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Chronic Kidney Disease prediction Using Deep Learning

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Abstract: *Chronic Kidney Disease (CKD) is a medical condition that affects the normal functioning of the kidneys. Early detection of kidney abnormalities is important to prevent serious health complications. This project presents a deep learning based system for identifying kidney diseases from CT scan images. The model uses a Convolutional Neural Network with the ResNet50 architecture to extract important features from images and classify them into different categories such as normal, cyst, tumor, and stone. Image preprocessing techniques are applied to prepare the dataset for training the model. The trained system predicts the disease type and provides a confidence score for the prediction. This approach helps in faster analysis of medical images and can support doctors in the early detection of kidney diseases*

Keywords: Chronic Kidney Disease (CKD) ,Deep Learning, Convolutional Neural Network (CNN), ResNet50 Medical Image Classification, Kidney CT Images ,Disease Prediction

1. INTRODUCTION

Chronic Kidney Disease (CKD) is a serious medical condition that affects the normal functioning of the kidneys. Early detection of kidney abnormalities is important to prevent severe health complications. Medical imaging techniques such as CT scans are commonly used to identify kidney problems like cysts, tumors, and stones. However, manual analysis of medical images can be time-consuming and may lead to errors. Deep learning techniques, especially Convolutional Neural Networks (CNN), have shown excellent performance in medical image analysis. In this work, a deep learning based system is developed to automatically detect kidney diseases from CT scan images. The proposed model uses the ResNet50 architecture to classify kidney images into normal, cyst, tumor, and stone categories, helping in faster and more accurate diagnosis.

2. LITERATURE SURVEY

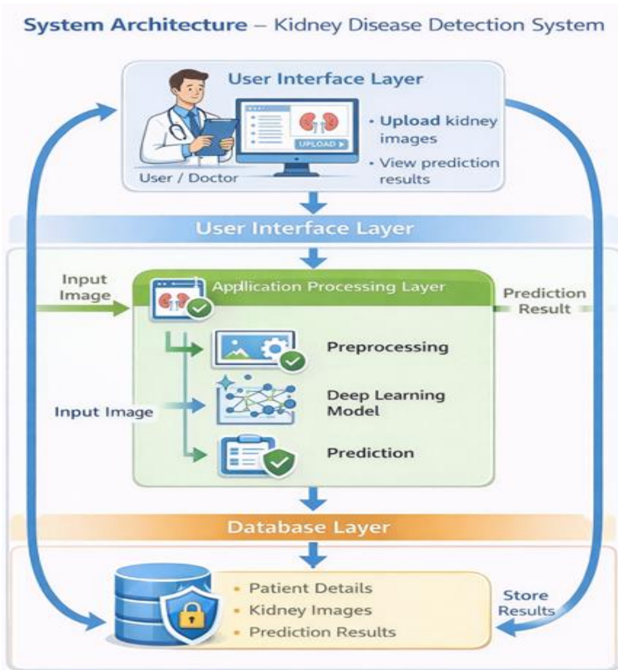
Deep learning is a branch of machine learning that focuses on learning complex patterns from large datasets using multi-layer neural networks. Representation learning allows models to automatically extract important features

from raw data without manual feature engineering. Techniques such as Convolutional Neural Networks (CNN) are widely used for image analysis because they can learn hierarchical image features like edges, textures, and shapes. These methods form the foundation for many modern medical image classification systems, including kidney disease detection models

The dataset used in this project consists of kidney CT scan images categorized into four classes: normal, cyst, tumor, and stone. These images are used to train and evaluate the deep learning model. Before training, images are preprocessed using techniques such as resizing and normalization to improve data quality. For feature extraction, a Convolutional Neural Network with the ResNet50 architecture is used. The model automatically learns important features from the kidney images, such as shapes, textures, and patterns, which help in accurate classification of kidney diseases

3. PROPOSED SYSTEM

In the existing system, kidney disease detection is performed using CT scan images and deep learning techniques. A Convolutional Neural Network (CNN) model such as VGG16 is used to classify kidney images into categories like normal, cyst, tumor, and stone. The system analyzes medical images and predicts the disease type based on learned features. Visualization techniques such as Grad-CAM are sometimes used to highlight important regions in the image that influence the prediction. However, the existing approach may require high computational resources and may not always achieve optimal accuracy.



System Architecture

The system architecture of the kidney disease detection system consists of three main layers: User Interface Layer, Application Processing Layer, and Database Layer. The User Interface Layer allows the user or doctor to upload kidney images and view the prediction results. The uploaded image is then sent to the Application Processing Layer, where preprocessing is performed to improve the image quality. After preprocessing, a deep learning model analyzes the image and predicts the kidney condition. Finally, the Database Layer stores patient details, kidney images, and prediction results for future reference. This architecture helps in providing fast and accurate kidney disease detection.

4. METHODOLOGY

The proposed system uses deep learning techniques to detect kidney diseases from CT scan images. First, the dataset of kidney images is collected and organized into different classes such as normal, cyst, tumor, and stone. The images are then preprocessed using techniques such as resizing and normalization to improve the quality of input data. After preprocessing, the images are given to a Convolutional Neural Network model based on the ResNet50 architecture for feature extraction and classification. Transfer learning is applied to improve model performance and reduce training time. The trained model analyzes the input image and predicts the disease category along with a confidence score. This methodology helps in accurate and automated detection of kidney diseases from medical images.

5. Experimental Results and Observations

The proposed Kidney Disease Detection System was tested using kidney CT scan images to evaluate its performance. The images were first preprocessed and then given as input to the deep learning model for prediction. The system successfully analyzed the images and classified them as normal or kidney disease. During the experiments, the model produced accurate prediction results for most of the test images. The system interface allows users to upload kidney images and quickly view the prediction results. The results show that the proposed system can effectively assist in the early detection of kidney disease. The observations indicate that the use of deep learning techniques improves the accuracy and efficiency of medical image analysis. The system also reduces manual effort and helps doctors in making faster diagnostic decisions.

Key Observations:

The system successfully processes kidney CT scan images and predicts the presence of kidney disease.

The deep learning model provides accurate and fast prediction results.

The preprocessing of images improves the quality of input data and enhances model performance.

The user interface allows users to easily upload images

The proposed system helps in early detection of kidney disease and supports medical diagnosis.

System Implementation
Modules:

1. Image Upload Module This module allows the user or doctor to upload kidney CT scan images into the system for analysis.
2. Image Preprocessing Module In this module, the uploaded image is processed by resizing and normalizing to improve the quality of the image for better analysis.
3. Deep Learning Model Module This module uses a deep learning model to extract features from the image and classify the kidney condition.
4. Prediction Module The prediction module analyzes the processed image and provides the final result such as normal kidney or kidney disease.
5. Database Module This module stores patient details, uploaded images, and prediction results for future reference.

A. Home Page of the Stress Detection System

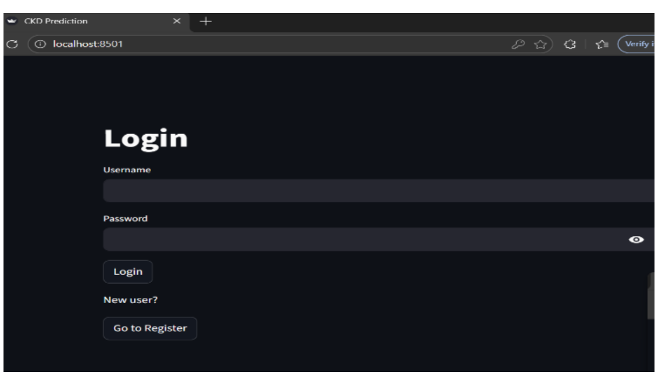


Fig 1: Home Page of the Stress Detection System

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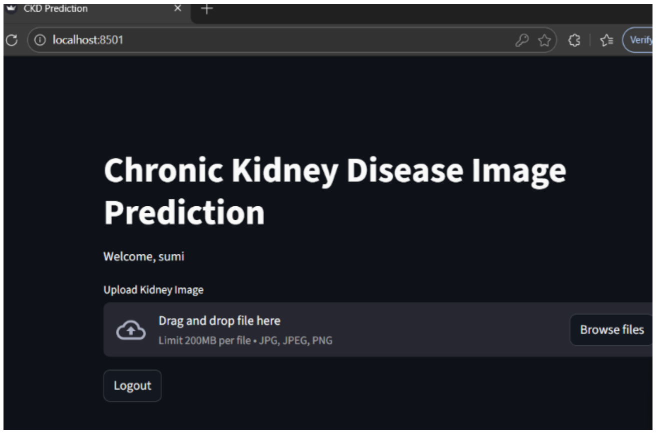
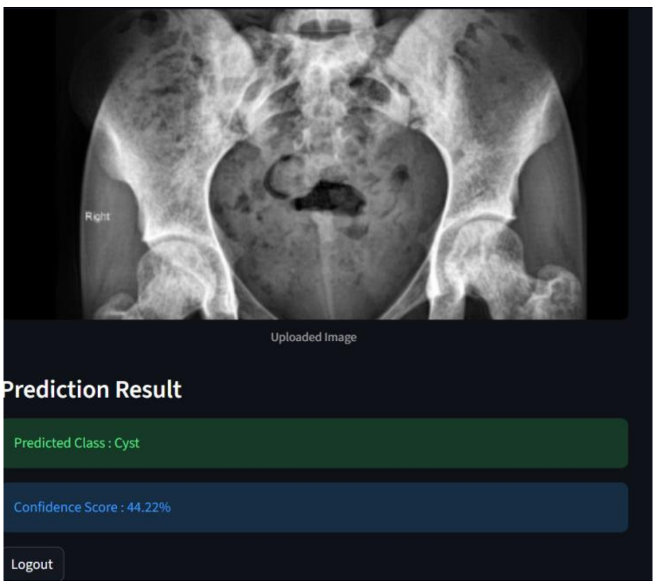
Fig 1 shows the system consists of several modules that help in managing user access and system functionality. The User Registration Module allows new users to create an account by providing a username and password. The Login Module enables registered users to access the system securely by entering their credentials. The Authentication Module verifies the entered username and password to ensure that only authorized users can log in. After successful login, the Navigation Module redirects the user to the main application where they can access other features of the system. These modules help in maintaining security and providing controlled access to the kidney disease detection system.





6. CONCLUSION

The proposed system uses deep learning techniques to detect kidney diseases from CT scan images. A CNN model with the ResNet50 architecture is used to classify kidney images into different categories such as normal, cyst, tumor, and stone. The experimental results show that the system can analyze kidney images effectively and provide accurate predictions. This helps in early detection of kidney diseases and supports doctors in faster diagnosis. In future work, the system can be improved by using larger datasets and more advanced deep learning models to increase prediction accuracy. Additional medical information such as patient history and laboratory data can also be integrated to enhance the performance of the system. The model can also be developed as a web or mobile application to make it more accessible for medical use.

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