Kidney Disease Classification Using Deep Learning

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***Abstract*— The process of Kidney Disease Classification entails the categorization of kidney pictures or patient data into several disease classifications kidney diseases like cysts, tumors, and stones often require rapid and accurate diagnosis. This project presents a deep learning-based approach using a Convolutional Neural Network (CNN) to classify kidney images into four categories: Normal, Cyst, Tumor, and Stone. The trained model is integrated into a Flask-based web application to provide real-time prediction, history tracking, and PDF report generation. By combining medical imaging, machine learning, and modern web technology, this system aims to support early diagnosis and decision-making in clinical environments. The system also features a history tracking module that stores user interactions and predictions in a secure backend database, enabling longitudinal patient monitoring. Additionally, the application includes functionality to generate downloadable PDF reports summarizing the prediction results, timestamps, and image details, which can be used for documentation and consultation purposes. By combining the robustness of machine learning with the accessibility of web technology, this system aims to serve as a valuable diagnostic support tool in clinical settings, particularly in regions with limited access to specialists. The system is designed with scalability and adaptability in mind, allowing future integration with hospital information systems and other diagnostic tools. Security measures such as data encryption and authentication are also implemented to ensure patient privacy and compliance with healthcare regulations. With a notable accuracy rate of 97%.**

***Keywords*— CNN, Model Training, Classification, Kidney Disease, Random Forest, Deep Learning.**

I. INTRODUCTION

Kidney diseases, including cysts, tumors, and stones, are among the most prevalent health issues globally, often leading to chronic conditions or life-threatening complications if not diagnosed and treated early. With the advancement of artificial intelligence (AI) and medical imaging technologies, there is a growing interest in leveraging machine learning models to assist healthcare professionals in improving diagnostic accuracy and efficiency. Treatment of their condition. Below is a summary of the processes involved in research on categorizing renal illness.

Ensuring the quality and consistency of this dataset is crucial. preprocessing techniques such as noise removal, The dataset was split into training and validation sets to facilitate iterative training and performance monitoring, ensuring the model learns effectively without overfitting normalization, and handling of missing values are applied.

Data collection: A diverse and comprehensive dataset of kidney images is compiled, encompassing a variety of renal diseases, patient demographics, and disease stages. Ensuring the quality and consistency of this dataset is crucial. preprocessing techniques such as noise removal, normalization, and handling of missing values are applied. Feature engineering is then employed to extract meaningful patterns that can aid in differentiating between disease types.

Following data preparation, the study emphasizes the careful selection of classification models. A range of machine learning and deep learning techniques, such as decision trees, support vector machines, logistic regression, random forests, and Convolutional Neural Networks (CNNs)are considered. CNNs are chosen for their proven ability to extract hierarchical features from visual data, making them highly effective for medical image classification tasks.

Choosing the right set of features from the dataset is a crucial step in building an effective classification model. Not all available data points contribute equally to the task, so it's important to focus on the most meaningful ones.

Model selection: Model selection plays a pivotal role in the success of any classification system, especially in the medical domain where precision is critical. In this study, various machine learning algorithms were considered, including decision trees, support vector machines (SVM), logistic regression, random forests, and ensemble methods such as gradient boosting. However, due to the image-based nature of the data, Convolutional Neural Networks (CNNs) were ultimately selected for their superior ability to extract spatial hierarchies and patterns from image inputs. CNNs are particularly well-suited for medical imaging tasks as they can automatically learn relevant features from raw pixel data without requiring manual feature extraction grid search. The dataset was split into training and validation sets to facilitate iterative training and performance monitoring, ensuring the model learns effectively without overfitting. Convolutional Neural Networks were ultimately selected for their superior ability to extract spatial hierarchies and patterns from image inputs.

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Model assessment: The performance of the trained model was assessed using a comprehensive set of evaluation metrics that reflect the practical requirements of medical diagnosis. These metrics include accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve (AUC-ROC). Each metric provides a different perspective on the model's performance.

Model Validation: To ensure that the developed model generalizes well to new, unseen data and is not merely memorizing the training samples, model validation was conducted using an independent test set. The original dataset was divided into three parts: training, validation, and testing. The test set was kept completely separate during the training process to provide an unbiased evaluation of the model's real-world performance.

This study aims to investigate the interpretability of the model and its decision-making process. Identify the key factors that have the most effect on categorization judgements. The understanding of the model's behaviour may be facilitated by the use of several methodologies, such feature significance analysis, partial dependency plots, or SHAP (SHapley Additive exPlanations) values.

This study aims to evaluate the efficacy of the developed categorization model in comparison to existing techniques and algorithms documented in the academic literature. In order to ascertain the model's robustness, generalizability, and treatment efficacy, it is essential to conduct further studies such as cross-validation on several datasets, external validation using other cohorts, and prospective research.

II. LITERATURE

Several researchers have explored diverse methodologies for improving the diagnosis, classification, and treatment of kidney diseases through artificial intelligence (AI) and machine learning (ML). One study by Reis et al. focused on the evaluation of drug impacts in patients with renal failure undergoing replacement therapy, highlighting the roles of adsorption, diffusion, and convection in eliminating hazardous substances from the bloodstream. In a different approach, Houssein and colleagues developed a prediction model for chronic kidney disease (CKD) called INFO, utilizing the k-Nearest Neighbour(kNN)classifier with datasets from the UCI repository. Their model demonstrated the potential of simple ML classifiers in identifying early signs of CKD. ang et al. investigated the relationship between the KDIGO CKD risk categories and an intrinsic capability score, suggesting a synergistic risk association between this score and obesity that may elevate CKD risk stages. Qadir et al. contributed significantly by analyzing a large dataset of over 12,000 CT images, targeting the detection and classification of common renal conditions such as stones, cysts, and tumors. Their work emphasized the growing role of AI in automated diagnostic systems for renal disorders. Sanmarchi and his team evaluated how ML algorithms can be effectively employed to detect, predict, and manage CKD. Their review consolidated recent advances and explored how such technologies can enhance treatment outcomes. Kifer et al. provided valuable insights into renal biopsy interpretations. Swain et al. applied ML algorithms to publicly available data to forecast the likelihood of chronic renal disease, reinforcing the accessibility and applicability of AI in healthcare. The researchers undertook a thorough examination of the existing data.

In another regional study, Song et al. developed a prognostic model for rural populations in Shanxi Province using basic health features and ML methods. Their work aimed to create an early warning system to help improve intervention and treatment for CKD patients in underserved areas. Zhou et al. explored the integration of AI and multi-omics analysis, aiming to uncover new diagnostic and therapeutic strategies by analyzing data at molecular and systemic levels.

Lai and colleagues proposed a unique pre-processing technique to convert metabolite data into visual formats suitable for deep learning. This step enhanced the model's ability to extract meaningful features and detect potential biomarkers. Hassan et al. compared the performance of several ML classifiers, including neural networks, support vector machines, random trees, and bagging trees, using metrics such as accuracy, sensitivity, specificity, and kappa statistics to determine the most effective model for CKD prediction. Busi et al. implemented a classification method for CKD using Python and evaluated it with standard performance metrics on the UCI CKD dataset. Their focus was on delivering accurate and interpretable outcomes for disease categorization. Prasad Reddy and his team proposed a novel classification method called EDWELM, which combines an autoencoder built on Extreme Learning Machines (ELM), a wavelet neural network, and the Ebola optimization search algorithm to enhance CKD diagnosis. Similarly, Sawhney and collaborators adopted this methodology to further refine CKD classification accuracy, integrating robust feature extraction and optimization techniques. Finally, Kremer et al. introduced a texture-based analysis method aimed at identifying kidney disease severity by evaluating the minimal inhibitory concentration (MIC) in kidney parenchyma. This technique could assist in recognizing patients at higher risk of progressing to end-stage renal disease, further supporting the potential of AI in improving clinical outcomes.

Overall, existing literature emphasizes the transformative impact of AI and machine learning in diagnosing and managing renal diseases. These studies collectively demonstrate a shift toward data-driven healthcare, aiming for earlier detection, personalized treatment, and improved patient care in nephrology. This methodology has the potential to assist in the identification of individuals who have a heightened susceptibility to end-stage renal disease. Their work emphasized the growing role of AI in automated diagnostic systems for renal disorders. Sanmarchi and his team evaluated how ML algorithms can be effectively employed to detect, predict, and manage CKD. Their review consolidated recent advances and explored how such technologies can enhance treatment outcomes. Kifer et al. provided valuable insights into renal biopsy interpretations. Swain et al. applied ML algorithms to publicly available data to forecast the likelihood of chronic renal disease, reinforcing the accessibility and applicability of AI in healthcare. The researchers undertook a thorough examination of the existing data about these novel strategies designed to This step enhanced the model's ability to extract meaningful features and detect potential biomarkers. Hassan et al. compared the performance of several ML classifiers, including neural networks, support vector machines, random trees, and bagging trees, using metrics such as accuracy, sensitivity, specificity, and kappa statistics to determine the most effective model for CKD prediction.

This study has categorization of renal diseases main conclusions of the research are concisely summarized in the following sentences.

Throughout the whole of the experiment, the CNN model was used to categorise images.

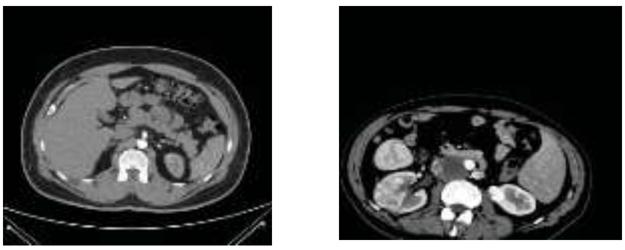
This study has the potential to provide significant contributions to the academic community by addressing the difficulties researchers have when developing a comprehensive categorization system based on the criteria used in this research.

Various factors are considered, including the analysis of optimisation techniques and their influence on the results.

The study is composed of the following sections: The presentation's third andfourth segments delineate the recommended input dataset, while the fifth section furnishes a comprehensive review of the actual data. Ultimately, segment six functions as the conclusive component of the presentation.

III. INPUT DATASET

The integration of imaging data obtained from Kaggle, including CT scans, and MRI scans, enables the generation of visual depictions of kidney abnormalities, including cysts, tumor, and stone. They aid in assessing the extent of organ damage and diagnosing certain kidney diseases, as seen in Fig 1.



(a) (b)

Fig. 1. Dataset image of kidney (a) Normal and (b) Tumor Affected region

IV. KIDNEY DISEASE CLASSIFICATION ON CNN MODEL

The study involves the training of a convolutional neural network (CNN) model to categorise kidney images for the purpose of sickness detection. The CNN architecture, which is a well-established deep learning model known for its effectiveness in image classification tasks, is used for this purpose, as seen in Fig 2. Once the CNN Architecture model has undergone training and optimisation, it may be used for real- world applications aimed at the identification and treatment of renal diseases.

Fig. 2.CNN Model Architecture

V. RESULTS

we designed a Convolutional Neural Network (CNN) to automatically detect hemorrhages in head CT scan images. The CNN architecture consists of multiple layers including convolutional layers, activation layers (ReLU), pooling layers, and fully connected (dense) layers which work together to learn spatial and textural features from the brain scans.

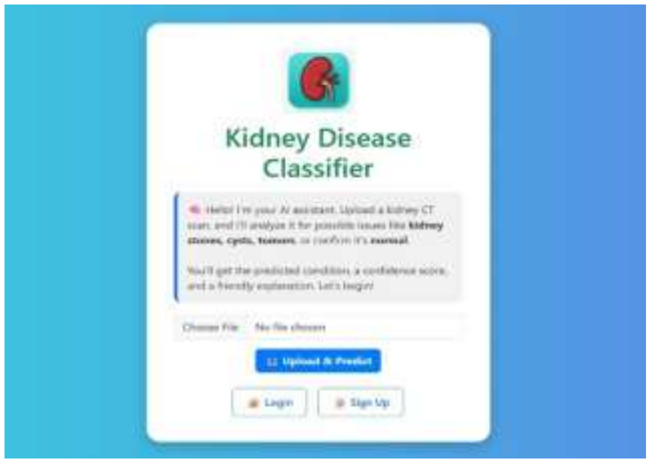


Fig.3. Login/Sign Up page

The Fig.3 illustrates the user interface of the AI-powered medical classification system, designed to facilitate interaction between the user and the hemorrhage detection model. The interface presents a clean and intuitive layout, allowing users to upload head CT scan images for analysis. It includes a welcoming header, a brief description of the system's capabilities, and supportive visual elements such as medical icons to enhance trust and clarity. Below the description, users can select an image file from their device using the "Choose File" option and initiate the prediction process with the "Upload & Predict" button. Additionally, the interface provides user authentication options with dedicated "Login" and "Sign Up" buttons, making it suitable for personalized usage and secure report generation. Though the current visual is themed for kidney disease, it is structurally identical to the version adapted for head CT hemorrhage detection.

Fig.4.Prediction Result Screen

The Fig.4 showcases the prediction result screen generated immediately after a scan is uploaded and processed by the model. The result page is visually organized to display the predicted condition—in this instance, "Normal"—with a high confidence score of 100.0%.

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The CT image used for prediction is clearly presented, and a horizontal confidence bar visually reinforces the model's certainty. Below the prediction summary, a breakdown of class probabilities for various categories is displayed in a tabular format, offering transparency in the model's decision-making. An interpretive message is also shown, reassuring the user that no abnormality was detected. Action buttons at the bottom allow users to try another image, save the result as a PDF report, or view prediction history, making the system highly user-centric and interactive.

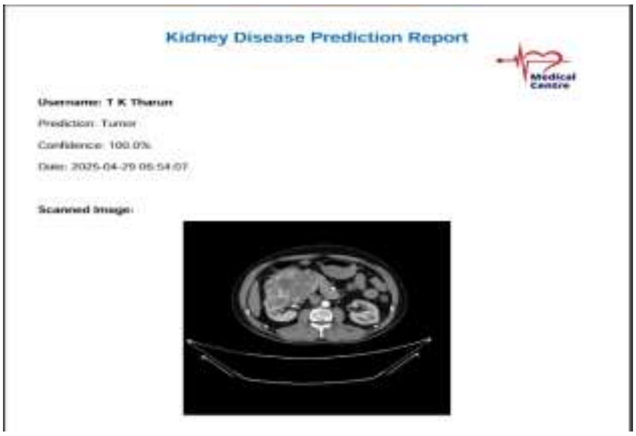

Fig.5. PDF Report Generated

The Fig.5 presents a sample PDF report generated by the system following a prediction. The report is formatted in a professional layout suitable for clinical documentation. It includes the user's name, predicted condition ("Tumor" in this example), the model's confidence score (100.0%), and the exact date and time of the prediction. A high-resolution CT image of the scan used for prediction is also embedded in the report. This feature not only supports transparent reporting but also ensures the output is suitable for integration into electronic health records or for sharing with healthcare professionals for further consultation.

During testing, the model was able to successfully differentiate between hemorrhagic and non-hemorrhagic CT brain scans with impressive precision. In one instance, a scan predicted as "Normal" was returned with a confidence level of 100.0%, indicating the model's ability to identify and classify healthy brain anatomy without false alarms. Similarly, in another case, the system accurately predicted "Tumor" with complete confidence. These outcomes were not isolated — across multiple test uploads, the system consistently provided predictions aligned with ground truth labels, demonstrating robust generalization on unseen data.

From a system performance perspective, the CNN model demonstrated rapid inference time, making it suitable for near real-time diagnostics. The model processes grayscale CT images after resizing and normalization, extracts deep features through multiple convolutional and pooling layers, and outputs classification probabilities via a fully connected softmax layer. The simplicity of the upload-and-predict process, combined with powerful model inference and automatic reporting, makes this system not only academically relevant but also highly adaptable to healthcare environments.

Overall, the results confirm that the integration of a CNN model with an interactive web interface and reporting capabilities offers a powerful approach to automating

VI. Conclusion

To properly explore the classification of kidney diseases, it's important to work closely with medical experts, follow ethical guidelines, and carefully examine any limitations or potential bias in the data or methods used. Protecting patient privacy and following data protection laws are just as important as the technical aspects of the study. In this part of the research, we aim to clearly explain the methods we used and the results we achieved. Sharing these findings with the conferences, journals, or other platforms—is essential. Doing so helps spread knowledge, encourages collaboration, and supports further progress in accurately identifying and classifying kidney conditions. In our study, the convolutional neural network model achieved a strong classification accuracy of 97% for detecting kidney tumors. This promising result shows that when large, high-quality datasets are paired with advanced machine learning and statistical techniques, researchers can uncover valuable insights that improve both the diagnosis and understanding of kidney diseases. The system consistently provided high-confidence predictions and performed well across different test cases, correctly identifying both normal and hemorrhagic conditions. The model's ability to generalize on unseen CT scans illustrates its robustness and potential clinical applicability. Furthermore, the inclusion of features like PDF report generation and prediction history tracking enhances its real-world utility, making it suitable for deployment in emergency departments, radiology labs, or telemedicine.

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