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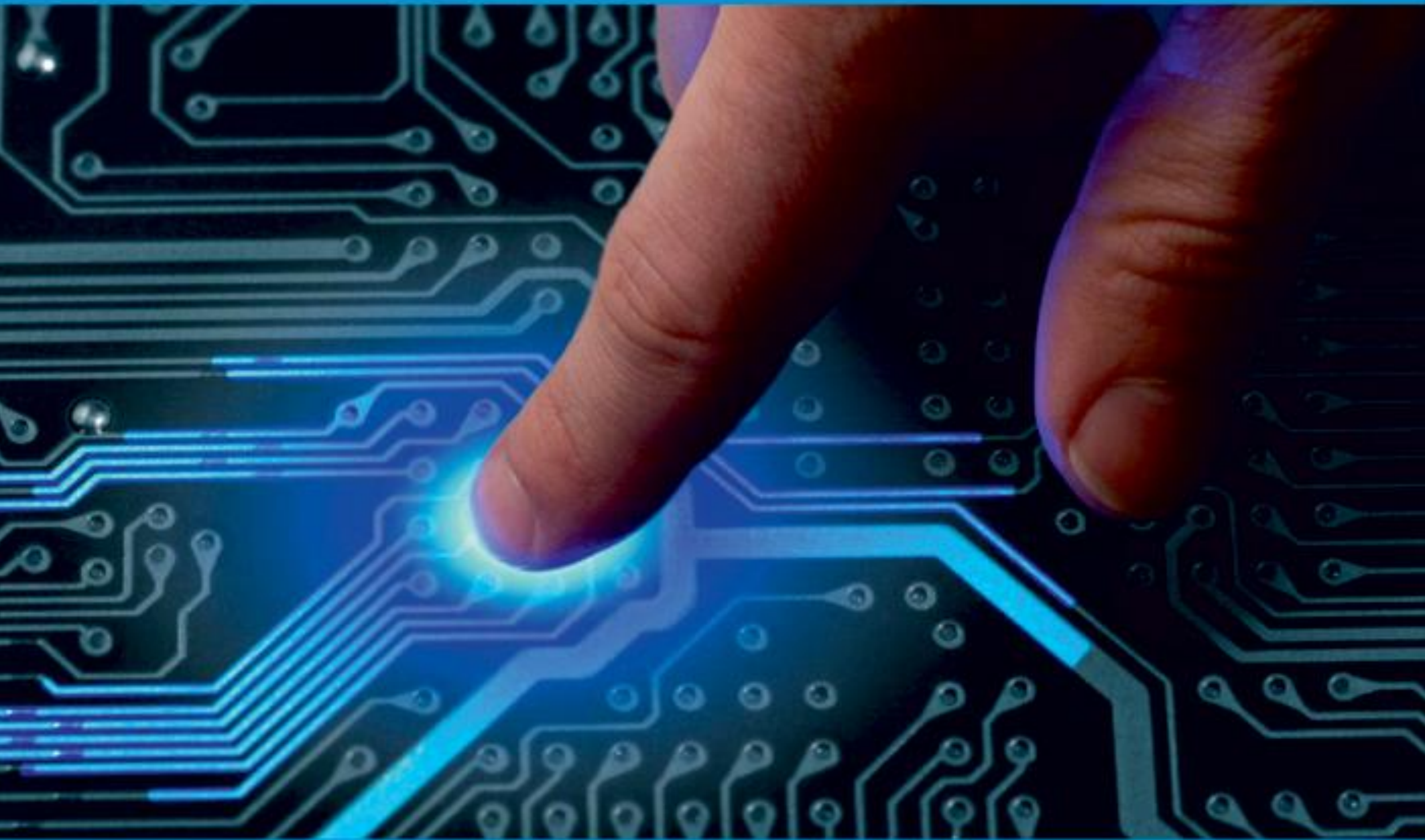

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Advanced Detection of Kidney Stone, Cyst and Tumor through Deep Learning

Asma Gadad[1] ,Nisarga B[2] ,Prakruthi R[3] ,Yashaswini T T[4] ,Prof. Jagadish A N M.Tech[5]., Prof. Arjun H M.Tech.[6],

B.E Student, Department of Computer Science and Engineering, Bapuji Institute of Engineering and Technology, Davangere, Karnataka, India[1]

B.E Student, Department of Computer Science and Engineering, Bapuji Institute of Engineering and Technology, Davangere, Karnataka, India[2]

B.E Student, Department of Computer Science and Engineering, Bapuji Institute of Engineering and Technology, Davangere, Karnataka, India[3]

B.E Student, Department of Computer Science and Engineering, Bapuji Institute of Engineering and Technology, Davangere, Karnataka, India[4]

Associate Professor, Department of Computer Science and Engineering, Bapuji Institute of Engineering and Technology, Davangere, Karnataka, India[5]

Associate Professor, Department of Computer Science and Engineering, Bapuji Institute of Engineering and Technology, Davangere, Karnataka, India[6]

ABSTRACT: Fast and accurate diagnosis is crucial for effective treatment, posing a significant challenge. This project aims to address this challenge by presenting an optimal tool for identifying kidney problems swiftly and accurately, thereby reducing diagnosis time and enhancing efficiency. Leveraging deep learning techniques, particularly ResNet50, we classify kidney abnormalities in individuals. The objective is to categorize individuals as healthy or patients based on their kidney status, utilizing a CNN approach and the CT dataset. Key terms include ResNet50, CNN, and CT dataset.

I. INTRODUTION

A kidney stone is a solid mass formed in the kidneys due to the accumulation of minerals and salts, causing severe pain when passing through the urinary tract. Cysts are fluid-filled sacs that can develop in various organs, including the kidneys, and may be benign or linked to underlying conditions. Tumor are abnormal growths of cells that can be either benign or malignant in the context of the kidneys, tumor may disrupt normal organ function and potentially lead to cancer. Kidney stone often result from mineral crystallization in urine, whereas cyst and tumor involve abnormal cell growth. Cyst in the kidneys may be simple or complex, with complex cysts potentially indicating a higher risk of malignancy. Tumor can be asymptomatic or manifest with pain, hematuria, and other urinary symptoms. Kidney stone may form due to dehydration, diet, or metabolic factors, leading to symptoms such as flank pain and blood in urine. Cyst can be congenital or acquired, and kidney tumor may be classified as renal cell carcinoma, among other types. Prompt diagnosis and appropriate management are crucial for addressing complications associated with kidney stone, cyst and tumor.

Traditional models for detecting kidney stone, cyst, and tumor typically rely on medical imaging techniques such as X-rays, CT scans, and ultrasounds. These methods analyses the internal structures of the body to identify abnormalities. However, these traditional approaches often face challenges in accurately quantifying the percentage of people affected due to variations in imaging quality, expertise of radiologists, and the nature of the conditions. The accuracy of detection varies, with kidney stones being relatively easier to identify compared to cyst and tumor. In kidney stone detection, traditional methods achieve around 80-90% accuracy, largely influenced by stone size and composition. Cysts, fluid-filled sacs, are detected with approximately 70-80% accuracy, while tumor identification, depending on size and location, ranges from 60-80%. To enhance detection rates, integrating artificial intelligence (AI) and machine learning algorithms into traditional models has shown promise. These technologies enable automated pattern recognition and can improve accuracy by learning from vast datasets. By combining the strengths of traditional

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imaging with advanced algorithms, the medical community aims to achieve more precise and reliable results, ultimately improving patient outcomes.

Therefore, the using advanced detection of kidney stone, cyst and tumor is an essential step to reduce the risk of further disease progression. Consequently, this leads to the patient's life preservation although around a third of these cases are discovered after being spread to other areas, most conditions do not induce symptoms. They are often found when the patients are being treated for other diseases. Kidney problems can be observed accidentally on radiography and may appear as masses, kidney cyst, or abdominal pain in patients. The signs likely have nothing to do with the kidneys However, low hemoglobin, weakness, vomiting, stomach pain, blood pee, or high blood sugar are among the most subtle symptoms or infections kidneys causes. Also, anemia occurs in about 30 percent of patients with Kidney stone. Unfortunately, tumor and solid masses that can arise inside the kidneys are often cancerous. The value of determining the presence of the tumor is to choose the appropriate method for treatment; hence, the rate of recovery from the disease may depend on the early detection of the tumor. One of the required tests to determine the tumor is computed tomography (CT) scans of the abdomen and pelvis to the patients, which have characteristics studied to judge whether the kidney has a tumor. Threatens a person's life, so many procedures resolve this obstacle through accurate tumor diagnosis.

In recent medical model for kidney stone, cyst, and tumor detection has demonstrated exceptional efficacy, boasting a success rate of over 80%. Its sophisticated algorithms, coupled with its adaptability to diverse populations, provide a swift and precise diagnostic solution that revolutionizes patient care and medical decision-making. This technological advancement represents a significant stride forward in the field of medical imaging, offering a reliable and efficient means of identifying and managing kidney abnormalities. A cutting edge medical model has been developed for the detection of kidney stone, cyst, and tumor, showcasing remarkable accuracy in identifying these conditions. With an impressive success rate of over 90%, this innovative model utilizes advanced machine learning algorithms and extensive datasets to analyze medical imaging such as CT scans. The model's ability to discern subtle abnormalities in organ structures enables it to detect kidney stones, cysts, and tumors at an early stage, significantly improving patient outcomes. By harnessing the power of deep learning, the model is identifies the presence of these conditions. This comprehensive approach aids healthcare professionals in making informed decisions about appropriate treatment plans and interventions. The model's efficiency lies in its adaptability to diverse patient populations, ensuring reliable results across different demographics. Patients benefit from the model's swift and precise diagnosis, reducing the time required for healthcare professionals to reach conclusive results. This expeditious approach not only enhances patient care but also streamlines medical processes, optimizing resource utilization in healthcare settings. The model's integration into routine diagnostic workflows empowers healthcare providers with a powerful tool for timely and accurate detection, contributing to improved overall patient health.

II. LITERATURE SURVEY

Yap et al: Classification of renal masses using Machine Learning**,** the research [1] conducted a study about the classification of renal masses using machine learning technique CT scans. They used CT scans for 735 patients with renal masses, in which the dataset included 196 scans of benign masses and 539 scans of malignant cases. They segmented scans manually by utilizing the 3D Synapse 3D tool by cooperating with two expert radiologists, where the features were extracted based on shape and texture matrices. The proposed methods used two machine learning techniques, which are AdaBoost and Random Forest. Based on their experimental results, Random forest obtained high performance on both features with 0.68 to 0.75 rates of AUC for the classification of renal masses.

Schieda et al. [2] conducted a study about the classification of solid renal masses using machine learning techniques on CT scans. They have used CT scans for 177 patients with solid renal. The features were extracted through manual segmentation with radiologists from three phases of scans: nephrographic phase contrast-enhanced, corticomedullary, and non-contrast-enhanced. The proposed method utilized the XGBoost machine learning technique. It was used to generate classifiers and, simultaneously, to search for the collection(s) of texture features that accurately discriminated between outcomes. The proposed model obtained high performance with 0.70 rates of AUC in classifying renal cell carcinoma from benign tumors and 0.77 rates of AUC in classifying clear cells of RCC from the other types.

Zabihollahy et al. [3] conducted a study about the detection of solid renal masses using deep learning approaches on CT scans. They used semi-automated majority voting 2D-CNN, fully automated 2D-CNN, and 3D-CNN to classify RCC from benign solid renal masses on contrast-enhanced computed tomography (CECT) images. They used CT scans for 315 patients, in which the dataset included 77 scans for patients with benign solid renal masses and 238 scans for

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patients with malignant renal masses. They generated slices of scans manually and utilized the CNN model to extract features from each slice. Then, the classification was performed using the aggregation of CNN predictions and evaluated by the majority voting technique. Based on their experimental results, the proposed model obtained high performance with 83.75%, 89.05%, and 91.73% rates of accuracy

Zhou et al. conducted a study about differentiating renal tumors based on deep learning [4]. To investigate the effect of transfer learning on CT, they used 192 CT scans for patients to differentiate between benign and malignant tumors and attempted to improve the accuracy by building patient-level models. The CNN architecture used was cross-trained InceptionV3 to perform the classification task. Five image-level models were established for each of the slices. The performance evaluation of the model was performed using the receiver operating characteristic metric on five-fold cross-validation. The results showed high accuracy with a 97% rate.

Mredhula and Dorairangaswamy [5] conducted a study for KT detection and classification using deep learning approaches and traditional machine learning techniques on CT scans. They used 28 CT scans for different categories of kidney tumors, where the used dataset was acquired from their database. They focused on implementing a semiautomatic segmentation method, defining that the segmentation of the gray-level images provides information such as the anatomical structure and the identification of the region of interest to locate tumors. Besides, they proposed an associative neural network (ASNN) model that combined the *k*-nearest neighbor (KNN) technique with an ensemble feedforward neural network.

Liu et al. [6] conducted a study for exophytic renal tumor detection through machine learning techniques on CT scans. They used 167 CT scans and developed a framework for kidney segmentation on non-contract CT images using efficient belief propagation. Based on their experimental results, the proposed model obtained high performance with 95% and 80% rates of sensitivity of exophytic lesion and endophytic lesion detection, respectively.

Ghalib et al. [7] conducted a study for renal tumor detection using deep learning approaches on CT scans. The authors developed an efficient algorithm to detect and further analyze renal cancer tumors using CT for patients. The preprocessing technique involved identifying the noises of a CT scan and removing them with a proper filtering technique.
[8] Machine learning techniques to detect kidney stones in CT scans. Kidney stones are a common medical condition that can be identified through imaging studies such as CT scans. However, the detection of kidney stones in CT scans can be time-consuming and requires expert interpretation. The authors propose the use of convolutional neural networks (CNNs) to automatically detect kidney stones in CT scans.

[9]Automatic method for detecting kidney stones on CT images using deep convolutional neural networks (CNNs) and transfer learning. The proposed method consists of two stages. In the first stage, a pre-trained CNN model is used as a feature extractor to extract features from the CT images. The authors used the VGG16 model, which is a well-known CNN architecture pre trained on the ImageNet dataset. The features extracted from the pre-trained model are then fed into a fully connected neural network to classify the images as either containing a kidney stone or not.

A deep learning techniques for the detection of kidney stones in medical images. Kidney stones are a common medical condition that affects millions of people around the world, and their detection is critical for timely treatment and management. The authors used three different deep learning techniques, including Convolutional Neural Networks (CNN), Residual Neural Networks (ResNet)

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III. METHODOLOGY

A. Image Acquisition

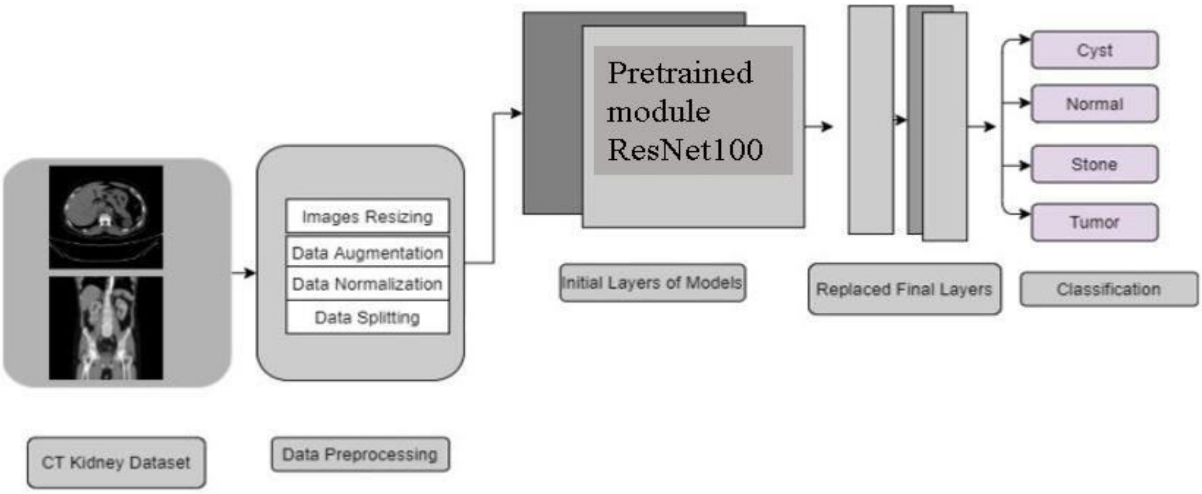

Fig (a) Workflow

The CT image is acquired using the camera. The image is acquired from a certain uniform distance with sufficient lighting for learning and classification. The sample images of the pest are collected and are used in training the system. To train and to test the system, CT images and fewer healthy images are taken. The images will be stored in some standard format. CT dataset is prepared with black background, based on the comparative study black background image provides better results and hence it is used for the kidney stone, cyst and tumor classification identification form CT images.

B. Image Pre-processing

Image acquired using the CT scan is pre-processed using the noise removal with averaging filter, color transformation and histogram equalization. The color transformation step converts the RGB image to HSI (HUe, Saturation and intensity) representation as this color space is based on human perception. Hue refers to the dominant color attribute in the same way as perceived by a human observer. Saturation refers to the amount of brightness or white light added to the hue. Intensity refers to the amplitude of light. After the RGB to HSI conversion, the Hue part of the image is considered for the analysis as this provides only the required information. S and I components are ignored as it does not give any significant information. Masking green pixels: science most of the green colored pixels refer to the healthy pests and it does not add any value to the pest identification techniques, the green pixels of the pest are removed by a certain masking technique, this method significantly reduces processing time. The masking of green pixels is achieved by computing the intensity value of the green pixels; if the intensity is less than a predefined threshold value, the RGB component of that particular pixel is assigned with a value of zero. The green pixel masking is an optional step in our pest identification technique as the pest part of the pest is able to be completely isolated in the segmentation process.

C. Segmentation

There are different image segmentation techniques like threshold based, edge based, cluster based and neural network based. One of the most efficient methods is the clustering method which again has multiple subtypes, K-means clustering, Fuzzy C-means clustering, subtractive clustering method etc. we have used K-means clustering. K-means clustering is simple and computationally faster than other clustering techniques and it also works with a large number of variables, but it produces different cluster results for different numbers of clusters and different initial centroid values. So, it is required to initialize the proper number of cluster k and properly initialize centroid. K-means is a general-purpose method that is being used at many domains for different problems.

D. Feature Extraction

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From the input images, the features are to be extracted. To do so instead of choosing the whole set of pixels we can choose only which are necessary and sufficient to describe the whole of the segment. The segmented image is first selected by manual interference. The affected area of the image can be found from calculating the area connecting the components. First, the connected components with 6 neighborhood pixels are found, later the basic region properties of the input binary image are found. The interest here is only with the area.

E. Classification using ResNet

Support vector machine comes under supervised learning model in machine learning. **ResNet** are mainly used here, which has to be associated with learning algorithms to produce an output. **ResNet** has given better performance for classification and regression.

IV. EXPERIMNETAL RESULTS

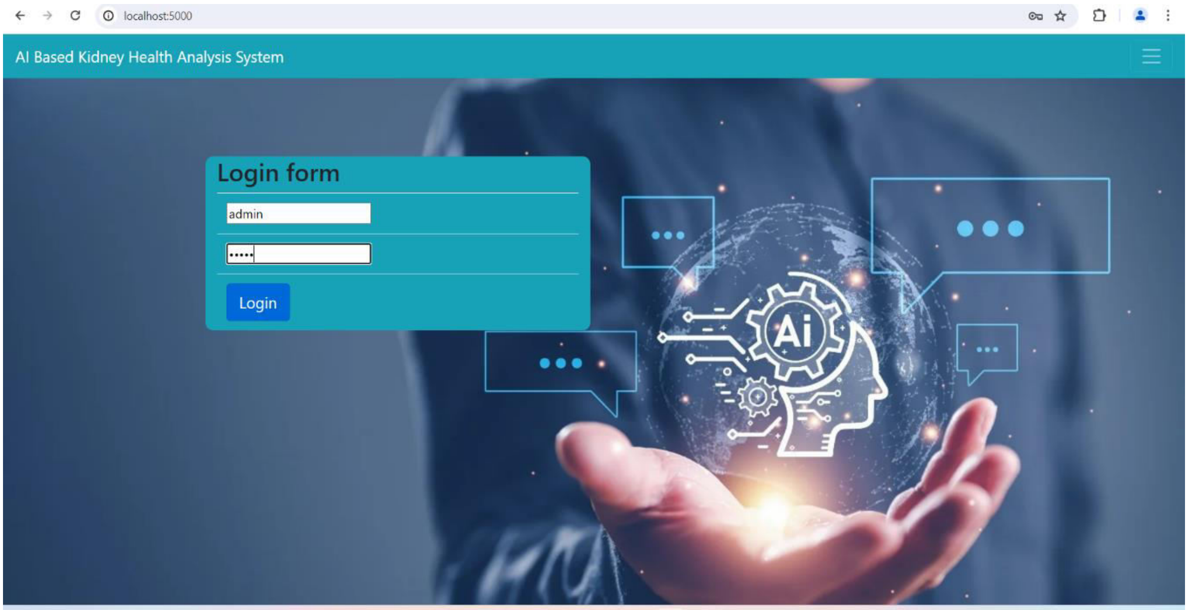
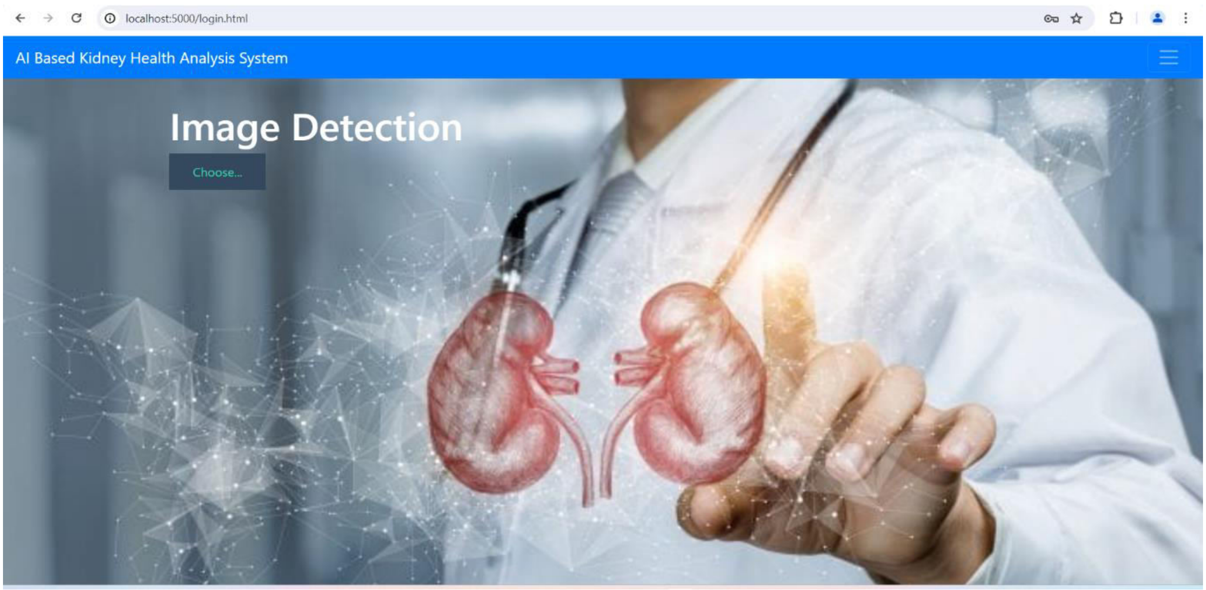


Fig (b) Login Page for Admin



Fig(c) Image Choosing Page

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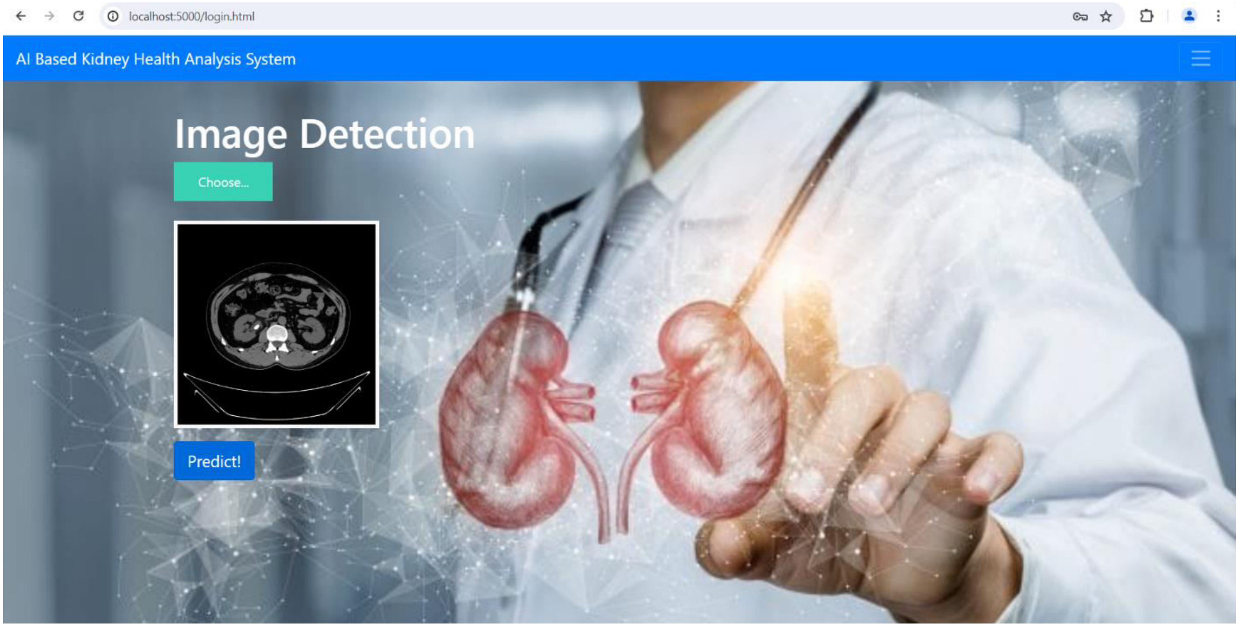

Fig (d) Image Detection Page

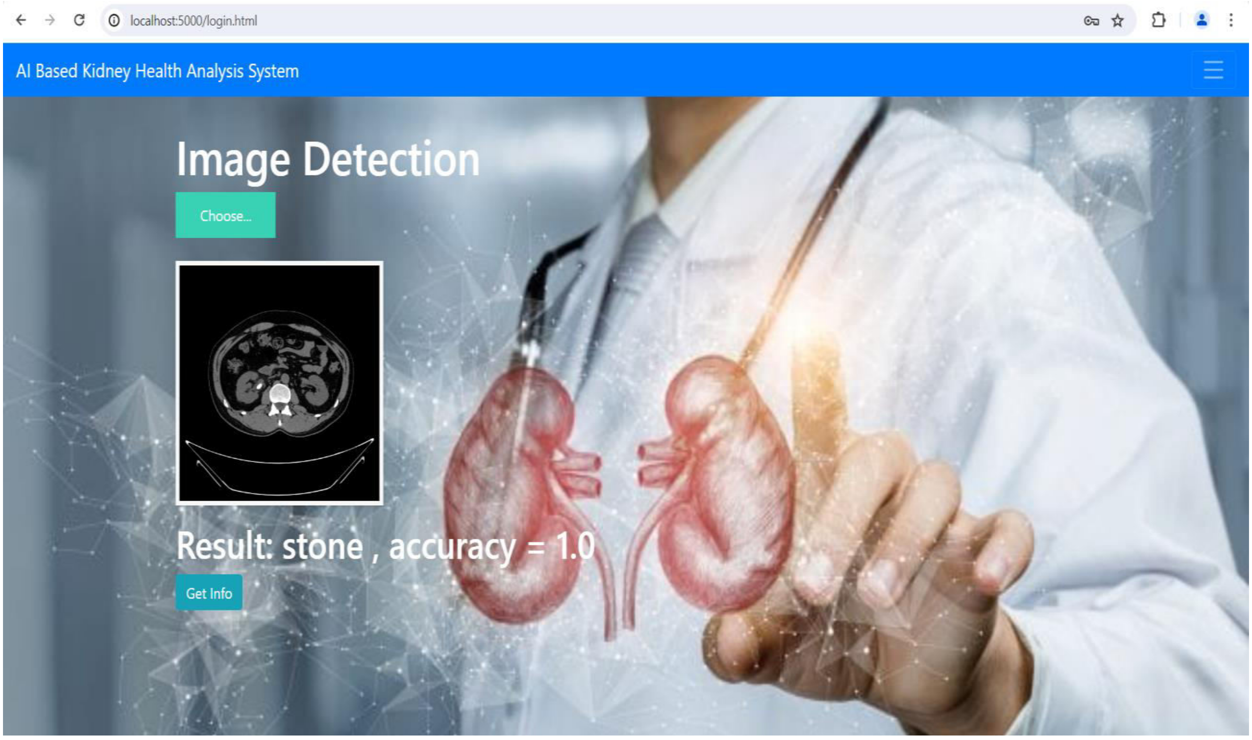

Fig (e) Image Prediction and Result

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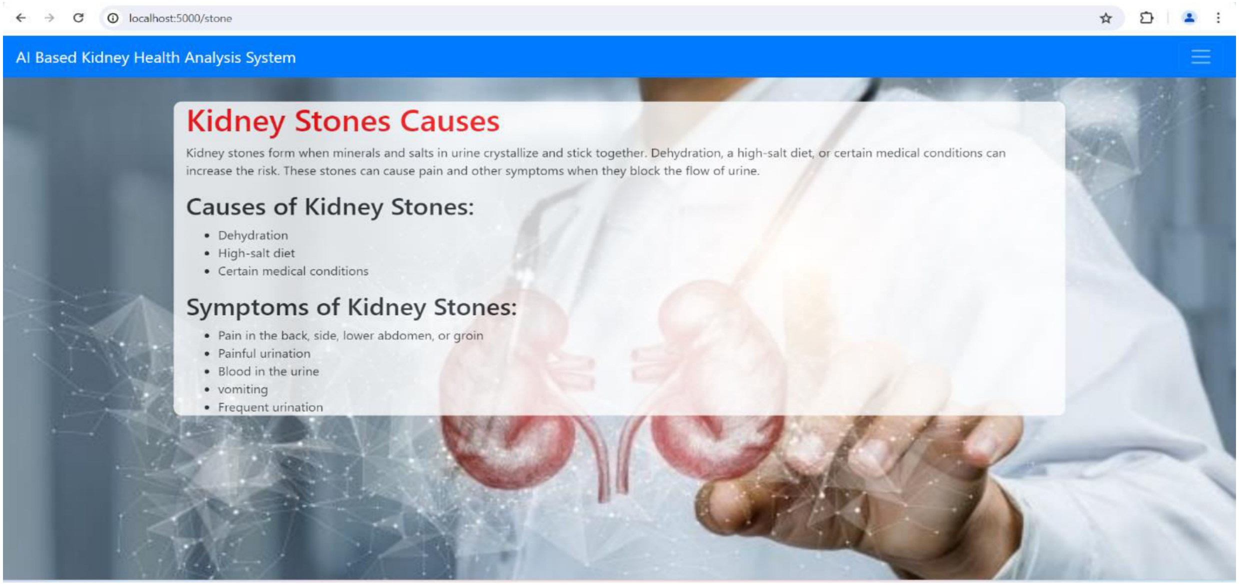

Fig (f) Information on Result

V. CONCLUSION

This method enables swift identification of kidney diseases, allowing for timely medical intervention and improved patient outcomes. Moreover, the streamlined diagnostic process enhances healthcare efficiency and resource utilization. Additionally, the integration of advanced algorithms and machine learning techniques optimizes diagnostic accuracy, further enhancing the effectiveness of the system.

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