Let's Start

INCEPTIA

A NATIONAL LEVEL HACKATHON

CT Image Denoising

PROJECT TITLE – CT Image Denoising

SELECTED DOMAIN – Artificial Intelligence & Machine learning

TEAM NAME – UNO REVERSE

Problem Statement

Understanding the Problem

In medical imaging, particularly brain CT scans, image quality is often compromised by two prevalent types of noise:

1. Poisson Noise:

- Originates from the statistical nature of photon detection during image acquisition.

2.Periodic Noise:

- Caused by interference from electronic and mechanical components in the CT scanner.

Aim of the Solution

The objective is to develop a **software tool** capable of:

- **Reading and displaying CT brain scans** in DICOM format.
- **Designing an algorithm** that reduces Poisson and periodic noise effectively.
- Enhancing image clarity while preserving essential diagnostic information, leading to **more accurate diagnoses**.

Proposed Solution

- We propose a **convolutional autoencoder** that learns to **remove both Poisson noise and Periodic noise** from **brain CT images** by **enhancing image clarity**, while **preserving the important diagnostic features**.

- The system will **read and process CT scans in DICOM format** while **preserving all essential imaging metadata**. Because of this, the system will be **directly compatible with real-world clinical workflows**.

- The framework may also be **extended to MRI and ultrasound** as well and potentially fit into **real-time hospital systems** for **AI-assisted diagnostics**.

Key Functional Modules

- **Encoder**
  Extracts low-level features and compresses noisy input.
- **Bottleneck**
  Captures critical patterns while discarding noise.
- **Decoder**
  Reconstructs high-quality, denoised CT images.
- **Activation Functions**
  Uses ReLU for layers and Sigmoid for output.
- **Loss Function**
  Mean Squared Error (MSE) ensures pixel-level restoration accuracy.

Innovation / Uniqueness

Dual Noise Elimination

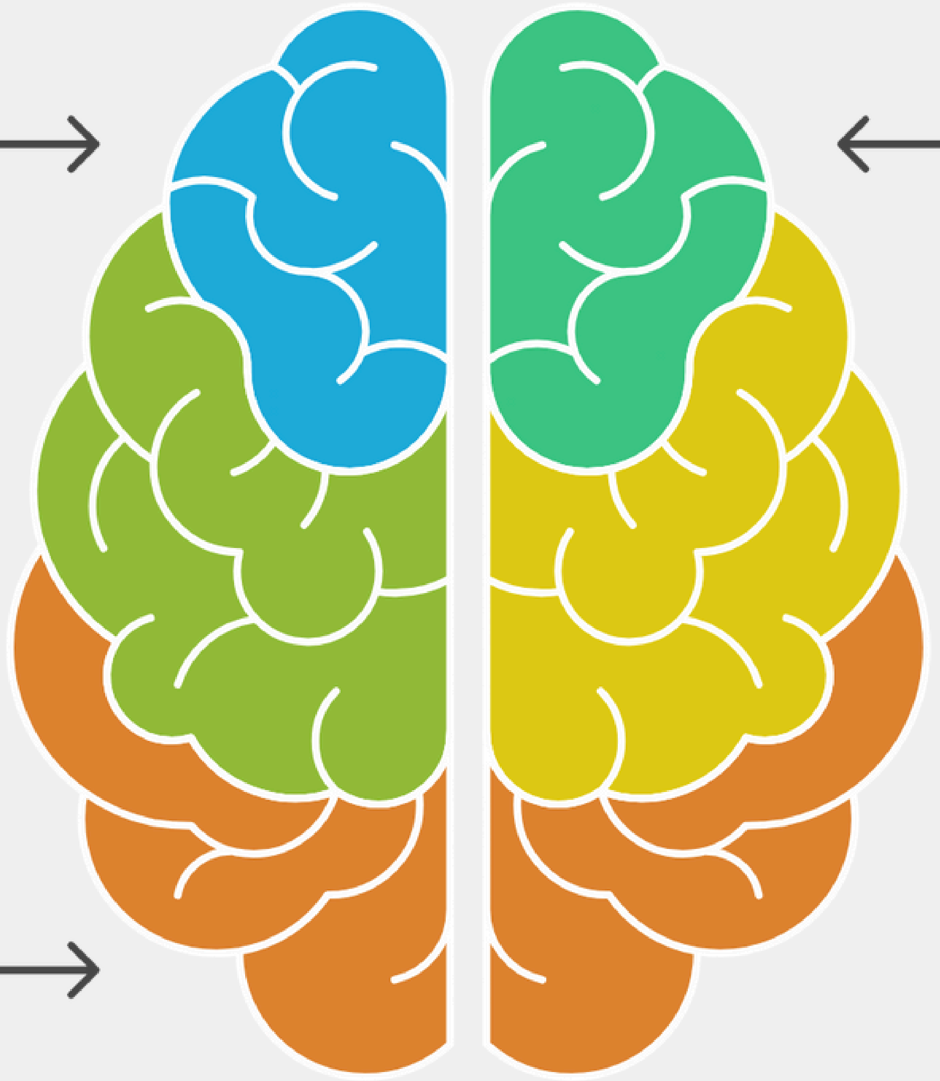
Targets both Poisson and Periodic noise for cleaner, clearer CT scans.

Native DICOM Integration

Works with native DICOM scans, retaining full medical data integrity and compatibility.

Scalable & Future-Ready

Easily extendable to MRI, ultrasound, and real-time clinical systems.



Improved Diagnostic Outcomes

Improved disease prediction due to better feature clarity in denoised images.

Deep Learning-Driven Autoencoder

Uses deep encoder-decoder model to learn and remove noise while preserving vital image details.

Tech Stack

🧠 Machine Learning & Deep Learning

TensorFlow

Keras

scikit learn

pandas

🩻 Medical Imaging

pydicom

OpenCV

☁️ Deployment & Infrastructure

Amazon EC2

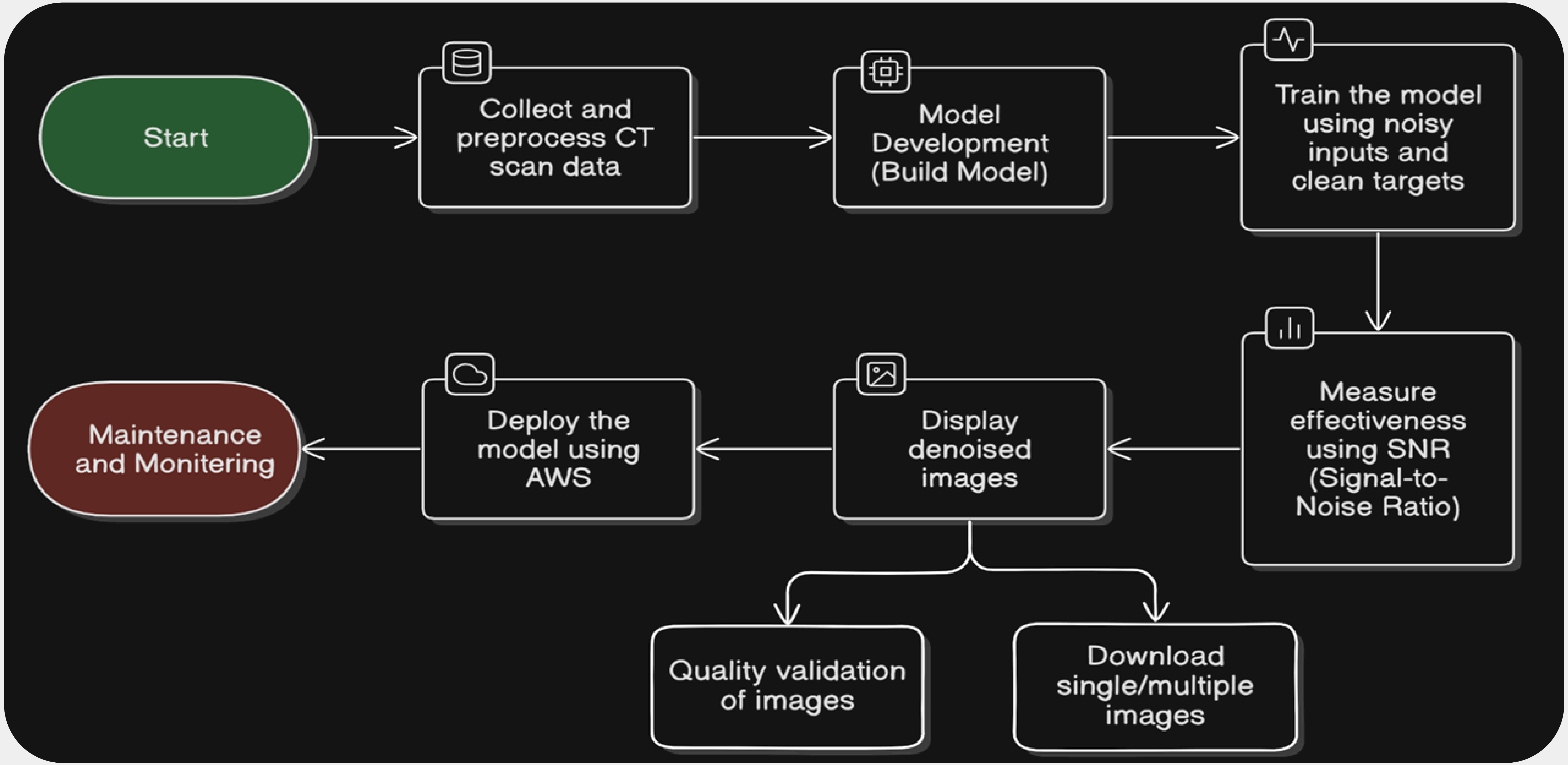
Flask

📊 Evaluation & Monitoring

matplotlib

seaborn

Architecture / Workflow



Execution Plan

6 **Monitoring & Maintenance**

Ensuring long-term reliability through regular updates

5 **Deployment**

Deploying the model on AWS Cloud for accessibility

4 **User Interface**

Creating a user-friendly interface for interaction

3 **Evaluation & Testing**

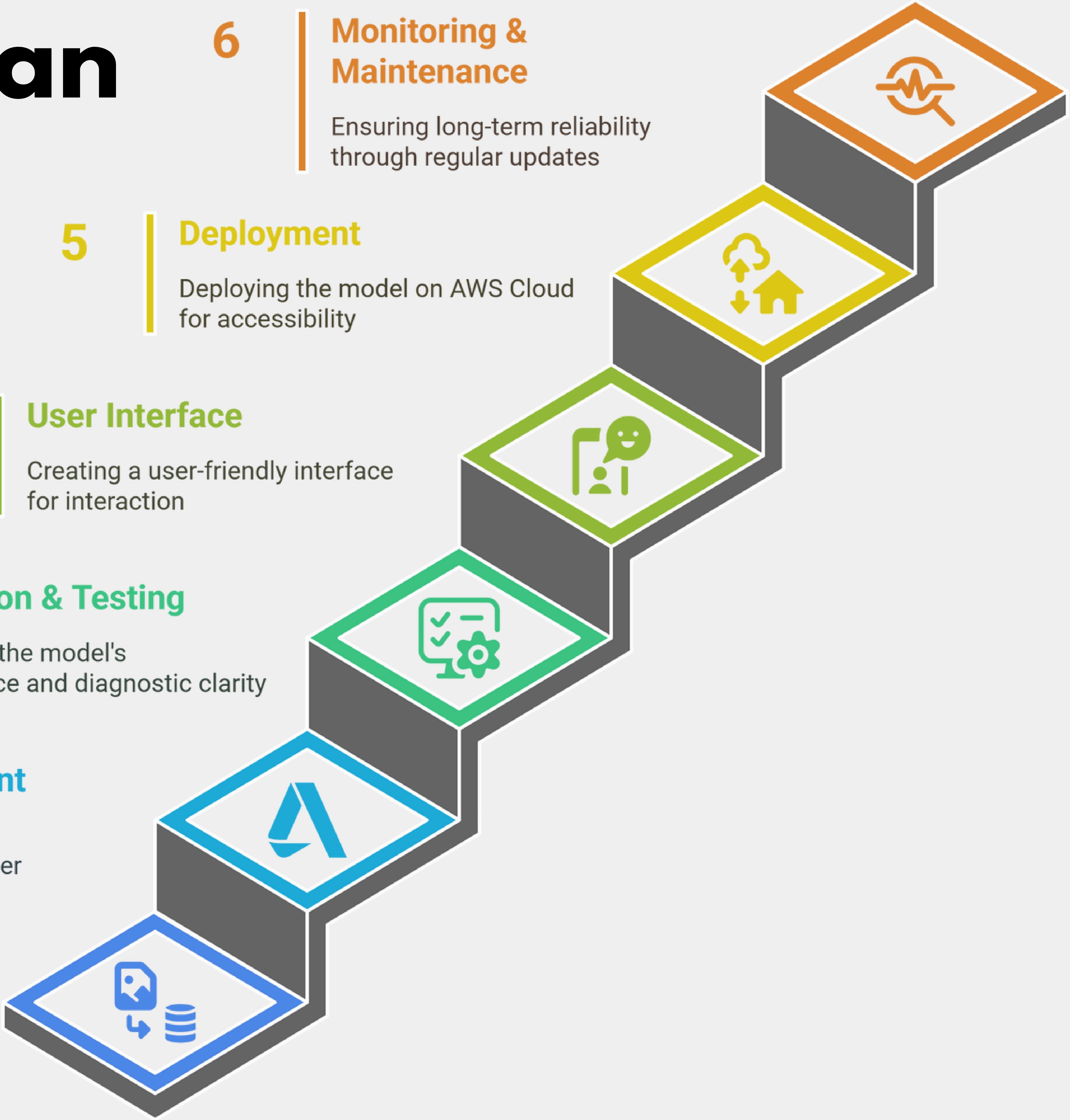
Assessing the model's performance and diagnostic clarity

2 **Model Development**

Designing and training a convolutional autoencoder

1 **Data Collection**

Gathering and preparing CT brain scans for processing



Anticipated Challenges

Data Limitations:

- Difficult to get large numbers of clean-labeled DICOM brain scans
- Privacy issues and access restrictions in medical datasets

High Computational Requirements:

- Model building and real-time inference require GPU-based systems
- Might hinder the deployment at hospitals where resources are limited

Diagnostic Sensitivity:

- Over-denoising may occur resulting in subtle abnormality patterns becoming blurred
- Very important to balance denoising while preserving medical-based features

Regulatory & Ethical Compliance:

- Must comply with HIPAA, GDPR, and medical data handling policies
- Legal barriers of introducing AI-based tools into clinical settings

Clinical Acceptance:

- Resistance from radiologists towards AI-based tools
- Will require considerable explainability, validation and trust in order to overcome existing resistance

Strategies to Overcome the Challenges

Managing Data Constraints:
- Make use of publicly available medical datasets (Kaggle, TCIA) with anonymized CT scans
- Engage with institutions under data-sharing agreements ensuring privacy compliance

Monitoring Computational Load:
- Take advantage of GPU instances in the cloud (AWS EC2 with auto-scaling)
- Optimize model with lightweight architectures, and quantization to reduce inference requirements

Monitoring Clinical Interpretability:
- Implement early stopping and carefully tuned regularization to avoid over-denoising
- Validate the output to radiologist feedback and feature retention analysis

Managing Regulatory Compliance:
- Follow best practices for medical data handling (HIPAA/GDPR) during training and deployment
- Incorporate audit logs, consent protocols, and explainable AI report

Building Clinical Trust and Adoption:
- Show visual comparisons and reports of model performance to medical staff
- Concentrate on maintaining transparent AI models, explainability (e.g., SHAP/Grad-CAM), and human-center

Scalability & Real World Impact

Scalability

- **Cross-Modality Extension:** The model can be adapted for MRI, PET, and ultrasound imaging with minimal architectural changes.
- **Real-Time Integration:** Can be integrated with live CT workflows to enhance the quality of images immediately during the diagnosis.
- **Cloud Deployment:** Scalable hosting on plaforms like AWS for hospital-wide or cross-institution deployment.
- **Modular Architecture:** Can easily be upgraded with future AI advances or additional noise profiles.

Real World Impact

- **Improved Diagnostic Accuracy:** Cleaner images give doctors greater confidence in detecting tumors, hemorrhages and abnormalities.
- **Clinical Workflow Enhancement:** Seamless DICOM handling and user interface reduces radiologist burden and reduces manual filtering.
- **Reduced Misdiagnosis Risk:** Denoised images reduce the false-positive/false-negative rates when it comes to assessing critical brain scans.
- **Global Applicability:** Can benefit hospitals that lack resources or even telemedicine platforms as a way of providing high-quality imaging periodically.

Conclusion

- Our model successfully **reduced both Poisson and Periodic noise**, producing **much cleaner CT brain scans**.
- While denoising we **maintained the integrity of the scans** and **all relevant diagnostic features were preserved**
- To validate the effectiveness of our approach, we created a **predictive classification model** that assessed how well the **denoised images supported accurate diagnosis** — comparing performance **before and after denoising**.
- The complete solution was **deployed on AWS EC2 instance** where users process the CT scan data by **single and bulk upload**, ensuring **high performance and scalability** in real-world use.

Because behind every clear scan is a life depending on it!

End

Thank you