MKSSS’s Cummins College of Engineering for Women, Pune

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BrainScanX: Deep Learning - Based Brain Tumor Detection with Grad - CAM Explainability

Submitted By :
A1 Batch Group 1

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Abstract

Brain tumors pose serious health risks and require early, accurate diagnosis. Manual interpretation of MRI scans is time-consuming, subjective, and requires high expertise. Our project presents a Deep Learning–based automated system that classifies MRI images into Tumor and No Tumor with high accuracy.

A custom-trained CNN model serves as the primary classifier, while Grad-CAM is integrated to generate explainable heatmaps. These heatmaps highlight critical tumor-suspected regions, enabling transparency and trust in decision-making.

A Streamlit-based user interface allows real-time image uploading, prediction, confidence scoring, and visualization. Additionally, a Support Vector Machine (SVM) model is implemented to compare classical ML performance with modern CNN architecture.
Results demonstrate that CNN significantly outperforms SVM and is more suitable for medical image diagnosis.

Introduction

MRI imaging is the standard technique for identifying brain abnormalities. However:

- It requires expert radiologists.
- Manual diagnosis is prone to oversight.
- Increasing MRI volumes require automation.

Goal of the Project:

To design a fully automated system that can:

1. Process and analyze MRI images
2. Classify them accurately using a CNN
3. Provide explainable results using Grad-CAM
4. Offer an easy-to-use interface for real-time diagnosis
5. Compare CNN with SVM to justify model selection

This project addresses both automation and explainability, two major needs in modern medical AI.

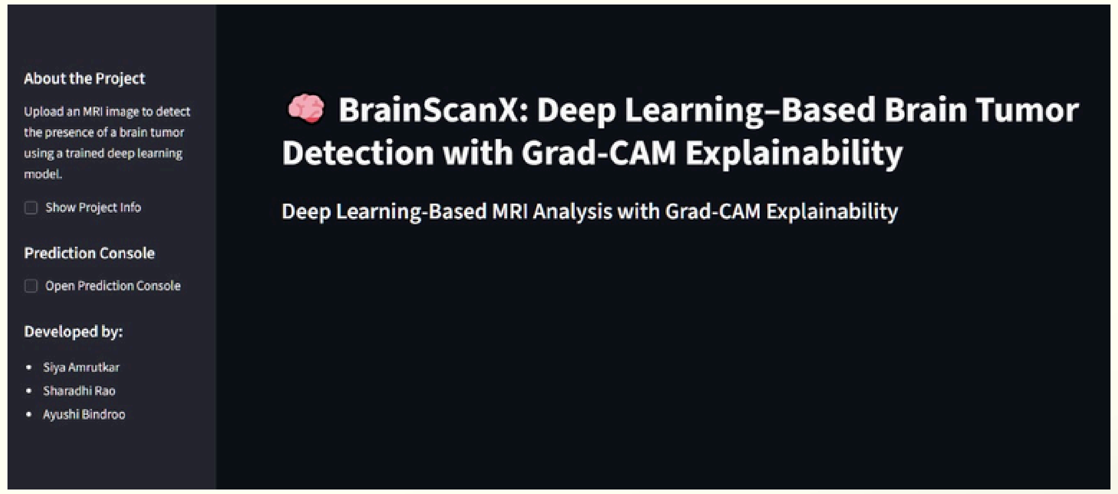
Problem Statement

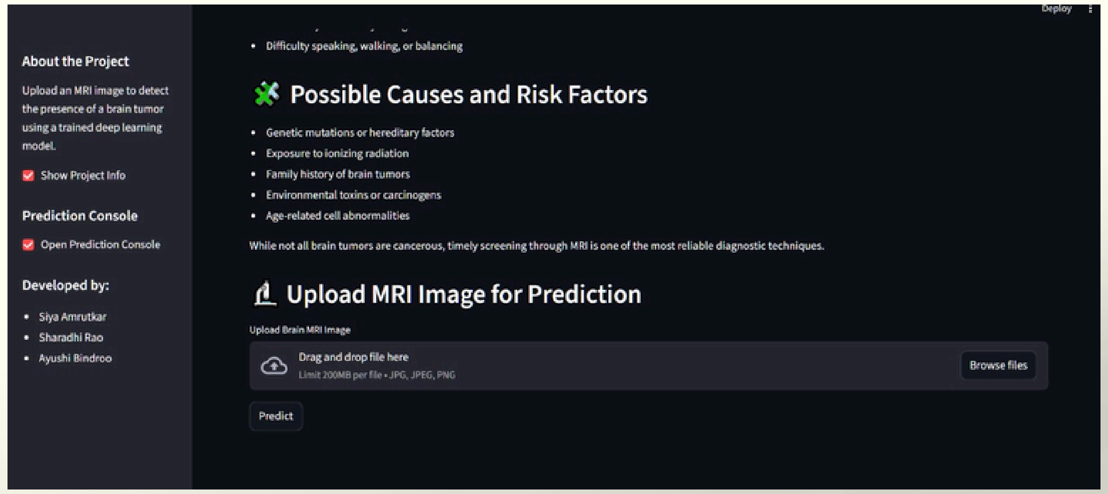
Brain tumors can exhibit very subtle texture differences that humans may overlook.
Traditional ML algorithms require hand-crafted features, which are insufficient for medical imaging.
Doctors often ask: “Why did the model predict this?” — most AI systems cannot answer that.
A practical system must be:

- Accurate
- Transparent
- Fast
- Easy to use

Our solution:

Deep Learning–based automated system that classifies MRI images into Tumor and No Tumor with high accuracy while Grad-CAM is integrated to generate explainable heatmaps. These heatmaps highlight critical tumor-suspected regions, enabling transparency and trust in decision-making..





Dataset Description

Dataset: Brain Tumor MRI Dataset

Total Images: ~ 460

- Tumor: 255
- No Tumor: 205

Why this dataset?

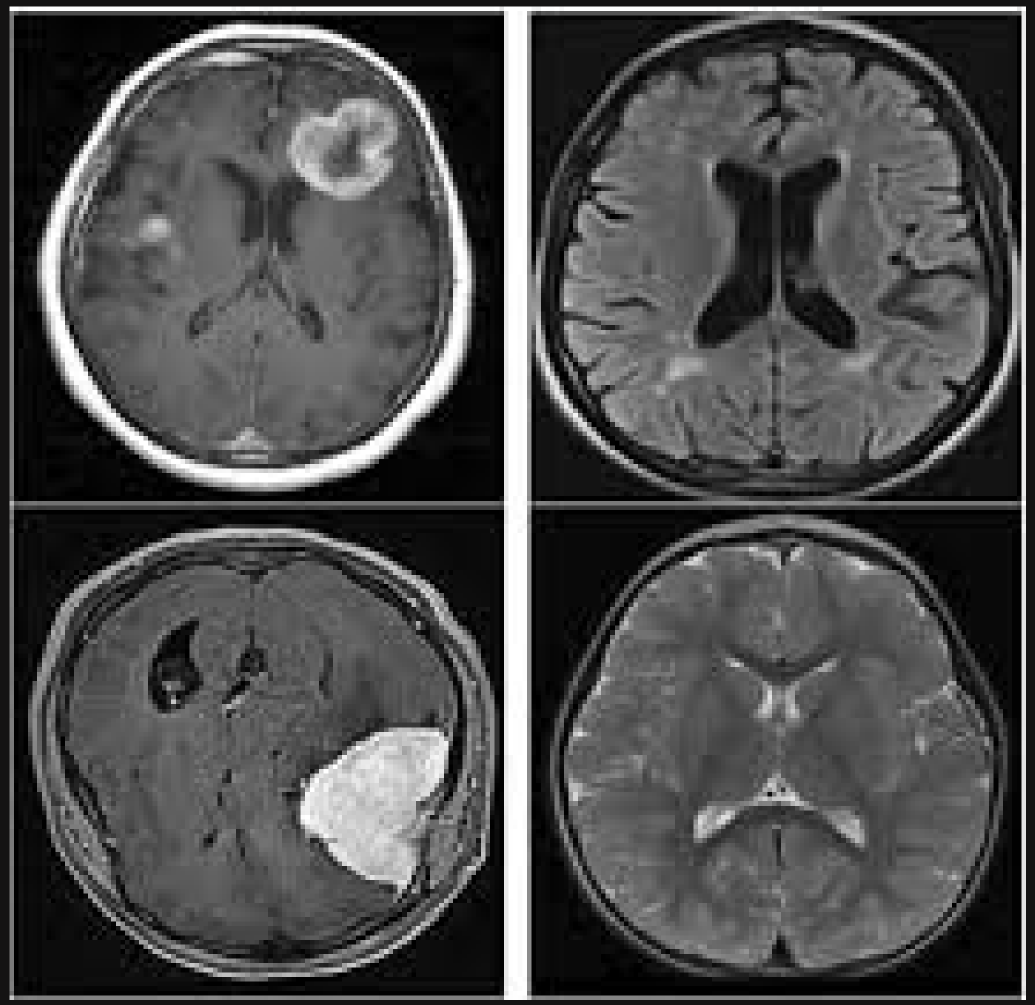
- Real MRI images
- Variation in texture, orientation, and scan conditions
- Balanced enough for binary classification

Preprocessing Applied:

- Image resizing to 224×224
- Normalization (pixel value scaling)
- RGB → Array conversion
- Train-test split for unbiased evaluation

Strength: CNN learns patterns such as:

- Tumor boundaries
- Abnormal tissue density
- Texture distortions
- Shape irregularities



Methodology: CNN Model

Our CNN architecture includes:

Layers

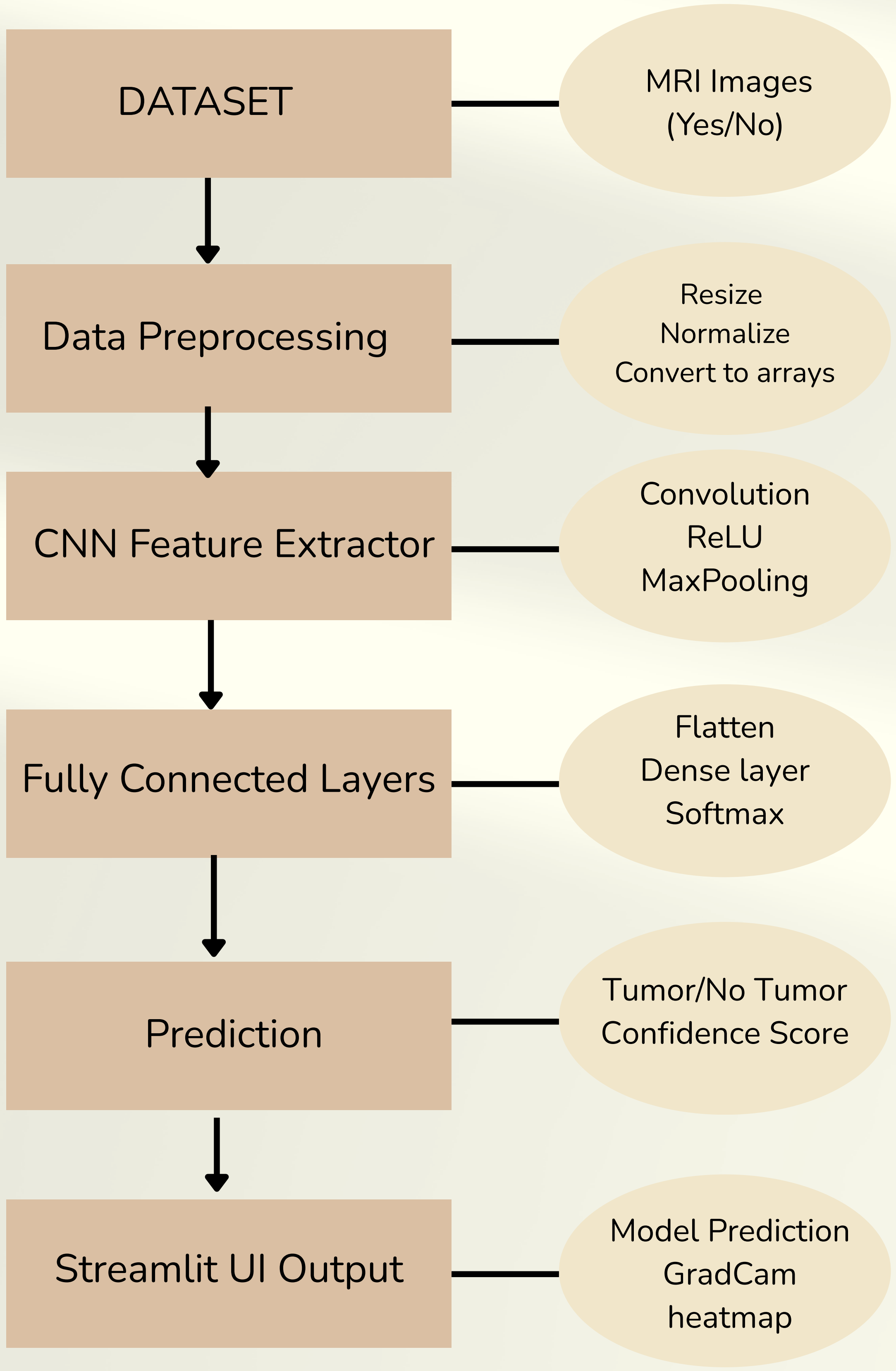
- Multiple Convolutional layers to extract tumor patterns
- ReLU activations for non-linearity
- MaxPooling for spatial downsampling
- Flatten layer for vector representation
- Dense layers for classification
- Softmax output layer predicting:
  - 0 = No Tumor
  - 1 = Tumor

Training Details:

- Optimizer: Adam
- Loss function: binary_crossentropy
- Epochs: Sufficient for convergence (as per your notebook)
- Achieved accuracy: ~ 83–85%
- Saved as brain_tumor_model.h5

CNN automatically learns edges, shapes, intensity variations, tumor patches, and overall spatial structure.

CNN Pipeline



Explainable AI: Grad-CAM

Medical AI MUST be explainable.
Grad-CAM helps visualize:

- Where the model is focusing
- Why the model predicted “Tumor”
- Whether focus aligns with tumor regions

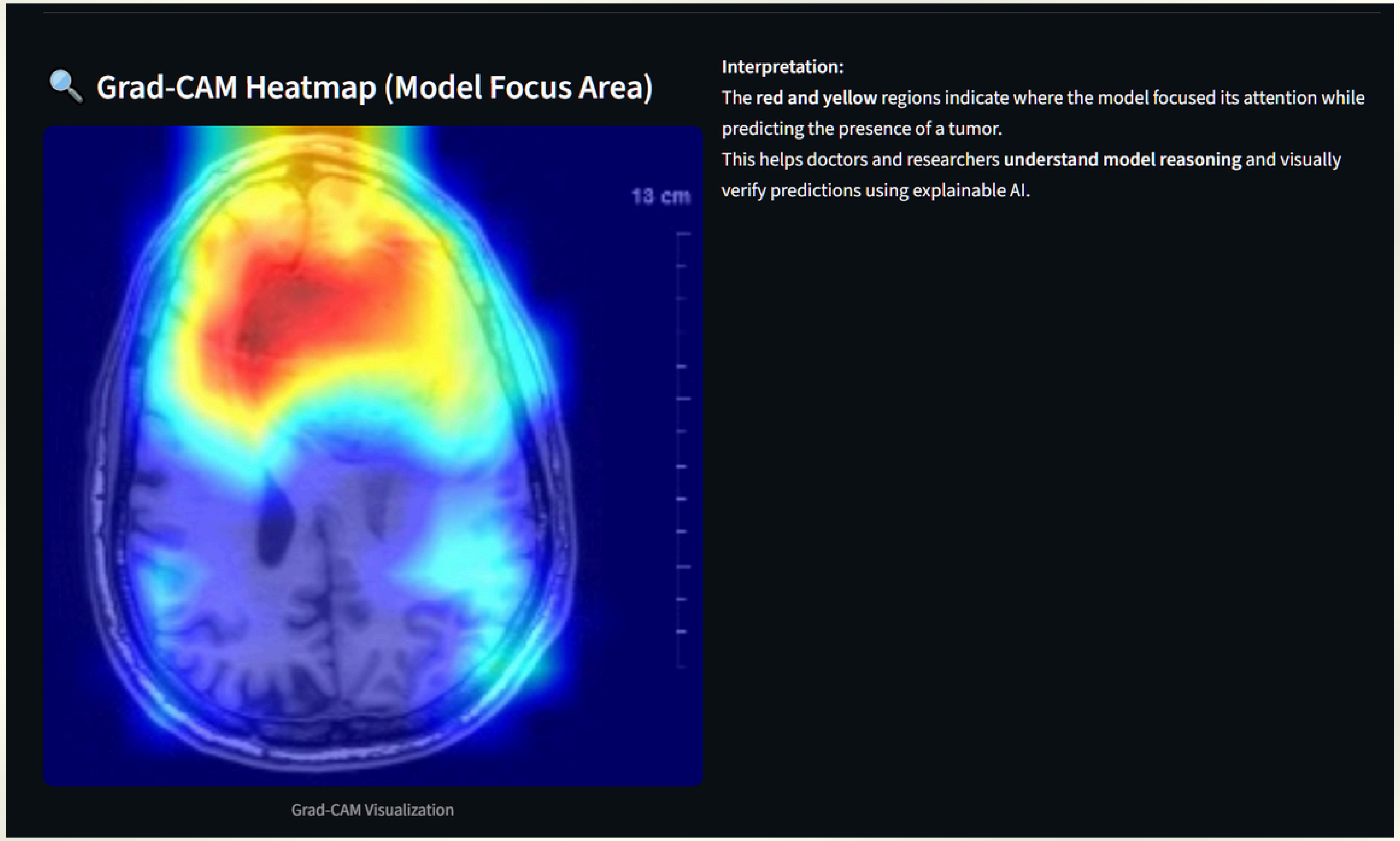
What Grad-CAM does:

- Computes gradients of the predicted class
- Identifies important feature maps
- Creates a heatmap showing model attention
- Colors:
  - 🔴 Red – highest activation
  - 🟡 Yellow – medium
  - 🔵 Blue – low

Significance:

- Doctors can validate model decisions
- Increases trust
- Reveals bias or misclassification reasoning

This is a MAJOR innovation in our project.



System Architecture

MRI Image Upload

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Preprocessing(224 x 224)

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CNN - Based Classification

Outputs Tumor / No Tumor

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Grad - CAM Heatmap Generation

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Streamlit Web Interface

SVM Baseline Model

To justify using CNN, we implemented SVM with PCA, a traditional ML approach.

SVM Pipeline:

- Convert MRI → Grayscale
- Resize to 64×64
- Flatten to 4096 features
- Apply PCA (dimensionality reduction)
- Train SVM (RBF kernel)
- Output

Why SVM?

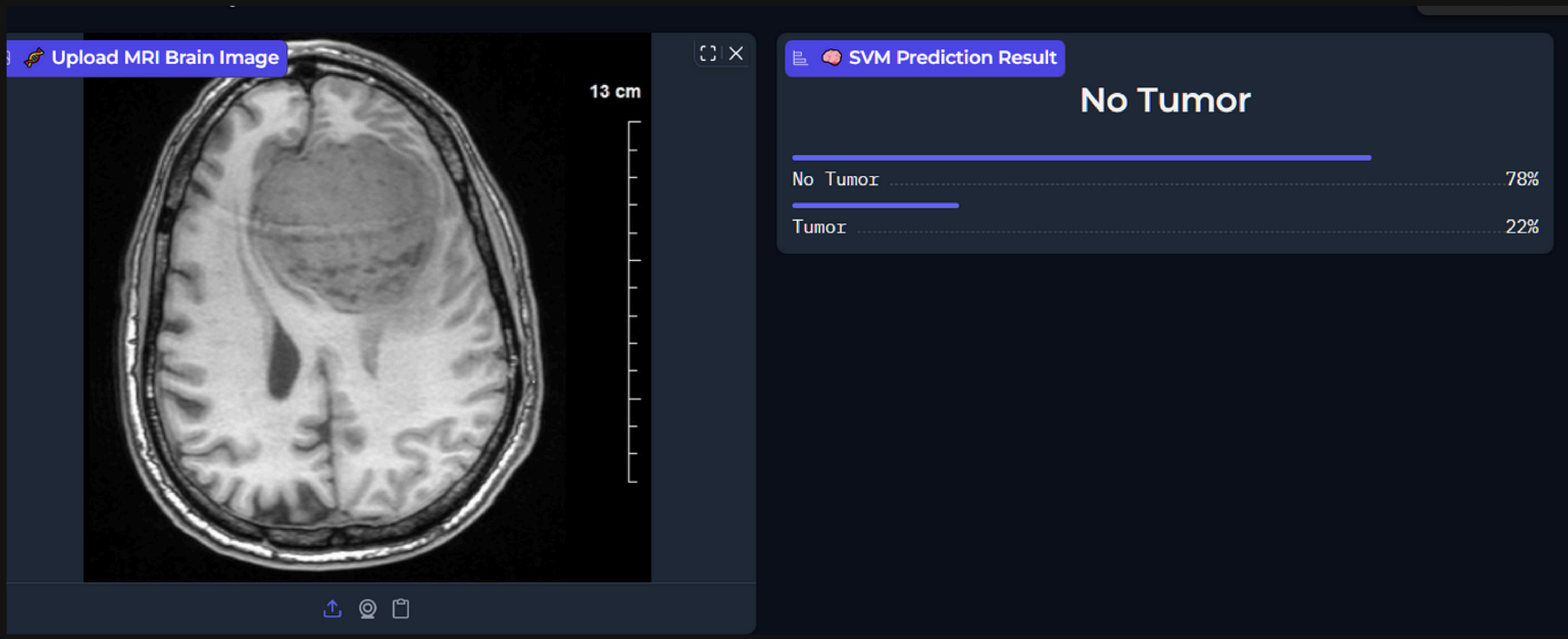
- Classical baseline
- Shows how older ML models compare with modern DL
- Provides clear justification for CNN choice

Performance:

- Accuracy: ~74.5%
- Misclassified many no-tumor images
- No explainability
- Cannot learn texture or spatial features

This strengthens our argument that CNN is the right model.

Misclassification



Results & Discussion

CNN Results

- Accuracy: 80 - 85%
- Confusion matrix shows high TP and TN
- Grad-CAM highlights precise tumor regions
- High confidence scores
- Consistent across different MRI qualities

SVM Results

- Accuracy: 74.51%
- Incorrect predictions mainly for "No Tumor"
- Lacks feature learning
- Performance depends heavily on PCA

Accuracy: 0.8235

	precision	recall	f1-score	support
no	0.74	0.85	0.79	20
yes	0.89	0.81	0.85	31
accuracy			0.82	51
macro avg	0.82	0.83	0.82	51
weighted avg	0.83	0.82	0.83	51

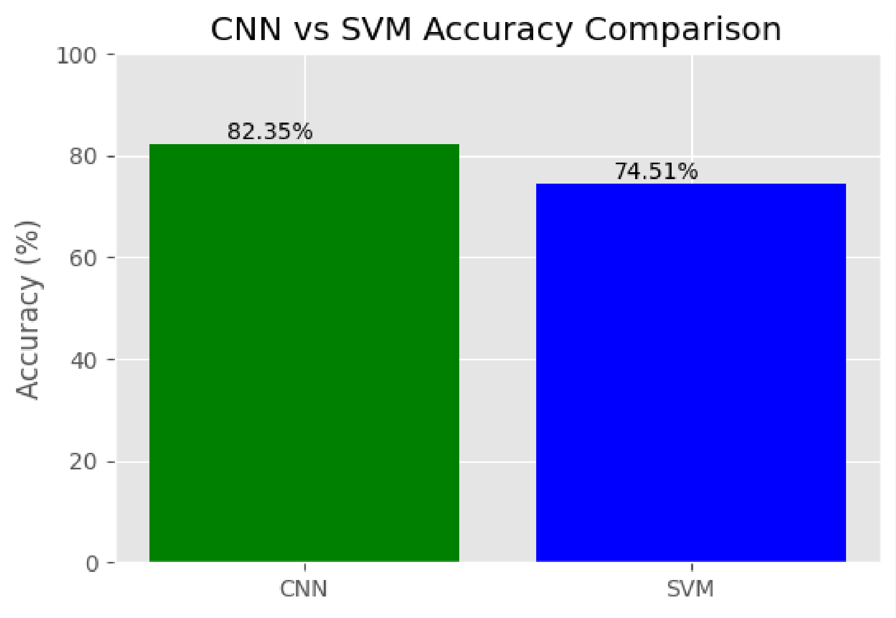
SVM Accuracy: 74.51%

Classification Report:

	precision	recall	f1-score	support
No Tumor	0.67	0.70	0.68	20
Tumor	0.80	0.77	0.79	31
accuracy			0.75	51
macro avg	0.73	0.74	0.73	51
weighted avg	0.75	0.75	0.75	51

Conclusion of comparison:

- CNN performs significantly better than SVM for MRI brain tumor detection.
- CNN achieves higher accuracy and captures complex spatial features that SVM cannot.
- Convolution layers capture spatial patterns, textures, shapes, and tumor regions. SVM loses image information during flattening + PCA compression.
- Grad-CAM explainability gives CNN medical transparency; SVM has none.



Why we implemented RANDOM FOREST

1. Handles small datasets well Perfect for our dataset of ~500 images after feature extraction
2. Low risk of overfitting Ensemble of many trees reduces variance compared to a single decision tree
3. Robust to noisy or low-quality features Works well even when input features lack deep spatial information
4. Non-linear decision making Can model complex relationships between intensity & texture features
5. Easy to interpret Provides feature importance rankings for medical explainability
6. Fast to train & deploy Suitable for academic projects with limited compute
7. Stable performance Performs decently even with handcrafted features and heterogeneous MRI images

Random Forest was selected because it is stable, explainable, and effective for small, structured datasets where features are manually extracted. Its ensemble nature reduces overfitting and provides reliable baseline performance — making it an appropriate classical ML choice before moving to CNNs.

How we implemented RANDOM FOREST

1. Preprocessing the MRI images

Converted all MRIs to grayscale
Resized each image to a standard dimension (256×256)
Applied histogram & intensity normalization to reduce scanner variation

2. Handcrafted Feature Extraction

From every MRI, we extracted 8 quantitative descriptors:

1. Mean intensity
2. Standard deviation
3. Entropy
4. Contrast
5. Energy
6. Homogeneity
7. Edge density
8. Edge mean

These features acted as a numerical summary of the MRI image.

3**. Dataset Preparation**

Constructed a CSV of shape (N images × 9 columns)
Columns = 8 features + 1 label (Tumor / No Tumor)
Normalized all values
Split data using 80/20 train-test split

4**. Random Forest Training**

Used 300 decision trees
Criterion: Gini impurity
Enabled bootstrap sampling
Combined predictions using majority voting
Output probability = ratio of trees predicting “Tumor”

5. Evaluation Metrics

Accuracy ≈ 70%
Precision/Recall measured for both classes
Extracted feature importances to see which MRI features influenced predictions most

Comparison between Random Forest and CNN

RANDOM FOREST	CNN
Loses MRI information	Preserves MRI information with all spatial and texture details.
Only uses mean, entropy and edge details.	Learns features automatically.
No spatial understanding.	Understands shapes, regios,boundaries, textures.
Model becomes blind to actual tumor patterns.	Model learns the actual tumor structure.
Produces weak predictions due to limited information	Produces high accuracy and confidence.

Conclusion

- Developed a fully functional, high-accuracy tumor detection system
- CNN performs extremely well on medical image data
- Grad-CAM makes the model explainable and doctor-friendly
- SVM comparison proves CNN is the superior choice
- This system demonstrates the integration of AI + Explainability + Deployment.

Future Work

- Use multimodal MRI data (T1, T2, FLAIR)
- Include multi-class tumor classification
- Apply transfer learning (EfficientNet, ResNet)
- Add Grad-CAM++ for sharper explanations
- Build cloud API or mobile-friendly app
- Train on 3D MRI volumes
- Add severity-level prediction

References

MRI Brain Tumor Dataset (Yes/No) – Kaggle

Grad-CAM Original Research Paper

Convolutional Neural Networks - Foundational Paper

SVM Paper (M.A. Hearst; S.T. Dumais; E. Osuna; J. Platt; B. Scholkopf)

PCA (Principal Component Analysis) Explanation – sklearn

Support Vector Machines – sklearn

THANK YOU