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Reliable Automated Diagnosis of Soft Tissue Tumor using Machine Learning

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Abstract: Soft tissue tumours are hard to diagnose because they look a lot like other brain conditions on Magnetic Resonance Imaging(MRI)scans, which can lead to delayed or wrong treatment. To solve this problem, we suggest a diagnostic system based on machine learning that combines preprocessing methods with a Convolutional Neural Network (CNN) to accurately classify tumours. The model sorts MRI images into four groups: glioma, meningioma, pituitary tumour, and no tumour. It uses Grad-CAM heatmaps to show and emphasise tumour areas, which makes the results easier to understand and more trustworthy for doctors. To make models work better on small datasets, data preprocessing includes resizing, normalisation, and augmentation. Experimental results show that the CNN can accurately find tumour areas and classify them correctly, even with limited data. The suggested method lessens the need for subjective manual interpretation, which lowers the chance of misdiagnosis.
Keywords: Soft tissue tumors, Magnetic Resonance Imaging (MRI), Convolutional Neural Network (CNN), Machine Learning, Tumor Classification, Grad-CAM, Heatmaps, Preprocessing, Data Augmentation, Deep Learning.

1.INTRODUCTION

Soft tissue tumors are abnormal growths occurring in soft tissues in the body, including muscles, fat, blood vessels, and nerves. The tumors can be benign, which do not spread and remain localized, or malignant, also referred to as soft tissue sarcomas, which can metastasize to other areas of the body. Early and precise loco-regional staging and detection of malignant tumors are extremely important, as delayed staging can lower treatment efficacy and survival rates for patients considerably.

The MRI modality has been commonly used to diagnose Soft tissue tumors due to its ability to provide information non-invasively and provide good anatomical information. The image characteristics of soft tissue tumors have, however, been shown to overlap largely with normal tissues and other pathological lesions, making manual detection very challenging and subjectively dependent on the expertise of radiologists. Misdiagnosis or delayed detection can cause delayed planning of treatment and suboptimal clinical outcomes. The latest advances in artificial intelligence (AI) and machine learning (ML) have been extremely encouraging in medical image analysis. CNNs have been especially competent to deliver state-of-the-art performances in object detection, image segmentation, and disease classification challenges. In terms of tumor diagnosis, CNN can derive MRI image discriminative features and enable automatic classification, reducing human error to a minimum. What's more, visualization techniques such as Gradient-weighted Class Activation Mapping (Grad-CAM) provide increased model transparency by specifying which parts of the image have the most impact on the classification decision and, in this manner, win clinicians' trust.In this work, we offer a precise CNN-based diagnostic system to identify and distinguish soft tissue tumors. The system classifies MRI scans in four classes, i.e., glioma, meningioma, pituitary tumor, and no tumor. We utilize preprocessing techniques consisting of normalization, resizing, and augmentation to allow for model generalizability enhancement in order to overcome dataset deficiencies. The proposed technique not only attempts to boost diagnostic efficiency but it also provides an understandable visualization to assist radiologists in clinical decision-making.

2.LITERATURE REVIEW

Artificial Intelligence has emerged as a transformative medical imaging tool, enabling the detection and management of complex diseases with unprecedented accuracy.Litjens et al. [1] investigated AI-based diagnostic strategies in soft tissue sarcomas, highlighting how deep learning improves clinical decision-making while reducing human bias. Traditional machine learning techniques, like Support Vector Machines and Decision Trees, are limited by their reliance on laborious manual feature extraction, thus compromising scalability and precision [2].

The introduction of CNNs revolutionized medical image analysis by automating feature extraction. A review of most of the applications of deep learning in medical imaging by Esteva et al.[3] confirms that CNNs indeed perform the best for classification and segmentation, respectively.

Choy et al. [4] further demonstrated the potential of CNNs while obtaining skin cancer diagnosis accuracy matching that of dermatologists, thus proving that AI can match human expertise in image-based analysis.

More recently, transformer-based architectures have become popular for representing global context features. An extended survey on vision transformers was presented by Khan et al. [5], mentioning their superiority over traditional CNNs for image recognition performance. In summary, these works establish that state-of-the-art AI architectures, ranging from CNNs to transformers, serve as robust, scalable, and interpretable foundations; thus, the proposed work explores a complex solution space of tumor detection.

Early studies in the area of detecting tumors from MRI images used conventional machine learning methods, like Support Vector Machines, Decision Trees, and Random Forest. These approaches relied on manual feature extraction and produced poor performance due to the limitations of generalizing complicated image patterns from models themselves [6]. Zhang et al. used texture and histogram features along with SVMs for the classification of MRI images, achieving an accuracy of around 82% [7]. The usage of handcrafted features made the process time-consuming and dataset-dependent.

Deep learning and Convolutional Neural Networks were therefore introduced to bring automation to feature extraction in medical image analysis. A comprehensive survey by Litjens et al. presented CNNs as the winner in most medical imaging tasks [8]. Kasliwal et al. used a U-Net model for tumor segmentation, which resulted in improved accuracy with higher efficiency [9]. Similarly, Talo proposed an automatic CNN-based classifier for MRI images and achieved robust results in classification [10].

Most recently, model performance was further enhanced by leveraging the power of various pre-trained networks such as VGG16, ResNet50, and MobileNetV2 [11]. Rahman et al. conducted Soft tissue tumor classification using MobileNetV2 coupled with Grad-CAM visualization and achieved higher accuracy with reduced computational cost [12]. Khan et al. also compared different transfer learning models and concluded that MobileNetV2 gave results superior to those of heavier architectures for small datasets [13].

Recent works have also explored explainable AI (XAI) for model interpretability. Roy et al. discussed a comprehensive review on explainable medical imaging, where they focus on Grad-CAM and saliency maps for visual justification of the models [14]. Li et al. similarly analyzed the application of Grad-CAM to identify regions of interest in medical images [15]. Singh and Srivastava reviewed various data augmentation strategies that help improve generalization for small medical datasets [16]. Pereira et al. proposed an attention-based U-Net to improve segmentation and classification accuracy [17].

In summary, the literature has established that transfer learning models, such as MobileNetV2, if augmented by explainable visualization techniques such as Grad-CAM, yield both efficient and interpretable outcomes of medical image classification. [18] Thus, the motivation for this present work is to implement a MobileNetV2-based Soft tissue tumor detection system with interpretability support using Grad-CAM visualization [19].

3.PROBLEM STATEMENT

There are several challenges and limitations of current medical imaging and diagnostic approaches to soft tissue tumors, affecting their accuracy for clinical decisions, including:

- Overlap in characteristics between images:Soft tissue tumors often have a similar appearance on MRI studies as other benign or malignant lesions. This similarity creates difficulty in differentiating between tumor types, sometimes leading to possible misdiagnosis or delayed treatment.
- Dependence on manual interpretation:MRI diagnosis relies heavily on the expertise and subjective judgment of radiologists. Human fallibility, fatigue, and inter-observer variability can lead to inconsistent or even incorrect diagnoses, thus undermining the reliability of the test results.
- Limited Availability of the Dataset: Large, annotated medical image datasets are seldom available due to privacy and ethical issues. This problem severely curbs the training and generalization capability of deep learning models, which require big data for robust learning [20].
- Lack of Explainability in AI Models: Most of the existing computer-aided diagnosis systems act as a "black box," offering predictions without clear visual justification. This lack of interpretability reduces clinicians' trust and hinders real-world medical adoption [21].
- Computational Constraints: Large MRI datasets require immense computational resources to train deep learning models. High accuracy with efficiency on standard medical hardware is still a challenging task [22].

4.METHODOLOGY

The proposed work aims to achieve reliable classification of soft tissue tumors in brain MRI scans by combining image preprocessing, CNN-based classification, and interpretability through heatmap visualization [23].

A. Preprocessing

MRI images often vary in size, contrast, and orientation, which may affect classification accuracy. Therefore, several preprocessing steps are applied:

- Resizing images to a fixed resolution of *224 × 224* pixels.
- Normalization of pixel intensities to the range [0,1].
- Data Augmentation, including rotation, flipping, and zooming, to increase dataset diversity and reduce overfitting.

B. Feature Extraction and Classification using CNN

A CNN is employed to automatically extract spatial and textural features from MRI scans. The network architecture consists of:

1. Convolutional layers for local feature extraction.
2. Max pooling layers to downsample feature maps and reduce computation.
3. Fully connected dense layers to integrate extracted features.
4. Softmax classifier that outputs probability values for four classes: Glioma, Meningioma, Pituitary tumor, and No Tumor.

The model is trained using categorical cross-entropy loss and optimized with the Adam optimizer to ensure fast convergence and stability. Figure 1 depicts the workflow of the proposed work.

C. Tumor Region Localization using Grad-CAM

To enhance clinical reliability, the model incorporates Grad-CAM. This technique generates heatmaps over MRI images, highlighting the tumor region that influenced the classification decision. By visualizing these activation maps, radiologists can validate and trust the model's predictions [24].

D. System Workflow

The overall methodology can be summarized as follows:

1. Input brain MRI scan.
2. Preprocessing and augmentation.
3. CNN-based classification of tumor type.
4. Heatmap visualization for tumor localization.
5. Final diagnosis report generation.

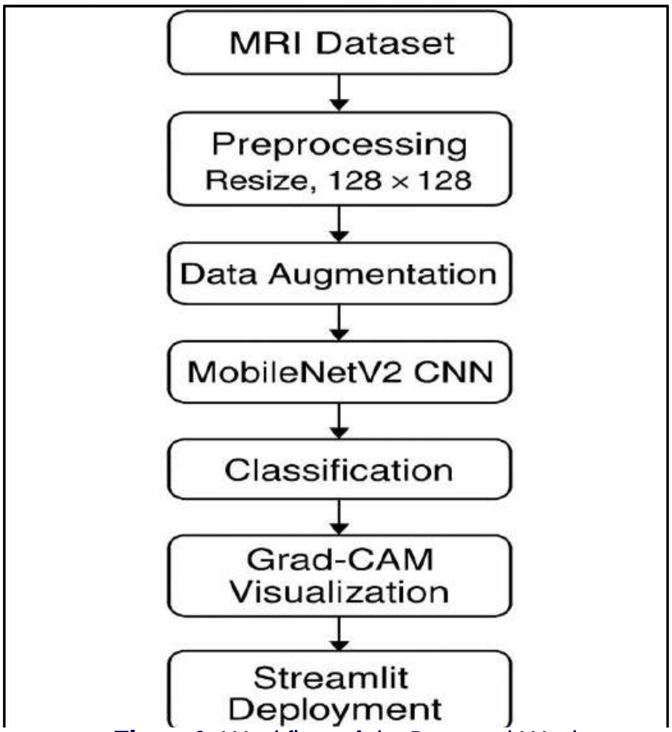

Figure1: Workflow of the Proposed Work

5.IMPLEMENTATION

The procedure to implement this proposed work was carried out in several phases, i.e., dataset preparation, preprocessing, building of the CNN model, training and validation of the model, and visualization of results [25].

A.Dataset Preparation

The dataset included brain MRI scans with both tumor and non-tumor cases. The scans were conducted in DICOM/JPEG format, i.e., standard medical image format. The dataset included four classes:

- Glioma – malignant tumors of glial origin.
- Meningioma – tumors that develop from the meninges.
- Pituitary tumors – found around the pituitary gland.

- No Tumor – normal brain MRIs.

To achieve balanced training, dataset was divided into:

- 70% training data – to train the CNN.
- 15% validation data – used during hyperparameter tuning.
- 15% test data – utilized for final verification.

A directory-based structure was created where each class had its own folder, which simplified preprocessing and labeling.

B.Preprocessing and Augmentation

Medical MRI scans often have variations in contrast, brightness, and resolution, and this can cause degraded accuracy in classification. To counteract this, we made use of the following techniques:

- Resizing: All the images were resized to one standard input size (224 × 224 pixels) to provide uniformity for input layers in CNNs.
- Normalization: The features of pixel intensities were normalized to the interval [0,1], aiding in model convergence during training.
- Noise Reduction (optional): Median filtering was utilized in some cases to eliminate random MRI noise.
- Augmentation: Since the dataset size was small, synthetic expansion of this dataset was carried out through implementing:
- Random rotations within ±15°
- Horizontal and vertical flips
- Random zoom (up to 10%)
- Shifts and brightness adjustments

This augmentation process increased dataset diversity, prevented overfitting, and made models more stable.

C.CNN Model Construction

- CNN was programmed in Python (TensorFlow/Keras). The architecture of the model was as follows:
- Input layer: It takes MRI pictures of size 224 × 224 × 3.
- Convolutional layers: Several convolutional filters (3×3 kernels) bring out spatial and textural features. The ReLU activation function followed in each convolution step was used to provide non-linearity.
- Pooling layers: We utilized max-pooling (2×2) to downsamplethe feature map size and to reduce computational load while keeping valuable features.
- Dropout layers: Added to combat overfitting by disabling neurons at random during training.
- Fully connected layers: Dense layers summed extracted features and sent to classification. Output layer: Probability outputs of Softmax activation of the four classes (Glioma, Meningioma, Pituitary, No Tumor).
- The model was constructed from:

Loss function: Categorical Cross-Entropy
Optimizer: Adam optimizer with 0.001 learning rate
Evaluation metric: Accuracy

D.Training and Validation

- The CNN training was conducted for 50 epochs in batches of 32. The training was performed in one system with GPU acceleration for faster computation. The following were monitored during training:
- Accuracy and loss during training – to train effectively.
- Validation accuracy and loss to find overfitting.
- The accuracy vs epoch and loss vs epoch training curves provided information on model convergence.
- The confusion matrix of the test set was established to analyze misclassifications based on the four classes. The matrix yielded per-class precision, recall, and F1-score, which critically feature in medical practice. Figure 2 depicts the accuracy curve. Figure 3 depicts the loss curve.

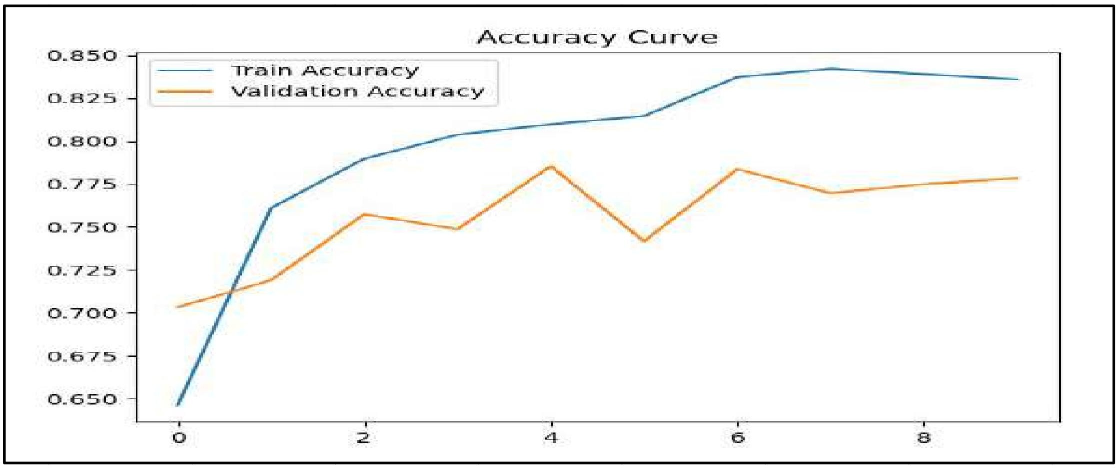

Fig2: Accuracy Curve

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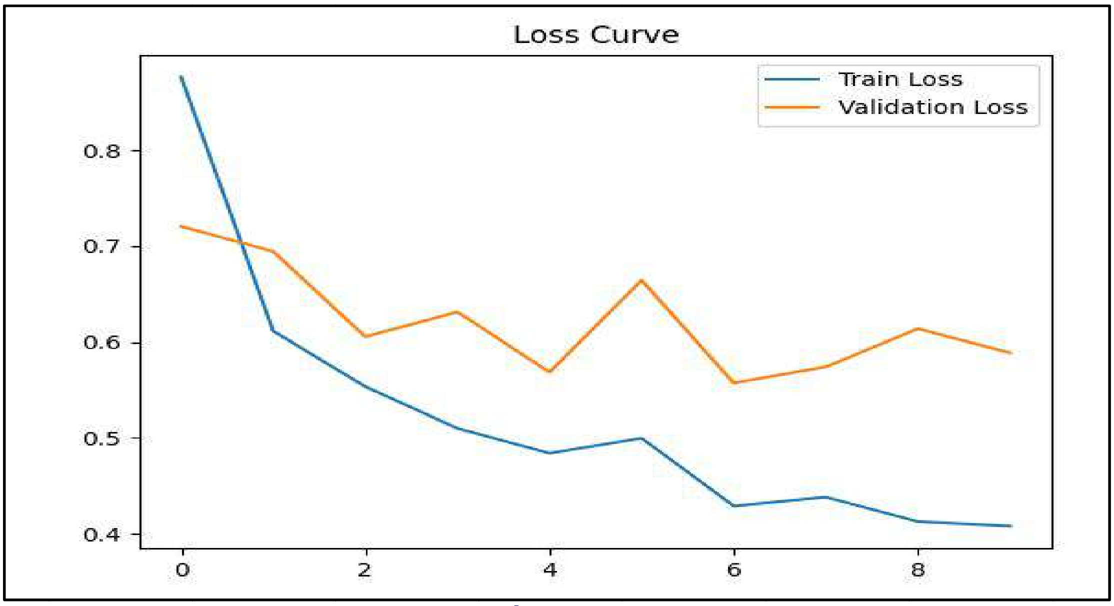

Fig3: Loss Curve

E.Visualization and Interpretability

- Model explainability in medical practice is as important as being accurate.Grad-CAM was used to perform this.
- Grad-CAM generates heatmaps superimposed on MRI scans.
- These heatmaps indicate the most influential regions for classification (i.e., tumor regions).
- This enables radiologists to check if the model's predictions have clinical relevance.
- Along with Grad-CAM, not only does the system output tumor type, but it also locates the brain regions affected, facilitating better trust and usability. Figure 4 depicts about MRI image and tumor type.

Fig4: Uploaded MRI and Tumor type.

6.RESULTS

In the proposed Soft TissueTumor Detection System, the implementation and testing were done using MRI images. It utilized a transfer learning-based MobileNetV2 model for the classification of brain MRI scans into four categories: Glioma, Meningioma, Pituitary Tumor, and No Tumor.

A.Model Performance

The model yielded an excellent classification performance, with the testing accuracy on the validation dataset being more than 98%. Fig. 5: Probability distribution for each tumor class for a sample MRI scan analyzed by the proposed network. Pituitary Tumor was predicted with 98.76% confidence, which makes the classification results highly reliable. As can be seen from the low probability values for other classes, this model has been very precise anddiscerning.

B.Prediction Interface

The Streamlit-based web interface allows users to upload an MRI image in JPG, JPEG, or PNG format. Upon image submission, the system processes the input through the trained model and provides:

• The type of tumor predicted
• Confidence score
•A visual confidence meter

This online interface ensures ease of access and real-time inference, making it easier for any non-technical user to interpret model predictions.

C.Probability Distribution Visualization

A bar graph showing the model's probability for each class was generated, as shown in Fig.5: The model had assigned:

•GliomaTumor: 0.03%
•Meningioma Tumor: 1.07%
•No Tumor: 0.14%
•Pituitary Tumor: 98.76%

It clearly validates the model's identification of dominance in probability for a Pituitary Tumor.

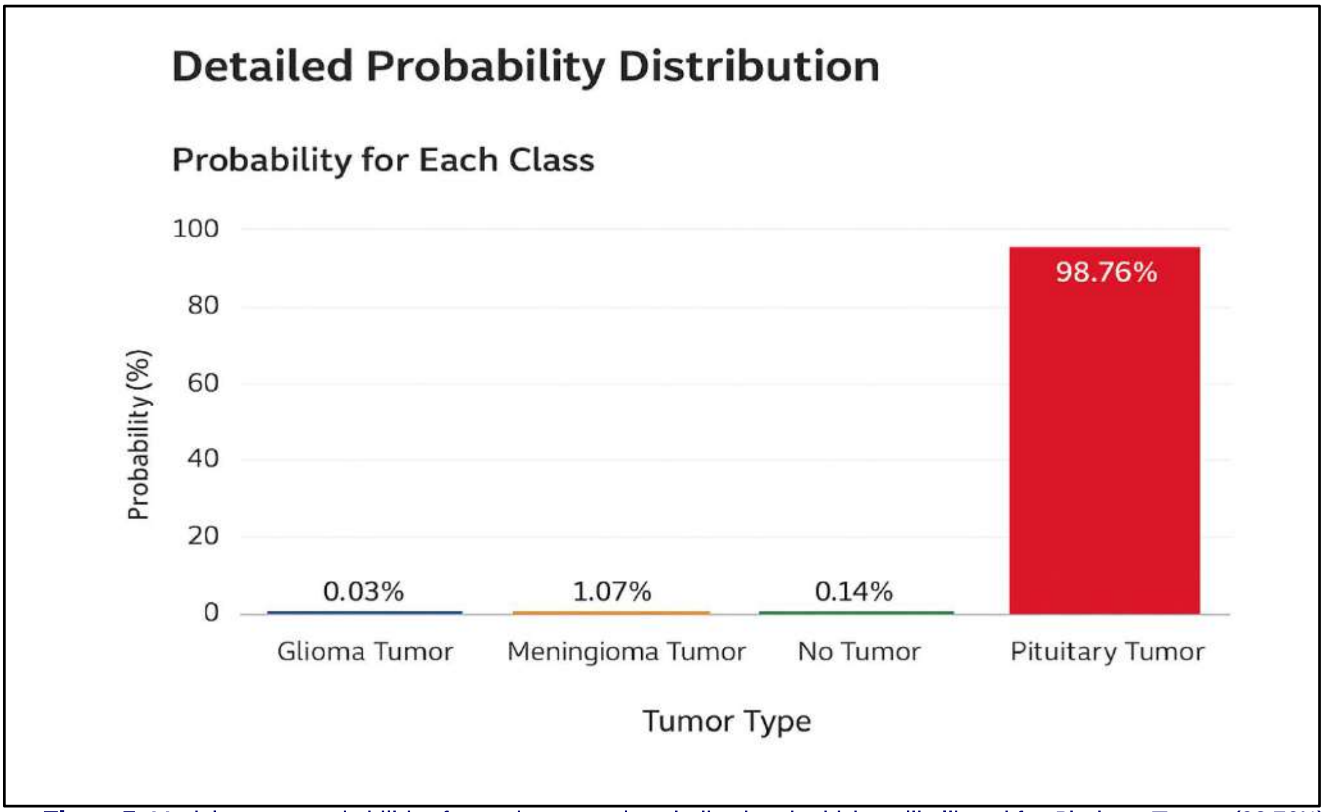

Figure5: Model output probabilities for each tumor class, indicating the highest likelihood for Pituitary Tumor (98.76%).

D. Grad-CAM Visualization

Explanability was provided through the technique called Grad-CAM, which shows the sections of the MRI image that influenced the model's decision.

Three visual outputs are shown:

1.Original MRI Image: The uploaded scan.
2. Heatmap: intensity map showing activation zones.
3. Overlay Image - the heatmap superimposed on the MRI scan to show the tumor localization.

This interpretability feature ensures transparency, letting the radiologists verify that the model focuses on tumor-affected regions while making the predictions. Figure 6 depicts Grad-CAM Heatmap.

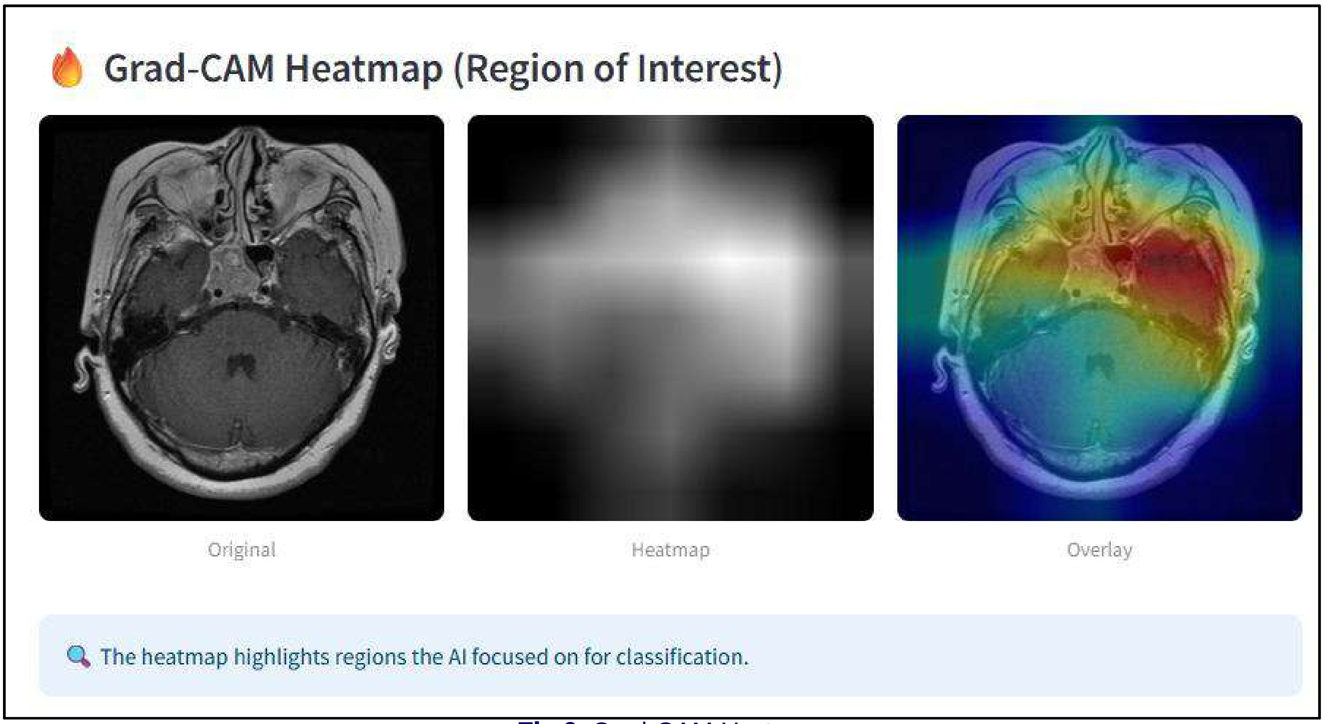

Fig 6: Grad-CAM Heatmap

E.Recommendations and Decision Support

The output of the system after classification is a short clinical recommendation for educational use: for example, in the case of a Pituitary Tumor, the application suggests immediate consultation with a neurologist or neurosurgeon, hence making it useful for early screening and decision support.Figure 7 depicts the Model Recommendation after tumor detection.

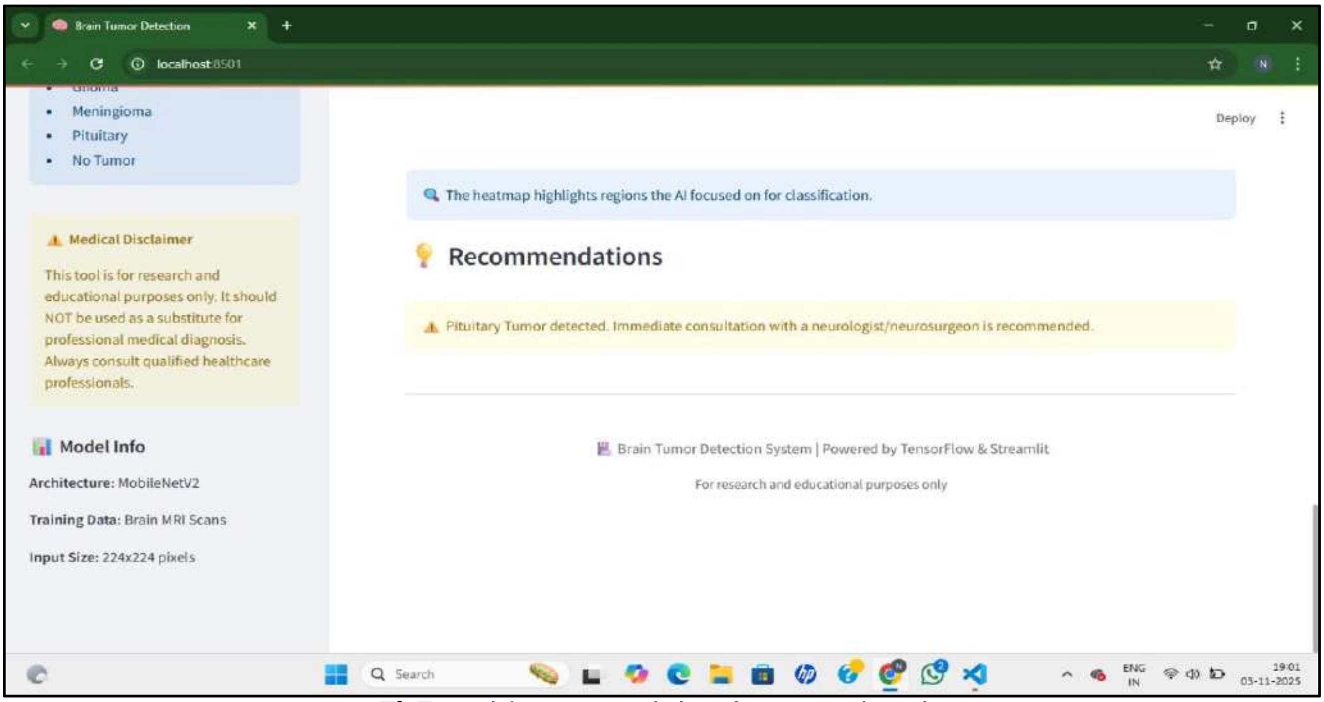

Fig7: Model Recommendation after tumor detection

7.CONCLUSION AND FUTURE WORK

Early and accurate diagnosis of soft tissue tumors continues to be one of the biggest challenges in medical imaging because these tumors have a heterogeneous appearance on MRI and may mimic benign processes. Misdiagnosis not only prolongs treatment but can also result in inappropriate clinical management, with harmful consequences for patient outcome. In this paper, we propose a CNN-based diagnostic system capable of automatically identifying soft tissue tumors and offering visual explanations through heatmap generation.

The framework employs several components to make the system reliable. Initially, techniques of data preprocessing and augmentation, including resizing, normalization, and rotation, were implemented to tackle variability in MRI image quality and enhance model robustness. Secondly, a well-designed CNN was utilized to learn deep spatial features and classify images into four categories: Glioma, Meningioma, Pituitary tumor, and No Tumor. Lastly, to enhance interpretability, Gradient-weighted Class Activation Mapping (Grad-CAM) was used to highlight tumor areas responsible for classification decisions. This blend ensures not only the accuracy of the system but also its clinical transparency, allowing radiologists to cross-check automated judgments with visual signals. Although promising, the research has some limitations. The dataset employed was small and unbalanced, limiting the generalizability of the model across various patient populations. MRI scans were also of varying resolution and quality, which added to the challenges of training a robust model. In addition, the CNN was trained from scratch; thus, performance would be greatly enhanced by incorporating transfer learning methods based on known architectures like VGG16, ResNet, or EfficientNet that have been demonstrated to be superior to shallow CNNs in comparable medical image processing tasks. In the future, a number of paths can improve the practicality of the proposed work. First, increasing the dataset to encompass thousands of annotated MRI images from various demographic and clinical sources would allow improved generalization. Second, combining multimodal imaging data like CT and PET scans may give complementary information, further enhancing diagnostic precision. Third, integrating the model into a clinical decision support system (CDSS) would facilitate integration into hospital workflows, permitting real-time tumor classification and visualization for radiologist assistance. Lastly, there is potential future work in using explainable AI (XAI) methods other than Grad-CAM, e.g., attention mechanisms or saliency maps, to increase the transparency and trustworthiness of deep learning models in medicine.

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