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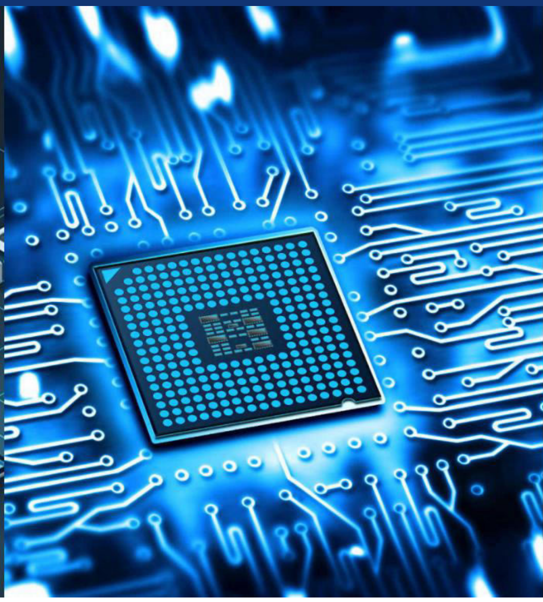

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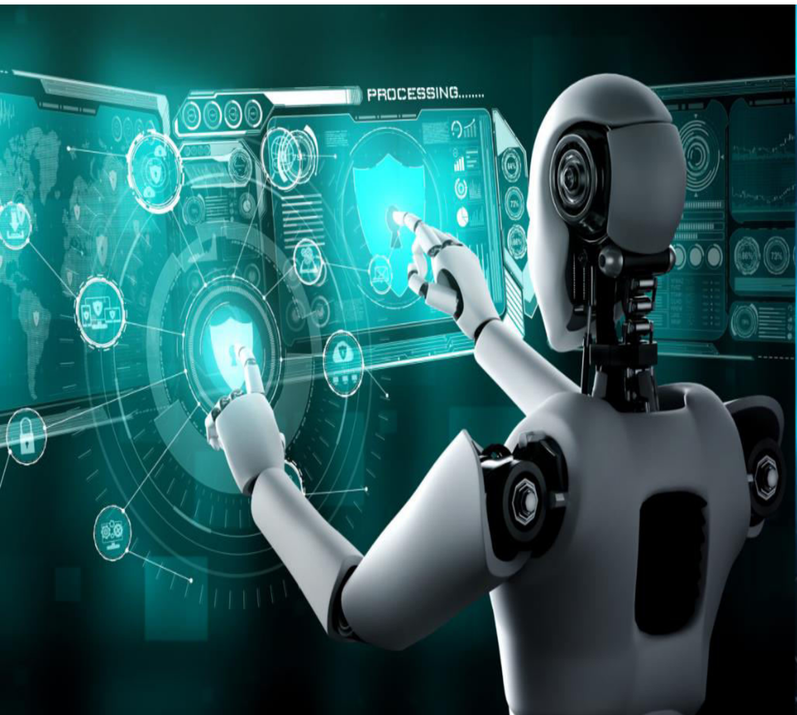

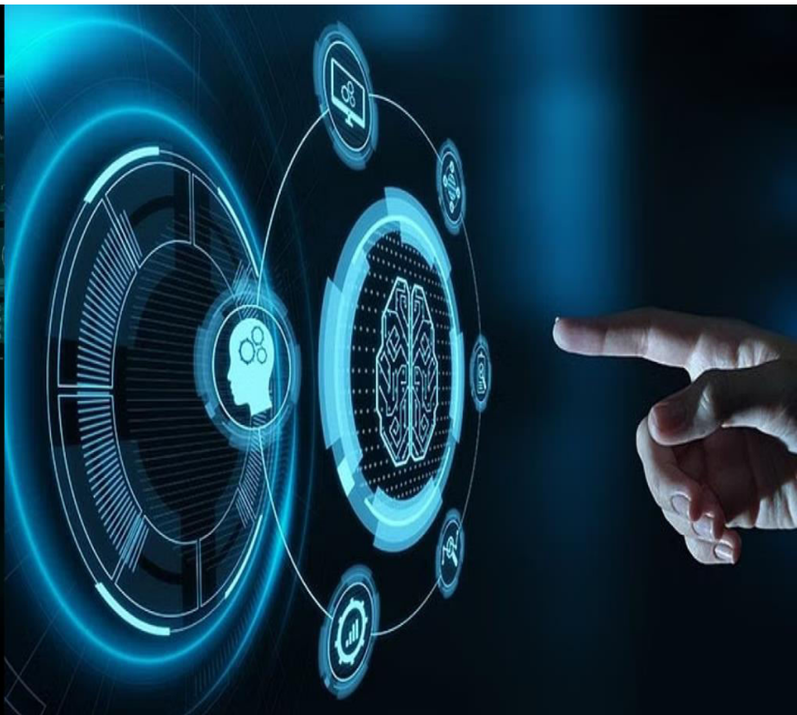

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AI-Based Kidney Stone Detection Using Deep Learning and Ultrasound Images

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ABSTRACT: Kidney stone disease is one of the most common urinary tract disorders affecting millions of people worldwide. Early diagnosis is essential to prevent severe complications such as kidney damage and urinary obstruction. Conventional diagnosis using ultrasound images requires expert interpretation and is often affected by image noise and human error. This paper presents an Artificial Intelligence-based Kidney Stone Detection System using Deep Learning techniques for automatic classification of kidney ultrasound images.

The proposed system utilizes a Convolutional Neural Network (CNN) model implemented using TensorFlow and Keras to classify ultrasound images into Normal Kidney and Kidney Stone categories. Image preprocessing techniques including resizing, normalization, and noise reduction are applied before training the model. A Streamlit-based web application is developed to provide an interactive interface where users can upload ultrasound images and instantly receive prediction results with confidence scores.

Experimental results demonstrate that the proposed system achieves high prediction accuracy while reducing manual diagnostic effort. The developed application provides a fast, reliable, and user-friendly solution that can assist healthcare professionals in early kidney stone diagnosis.

KEYWORDS: Artificial Intelligence, Deep Learning, Convolutional Neural Network, Kidney Stone Detection, Ultrasound Images, TensorFlow, Streamlit, Medical Image Processing.

I. INTRODUCTION

Kidney stone disease is a common medical condition affecting people of all age groups. The disease develops when minerals and salts accumulate inside the kidneys, forming hard deposits that may cause severe pain, urinary obstruction, infection, and kidney damage. Early diagnosis is essential for effective treatment and prevention of complications.

Ultrasound imaging is widely used because it is non-invasive, inexpensive, radiation-free, and easily available. However, manual interpretation of ultrasound images depends heavily on radiologists and is prone to human error.

Recent advances in Artificial Intelligence and Deep Learning have significantly improved medical image analysis. Convolutional Neural Networks (CNNs) automatically learn image features and provide accurate classification without manual feature extraction.

This paper proposes an AI-Based Kidney Stone Detection System that automatically classifies kidney ultrasound images using CNN and provides instant prediction through a Streamlit web application.

The remainder of the paper is organized as follows. Section II presents the objectives. Section III reviews existing literature. Section IV explains the methodology. Section V discusses the experimental results. Finally, the paper concludes with future scope.

OBJECTIVES OF THE STUDY

1. Develop an AI-based kidney stone detection system using CNN.
2. Improve ultrasound image quality through preprocessing.
3. Automatically classify ultrasound images into Normal Kidney and Kidney Stone.
4. Reduce dependency on manual diagnosis.
5. Develop a Streamlit web application for real-time prediction.
6. Display prediction confidence scores.
7. Improve diagnostic accuracy and reliability.

II. REVIEW OF RELATED LITERATURE

The rapid advancement of Artificial Intelligence (AI) and Deep Learning has significantly transformed the field of medical image analysis. Traditional diagnosis of kidney stone disease using ultrasound imaging depends on radiologists' experience and manual interpretation, which may lead to variations in diagnosis due to image quality and human factors.

Early computer-aided diagnosis systems employed conventional image processing techniques combined with Machine Learning algorithms such as Support Vector Machine (SVM), Decision Tree, Random Forest, and K-Nearest Neighbor (KNN). These methods relied on handcrafted feature extraction techniques including texture analysis, edge detection, Histogram of Oriented Gradients (HOG), and Gray Level Co-occurrence Matrix (GLCM). Although these approaches achieved acceptable performance, their accuracy depended heavily on manual feature engineering.

Recent developments in Deep Learning have introduced Convolutional Neural Networks (CNNs), which automatically learn discriminative features directly from medical images without requiring manual feature extraction. CNN-based models have demonstrated remarkable performance in medical image classification tasks including tumor detection, pneumonia detection, diabetic retinopathy classification, and kidney stone identification.

Several researchers have proposed AI-based kidney stone detection systems using CT scan, X-ray, and ultrasound images. Among these imaging modalities, ultrasound is widely preferred because it is radiation-free, inexpensive, non-invasive, and easily accessible in healthcare facilities. However, ultrasound images often contain speckle noise and low contrast, making automatic detection more challenging.

Recent studies have also integrated transfer learning architectures such as ResNet, EfficientNet, DenseNet, and MobileNet to improve classification accuracy. While these models provide excellent performance, they generally require large annotated datasets and high computational resources. Consequently, lightweight CNN architectures remain highly suitable for real-time clinical applications.

Based on the reviewed literature, it is observed that Deep Learning-based approaches provide higher accuracy, improved automation, and better generalization compared to conventional Machine Learning methods. Therefore, this research proposes a CNN-based Kidney Stone Detection System using ultrasound images integrated with a Streamlit web application for real-time prediction and clinical assistance.

III. METHODOLOGY

A. Dataset Collection

The proposed system utilizes kidney ultrasound image datasets containing two classes namely **Normal Kidney** and **Kidney Stone**. The dataset is divided into training and testing folders for supervised learning. Images are collected from publicly available medical datasets and academic research sources.

B. Image Preprocessing

The collected ultrasound images undergo preprocessing before model training. Each image is resized to **128 × 128 pixels**, normalized, and augmented using image rotation, zooming, and horizontal flipping techniques. These preprocessing operations improve image quality and enhance model generalization.

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C. CNN Model Development

A Convolutional Neural Network (CNN) consisting of multiple convolutional layers, max-pooling layers, flatten layer, fully connected dense layer, dropout layer, and sigmoid output layer is designed for binary image classification. TensorFlow and Keras frameworks are used to implement the proposed CNN architecture.

D. Model Training

The CNN model is trained using the prepared dataset with Binary Cross Entropy loss function and Adam optimizer. The training process automatically extracts image features and learns discriminative patterns associated with kidney stone and normal kidney images.

E. Prediction Module

After successful training, the model is deployed using a Streamlit web application. Users upload ultrasound images through the interface, and the trained model predicts whether the kidney is **Normal** or contains a **Kidney Stone**. The application also displays prediction confidence scores.

F. Performance Evaluation

The performance of the proposed model is evaluated using Accuracy, Loss, Confusion Matrix, and Classification Report. Training Accuracy and Validation Accuracy graphs are generated to analyze model learning performance.

IV. RESULTS AND DISCUSSION

The proposed AI-Based Kidney Stone Detection System was evaluated using testing ultrasound images to analyze the effectiveness of the trained CNN model. Experimental results indicate that the developed model successfully distinguishes between Normal Kidney and Kidney Stone images with high prediction accuracy.

The Streamlit web application provides an intuitive interface where users can upload ultrasound images and instantly obtain prediction results along with confidence scores. The integration of TensorFlow, Keras, and Streamlit enables real-time diagnosis with minimal processing time.

Training Accuracy and Validation Accuracy graphs demonstrate stable model convergence without significant overfitting. Similarly, the Loss graph shows a gradual decrease during training, indicating effective optimization of model parameters.

The Confusion Matrix and Classification Report further confirm that the proposed CNN model achieves reliable classification performance for both Normal Kidney and Kidney Stone categories. The developed system reduces manual diagnostic effort and assists healthcare professionals in early disease identification.

Overall, the proposed AI-Based Kidney Stone Detection System provides an efficient, accurate, and user-friendly solution for automated kidney stone diagnosis using ultrasound images.

V. CONCLUSION

This paper presented an Artificial Intelligence-Based Kidney Stone Detection System using Deep Learning techniques for automatic classification of kidney ultrasound images. The proposed Convolutional Neural Network successfully identifies Normal Kidney and Kidney Stone images with high prediction accuracy.

The developed Streamlit application provides a simple and interactive platform for real-time kidney stone prediction, enabling users to upload ultrasound images and receive instant diagnostic results with confidence scores. Experimental evaluation demonstrates that the proposed system offers improved diagnostic accuracy, reduced manual effort, and faster prediction compared with traditional approaches.

Future work includes incorporating larger ultrasound datasets, advanced deep learning architectures such as EfficientNet and Vision Transformers, Explainable Artificial Intelligence (XAI), and cloud deployment to enhance scalability and clinical usability.

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