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Generative Artificial Intelligence Recommendations for Clinical Measurement-Based Diagnosis of Chronic Kidney Disease

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Abstract

Using relevant diagnostic measurements such as systolic blood pressure, diastolic blood pressure, fasting blood sugar level, hemoglobin A1c level, serum creatinine level, blood urea nitrogen level, glomerular filtration rate, protein levels in urine, albumin-to-creatinine ratio, serum sodium level, serum potassium level, serum calcium level, serum phosphorus level, hemoglobin level, total cholesterol level, low-density lipoprotein cholesterol level, high-density lipoprotein cholesterol level, triglycerides level, as well as lifestyle and environmental factors, suitably complex artificial intelligence (AI) models generated based on suggestions extracted from generative AI tools such as large language models (LLMs) through prompt engineering are trained and deployed to automatically diagnose chronic kidney disease for clinical decision support purposes. The results indicate that the application of prompt engineering to generative AI tools coupled with AI expertise is a viable approach to the development of AI models for automatic chronic kidney disease diagnosis on the basis of diagnostic measurements, lifestyle and environmental factors. The trained AI models could be incorporated into a modular comprehensive AI-driven healthcare system designed to provide actionable insights that can support clinical decision-making practice.

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

1. Introduction

The debilitating effects of chronic kidney disease (CKD) are borne by a large number of people worldwide [1]. Chronic kidney disease features prominently as one of the top ten leading causes of mortality globally according to Word Health Organization (WHO) statistics [2]. People in low- and middle-income countries (LMIC) with inadequate healthcare facilities and limited access to affordable healthcare services with healthcare systems characterized by chronic and acute shortages of qualified service providers are particularly hard hit. Accurate and timely diagnosis of CKD can significantly improve health outcomes and ameliorate the economic, physical, psychological and emotional toll of the disease.

Ekpar [3] created a comprehensive artificial intelligence-driven healthcare system that can incorporate modules for the automated diagnosis of CKD and a wide variety of health conditions and sporting features for the adoption of novel three-dimensional multilayer electroencephalography (Ekpar EEG) systems for greater insights into brain-related health conditions, rehabilitation and practical human machine interfaces (HMIs) such as high performance brain computer interfaces (BCIs) and brain-to-brain communication [3], [4], [5], [6].

This comprehensive AI-driven healthcare system (Scholar Medic) [3] enables ten or higher-fold improvements in medical doctor productivity, permitting the availability of high-quality healthcare services even in resource-constrained settings such as LMICs and mitigating the deleterious effects of the brain drain occasioned by the emigration of qualified medical doctors from LMICs to developed countries for greener pastures. In a previous study, Ekpar [7] synthesized suitably complex AI models and more specifically, artificial neural networks for the automated diagnosis of CKD based on clinical measurements, lifestyle and environmental considerations for incorporation into a comprehensive AI-driven healthcare system [3]. Additional studies by Ekpar [8], [9] applied two-dimensional (2D) convolutional neural networks (CNNs) built from the ground up on the basis of expert knowledge as well as on the basis of prompt engineering of generative AI tools to the development of image-based automated chronic kidney disease diagnosis systems. This paper introduces a system that relies on prompt engineering to extract suggestions from generative AI tools on the development of AI models for automated diagnosis of CDK based on clinical measurements, lifestyle and environmental factors and then the recommended AI models are implemented and trained, tested and validated on publicly accessible data with the potential for refinement and incorporation into the comprehensive AI-powered healthcare system – Scholar Medic – created by Ekpar [3].

A wide range of published studies have applied AI to the diagnosis and prediction of diseases such as heart disease, epilepsy, diabetes mellitus and other conditions [10] – [28]. The vast majority of these studies were designed around conditions and data in developed countries and consequently report results that are liable to bias and prone to limited global relevance.

There is as yet at best limited application of large language models (LLMs) with the ability to draw inferences using AI models trained on input data and to learn structured representations of the underlying data [29], [30] to the prediction and diagnosis of health conditions and the construction of BCIs. Brain computer interfaces (BCIs) including those based on electroencephalography (EEG) provide opportunities for rehabilitation and for interaction with the environment but are hampered by limitations such as poor performance, high cost, risks associated with surgery for implanted systems, and so on, severely limiting their application in practice [31] – [49]. Ekpar EEG systems – novel three-dimensional multilayer EEG systems [4], [5], [6] offer high performance typically only attainable in systems requiring surgical implantation of electrodes while actually operating non-invasively and obviating the need for risky and expensive surgeries and enabling a wide range of novel and game-changing applications.

2. Materials and Methods

Participant Recruitment

Individuals volunteered to participate in the research that contributed to the creation of the comprehensive AI-powered healthcare system, with all participants providing informed consent prior to their involvement in the studies.

Ethical Approval

The Health Research Ethics Committee at the Rivers State University Teaching Hospital, located within Rivers State University, granted ethical clearance for the studies. The research adhered to all applicable ethical and regulatory standards. Publicly available data were used in compliance with the licensing terms set by the original creators.

3. Methodology

Healthcare datasets that are publicly available can be enhanced by integrating data collected from local experiments and data collection initiatives. This combined data can then be used to train AI models to make actionable predictions based on new inputs. Public healthcare dataset sources include the Centers for Disease Control, the

University of California Irvine Machine Learning Repository, the American Epilepsy Society, and Kaggle.

Incorporating local data strengthens the model, minimizes bias, and ensures broader inclusivity and global relevance. A distinctive aspect of this project involves merging diagnostic data (which may include electrocardiographic results) from local experiments with EEG data, utilizing both traditional and innovative three-dimensional multilayer EEG systems.

Local data collection efforts for the project have received ethical approval from research ethics committees in the regions where the experiments take place. Additionally, partnerships have been formed with licensed medical doctors who have direct access to patients and healthcare professionals in the community. These doctors are contributing anonymized clinical data to validate the AI models.

The AI models, once trained, will be integrated into a comprehensive healthcare system designed to assist medical practitioners with clinical decision-making and generate Brain-Computer Interfaces (BCIs). The system will offer actionable predictions and insights derived from new clinical data provided by healthcare professionals. This will help with the early detection, diagnosis, treatment, prediction, and prevention of various conditions such as diabetes, heart disease, stroke, autism, and epilepsy.

This project is dedicated to advancing open science, reproducibility, and collaboration, and as such, the generated data will be shared on public platforms like GitHub.

4. System Design and Implementation

The healthcare system outlined in this paper adopts a modular design, where each health condition (such as diabetes mellitus, heart disease, stroke, epilepsy, autism, etc.) is managed by a separate module. This structure ensures the system can be extended to diagnose and predict additional conditions in the future, while also enabling efficient updates to existing modules with new data. Modules designed for Brain-Computer Interfaces (BCIs), including those utilizing the motor imagery paradigm, are capable of processing EEG data to generate actionable commands and appropriate responses.

The system also includes guidelines for adapting traditional EEG systems to innovative game-changing three-dimensional multilayer EEG systems. These novel systems, developed by Ekpar [4], [5], [6] follow a conceptual framework that uses approximations of key features from the bio-signal sources to analyze or manipulate the underlying biological systems.

For each module, advanced AI models are developed and trained on properly formatted data, as outlined in the paper. These AI models can incorporate genetic, environmental, lifestyle, and other pertinent information to provide more accurate depictions of the participants' circumstances.

Key aspects of the system are represented graphically in Fig. 1

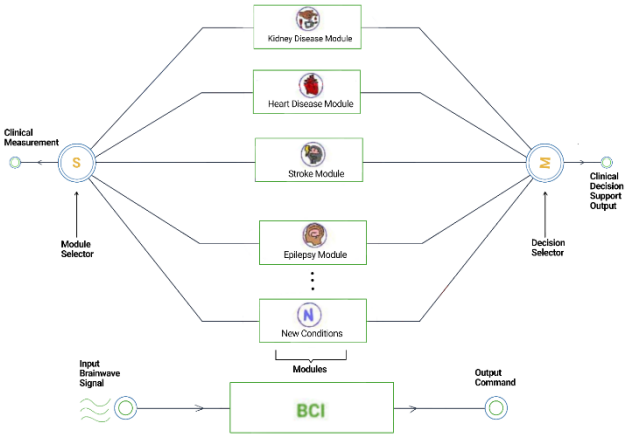

Fig. 1: System Schematic Design Diagram for the Comprehensive AI-Driven Healthcare Solution and Brain Computer Interface System. The New Conditions component represents additional health conditions that can be incorporated into the solution via new modules.

The AI models are developed using four distinct methods:

1. Direct Utilization of LLMs like GPT-4 as inference engines, leveraging data formatted as multidimensional input

vectors. This process may involve fine-tuning the LLM.

2. Prompt Engineering applied to LLMs such as Bard and GPT-4 (including future versions) to propose a sequence of actions for developing the AI system. These steps are then executed using the creator's expertise in AI, neural networks, deep learning, Python, TensorFlow, Keras, and other machine learning and visualization tools like Scikit-learn and Matplotlib.
3. Automated Generation of AI Models using LLMs such as Bard and GPT-4 (and their future iterations) through an automated pipeline to create specific models.
4. Direct Design of an AI Architecture based on the creator's deep knowledge of AI, neural networks, deep learning, Python, TensorFlow, Keras, and other ML and visualization tools like Scikit-learn and Matplotlib.

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

The generated AI models are evaluated and compared based on their performance (using metrics like specificity, sensitivity, etc.) and their suitability for addressing the challenges at hand.

Automated Chronic Kidney Disease Diagnosis Based on Diagnostic Measurements

This study adopts the second approach to the construction of AI models in the foregoing list of approaches, namely, prompt engineering of generative AI tools such as large language models (LLMs). More specifically, the ChatGPT 4o mini LLM was used for the generation of suggestions on how to build a system to solve the problem at hand – the development of a suitable AI model for the automated diagnosis of chronic kidney disease based on clinical measurements, lifestyle and environmental factors.

First, ChatGPT is prompted with a generalized query on the design of the system. Based on the response generated by ChatGPT to the first prompt, a more specialized second prompt is created and used to elicit concrete instructions and source code for the development of the suggested AI model. Finally, the suggested AI model is implemented, trained, tested and validated on a publicly accessible chronic kidney disease dataset. The resulting AI model could be refined and then incorporated into a Kidney Disease Module within the comprehensive AI-driven healthcare system created by Ekpar [3].

Following is a brief description of the dataset employed and a presentation of the exact prompts fed into ChatGPT (accounting for the number of features in the dataset) and copies of the responses generated by Chat GPT.

DATASET

The chronic kidney disease dataset used in this study was sourced from the Kaggle dataset repositor. It comprises a total of 1659 rows or complete data samples each of which contains 52 columns of interest. Clinical measurements, lifestyle and environmental factors relevant for the diagnosis of chronic kidney make up the first 51 columns of each row while the last column is the associated diagnosis representing presence or absence of chronic kidney disease. A value of 1 represents a positive diagnosis (chronic kidney disease present) while a value of 0 represents a negative diagnosis (chronic kidney disease absent).

Captured in the first 51 columns of input are the relevant measurements from each participant. These measurements include patient information like demographic particulars and lifestyle factors (age, gender or sex, ethnicity, education level, socioeconomic status, body mass index, physical activity, smoking, alcohol consumption, diet quality, sleep quality), medical history (family history of kidney disease, family history of hypertension, family history of diabetes, previous acute kidney injury, urinary tract infections), diagnostic measurements (systolic blood pressure, diastolic blood pressure, fasting blood sugar level, hemoglobin A1c level, serum creatinine level, blood urea nitrogen level, glomerular filtration rate, protein levels in urine, albumin-to-creatinine

ratio, serum sodium level, serum potassium level, serum calcium level, serum phosphorus level, hemoglobin level, total cholesterol level, low-density lipoprotein cholesterol level, high-density lipoprotein cholesterol level, triglycerides level), medications (use of ACE inhibitors, use of diuretics, frequency of NSAIDs use, use of statins, use of antidiabetic medications), symptoms and quality of life (presence of edema, fatigue level, frequency of nausea and vomiting, frequency of muscle cramps, itching severity, quality of life score), environmental and occupational exposures (exposure to heavy metals, occupational exposure to harmful chemicals, quality of water), and health behaviors (frequency of medical check-ups per year, medication adherence score, health literacy score).

Data Availability

The data collections that support the conclusions of this study are contained in the chronic kidney disease dataset publicly available from the Kaggle dataset repository at https://www.kaggle.com/datasets/rabieelkharoua/chronic-kidney-disease-dataset-analysis.

FIRST Chat GPT PROMPT

Design a system for automated diagnosis of chronic kidney disease based on diagnostic measurements such as systolic blood pressure, diastolic blood pressure and fasting sugar level.

FIRST Chat GPT RESPONSE

Designing a system for automated diagnosis of chronic kidney disease (CKD) using diagnostic measurements such as systolic blood pressure (SBP), diastolic blood pressure (DBP), and fasting sugar level (FSL) involves developing a comprehensive workflow incorporating data collection, preprocessing, analysis, and output generation. Below is a step-by-step approach to design this system.

1. Data Collection

The first step is to collect accurate and relevant data. The system will require the following measurements:

- **Systolic Blood Pressure (SBP):** A measure of the pressure in your arteries when the heart beats.
- **Diastolic Blood Pressure (DBP):** The pressure in the arteries when the heart rests between beats.
- **Fasting Sugar Level (FSL):** The blood glucose level after fasting for at least 8 hours.

The system can receive this data either through:

- Direct input from a medical practitioner or patient
- Automated integration with digital health devices (e.g., blood pressure monitors, glucose meters)

2. Data Preprocessing

Once the data is collected, preprocessing steps are necessary to ensure the data is clean and usable for analysis:

- **Handle missing values:** If any measurement is missing, decide on an appropriate strategy, such as asking for a recheck or estimating values based on historical data.
- **Normalize measurements:** Standardize units for consistency (e.g., converting BP from mmHg if different units are used).
- **Check for outliers:** Values significantly higher or lower than typical ranges should be flagged for further review.

3. Feature Engineering

Extract features relevant to CKD diagnosis from the raw data:

- **Blood Pressure Ratio:** Calculate the ratio of SBP to DBP to evaluate blood pressure health (e.g., high ratios can indicate potential hypertension).
- **Fasting Glucose Categories:** Classify FSL into categories such as normal, prediabetic, or diabetic based on standard glucose thresholds:
  - Normal: 70–100 mg/dL

- Prediabetic: 101–125 mg/dL
- Diabetic: ⩾126 mg/dL

- **Risk Scoring:** Create a composite score by aggregating the blood pressure and fasting sugar level data, which correlates with CKD risk.

4. CKD Risk Prediction Model

A machine learning model can be trained to predict the likelihood of CKD based on the input parameters (SBP, DBP, and FSL). The model could be trained on historical patient data with labels indicating the presence or absence of CKD. The steps to build the model:

- Data Collection for Model Training: Gather a dataset containing labeled examples of patients with and without CKD, with corresponding measurements for SBP, DBP, and FSL.
- Model Choice: Select a machine learning algorithm (e.g., logistic regression, decision trees, random forests, or neural networks) suitable for classification problems.
- Feature Selection: Use statistical techniques (e.g., correlation analysis) to identify the most influential features.
- Model Training: Split the data into training and test sets, then train the model to predict CKD based on the input measurements.
- Model Evaluation: Evaluate the model's performance using metrics like accuracy, precision, recall, F1 score, and ROC-AUC.

5. Classification Logic

- Once the model is trained, the system will process incoming data as follows:
- Input the measurements: Enter SBP, DBP, and FSL into the system.
- Feature extraction: Extract relevant features (ratios, categories, etc.).
- Prediction: Feed the processed data into the trained model.

Output the diagnosis: Based on the model's output, classify the patient as:

- CKD Risk: Low
- CKD Risk: Moderate
- CKD Risk: High

6. System Interface and Feedback

The system should provide a user-friendly interface for both medical practitioners and patients. The interface should:

- **Input Interface:** Allow for easy data entry, either manually or via automated device integration.
- **Results Output:** Display the CKD risk classification with associated recommendations (e.g., "Monitor blood pressure," "Consult a doctor," or "Start diabetes management").
- **Recommendations:** Provide health tips or advice based on the risk classification (e.g., lifestyle changes, diet, and exercise).
- **Data Logging:** Store historical data and track changes over time, enabling long-term monitoring of CKD risk.

7. Further Analysis and Diagnostics

To enhance the accuracy and utility of the system:

- Integrate Additional Parameters: Incorporate other relevant parameters such as age, gender, eGFR (estimated glomerular filtration rate), and creatinine levels, which are commonly used in CKD diagnosis.
- Multi-Model Integration: Combine the blood pressure and fasting sugar-based model with other existing CKD prediction tools to create a hybrid model for better accuracy.

8. System Deployment

The system should be deployed in a clinical setting, either:

- **Cloud-based platform:** Accessible from various devices for doctors and patients.

- **Standalone Medical Devices:** Embedded in digital health devices or apps for home use by patients.

9. Security and Privacy Considerations

Ensure the system complies with medical data privacy standards such as HIPAA or GDPR. All personal and medical data should be encrypted, and secure access should be implemented.

10. Continuous Learning and Model Improvement

To improve the model over time:

- **Continuous Data Collection:** Gather feedback and data from real-world usage to retrain and fine-tune the model periodically.
- **Model Updates:** As new research and medical guidelines are published, update the risk prediction model to reflect the latest findings.

Summary

The system uses key diagnostic measurements like blood pressure and fasting glucose levels to assess the risk of CKD. A machine learning-based model, trained on historical data, predicts CKD risk and provides personalized recommendations. This system can be used both in clinical settings and by individuals at home to monitor kidney health, ensuring early detection and intervention.

System Design Considerations

The comprehensive AI-driven healthcare system created by Ekpar [3] incorporates a wide variety of relevant system design considerations including those recommended in the above listed ChatGPT response with provision for model updates facilitated by the modular design in addition to ethical, security and privacy considerations.

SECOND ChatGPT PROMPT

Design an artificial neural network for binary classification of a set of 51 inputs.

SECOND ChatGPT RESPONSE

To design an artificial neural network (ANN) for binary classification with 51 input features, we need to consider the architecture, activation functions, and training setup. Below is a step-by-step guide for creating a neural network suitable for this task:

1. Input Layer:

- **Number of Nodes:** 51 (equal to the number of input features).
- **Purpose:** Each node will represent a feature from the input dataset.

2. Hidden Layers:

- First Hidden Layer:
  - **Number of nodes:** 64 (typically, this is chosen empirically or through cross-validation).
  - **Activation function:** ReLU (Rectified Linear Unit) is commonly used for hidden layers due to its simplicity and efficiency.
- **Second Hidden Layer:**
  - **Number of nodes:** 32 (can vary based on the complexity of the problem).
  - **Activation function:** ReLU.
- You can add more hidden layers if necessary, depending on the complexity of your dataset. However, two hidden layers should be sufficient for many problems.

3. Output Layer:

- Number of Nodes: 1 (since it's a binary classification task, the output is a single scalar).
- Activation Function: Sigmoid, which will output a value between 0 and 1, indicating the probability of belonging to the positive class.

4. Loss Function:

- Since it's a binary classification, use Binary Cross-Entropy (also called log loss) as the loss function. This is suitable for tasks where the output is a probability (as given by the sigmoid activation).

5. Optimizer:

- Use Adam Optimizer for efficient gradient descent with adaptive learning rates.

6. Model Architecture in Python (with Keras/TensorFlow):

```
from tensorflow. keras. models import Sequential

from tensorflow. keras. layers import Dense

from tensorflow.keras.optimizers import Adam

# Initialize the model

model = Sequential ()

# Input Layer: 51 inputs

model.add(Dense(64,

input_dim=51, activation='relu'))

# Hidden Layer 1: 64 neurons, ReLU activation

model.add(Dense(32, activation='relu'))

# Output Layer: 1 output neuron, sigmoid activation for binary classification

model.add(Dense(1, activation='sigmoid'))

# Compile the model with Adam optimizer and binary cross-entropy loss

model.compile(optimizer=Adam(),
loss='binary_crossentropy', metrics=['accuracy'])

# Model Summary

model.summary()
```

7. Model Training:

- You can now train the model using your dataset:

```
# Assuming X_train and y_train are your training data and labels

model.fit(X_train, y_train, epochs=50, batch_size=32, validation_data=(X_val, y_val))
```

8. Evaluation:

After training, evaluate the model on a test set (e.g., X_test and y_test) to determine its performance.

```
# Assuming X_test and y_test are your test data and labels

test_loss, test_accuracy = model.evaluate(X_test, y_test)

print (f'Test Loss: {test_loss}, Test Accuracy: {test_accuracy}')
```

Notes on Tuning:

- You may need to experiment with the number of layers, the number of neurons in each layer, and the learning rate of the optimizer.
- You can use techniques like dropout or batch normalization if overfitting becomes an issue.
- Early stopping is useful to prevent overfitting by stopping training when the validation accuracy stops improving.

Summary:

This architecture is a simple yet powerful design for binary classification with 51 inputs. The network starts with 51 input nodes, followed by two hidden layers with ReLU activation, and ends with a sigmoid output layer for binary classification. The model uses the Adam optimizer with binary cross-entropy loss, and the final output is a probability indicating class membership.

Artificial Neural Network (Ann) Architecture

The artificial neural network (ANN) recommended by ChatGPT is a multilayer perceptron with 51 input units, two hidden layers with the first hidden layer featuring 64 units and the second hidden layer featuring 32 units and a single unit in the output layer. ReLU activation was recommended for all units except the output unit for which sigmoid activation was recommended.

Figure 2 illustrates a generalized depiction of the artificial neural network. In Fig. 2, CM1, CM2, ..., CMN represent the relevant clinical measurements (a total of N=51 to cover all the measurements taken for each patient or participant as explained

in the foregoing) while CD represents the clinical diagnosis which maps to the output of the artificial neural network.

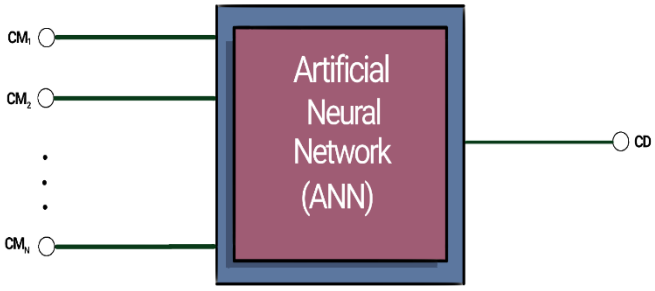

Fig. 2: Schematic Graphical Representation of Artificial Neural Network (ANN) Architecture. CM1, CM2, ..., CMN represent the inputs while CD represents the output indicating the suggested clinical diagnosis.

5. Results

The artificial neural network was implemented by utilizing the TensorFlow platform and the Keras API in the Python programming language [50], [51]. A split in the original input chronic kidney disease dataset was implemented such that 60% of the dataset was reserved for training of the artificial neural network while 40% of the dataset was reserved for testing and validation. Random shuffling of the dataset was introduced as a bias-mitigating measure. The artificial neural network was trained over 500 epochs utilizing the Adam Optimizer [52], [53], binary cross-entropy loss function, a default learning rate of 0.001 and a default batch size of 32. The trained AI model was characterized by performance metrics of approximately 93% precision, approximately 93% specificity and approximately 95% sensitivity, performing substantially on par with the expert-synthesized system developed in the comparable earlier study [7].

Figure 3 shows a subset of clinical measurements for a selected patient and the corresponding diagnosis suggested by the trained AI model.

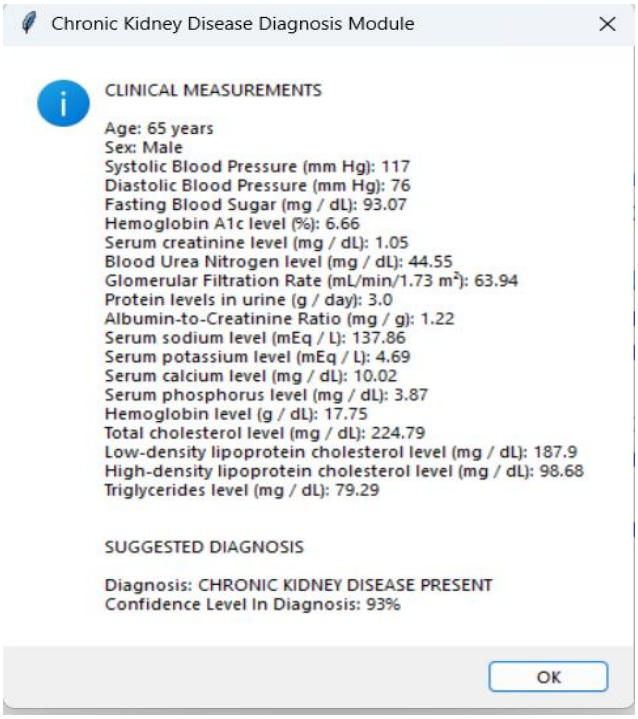

Fig. 3: Chronic Kidney Disease Diagnosis Module of Scholar Medic Showing Clinical Measurements and Corresponding Suggested Diagnosis.

Computation of the precision, sensitivity or recall and specificity performance metrics is as follows:

$$\boldsymbol{Precision} = \frac{\boldsymbol{TP}}{\boldsymbol{TP + FP}}$$

$$\boldsymbol{Sensitivity} = \frac{\boldsymbol{TP}}{\boldsymbol{TP + FN}}$$

$$\boldsymbol{Specificity} = \frac{\boldsymbol{TN}}{\boldsymbol{TN + FP}}$$

In the foregoing equations, TN refers to true positives, FP refers to false positives, FN refers to false negatives, and TN refers to true negatives. Negative here indicates normal kidney functioning or absence of chronic kidney disease while positive indicates the presence of chronic kidney disease. Implementing the comprehensive AI system outlined here will provide actionable insights for clinical decision-making, ultimately saving lives and enhancing living conditions. This is achieved by reducing the economic, social, psychological, and physical burdens of conditions that could be predicted, prevented, detected early, diagnosed, treated, and managed more effectively.

Electronic Health Records (EHR), including clinical diagnostic data and EEG information, could be created by participating medical professionals and their colleagues. EEG data may also be collected during experiments involving Brain-Computer Interfaces (BCIs). All data will be gathered in line with ethical guidelines, anonymized, and then made publicly available in repositories alongside relevant research publications.

6. Discussion

Predictions from the comprehensive AI-driven healthcare system [3] could be utilized to guide recommendations for lifestyle changes that may help prevent diseases and significantly enhance health outcomes. The system's modular architecture enables the potential for diagnosing and predicting additional conditions in the future, while also allowing for efficient updates to specific modules with new data. Incorporating environmental and genetic data into the AI models could provide a more accurate representation of participants' living conditions, thus making medical practitioners' prescriptions more effective. A variety of strategies, such as the use of large language models and smaller AI models, could be explored, evaluated, and compared to determine the most suitable approach based on resource availability and urgency, with the best method being implemented in each situation.

The responses of generative AI tools such as large language models could be leveraged with AI expertise to create AI models with performance on par with expert-crafted systems or where performance is sub-par, could be refined on the basis of AI expertise to generate usable systems as demonstrated by this study. Further advancements in the technologies outlined here, through ongoing research and development (including the creation of the novel three-dimensional multilayer EEG system [4], [5], [6] introduced by Ekpar, which could enable much higher electrode densities and superior performance compared to traditional EEG systems), will enhance societal capabilities, aid in the rehabilitation of individuals with neurological conditions, and generally improve overall quality of life.

7. Conclusion

Suggestions were elicited from generative AI tools - a large language model (LLM) in this case - for AI models which were then implemented, trained, tested and validated on publicly available data for the automated diagnosis of chronic kidney disease relying on clinical measurements, lifestyle and environmental factors for clinical decision support. The resulting models could be refined and incorporated into the comprehensive AI-driven healthcare system created by the author. The results of this study lend credence to the suitability of prompt engineering of LLMs combined with AI expertise as a viable pathway to the synthesis, training, testing, validation and deployment of AI models for the automated diagnosis of chronic kidney disease based on diagnostic measurements, lifestyle and environmental factors.

Conflicts of Interest

There are no conflicts of interest to disclose.

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