Generative Artificial Intelligence-Assisted Automated Image-Based Pneumonia Diagnosis

FRANK EDUGHOM EKPAR[1, 2, 3]
[1] *Founder, Scholars University Ltd*
[2] *Associate Professor, Department of Computer Engineering, Rivers State University*
[3] *Principal Investigator, Department of Computer Engineering, Topfaith University*

Abstract- ***Prompt engineering is leveraged to get generative artificial intelligence systems such as large language models to proffer steps for the development of a system for automated image-based diagnosis of pneumonia using two-dimensional convolutional neural networks. An initial prompt is utilized to get the large language model to divulge the general design of the system. The initial response of the generative artificial intelligence system is then followed up by a prompt that precipitates the generation of specific instructions and source code for the construction, training and testing of convolutional neural networks that are cognizant of the nature of the datasets employed. The trained artificial intelligence models could be adapted through refinements in robustness and performance for incorporation as automated image-based pneumonia detection modules into a comprehensive artificial intelligence-driven healthcare system.***

Indexed Terms- ***Pneumonia, Automated Pneumonia Diagnosis, Artificial Intelligence (AI), Deep Learning (DL), Artificial Neural Network (ANN), Convolutional Neural Network (CNN), Generative Artificial Intelligence, Large Language Model (LLM), ChatGPT, DeepSeek, TensorFlow, Healthcare System.***

I. INTRODUCTION

According to the World Health Organization (WHO), pneumonia affects people of all age groups and is an acute respiratory infection that can precipitate mild to life-threatening maladies. It is the leading cause of infectious mortality among children globally [1] – [2].

Low-and middle-income countries (LMICs) must deal with a disproportionate burden of the disease owing to dilapidated facilities, resource constraints and low doctor-to-patient ratios aggravated by the brain drain in the form of the exodus of healthcare professionals eager to relocate to more developed countries in search of better living and working conditions.

As it is well known, early and accurate diagnosis could lead to more effective treatment regimens and improved health outcomes.

In addition to other methods of diagnosis, the processing of chest x-ray image sequences could yield valuable insights for diagnostic decision support.

Machine learning (ML) and artificial intelligence (AI) systems have been applied to the diagnosis and prediction of diseases [3] – [21]. These systems are typically prone to bias and limited global relevance as they are traditionally centered around developed countries and the populations therein.

Generative artificial intelligence systems like large language models can learn representations from data and generate inferences [22] – [23] and consequently are amenable to utilization in the task of disease diagnosis and prediction using computing systems.

This paper presents a system that leverages the recommendations of generative artificial intelligence systems such as large language models, obtained via appropriate prompt engineering processes, to build, train, test and validate artificial intelligence models comprising two-dimensional convolutional neural

networks (2D CNNs) for the automated detection of pneumonia given input chest x-ray images.

In earlier studies, Ekpar [24] – [27] introduced Scholar Medic, a comprehensive artificial intelligence-driven healthcare system with a modular design and support for innovative and advanced three-dimensional multilayer electroencephalography (Ekpar EEG) [28] – [30] that could revolutionize applications of electroencephalography (EEG) in medicine, rehabilitation, brain-computer interfaces (BCIs) [31] – [49] and myriads of other domains.

Scholar Medic [24] – [27] dramatically improves the productivity of medical doctors and other healthcare professionals by automating the prediction, detection, diagnosis and management of a wide variety of health conditions and offers a sustainable solution to the healthcare challenges experienced by low- and middle-income countries (LMICs) as well as other environments without such severe resource limitations.

Further refinement of the system developed in this study would enable its integration into Scholar Medic (comprehensive artificial intelligence-driven healthcare system) [24] – [27] as a module for the automated diagnosis of pneumonia on the basis of chest x-ray images.

II. MATERIALS AND METHODS

Participant Recruitment

Participants voluntarily decided to take part in the research studies that contributed to the development of the AI-powered healthcare system. Prior to their involvement, all participants provided informed consent.

Ethical Approval

The research studies received approval from the Health Research Ethics Committee at the Rivers State University Teaching Hospital. They adhered to all applicable ethical and regulatory standards. Publicly available data were utilized in compliance with the licensing terms established by their respective providers.

III. METHODOLOGY

Publicly available healthcare datasets can be enhanced by incorporating data from local experiments and data collection efforts. This merged dataset can then be used to train AI models that generate actionable predictions from new input. Notable examples of such publicly accessible healthcare datasets include those from the Centers for Disease Control, the University of California Irvine Machine Learning Repository, the American Epilepsy Society, and Kaggle.

Integrating local data improves model accuracy, minimizes biases, and fosters inclusivity and global relevance. A key element of this project is the fusion of diagnostic data, like electrocardiographic information, from local studies with EEG data, when applicable, utilizing both traditional and advanced three-dimensional multilayer EEG systems.

Ethical approval for data collection has been secured from the relevant research ethics committees in the regions where the studies are conducted. The project also collaborates with licensed medical professionals who have direct patient access and work with clinical teams. These experts are supplying anonymized clinical data to validate the AI models.

At the completion of training, the models will be integrated into a comprehensive healthcare system designed to provide clinical decision support to healthcare providers and enable brain-computer interfaces (BCIs).

The system will offer actionable insights and predictions from new clinical data, assisting in the early detection, diagnosis, treatment, prediction, and prevention of a variety of conditions, including preeclampsia, tuberculosis, chronic kidney disease, liver disease, diabetes, heart disease, stroke, autism, and epilepsy.

This project is dedicated to advancing open science, reproducibility, and collaboration, with all generated data being made publicly accessible on platforms such as GitHub.

IV. SYSTEM DESIGN AND IMPLEMENTATION

This paper introduces a healthcare system with a modular structure, where each health condition (e.g., chronic kidney disease, heart disease, liver disease, stroke, epilepsy, autism, etc.) is assigned to its own distinct module. This design not only provides flexibility in diagnosing and predicting future conditions but also facilitates easy module updates through the incorporation of new data. Additionally, Brain-Computer Interface (BCI) modules, such as those utilizing the motor imagery paradigm, can process EEG data to generate actionable commands and appropriate responses.

The system also describes a method for upgrading traditional EEG systems to advanced three-dimensional, multilayer EEG systems. These systems, developed by Ekpar and referred to as Ekpar EEG systems [28] - [30], are based on a conceptual framework that utilizes approximations of carefully selected bio-signal features to model or influence the biological systems involved.

For each module, AI models are created and trained with well-structured data, as outlined in the paper. These models incorporate genetic, environmental, and lifestyle factors to deliver more accurate assessments of the participants' conditions.

Figure 1 provides a conceptual overview of the system's design.

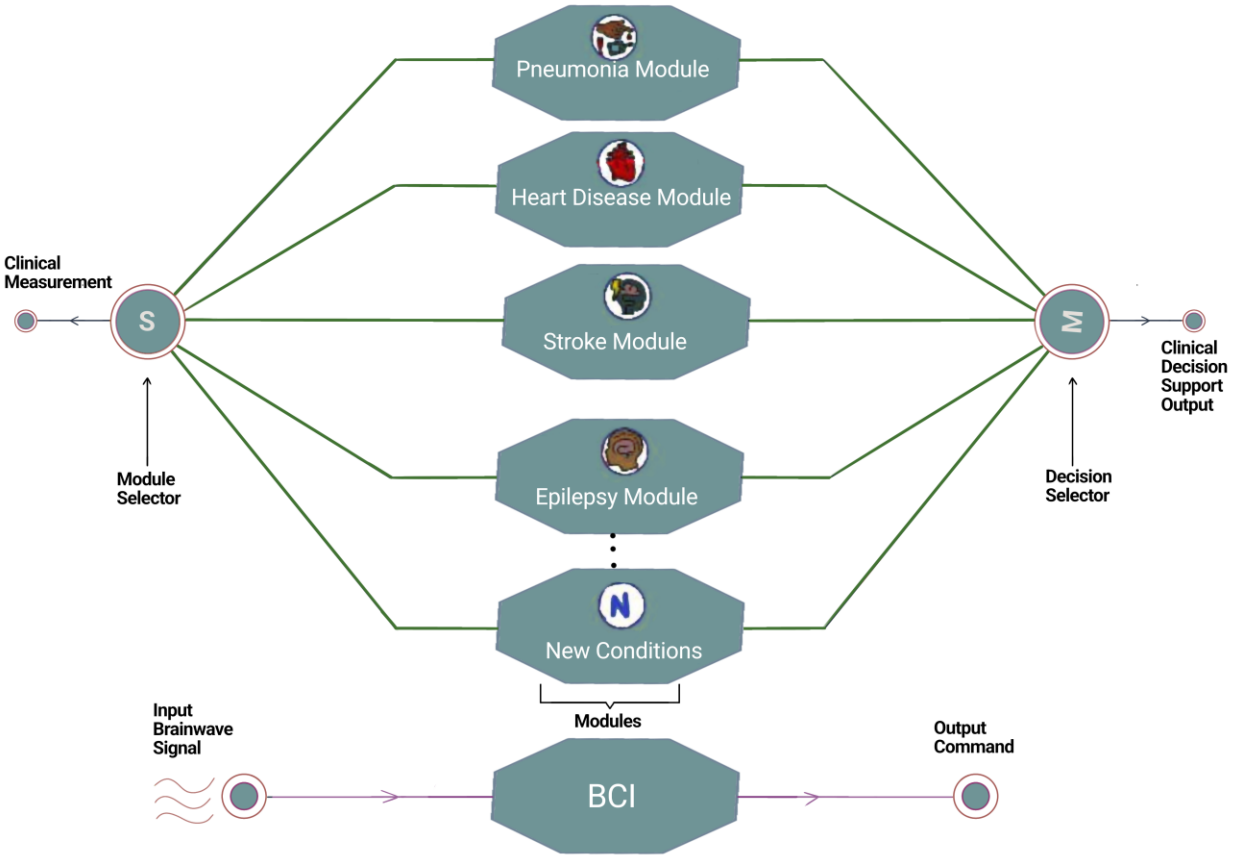

Fig. 1: System Schematic Design Diagram for the Comprehensive AI-Driven Healthcare Solution and Brain Computer Interface System. The New Conditions component represents additional health conditions that can be incorporated into the solution via new modules.

The development of AI models follows four distinct approaches, as described below:

1. Direct Use of Large Language Models (LLMs): Large Language Models (LLMs), such as GPT-4 and DeepSeek act as inference engines that process data formatted into multidimensional input vectors. Fine-tuning the LLMs may also be part of the development process.

2. Prompt Engineering with LLMs: LLMs like GPT-4, Bard and DeepSeek (including future versions) are used for prompt engineering to outline the necessary steps for building the AI system. Developers then apply their expertise in AI, neural networks, deep learning, and tools such as Python, TensorFlow, Keras, Scikit-learn, and Matplotlib to implement these steps.

3. Automated Model Generation: Specific AI models are generated automatically through a pipeline that utilizes the capabilities of LLMs, such as Bard, GPT-4 and DeepSeek (and future versions).

4. Manual AI Architecture Design: The AI architecture is created based on the developer's extensive knowledge of AI, neural networks, deep learning, and programming frameworks like Python, TensorFlow, Keras, Scikit-learn, and Matplotlib.

All tools and processes used in the development are thoroughly documented to ensure the solution can be easily transferred and reused.

The performance of the resulting AI models is evaluated using metrics such as accuracy, specificity, and sensitivity to assess their effectiveness in solving the problems encountered.

V. AUTOMATED PNEUMONIA DIAGNOSIS MODULE

Adopting the second approach, ChatGPT is prompted to generate specifications for the design of the system.

The initial prompt seeks to elicit general-purpose recommendations for the overall design of the system. This is followed by a more specific follow-up prompt that seeks specifications for the two-dimensional convolutional neural network that was suggested in the response to the initial prompt.

Finally, the recommended steps are followed meticulously, including the utilization of the exact source code generated by ChatGPT.

The following sections provide a brief description of the dataset and immediately precede the actual initial and follow-up ChatGPT prompts and the corresponding responses from ChatGPT.

VI. DATASET

A chest x-ray image dataset containing 5,840 images with varying dimensions was obtained from the publicly accessible Kaggle dataset repository.

Of the 5,840 images in the original dataset, 4,265 images were in a class with the presence of pneumonia while 1,575 were in a class representing normal functioning or the absence of pneumonia.

Preprocessing was implemented to effectively reduce the dimensions of each image in the dataset to 180 pixels by 180 pixels for faster and more efficient processing.

Figure 2 illustrates a suite of randomly selected images from the chest x-ray image dataset.

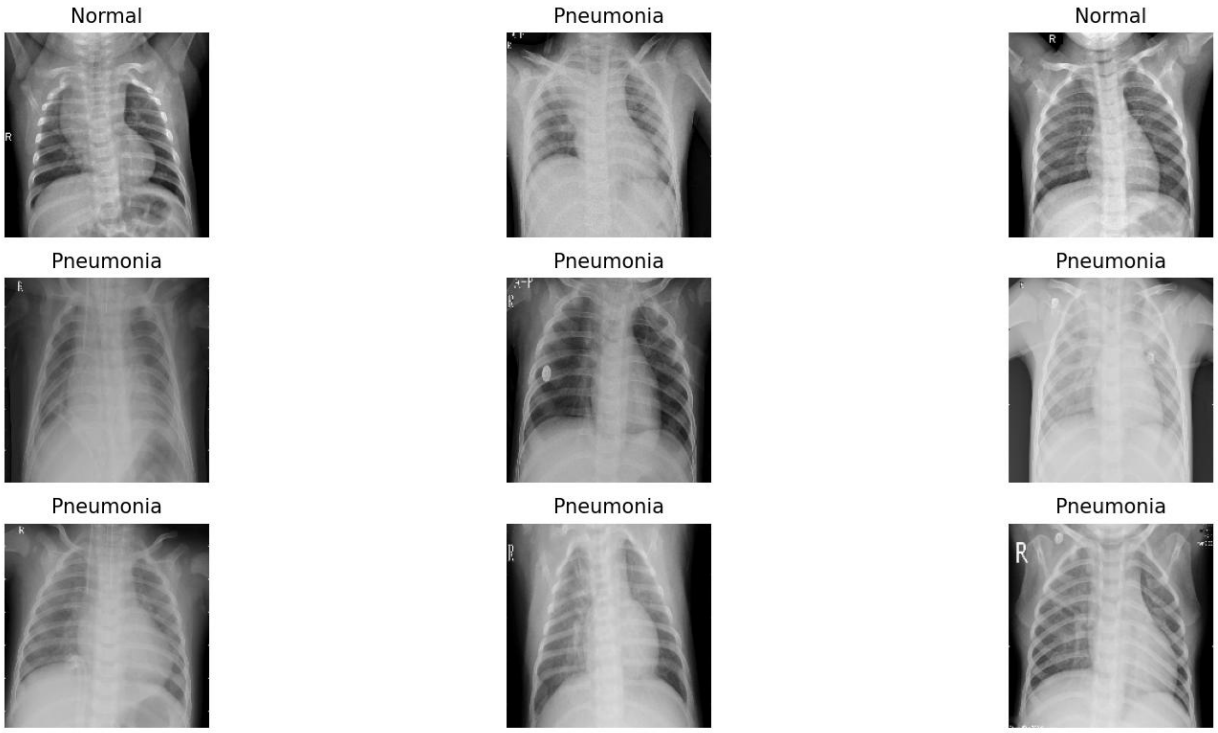

Fig. 2: A random subset of the original dataset indicating the class (Pneumonia or Normal) of the image.

VII. DATA AVAILABILITY

The chest x-ray image dataset employed in this study is available from Kaggle at https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia/data.

INITIAL ChatGPT PROMPT

Design a system for automated image-based diagnosis of pneumonia.

INITIAL ChatGPT RESPONSE

Automated Image-Based Diagnosis System for Pneumonia
This system is designed to automatically detect pneumonia from chest X-ray images using deep learning techniques. The system consists of five main components: data acquisition, preprocessing, model training, diagnosis, and reporting.

1. System Architecture
A. Data Acquisition

- Input: Chest X-ray images (CXR) collected from hospitals and medical databases (e.g., NIH, RSNA, or private datasets).
- Data Sources: PACS (Picture Archiving and Communication System), cloud storage, or direct uploads from radiology equipment.

B. Image Preprocessing

- Noise Reduction: Use image filters to remove artifacts and enhance clarity.
- Normalization: Convert images to a standard size (e.g., 224×224 or 512×512 pixels).
- Augmentation: Apply transformations like rotation, flipping, contrast adjustment, and cropping to improve model generalization.
- Segmentation: Use U-Net or similar architectures to focus on lung regions and remove irrelevant areas.

C. Model Training (Deep Learning-Based Classification)

- Architecture: Convolutional Neural Networks (CNNs) such as ResNet, DenseNet, VGG16, or custom-built models.

- Transfer Learning: Fine-tune pre-trained models (e.g., ResNet50, EfficientNet) on pneumonia datasets.
- Training Process:
  - Dataset: Labeled X-ray images (Normal vs. Pneumonia, or Bacterial vs. Viral Pneumonia).
  - Loss Function: Binary cross-entropy (for two classes) or categorical cross-entropy (for multiple classes).
  - Optimization: Adam or SGD with a learning rate scheduler.
  - Validation: K-fold cross-validation to prevent overfitting.
  - Evaluation Metrics: Accuracy, sensitivity, specificity, AUC-ROC.

D. Pneumonia Diagnosis (Inference Engine)

- Input: New chest X-ray images from patients.
- Processing:
  - Preprocess the image.
  - Pass it through the trained model.
  - Output a probability score (e.g., likelihood of pneumonia).
- Thresholding: If the probability exceeds a set threshold (e.g., 0.7), classify it as pneumonia.

E. Reporting & Decision Support

- Automated Report Generation:
  - Normal vs. Pneumonia classification result.
  - Confidence score.
  - Heatmap overlay (using Grad-CAM) to highlight affected regions.
- Integration with Medical Systems:
  - Send results to Electronic Health Records (EHR).
  - Allow radiologists to review and validate.
- Doctor Feedback Loop:
  - Collect feedback from radiologists for model improvement.
  - Use human-verified cases for continuous learning (active learning approach).

2. Deployment & Scalability

A. Deployment Options

- Cloud-Based (e.g., AWS, Azure, Google Cloud): Scalable and accessible remotely.
- Edge AI (On-Premise): Deploy on local hospital servers for faster diagnosis.
- Mobile App/Web Portal: Doctors can upload images and get instant results.

B. Security & Compliance

- HIPAA/GDPR Compliance: Ensure patient data privacy.
- Secure Data Transmission: Encrypt patient X-ray images and reports.
- Access Control: Restrict access to authorized medical professionals.

3. Performance Optimization & Challenges

A. Model Performance Enhancement

- Data Balancing: Handle class imbalance using oversampling or synthetic image generation (GANs).
- Explainability: Use AI explainability techniques like Grad-CAM or SHAP to make predictions interpretable.
- Real-Time Processing: Optimize inference speed using TensorRT or ONNX for deployment.

B. Challenges

- Variability in X-ray Quality: Differences in X-ray machine settings and image resolution.
- Distinguishing Pneumonia from Other Diseases: Differentiate pneumonia from tuberculosis or lung cancer.
- Regulatory Approval: Compliance with medical AI regulations (FDA, CE marking).

4. Future Enhancements

- Multi-Disease Detection: Extend the system to detect other lung diseases (e.g., tuberculosis, COVID-19).
- Self-Learning AI: Continually improve model accuracy using real-world patient data.
- Integration with Wearable Devices: Connect with smart devices for continuous monitoring.

CONCLUSION

This system leverages deep learning for automated pneumonia diagnosis, improving speed, accuracy, and accessibility. By integrating it into medical workflows, it can assist radiologists, reduce diagnostic errors, and enhance patient care.

FOLLOW-UP ChatGPT PROMPT

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

FOLLOW-UP ChatGPT RESPONSE

Here's a simple yet effective Convolutional Neural Network (CNN) for classifying images of size 180×180 pixels into two classes (binary classification). The network is built using TensorFlow and Keras.

CNN Architecture

- Conv Layer 1: 32 filters, (3×3) kernel, ReLU activation
- MaxPooling Layer 1: (2×2) pool size
- Conv Layer 2: 64 filters, (3×3) kernel, ReLU activation
- MaxPooling Layer 2: (2×2) pool size
- Conv Layer 3: 128 filters, (3×3) kernel, ReLU activation
- MaxPooling Layer 3: (2×2) pool size
- Flatten: Converts feature maps into a 1D vector
- Fully Connected Layer (Dense): 128 neurons, ReLU activation
- Dropout: 50% dropout to prevent overfitting
- Output Layer: 1 neuron (sigmoid activation for binary classification)

Implementation in TensorFlow/Keras

```
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers

# Define the CNN model
def build_model():
    model = keras.Sequential([
        # First convolutional block
        layers.Conv2D(32, (3,3), activation='relu', input_shape=(180, 180, 3)),
        layers.MaxPooling2D(2, 2),

        # Second convolutional block
        layers.Conv2D(64, (3,3), activation='relu'),
        layers.MaxPooling2D(2, 2),

        # Third convolutional block
        layers.Conv2D(128, (3,3), activation='relu'),
        layers.MaxPooling2D(2, 2),

        # Flatten layer
        layers.Flatten(),

        # Fully connected layer
        layers.Dense(128, activation='relu'),
        layers.Dropout(0.5),  # Prevent overfitting

        # Output layer (sigmoid for binary classification)
        layers.Dense(1, activation='sigmoid')
    ])

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

    return model

# Create the model
model = build_model()

# Display model summary
model.summary()
```

Training the Model

You can train this model using:

```
# Assume train_data and val_data are preprocessed datasets
model.fit(train_data, epochs=10, validation_data=val_data)
```

- train_data and val_data should be tf.data.Dataset or a generator with image-label pairs.
- Use Data Augmentation to improve generalization if needed.

Why This Design?

- Small & Efficient: Uses 3 convolutional layers, reducing parameters.
- ReLU Activation: Prevents vanishing gradient issues.
- Dropout: Helps reduce overfitting.
- Binary Classification Optimized: Uses sigmoid activation and binary_crossentropy loss.

VIII. TWO-DIMENSIONAL CONVOLUTIONAL NEURAL NETWORK (2D CNN) ARCHITECTURE

The 2D CNN was designed in accordance with the specifications suggested by ChatGPT in the response to the follow-up prompt.

The architecture of the 2D CNN is highlighted in the enclosed ChatGPT response.

Figure 3 is a generalized depiction of the 2D CNN showing the key blocks and components.

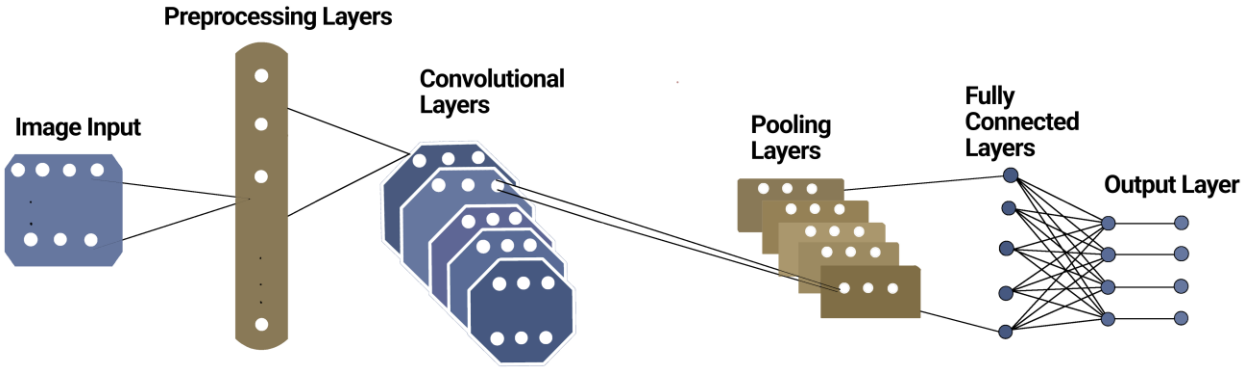

Fig. 3: Generalized Schematic Graphical Representation of Two-dimensional Convolutional Neural Network (2D CNN) Architecture Adapted for Image Classification.

IX. RESULTS

The python programming language source code generated by ChatGPT was utilized to implement the 2D CNN within the TensorFlow platform and the Keras Application Programming Interface [50] – [51].

Splitting of the dataset into training and validation/testing sets occurred on the basis of 80% to 20%, respectively.

Training was accomplished as recommended by ChatGPT over 10 epochs using binary entropy loss function and Adam Optimizer [52] – [53].

Figure 4 is a plot of the performance metrics indicating the history of the training and validation accuracy and loss over epochs.

As is evident from Fig. 4, the performance of the system on the training dataset dovetailed with the performance of the system on the validation dataset with the accuracy reaching approximately 95%.

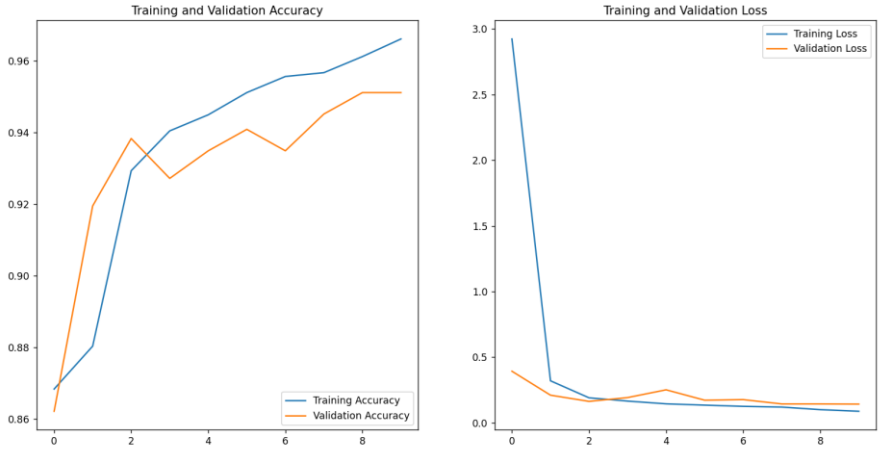

Fig 4: Performance Metrics: History of Training and Validation Accuracy and Loss.

CONCLUSION

A system for automated image-based diagnosis of pneumonia was created by harnessing prompt engineering of generative artificial intelligence systems such as large language models which generated recommendations that were followed through to design, construct, train, test and validate artificial intelligence models comprising two-dimensional convolutional neural networks. With further improvements including the utilization of local datasets, the trained artificial intelligence models could be integrated into a comprehensive artificial intelligence-driven healthcare system as modules for the automated image-based detection of pneumonia to inform clinical decision making.

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