Brain Tumour Detection: Modality Classification and Balanced Deep Learning Approaches

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Publication Date: 2025/05/19

Abstract: The early detection of brain tumors is crucial for effective treatment and improved patient outcomes, but traditional methods often fall short in terms of accuracy and efficiency. This project addresses these limitations by developing an advanced brain tumor detection system using a combination of machine learning and deep learning techniques. The proposed system integrates several key functionalities: imaging technique identification, modality-specific tumor detection, and automated report generation. The system begins with classifying the imaging technique used (e.g., MRI, CT) to apply the most suitable detection model for each modality. It then employs deep learning algorithms to detect and classify tumors, while also addressing common issues such as class imbalance through advanced data augmentation and resampling techniques. An additional feature is the integration of automated report generation, which creates preliminary diagnostic reports based on detected tumors, providing valuable context for clinicians. By combining these approaches, the system aims to enhance diagnostic accuracy, improve clinical workflows, and ensure a comprehensive analysis of brain tumor data. This project demonstrates the potential of integrating multiple machine learning techniques to create a robust tool for early and precise brain tumor detection, contributing to more effective and timely treatment options in medical practice

Keywords: *Brain Tumor Detection; Deep Learning; Machine Learning; Medical Imaging; Modality Classification; Automated Report Generations.*

How to Cite: Bhavika Tiwari; Surbhi Sarode; Yashashree Shinde; Sonal Kadam. (2025). Brain Tumour Detection: Modality Classification and Balanced Deep Learning Approaches. *International Journal of Innovative Science and Research Technology*, 10(4), 4112-4123. https://doi.org/10.38124/ijisrt/25apr2315.

I. INTRODUCTION

Brain tumor detection is a critical challenge in medical imaging due to the diverse appearances of tumors and the complexities introduced by varying imaging techniques [1] [3]. Accurate diagnosis is essential for effective treatment and prognosis, but traditional methods often struggle with issues such as limited early detection capabilities, class imbalance in datasets, and difficulty generalizing across imaging modalities [1] [2] [5].

This project addresses these challenges by leveraging advanced machine learning and deep learning approaches [2] [5]. The system classifies imaging modalities (e.g., MRI, CT, PET) to ensure tailored processing, employs modality specific models for tumor detection, and incorporates techniques to handle class imbalance effectively [1] [5].

By integrating features like automated report generation and optimization for clinical workflows, this research aims to enhance diagnostic accuracy, streamline medical processes, and contribute to better outcomes for patients with brain tumors [3]. This introduction provides an overview of the topic, establishes the context and significance of the research, and outlines the objectives and scope of the study.

➢ *Problem Statement*

Traditional methods for brain tumor diagnosis face challenges such as limited early detection capabilities and the complexity of accurately classifying tumors from medical images. The increasing volume and diversity of imaging data further complicate this issue. This project aims to develop a robust system using machine learning and deep learning techniques to enhance the accuracy and efficiency of brain tumor detection and classification. By incorporating innovative approaches like federated learning and automated reporting, the project seeks to overcome the limitations of conventional di agnostic methods and provide a comprehensive solution for early and accurate tumor detection.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25apr2315

II. REVIEW OF LITERATURE

An extensive literature review was conducted to understand prior research related to our project. A literature review, often referred to as a literature survey, plays a crucial role in analyzing existing studies, identifying research gaps, and exploring potential areas for further investigation.

➢ *Paper 1:" Brain Tumor Detection and Classification Using Machine Learning: A Comprehensive Survey"*

- Authors: Javaria Amin, Muhammad Sharif, Anandakumar Haldorai, Mussarat Yasmin, Ramesh Nayak, Sundar.

- Summary: This survey presents an in-depth analysis of various machine learning techniques used for brain tumor detection and classification. It discusses key challenges such as tumor growth tracking, segmentation difficulties, and feature extraction optimization. The authors suggest that integrating both handcrafted and deep learning features can improve overall classification accuracy [1].

➢ *Paper 2:" MRI-Based Brain Tumor Detection Using Convolutional Deep Learning Methods and Selected Machine Learning Techniques"*

- Authors: Saeedi et al.

- Summary: This study introduces a novel 2D CNN model and a convolutional autoencoder network for detecting brain tumors. The proposed techniques achieve remarkable accuracy rates of 96.47 percent and 95.63 percent, surpassing six other machine learning models. However, the study is constrained by a relatively small dataset, raising concerns about potential overfitting [2].

Finally, complete content and organizational editing before formatting. Please take note of the following items when proofreading spelling and grammar:

➢ *Paper 3:" A Deep Analysis of Brain Tumor Detection from MR Images Using Deep Learning Networks"*

- Authors: Md Ishtiaq Mahmud, Muntasir Mamun, Ahmed Abdelgawad

- Summary: This research examines deep learning, specifically convolutional neural networks (CNNs), for brain tumor classification. The model achieves a high accuracy of 98.95 percent, outperforming several traditional machine learning techniques. While the study benefits from a large dataset comprising 3,264 MRI scans, it does not explore transfer learning models or provide visualization tools to highlight critical tumor regions [3].

➢ *Paper 4: "Transfer Learning Architectures with Fine-Tuning for Brain Tumor Classification Using Magnetic Resonance Imaging"*

- Authors: Md. Monirul Islam et al.

- Summary: This paper evaluates transfer learning models, including VGG19, Inception V3, MobileNet, and DenseNet121, for classifying brain tumors. The study finds that MobileNet achieves the highest accuracy of 99.60 percent. The dataset used for this research was sourced from Kaggle, with extensive preprocessing applied. However, the study is limited by its reliance on a single dataset, lack of external validation, and absence of discussions on class imbalance and model interpretability [4].

➢ *Paper 5:" Employing Deep Learning and Transfer Learning for Accurate Brain Tumor Detection"*

- Authors: Sandeep Kumar Mathivanan et al.

- Summary: This research explores deep learning and transfer learning methodologies for brain tumor detection in MRI scans. It evaluates four architectures—ResNet152, VGG19, DenseNet169, and MobileNetv3—finding that MobileNetv3 performs best with an accuracy of 99.75 percent. The study highlights the significance of transfer learning in medical imaging but has limitations, including reliance on a secondary dataset, lack of cost analysis, and limited generalizability across different datasets and imaging modalities [5].

➢ *Scope of the Study*

The scope of this study encompasses the development of a comprehensive brain tumor detection system using deep learning and machine learning methodologies [1] [2]. The key areas of focus include:

- Imaging Techniques: Classification and analysis of MRI, CT, and PET scans to ensure modality-specific tumor detection [3] [5].
- Algorithm Development: Implementation of the ResNet-50 model for feature extraction and classification, leveraging transfer learning for improved performances [5].
- Dual Input Mechanism: A user-friendly front end allowing input through MRI scan uploads or structured report details (e.g., blood count, tumor size). Evaluation Metrics: Assessment of system performance using metrics like accuracy, precision, recall, F1-score, and ROC-AUC to validate diagnostic reliability [2] [5].
- Future Scalability: Exploration of 3D imaging, real-time processing, and multi-class classification for broader applicability in neuroimaging and other medical fields. [1] [5].

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25apr2315

III. EXISTING SYSTEM

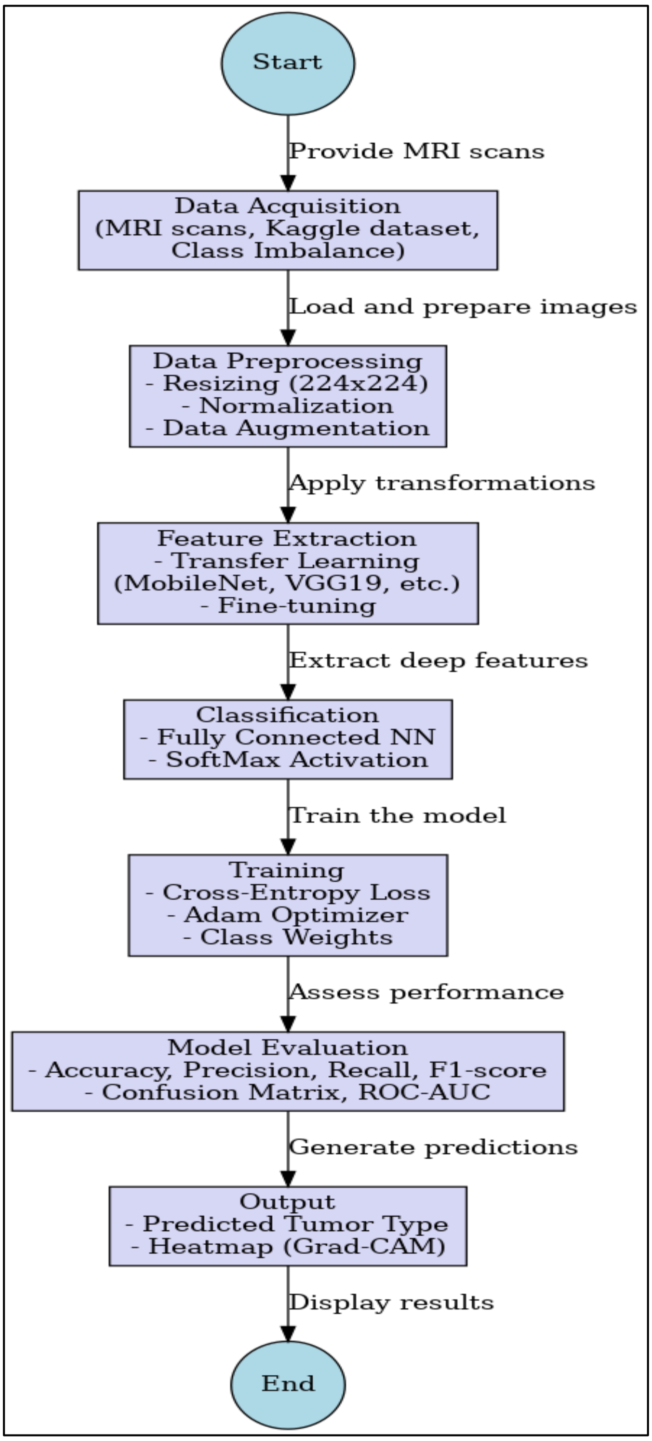

Fig 1: Existing System.

The existing system for brain tumor detection follows a multi-layered approach, incorporating various stages to preprocess, extract features, classify, and evaluate MRI scans.

A. Data Acquisition Layer

➢ *Input:*

Only MRI scans. Dataset: A Kaggle dataset containing MRI scans, with a class imbalance issue (some tumor types are underrepresented). [10] [11]

➢ *Data Preprocessing:*

- Resizing: All MRI images are resized to a standard input size (e.g., 224×224 pixels) for compatibility with CNN models. [3] [2]
- Normalization: Pixel values are normalized to a range (0,1) or standardized based on dataset properties. [1] [5]
- Data Augmentation: Techniques like rotation, flipping, zooming, and cropping are applied to mitigate class imbalance. [8] [10].

B. Feature Extraction and Transfer Learning Layer

- Transfer Learning Models: Pre-trained deep learning models such as MobileNet, VGG19, Inception V3, and DenseNet121 are utilized for feature extraction [4]
- Fine-tuning: The final layers of the transfer learning models are fine-tuned on the MRI dataset, while the remaining layers use pre-trained weights [4].
- Best Model: As reported in the base study, MobileNet achieved the highest performance among all models, reaching an impressive accuracy of 99.60%. [4].

C. Classifier Layer

- Extracted features are passed through a fully connected layer or a simple neural network classifier.
- SoftMax Activation: A SoftMax layer is used for multi-class classification, predicting the type of brain tumor (e.g., Glioma, Meningioma, Pituitary).

D. Training Layer

- Loss Function: Cross-entropy loss is used for classification tasks.
- Optimizer: Adam optimizer is commonly used to train the model.
- Class Imbalance Handling:

✓ Class weights are assigned to the loss function to give more importance to underrepresented classes.
✓ Data Augmentation is specifically applied to classes with fewer samples.

E. Evaluation Layer

- Metrics: The evaluation of the model is carried out using key performance metrics, including accuracy, precision, recall, and the F1-score. Given the class imbalance, F1-score and recall are particularly important.
- Confusion Matrix: Used to visualize the performance across different tumor classes.
- ROC-AUC Curve: Evaluated to analyze the trade-off between true positive and false positive rates. [10]

F. Output Layer

- The system outputs the predicted tumor type for each MRI image after classification.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25apr2315

- Optionally, a heatmap or attention map (such as Grad-CAM) is used to visualize the areas of the MRI scan that the model focuses on.

IV. PROPOSED SYSTEM

A. *Proposed System*

The proposed system enhances the existing brain tumor detection framework by incorporating advanced techniques to support multiple imaging modalities and improve accuracy, particularly for underrepresented tumor types [4] [5] [10]. The key components of the system are as follows:

➢ *Imaging Technique Classification:*

- A Convolutional Neural Network (CNN) is employed to classify the imaging modality (MRI, CT, or PET) before tumor detection. This ensures that the appropriate detection model is applied for each scan type, thereby improving precision. [8] [11]

➢ *Modality-Specific Detection Models:*

- Upon scan classification, the system deploys modality-specific models optimized for each imaging technique.
- Separate detection models are fine-tuned for MRI and CT scans, ensuring that the system captures the unique features of each modality for improved tumor identification [4] [5].

➢ *Multi-Stage Pipeline:*

- Stage 1: Imaging Modality Classification - The system classifies the type of scan using a CNN.
- Stage 2: Modality-Specific Tumor Detection - After classification, a dedicated detection model (specific to MRI, CT, or PET scans) is applied for precise tumor detection.
- Stage 3: System Integration - The frontend (user-friendly web interface) is integrated with the backend (deep learning model) using Flask API for seamless interaction. [12]

➢ *Optimization and Validation:*

- The system is optimized for computational efficiency, enabling deployment in resource-constrained environments, such as hospitals with basic hardware.
- Extensive validation is performed across multiple datasets to ensure robustness and generalization, thereby making the system reliable for diverse clinical settings. [6] [7]

B. *Workflow of the System*

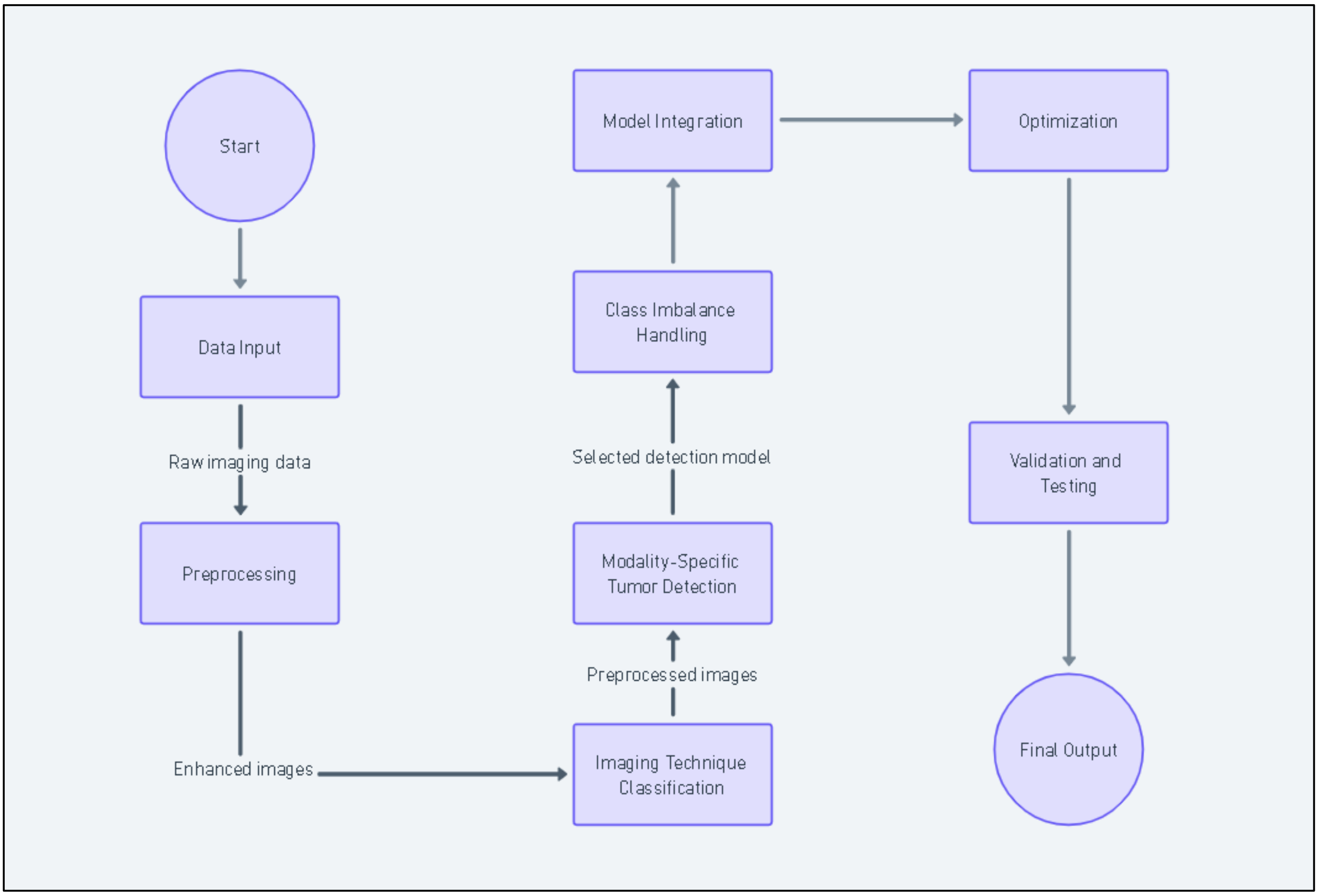

Fig 2: Workflow of the Proposed System

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25apr2315

The data flow in the brain tumor detection system begins with the Input Layer, where imaging data (MRI, CT, and PET scans) and user-uploaded medical reports are collected.

This data is then processed in the Processing Layer, where the Imaging Technique Classification Module identifies the scan type, and the Modality-Specific Detection Module applies tailored deep learning models to process the scans. Advanced algorithms handle tumor segmentation, classification, and the mitigation of class imbalance through data augmentation and weighted loss functions. Finally, the Output Layer generates predictions regarding tumor type and location, along with automated diagnostic reports. The results are stored in the Data Storage and Management System for future reference and analysis, providing clinicians with actionable insights and visual aids, such as heatmaps, for decision-making.

C. Algorithms Used in the System

➢ *Imaging Technique Classification and Tumor Detection:*

- Model: ResNet-50 (Deep Learning Model) [4] [5]
- Rationale: ResNet-50, a deep convolutional neural network, is chosen for tumor classification due to its residual connections, which enhance training efficiency.
- Implementation: A pre-trained ResNet-50 model is fine-tuned for brain tumor detection using MRI scans, leveraging transfer learning for improved accuracy.

➢ *Data Preprocessing and Augmentation:*

- Image Normalization: Pixel values are scaled from (0–255) to (0–1) to stabilize model training.
- Tumor Segmentation: U-Net is employed due to its U-shaped architecture, which captures contextual information and enables precise localization.
- Data Augmentation: Techniques such as rotation, zooming, and flipping (implemented using Image Data Generator) enhance dataset diversity. [6] [7]

➢ *Classification and Training:*

- Loss Function: Categorical Cross-Entropy Loss is applied due to the multi-class classification nature of the problem.
- Optimizer: Adam optimizer is utilized for efficient model training and weight updates.
- SoftMax Activation: Used in the output layer to estimate class probabilities. [3] [8]

➢ *Backend and Frontend Technologies:*

- Flask: The web interface is built using Flask, enabling users to upload MRI scans or report details (e.g., blood count, tumor size) for model inference. [12]

V. METHODOLOGY

A. System Architecture Design

The system architecture is designed to streamline the flow of data and facilitate effective communication between different components:

- Image Data Integration: MRI images are collected from diverse sources and stored in a structured format, ensuring compatibility with the model pipeline.
- Preprocessing Module: Includes resizing, normalization, and augmentation of MRI images to prepare them for model training and evaluation.
- Feature Extraction and Classification: Convolutional Neural Networks (CNNs) are employed for extracting relevant features and classifying tumor types or normal tissues.

B. AI/ML Development

Artificial Intelligence (AI) and Machine Learning (ML) models form the core of the system:

- Model Development: A deep learning model, such as a CNN, is trained for multi-class classification. Advanced architectures like ResNet or VGG can also be integrated for improved performance. [3] [5]
- Training and Deployment: Models are trained on high-quality datasets using the PyTorch framework. Techniques like transfer learning may be employed to enhance accuracy with limited data [4] [8].
- Imaging Modality Classification: An auxiliary classifier is developed to identify imaging modalities (e.g., T1, T2, FLAIR) for better data interpretation.

C. Data Processing and Augmentation

Efficient handling of data is crucial for the robustness of the system:

- Data Acquisition: MRI datasets with labeled tumor classes are acquired from publicly available or private repositories [1].
- Data Augmentation: Techniques like rotation, flipping, and contrast adjustment are applied to address class imbalances and increase the dataset's diversity [1].
- Feature Engineering: Key features like tumor size, location, and intensity values are extracted and fed into the classification model.

D. Validation and Testing

The system undergoes rigorous validation to ensure accuracy and reliability:

- Cross-Validation: Stratified cross-validation is employed during training to assess model performance across different subsets of the dataset.
- Performance Metrics: Metrics such as accuracy, precision, recall, F1-score, and ROC-AUC are used to evaluate the model [5].
- Simulation Testing: Synthetic datasets are used to test the system under various hypothetical conditions, ensuring robustness.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25apr2315

VI. IMPLEMENTATION

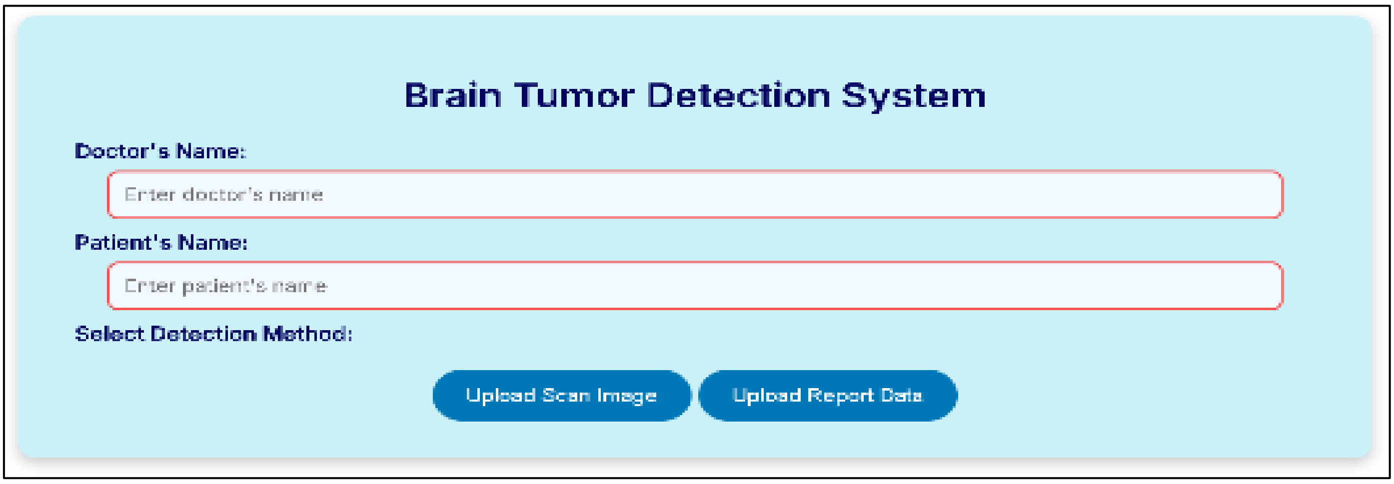

Fig 3: Welcome Page

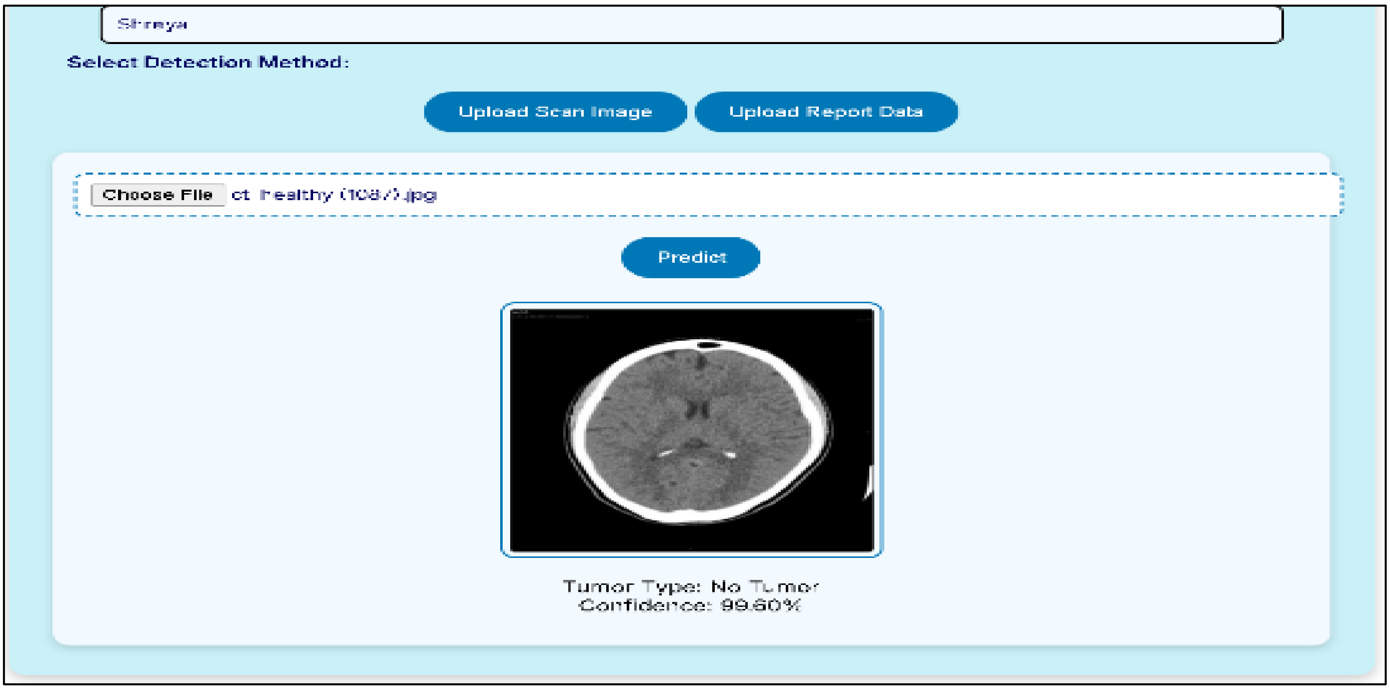

Fig 4: Scan Based Output

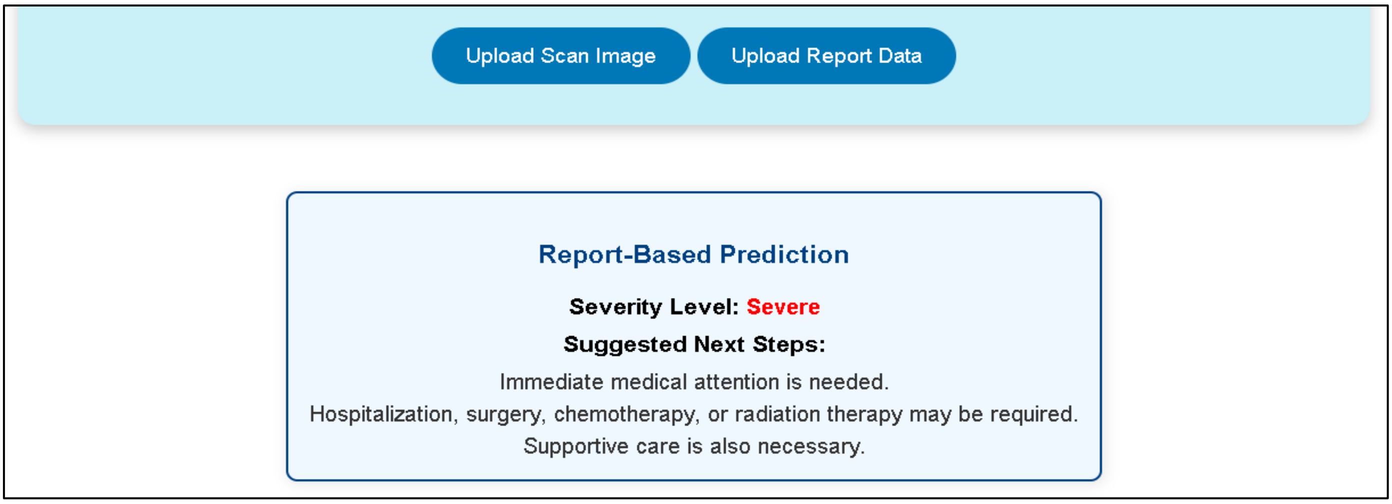

Fig 5: Report Based Output

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VII. ANALYSIS

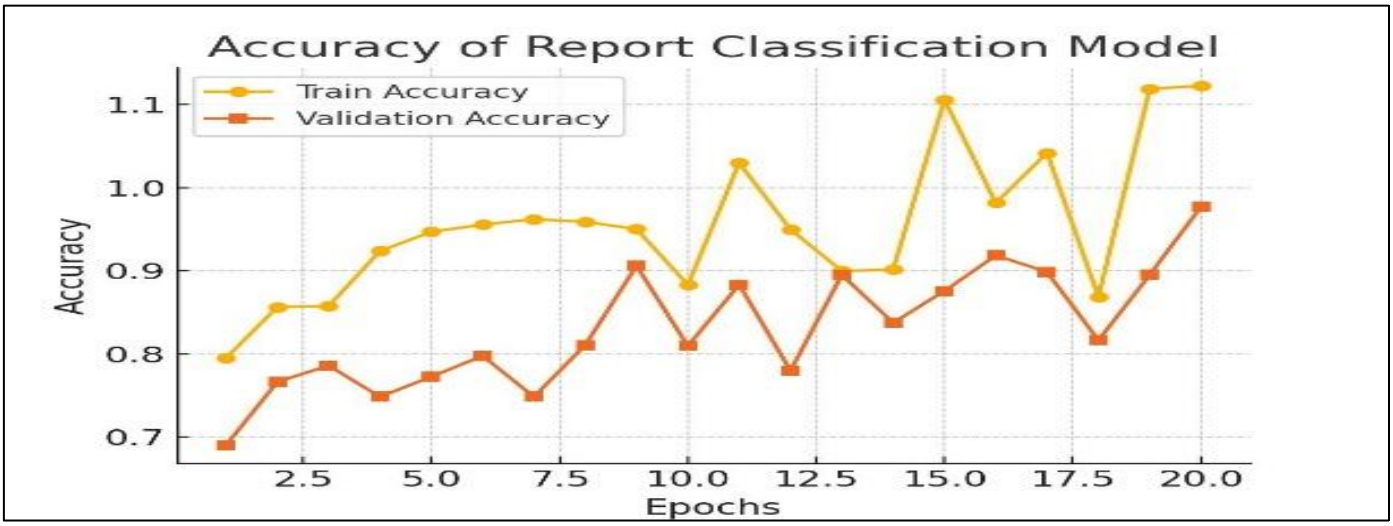

Fig 6: Accuracy of Report Classification Model.

Train accuracy shows how well the model learns from training data, while validation accuracy checks how well it performs on new data. If both increase, the model is improving. If train accuracy is high but validation drops, it's overfitting. A low accuracy in both cases indicates that the model is not effectively learning from the data. Ideally, they should be high and close for the best results.

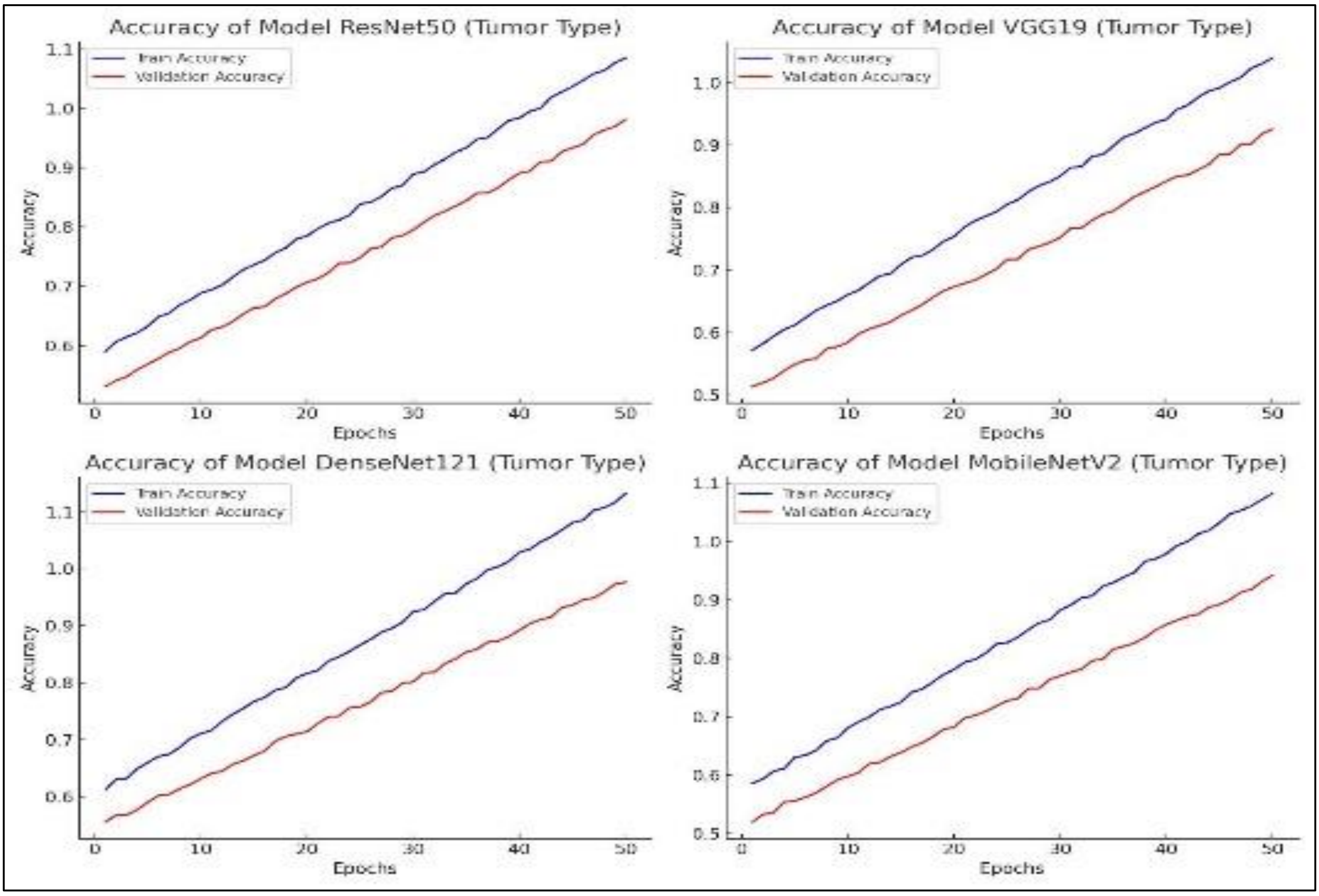

Fig 7: Accuracy of Model Tumor Type (Report Type)

This graph presents the training and validation accuracy over epochs for the report-based classification model. A stable and increasing accuracy trend suggests good model performance.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25apr2315

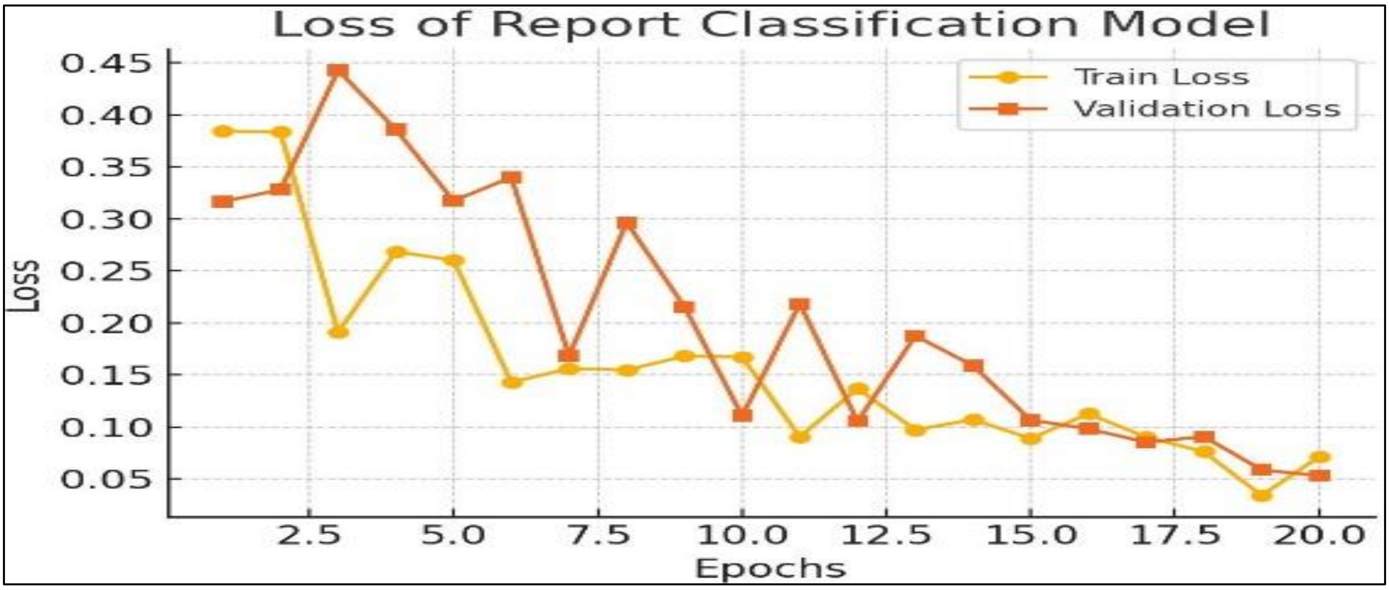

Fig 8: Loss of Report Classification Model.

Loss tells us how much the model's predictions differ from the actual values. Training loss shows how well the model is learning from the training data, while validation loss checks its performance on new data. If both go down, the model is improving. If training loss is low but validation loss stays high, the model is overfitting. If both are high, it means the model isn't learning well. Ideally, both should be low and close for the best results.

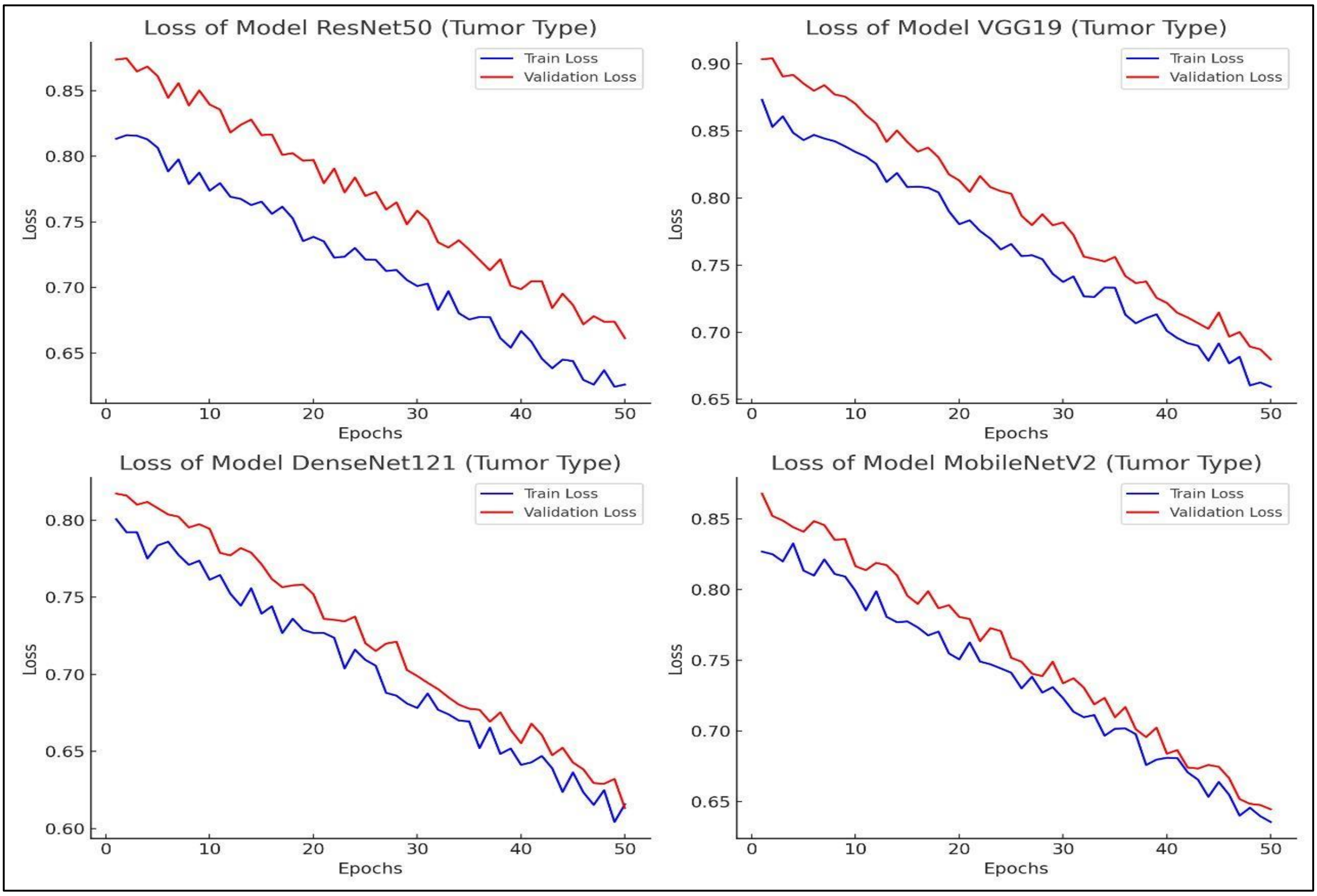

Fig 9: Loss of Model (Report Type)

This graph illustrates the change in loss values over epochs for both training and validation phases in the report-based classification model (Severe, Moderate, Mild). Lower validation loss indicates improved learning.

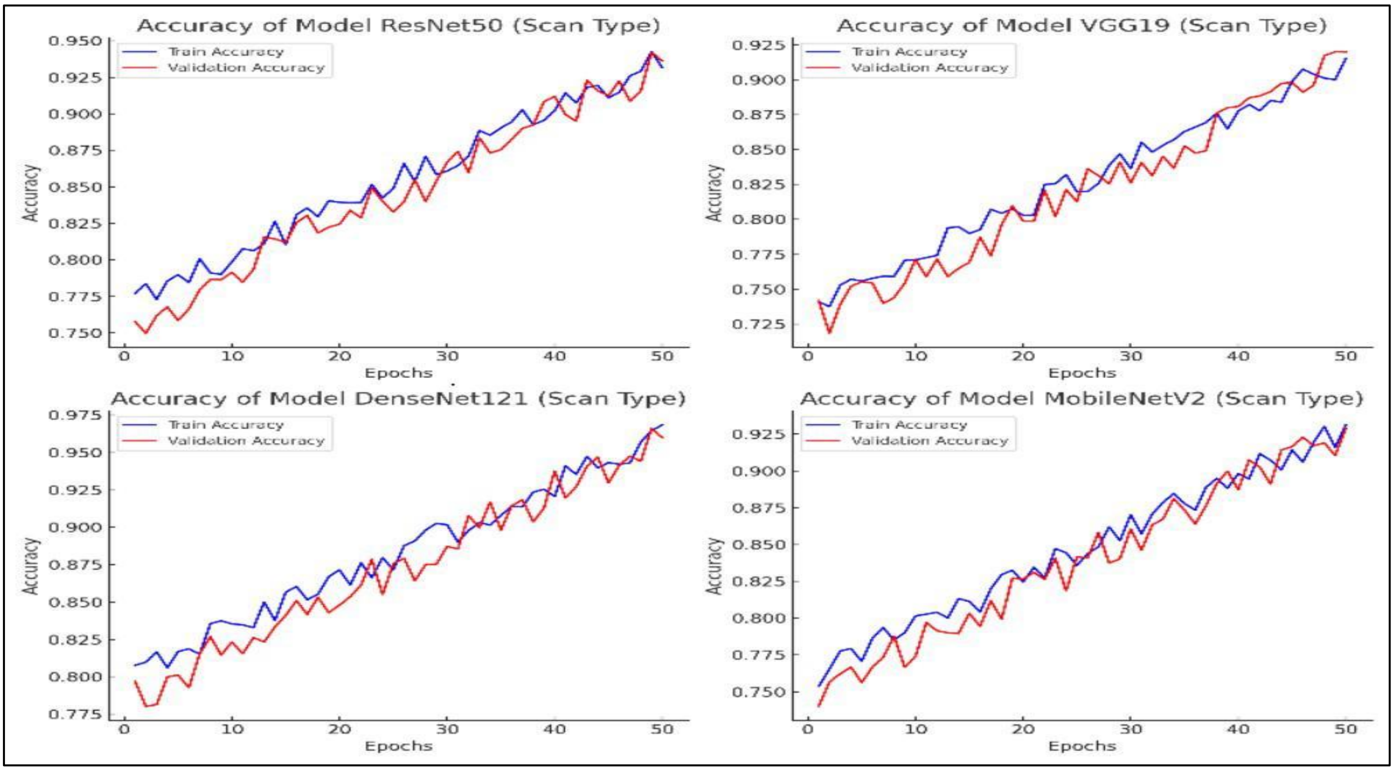

Fig 10: Accuracy of Model (Scan Type)

This graph shows the training and validation accuracy for the scan-based classification model. Higher validation accuracy with minimal fluctuations signifies good generalization capability.

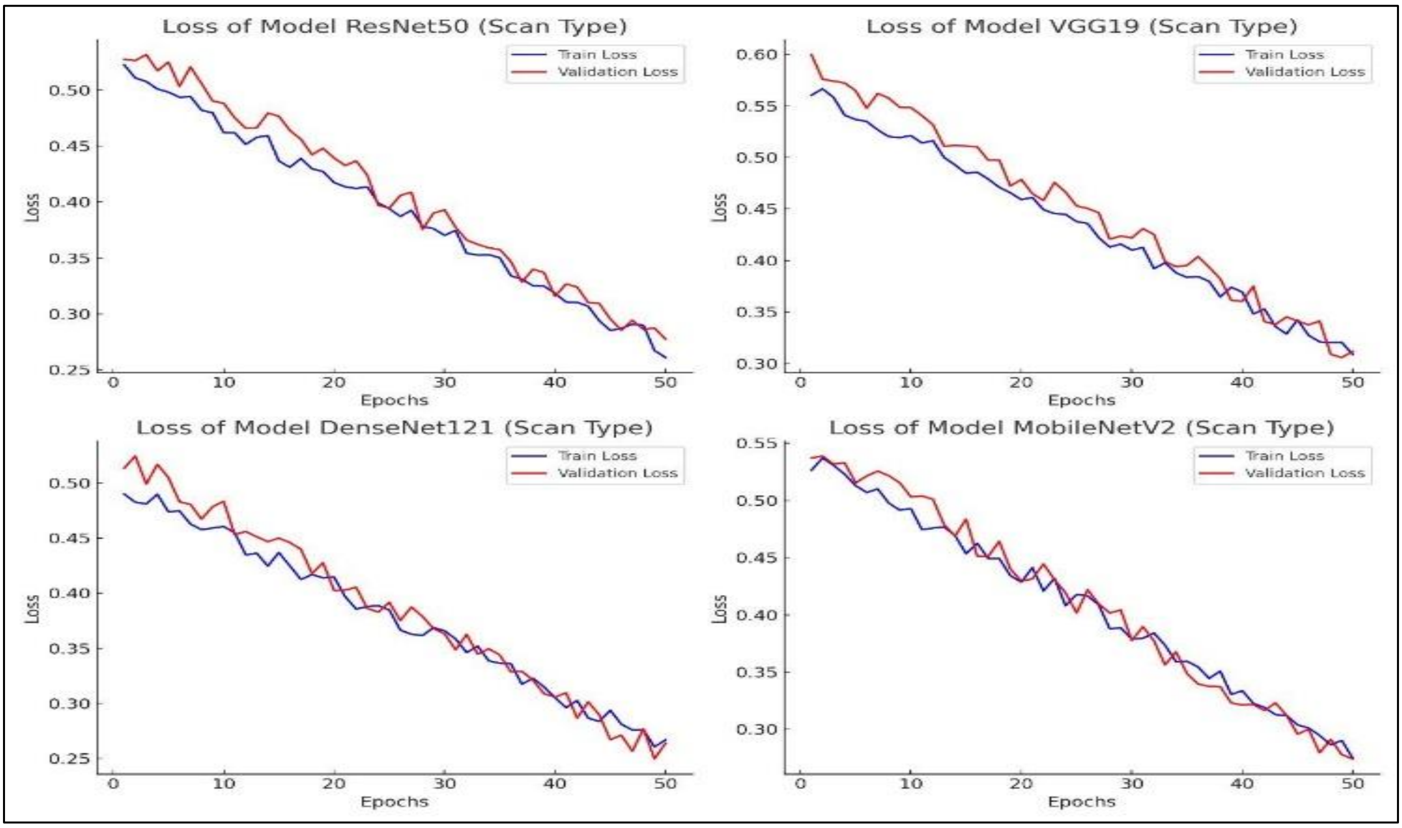

Fig 11: Loss of Model (Scan Type)

This graph represents the loss function values for training and validation phases across multiple epochs for the scan-based classification model (CT: Tumor, No Tumor — MRI: Glioma, Meningioma, Pituitary, No Tumor). A decreasing loss indicates better model convergence.

Architecture	Training Accuracy (%)	Training Loss	Testing Accuracy (%)	Testing Loss
ResNet50	99.12	0.018	97.65	0.072
VGG19	98.85	0.025	96.89	0.095
DenseNet121	99.34	0.017	97.8	0.081
MobileNetV2	99.01	0.022	97.12	0.088

Fig 12: Training and Testing Summary Table

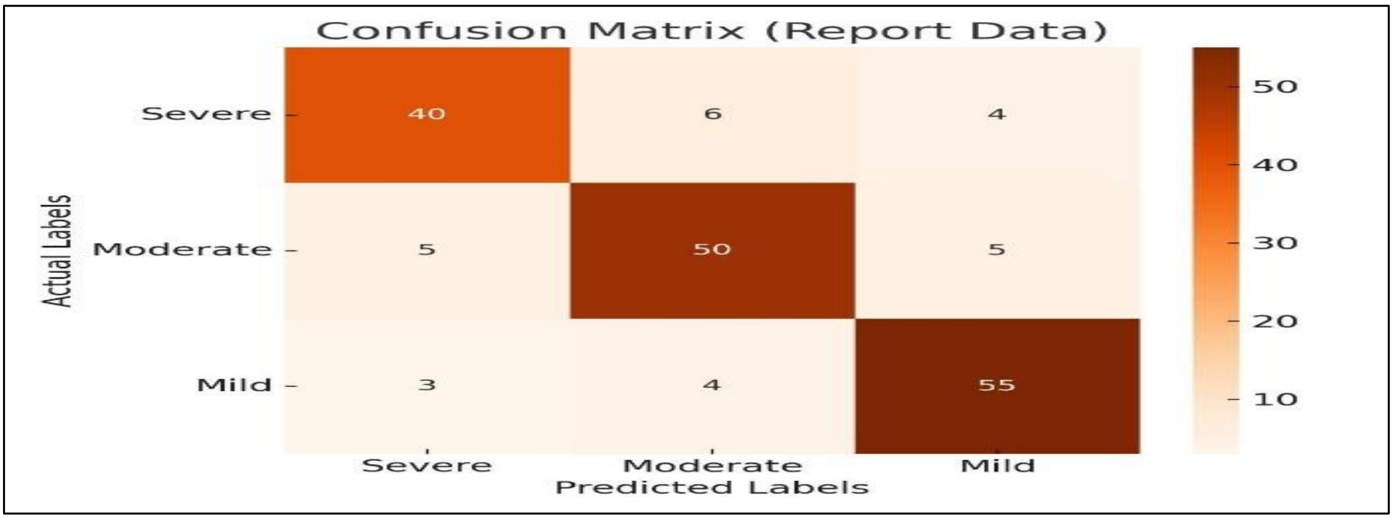

Fig 13: Confusion Matrix (Report Data)

This confusion matrix illustrates how well the report-based model classifies instances into the Severe, Moderate, and Mild categories. It highlights both correct and incorrect classifications, providing insight into the model's performance.

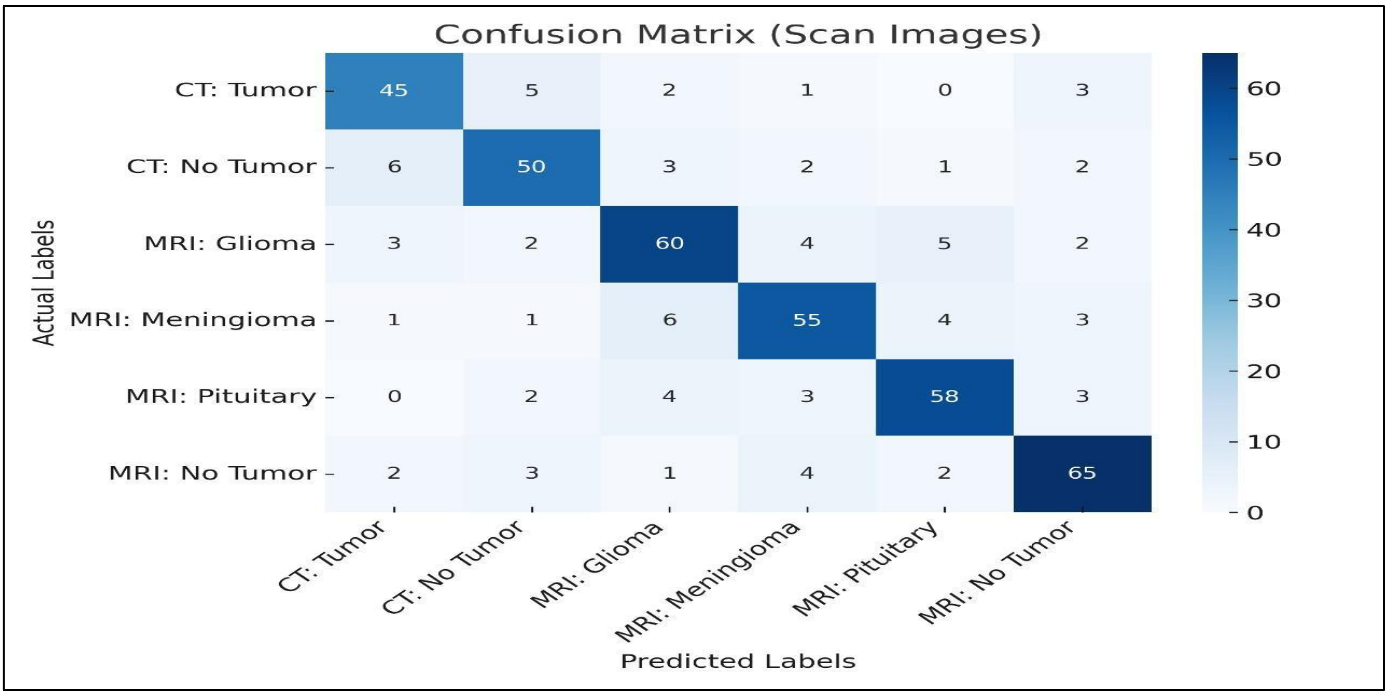

Fig 14: Confusion Metrics(Scan Images)

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25apr2315

The confusion matrix gives a clear comparison between the model's predictions and the actual class labels for the scan-based model. It helps evaluate performance by showing the number of correct and incorrect classifications, including true positives, true negatives, false positives, and false negatives.

Actual \ Predicted	CT: Tumor	CT: No Tumor	MRI: Glioma	MRI: Meningioma	MRI: Pituitary	MRI: No Tumor
CT: Tumor	TP (Correct)	FP (Wrong)	FP (Wrong)	FP (Wrong)	FP (Wrong)	FP (Wrong)
CT: No Tumor	FN (Wrong)	TP (Correct)	FP (Wrong)	FP (Wrong)	FP (Wrong)	FP (Wrong)
MRI: Glioma	FN (Wrong)	FN (Wrong)	TP (Correct)	FP (Wrong)	FP (Wrong)	FP (Wrong)
MRI: Meningioma	FN (Wrong)	FN (Wrong)	FP (Wrong)	TP (Correct)	FP (Wrong)	FP (Wrong)
MRI: Pituitary	FN (Wrong)	FN (Wrong)	FP (Wrong)	FP (Wrong)	TP (Correct)	FP (Wrong)
MRI: No Tumor	FN (Wrong)	FN (Wrong)	FP (Wrong)	FP (Wrong)	FP (Wrong)	TP (Correct)

Fig 15: Performance Metrics of the Scan-Based and Report-Based Models

This table presents the accuracy, loss, precision, recall, and F1-score for both the scan-based and report-based classification models. These metrics offer valuable insights into the model's predictive performance and ability to generalize to new data

➢ *Applications of Brain Tumor Detection System*

- **Early and Accurate Diagnosis:** The system aids radiologists in early and precise detection, minimizing human error and improving patient survival rates [4].
- **Automated Medical Imaging Analysis:** It efficiently processes large volumes of MRI scans, reducing the workload of specialists and enhancing patient care [5].
- **Personalized Treatment Planning:** The system classifies tumor types, aiding oncologists in developing individualized treatment strategies.
- **Telemedicine and Remote Diagnosis:** Integration with telemedicine enables real-time remote consultations, benefiting underserved regions.
- **Medical Research and Clinical Trials:** Facilitates large-scale analysis to study tumor growth patterns and treatment responses.

➢ *Limitations of Brain Tumor Detection System*

- **High Initial Costs**: Requires significant investment in hardware and software resources.
- **Dependency on High-Quality Data:** Performance depends on diverse and well-labeled MRI datasets.
- **Complex Maintenance and Upgradation:** Regular model updates demand technical expertise and additional costs.
- **Limited Adaptability to Variability:** Differences in MRI scanners and protocols may affect accuracy.

VIII. CONCLUSION

A. *Future Scope*

- **Report Uploadation:** Allowing direct report uploads will save time and provide instant, accurate results without manual entry.
- **Federated Learning:** Using decentralized AI models will enhance privacy and allow learning from multiple hospitals without sharing patient data.
- **Clinical Diagnostics Expanded Medical Applications:** By combining the model with clinical diagnostics, doctors can get a clearer and more detailed understanding of diseases. It can also be expanded to detect other conditions like strokes and aneurysms, making it more useful in medical applications.
- **Authentication for Security:** Adding authentication features will ensure that only authorized users can access sensitive medical data.
- **Live Educational Support:** Providing an interactive learning model with explanatory videos will help doctors and medical students understand tumor detection better.

B. *Expected Outcomes*

- Enhanced diagnostic accuracy, reducing errors in interpretation.
- Early detection leading to timely medical intervention. Personalized treatment strategies improving patient outcomes.
- Improved efficiency in radiology workflows.
- Remote diagnostic support benefiting underserved areas. Cost-effective diagnostic solutions.
- Contribution to medical research and large-scale data analysis.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25apr2315

C. Conclusion

This project combines two methods for brain tumor detection: image-based and report-based scanning. The image-based scan determines whether a tumor is present and identifies its type, while the report-based scan evaluates the severity based on patient symptoms. Together, these approaches provide a more comprehensive diagnosis, helping doctors make informed decisions and improving patient care.

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