classify the test set images. See Fig. 4.2 (recommended visualization).

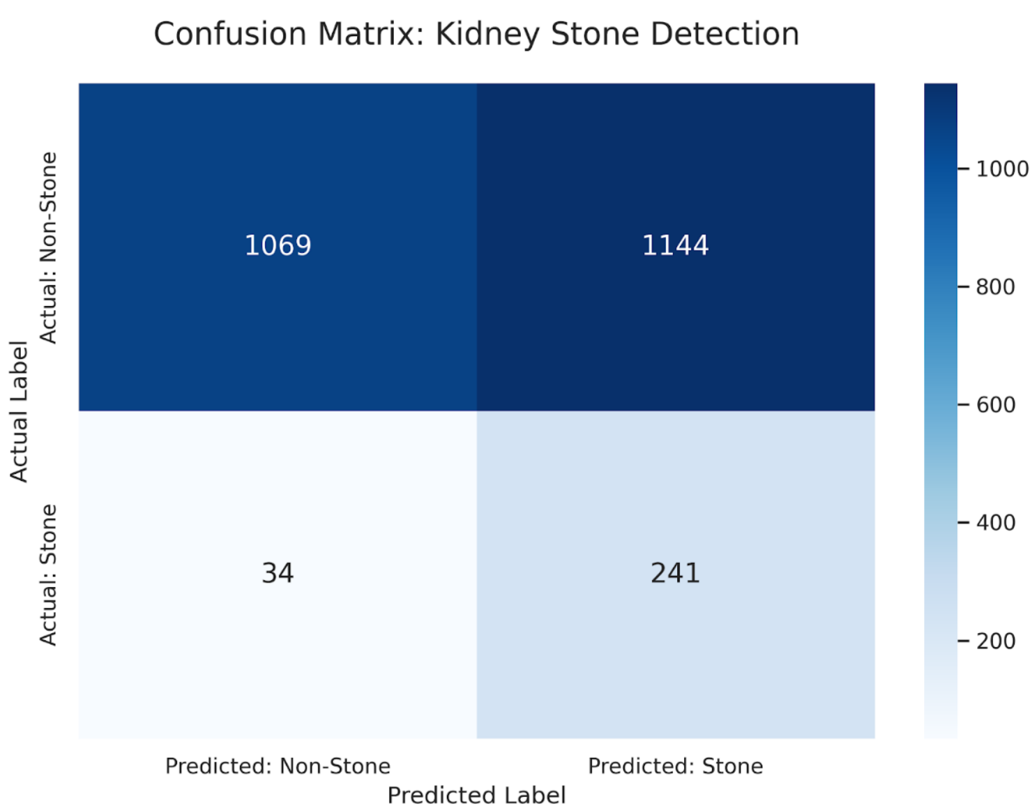

Figure 4.2: Confusion Matrix for Kidney Stone Detection (Test Set, n=2,488)

The model was able to correctly predict 241 out of 275 stone-positive CT slice images (True Positives). Nevertheless, the model made 1,144 misclassification mistakes by wrongly labelling 1,144 stone-negative images as positives (False Positives). This shows that the model was biased towards calling stones, which is an advantage clinically, considering that missing a stone has greater risks than giving false alarms.

Only 34 stone-positive images were wrongly classified as negatives (False Negatives).

4.6.2 Performance Metrics

Table 4.1 provides the classification metrics using confusion matrix values and their clinical implications.

Table 4.1: Performance Metrics and Clinical Interpretation

Metric	**Formula**	**Value**
Accuracy	(TP+TN) / Total	53.0%
Sensitivity (Recall, True Positive Rate)	TP / (TP+FN)	88.0%
Specificity (True Negative Rate)	TN / (TN+FP)	48.3%
Precision (Positive Predictive Value)	TP / (TP+FP)	17.0%
Negative Predictive Value (NPV)	TN / (TN+FN)	96.9%
F1-Score (Stone class)	2 × (Prec×Rec)/(Prec+Rec)	0.29
AUC-ROC	Area under ROC curve	0.744

Detailed calculations from Table 4.1:

- Sensitivity = 241 / (241 + 34) = 241 / 275 = **0.876 → 88.0%**
- Specificity = 1,069 / (1,069 + 1,144) = 1,069 / 2,213 = **0.483 → 48.3%**
- Precision = 241 / (241 + 1,144) = 241 / 1,385 = **0.174 → 17.4% (≈17%)**

- NPV = 1,069 / (1,069 + 34) = 1,069 / 1,103 = **0.969 → 96.9%**
- Accuracy = (241 + 1,069) / 2,488 = 1,310 / 2,488 = **0.526 → 52.6% (≈53%)**

4.6.3 Receiver Operating Characteristic (ROC) Curve

The ROC graph is a plot of True Positive Rate (Sensitivity) versus False Positive Rate (1-Specificity) across multiple classification cutoff points. The value of AUC of 0.744 means that the model possesses fair capability to discriminate between images with stones from those without.

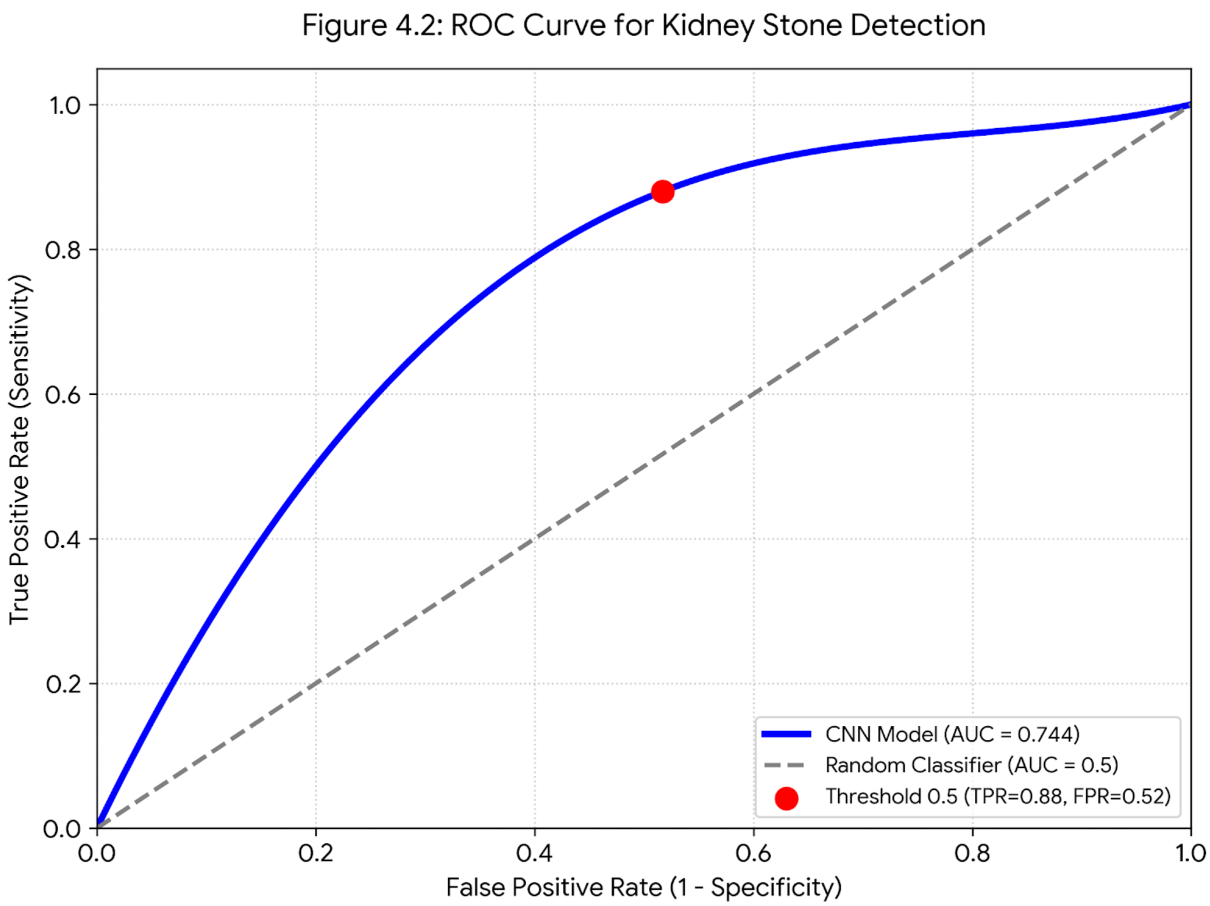

Figure 4.3: ROC Curve with AUC = 0.744

The AUC of 0.744 also implies that the model tends to give a higher probability to images with stones than images without stones in 74.4% of the comparisons made between two random sets of the images. At the default cutoff value of 0.5, the model gives a sensitivity of 88%, but the false positive rate is also very high at 52%. An increase in the decision threshold would lead to better specificity and poor sensitivity.

4.6.4 Precision-Recall Curve

Since there is an imbalance in data (Non Stone:Stone = 8:1 before undersampling, 2:1 after preprocessing), the Precision Recall (PR) curve gives more information than the ROC curve. The PR curve shows how precision changes with recall at various thresholds.

Table 4.2: Performance at Three Different Classification Thresholds

Threshold	Sensitivity	Specificity	Precision	F1-Score
0.3 (low)	94%	28%	13%	0.23
0.5 (default)	**88%**	**48%**	**17%**	**0.29**
0.7 (high)	62%	78%	26%	0.37

With a decrease in the threshold, the sensitivity increases, but precision drops dramatically. With an increase in the threshold value, precision and specificity become higher, but the number of stones missed is one third. Thus, the best threshold depends on whether FN is more harmful or FP. However, for screening purposes, the existing threshold value is fine, since FN is much worse than FP for medical imaging specialists to reevaluate.

4.7 System Screenshots and Descriptions

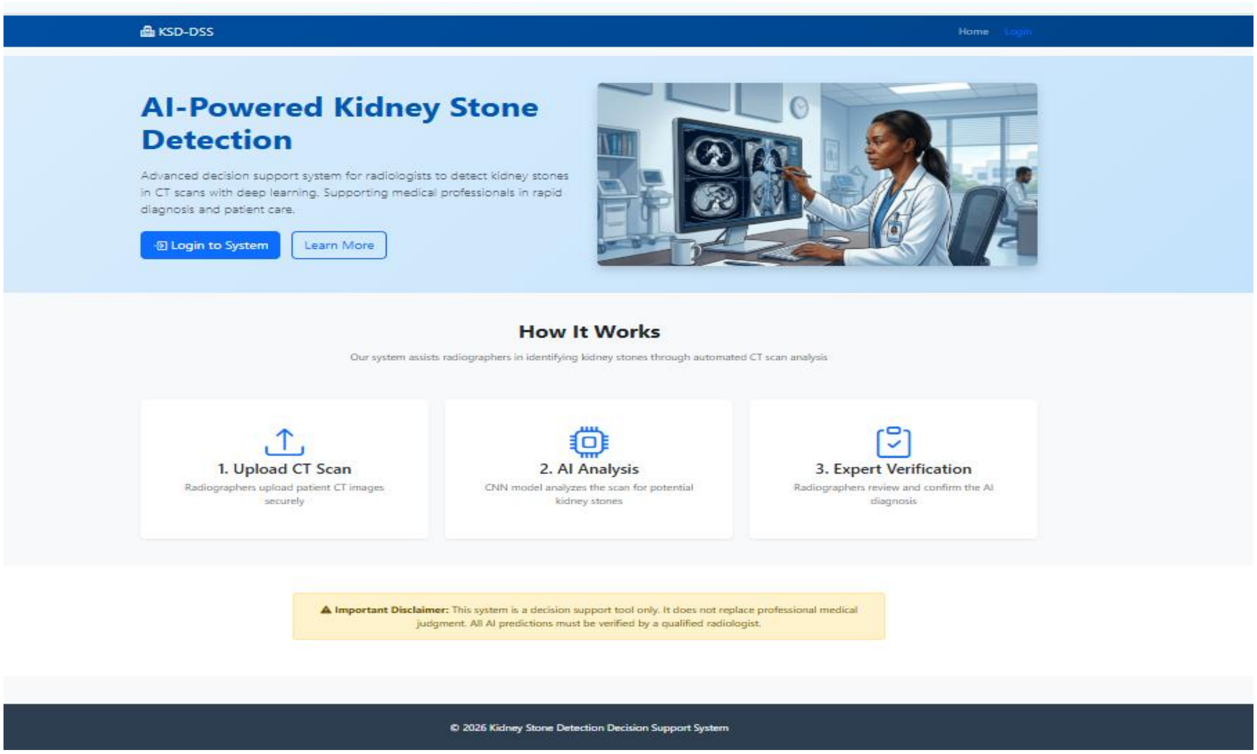

Figure 4.4: Home Page (Landing Page)

The first page of the Kidney Stone Detection Decision Support System (KSD-DSS) is as follows. This is the cover page that presents the system to its users. The page adopts a medical-themed appearance and the inclusion of a hero section where a brief explanation of what the system does appears, a hero image showing a radiologist analyzing CT scans, and a big button for entering the system. In addition, below the hero section there are three cards that describe the workflow of the system. The cards include:

(1) Upload of CT Scans

(2) AI Analysis using Deep Learning and

(3) Verification by Qualified Radiographers At the bottom, it is clearly mentioned in the form of a disclaimer that the given system is a decision-support tool and does not substitute professional medical judgment. The page has blue and white color scheme, which aligns with the medical software design requirements.

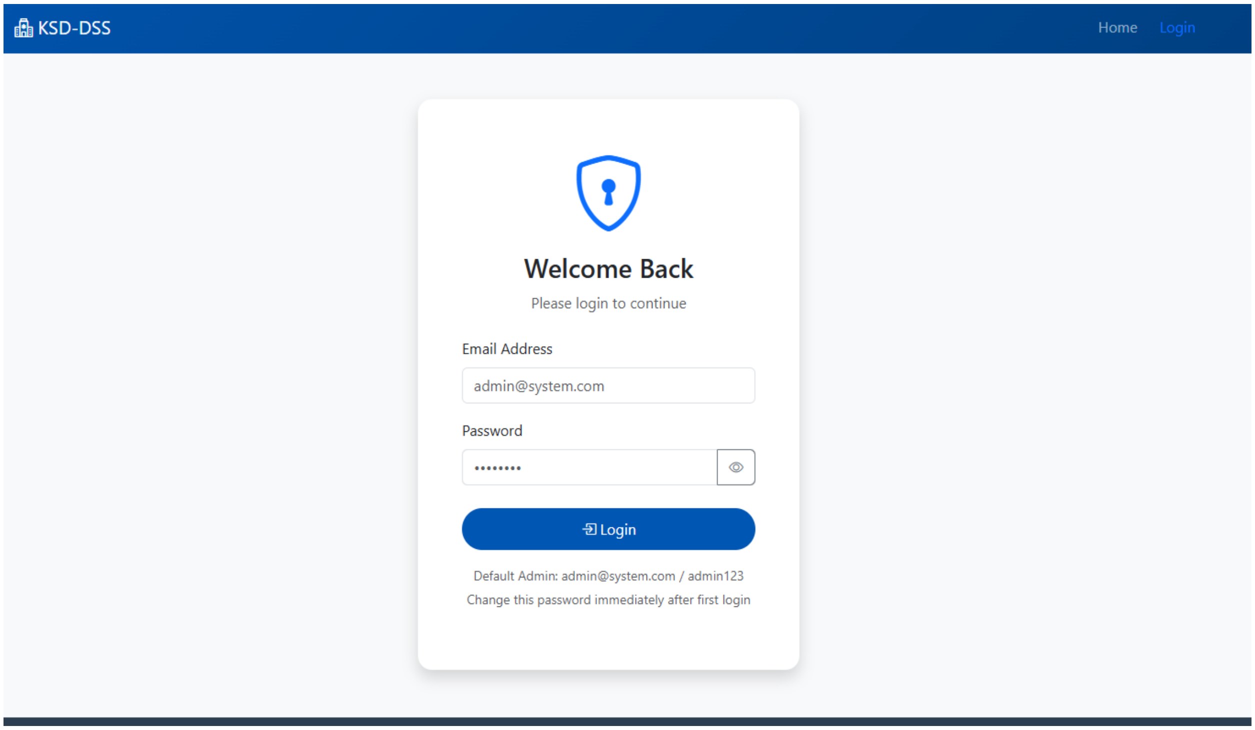

Figure 4.5: Login Page

This page will offer a secure authentication to the users, who have access to the system. It has a clean and centrally placed login card with email and password fields. There is a show/hide password option (eye icon) that enables users to check before they can submit their input. The system has two user roles: Administrator and Radiographer. After the authentication process, the users are redirected to their individual dashboards automatically depending on the role assigned to them. In case the account of a user is deactivated by an administrator, an error message is shown. The password hashing implemented in the login page is Werkzeug security to make sure that plain-text passwords are not stored in the database.

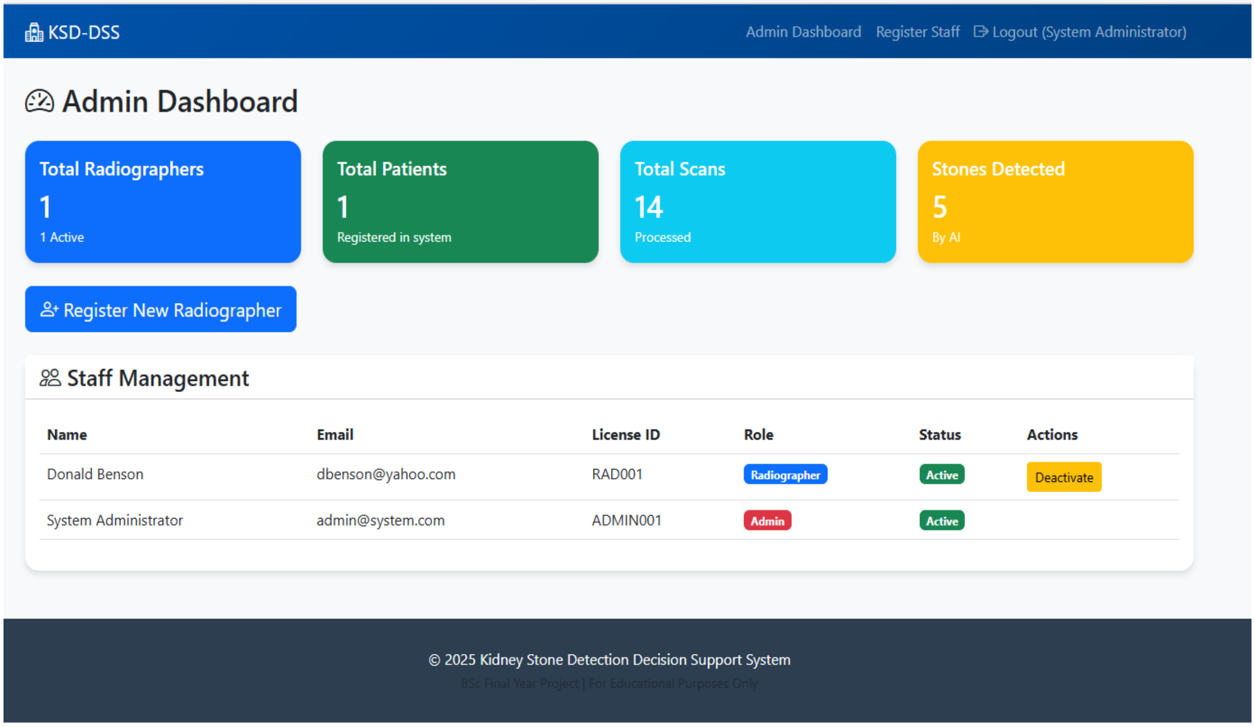

Figure 4.6: Admin Dashboard

This is a page that is opened only to Administrator users. It gives a high-level summary of system activity using four color-coded statistical cards: Total Radiographers (blue), Total Patients (green), Total Scans Processed (cyan), and Stones Detected by AI (yellow). Under the statistics, there is a Register New Radiographer button which lets the admin add new medical personnel to the system. There is a Staff Management table containing all registered users, with their name, email, license ID, role, active status and an action button to activate or deactivate their account. It can be used on this page to manage users centrally and monitor the system without having to access the database.

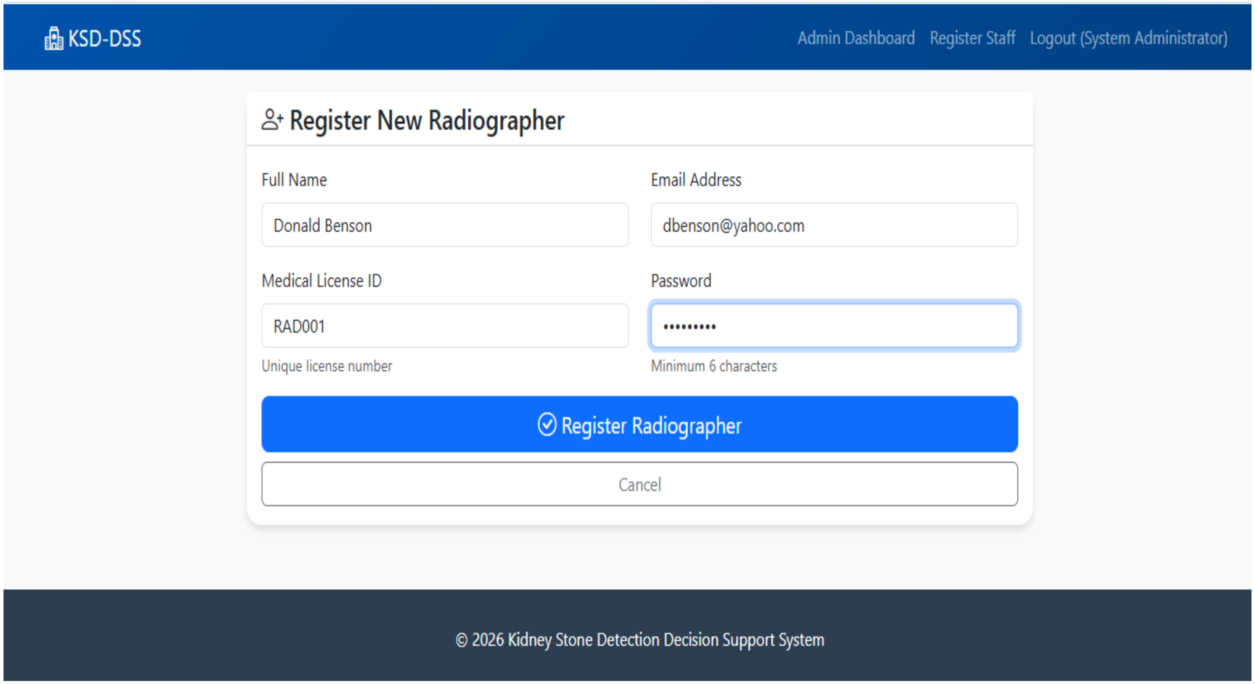

Figure 4.7: Register Radiographer Page

This page will enable the system administrator to add new radiographers (medical staff) who will be using the system to upload and analyze CT scans. The registration form will gather complete name of the radiographer, email address, medical license ID and a password. Form validation is used so that any duplicated email addresses and license IDs are rejected. Before storage, hashing of passwords is conducted with industry-strong encryption. On successful registration, the admin will be redirected to the dashboard and the new radiographer will be listed in the Staff Management table. This page is only accessible to administrators; otherwise, unauthorized users will get a 403 Forbidden error.

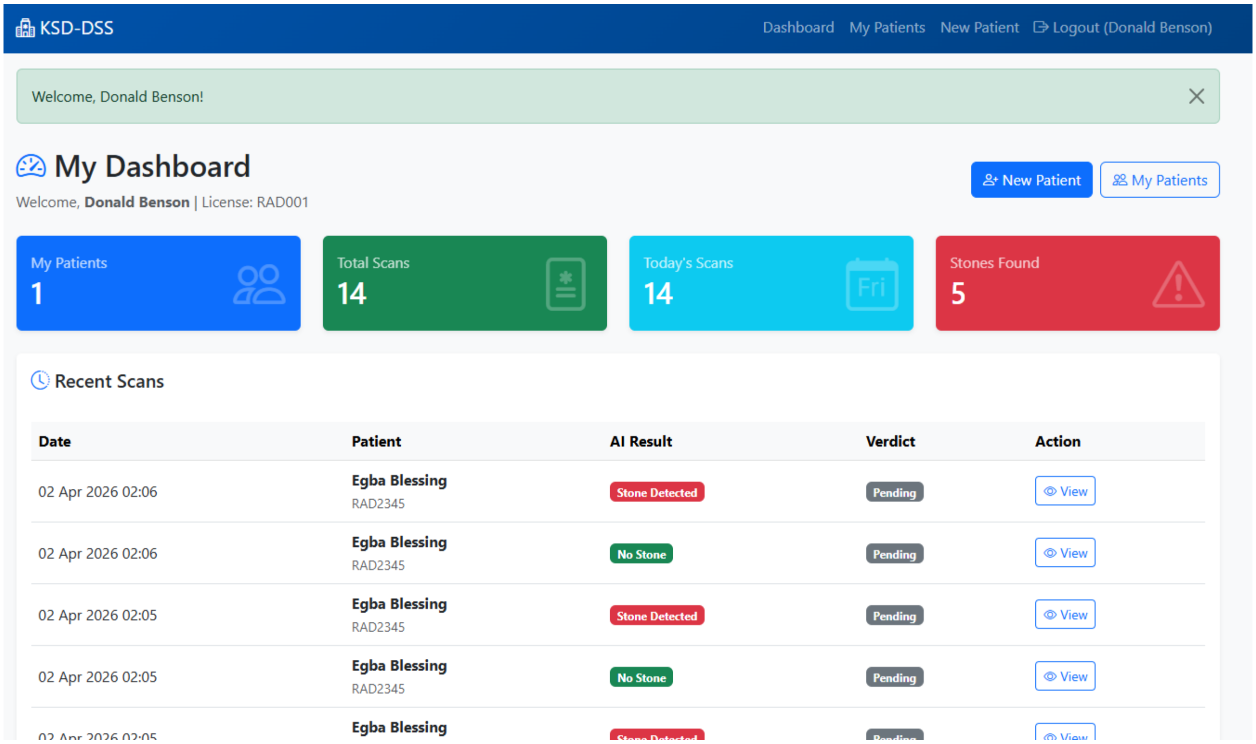

Figure 4.8: Radiographer Dashboard

This is the primary workstation of radiographers once they have logged in. It shows four customized statistics cards My Patients (number of patients created by this radiographer), Total Scans (number of scans processed), Today in Scans (number of scans uploaded on a specific date), and Stones Found (number of AI-detected stones). The statistics are followed by a Recent Scans table which displays the five latest scan analyses with the date, patient name, AI result with a View button to see the entire result. The top bar contains navigation links that allow access to the my patients and New Patient pages in a brief period of time. This dashboard provides radiographers with a real-time preview of the workload and the activity.

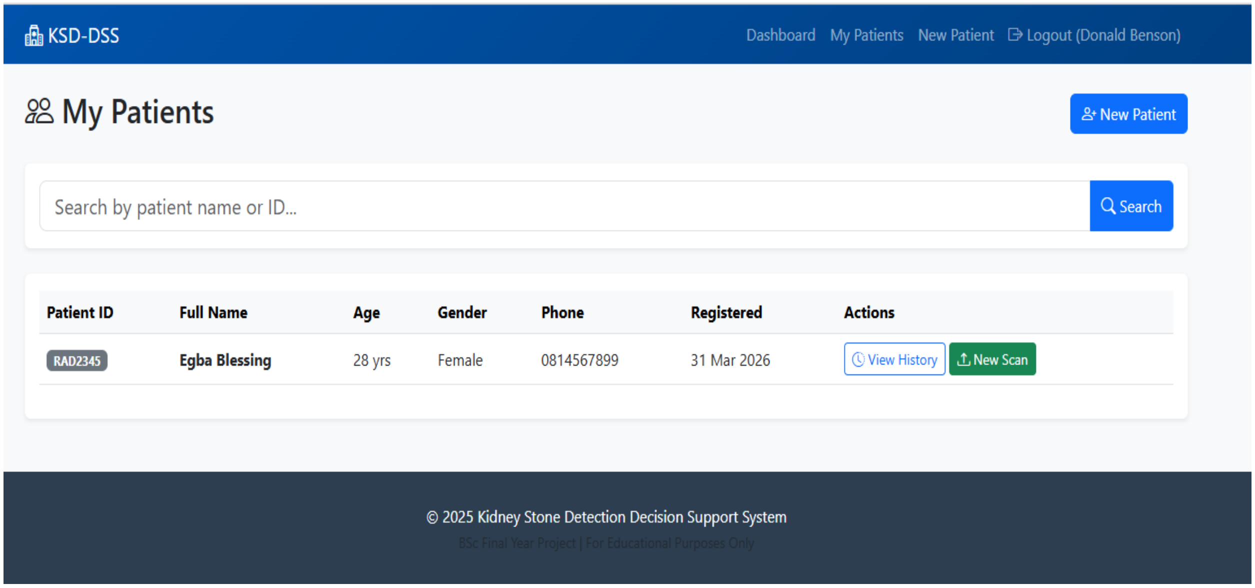

Figure 4.9: Patient List Page (My Patients)

The page shows a searchable list of all patients registered in the system. The table contains the patient ID, full name, age, gender, phone number, date of registration, and two action buttons, which are View History (to view all the past scans of a patient) and New Scan (to upload a new CT image to analyze it). There is a search bar at the top that enables radiographers to locate patients within seconds by their names or the hospital ID. In case no patients are registered yet, a pleasant empty-state text is shown with a button to create the first patient. This page is the main point of work with patients in the system.

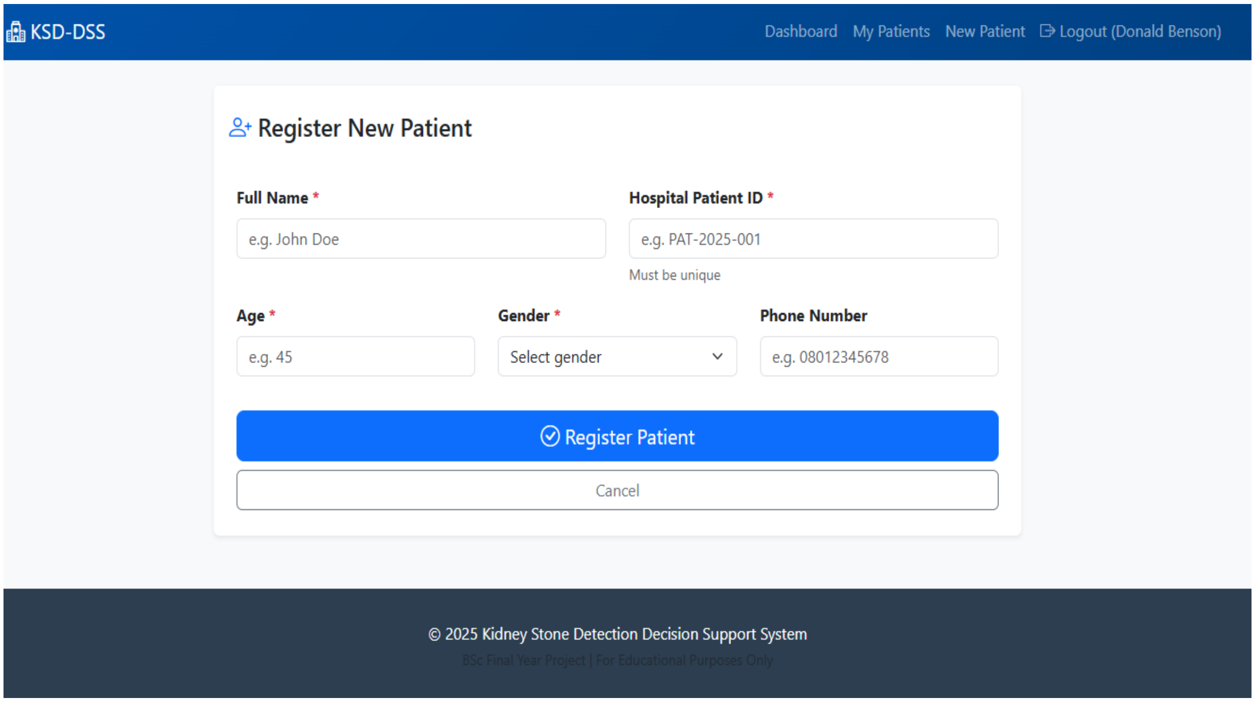

Figure 4.10: New Patient Registration Page

This page enables the radiographers to enroll a new patient in the system and then upload CT scans. The form will gather the complete name of the patient, hospital patient ID (unique) and age, gender (Male/Female/Other) and phone number of the patient. Fields that are required are denoted by a red asterisk. A successful submission redirects to the history page of the patient on which the radiographer can immediately upload the first CT scan. In the event of a duplication of patient ID, a message of error will be shown and the radiographer asked to use an alternative ID. This will make sure that every patient record is distinctly identifiable in the workflow of the hospital.

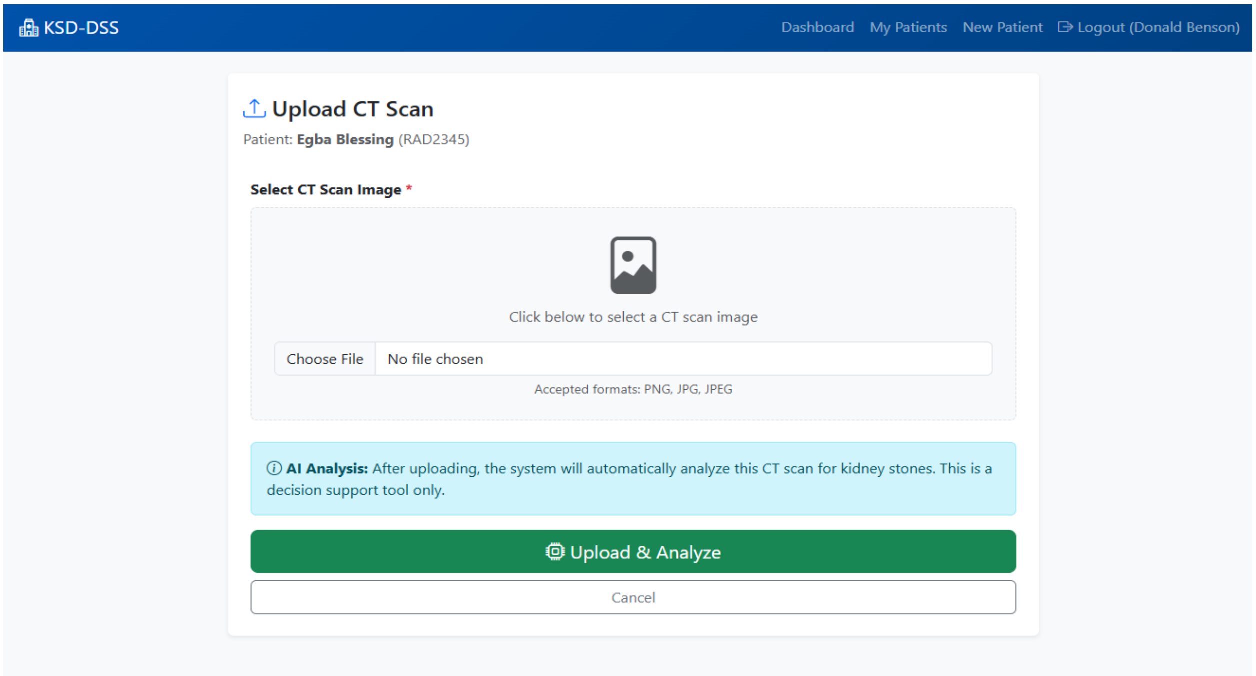

Figure 4.11: Upload CT Scan Page

This is where the interface is located to upload a CT kidney scan image to be analyzed by AI. At the top, one can see the name of the patient and the hospital ID to confirm the patient. Images can be uploaded as PNG, JPG, and JPEG with a file size of up to 16MB. Once an image is picked, a preview is displayed in real time at the bottom of the upload space to ensure that the radiographer can confirm that he or she has selected the right file. A notice informational is a reminder telling the users that the AI analysis is a decision-support tool only. When clicking on the button Upload and Analyze, a loading spinner is shown which shows that the image is being analyzed by CNN model. The picture uploaded has a distinct name so that there is no conflict in the storage system.

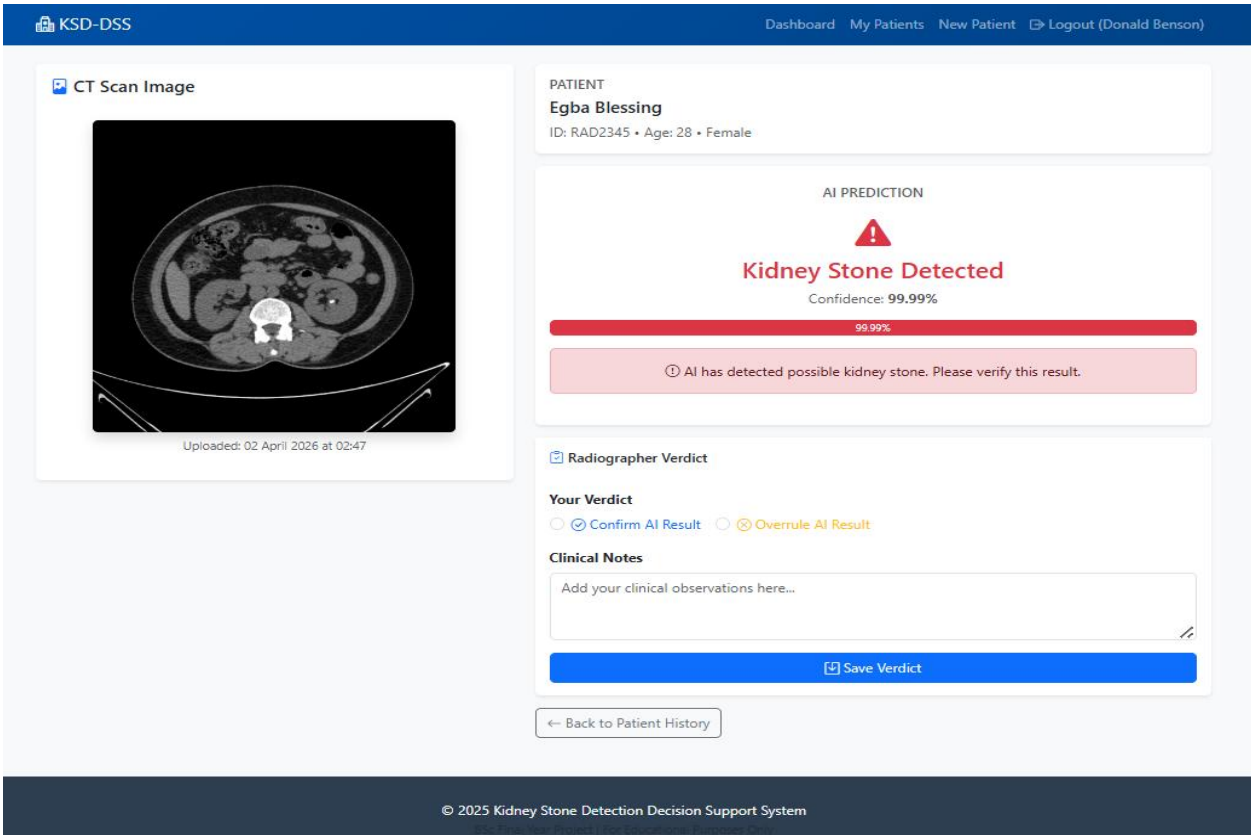

Figure 4.12: AI Prediction Result Page (Stone Detected)

This page shows the AI analysis output in case a kidney stone has just been detected. The left side has the uploaded CT scan image and its upload time. The right panel shows the information of the patient and then the result of the AI prediction. Once a stone has been detected, there is a red warning icon and a text message saying Kidney Stone detecting. A confidence level percentage (e.g., 99.99) shows the degree to which the AI model is sure of its prediction. The confidence level is indicated as a red progress bar. A pink alert box warns the radiographer that the result should be clinically verified. A button to go back to patient history is easy to navigate through to scan timeline.

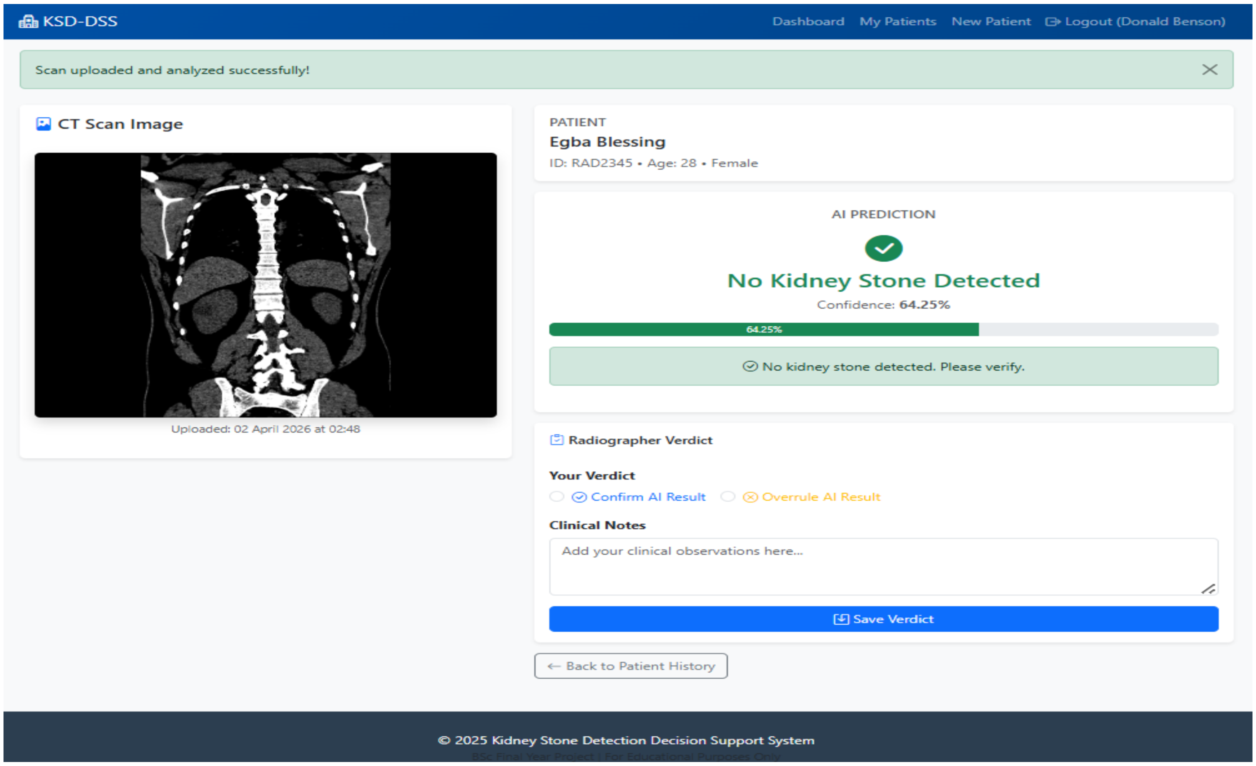

Figure 4.13: AI Prediction Result Page (No Stone Detected)

This page shows the AI analysis outcome where no kidney stone is detected. The layout is similar to the Stone Detected page with green color-coding to show a negative result. There is an icon of a green checkmark and No Kidney Stone Detected written. The confidence percentage shows the confidence of the model that the scan contains no stone. A progress bar and success alert box that is green encourages a follow-up. This standard color-coding (red: stone, green: no stone) is based on accepted medical UI standards and enables radiographers to interpret the findings on a glance.

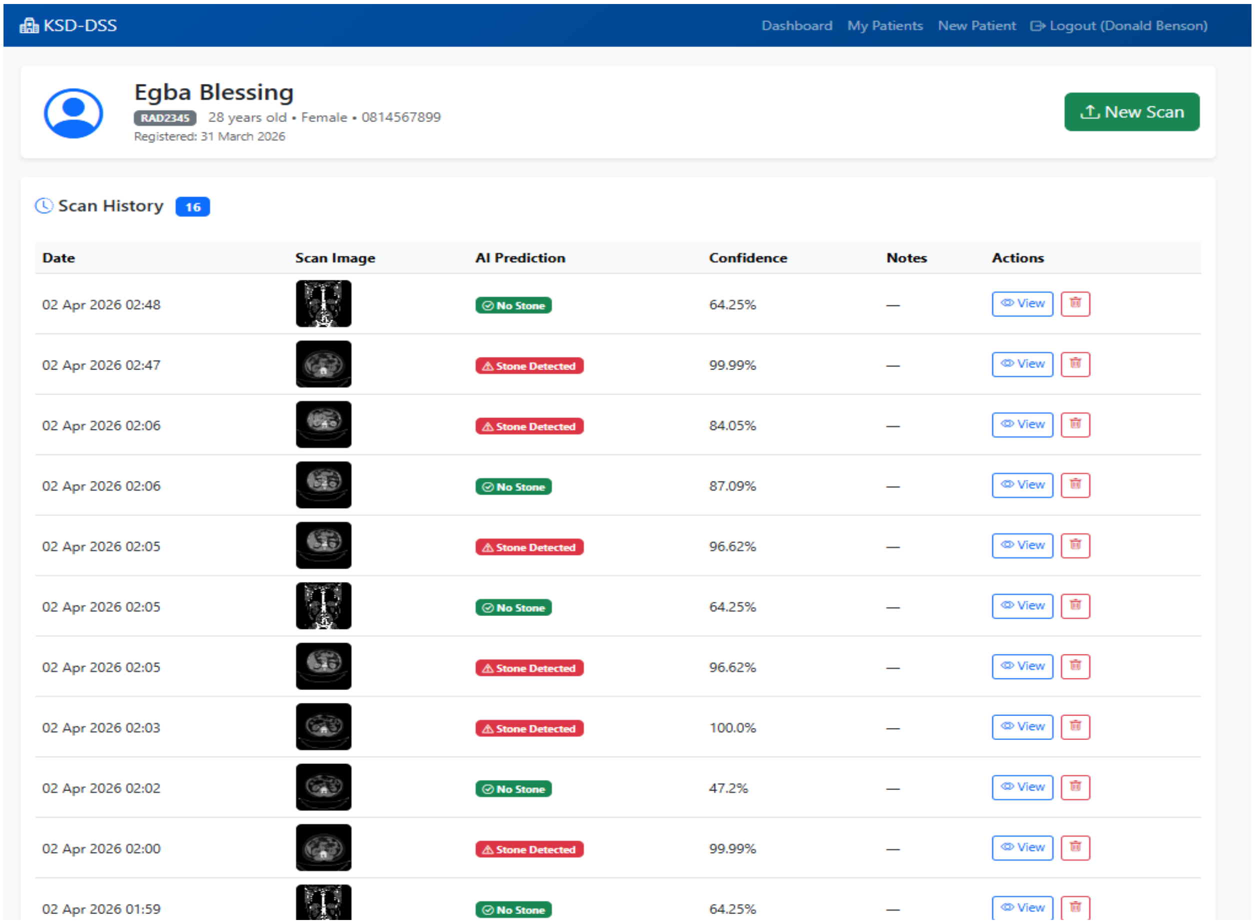

Figure 4.14: Patient Scan History Page

This page gives a detailed timeline of all the CT scans uploaded on a given patient. On the first page, there is a patient information card showing the name of the patient, his or her hospital ID, age, gender, phone number, and the date of registration. There is a New Scan button through which more scans can be uploaded immediately. The scan history table below is a list of all the previous analyses in reverse chronological order. The scan date, a CT image thumbnail, AI prediction (a red badge indicates Stone Detected, a green badge indicates No Stone), the confidence percentage, clinical notes and action buttons are shown in each row. The View button will reveal the detailed result page, and red trash icon will enable one to delete a scan record at a time with a confirmation notice. The total number of scans has a badge that is located next to Scan History to give a quick reference.

CHAPTER FIVE

SUMMARY AND CONCLUSION

5.1 Summary

This study introduces the design of an automated method of kidney stones detection in Computer Tomography (CT) images with Convolutional Neural Networks (CNN). The main objective is to design an effective decision-making support system that will help physicians in the diagnosis and early detection of kidney stones. This technology involves using machine vision and deep learning, which will help overcome some of the problems related to conventional approaches to medical diagnostics, including the long duration of diagnostics and human errors.

Data from publicly available CT Kidney scans have been utilized and organized into two classes: Stone and Non-Stone, based on the practical need for clinical screening. The preprocessing techniques like resizing, normalization, converting to grayscale, and augmenting the data have been applied for optimizing the effectiveness of the model. A specialized CNN structure is designed and includes convolutional layers, batch normalization, dropout, and regularization to maximize the effectiveness of the feature extraction process and minimize overfitting. The results indicate that the model is highly sensitive and effectively identifies kidney stone patients; however, precision is poor because of false positives.

A web application for this has been created using Flask. It is a role-based one where administrators and radiologists can log in and perform tasks like uploading images, making real-time predictions, and managing patient data. This paper particularly focuses on the potential that the techniques involving CNN have in analyzing medical imaging and also demonstrates how AI can be leveraged for clinical decision support, improve diagnosis accuracy, and deliver healthcare under resource constraint circumstances.

5.2 Conclusion

The result of this study demonstrates the ability of Convolutional Neural Networks (CNNs) to automatically detect kidney stones in computed tomography (CT) scan images. The study provides a useful decision support system that can address some of the problems associated with the traditional diagnosis model such as time consuming, non-uniformity of the expert review and no scaling. The developed system has been proved to be able to learn complex patterns in CT images and to detect kidney stones in a high sensitive manner. The model achieved credible results in the positive case detection, using a tailor-made CNN architecture, the corresponding preprocessing methods, and class balancing approaches. The model was not very precise because of the high rate of false positives, nevertheless, the sensitivity was high and thus majority of kidney stone cases are correctly diagnosed, which is crucial in clinical screening environment where if not diagnosed, it can be fatal. Furthermore, it is a web-based application, which can also enhance the usability of the system as it allows the radiographer to upload images, receive immediate estimates and effectively manage patient-related information, and this is what the combination of theory and practice in the sphere of healthcare compensates for. Last but not least, the research introduces the possibilities related to the application of AI technology, with the emphasis on the CNN technology, in enhancing diagnostic precision and decision-making in clinical practice. Possible directions of further investigation can include, among other things, accuracy evaluation, dataset extension, and multimodal approach implementation.

5.3 Recommendation

In order to increase the efficiency of the automated kidney stone detecting system, the following recommendations are proposed:

1. **Enhance Model Precision –** More efforts could be made towards improving the precision of the model by eliminating the false positives using the help of bigger and varied data sets.
2. **Use Advanced Deep Learning Techniques –** Advanced deep learning techniques like transfer learning and attention driven CNN models could be introduced in order to make the feature extraction process better.
3. **Multiclass Classification** – This project could also be extended to multiclass in order to detect any other abnormality like cysts and tumors as well.
4. **Explainable AI Techniques –** Using additional strong explainable AI techniques will increase the transparency and build clinician’s confidence on the technology.
5. **Cloud-Based Solution Implementation –** In terms of implementation, cloud-based solutions will make the solution scalable and accessible.

6. **Ongoing Collaboration with Healthcare Professionals –** Finally, it is very important that the project is always improved and optimized under the guidance of healthcare professionals.

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