DL MINI-Project — Technical Report

Team Members

This mini-project was carried out by the following team members:

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Enhancing Brain Medical Image Quality Using Deep Stacked Auto encoders

1. General Introduction

Medical imaging plays a critical role in the diagnosis, monitoring, and treatment of numerous pathologies, particularly brain tumors, which are among the most serious neurological conditions. In this context, the quality of MRI (Magnetic Resonance Imaging) scans is a decisive factor in enabling precise interpretation by healthcare professionals or AI-assisted decision support systems.

However, these images are often degraded by random noise, especially Gaussian noise, resulting from hardware limitations or difficult acquisition conditions. These disturbances compromise the accuracy of medical interpretation and the reliability of automated diagnostic models.

Our project aims to design a solution based on deep neural networks, particularly Stacked auto encoders, to restore noisy brain MRI images. The goal is to enhance the visual and informational quality of medical data while faithfully preserving critical details such as tumor boundaries.

2. Problem Statement and Medical Context

2.1 Context

Early diagnosis of brain tumors depends heavily on the precision of medical imaging. Abnormalities may be very subtle and low-contrast, highlighting the importance of high-quality imaging. Unfortunately, MRI scans are often corrupted by noise due to various factors (electromagnetic interference, patient motion, etc.).

2.2 Problem Statement

• How can we effectively reduce noise in brain MRI images without altering essential medical features?

• What type of deep learning model can perform this task autonomously, without explicit supervision?

• Can this enhancement be integrated into an automatic brain tumor detection pipeline?

3. Project Objectives

• Implement deep Stacked auto encoders capable of removing artificially added Gaussian noise from brain MRI images.

• Preserve discriminative features of brain tissues, particularly tumor contours.

• Evaluate reconstruction quality using both objective and subjective metrics (PSNR, MSE, visualization).

• Provide a generalizable model ready to be integrated into an AI-assisted diagnostic pipeline.

4. Data and Preprocessing

4.1 Data Source

The images are sourced from a public Kaggle dataset, composed of brain MRI scans with and without tumors. This dataset serves as a reference for medical deep learning projects.

4.2 Preprocessing Steps

• Uniform resizing of images to 64×64 pixels.

• Normalization of pixel values to the [0, 1] range.

• Artificial generation of Gaussian noise (mean = 0, variance = 0.2).

• Split into training set (80%) and test set (20%).

• Use of data augmentation to increase input diversity.

5. Proposed Models: Stacked Auto encoders

5.1 Auto encoder Principle

An auto encoder is an unsupervised neural network that learns to reconstruct its input after compressing it into a latent representation. In our case, the goal is to reconstruct the original, noise-free image from a noisy version.

5.2 Model Architectures

Base Model (Auto encoder 1)

Component	Layer Details
Encoder	Conv2D (64 filters, 3x3, relu), MaxPooling2D (2x2)
	Conv2D (64 filters, 3x3, relu), MaxPooling2D (2x2)
Decoder	Conv2D (64 filters, 3x3, relu), UpSampling2D (2x2)
	Conv2D (64 filters, 3x3, relu), UpSampling2D (2x2)
	Conv2D (1 filter, 3x3, sigmoid)

Improved Model (Auto encoder 2)

Component	Layer Details
Encoder	Conv2D (256 filters, 3x3, relu), MaxPooling2D (2x2)
	Conv2D (256 filters, 3x3, relu), MaxPooling2D (2x2)
Decoder	Conv2D (256 filters, 3x3, relu), UpSampling2D (2x2)
	Conv2D (256 filters, 3x3, relu), UpSampling2D (2x2)
	Conv2D (1 filter, 3x3, sigmoid)

Loss Function: Mean Squared Error

Optimizer: Adam

6. Experimentation and Results

6.1 Training

• Duration: 50 to 70 epochs.

• Batch size: 32

• Monitoring of reconstruction metrics at each epoch.

6.2 Quantitative Results

Higher PSNR values indicate better perceived quality. The improved model shows stronger noise removal capacity while preserving fine structures.

Model	MSE (↓)	PSNR (↑)
Auto encoder 1	0.0106	~18.8 dB
Auto encoder 2	0.0087	~19.9 dB

6.3 Qualitative Results

Comparative visualization:

• Original Image (Before)

• Noisy Image (With Gaussian noise)

• Restored Image (After denoising by auto encoder)

Tumor region boundaries are more clearly defined after denoising.

7. Deployment and Reusability

The models were saved as. keras files, accompanied by their source code:

• autoencoder_brain. keras

• autoencoder_brain_v2. keras

To facilitate demonstration and user interaction, we used **Gradio**, an open-source Python library, to build a simple web interface. This allowed users to:

• Upload a noisy brain MRI image.

• Visualize the denoised output instantly.

• Compare input and output side by side in the browser.

This interface is valuable for showcasing the model to both technical and non-technical stakeholders, such as medical staff or collaborators.

The models and interface can be reintegrated into medical pipelines for future applications such as:

- Preprocessing of MRI scans for automatic detection systems.
- Visualization tools for radiologists.
- Embedded diagnostic assistance systems in low-resource environments.

8. Conclusion and Future Work

This project demonstrates that Stacked auto encoders are an effective solution for restoring noisy brain medical images. Their ability to extract meaningful representations and accurately reconstruct data makes them ideal for preparing clean images for tasks such as classification or segmentation, like automatic tumor detection.

Future Work:

• Extend the model to 3D (volumetric) MRI scans.

• Integrate adversarial techniques (GANs) for more realistic reconstruction.

• Apply the model in a real-time medical system.

GitHub Link : https://github.com/MohemedAmine/DL-MINI-Project.git