



Constructing Artificial Intelligence Models for the Diagnosis of Heart Disease Based on the Recommendations of Generative Artificial Intelligence

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Abstract: Recommendations extracted from generative artificial intelligence tools such as large language models via prompt engineering for the design of a system for the automated diagnosis of heart disease are followed through to construct suitable artificial intelligence models for the automated diagnosis of heart disease using clinical measurements. The resulting artificial intelligence models are trained, tested and validated on a clinically validated and publicly accessible heart disease dataset. Observed system performance was reasonable compared to the performance of systems developed by artificial intelligence experts by adopting a custom synthesis approach. The artificial intelligence models could be further refined using inputs such as expert and domain knowledge and ultimately incorporated as an automated heart disease diagnosis module in a comprehensive artificial intelligence-driven healthcare system.

Keywords: Heart Disease, Generative Artificial Intelligence (AI), Large Language Model (LLM), ChatGPT, DeepSeek, Artificial Neural Network (ANN), Deep Learning (DL), TensorFlow, Healthcare System, Disease Diagnosis and Prediction.

I. INTRODUCTION

Estimates indicate that millions of people worldwide present with heart conditions and other non-communicable diseases (NCDs) worldwide, including in low- and medium-income countries (LMICs) [1]. While the deleterious effects of heart disease are acute and distressing, they are exacerbated in LMICs due to a combination of insufficiency of healthcare facilities and a dearth of qualified healthcare service provided further worsened by the emigration of the already limited pool of qualified healthcare professionals to developed countries for greener pastures. NCDs, including heart disease, are reported to be among the leading top ten causes of mortality across the globe and are associated with untold physical, psychological and emotional trauma as well as a severe economic burden for patients and their relatives [2].

It is well known that early diagnosis of heart disease can lead to substantially improved health outcomes by driving more efficacious therapies and relevant lifestyle modifications. The application of automated systems for the diagnosis of heart disease represents a potent tool for the early and accurate diagnosis and prediction of the future course of the disease – enabling effective therapies, lifestyle adjustments and ultimately improved health outcomes.

A variety of diagnostic systems for a wide range of health conditions based on artificial intelligence (AI) have been developed and deployed with varying degrees of success or effectiveness [3] – [22]. Furthermore, generative AI tools such as large language models [23] – [24] capable of extracting inferences by relying on AI models trained on vast amounts of input data and designed to learn structured views data have been leveraged to generate suggestions that were then harnessed for the development of sufficiently complex AI models for the automated diagnosis of various health conditions [25] – [26].

Scholar Medic, a comprehensive artificial intelligence-driven healthcare system created by Ekpar [27] – [30] features an extensible and modular design for the automated diagnosis and prediction of a wide range of health conditions as well as brain computer interfaces (BCIs) based on the traditional two-dimensional (2D) single-layer electroencephalography (EEG) paradigms and comparable systems [31] – [49] with unique support for a novel three-dimensional multilayer electroencephalography paradigm (Ekpar EEG) featuring hitherto unattainable performance and enabling hitherto



unrealizable applications across a wide range of application domains from computing to medicine [50] – [52]. The unique features of Scholar Medic [27] – [30], [25] – [26] can enable ten or higher-fold increases in medical doctor productivity (permitting even resource-limited healthcare settings in LMICs to provide high quality healthcare services), mitigate the effects of the brain drain associated with healthcare professionals in developing countries, mitigate healthcare professional staff shortages and prevent burnout for vastly improved healthcare outcomes.

In a previous study, Ekpar [27] utilized custom-synthesized artificial neural networks to build AI models for the automated diagnosis of heart disease based on clinical measurements. This study leverages prompt engineering of generative AI tools such as large language models (LLMs) to generate a sequence of recommendations for the design of a system for the automated diagnosis of heart disease. Consequently, the recommendations of the LLM are followed meticulously to implement, train, test, validate and deploy AI models for the automated diagnosis of heart disease while relying on publicly available heart disease data. The resulting system could be refined and incorporated into the comprehensive artificial intelligence-powered healthcare system created by Ekpar [27].

This approach utilizes two separate prompts to accomplish the task of generating the recommendations from the LLM. The first prompt is a generalized prompt for system design suggestions while the second prompt is a specific prompt outlining the number of features of the target AI model architecture based on the structure of the input dataset.

II. MATERIALS AND METHODS

Participant Recruitment

Individuals volunteered to participate in the research contributing to the development of the AI-driven healthcare system, and each participant provided informed consent before taking part in the studies.

Ethical Approval

The Health Research Ethics Committee at Rivers State University Teaching Hospital granted ethical approval for the studies. All research adhered to the applicable ethical and regulatory standards. Publicly accessible data were used in line with the licensing terms set by their creators.

METHODOLOGY

Publicly accessible healthcare datasets can be enhanced by incorporating data gathered from local experiments and data collection initiatives. This integrated dataset can then be used to train AI models that provide actionable predictions based on new data. Public healthcare datasets are available from sources such as the Centers for Disease Control, the University of California Irvine Machine Learning Repository, the American Epilepsy Society, and Kaggle.

Incorporating local data improves the reliability of the models, minimizes potential biases, and supports inclusivity and global applicability. A central approach in this project is to combine diagnostic data, such as electrocardiographic readings, from local studies with EEG data, including both traditional and innovative three-dimensional multilayer EEG systems.

For data collection, the research has received ethical approval from relevant ethics committees in the regions where the experiments are conducted. Additionally, the project has partnered with licensed medical professionals who have direct access to patients and healthcare teams in the community. These doctors are providing anonymized clinical data to validate the AI models.

After training, the AI models will be integrated into an all-encompassing healthcare system aimed at supporting clinical decision-making and developing brain-computer interfaces (BCIs). This system will generate actionable predictions and insights from new clinical data, assisting with early detection, diagnosis, treatment, prediction, and prevention of conditions like diabetes mellitus, heart disease, stroke, autism, and epilepsy.

The project is dedicated to advancing open science, reproducibility, and collaboration. Therefore, all generated data will be made publicly accessible through platforms such as GitHub.



SYSTEM DESIGN AND IMPLEMENTATION

The healthcare system described in this paper utilizes a modular approach, where each health condition (such as diabetes, heart disease, stroke, epilepsy, autism, etc.) is assigned to its own separate module. This design not only allows for flexibility in diagnosing and predicting potential health issues but also facilitates the easy updating of modules as new data becomes available. Additionally, modules related to Brain-Computer Interfaces (BCIs), particularly those utilizing the motor imagery paradigm, are capable of processing EEG data to produce actionable commands and responses.

The system also includes guidelines for upgrading traditional EEG systems to more advanced three-dimensional multilayer EEG systems. These cutting-edge systems, developed by Ekpar [50] - [52], rely on a conceptual framework that approximates specific bio-signal features to model or influence the biological systems involved.

For each module, AI models are developed and trained using appropriately formatted data, as described in this paper. These AI models can integrate various factors, such as genetic, environmental, and lifestyle information, to offer more accurate depictions of the participants' situations.

Figure 1 shows a schematic representation of the systems with a selection of modules.

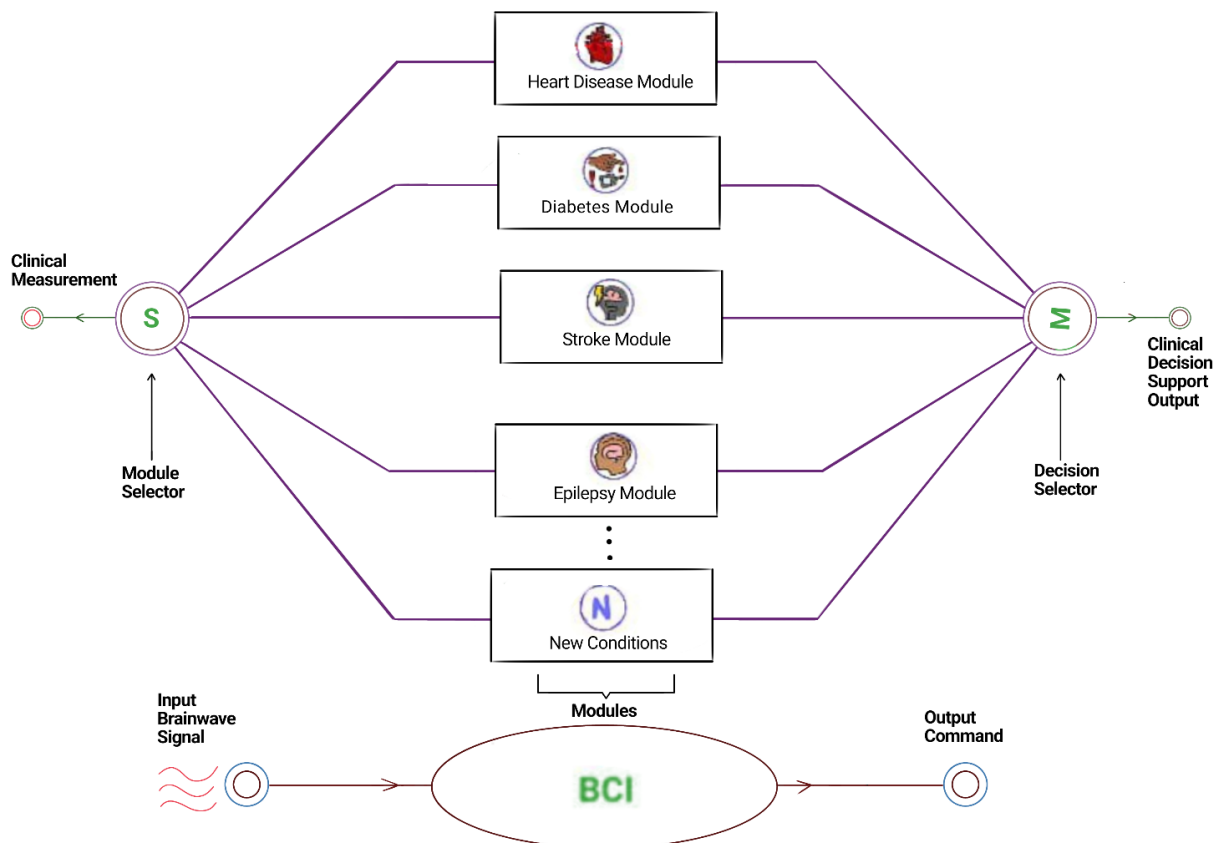


Fig. 1: System Schematic Design Diagram for the Comprehensive AI-Driven Healthcare Solution and Brain Computer Interface System. The New Conditions component represents additional health conditions that can be incorporated into the solution via new modules.

The AI models are created using four distinct methods, as outlined below:

1. **Direct Use of LLMs:** Large Language Models (LLMs) like DeepSeek and GPT-4 serve as inference engines, processing the collected data formatted as multidimensional input vectors. This process may involve fine-tuning the LLM.



2. **Prompt Engineering with LLMs:** LLMs such as DeepSeek, Bard and GPT-4 (including their future versions) are used with prompt engineering to define the necessary steps for developing the AI system. These steps are then carried out by the developer, who applies expertise in AI, neural networks, deep learning, and tools like Python, TensorFlow, Keras, and machine learning frameworks like Scikit-learn and Matplotlib.
3. **Automated Model Generation:** AI models are generated through an automated pipeline that utilizes the capabilities of LLMs like DeepSeek, Bard and GPT-4 (and their future versions).
4. **Manual AI Architecture Synthesis:** The AI architecture is manually crafted based on the developer's deep knowledge of AI, neural networks, deep learning, and programming tools such as Python, TensorFlow, Keras, Scikit-learn, and Matplotlib.

All development processes and tools are meticulously documented to ensure easy transfer and reuse of the solution. The AI models are then assessed and compared based on performance metrics such as specificity and sensitivity to determine their effectiveness in addressing the intended challenges.

AUTOMATED HEART DISEASE DIAGNOSIS MODULE

The second approach involving prompt engineering of generative AI was adopted by entering a generalized first prompt for system design instructions followed up by a specialized second prompt for AI model architecture design suggestions and source code by taking the number of features in the dataset into consideration. Recommendations of the LLM were then implemented to generate AI models for automated heart disease diagnosis on the basis of clinical measurements for possible refinement and incorporation into the comprehensive artificial intelligence-driven healthcare system introduced by Ekpar [27].

ChatGPT 4o mini tool was accessed for the submission of prompts and extraction of responses.

DATASET

Clinically validated data in the form of the publicly accessible Cleveland Heart Disease dataset were employed for the development of the AI models recommended by the LLMs. The dataset was first pre-processed to remove incomplete entries, resulting in 297 rows each containing 14 columns. The first 13 columns correspond to relevant clinical measurements for the participant or patient under consideration as per the row or data, namely, resting blood pressure, serum cholesterol, fasting blood sugar, resting electrocardiographic (ECG) results, maximum heart rate, exercise-induced angina presence, ST depression induced by exercise relative to rest, slope of peak exercise ST segment, number of major vessels (0 - 3) colored by fluoroscopy, heart performance, sex and age. The fourteenth column indicates the diagnosis (for the corresponding participant represented by the selected row of data) with a value of 0 indicating normal heart function while values 1, 2, 3 and 4 indicate the presence of heart disease. Since this is inherently a binary classification problem, further pre-processing of the dataset proceeded as follows: For each row, the value in the fourteenth column was mapped into 0 (absence of heart disease) for an original value of 0 and 1 (presence of heart disease) for original values of 1, 2, 3 and 4.

DATA AVAILABILITY

All the data employed in this study are available from **GitHub** at https://github.com/frankepar/cleveland_heart_disease_dataset/blob/main/dataset.zip and derived from the Cleveland Heart Disease dataset publicly available from the University of California Irvine Machine Learning Repository at <https://archive.ics.uci.edu/>.

FIRST PROMPT

Design a system for automated diagnosis of heart disease based on clinical measurements such as resting blood pressure, serum cholesterol and fasting blood sugar.

FIRST ChatGPT RESPONSE

Designing an automated system for diagnosing heart disease based on clinical measurements requires a combination of data collection, preprocessing, feature extraction, and machine learning models to make accurate predictions. Here's an



outline for a system based on clinical measurements such as resting blood pressure, serum cholesterol, and fasting blood sugar:

- 1. System Components

A. Data Collection

The first step is to gather clinical measurements from patients, such as:

- Resting Blood Pressure: Measures the force of blood against the artery walls when the heart is at rest.
- Serum Cholesterol Levels: High levels of total cholesterol, LDL, and triglycerides can be indicators of heart disease.
- Fasting Blood Sugar: The glucose levels after a period of fasting, high levels can indicate diabetes or pre-diabetes, which are risk factors for heart disease.

In addition to these, other clinical data such as age, sex, family history of heart disease, and lifestyle factors like smoking or exercise may also be included.

B. Data Preprocessing

- Handling Missing Values: Use imputation methods such as mean or median imputation to handle missing or incomplete data.
- Normalization/Standardization: Normalize the clinical measurements (blood pressure, cholesterol, blood sugar) so that they are within a similar range, using techniques like Min-Max scaling or Z-score normalization.
- Categorical Encoding: If there are categorical features (e.g., sex), encode them into numerical values using one-hot encoding or label encoding.

C. Feature Engineering

- Risk Factors: Based on clinical expertise, you can create new features that capture interactions between variables or convert continuous variables into categorical ones. For example:
 - Cholesterol Levels: Categorize serum cholesterol as low, normal, or high.
 - Blood Pressure: Categorize as normal, elevated, hypertensive, etc.
 - Fasting Blood Sugar: Categorize as normal, pre-diabetic, or diabetic.
- Composite Risk Scores: Combine multiple features to create a "heart disease risk score" based on expert knowledge or previous research studies.
- 2. Model Selection

Given that clinical data often involve a mixture of continuous and categorical features, and the goal is to predict a binary outcome (heart disease vs. no heart disease), machine learning models suitable for classification tasks can be applied. These models could include:

A. Traditional Machine Learning Models

- Logistic Regression: Simple, interpretable model that can provide probabilities of heart disease.
- Random Forest: Ensemble method that can handle complex relationships between variables and is robust to overfitting.
- Support Vector Machines (SVM): Effective for high-dimensional data, particularly if the data is non-linearly separable.
- K-Nearest Neighbors (KNN): Non-parametric method that can work well when the relationships between features are not easily defined.

B. Advanced Machine Learning Models

- Gradient Boosting Machines (GBM): Algorithms like XGBoost, LightGBM, or CatBoost, which are powerful for structured data and can handle non-linearities and interactions.
- Neural Networks: If you have a large dataset, a multi-layer perceptron (MLP) can also be used, although this requires more computational resources.
- 3. Model Training & Evaluation
- Train/Test Split: Split the dataset into training and testing subsets (e.g., 80% for training, 20% for testing) to evaluate the model's performance on unseen data.
- Cross-validation: Use cross-validation to ensure that the model's performance is consistent across different subsets of the data.
- Performance Metrics: Evaluate the model based on:
 - Accuracy: Proportion of correct predictions.
 - Precision/Recall: Especially important in healthcare, where false negatives (missing heart disease diagnoses) are critical.
 - F1-score: A balanced metric that combines precision and recall.
 - ROC-AUC: Receiver Operating Characteristic curve and Area Under Curve to measure the ability to discriminate between classes.

C. Hyperparameter Tuning



Use techniques such as Grid Search or Random Search to fine-tune the hyperparameters of the selected model to improve accuracy and avoid overfitting.

- 4. Deployment
- Model API: Once the model is trained and validated, deploy it as an API for integration with hospital systems or wearable devices.
- Real-time Data: The system should be capable of accepting real-time clinical data and provide instant heart disease risk predictions.
- User Interface: A dashboard for healthcare providers to review the patient's heart disease risk, along with relevant recommendations for further tests or lifestyle changes.
- 5. Continuous Improvement
- Model Monitoring: Continuously monitor model performance in the field and retrain it periodically with new data to ensure its accuracy.
- Feedback Loop: Incorporate feedback from healthcare professionals to further improve the system, adding additional features, or adjusting risk factors based on real-world experiences.
- Example Flow of the System
 1. Input: The patient provides clinical data: resting blood pressure, serum cholesterol levels, fasting blood sugar, age, gender, etc.
 2. Preprocessing: The system processes this data (normalization, encoding, handling missing values).
 3. Prediction: The trained machine learning model takes this data as input and predicts whether the patient is at high risk for heart disease or not.
 4. Output: The system displays the prediction result along with relevant recommendations for follow-up actions (e.g., further tests, lifestyle changes, etc.).
- Technologies & Tools to Use
- Programming Language: Python or R (commonly used in machine learning and healthcare).
- Libraries:
 - Scikit-learn for traditional machine learning models.
 - TensorFlow or PyTorch for deep learning models (if required).
 - Pandas and NumPy for data manipulation.
 - Flask or FastAPI for deploying the model as a web service.
- Cloud Infrastructure: AWS, Azure, or Google Cloud for hosting the model and managing the database.

This system would provide healthcare professionals with an automated tool to diagnose heart disease early, leveraging clinical measurements, and assist in personalized care planning.

SECOND PROMPT

Design an artificial neural network for binary classification of a set of 13 inputs.

SECOND ChatGPT RESPONSE

To design an artificial neural network (ANN) for binary classification with 13 input features, we can break it down into a few basic steps:

- **1. Input Layer**
- You have 13 features, so the input layer will consist of 13 neurons.
- Each neuron in this layer will represent one of the input features.
- **2. Hidden Layers**
- We can start with one hidden layer and decide the number of neurons in it. The number of neurons in the hidden layer(s) is often chosen through experimentation or by trial and error.
- For simplicity, let's assume we start with 64 neurons in the hidden layer. Depending on the complexity of your dataset, this can be adjusted.
- The activation function for the hidden layer will typically be a nonlinear function like ReLU (Rectified Linear Unit).
- **3. Output Layer**
- Since this is a binary classification problem, the output layer will have 1 neuron. The output will be either 0 or 1, depending on the classification.
- The activation function for the output layer will be a sigmoid function because it outputs values between 0 and 1, which is perfect for binary classification.



- **4. Architecture Overview**

- **Input Layer:** 13 neurons (corresponding to the 13 input features)
- **Hidden Layer:** 64 neurons (ReLU activation function)
- **Output Layer:** 1 neuron (Sigmoid activation function)

- **5. Loss Function**

- For binary classification, we typically use **binary cross-entropy** as the loss function.

- **6. Optimizer**

- A common optimizer for training neural networks is **Adam** because it adapts the learning rate during training.

- **7. Network Summary**

Here's how the architecture would look in a typical high-level framework like TensorFlow/Keras:

```
from tensorflow.keras.models import Sequential
```

```
from tensorflow.keras.layers import Dense
```

```
# Initialize the model
```

```
model = Sequential()
```

```
# Input layer (implicitly included in the first hidden layer)
```

```
model.add(Dense(64, input_dim=13, activation='relu'))
```

```
# Output layer
```

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

```
# Compile the model
```

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

```
# Summary of the model
```

```
model.summary()
```

- **8. Training**

- To train the model, you would use your dataset. Assuming X_{train} is the set of 13 input features and y_{train} contains the corresponding binary labels (0 or 1):

```
model.fit(X_train, y_train, epochs=50, batch_size=32, validation_split=0.2)
```

- **9. Evaluation**

- Once trained, you can evaluate the model using the test data (X_{test} and y_{test}):

```
model.evaluate(X_test, y_test)
```

- **10. Predictions**

- To make predictions on new data:

```
predictions = model.predict(X_new)
```

```
# Output will be a probability between 0 and 1. You can convert this to a class label by thresholding at 0.5
```

```
class_labels = (predictions > 0.5).astype(int)
```

- **11. Adjustments**

- Depending on the performance of the model, you may experiment with:

- Adding more hidden layers or neurons.
- Changing the activation functions (e.g., tanh, LeakyReLU).
- Tuning hyperparameters like learning rate, batch size, and the number of epochs.

This is a basic framework, and based on the specifics of your data and problem, you can refine and optimize the architecture further.

ARTIFICIAL NEURAL NETWORK (ANN) IMPLEMENTATION

The recommended artificial neural network (ANN) outlined in the second ChatGPT response was implemented strictly using the source code produced by the generative AI tool

Figure 2 depicts a generalized graphical representation of an artificial neural network could be wielded for the automated diagnosis of heart disease based on clinical measurements.

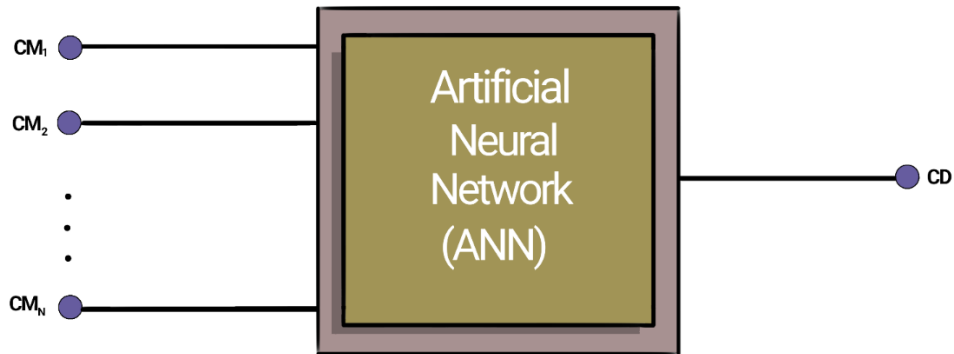


Fig. 2: Schematic Graphical Representation of Artificial Neural Network (ANN) Architecture. CM_1, CM_2, \dots, CM_N represent the inputs while CD represents the output indicating the suggested clinical diagnosis.

III. RESULTS

Note that the architecture of the artificial neural network recommended by ChatGPT in the second response is comparable with that custom-synthesized in the earlier study [27]. The earlier studies [27] – [30], [25] – [26] have handled a slew of system design and implementation considerations such as ethics and data management.

TensorFlow framework coupled with Keras Application Programming Interface (API) was used to implement the recommendations in the Python programming language [53] – [54].

Seventy percent (70%) of the original dataset was reserved for training of the AI model while the remaining 30% was reserved for validation and testing of the trained AI model. In order to mitigate bias, the rows in the dataset were shuffled at random. Training was carried out with an iteration of 500 epochs. Optimization was performed via the Adam Optimizer [55] – [56]. The learning rate used was 0.001 while the batch size employed was 32, both default settings.

The following equations can be utilized to calculate the precision, sensitivity or recall and specificity performance metrics, where TN refers to true positives, FP refers to false positives, FN refers to false negatives, and TN refers to true negatives. In this context, negative represents normal heart functioning or absence of heart disease while positive indicates the presence of heart disease.

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

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

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

As per the performance metrics, the trained AI model had a precision of 70%, a specificity of 77% and a sensitivity of 82% for the training and validation datasets. These performance metrics are not on par with those exhibited by the custom-built AI models [27] but compare favourably considering the fact that the AI models have not been optimized in any way but simply implemented as recommended by ChatGPT. Figure 3 illustrates a screenshot of relevant clinical measurements and the associated diagnostic decision as suggested by the trained AI model.

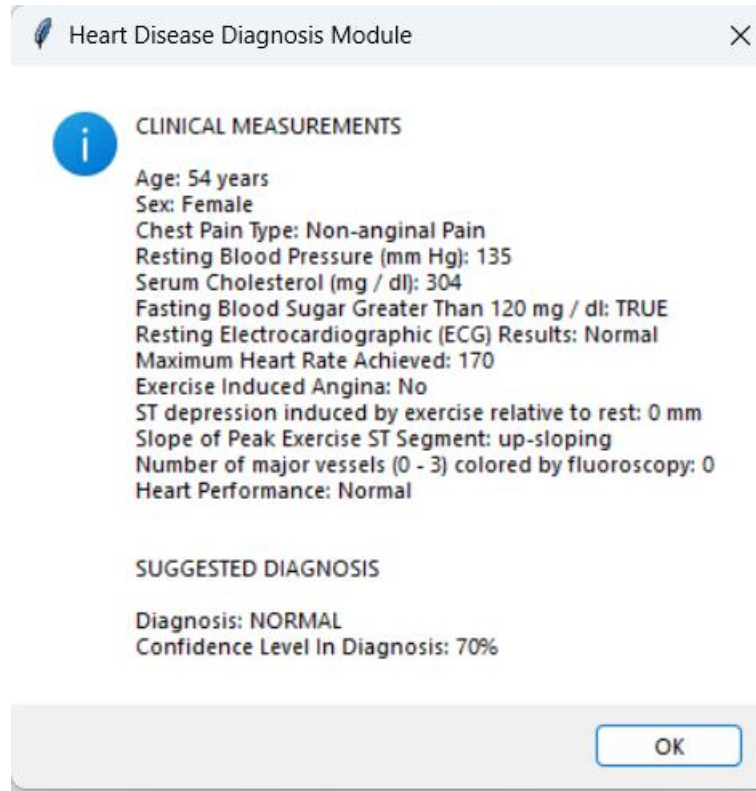


Fig. 3: Heart Disease Diagnosis Module of Scholar Medic Showing Clinical Measurements and Corresponding Suggested Diagnosis.

Implementing the comprehensive AI system described here will offer valuable insights for clinical decision-making, ultimately improving patient outcomes and quality of life. This is achieved by alleviating the economic, social, psychological, and physical burdens of conditions that can be predicted, prevented, detected early, diagnosed, treated, and managed more efficiently.

Medical professionals and their teams could generate Electronic Health Records (EHR), which would include clinical diagnostic data and EEG information. Additionally, EEG data may be collected during experiments using Brain-Computer Interfaces (BCIs). All collected data will adhere to ethical standards, be anonymized, and made publicly accessible in repositories alongside related research publications.

IV. CONCLUSION

This paper presented a system for the development of artificial intelligence models for automated heart disease diagnosis on the basis of clinical measurements by following through on recommendations extracted from generative artificial intelligence tools such as large language models via prompt engineering for the design of a system for the automated diagnosis of heart disease are followed through to construct suitable artificial intelligence models for the automated diagnosis of heart disease using clinical measurements. Trained, tested and validated using a publicly available heart disease dataset, the resulting system exhibited reasonable performance compared to expert-generated systems created via custom synthesis of artificial intelligence models. Further refinement and finetuning of the artificial intelligence models suggested by the generative artificial intelligence could enable the incorporation of the results into a comprehensive artificial intelligence-driven healthcare system.

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