# **Application of AI Methods for Multi-modal Disease Diagnosis**

## **Abstract:**

We developed AI techniques to detect these diseases with multi-modal data. The solution and project merge patients' health records and X-ray images to detect diseases including heart disease, diabetes, stroke, and pneumonia. High accuracy is achieved in classifying these diseases using machine learning (ML) and deep learning (DL) models. It aims to develop a decision-support tool that can help with early diagnostics as well as continuous health monitoring. This hybrid approach allows for a comprehensive diagnosis that incorporates tabular and image data (X-ray images) from patients. Finally, this report underscores the impact of AI on healthcare, types of models, and potential implications of these technologies for improved healthcare outcomes.

## **Introduction:**

Artificial intelligence (AI) has revolutionized many industries, and healthcare is no exception. In recent years, AI methods have made significant strides in disease detection, diagnosis, and even in predicting patient outcomes. Early diagnosis, particularly of chronic diseases, has become a critical element in improving patient health and reducing healthcare costs. In this project, we focus on the application of AI techniques for disease diagnosis, specifically using two types of data: patient health records and X-ray images. The diseases under consideration include heart disease, diabetes, stroke, and pneumonia.

The importance of AI in healthcare cannot be overstated. AI models can analyze vast amounts of data, including patient demographics, medical history, lifestyle choices, and even radiographic images, to predict the likelihood of disease. Early diagnosis through these AI-powered tools could lead to more effective treatments, better resource management, and ultimately, improved patient outcomes.

This project addresses two key aspects of AI in healthcare. First, it focuses on using patient health data to predict the presence of diseases like heart disease, stroke, and diabetes. Second, it explores the use of convolutional neural networks (CNN) and generative models to classify pneumonia using X-ray images. The interdisciplinary nature of this work—combining healthcare knowledge with advanced AI techniques—shows the potential for AI to significantly enhance diagnostic accuracy.

## **Background:**

### AI in Healthcare

AI, particularly machine learning (ML) and deep learning (DL), has found widespread application in healthcare. Predictive analytics, powered by machine learning, enables the identification of high-risk patients before symptoms arise. Models such as decision trees, support vector machines (SVMs), and ensemble methods have been widely used for classifying medical data and predicting the risk of diseases. On the other hand, deep learning techniques, such as convolutional neural networks (CNNs), have proven particularly effective in medical imaging tasks, enabling the detection of diseases like pneumonia, cancer, and brain disorders from radiographic images.

### **Disease Diagnosis Methods**

The diseases considered in this report—heart disease, diabetes, stroke, and pneumonia—pose significant health risks globally. Early detection can significantly improve treatment outcomes.

* Heart Disease: The condition involves the narrowing or blockage of blood vessels, which can lead to heart attacks or strokes. Common risk factors include high blood pressure, smoking, and diabetes.
* Diabetes: A chronic condition that affects how the body processes blood sugar, diabetes is often linked with obesity, poor diet, and lack of physical activity.
* Stroke: A stroke occurs when blood flow to the brain is disrupted, either by a blockage or a rupture in blood vessels. Early detection of stroke risk factors can help in preventing the occurrence of strokes.
* Pneumonia: A lung infection typically caused by bacteria or viruses, pneumonia can be diagnosed using chest X-ray images. Early detection is essential for preventing severe complications, especially in pediatric populations.

### **Tabular Data Analysis**

Tabular data, such as patient health records, is frequently used in medical diagnostics. Features like age, weight, blood pressure, smoking habits, and other medical conditions are collected to assess a patient's likelihood of developing various diseases. However, not all features in this dataset are equally important. Feature selection methods are essential to ensure that only the most relevant attributes are used for classification tasks.

### **Image-based Diagnosis**

Medical imaging, particularly X-ray images, is a crucial aspect of diagnosing various diseases. In this project, CNNs are employed to classify X-ray images for pneumonia detection. Additionally, generative models such as variational autoencoders (VAE) and generative adversarial networks (GAN) are used to clean noisy images, enhancing the performance of the diagnostic model.

## **Methodology and Data:**

### **Data Description**

Patient Health Dataset: The tabular dataset used for heart disease, stroke, and diabetes diagnosis includes features such as high blood pressure (HighBP), cholesterol levels (HighChol), body mass index (BMI), smoking habits, and other medical conditions. This dataset requires preprocessing to handle missing values and ensure that features are normalized or standardized for use in machine learning models. Feature selection methods are applied to choose the most relevant features for predicting the presence of the diseases in question.

Pneumonia X-ray Dataset: The pneumonia dataset consists of 5,856 pediatric chest X-ray images. These images are 28x28 grayscale images, with two classes: normal and pneumonia. The dataset is split into training, validation, and test sets, with 90% of the images used for training, 10% for validation, and the remaining 10% for testing. The raw images are preprocessed by resizing, normalization to improve the model's ability to generalize.

### **Model Development**

Tabular Data Models: For binary classification (diabetes, stroke, heart disease), logistic regression, decision trees, and random forests are trained on the selected features from the health dataset. These models help predict the presence or absence of a disease based on patient health records. For multi-class classification, a model is trained to detect multiple diseases simultaneously using a multi-class classification scheme.

### **X-ray Image Models:**

Classification Model (CNN): The CNN architecture used for pneumonia detection involves multiple convolutional layers, pooling layers, and fully connected layers, followed by a softmax layer for classification into two categories: normal and pneumonia.

Generative Model (VAE/GAN): A generative model is employed to enhance image quality. By introducing noise to the X-ray images, the model learns to reconstruct the clean, original images, which are then fed into the CNN for classification.

### **Evaluation Metrics**

For classification models, the performance is evaluated using metrics such as accuracy, precision, recall, F1 score, and the confusion matrix. These metrics provide insights into the model's ability to correctly classify both positive and negative instances.

For the generative model, the evaluation includes image reconstruction metrics such as Root Mean Square Error (RMSE) and Structural Similarity Index (SSIM), which quantify the quality of the reconstructed images.

## **Analysis and Discussions:**

### **Model Performance**

The models developed for both disease prediction and pneumonia detection exhibit promising results. The binary classification models for heart disease, stroke, and diabetes show high accuracy and precision, with early stopping techniques preventing overfitting and saving training time. The pneumonia detection model, based on CNN, achieves excellent performance in classifying X-ray images into normal and pneumonia categories. The generative model improves the quality of the X-ray images, leading to better classification accuracy.

### **Impact on Healthcare**

AI-driven disease diagnosis tools have the potential to accelerate the health monitoring process, reduce human error, and support medical professionals in their decision-making. By automating disease detection, these tools can save time and resources, especially in busy healthcare settings. The integration of both tabular and image-based data provides a comprehensive approach to diagnosing diseases, which could lead to more accurate and reliable results.

### **Ethical Considerations**

While AI can enhance healthcare practices, ethical issues must be considered. The use of patient health data raises concerns about privacy and data security. It is crucial to ensure that AI models comply with data privacy laws and regulations. Additionally, AI systems should be seen as tools to support healthcare professionals rather than replace them, emphasizing the importance of human oversight in the decision-making process.

## **Conclusions and Suggestions for Future Work:**

### **Major Findings**

This project demonstrates the effectiveness of AI techniques in diagnosing diseases like heart disease, stroke, diabetes, and pneumonia. The integration of both tabular data and image-based data allows for a comprehensive approach to disease detection, improving diagnostic accuracy and decision-making processes in healthcare.

### **AI Solutions**

The AI models developed show good accuracy and generalization. However, challenges such as data quality, class imbalance, and feature selection need to be addressed to further improve the models. Despite these challenges, the use of AI in healthcare holds great promise, with potential applications in early disease detection, risk prediction, and patient monitoring.

### **Future Work**

Future research could focus on increasing the dataset size to improve model accuracy. Additionally, integrating additional data sources, such as genetic information, could further enhance the models' ability to predict disease risk. Exploring more advanced generative models and real-time diagnostic tools would be valuable for deploying AI systems in healthcare settings.