Image-based Chronic Kidney Disease Diagnosis Using 2D Convolutional Neural Networks in the Context of a Comprehensive Artificial Intelligence-Driven Healthcare System

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Abstract: - Reports published by the World Health Organization (WHO) indicate that noncommunicable diseases (NCDs) including chronic kidney disease (CKD) are among the top ten causes of mortality worldwide. Accurate and early diagnosis of chronic kidney disease could save lives, ameliorate deleterious effects and dramatically improve quality of life. This paper presents a system that harnesses convolutional neural networks (CNNs) that could be incorporated into a comprehensive artificial intelligence (AI)-driven healthcare system for the automated diagnosis of chronic kidney disease. Utilizing publicly available image datasets featuring images representing normal kidney states, cysts, tumors and kidney stones split into training and validation samples, the system achieves an accuracy approximating 97% on the training and validation datasets.

Key-Words: - Chronic Kidney Disease (CKD), Artificial Intelligence (AI), Deep Learning (DL), Convolutional Neural Network (CNN), Two-dimensional (2D) Convolutional Neural Network (2D CNN), Healthcare System, CT Image

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1 Introduction

In addition to the high mortality rate measured in millions per annum globally, chronic kidney disease exerts an enormous toll in terms of lost economic opportunities and physical and psychological suffering [1] – [2]. Accurate and early diagnosis could be leveraged to create more efficacious therapies and management strategies and consequently save lives and enhance quality of life indicators and achieve improved health outcomes across board. Ekpar [3] introduced a comprehensive artificial intelligence (AI)-driven healthcare system with a modular design that could accommodate AI models for the diagnosis of chronic kidney disease.

Previous work has been reported in the literature featuring the utilization of AI models for the diagnosis of a wide range of health conditions including chronic kidney disease [4] – [29] with varying degrees of success.

This paper presents a system built on convolutional neural networks (CNNs) trained to classify diagnostic images. The system employs publicly available diagnostic CT-radiography images indicating the normal kidney state as well as the presence of kidney cysts, stones and tumors [4] with the possibility of incorporating the resulting system into a comprehensive artificial intelligence (AI)-driven healthcare system.

Further integration of genetic and environmental factors could enhance the utility of the system with more accurate representations of the circumstances of the participants. Additionally, locally aggregated datasets could augment and/or replace the publicly available datasets currently harnessed to reduce bias and promote the global relevance of the decisions that could be supported by the inferences drawn from the system.

The modular design makes the system amenable to the incorporation of new modules for the diagnosis, prediction and management of additional health conditions and the enhancement of existing modules on the basis of fresh data.

2 Materials and Methods

This section outlines how participants could be recruited for experiments on the basis of ethical clearances obtained as well as the methods pursued for the actualization of the system.

2.1 Participant Recruitment

Participants willingly took part in the studies focused on developing a comprehensive AI-driven healthcare system, each providing informed consent for their participation.

2.2 Ethical Clearance

The Health Research Ethics Committee at the Institute of Biomedical Research, University of Uyo, approved the studies ethically. All research complied with relevant ethical and regulatory standards, and publicly available data was utilized in line with the licensing terms established by its creators.

2.3 Methodology

Publicly accessible healthcare datasets can be improved by integrating data collected from local experiments and data collection initiatives, which can be used to train AI models for actionable predictions based on new data. Sources of public healthcare datasets include the Centers for Disease Control, the University of California Irvine Machine Learning Repository, the American Epilepsy Society, and Kaggle.

Incorporating local data enhances robustness, minimizes bias, and fosters inclusivity and global relevance.

One innovative approach in this project is combining diagnostic measurements, including electrocardiographic results, from local experiments with EEG data from both traditional and novel advanced three-dimensional multilayer EEG systems.

For local data collection efforts, the research has received ethical approval from the relevant ethics committees overseeing the regions where the experiments take place. Furthermore, partnerships have been established with licensed medical doctors experienced in these areas, who have direct access to patients and other clinicians in the community. These doctors will collaborate with the project to provide anonymized clinical measurements for validating the AI models.

The trained AI models could be integrated into a comprehensive healthcare system that offers clinical decision support to medical practitioners and facilitates the generation of brain-computer interfaces (BCIs). This support will be based on actionable insights derived from new clinical data provided by medical professionals, aiding in the early detection, diagnosis, treatment, prediction, and prevention of various conditions, including diabetes mellitus, heart disease, stroke, autism, and epilepsy.

This project is dedicated to advancing open science, reproducibility, and collaboration. As such, the generated data will be made available in public repositories like GitHub and Kaggle.

3 Systemic Solution

3.1 System Design and Implementation

The comprehensive healthcare system outlined in this paper features a modular design, with each condition (such as chronic kidney disease, heart disease, diabetes mellitus, stroke, epilepsy, and autism) assigned to its own module. This structure allows for future applicability in diagnosing and predicting additional conditions and facilitates efficient updates to existing modules with new data. Brain-computer interface (BCI) modules, such as those using the motor imagery paradigm, can process EEG data to generate actionable commands and other appropriate responses.

The system includes guidelines for adapting traditional EEG systems to innovative three-dimensional multilayer EEG systems. These novel systems, developed by Ekpar [30] – [31], are based on a conceptual framework that employs approximations of carefully chosen representative features of bio-signal sources for characterizing or manipulating the underlying biological systems.

For each module, robust AI models are developed and trained using appropriately formatted data collected as described. These AI models can integrate genetic, environmental, lifestyle, and other relevant factors to provide more accurate representations of participants' circumstances.

Fig. 1 depicts the design of the system with a simplified graphical representation of the modules and other key components of the system.

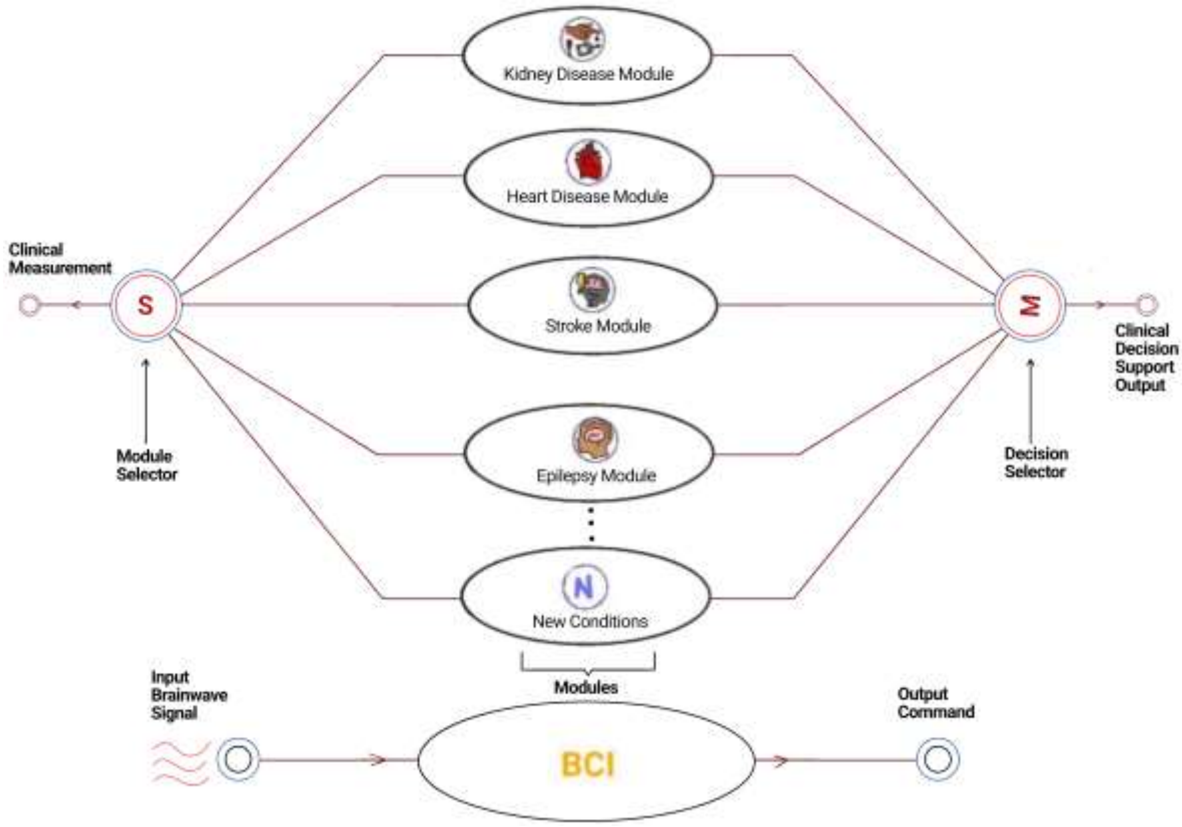

Fig. 1: System Schematic Design Diagram for the Comprehensive AI-Driven Healthcare Solution and Brain Computer Interface System. The New Conditions component represents additional health conditions that can be incorporated into the solution via new modules.

The AI models are developed using the four distinct approaches listed below. Note that in addition to the four distinct approaches highlighted herein, additional approaches (possibly incorporating modern topological and algebraic methods) could be adopted and the results (in terms of performance metrics) compared and contrasted for possible integration of the models into the system.

1. **Direct Use of Large Language Models (LLMs)**: Leveraging large language models (LLMs) like GPT-4 as inference engines, utilizing the collected data formatted as multidimensional input vectors. This process may include fine-tuning the LLM.

2. **Prompt Engineering with LLMs**: Applying prompt engineering techniques to LLMs like Bard and GPT-4 (and their future iterations) to outline a series of steps for constructing the AI-based system. The proposed steps are executed using the creator's deep expertise in AI, neural networks, and deep learning, along with programming in Python and using tools like TensorFlow, Keras, and other machine learning and visualization libraries such as Scikit-learn and Matplotlib.

3. **Automated Model Generation**: Creating specific AI models by harnessing the features of LLMs like Bard and GPT-4

through an automated model generation pipeline.

4. **Direct Synthesis of AI Architecture**: Synthesizing a suitable AI architecture based on the creator's substantial experience in AI, neural networks, and deep learning, employing Python, TensorFlow, Keras, and additional machine learning and visualization tools.

All processes and tools used in developing the solution are thoroughly documented to ensure smooth transfer and reuse of the system. The performance of the generated AI models is evaluated and compared using metrics such as specificity and sensitivity, assessing their suitability for the challenges presented.

3.2 Convolutional Neural Network Architecture and Data Processing

Custom-synthesized two-dimensional (2D) convolutional neural networks (CNNs) were harnessed in the AI models of the system and leveraged for multiclass (four-class: normal, cyst, tumor, stone) image classification for the purpose of diagnosis of chronic kidney disease from CT-radiography. Figure 2 illustrates a generalized depiction of the CNN architecture. The CNNs were realized via toolsets provided by the TensorFlow framework coupled with the Keras API in the Python programming language [32] - [33].

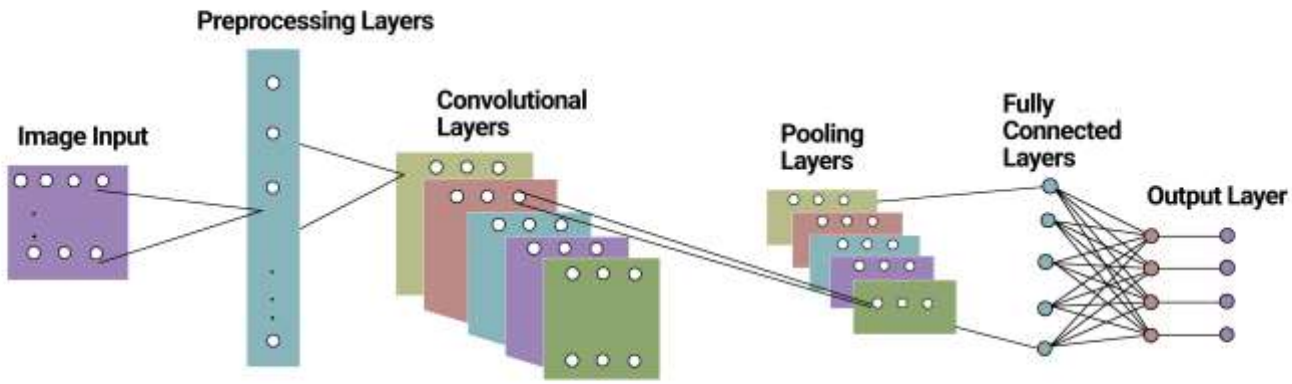

Fig. 2: Generalized Illustration of the Convolutional Neural Network (CNN) Architecture.

The 2D CNN comprised three separate 2D convolutional blocks each coupled with a 2D max pooling layer. ReLU activation was utilized. The first 2D convolutional layer featured 16 filters, the second featured 32 filters while the third layer featured 64 filters. The kernel size used was 3. A preprocessing data augmentation layer implementing rotation of the images by 18 degrees was added to prevent overfitting. Z-normalization was applied via the batch normalization function. Before flattening and connection to the fully connected layers, a dropout layer with a dropout rate of 0.2 was added to the AI model.

Public CT-radiography image datasets [4] were utilized in training and validation of the AI model. The dataset comprised a total of 12,446 clinically validated images spread across four distinct classes representing normal kidney function (5,077 images), presence of kidney cyst (3,709 images), presence of kidney stone (1,377 images) and presence of kidney tumor (2,283 images). First, the images were shuffled to ensure balance and then split into training and validation datasets with the training dataset being allocated 80% of the data and the validation dataset being allocated 20% of the data. Furthermore, a new data partition containing 20% of the data was generated after random shuffling for evaluation of the CNN after training and validation. The images were resized to a width of 180 pixels and a height of 180 pixels before processing. Processing proceeded with a batch size of 32.

Figure 3 shows a randomly selected sample of images from the dataset representing all four classes: Normal, Cyst, Tumor and Stone.

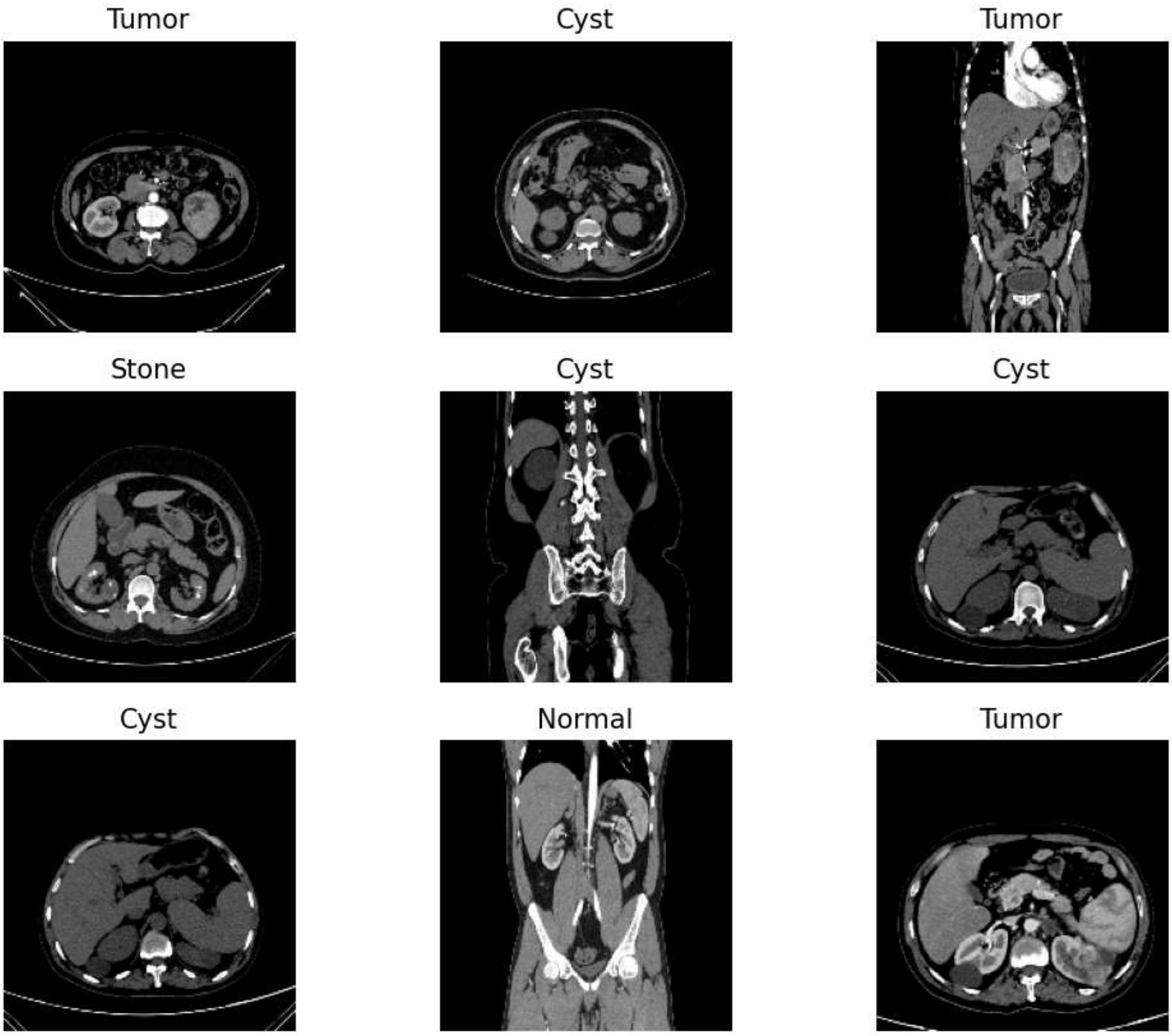

Fig. 3: Sample Images from the Dataset Representing All Four Classes: Normal, Cyst, Stone and Tumor.

3.3 Data Availability

The data utilized in this study are available from **Kaggle** at https://www.kaggle.com/datasets/nazmul0087/ct-kidney-dataset-normal-cyst-tumor-and-stone.

4 Results

The CNN was trained on the training dataset (9957 images or 80% of the original 12,446 images) and validated on the validation dataset (2,489 images or 20% of the original 12,446 images) over 10 epochs. Sparse categorical cross entropy loss function was utilized. The AI model was optimized via the Adam Optimizer [34] – [35] with a learning rate of 0.001. Figure 4 illustrates the performance of the AI model on the training and validation datasets.

As can be seen from Fig. 4, the performance of the CNN improved over the training and validation cycles until an accuracy of approximately 97% was achieved for the training and validation datasets. Evaluation of the resulting AI model after training and validation on a randomly selected test dataset comprising 20% of the original data yielded comparable results.

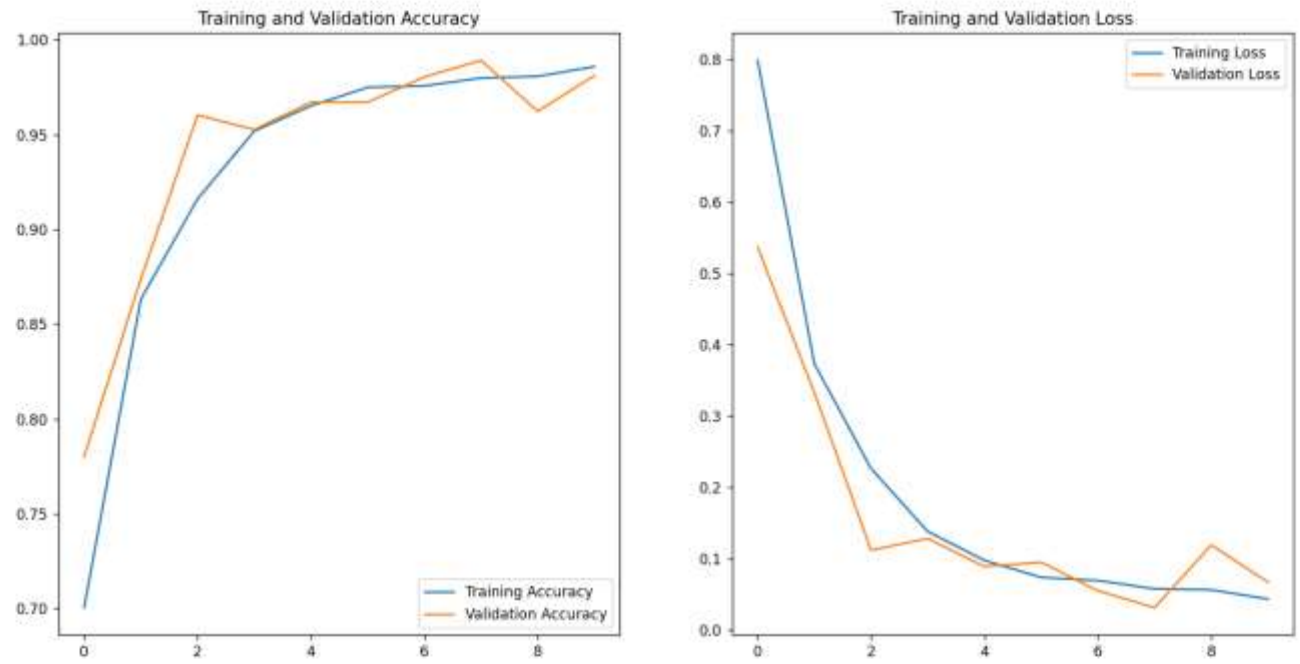

Fig. 4: Performance of the Convolutional Neural Network (CNN) on Training and Validation Datasets.

Implementing the comprehensive AI system outlined here will provide valuable insights for clinical decision-making, ultimately saving lives and enhancing quality of life. It aims to alleviate the economic, social, psychological, and physical burdens associated with conditions that can be predicted, potentially prevented, detected early, diagnosed, and managed more effectively.

Participating medical doctors and their colleagues can generate Electronic Health Records (EHR) that include clinical diagnostic measurements and EEG data. EEG data may also be collected during experiments with Brain-Computer Interfaces (BCIs). This data is gathered in compliance with ethical approvals and is anonymized prior to being published in publicly accessible repositories alongside academic research articles.

5 Conclusion

Convolutional neural networks were harnessed for the classification of medical images representing kidney states indicating normal function, the presence of cysts, the presence of tumors as well as the presence of kidney stones. The resulting AI model could be integrated into a chronic kidney disease diagnosis module within the context of a comprehensive AI-driven healthcare system. The system exhibited excellent performance, achieving an accuracy approximating 97% for the training and validation datasets. Adopting the comprehensive AI-powered healthcare system in resource-limited settings such as low- and middle-income countries (LMIC) with low doctor-to-patient ratios and limited healthcare funding could permit a single medical doctor or healthcare worker to serve up to ten or more times the usual number of patients, effectively increasing the doctor-to-patient ratio and dramatically improving health outcomes and saving lives without significant additional investments. Generally, the high accuracy of the system encourages adoption and utilization of the system for improved health outcomes in both developed and developing countries and regions. In the future, the system could incorporate genetic and lifestyle factors for a more accurate reflection of the patient's circumstances and to facilitate recommendations for lifestyle modifications that could help prevent disease.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

Frank Edughom Ekpar took charge of all aspects of this work including conceptualization, design, implementation, experiment design, execution and administration, data gathering (including from public sources) and data analysis and processing as well as manuscript preparation.

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