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Leveraging Generative Artificial Intelligence Recommendations for Image-based Chronic Kidney Disease Diagnosis

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Abstract: This paper presents work leveraging the recommendations of generative artificial intelligence (AI) tools such as large language models (LLMs) to create suitable AI models for automated image-based diagnosis of chronic kidney disease (CKD) within the context of a comprehensive AI-driven healthcare system. The LLMs suggested the synthesis of image-based AI solutions such as convolutional neural networks (CNNs) and these suggestions were followed meticulously to build AI models that were then trained on computed tomography (CT) image data representing the normal kidney state as well as the presence of cysts, stones and tumors and then tasked with the diagnosis of CKD based on the classification of the input CT images. Featuring reasonable performance metrics, the resulting AI models demonstrated the effectiveness of generative AI as a tool in the synthesis, training, testing and deployment of practical AI models within healthcare settings.

Keywords: Generative Artificial Intelligence (AI), Large Language Model (LLM), Convolutional Neural Network (CNN), TensorFlow, Healthcare System, Disease Diagnosis and Prediction, Chronic Kidney Disease (CKD)**.**

I. INTRODUCTION

Chronic kidney disease (CKD) affects millions of people worldwide and exerts an enormous toll in terms of physical and phycological suffering, deterioration in economic and living conditions with attendant degradation of quality of life, significant disability and even mortality. CKDs are reported to be one of the top ten leading causes of mortality around the globe [1] – [2]. The deleterious consequences of CKDs are exacerbated by inadequate healthcare service access and availability in low- and middle-income countries (LMICs).

Early diagnosis of CKDs can lead to more effective therapies and interventions with vastly improved health outcomes. Images captured using suitable CT equipment can be analyzed manually or automatically using AI to diagnose CKD. Studies have been published utilizing CT images and AI models for the diagnosis of CKD [3].

In an earlier study, the author synthesized suitable convolutional neural networks (CNNs) for the construction of modules that could be incorporated into a comprehensive AI-driven healthcare system for the automated diagnosis of CKD based on CT images with excellent results [4].

This study adopts an approach that leverages prompt engineering of generative AI tools such as LLMs to suggest the complete design of an effective AI model for the image-based diagnosis of CKD. The system proceeds by first creating and entering a prompt for the design of the entire system and then drills down to the detailed AI model architecture based on the suggestions elicited by the general prompt using more specific prompts inspired by the peculiar characteristics of the system with respect to the data available and the types of outputs expected. All suggestions generated by the generative AI tool are then summarized and used to build, train, test and deploy the resulting AI model. The resulting AI model could then be incorporated into a module for automated image-based diagnosis of CKD within the framework of the comprehensive AI-driven healthcare system created by the author [5].

Researchers have generally focused on applying AI to diagnose and predict diseases such as heart disease, diabetes mellitus and other health conditions [6] – [24], primarily in developed countries. This has led to results that may be biased and have limited global applicability.

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The use of large language models (LLMs), which can make inferences from AI models trained on input data and learn structured representations of that data [25] – [26], in the prediction and diagnosis of health conditions, as well as in the development of brain-computer interfaces (BCIs), is still not widespread.

Additionally, brain computer interfaces (BCIs), including those based on motor imagery paradigms, have been developed using various AI platforms and architectures, such as convolutional neural networks (CNNs), alongside traditional techniques like principal component analysis [27] – [45]. For electroencephalography (EEG)-based BCIs, novel three-dimensional multilayer EEG systems, also known as Ekpar EEG systems [46] - [48] offer enhanced performance and promise hitherto impossible features.

The AI-driven healthcare system designed by the author [5] features a modular architecture, with dedicated modules for specific health conditions. This system allows for the addition of new modules and the enhancement of existing ones through the integration of fresh data and improved algorithms, including those derived from generative AI tools.

II. MATERIALS AND METHODS

Participant Recruitment

Participants volunteered to take part in the studies leading to the development of the comprehensive AI-driven healthcare system and each participant gave informed consent for participation in the studies.

Ethical Approval

The Health Research Ethics Committee of the Rivers State University Teaching Hospital at Rivers State University provided ethical clearance/approval for the studies. The studies complied with all relevant ethical and regulatory requirements. Publicly available data were utilized in accordance with the licensing provisions stipulated by their creators.

METHODOLOGY

Publicly available healthcare datasets can be enriched by integrating data collected from local experiments and data collection efforts. This combined data can then be used to train AI models capable of making actionable predictions from new data. Public sources of healthcare datasets include institutions such as the Centers for Disease Control, the University of California Irvine Machine Learning Repository, the American Epilepsy Society, and Kaggle.

Incorporating local data enhances the robustness of the models, reduces potential biases, and promotes inclusivity and global relevance. A key approach in this project involves merging diagnostic measurements - such as electrocardiographic results - from local experiments with EEG data, which includes both conventional and novel three-dimensional multilayer EEG systems.

For data acquisition, the research has obtained ethical approval from the relevant research ethics committees in the geographic regions where the experiments are conducted. Furthermore, the project has secured collaboration with licensed medical doctors, who have direct access to patients and clinical teams in the community. These medical professionals are contributing anonymized clinical measurements for the validation of AI models.

Once trained, the AI models will be integrated into a comprehensive healthcare system designed to provide clinical decision support to medical practitioners and generate brain-computer interfaces (BCIs). The system will offer actionable predictions and insights based on new clinical data provided by practitioners, supporting early detection, diagnosis, treatment, prediction, and prevention of a variety of conditions, including diabetes, cardiovascular diseases, stroke, autism, and epilepsy.

This project is committed to advancing open science, reproducibility, and collaboration. As such, all generated data will be made publicly available through repositories like GitHub.

SYSTEM DESIGN AND IMPLEMENTATION

The healthcare system outlined in this paper adopts a modular design, with each health condition (such as diabetes, heart disease, stroke, epilepsy, autism, etc.) assigned to its own distinct module. This structure not only makes the system adaptable for diagnosing and predicting future conditions but also supports the efficient updating of existing modules

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through the integration of new data. Additionally, modules for Brain-Computer Interfaces (BCIs), like those based on the motor imagery paradigm, can process EEG data to generate actionable commands and appropriate responses.

The system also includes a set of guidelines for adapting traditional EEG systems to advanced three-dimensional multilayer EEG systems. These innovative systems, developed by Ekpar [46] - [48], are based on a conceptual framework that uses approximations of carefully selected bio-signal features to characterize or manipulate the underlying biological systems.

For each module, robust AI models are developed and trained using appropriately formatted data, as outlined in this paper. These AI models can incorporate diverse factors, including genetic, environmental, and lifestyle information, to provide more accurate representations of the participants' circumstances.

Fig. 1 depicts a conceptual representation of the design of the system.

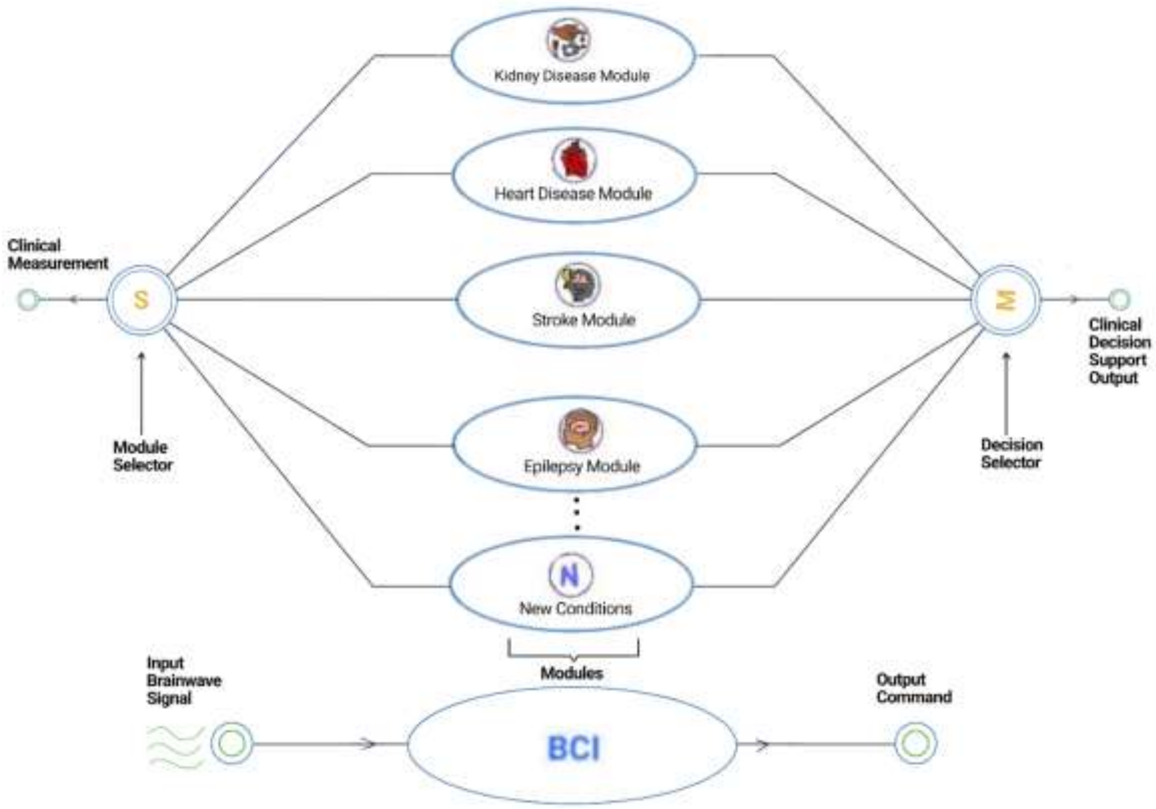

Fig. 1: System Schematic Design Diagram for the Comprehensive AI-Driven Healthcare Solution and Brain Computer Interface System. The New Conditions component represents additional health conditions that can be incorporated into the solution via new modules.

The AI models are developed using four distinct approaches, as outlined below:

1. **Direct Use of LLMs:** Large Language Models (LLMs) such as GPT-4 are employed as inference engines, utilizing the collected data formatted into multidimensional input vectors. This process may include fine-tuning the LLM.

2. **Prompt Engineering with LLMs:** LLMs like Bard and GPT-4 (along with their future enhanced versions) are used through prompt engineering to outline the steps required for building the AI-based system. These steps are then executed by the developer, who applies their deep expertise in AI, neural networks, deep learning, and relevant tools such as Python, TensorFlow, Keras, and other machine learning and visualization frameworks like Scikit-learn and Matplotlib.

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3. **Automated Model Generation:** Specific AI models are created through an automated pipeline that leverages the capabilities of LLMs like Bard and GPT-4 (and their future iterations).

4. **Manual AI Architecture Synthesis:** The AI architecture is directly designed based on the developer's profound knowledge of AI, neural networks, deep learning, and the use of programming languages and frameworks such as Python, TensorFlow, Keras, Scikit-learn, and Matplotlib.

All processes and tools used in the system's development are thoroughly documented to ensure smooth transfer and reuse of the solution.

The resulting AI models are evaluated and compared based on their performance metrics - such as specificity, sensitivity, etc. - to assess their suitability for addressing the challenges at hand.

AUTOMATED IMAGE-BASED CHRONIC KIDNEY DISEASE DIAGNOSIS MODULE

An automated image-based chronic kidney disease diagnosis module was developed that could incorporate AI models generated using the second approach outlined earlier, namely, prompt engineering of generative AI tools such as LLMs.

More specifically, ChatGPT 4o mini was utilized in the development of the system.

In summary, the study utilized a strategy that involves prompt engineering with generative AI tools like large language models (LLMs) to design an effective AI model for image-based diagnosis of chronic kidney disease (CKD). The process begins by generating an initial prompt to outline the design of the entire system. Then, more specific prompts are used to refine the AI model architecture, tailored to the system’s unique data characteristics and expected outputs. The suggestions from the generative AI tool are compiled and applied to build, train, test, and deploy the AI model. This final model can then be integrated into a module for automated CKD diagnosis within the broader AI-driven healthcare system developed by the author [5].

DATASET

Before proceeding with the initial and subsequent steps, note that the data comprised four distinct classes of publicly accessible diagnostic CT-radiography image datasets [3] with 5,077 images for the normal kidney function class, 2,283 images for the kidney tumor class, 1,377 images for the kidney stone class and 3,709 images for the kidney cyst class for a total of 12,446 images. All the images in the dataset were clinically validated. Fig. 2 displays a randomly selected set of sample input images from all four classes.

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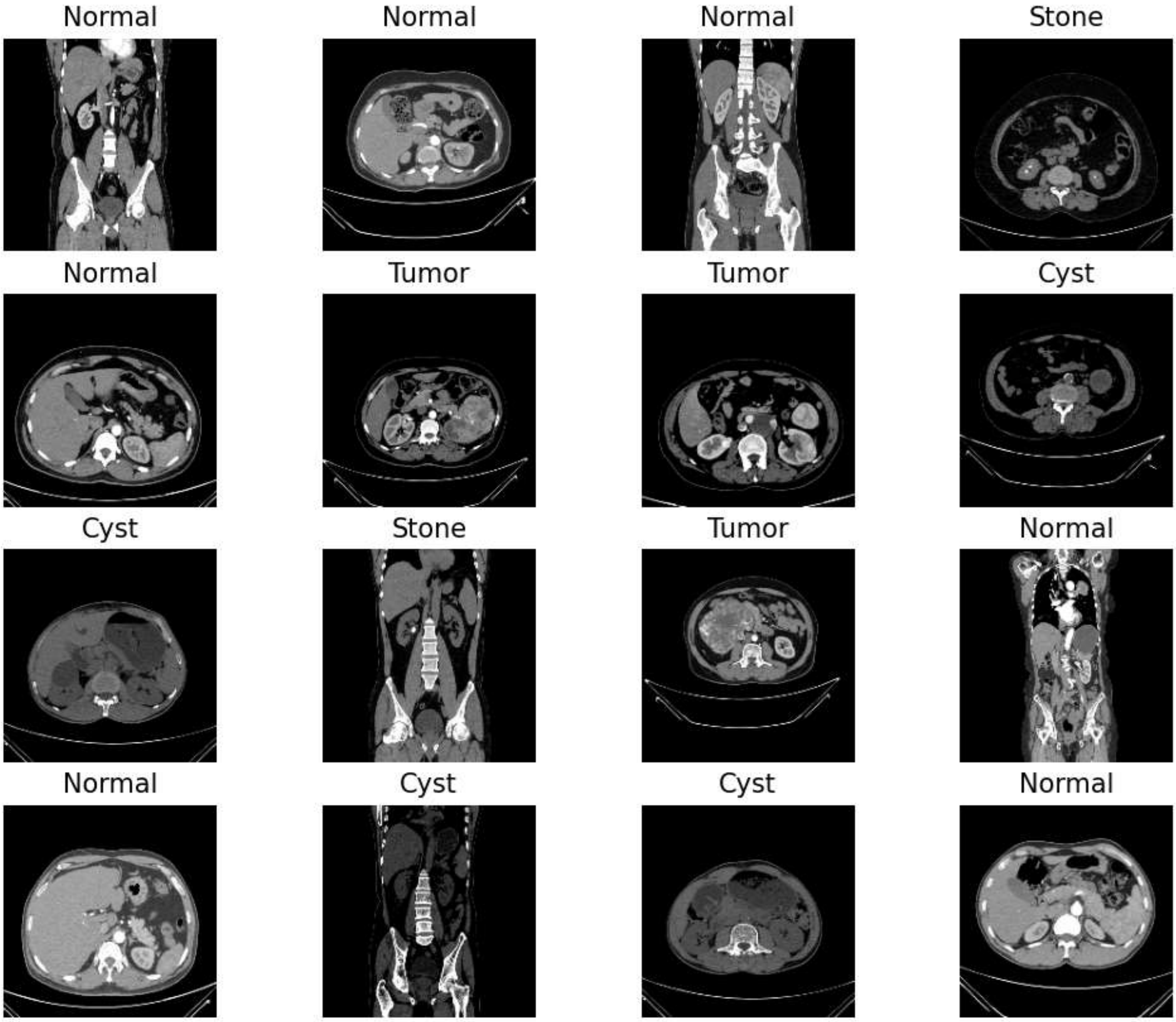

Fig. 2: Randomly Selected Sample CT-tomography Images Containing Images For Each Class: Normal, Tumor, Cyst, Stone.

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.

Now revert to the design of the system on the basis of responses generated by ChatGPT in response to suitably crafted prompts.

INITIAL PROMPT

Design a system for automated image-based diagnosis of chronic kidney disease**.**

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ChatGPT RESPONSE

Designing a system for automated image-based diagnosis of chronic kidney disease (CKD) involves integrating medical imaging, machine learning, and clinical workflows to provide accurate, real-time assistance to healthcare professionals. Below is a comprehensive system design that outlines key components, technologies, and steps required to develop such a system.

1. System Overview

The system would be capable of analyzing medical images (e.g., ultrasound, CT scans, or MRI) to detect early signs of chronic kidney disease, such as changes in kidney size, texture, or abnormalities in the renal vasculature. The system would generate automated reports, highlighting key diagnostic features and suggesting potential CKD stages.

2. Core Components

1. Medical Image Acquisition
   - Input Types: Ultrasound, CT scans, MRI, and potentially other imaging modalities like X-rays or nuclear imaging.
   - DICOM Compliance: Ensure compatibility with the Digital Imaging and Communications in Medicine (DICOM) standard for medical imaging.
   - Preprocessing: The system will preprocess images to normalize brightness, reduce noise, and enhance key features of interest (e.g., kidney boundaries, lesions, or abnormal structures).
2. Image Analysis
   - Feature Extraction: Identify and extract relevant features related to kidney health, including:
     - Kidney size and volume (indicating potential atrophy or swelling).
     - Cortical thinning (may indicate glomerular damage).
     - Parenchymal texture (irregularities could suggest fibrosis or scarring).
     - Renal artery and vein abnormalities (suggestive of vascular issues).
   - Segmentation: Use machine learning-based segmentation algorithms (like U-Net, Mask R-CNN) to precisely identify kidney regions in medical images.
   - Classification and Detection: Apply deep learning algorithms (such as CNNs—Convolutional Neural Networks) to detect and classify abnormalities associated with CKD.

3. AI and Machine Learning Models

- Model Training: Train the AI models on large, labeled datasets of kidney images that include various stages of CKD (mild, moderate, severe). These datasets can be sourced from hospitals, academic institutions, or public databases like the Kidney Imaging Data Repository.
- Model Architecture: Use a combination of deep convolutional neural networks (CNNs), recurrent neural networks (RNNs), and/or transformer models for:
  - Detection: Identifying abnormalities in the kidneys.
  - Segmentation: Precise delineation of kidney tissue and vasculature.
  - Classification: Categorizing the severity or stage of CKD based on the extracted features.
- Validation and Testing: Validate models against expert clinicians to ensure clinical relevance and accuracy (precision, recall, and F1 score).

4. Automated Report Generation

- Interpretation Engine: Generate a diagnostic report with the following components:
  - Annotations on the image, highlighting areas of concern (e.g., cysts, kidney atrophy).
  - Quantitative metrics such as kidney volume, cortical thickness, and size asymmetry.
  - Suggested CKD stage based on predefined thresholds for the degree of kidney dysfunction or morphological changes (e.g., based on the KDIGO guidelines).
- Confidence Score: Include a confidence score for each diagnosis to indicate the reliability of the result.
- Integration with EMR: Ensure seamless integration with Electronic Medical Records (EMR) systems, allowing for easy sharing of results with clinicians and storing them for future reference.

5. Clinical Decision Support System (CDSS)

- Early Warning Alerts: Provide real-time alerts for high-risk patients based on detected abnormalities, which can help clinicians prioritize care for patients with potentially severe CKD.
- Risk Stratification: Use machine learning to stratify patients into different risk categories (low, medium, high risk for CKD progression).

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- Suggested Next Steps: Based on the severity of CKD, the system can suggest appropriate diagnostic tests, referrals to specialists, or treatment options.

6. **User Interface (UI)**
   - Clinical Dashboard: A simple, intuitive dashboard for healthcare professionals to interact with the system.
   - View images with highlighted areas of concern.
   - Access the automated report with relevant metrics.
   - Provide annotations or feedback on the system's output.
   - Track patient progression over time (longitudinal monitoring).
   - Feedback Loop: Allow clinicians to provide feedback on the system's suggestions, helping to retrain and refine the model for better accuracy.

7. **Data Privacy and Compliance**
   - HIPAA Compliance: Ensure the system adheres to relevant health data privacy regulations like HIPAA in the U.S. or GDPR in Europe.
   - Data Encryption: Secure the transmission and storage of medical images and reports.
   - Audit Trail: Maintain an audit trail of system actions, user interactions, and changes to ensure accountability.

FOLLOW-UP PROMPT

Design a convolutional neural network for classification of images into four classes where each image is 180 pixels by 180 pixels.

ChatGPT RESPONSE

FULL ChatGPT RESPONSE TEXT

Designing a Convolutional Neural Network (CNN) for classifying images into four classes, each with dimensions of 180x180 pixels, involves selecting an architecture with layers that can extract relevant features and learn meaningful representations from the images. Below is a sample CNN architecture using Keras (with TensorFlow backend) for this task:
Assumptions:

- The images are color (RGB) images, so the input shape will be (180, 180, 3).
- The task is multi-class classification (4 classes), so the output will have 4 neurons with softmax activation for probability distribution.

CNN Architecture

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout, BatchNormalization
from tensorflow.keras.optimizers import Adam

# Initialize the CNN model
model = Sequential()

# 1st Convolutional Block: 32 filters, 3x3 kernel, ReLU activation
model.add(Conv2D(32, (3, 3), input_shape=(180, 180, 3), activation='relu', padding='same'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(BatchNormalization())

# 2nd Convolutional Block: 64 filters, 3x3 kernel, ReLU activation
model.add(Conv2D(64, (3, 3), activation='relu', padding='same'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(BatchNormalization())

# 3rd Convolutional Block: 128 filters, 3x3 kernel, ReLU activation
model.add(Conv2D(128, (3, 3), activation='relu', padding='same'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(BatchNormalization())
```

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```
# Flatten the output from the convolutional layers
model.add(Flatten())

# Fully connected layer with 128 neurons and ReLU activation
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.5))  # Dropout for regularization

# Output layer: 4 neurons for 4 classes with softmax activation
model.add(Dense(4, activation='softmax'))

# Compile the model with Adam optimizer and categorical crossentropy loss
model.compile(optimizer=Adam(), loss='categorical_crossentropy', metrics=['accuracy'])

# Summary of the model architecture
model.summary()
```

Key Components of the Architecture:

1. **Conv2D layers:**
   - First Block: 32 filters with a 3x3 kernel. This layer will help in detecting simple patterns (edges, textures, etc.).
   - Second Block: 64 filters with a 3x3 kernel, extracting more complex patterns.
   - Third Block: 128 filters with a 3x3 kernel, capturing even more abstract and high-level features.
   - All convolutional layers use ReLU activation functions.
2. **MaxPooling2D layers:**
   - After each convolutional layer, max pooling (2x2) is applied to reduce spatial dimensions and make the network invariant to small translations of the input.
3. **BatchNormalization:**
   - Batch normalization is used after each convolutional block to help the model converge faster and to reduce overfitting.
4. **Flatten layer:**
   - After the convolutional and pooling layers, the 3D feature maps are flattened into a 1D vector to be fed into the fully connected layers.
5. **Fully connected (Dense) layer:**
   - The first dense layer has 128 neurons with ReLU activation, allowing the network to learn complex representations.
   - A Dropout layer with a rate of 0.5 is added to prevent overfitting.
6. **Output layer:**
   - The output layer consists of 4 neurons (for the 4 classes) with a softmax activation function to produce probabilities for each class.

Hyperparameters:

- Kernel size: (3, 3) is standard for CNNs.
- Filters: The number of filters increases as you go deeper into the network (32, 64, 128) to capture more complex features.
- Activation functions: ReLU for the convolutional and dense layers, and softmax for the output layer (since it's a multi-class classification problem).
- Optimizer: Adam is a commonly used optimizer for CNNs, as it adjusts learning rates automatically and tends to work well with deep networks.
- Loss function: Categorical crossentropy is used for multi-class classification.

Data Augmentation (Optional but recommended):
To prevent overfitting and improve generalization, you can use data augmentation techniques such as rotation, flipping, and zooming:

```
from tensorflow.keras.preprocessing.image import ImageDataGenerator

# Data augmentation setup
train_datagen = ImageDataGenerator(
    rescale=1.0/255.0,        # Normalize pixel values to [0, 1]
    rotation_range=30,        # Random rotations
    width_shift_range=0.2,    # Random horizontal shifts
```

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```
    height_shift_range=0.2,   # Random vertical shifts
    shear_range=0.2,          # Shear transformations
    zoom_range=0.2,           # Random zoom
    horizontal_flip=True,     # Random horizontal flip
    fill_mode='nearest'       # Fill pixels after transformation
)

validation_datagen = ImageDataGenerator(rescale=1.0/255.0)  # Only rescaling for validation

# Train and validation generators (assuming directory structure: train/ and validation/)
train_generator = train_datagen.flow_from_directory(
    'path_to_train_data',
    target_size=(180, 180),
    batch_size=32,
    class_mode='categorical'
)

validation_generator = validation_datagen.flow_from_directory(
    'path_to_validation_data',
    target_size=(180, 180),
    batch_size=32,
    class_mode='categorical'
)
```

Training:

```
# Train the model
history = model.fit(
    train_generator,
    steps_per_epoch=100,  # Example value, adjust based on your dataset
    epochs=20,
    validation_data=validation_generator,
    validation_steps=50  # Example value, adjust based on your dataset
)
```

Model Summary and Performance:

After training, you can evaluate the model performance using the validation data, and if necessary, fine-tune the model by adjusting hyperparameters (learning rate, batch size, number of layers, etc.).

```
# Evaluate the model on the validation set
loss, accuracy = model.evaluate(validation_generator)
print(f'Validation Accuracy: {accuracy * 100:.2f}%')
```

This architecture should work well for classifying 180x180 images into four classes. You can adjust the number of layers or filters based on the complexity of your dataset, but this is a solid baseline model.

A generalized graphical representation of a two-dimensional (2D) convolutional neural network (CNN) such as that suggested by ChatGPT appears in Fig. 3.

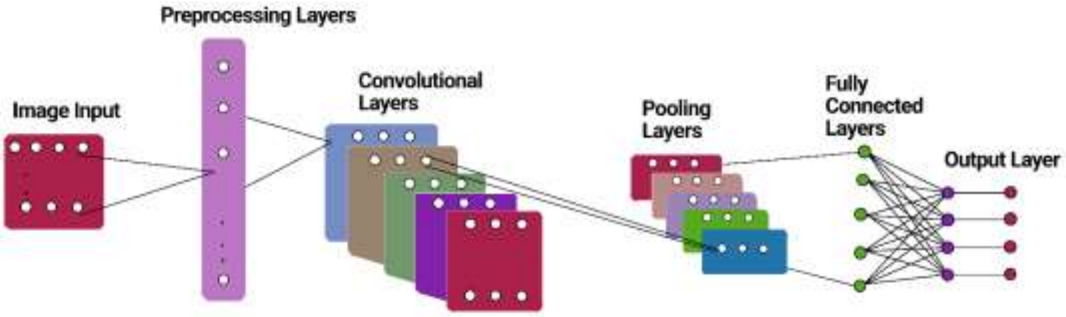

Fig. 3: Generalized Two-dimensional (2D) Convolutional Neural Network (CNN).

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III. RESULTS

The responses of ChatGPT to the prompts crafted herein were implemented faithfully to create a system for automated image-based diagnosis of chronic kidney disease. In particular, the response to the initial prompt was followed up by a more specific prompt. Note that the system issues recommended in the initial response including ethics have been dealt with in the design of the comprehensive AI-driven healthcare system under consideration [5].

Since ChatGPT recommended the use of convolutional neural networks (CNNs) while responding to the initial prompt, the follow-up prompt requested the design of a suitable CNN where the input images are resized to 180 pixels by 180 pixels in order to render the results comparable to those obtained by leveraging expert-synthesized CNNs [4].

Implemented via the Python programming language using the TensorFlow platform and Keras Application Programming Interface [49] – [50], the system conformed to the recommendations of the generative AI.

To make the results more amenable to comparison with the expert-generated system, the same default training parameters were employed over 10 epochs [4] using the Adam Optimizer [51] - [52] with the data split into a training dataset containing 80% of the original dataset and a corresponding validation dataset comprising 20% of the original data.

Fig. 4 illustrates the performance metrics of the system by graphically representing the historical changes in the training and validation accuracy as well as the training and validation loss over the training epochs.

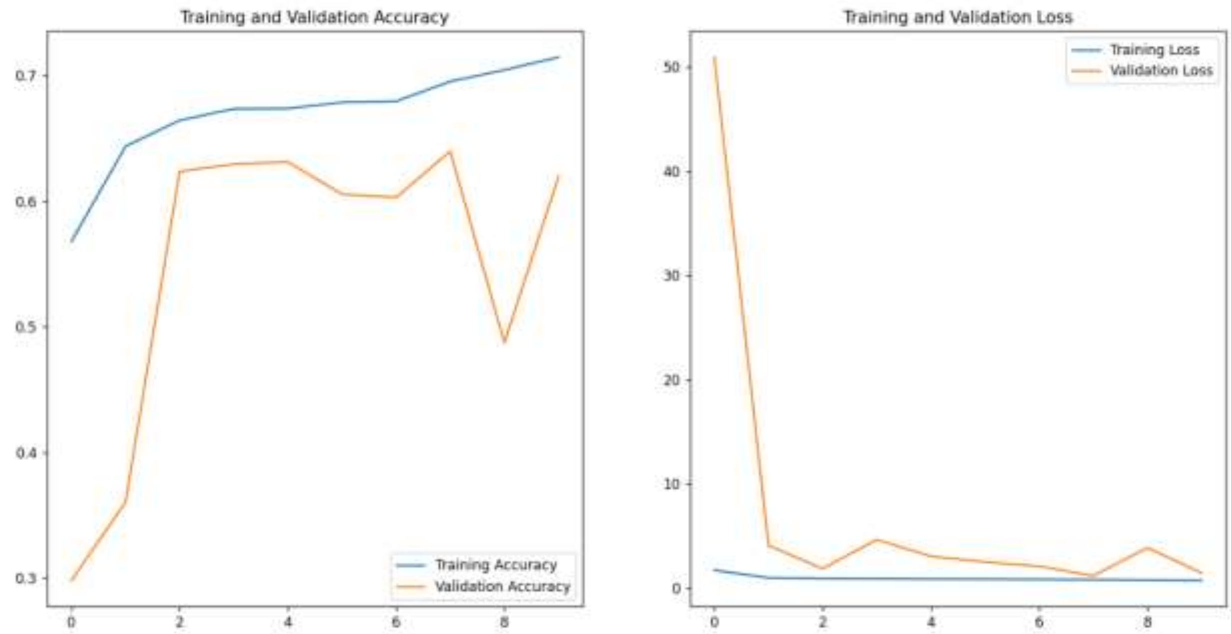

Fig. 4: Historical Plot of Training and Validation Accuracy and Training and Validation Loss Performance Metrics.

As can be seen from Fig. 4, the accuracy increased over time while the loss decreased over time with the validation performance metrics substantially tracking the training performance metrics.

The implementation of the comprehensive AI system outlined here will provide actionable insights for clinical decision support, ultimately saving lives and improving quality of life by alleviating the economic, social, psychological, and physical burdens associated with conditions that may be predicted, prevented, detected early, diagnosed, treated, and managed more effectively.

Electronic Health Records (EHR), including clinical diagnostic measurements and EEG data, will be generated by participating medical professionals and their affiliated teams. EEG data may also be collected as part of experiments involving Brain-Computer Interfaces (BCIs). All data will be gathered in compliance with ethical guidelines, anonymized prior to publication, and shared in publicly accessible repositories alongside relevant research articles.

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IV. CONCLUSION

The recommendations of generative artificial intelligence (AI) tools were elicited via prompt engineering and leveraged to construct, train, test and deploy AI models for automatic image-based diagnosis of chronic kidney that could be incorporated into suitable modules within a comprehensive artificial intelligence-driven healthcare system. Results indicate that the resulting AI models exhibited reasonable performance, suggesting that generative AI tools combined with AI expertise represent an effective approach to the creation of systems for the automated image-based diagnosis of chronic kidney disease within the framework of a comprehensive AI-powered healthcare system.

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