

Problem Statement

AI-Assisted Medical Imaging Analysis - Detect anomalies in X-rays, MRIs, or CT scans automatically.

Challenges

Late Diagnosis of Vestibular Schwannoma (VS):

Tumors are often detected in later stages due to subtle early symptoms and delays in MRI interpretation.

Traditional Methods Offer Only Binary Classification:

Existing diagnostic systems typically classify tumors as present or absent — they do not quantify the seriousness or stage of the tumor

No Quantitative Confidence Score:

Traditional diagnostic reports do not provide a confidence score or severity scale to guide clinical decisions.

Symptoms Often Ignored or Misclassified:

Patients' self-reported symptoms are not integrated with imaging for holistic evaluation.

Proposed Solution

- We propose a deep learning pipeline combining volumetric tumor analysis and symptom-based scoring to quantify vestibular schwannoma severity.
- A CNN regression model is trained on preprocessed DICOM MRI scans, using tumor volume-derived confidence scores as ground truth for supervised learning.
- The system integrates multi-modal inputs image-based predictions and patient-reported symptoms to output a unified confidence score and stage classification.
- The final output not only predicts the tumor's severity but also dynamically generates AI-driven clinical suggestions for improved patient awareness.

Tools & Technologies

Language

• Python



Framework

Pytorch

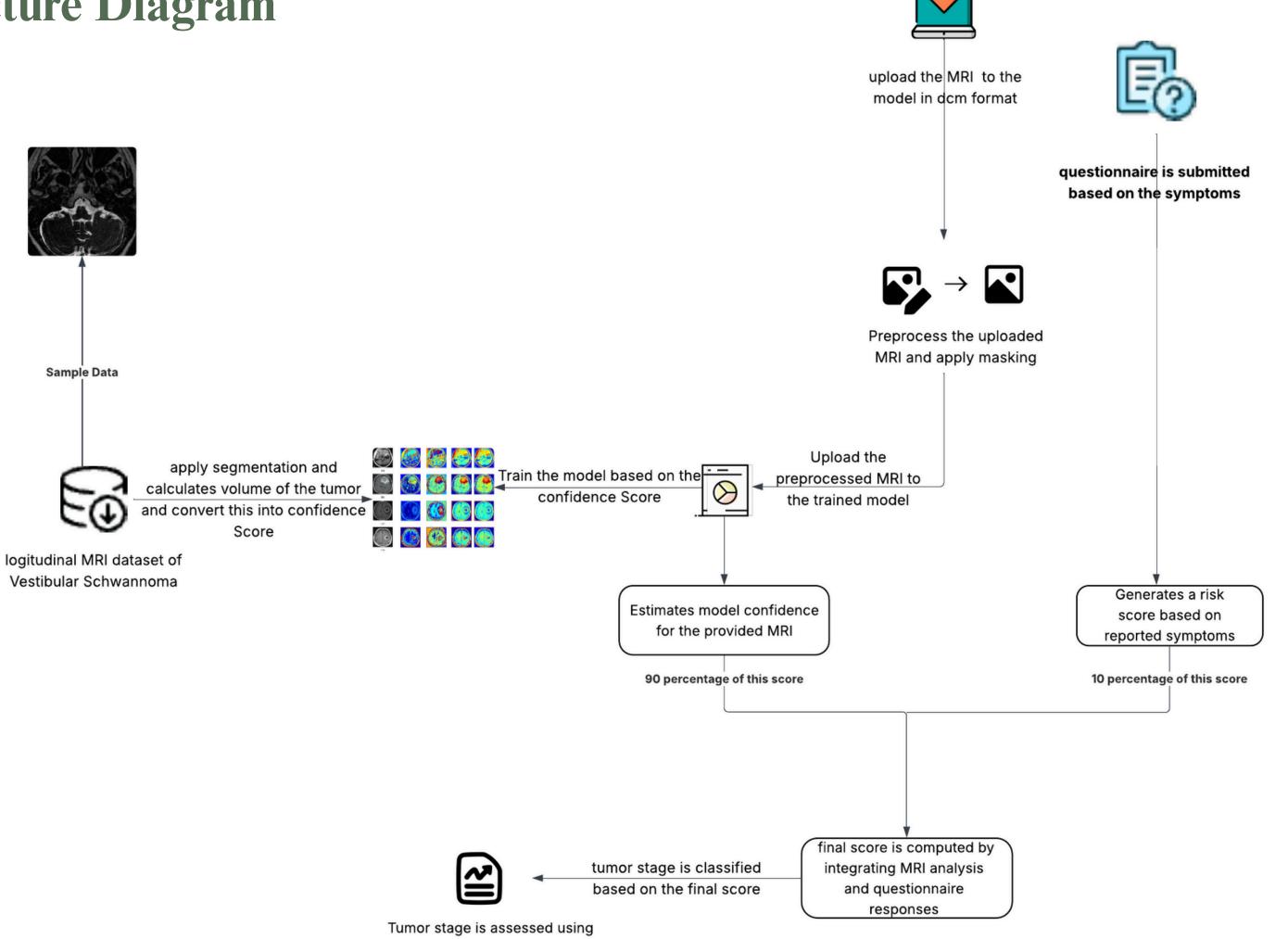


Tools

• Pycharm



Architecture Diagram



umor stage is assessed using
Al-driven analysis

Dataset Overview

- The longitudinal MRI dataset of Vestibular Schwannoma has been taken in the format of raw DICOM volumes, organized by patient and scan series.
- 124 subjects were analyzed, and the Scan Modalities are T1, T2-weighted. Each patient folder contains multiple timepoints/series.

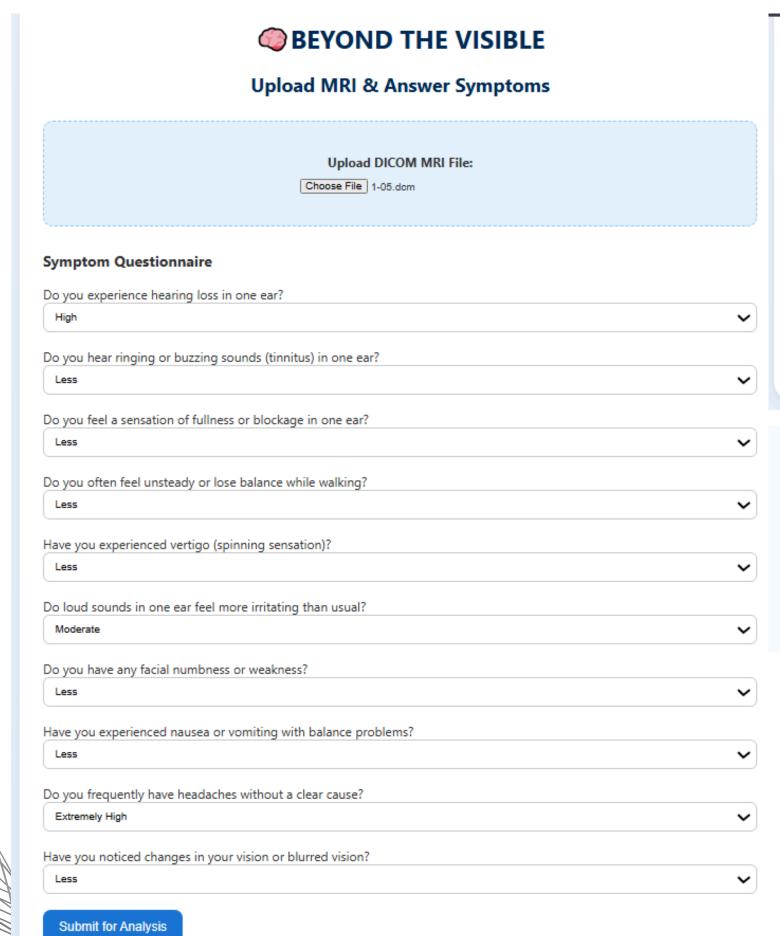
Questionnaire

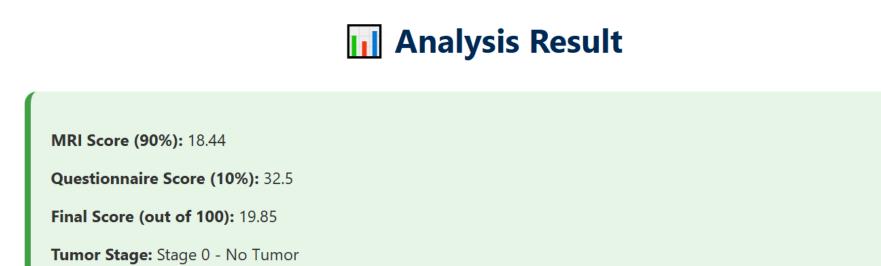
- A symptom-driven screening tool designed to gather patient-reported indicators commonly associated with Vestibular Schwannoma (VS).
- It transforms subjective clinical symptoms into quantitative scores

Preprocessing

- Original MRI scans in DICOM format are converted to NIfTI (.nii) format for standardized 3D volume representation.
- Volumes are cropped to the region of interest to a fixed shape. Tumor region is encoded as 1, and background as 0, forming a binary 3D mask of the same shape as the input MRI scan.
- Preprocessed NIfTI volumes are saved as .npy files for faster loading during training and inference.
- Metadata is linked to each volume with its subject ID, scan date, and label, which is used to build growth pairs mapping how a tumor evolves.
- Outputs a confidence score that quantifies the certainty of the prediction by the tumor volume.

Trained CNN Model





Al-Generated Suggestions

← Back to Home

- Avoid long exposure to loud noise or headphones.

Evaluation

```
↑ Mean Absolute Error (MAE): 20.24

→ Mean Squared Error (MSE): 696.76

→ R<sup>2</sup> Score: -0.01

Accuracy (approx): 79.74%

>
```

Accuracy

The trained CNN model demonstrates a strong foundational performance, achieving an accuracy of 79.74% (approximately 80%) in predicting tumor confidence scores.

Confidence Score

MRI Confidence Score (90%):

Model processes DICOM MRI scans and outputs a confidence value between 0–100.

Questionnaire Score (10%):

- Calculated based on answers to 10 symptom-related questions.
- The questionnaire captures subjective symptoms like hearing loss, vertigo, imbalance, facial numbness, etc. This adds clinical context that might not show strongly in early MRI scans.

Final Confidence Score:

 $final_score = (0.9 * mri_score) + (0.1 * q_score)$

Tumor Stage Classification

Stage 0: final_score < 20 ----> *Stage 0 - No Tumor*

Stage 1: final_score < 40 ----> *Stage 1 - Early*

Stage 2: final_score < 60 ----> Stage 2- Moderate

Stage 3: final_score < 80 ----> Stage 3- Advanced

Stage 4: final_score > 80 -----> *Stage 4- Severe*