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Kidney Stone Detection Using Image Processing and Convolutional Neural Network

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1.*ABSTRACT*

The goal of this research is to create a sophisticated kidney stone detection system by combining deep learning techniques, image processing, and CNNs (convolutional neural networks) with the specially selected VGG16 architecture. Because of its deep and organized design, VGG16 has demonstrated effectiveness in picture classification tasks, which is the driving force behind its use. The methodology includes pre-processing procedures that involve the use of median filtering to remove noise and adaptive histogram equalization (AHE) to enhance the data. Kidney pictures are classified into normal and abnormal using the VGG16 CNN in the classification phase. An innovative feature that follows is the delivery of classification findings via speech output. When classification is abnormal, the system also uses a strong method of kidney stone identification based on level set segmentation The precision of this all-encompassing approach is a crucial component that enhances the dependability and effectiveness of the suggested automated kidney stone identification system, hence bearing noteworthy consequences for prompt and precise medical diagnosis.

Keywords: **Kidney Stones, Image Processing, CT image, CNN, Deep Learning Algorithm, Classification, Voice Output, Accuracy.**

2.INTRODUCTION

One significant development in medical diagnostics is the use of image processing and Convolutional Neural Networks (CNNs) to detect kidney stones. If left undiagnosed or untreated, kidney stones—crystalline mineral deposits in the kidneys—can cause terrible discomfort and serious health issues. This novel strategy seeks to distinguish between normal and diseased kidney structures based on visual data by utilizing CNNs and image processing techniques like segmentation and feature extraction. While defective kidney images may display anomalies such as stone formations or calcifications, normal kidney images have a smooth, homogeneous texture and consistent density. By utilizing CNNs, a subset of deep learning algorithms with a focus on picture identification, the system can independently discover complex patterns and characteristics that differentiate between healthy and damaged renal tissues. By combining cutting-edge neural networks with image processing techniques, kidney stones should be identified more accurately and quickly, allowing for prompt action to reduce health risks and promote early detection. .

3.LITERATURE SURVEY

[1] Chen Z, Bird VY, Prosperi M. in 2018. KSs prevalence for the most recent NHANES cycle, 2013–2014, was 10.1%. Males over 60 years old had the highest prevalence of KSs (17.8%), followed by males 40–59 years old (12.6%). In the age group of 20 to 39, this pattern reverses, with a larger incidence of females than males (7.5% for females against 4.5% for males). Over the course of the research cycles, the prevalence of KSs in female participants increased steadily, from 6.6% in 2007 to 9.5%in 2013 ($p < 0.05$). The incidence nearly doubled among women aged 20 to 39, rising from 3.9 to 7.5%.through out the years 2007–2013 ($p < 0.05$). The proportion of women over 60 has stayed constant, rising from 8.9% in 2007 to 9.8% in 2013. Between 2007 and 2014, the prevalence of males decreased somewhat, from 12.7% in 2007 to 11.4% in 2014. The prevalence was comparatively steady for both genders over 60.

[2] M. Borofsky, C. Stocks, and G. Foster in 2009. Urolithiasis, another name for kidney stone disease, is a major source of health care costs in the US. According to estimates, the lifetime prevalence of kidney stone illness is 7% for women and 13% for men, however these figures are rising.2. It has also been calculated that within 5 years of the original event, there is a 50 percent chance of a recurrence.3. Because kidney stones are so painful, patients often receive treatment in the emergency room (ED). Patients most frequently have excruciating pain in their lower back and flanks, which can sometimes spread to the groin. Nausea, vomiting, and blood in the urine (hematuria) are possible further symptoms.4 The choice of kidney stone disease treatment.

[3] AC Westphalen, RY Hsia, JH Maselli, R Wang, and R Gonzales in 2011 The overuse of computed tomography (CT) is becoming a significant public health concern because of rising health care expenses and radiation exposure; these factors need to be balanced against CT's potential advantages for better diagnosis and treatment planning. This study aimed to ascertain the national trends in the use of CT and ultrasound (US) for the evaluation of suspected urolithiasis in emergency departments (EDs) and whether these trends are associated with variations in the rates of hospitalization and diagnosis for urolithiasis or other major disorders. Retrospective cross-sectional analysis of ED visits from 1996 to 2007 was conducted using data from the National Hospital Ambulatory Medical Care Survey (NHAMCS). The percentage of patients who visited for flank or kidney pain and had CT or US testing was ascertained by the authors, and they computed the rates

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of urolithiasis diagnosis and hospitalization, together with other important illnesses. Variables related to CT utilization at the hospital and patient levels were investigated.

[4] Fwu CW, Eggers PW, Kimmel PL, Kusek JW, Kirkali Z in 2013 The prevalence of urolithiasis has increased in the US, although data on long-term trends—such as recurrence rates—are scarce. Here, we report on national trends in the rates of ER visits, imaging, and medication use. The National Hospital Ambulatory Medical Care Survey and the National Health and Nutrition Examination Survey are the main sources of data used to describe these trends and calculate the lifetime incidence of kidney stone passage. Between 1992 and 2009, the number of urolithiasis visits to emergency rooms rose from 178 to 340 per 100,000 people. Visit rates increased more for women, White people, and people in the 25–44 age range. Computed tomography was used by patients with urolithiasis more than three times as often, from 21 to 71%. In 14% of the cases, medical expulsive therapy was used.

[5] Wang DC, Parry CR, Feldman M, Tomlinson G, Sarrazin J, Glanc P in 2015 A retrospective analysis spanning 11 months was conducted on all patients who sought abdominal CT due to an acute abdomen and presented to the emergency department. Triage, physician assessment, CT request, porter schedule, CT start, CT complete, provision of first CT report, ED disposition decision, and physical discharge are the nine critical time points related to LOS and CT workflow that were gathered. For every interval, the 90th percentile and median timings were provided. During the study period, 96% (2194/2292) of ED interactions matched the inclusion criteria. 9.22 hours was the median ED LOS (90th percentile, 15.7 hours). 29% of all LOS was attributed to intervals related to CT process. The turnaround time for radiology took up 32% of the total CT workflow time. A timeline analysis revealed three distinct ED disposition patterns.

[6] Prevedello LM, Erdal BS, Ryu JL, et al in 2017 Objective To assess the efficacy of a deep learning algorithm-based artificial intelligence (AI) tool in identifying hemorrhage, mass effect, or hydrocephalus (HMH) during non-contrast material-enhanced head computed tomography (CT) exams, as well as the algorithm's performance in identifying suspected acute infarcts (SAI). Supplies and Procedures Once approved by the institutional review board, this retrospective study that complied with HIPAA was finished. A dataset for noncontract enhanced head CT exams was used for training and validation.

[7] Lakhani P, Sundaram B in 2017 This study made use of four deidentified HIPAA-compliant datasets, totaling 1007 posteroanterior chest radiographs, that were exempt from institutional review board evaluation. The datasets were divided into three categories: test (14.9%), validation (17.1%), and training (68.0%). The photos were classified as either healthy or showing signs of pulmonary tuberculosis (TB) using two separate deep neural networks (DCNNs), AlexNet and GoogLeNet. On ImageNet, both pretrained and untrained networks were employed, along with augmentation using various preprocessing methods. On the top-performing algorithms, ensembles were run. An independent board-certified cardiothoracic radiologist blindly assessed the images in cases where the classifiers couldn't agree in order to assess if a radiologist-augmented workflow might be implemented. receiver in use Receiver operating characteristic curves were statistically compared using the DeLong technique, and characteristic curves and areas under the curve (AUCs) .

4.EXISTING SYSTEM

It takes more than one step to detect kidney stones using image processing and Support Vector Machine (SVM) classification. Kidney images are first obtained by the imaging method (e.g., CT scans or ultrasounds). To improve the quality, these photos go through pre-processing techniques like noise removal and enhancement. After that, feature extraction occurs, during which pertinent attributes such as the stones' size, shape, and texture are determined. An SVM algorithm that was trained on a dataset of labeled cases of normal and pathological kidney stones is then fed these features. Based on these discovered patterns, the SVM classifies new occurrences and determines if the kidney stones shown in the picture are normal or pathological. This technique helps identify kidney stone anomalies quickly and accurately, allowing for prompt medical intervention.

5.PROPOSED SYSTEM

In the methodology for kidney stone detection, the process begins with the utilization of Image Processing and Convolutional Neural Networks (CNNs), specifically employing the VGG16 architecture known for its deep learning capabilities. The kidney images undergo a pre-processing stage, involving the removal of noise and contrast enhancement using Adaptive Histogram Equalization (AHE) techniques to refine their quality. The trained VGG16 CNN is then employed for classification, where the system categorizes the images into normal or abnormal. An innovative aspect involves the integration of voice output for the classification results, enhancing accessibility. If an abnormality is identified, the process extends to kidney stone detection using Fuzzy C means clustering for preliminary segmentation, followed by level set segmentation techniques for precise localization of the stones within the abnormal regions. This comprehensive approach not only ensures accurate identification of kidney stones but also enhances the interpretability of results through voice feedback, making it potentially more user-friendly and accessible in medical settings.

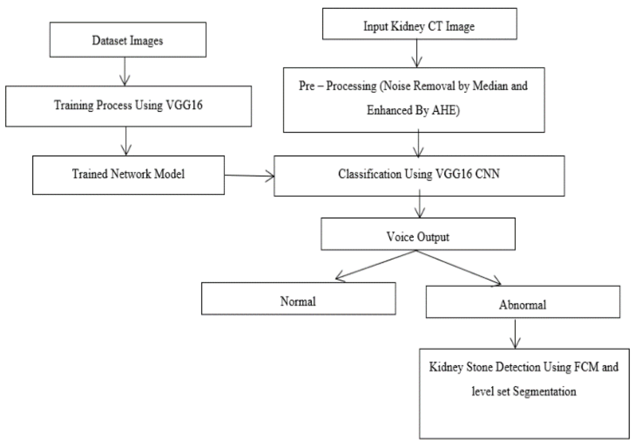

Fig 1: Block diagram of proposed model

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6.IMPLEMENTATION

1. Image Acquisition:

The process of gathering a picture from a source—typically one that is hardware-based—so that it can subsequently be processed using the necessary methods is known as image acquisition. Since processing cannot occur without photos, capturing photographs is always the initial stage in the workflow. Having a consistent foundation to work from is crucial in certain industries, because the final image is not fully processed; it is the result regardless of the equipment used to create it. Kidney CT scans are obtained for the public database

2. Preprocessing:

Including noise reduction, contrast enhancement, and picture scaling, this is the second step in the kidney stone identification procedure. The median filter is used in the preprocessing step of noise reduction to remove noise from the renal CT picture. Rectification uses Adaptive Histogram Equalization (AHE) to improve the contrast of the kidney CT image.

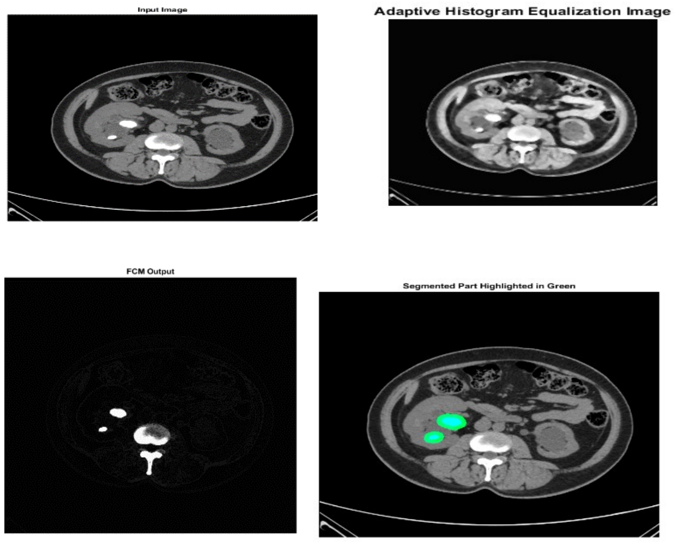
3. Classification:

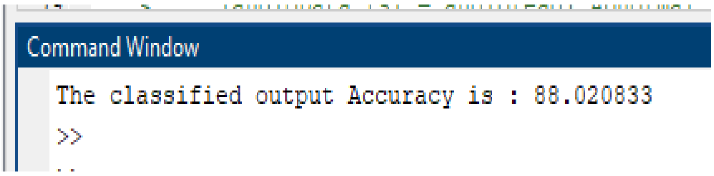
CNN is used to extract features and classify kidney CT images following pretreatment with the transfer learning model Vgg16. All of the information is learned by the VGG16 network from a large number of photos. A 16-layer convolutional neural network is called VGG16. The VGG network requires a picture with a pixel 224x224. Once the network structure has been established, alternate training must be chosen. The length should have been between five and five hundred for training purposes. To identify the renal CT images, network training uses layer-based architecture, schooling data, and schooling parameters. Lastly, test CT kidney pictures are classified into two groups, normal and diseased, based on their extremely rich function, using the suggested vgg16 CNN model.

4. Kidney Stone Detection:

Two properties should be present in the partition: homogeneity of clusters: Cluster homogeneity requires data from the same cluster to be as similar as possible Data heterogeneity: The greatest potential difference between data from several clusters is required to establish data heterogeneity. A classification technique called fuzzy c-means (or fuzzy c-means) is based on the fuzzy optimization of an aquadratic classification criterion. Prior knowledge of the number of classes is required for this strategy, which iteratively builds them using objective function reduction. Consequently, a fuzzy image is produced by assigning a degree of zone membership to each pixel. Lastly, the level set is used in a clustered image to identify only the stone region.

7. RESULT





8. CONCLUSION & FUTURE SCOPE

In summary, a promising development in image enhancement is the fusion technique suggested for contrast and color improvement-based haze removal from satellite images. Haze in satellite photography is a barrier that this solution successfully overcomes by combining chromatic and saliency-based weight maps. The outcomes show not only significant haze removal but also noteworthy gains in color fidelity and contrast in the images. This fusion process yields crisper, more detailed satellite images that are more useful in a variety of contexts, such as urban planning, environmental monitoring, and disaster relief. The effectiveness of this method highlights how widely it may be used in remote sensing, guaranteeing more precise analysis and well-informed decision-making processes that depend on high-quality satellite imagery thorough and accurate studies of the Earth's surface.

The potential for kidney stone identification by image processing appears bright, given the continuous progress in both technology and healthcare. The following are some possible areas

Integrate data from several imaging modalities (CT, X-ray, and ultrasound, for example) to improve kidney stone detection's precision and dependability. Combining various modalities can enhance diagnostic abilities and offer a more complete picture More advanced kidney stone detection

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algorithms may result from ongoing developments in deep learning and artificial intelligence (AI). It's possible that convolutional neural networks (CNNs), in particular, will get better at automatically identifying intricate patterns in medical images.
Provide kidney stone detection devices that can identify kidney stones in real time or almost real time during medical imaging procedures. This could facilitate quicker decision-making and enhance patient care for professionals.
Proceed from binary detection and focus on automated kidney stone quantity and characterisation. This involves assessing the stones' dimensions, forms, and composition, giving more precise information for treatment plans. For a more comprehensive patient profile, seamlessly integrate kidney stone detection equipment with electronic health records. This integration can improve patient care overall and facilitate professional-to-professional contact.
Expand the use of kidney stone detection technology to telemedicine to enable remote consultation and diagnosis. This can be especially helpful in areas where access to specialized healthcare services is scarce

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