Project name: #2**Image Classification for Medical Diagnosis**

Problem statement: AI is used in healthcare to classify images like X-rays, MRIs, or skin lesions. In this project, the goal is to classify images into categories such as healthy vs diseased.

What was the problem:

The core problem in traditional medical diagnosis via imaging—such as X-rays, CT scans, and MRIs—lies in the immense volume and complexity of the visual data generated. Clinicians and radiologists face massive workloads, operating under high-pressure conditions where fatigue and human perceptual limits can lead to diagnostic delays or subtle errors. Identifying minute cancerous nodules, tiny fractures, or early signs of complex diseases requires intense focus and consistent precision, a task that becomes overwhelmingly difficult when reviewing thousands of images daily. Furthermore, in acute care settings, speed is crucial; waiting hours for an expert interpretation can critically delay life-saving intervention. This creates a significant gap between the immediate availability of image data and the timely, highly accurate interpretation required for optimal patient outcomes. **The Role of AI and Machine Learning** specifically Machine Learning (ML) models like Deep Learning and Convolutional Neural Networks (CNNs), offers a transformative solution. CNNs are trained on massive, labeled datasets of medical images, allowing them to automatically learn and identify complex, hierarchical features indicative of disease. In image classification, the model can instantly categorize an image—for example, distinguishing between a benign and a malignant tumor, or identifying the presence of a stroke—often achieving diagnostic speed in seconds and accuracy comparable to human experts in specific tasks.

AI dramatically addresses the challenges of speed and consistency. It serves as an invaluable secondary layer of analysis, performing sophisticated triage by prioritizing critical cases, flagging subtle regions of interest for the clinician, and reducing the risk of human error. This semi-autonomous approach accelerates critical decision-making and streamlines the clinical workflow, ultimately acting as a powerful tool to augment, not replace, the diagnostic capability of medical professionals.

Collection of data:

To train and validate my AI models, I utilized publicly available, open-source datasets:

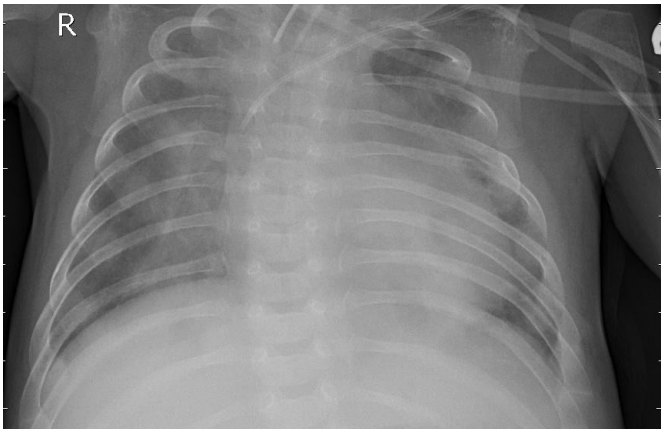
• Chest X-Ray (Pneumonia): https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia

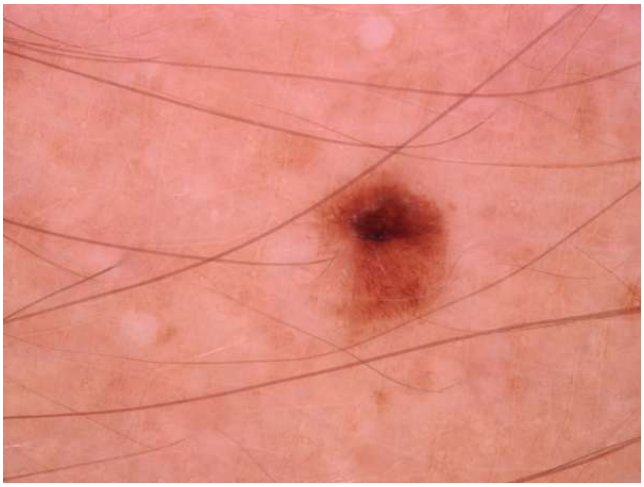
• Skin Cancer (HAM10000): https://www.kaggle.com/datasets/kmader/skin-cancer-mnist-ham10000

Data Type: Image data in JPG/PNG formats.

API Used: TensorFlow and Keras's ImageDataGenerator were used for efficient loading and real-time augmentation

Below are some sample snapshots included in dataset.





Data preprocessing:

The raw data in the dataset often needs refinement and correction so in this step I made sure to do :

- Resizing: All images resized to 224x224 pixels.

- Normalization: Pixel values scaled to 0–1 for stable and faster training

- Augmentation: Applied rotation, zoom, horizontal and vertical flips to prevent overfitting.

- Imbalance Handling: Used class weights to mitigate dataset imbalances. Purpose: Enhance model generalization and reduce overfitting.

This data is then fed in the models and in turn used in the dashboard to display correct information.

Data Visualization:

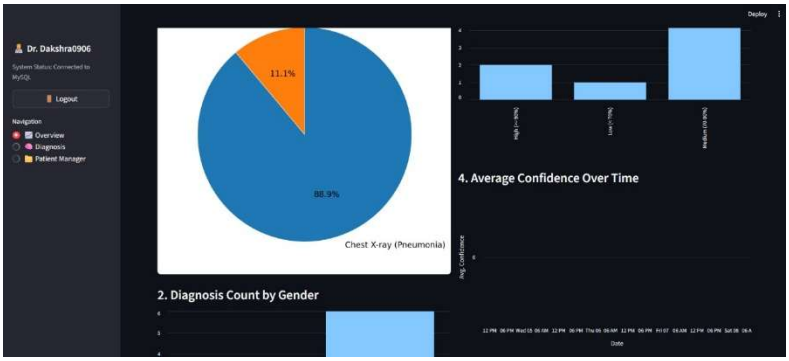
Good visualization of data helps understand dataset characteristics:

- Visualized sample images from each dataset.

- Checked class distribution using bar plots.

- Identified minor class imbalances, managed via weighted training. Tools: matplotlib and seaborn.

The data is displayed in the dashboard in a graphical and user-friendly manner using bar charts and pie charts. Below is an attached sample of the same.



Machine learning model:

I have applied and trained the machine learning models with data to provide the user with good accuracy results when an actual picture of pneumonia or skin cancer is uploaded. To achieve this I have a,

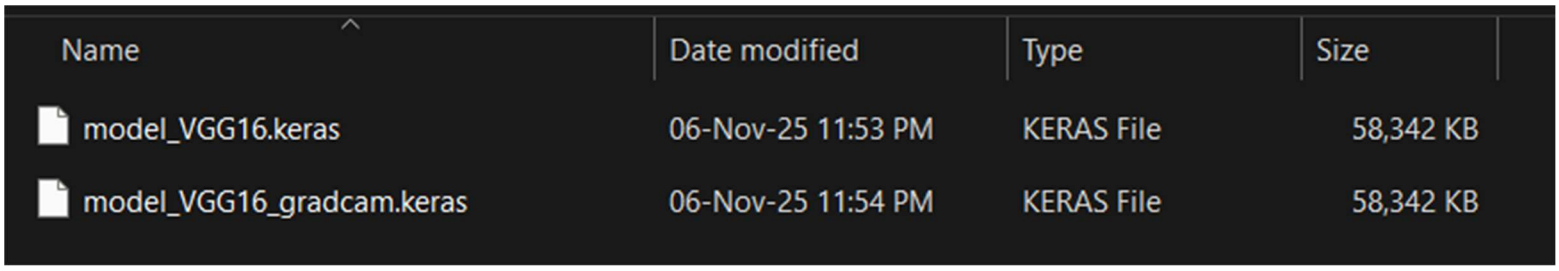
Approach: Transfer learning using pre-trained CNNs:

- Base Models: VGG16, ResNet50, EfficientNetB0.

- Custom Architecture: Added global average pooling, dense layers, dropout, and output layers (sigmoid for binary, SoftMax for multi-class).

- Training: 10 epochs with early stopping. Best Model: EfficientNetB0 achieved 97% accuracy for pneumonia detection.

With help of these models the app defines the result of the photo uploaded with accuracy of the decision labeled. Below is example of the model files.



Name	Date modified	Type	Size
model_VGG16.keras	06-Nov-25 11:53 PM	KERAS File	58,342 KB
model_VGG16_gradcam.keras	06-Nov-25 11:54 PM	KERAS File	58,342 KB

Model performance:

The performance of the trained model was calculated and found to be:

Results:

Dataset	Accuracy
Chest X-Ray (Pneumonia)	97.2%
Skin Cancer (HAM10000)	~88%

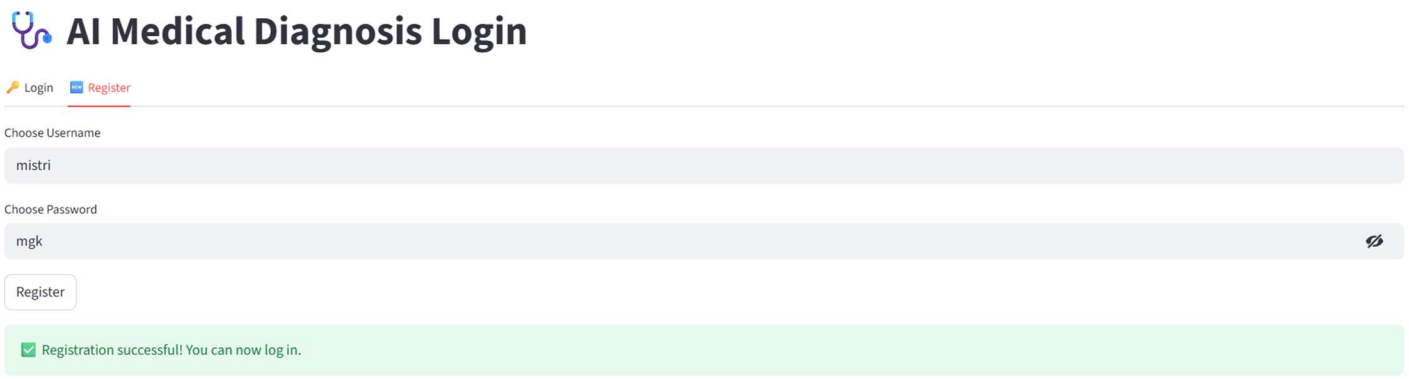
Metrics Evaluated: Accuracy, Loss, Precision, Recall, AUC.

Best Model: EfficientNetB0 outperformed others across all metrics.

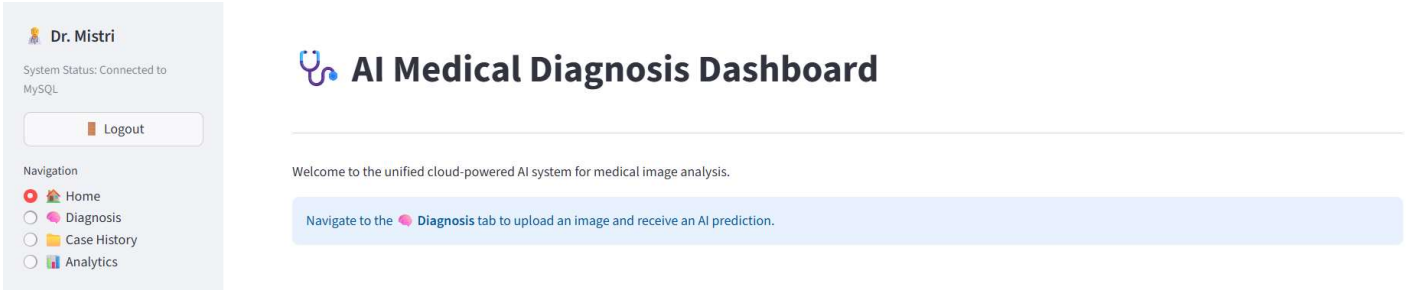
Efficiency of the model plays a major role in deciding the output of the decision of the uploaded photo if the diseases is present or not is yes then with how much percentage.

Deployment:

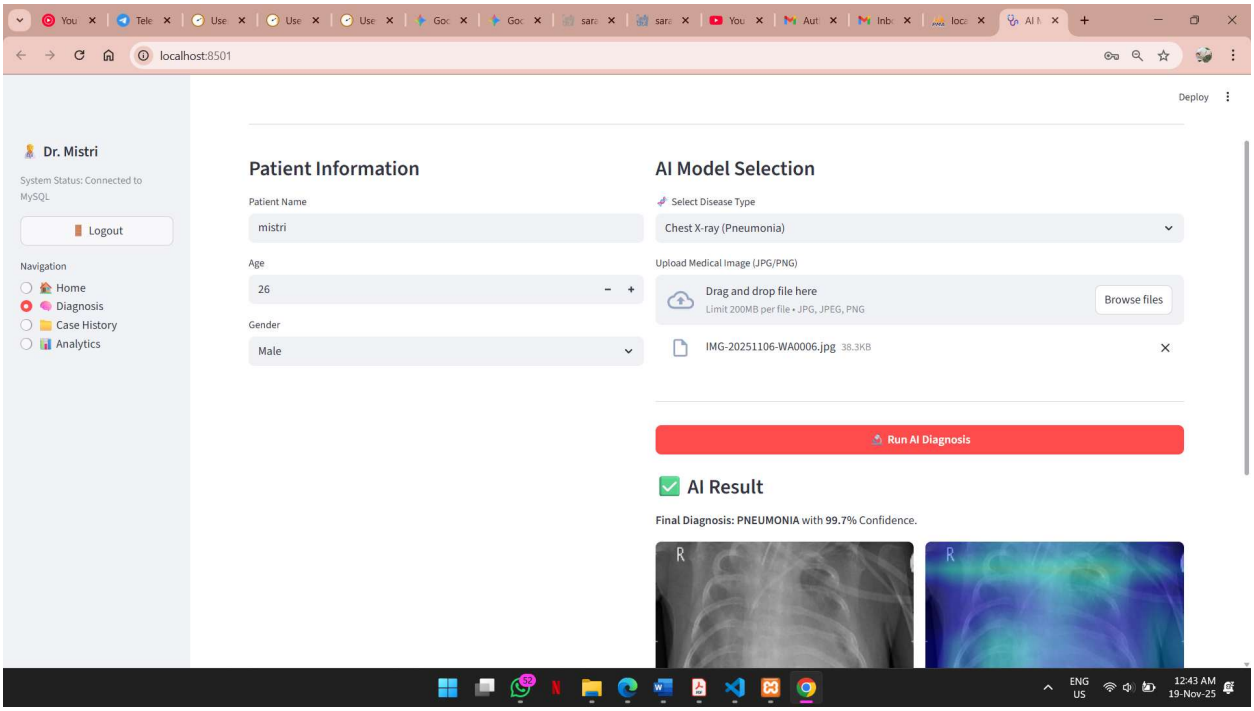
At the start of the app the user is greeted with a login interface where they login with their id which is stored in the Database which is accessible by the app



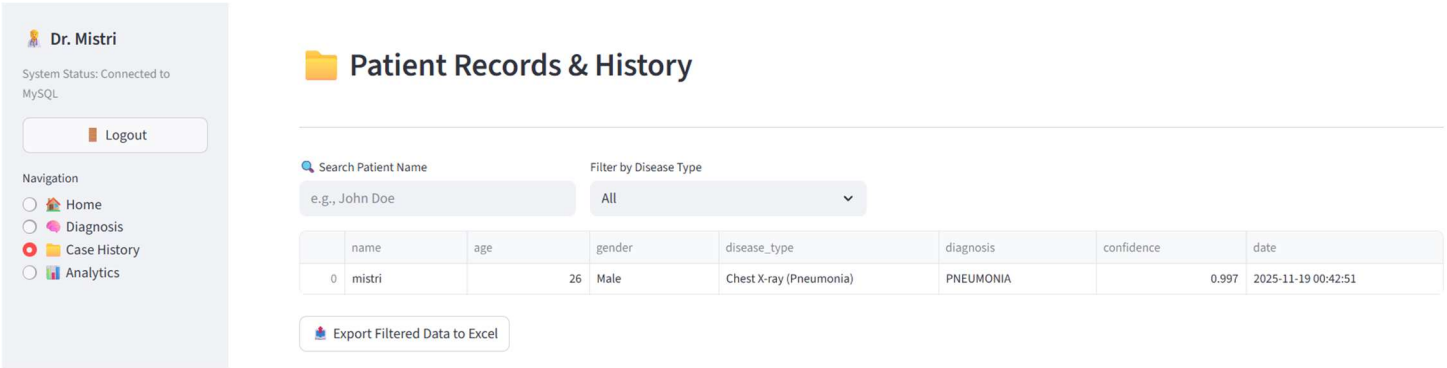
Upon successful login this is what is seen



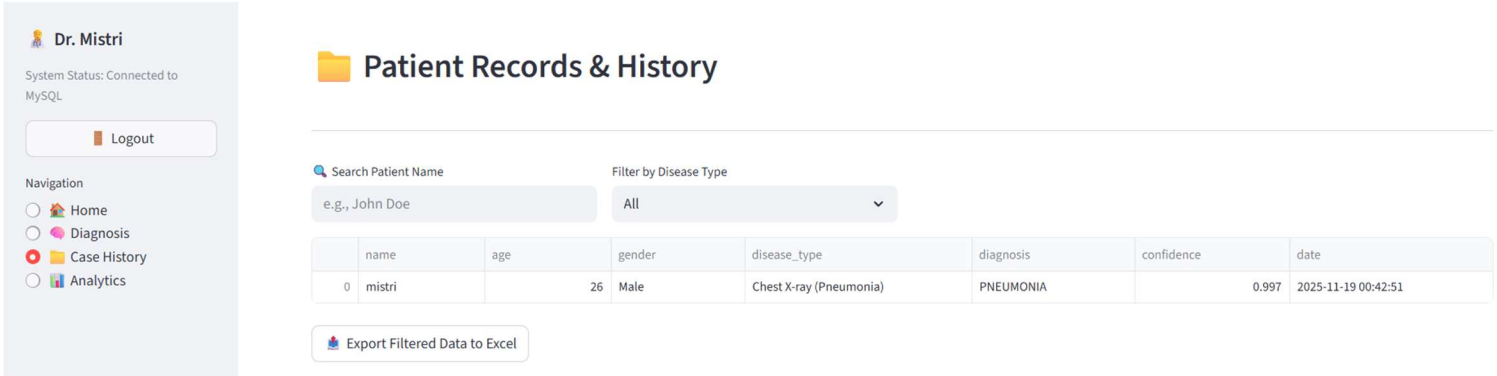
Then the user can drop the jpg and the model reads and compares it to the other stored data in the dataset and then it produces results which is then saved into sql database.



The past case history of all patients is also available to see in the dashboard.



Also the analytics are available in a graphical format for list of patients.



Conclusion:

This is how I crated a dashboard to cater to all people, be user friendly and practical. I wanted it to be very easy to use and provide accurate results.

The AI-based image classification system demonstrates high accuracy, reliability, and interpretability, making it an effective tool for assisting in pneumonia and skin cancer diagnosis.

Sources:

-Kaggle was used to downloaded dataset to train models

-Chat gpt was used to solve loopholes and errors.