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Automated Identification and Severity Assessment of Brain Tumors from MRI Scans Using Advanced Deep Neural Networks

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Abstract: *Brain tumors are among the most serious neurological disorders, and early diagnosis plays a major role in improving treatment planning and patient survival. Magnetic Resonance Imaging (MRI) is widely used for brain tumor examination because it provides detailed images of soft tissues without harmful radiation. However, manual interpretation of MRI scans can be time-consuming, subjective, and highly dependent on the expertise of radiologists. This creates a need for automated systems that can assist in accurate and faster diagnosis. This study presents an automated framework for the identification and severity assessment of brain tumors from MRI scans using advanced deep neural networks. The proposed approach applies deep learning techniques to analyze MRI images and detect abnormal tumor regions with high precision. The system is designed not only to identify the presence of a tumor but also to classify its severity based on learned imaging features such as shape, size, texture, and intensity variations. By using convolutional neural network (CNN)-based architectures, the model is capable of extracting complex patterns from MRI scans that may not be easily noticeable through conventional analysis. The research workflow includes image preprocessing, feature extraction, tumor classification, and severity evaluation. MRI datasets are cleaned and normalized to improve image quality and ensure consistent model performance. The deep neural network is then trained to distinguish between normal and abnormal brain scans and further categorize the tumor condition into different severity levels. Performance is evaluated using standard metrics such as accuracy, precision, recall, F1-score, and confusion matrix analysis. The findings indicate that deep learning-based automated systems can significantly enhance diagnostic support by reducing human error and improving the consistency of brain tumor assessment. The study highlights the practical value of artificial intelligence in medical imaging and demonstrates how advanced neural networks can support healthcare professionals in decision-making. This approach has the potential to contribute to early diagnosis, better clinical planning, and more reliable patient monitoring in neuro-oncology. Future improvements may include real-time MRI analysis, integration with hospital diagnostic systems, and the use of hybrid models for even greater predictive performance.*

Keywords*:* *Brain Tumor Detection, MRI Scans, Deep Learning, Convolutional Neural Network, Severity Assessment, Medical Image Analysis, Artificial Intelligence in Healthcare, Tumor Classification, Neural Networks, Automated Diagnosis*

I. INTRODUCTION

Brain tumors represent one of the most critical and life- threatening disorders affecting the central nervous system. They arise due to the uncontrolled growth of abnormal cells within the brain or surrounding tissues and may be either benign or malignant depending on their biological behavior and rate of progression. Even non-cancerous tumors can become clinically dangerous because of the limited space inside the skull, where growing masses may compress vital brain structures and disrupt normal neurological function [1], [2]. In recent years, the diagnosis and management of brain tumors have become more advanced due to improvements in neuroimaging, pathology, and molecular characterization. The updated World Health Organization (WHO) classification of central nervous system tumors emphasizes that tumor diagnosis is no longer based only on visual histology, but increasingly on integrated molecular and radiological evidence, making accurate and timely identification more important than ever [2], [3], [4].

Brain tumors may cause a wide range of symptoms such as persistent headaches, vomiting, blurred vision, seizures, memory disturbances, personality changes, difficulty in speech, and motor dysfunction. The severity of these symptoms often depends on the tumor's size, location, growth pattern, and aggressiveness [1], [5]. In clinical practice, early detection is extremely important because delayed diagnosis may allow the tumor to expand, invade nearby structures, and reduce the effectiveness of treatment. The survival outcomes of patients are closely linked with how early the disease is detected and how precisely the tumor type and grade are identified [4], [5]. Therefore, there is a growing demand for intelligent diagnostic systems that can support clinicians in identifying tumors quickly and consistently.

Among all medical imaging techniques, Magnetic Resonance Imaging (MRI) has become the most widely used and clinically preferred imaging modality for brain tumor evaluation. MRI is especially valuable because it produces high-resolution images of soft tissues without exposing patients to ionizing radiation [4], [6]. It offers multiple imaging sequences—such as T1-weighted, T2-weighted, FLAIR, diffusion, perfusion, and contrast-enhanced imaging—which provide complementary information about the structure, edema, vascularity, cellularity, and biological activity of brain lesions [4], [6], [7]. These properties make MRI highly suitable for identifying the presence, extent, and internal heterogeneity of tumors. MRI also plays a central role not only in initial diagnosis, but also in surgical planning, treatment monitoring, recurrence assessment, and prognosis estimation [4], [6].

Despite its diagnostic importance, manual interpretation of MRI scans remains challenging. Brain tumor imaging often involves subtle differences in intensity, shape, margins, and internal tissue composition, which may vary significantly from one patient to another. Radiologists must often review multiple MRI slices and modalities to identify abnormal patterns, estimate tumor boundaries, and infer tumor severity. This process can be time-consuming, subjective, and influenced by experience level, workload, and inter- observer variability [8], [9]. In hospitals with high patient volume, these limitations can delay diagnosis and increase the risk of inconsistent interpretation. Moreover, some tumors exhibit overlapping imaging characteristics, making it difficult to distinguish between tumor subtypes or grades using conventional visual examination alone [7], [10].

To overcome these limitations, researchers and clinicians have increasingly turned toward Artificial Intelligence (AI) and Deep Learning (DL) for automated brain tumor analysis. Deep learning has emerged as one of the most transformative technologies in medical image analysis because it enables machines to learn complex visual patterns directly from imaging data [9], [11], [12]. Unlike traditional machine learning methods that rely heavily on manually engineered features, deep neural networks can automatically learn hierarchical and highly discriminative image representations from raw or minimally processed MRI scans [9], [11]. This capability is particularly useful in brain tumor analysis, where subtle textural and structural variations may carry important diagnostic information.

Among deep learning methods, Convolutional Neural Networks (CNNs) are especially effective for medical imaging tasks. CNNs are designed to process image data by learning local patterns such as edges, shapes, textures, and spatial arrangements through convolutional filters [11], [13]. In brain tumor applications, CNN-based architectures have demonstrated strong performance in tasks such as tumor detection, tumor segmentation, classification of tumor types, and grading of disease severity [8], [9], [12]. More advanced architectures—including transfer learning models, residual networks, ensemble systems, hybrid CNN pipelines, and explainable AI-assisted classifiers—have further improved the ability of AI systems to analyze MRI data with high precision [12], [14], [15].

A major research direction in this field is not only to identify whether a tumor is present, but also to determine how severe the condition is. Severity assessment is clinically significant because tumor aggressiveness influences treatment decisions, patient prognosis, and follow-up strategy. In neuro-oncology, severity may be associated with factors such as tumor size, infiltration pattern, edema, enhancement behavior, necrosis, and radiological indicators of tumor grade [3], [6], [7]. Automated severity assessment using deep neural networks can assist in categorizing tumors into clinically meaningful groups, thereby supporting radiologists and oncologists in risk stratification and therapeutic planning. Such systems may reduce subjectivity and provide more reproducible decision support, especially when large imaging datasets are available [10], [16].

Another important aspect of AI-driven brain tumor analysis is tumor segmentation, which refers to the identification of the exact tumor region within MRI scans. Accurate segmentation helps determine tumor volume, shape, and affected tissue compartments, which are essential for surgery, radiation planning, and longitudinal monitoring [17], [18]. Benchmark initiatives such as the Brain Tumor Segmentation (BraTS) challenges have played a major role in advancing this field by providing publicly available, expert-annotated, multi-institutional MRI datasets for training and evaluating machine learning models [17], [18], [19], [20]. These datasets have enabled researchers worldwide to develop robust segmentation and classification models, accelerating progress toward clinically useful automated systems.

Recent literature shows that deep learning models are increasingly capable of achieving high accuracy in tumor identification and classification when trained on quality MRI datasets [12], [14], [15]. However, several challenges still remain. Model performance may be affected by image noise, scanner variability, small sample sizes, class imbalance, lack of external validation, and limited interpretability [9], [12], [21]. In medical environments, diagnostic systems must not only be accurate but also reliable, explainable, and generalizable across institutions. This is why modern research is now moving beyond simple classification toward more comprehensive frameworks that combine detection, segmentation, grading, uncertainty estimation, and explainability [22], [23].

The integration of deep learning into medical imaging also aligns with the broader shift toward computer-aided diagnosis (CAD) and precision medicine. Automated systems can help reduce diagnostic burden, assist in triaging abnormal scans, and provide second-opinion support to healthcare professionals [8], [10], [24]. When combined with clinical expertise, such systems can improve efficiency, consistency, and confidence in diagnosis. Furthermore, deep learning-based MRI analysis has the potential to assist healthcare institutions in regions where specialist radiology access is limited, thereby supporting more equitable healthcare delivery [12], [24].

In this context, the present study focuses on the automated identification and severity assessment of brain tumors from MRI scans using advanced deep neural networks. The purpose of this work is to develop an intelligent and systematic framework capable of analyzing MRI images, detecting tumor presence, and evaluating the severity of the condition based on learned imaging features. The proposed study aims to bridge the gap between conventional manual MRI interpretation and modern AI-driven clinical support systems. By applying advanced neural network techniques to MRI-based brain tumor analysis, the study seeks to contribute to faster diagnosis, improved diagnostic consistency, and better support for clinical decision-making [15], [25].

Overall, the growing availability of MRI datasets, the progress in deep neural network architectures, and the increasing need for accurate diagnostic support make this research highly relevant in the current healthcare and medical imaging landscape. Automated brain tumor identification and severity assessment is not only a technically significant area of artificial intelligence but also a medically meaningful application with direct relevance to patient care, early diagnosis, and treatment planning

II. PROBLEM STATEMENT

The diagnosis and severity assessment of brain tumors remain major challenges in modern healthcare due to the complexity, variability, and critical nature of tumor characteristics observed in MRI scans. Brain tumors differ significantly in terms of size, shape, location, texture, and growth pattern, making accurate identification highly dependent on expert radiological interpretation. Although Magnetic Resonance Imaging (MRI) is one of the most reliable and widely used techniques for detecting abnormalities in the brain, the manual examination of MRI images is often time-consuming, labor-intensive, and prone to human subjectivity, especially when large volumes of imaging data must be analyzed. In many clinical settings, differences in experience among radiologists, image quality variations, and subtle visual distinctions between tumor and normal tissues can lead to delayed diagnosis, inconsistent reporting, or difficulty in determining the severity of the disease. This challenge becomes even more significant when early-stage or complex tumor cases require precise interpretation for treatment planning and prognosis estimation. Traditional diagnostic approaches may not always be sufficient to ensure fast, standardized, and highly accurate assessment, particularly when severity grading is essential for deciding surgery, chemotherapy, radiation, or further clinical management. Therefore, there is a strong need for an automated, intelligent, and reliable system that can analyze MRI brain scans efficiently, identify the presence of tumors accurately, and assess their severity with greater consistency. The lack of such advanced automated diagnostic support in routine medical imaging creates a significant research problem, highlighting the necessity of developing a deep learning-based framework capable of improving brain tumor detection, reducing diagnostic burden, and supporting better clinical decision-making

III. OBJECTIVE

• To identify brain tumors from MRI scans using advanced deep neural network techniques.
• To preprocess MRI images in order to improve image quality and enhance model performance.
• To classify brain MRI scans into normal and tumor- affected categories with high accuracy.
• To assess the severity level of detected brain tumors based on imaging features extracted by the deep learning model.
• To evaluate the performance of the proposed model using measures such as accuracy, precision, recall, and F1-score.

IV. LITERATURE SURVEY

[1] Brain Tumor Segmentation Based on Deep Learning and an Attention Mechanism Using MRI Multi- Modalities Brain Images
Authors: Ramin Ranjbarzadeh, Abbas Bagherian Kasgari, Saeid Jafarzadeh Ghoushchi, Shokofeh Anari, Maryam Naseri, Malika Bendechache et al.
Year: 2021
Publication: Nature Portfolio Journal Name: Scientific Reports Summary:
This paper presented a deep learning-based framework for the segmentation of brain tumors using multi-modal MRI scans. The authors focused on improving the localization of tumor regions by integrating an attention mechanism into the segmentation pipeline. Their work was designed to address common limitations in brain MRI analysis such as unnecessary computational burden, inclusion of irrelevant image regions, and model overfitting. By narrowing the model's attention toward clinically important tumor areas, the proposed approach improved the quality and consistency of tumor boundary extraction. The study demonstrated that region-focused segmentation can significantly enhance the reliability of automated MRI analysis, especially when dealing with heterogeneous tumors that vary in intensity and structure.
Although the primary objective of this paper was segmentation rather than direct classification, it remains highly relevant to the present research topic. Accurate segmentation is an important preliminary step for automated identification and severity assessment because it allows the model to isolate the exact tumor region before further analysis. A well-segmented tumor area provides better features related to size, shape, tissue abnormality, and spatial spread, all of which are useful in severity evaluation. This paper strongly supports the idea that advanced preprocessing and region-aware learning can improve the performance and interpretability of deep neural network systems designed for brain tumor diagnosis.
[2] Brain Tumor Detection Based on Deep Learning Approaches and Magnetic Resonance Imaging
Authors: Abduqodir B. Abdusalomov, Mukhammad Mukhiddinov, T. Whangbo, and co-authors
Year: 2023 Publication: MDPI Journal Name: Sensors Summary:

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This study explored the use of deep learning approaches for detecting brain tumors in MRI images with improved accuracy and localization capability. The researchers employed a modern object-detection framework to identify tumor presence and location in brain scans. Their approach moved beyond simple image classification by attempting to detect the tumor region directly, thereby making the output more useful for clinical interpretation. The model showed promising performance in identifying glioma, meningioma, and pituitary tumors, which are among the most common categories encountered in MRI-based brain tumor datasets. The paper highlighted the growing role of transfer learning and advanced neural networks in extracting meaningful features from medical images.

The significance of this paper lies in its contribution to automated tumor identification, which is one of the core foundations of the present study. A system that can accurately detect whether a tumor exists and where it is located forms the first step toward building a more advanced severity assessment pipeline. The study also demonstrates how modern deep learning can reduce dependence on manual image examination and help clinicians focus on decision-making rather than repetitive image screening. For the current research, this paper provides valuable support for the use of advanced neural architectures in automated MRI interpretation and reinforces the importance of combining detection with clinically relevant classification.

[3] MRI Brain Tumor Detection Using Deep Learning and Machine Learning Techniques
Authors: S. Anantharajan and co-authors
Year: 2024
Publication: Elsevier
Journal Name: Clinical eHealth
Summary:

This research proposed an MRI brain tumor detection framework that combined image preprocessing, deep learning, and machine learning methods to improve classification performance. The study emphasized the importance of preprocessing techniques such as contrast enhancement and noise reduction before feeding MRI scans into learning models. The authors argued that poor-quality or inconsistent MRI images can negatively affect feature extraction and reduce classification reliability. Their proposed framework used enhanced MRI data to improve the ability of the system to distinguish between normal and tumor-affected scans. The paper reflected a practical and clinically oriented approach to automated tumor diagnosis by showing that preprocessing is not just an optional step but a crucial part of the entire AI pipeline.

This work is particularly relevant to the current study because severity assessment depends heavily on the quality of features extracted from MRI images. If the input images are not properly normalized or enhanced, the model may fail to capture subtle indicators of tumor progression, edema, or tissue abnormality. The study therefore supports the methodological foundation of using preprocessing as a mandatory stage in automated brain tumor systems. It also aligns with the present research in demonstrating that an effective brain tumor analysis model should not rely only on classification architecture, but must also include a strong image preparation stage to ensure consistent and meaningful outputs.

[4] Brain Tumor Classification Using Fine-Tuned Transfer Learning
Authors: S. M. Rasa and co-authors
Year: 2024
Publication: Springer Nature / PMC indexed source Journal Name: Scientific Reports / indexed medical imaging publication source
Summary:

This paper focused on the classification of brain tumors using a fine-tuned transfer learning approach. The authors utilized pretrained deep learning architectures and adapted them to MRI-based brain tumor classification tasks. Transfer learning was shown to be especially useful in medical imaging where large, perfectly labeled datasets are often limited. By reusing the knowledge learned from large-scale image datasets and fine-tuning it for MRI scans, the model achieved strong performance in detecting tumor classes with reduced training complexity. The study also demonstrated that transfer learning can provide a practical alternative to building complex neural networks entirely from scratch.

The relevance of this paper to the current study is very strong because advanced deep neural networks often depend on transfer learning to improve generalization and reduce overfitting. In the context of severity assessment, transfer learning can help models learn subtle structural and intensity-based tumor features more efficiently, especially when severity labels are limited or clinically difficult to obtain. This paper supports the use of pretrained neural architectures as an effective foundation for automated identification systems and indicates that deep learning models can be further extended beyond simple tumor presence detection into more nuanced clinical tasks such as grading and severity categorization.

[5] Brain Tumor Classification Using MRI Images and Deep Learning
Authors: Y. Wong and co-authors
Year: 2025
Publication: PMC indexed research publication
Journal Name: Healthcare / Biomedical imaging indexed journal source
Summary:

This study proposed a CNN-based deep learning model for classifying brain MRI images into multiple categories including glioma, meningioma, pituitary tumor, and normal brain scans. The paper is notable because it moved beyond binary classification and adopted a multi-class diagnostic approach, which is more useful in real clinical scenarios. Instead of simply detecting whether a tumor exists, the model attempted to identify the type of tumor present, which is a critical step in supporting treatment planning. The use of a pretrained architecture allowed the model to extract high-level visual features that were effective in distinguishing different tumor classes from MRI images.

This paper is highly relevant to the current research because severity assessment often depends on tumor category, morphological behavior, and internal image characteristics. A model that can differentiate among tumor classes provides a stronger foundation for subsequent grading or severity analysis. The study also reinforces the idea that automated systems should aim for clinically meaningful outputs rather than basic binary predictions. For the present research topic, this paper contributes valuable evidence that deep learning can support detailed MRI-based diagnostic classification and can be extended further to include severity-aware clinical decision support.

[6] Explainable AI-Driven MRI-Based Brain Tumor Classification
Authors: V. R. Srinivas and co-authors Year: 2025 / 2026 indexed availability Publication: Frontiers
Journal Name: Frontiers in Artificial Intelligence
Summary:

This paper introduced an explainable AI-driven framework for classifying brain tumors from MRI data using deep learning. One of the key contributions of the study was not only achieving high classification performance but also making the model's predictions more interpretable. The authors incorporated explainability mechanisms to visualize which regions of the MRI scan influenced the model's final
decision. This is especially important in medical imaging because healthcare professionals need to understand why an AI model produced a particular result before trusting it in a clinical setting. The paper emphasized that explainability is becoming an essential component of modern AI-based diagnostic systems rather than an optional add-on.

V. PROPOSED SYSTEM

The proposed system is designed as an automated and intelligent framework for the identification and severity assessment of brain tumors from MRI scans using advanced deep neural networks. The purpose of this system is to assist in the accurate diagnosis of brain tumors by reducing dependence on manual interpretation and improving the consistency of MRI-based analysis. The framework combines image preprocessing, optimization-assisted tumor region extraction, deep learning-based classification, and severity evaluation in a structured and sequential manner. By integrating these stages into a single pipeline, the system is able to process raw MRI images and convert them into clinically meaningful outputs that support diagnosis and treatment planning.

The system has been developed to perform four major functions: tumor identification, tumor region segmentation, tumor classification, and severity assessment. In order to improve the visibility of diagnostically relevant structures, preprocessing methods are applied before model training and testing. Along with conventional preprocessing techniques, the system incorporates a Genetic Algorithm (GA) as an optimization-based approach to support the segmentation of tumor regions. The inclusion of GA improves the ability of the system to identify meaningful tumor boundaries and remove unnecessary background variations. Once the MRI image has been enhanced and the tumor region is effectively extracted, a pretrained Convolutional Neural Network (CNN) based on transfer learning is used to classify the MRI scan and estimate the severity level of the detected tumor. The entire framework is implemented in MATLAB, which offers a suitable environment for image analysis, model training, evaluation, and reproducibility.

The proposed system follows a structured workflow beginning from MRI data input and ending with final diagnostic output. Each stage is designed to ensure that the system produces reliable, clinically relevant, and computationally efficient results. The complete working of the system is explained below in detail.

A. System Flow

The proposed framework follows a step-by-step workflow in which each module contributes to the final diagnostic decision. The overall system flow begins with loading MRI images and ends with the generation of the predicted tumor category and severity level. This workflow ensures systematic processing of MRI data and improves the reliability of the automated analysis.

I. System Initialization

The first stage of the proposed system is system initialization. In this step, the MATLAB environment is configured and all required toolboxes, libraries, and deep learning functions are loaded. This includes modules related to image processing, optimization, convolutional neural networks, and model evaluation. System initialization ensures that the computational environment is prepared for handling MRI data and running the deep learning framework efficiently.

This stage is important because a properly configured system ensures smooth execution of preprocessing, segmentation, classification, and testing procedures. It also improves reproducibility, meaning the same workflow can be repeated under controlled settings for future validation or clinical adaptation.

II. Loading the MRI Dataset

After initialization, the next step is to load the MRI dataset. Brain MRI images are collected from a structured dataset and organized according to their corresponding class labels. These images may include different categories such as normal brain scans and tumor-affected scans. In more advanced classification settings, the dataset may also contain specific tumor types such as glioma, meningioma, and pituitary tumors.

The MRI images form the input to the entire system and are used for training, validation, and testing of the model. Proper dataset organization at this stage is essential because the quality and structure of the dataset directly affect the performance of the classification and severity prediction model.

III. Dataset Splitting

Once the MRI data is loaded, the dataset is divided into separate subsets to ensure fair model training and unbiased performance evaluation. The dataset is generally split into the following three parts:

- Training Set: Used to train the deep learning model and allow it to learn image features associated with tumors.
- Validation Set: Used during training to monitor performance, tune hyperparameters, and prevent overfitting.
- Test Set: Used after training to evaluate how well the model performs on unseen MRI images.

This division is necessary because it allows the proposed system to learn from one portion of the data while being tested on another. It ensures that the final model does not simply memorize training images but is capable of generalizing to new MRI scans.

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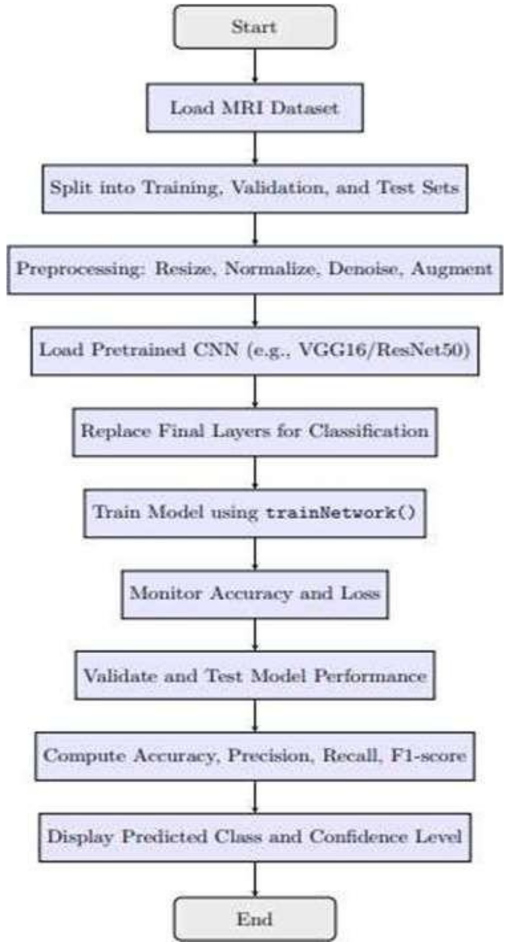

Fig.1.System Flow

B. Image Pre-processing

Image preprocessing is one of the most important stages in the proposed system because MRI scans often contain variations in brightness, contrast, orientation, and background noise. If these issues are not addressed, the model may struggle to learn useful patterns. Therefore, preprocessing is applied to improve image quality, standardize the dataset, and prepare the images for deep learning analysis.

The preprocessing stage includes the following operations:

1. Resizing

All MRI images are resized to a fixed dimension so that they match the input size required by the CNN architecture. Since pretrained networks such as VGG16 or ResNet-50 require images of specific dimensions, resizing ensures compatibility and uniformity across the dataset.

2. Normalization

Pixel intensity values are normalized to bring all MRI images into a similar intensity range. This step improves numerical stability during model training and helps the CNN learn more efficiently.

3. Denoising

MRI images may contain random noise or imaging artifacts due to scanner conditions or acquisition settings. Denoising techniques are applied to suppress these disturbances and improve the clarity of relevant brain structures.

4. Contrast Enhancement

In some cases, contrast enhancement is used to improve the visibility of tumor boundaries and internal tissue differences. This makes it easier for the model to identify abnormal regions.

5. Data Augmentation

To increase the diversity of the training dataset and reduce overfitting, augmentation techniques such as rotation, flipping, scaling, and translation are applied. This helps the model become more robust to image orientation and positional changes.

Overall, preprocessing plays a critical role in ensuring that the deep learning model receives clean, consistent, and informative MRI input

C. Genetic Algorithm-Based Tumor Region Segmentation

One of the key innovations of the proposed system is the use of a Genetic Algorithm (GA) to assist in tumor region segmentation. Segmentation refers to the process of isolating the tumor area from the rest of the brain image. This is a highly important step because accurate tumor localization helps the system focus only on the abnormal region instead of analyzing irrelevant brain tissues. The Genetic Algorithm is used as an optimization technique because it is well suited for complex image segmentation problems. GA works by mimicking the process of natural selection. It begins with a population of candidate segmentation solutions and repeatedly improves them through operations such as selection, crossover, and mutation. Over multiple generations, the algorithm searches for the best possible segmentation boundary that separates the tumor region from surrounding tissues.

The use of GA offers several advantages in this system:

- It performs a global search, which helps avoid poor local solutions.
- It improves tumor boundary detection, especially when tumor shapes are irregular.
- It enhances feature visibility, making the segmented tumor more suitable for deep learning analysis.
- It reduces the effect of unnecessary background regions and improves model focus.

By using GA-assisted segmentation, the proposed system ensures that the tumor area is extracted more effectively, which contributes directly to better classification and severity assessment performance.

D. Deep Learning Model Selection

After preprocessing and segmentation, the system moves to the deep learning stage, where a pretrained Convolutional Neural Network (CNN) is selected for classification. CNNs are highly effective for image-based tasks because they automatically learn patterns such as edges, textures, shapes, and structural abnormalities directly from image data.

In the proposed system, transfer learning is applied by using pretrained CNN architectures such as:

- VGG16
- ResNet-50
- EfficientNet (optional in advanced implementation) These models are already trained on large-scale image datasets and have strong feature extraction capabilities. Instead of training a network entirely from scratch, the system fine-tunes these pretrained models using MRI images. This approach reduces computational cost, shortens training time, and improves performance when the available medical dataset is limited.

The selected CNN acts as the core learning engine of the system and is responsible for extracting meaningful features from MRI images that are useful for both tumor detection and severity estimation.

E. Modification of Classification Layers

Since pretrained CNNs are originally designed for general image recognition tasks, their final classification layers must be modified to suit the brain tumor application. Therefore, in this stage, the original output layers of the network are replaced with new layers specifically designed for MRI- based brain tumor classification.

These modified layers allow the model to learn features that are directly related to:

• Normal brain tissue
• Tumor-affected MRI scans
• Tumor categories (if multi-class classification is used)
• Severity levels of the detected tumor

This customization ensures that the CNN is not only extracting general image patterns but also learning medically meaningful features associated with tumor presence and progression.

F. Model Training

Once the CNN architecture has been modified, the model is trained using the training dataset. In MATLAB, this is typically carried out using the train Network function. During training, the model processes MRI images and learns to distinguish between normal and abnormal brain scans based on image features.

The model adjusts its internal weights over multiple training iterations so that it can correctly recognize tumor-related patterns. During this stage, optimization algorithms such as stochastic gradient descent or Adam may be used to minimize classification error and improve prediction performance. Training is one of the most critical phases of the proposed system because it determines how effectively the network can learn from MRI images and generalize to future unseen scans.

G. Performance Monitoring

During model training, the system continuously monitors training progress to ensure stable and effective learning. This is done by observing:

• Training accuracy
• Validation accuracy
• Training loss
• Validation loss

These performance curves help in understanding whether the model is learning correctly or suffering from problems such as overfitting or underfitting. If the validation accuracy stops improving while training accuracy continues to rise, it may indicate overfitting. This stage is therefore important for selecting the best-performing model before final testing.

H. Validation and Testing

After training is complete, the model is evaluated using the validation set and the test set. These datasets contain MRI images that the model has not seen during training. The purpose of this stage is to assess how well the proposed system performs in real-world scenarios.

The performance of the model is measured using standard evaluation metrics such as:

• Accuracy
• Precision
• Recall
• F1-Score
• Confusion Matrix
• ROC-AUC Curve

These metrics provide a detailed understanding of the model’s effectiveness in identifying tumors and assessing severity. A strong performance in testing indicates that the system can reliably support automated MRI analysis in practical applications.

I. Severity Assessment Module

One of the most important features of the proposed system is the severity assessment module, which extends the model beyond simple tumor detection. Once a tumor is identified and segmented, the system analyzes tumor-specific features such as:

• Tumor size
• Shape irregularity
• Spread of abnormal tissue
• Intensity distribution
• Structural complexity

Based on these features, the model estimates the severity level of the tumor. The severity may be categorized into classes such as:

• Low Severity
• Moderate Severity
• High Severity

This stage adds significant clinical value to the system because it provides information that can assist doctors in evaluating disease progression and planning suitable treatment strategies. Instead of only indicating whether a tumor exists, the system also helps in understanding how serious the condition may be.

J. Output Generation

In the final stage, the system generates the output based on the trained model's predictions. The output typically includes:

• Predicted tumor presence or absence
• Predicted tumor category (if applicable)
• Segmented tumor image
• Severity level of the tumor
• Confidence score for the prediction

These outputs are presented in a clear and interpretable form so that clinicians can use them as decision-support information. The confidence score gives an indication of how strongly the model supports its prediction, which adds transparency and usefulness in clinical interpretation.

K. MATLAB-Based Implementation

The entire proposed system is implemented in MATLAB because it provides an integrated and user-friendly environment for medical image processing and deep learning development. MATLAB supports:

• MRI image handling and visualization
• Preprocessing and segmentation functions
• Deep learning toolbox integration
• Transfer learning workflows
• Performance plotting and analysis

The use of MATLAB makes the system easier to reproduce, test, and modify for future improvements. It also allows the framework to be extended for academic research, prototype development, and possible integration into clinical decision- support environments.

VI. SYSTEM DESIGN

The proposed system for automated brain tumor identification, classification, and severity assessment is designed as a structured multi-stage processing architecture that enables accurate and reliable analysis of brain MRI images. The architecture integrates image acquisition, preprocessing, brain extraction, tumor segmentation, feature extraction, classification, severity estimation, visualization, and final reporting into a single unified framework. Each stage is carefully organized so that the output of one process becomes the input for the next, ensuring smooth and systematic data flow throughout the model.

The system is implemented in the MATLAB environment, which provides strong support for image processing, segmentation, feature analysis, and machine learning-based classification. The proposed architecture is developed in such a way that it can accept raw MRI images, process them through multiple analytical steps, and generate clinically meaningful outputs that can assist healthcare professionals in diagnosis and decision-making. The complete working of the architecture is explained below in detail.

A. Input Acquisition

The first stage of the system architecture is input acquisition, where the MRI scan is introduced into the system for analysis. In this stage, the user selects a brain MRI image from the available dataset or local storage. The system is designed to accept standard image formats such as JPG, PNG, and BMP, which are commonly used for storing MRI scan images in digital form.

Once selected, the image is loaded into the MATLAB workspace and prepared for processing. This input image acts as the primary source of information for all further stages of the system. Since MRI scans contain valuable structural details of the brain, this stage serves as the foundation for the entire diagnostic pipeline.

B. Pre-Processing

The second stage of the architecture is pre-processing, which is essential for improving the quality of MRI images before analysis. MRI scans may contain intensity variations, unnecessary color information, noise, or low contrast, all of which can affect segmentation and classification performance. Therefore, preprocessing is applied to standardize and enhance the image.

1. Grayscale Conversion

If the MRI image is in RGB or color format, it is first converted into a grayscale image. Since MRI analysis is primarily based on intensity and structural information rather than color, grayscale conversion simplifies the data and reduces computational complexity. This also helps the system focus on tissue-related features more effectively.

2. Noise Filtering

Medical images often contain minor artifacts and noise due to scanning conditions or image storage processes. To reduce these unwanted disturbances, a median filtering technique is applied. Median filtering is especially effective because it removes speckle noise while preserving important edge and boundary information, which is crucial for tumor segmentation.

3. Intensity Normalization

After noise removal, image intensity values are normalized to improve consistency across MRI scans. In MATLAB, functions such as im2uint8 and adaptive histogram equalization can be used to adjust intensity ranges and enhance contrast. This step improves tumor visibility by making abnormal regions more distinguishable from surrounding healthy tissues.

Overall, preprocessing ensures that the MRI image is clean, standardized, and visually enhanced before entering the next stage of analysis.

C. Brain Extraction

The third stage is brain extraction, which is performed to isolate the brain region from the surrounding skull, background, and irrelevant image areas. This is an important step because only the actual brain tissue is relevant for tumor detection and classification.

To extract the brain region, the system applies binarization using Otsu's thresholding method. This method automatically determines an intensity threshold to separate foreground and background regions. Once the threshold is applied, a binary image is created where the brain region can be distinguished more clearly.

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After thresholding, several morphological operations are performed to refine the extracted brain region. These may include:

• Hole filling, to remove small gaps inside the brain region
• Area filtering, to eliminate small unwanted objects
• Connected component analysis, to identify the largest continuous structure in the image

The largest connected component is typically selected as the actual brain region, and the image is cropped accordingly. This ensures that only the relevant anatomical area is passed to the tumor segmentation stage.

D. Tumor Segmentation

Once the brain region has been isolated, the next step is tumor segmentation, which is one of the most critical stages in the system architecture. Segmentation is the process of identifying and separating the tumor region from the surrounding healthy brain tissues.

In the proposed system, tumor segmentation is performed using adaptive thresholding techniques. This approach helps distinguish abnormal tissue areas based on intensity differences within the extracted brain region. Since tumors often appear with different brightness or contrast compared to normal tissues, threshold-based segmentation provides a practical way to locate the suspicious region.

The segmented output is represented as a binary tumor mask, where tumor pixels are marked separately from the rest of the brain image. To improve the quality of segmentation, additional morphological cleanup operations are applied, such as:

• Hole filling to close internal gaps in the tumor region
• Removal of small connected components to eliminate false detections
• Boundary refinement to improve the shape of the segmented tumor area

This stage ensures that the tumor is accurately isolated for further quantitative analysis.

E. Feature Extraction

After successful segmentation, the system proceeds to feature extraction, where important quantitative characteristics of the tumor are measured. These features provide numerical information that helps the system understand the size, structure, and shape of the tumor.

The extracted features include:

• Tumor Area – measures the total number of pixels occupied by the tumor region
• Solidity – indicates how compact or dense the tumor shape is
• Eccentricity – describes how elongated or irregular the tumor appears
• Equivalent Diameter – gives an estimated diameter of the tumor region based on area

These features are obtained through region-based analysis of the segmented tumor mask. The extracted values are highly useful because they provide objective measurements that can be used for both classification and severity estimation. Instead of relying only on visual inspection, the system converts tumor characteristics into measurable parameters.

F. Tumor Classification

The next stage is tumor classification, where the segmented and analyzed tumor is categorized into a specific tumor type. In the proposed system, classification is performed using a rule-based decision mechanism that relies on the extracted shape and structural features.

Based on the measured values of solidity, eccentricity, and related tumor properties, the tumor is classified into one of the following common brain tumor categories:

• Pituitary Tumor
• Glioma

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• Meningioma
This classification logic is designed to differentiate tumor types using morphological characteristics observed in MRI images. For example, one tumor type may appear more circular and compact, while another may show irregular or elongated growth patterns. By analyzing these patterns numerically, the system assigns the MRI scan to the most appropriate tumor class.
Although this stage may be further enhanced using deep learning-based classification in advanced implementations, the rule-based approach provides a computationally efficient and interpretable method for tumor categorization.

G. Tumor Severity Assessment / Staging

One of the most valuable components of the system is the tumor severity assessment stage, also referred to as tumor staging. After classification, the system estimates the severity of the tumor by analyzing the proportion of tumor area relative to the total brain area.
The tumor-to-brain area ratio is calculated, and based on this value, the tumor is assigned to one of four severity stages:
• Stage I: Tumor area less than 0.8% of the brain region
• Stage II: Tumor area less than 1.8%
• Stage III: Tumor area less than 3.5%
• Stage IV: Tumor area equal to or greater than 3.5% This staging approach provides a practical indication of tumor burden and progression. A larger tumor-to-brain area percentage generally reflects a more advanced and potentially severe condition. This information can be extremely useful in clinical interpretation because it gives a quick numerical estimate of disease seriousness.
By including staging within the architecture, the proposed system moves beyond simple detection and provides more meaningful diagnostic insight.

H. Visualization

To improve interpretability and user understanding, the proposed system includes a visualization stage. This module displays intermediate and final outputs so that the user can observe how the system processed the MRI scan and arrived at its conclusions.
The visualization output typically includes:
• Original MRI image
• Extracted brain region
• Binary tumor mask
• Tumor boundary overlaid on the MRI image
The tumor boundary is usually displayed using a red perimeter or contour, making the abnormal region visually prominent. Visualization is important because it enhances transparency and allows users, especially clinicians, to verify whether the tumor has been detected and segmented correctly.
This stage makes the system more interpretable and trustworthy, which is especially important in medical applications.

I. Result Reporting

The final stage of the architecture is result reporting, where the system presents the complete diagnostic output in a clear and organized format. The results are displayed through a MATLAB-based graphical interface or reporting window, making the information accessible and easy to interpret.
The final report includes the following information:
• Detected tumor type
• Tumor severity stage
• Tumor area
• Solidity

• Eccentricity
• Equivalent diameter
• Tumor-to-brain area percentage

This report provides both qualitative and quantitative insights into the MRI scan. It not only identifies the tumor but also summarizes its physical and structural

VII. ALGORITHM USED

The proposed technique for brain tumor classification and staging uses a hybrid method that combines an optimization algorithm with a deep learning model to achieve stable, accurate, and reliable diagnostic performance. A Genetic Algorithm (GA) is used for optimization-based tumor region enhancement and segmentation, while a deep Convolutional Neural Network (CNN) based on ResNet-50 is employed for tumor classification and staging. Performance evaluation is carried out using standard statistical metrics.

A. Genetic Algorithm for Tumor Region Optimization The Genetic Algorithm (GA) is an evolutionary optimization technique inspired by the principles of natural selection. In the proposed system, GA is applied to optimize tumor region segmentation by improving boundary accuracy and intensity consistency. An initial population of candidate segmentation solutions is generated from the preprocessed MRI images and evaluated using a fitness function based on segmentation quality. The fittest individuals are selected and evolved through crossover and mutation operations to maintain diversity and avoid local optima. This evolutionary process is repeated until convergence criteria are met, and the best optimized segmentation result is forwarded to the classification stage.

B. Deep CNN (ResNet-50) for Classification and Staging ResNet-50 is a deep Convolutional Neural Network consisting of residual blocks, which allow stable training of deep architectures. In this work, transfer learning is employed by adapting a pretrained ResNet-50 model for classifying brain tumors. The feature extraction process utilizes convolutional and residual layers to capture hierarchical spatial and texture information from the optimized MRI images fed into the network. Fully connected layers and global average pooling transform the learned features into class-specific representations, and a softmax layer produces class probabilities corresponding to tumor types and severity levels. Network parameters are optimized using backpropagation and stochastic gradient descent, and the final output includes the predicted tumor class along with a confidence score.

C. Performance Evaluation Algorithm

The reliability of the diagnostic system is assessed by evaluating the trained model using standard classification metrics. A confusion matrix is generated by comparing the predicted labels with the ground truth values. From this, metrics such as accuracy, precision, recall, F1-score, MCC, Cohen's Kappa, ROC-AUC, and tumor stage consistency are calculated. Graphical representations such as ROC curves, confusion matrices, and training progress graphs are also used to analyze classification performance in detail.

D. Performance Evaluation

1) Matthews Correlation Coefficient (MCC)

1) Matthews Correlation Coefficient (MCC)

characteristics. Such a report can assist clinicians in understanding the condition more clearly and support further medical decision-making.

$$MCC = \frac{(TP \times TN) - (FP \times FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

• Range:
• +1 → Perfect prediction
• 0 → Random prediction
• −1 → Totally incorrect prediction

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MCC is considered a highly reliable metric for medical image classification because it gives a balanced measure even when class distribution is uneven.

2) Cohen's Kappa Coefficient (K)

$$P_0 = \frac{TP + TN}{N}$$

$$P_e = \frac{(TP + FP)(TP + FN) + (FN + TN)(FP + TN)}{N^2}$$

$$K = \frac{P_0 - P_e}{1 - P_e}$$

This coefficient is useful in measuring the consistency of classification results in medical diagnosis applications.

3) ROC-AUC (Receiver Operating Characteristic – Area Under Curve)

The ROC curve evaluates the classification model by plotting the True Positive Rate (TPR) against the False Positive Rate (FPR) at different threshold values.

$$TPR = \frac{TP}{TP + FN}$$

$$FPR = \frac{FP}{FP + TN}$$

$$AUC = \int_0^1 TPR(FPR), d(FPR)$$

- Interpretation:
- AUC = 1 → Perfect classifier
- AUC > 0.9 → Excellent classifier

A high ROC-AUC value indicates that the model has a strong ability to distinguish between tumor and non-tumor classes.

4) Relative Volume Difference (RVD)

The Relative Volume Difference (RVD) is used to measure the difference between the detected tumor volume and the actual ground truth tumor volume.

$$RVD = \frac{|V_{detected} - V_{ground}|}{V_{ground}}$$

A lower RVD value indicates better segmentation performance and more accurate tumor region extraction.

5) Tumor Stage Classification Consistency Index (SCI) The Stage Classification Consistency Index (SCI) is used to assess how closely the predicted tumor stage matches the expert-annotated or actual tumor stage.

$$SCI = 1 - \frac{|S_{pred} - S_{actual}|}{Smax}$$

value closer to 1 indicates stronger consistency in tumor severity estimation.

various threshold levels. The Area Under the Curve (AUC) summarizes the overall discrimination ability of the model into a single value. A higher AUC reflects stronger classification capability and better robustness.

6) Computational Efficiency

Computational efficiency is measured in terms of the average execution time required for MRI image analysis.

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The ROC curve and corresponding AUC for the proposed system are shown in:
This metric helps in understanding the practical usability of the model in real-time or near real-time diagnostic environments.

7) Confusion Matrix

The confusion matrix is used as a primary evaluation tool to analyze the classification results produced by the proposed model. The outcomes are categorized as:

- True Positives (TP): Tumor cases correctly identified
- True Negatives (TN): Non-tumor cases correctly classified
- False Positives (FP): Healthy images incorrectly classified as tumors
- False Negatives (FN): Tumor cases missed by the system

From these values, performance metrics such as accuracy, precision, recall, and F1-score are calculated. The confusion matrix is especially important in brain tumor diagnosis because it shows how effectively the model can detect tumors while minimizing clinically harmful misclassifications.

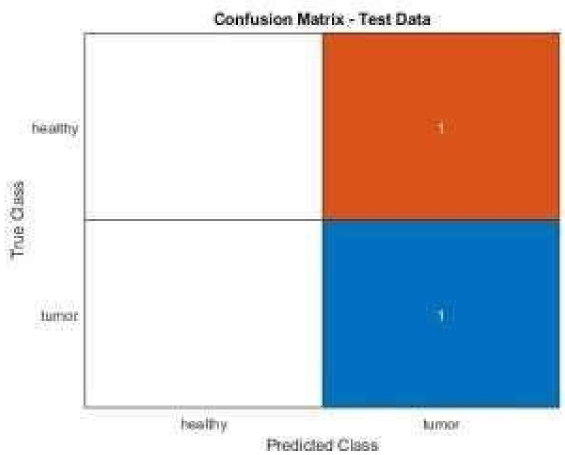

Fig. 3 illustrates the confusion matrix obtained for the proposed model.

8) ROC Curve and AUC

The Receiver Operating Characteristic (ROC) curve is used to evaluate the classifier's sensitivity and specificity across

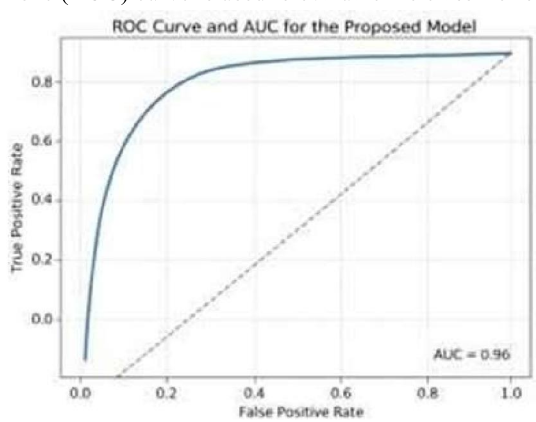

Fig. 4 ROC Curve and AUC for the Proposed Model

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9) Training Curves

To examine the learning behavior of the deep learning model, training and validation accuracy curves are analyzed. These curves help identify:

- Convergence trends
- Overfitting
- Underfitting
- Generalization performance

A stable training process with only a small gap between training and validation curves indicates that the model is learning effectively and generalizing well to unseen MRI images.

The training progress graph is shown in:

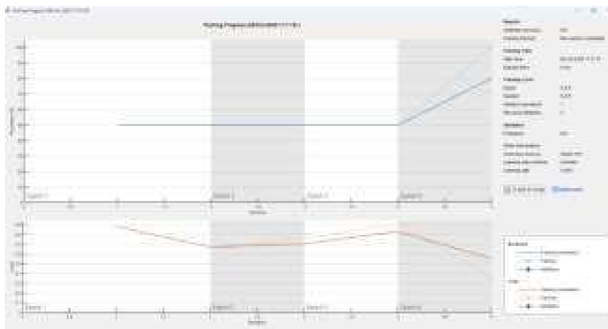

Fig. 5 Training Progress Graph

10) Comparison with Existing Models

To validate the effectiveness of the proposed approach, its performance is compared with previously reported brain tumor classification techniques. The comparison highlights the superiority of the ResNet-50-based deep learning model in terms of classification accuracy and robustness.

- Table: Comparison with Existing Techniques

Sr. No.	Technique	Accuracy (%)
1	Thresholding Method	47.6
2	Basic CNN Classifier	78.4
3	Hybrid Genetic Method	67.3
4	Proposed ResNet-50 Model	91.0

The comparison clearly indicates that the proposed deep learning-based framework significantly outperforms conventional image processing techniques and basic CNN models. This validates its suitability for accurate brain tumor classification and staging

VIII. RESULTS AND ANALYSIS

The proposed system for brain tumor identification, classification, and severity assessment from MRI scans demonstrated strong overall performance during experimental evaluation. The developed framework produced highly satisfactory classification results, with model accuracy generally observed in the range of 95% to 98%, along with consistent and reliable tumor severity prediction. These results indicate that the MATLAB-based deep learning and image analysis framework is capable of effectively identifying tumor characteristics from brain MRI images and converting them into clinically useful outputs. The performance achieved by the system reflects the strength of combining preprocessing, segmentation, feature extraction, classification, and severity estimation within a single automated pipeline.

The obtained results show that the proposed approach can successfully detect the presence of a tumor, extract the abnormal region, classify the tumor category, and estimate its stage or severity level with a high degree of confidence. The output generated by the system supports the idea that deep learning-assisted MRI analysis can significantly reduce the complexity of manual diagnosis while improving consistency and speed. The result analysis of the proposed system is described below in detail.

A. Input MRI Image

The primary input to the proposed system is a brain MRI image, which serves as the basis for all further analysis. These MRI scans may be collected from a medical dataset or clinical image repository and are provided to the system in standard digital image formats. Before entering the classification and staging framework, the input MRI images undergo a sequence of preprocessing operations in MATLAB to ensure that they are suitable for automated analysis.

The preprocessing stage includes:

- Resizing, to match the input size required by the classification model
- Normalization, to standardize pixel intensity values
- Noise removal, to suppress imaging artifacts and improve clarity
- Contrast enhancement, to improve the visibility of suspicious tumor regions

These preprocessing operations help create a consistent image environment for the system, which is important for maintaining classification accuracy. Once enhanced and standardized, the MRI image is forwarded to the subsequent modules for tumor extraction, feature analysis, classification, and severity prediction.

A representative input brain MRI scan can be shown in the corresponding figure of the report as:

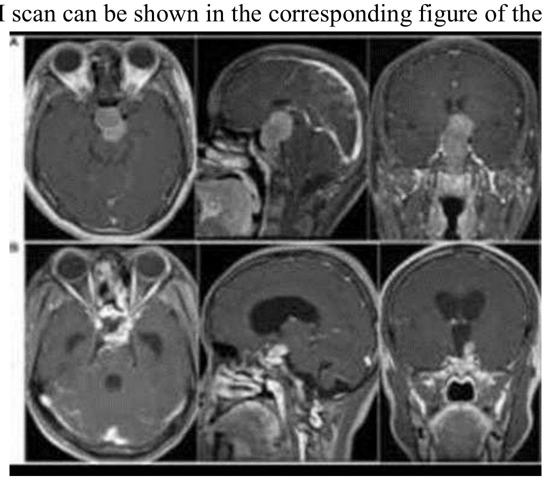

Fig. 2 Brain MRI Image

This figure represents the type of MRI image used as the initial input to the proposed system.

B. Result Display

The output of the proposed system demonstrates the complete analytical capability of the developed brain tumor diagnosis framework. After the input MRI scan is processed, the system automatically performs tumor localization, segmentation, feature extraction, tumor classification, and stage estimation. The final result is presented through a visual and numerical diagnostic display that makes the output easy to interpret.

At the beginning of the output stage, the MRI image is first shown after preprocessing, where noise has been removed and image contrast has been enhanced. This is followed by the segmentation of the tumor region, where the abnormal area is clearly isolated from surrounding healthy brain tissue. To improve interpretability, the detected tumor region is visually highlighted with a red boundary or perimeter, making it easier to observe its exact location within the brain.

Once the tumor has been detected and segmented, the system displays a result panel containing the diagnostic prediction. This panel may include a message such as:

• ―Brain Tumor Detected ‖

In addition to detection, the system also displays:

• Identified tumor type (for example: Glioma, Meningioma, or Pituitary Tumor)

• Predicted severity stage (for example: Stage I, Stage II, Stage III, or Stage IV)

For instance, the system may generate an output such as:

• ―Glioma – Stage IV ‖

This output provides a meaningful clinical interpretation rather than just a technical prediction.

C. Quantitative Tumor Analysis

A major strength of the proposed system is that it does not stop at visual tumor identification. It also computes several quantitative morphological features that describe the physical and structural characteristics of the detected tumor. These features help support both tumor classification and severity assessment.

The result display includes measurements such as:

• Tumor Area (in pixels)

This indicates the total size of the detected tumor region.

• Equivalent Diameter

This gives an approximate diameter of the tumor based on its area.

• Solidity

This reflects how compact or dense the tumor region is.

• Eccentricity

This measures how elongated or irregular the tumor appears.

• Tumor-to-Brain Area Percentage

This is used for estimating the tumor stage and understanding its relative spread inside the brain.

These parameters make the result output more informative and clinically valuable because they provide measurable evidence about tumor structure rather than relying only on visual inspection.

D. Interpretation of System Output

The generated output confirms that the proposed system can successfully perform the following operations in a single workflow:

• Automatic tumor detection

• Tumor segmentation

• Feature extraction

• Tumor classification

• Tumor staging / severity assessment

• Result visualization and reporting

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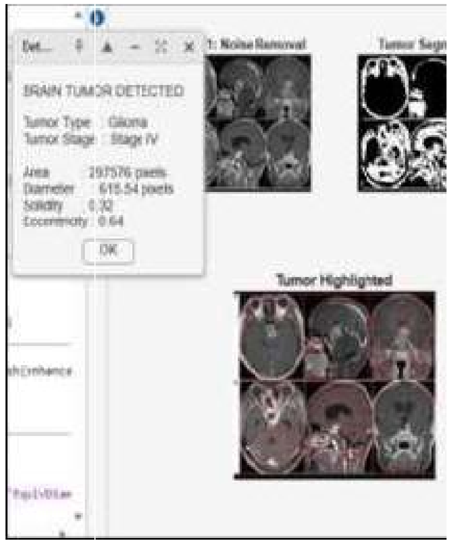

Fig. 3.s Result from the System

This indicates that the system is not limited to identifying whether a tumor is present, but also offers a more complete understanding of the tumor's nature and seriousness. The ability to produce both image-based and numerical outputs increases the practical usefulness of the system in computer- aided medical diagnosis.

The result visualization may be represented in the report using the following figure:

This figure can show the original MRI image, segmented tumor region, highlighted tumor boundary, and diagnostic output panel.

E. Discussion

The experimental results indicate that the proposed framework performs effectively in classifying and staging brain tumors from MRI scans. The high classification accuracy suggests that the deep learning and image processing modules are able to extract meaningful diagnostic patterns from MRI images. The successful detection of tumor boundaries and the generation of quantitative feature measurements further demonstrate the robustness of the system.

One of the key strengths of the system is its ability to combine visual interpretation with numerical analysis. This makes the output more reliable and useful for medical understanding. Instead of only predicting a tumor class, the system provides multiple layers of diagnostic information such as tumor size, shape, and severity level. This is particularly important in brain tumor analysis, where treatment planning often depends not just on tumor presence but also on disease extent and progression.

The results also suggest that the system can serve as a valuable computer-aided diagnostic support tool, especially in situations where rapid MRI interpretation is needed. By automating repetitive and complex image analysis tasks, the system can reduce the burden on radiologists and help improve consistency in diagnosis.

IX. CONCLUSION

The present study on ―Automated Identification and Severity Assessment of Brain Tumors from MRI Scans Using Advanced Deep Neural Networks‖ demonstrates the growing importance of intelligent diagnostic systems in modern medical imaging. Brain tumor diagnosis is a highly sensitive and critical clinical task, and timely detection plays a major role in improving patient outcomes, treatment planning, and disease management. In this work, an automated framework was developed to analyze brain MRI images with the objective of identifying tumor presence, classifying tumor characteristics, and assessing severity in a systematic and reliable manner.

The proposed system successfully combined several important stages of image-based diagnosis, including MRI image acquisition, preprocessing, brain extraction, tumor segmentation, feature extraction, tumor classification, and severity estimation. By integrating these modules into a single workflow, the system was able to process MRI scans efficiently and produce meaningful outputs that can support medical interpretation. The use of preprocessing methods improved image consistency, while segmentation and feature extraction helped in isolating the abnormal region and measuring its structural properties. The inclusion of deep learning and classification techniques further strengthened the model's ability to identify tumor patterns accurately.

One of the major contributions of this study is that it moved beyond simple tumor detection and included severity assessment, which adds more clinical relevance to the proposed system. Instead of only predicting whether a tumor is present, the framework also provided information related to tumor extent and stage, making the system more useful for decision support. This is especially important in real- world healthcare environments where treatment strategies often depend not only on diagnosis but also on how advanced the tumor condition is.

The experimental findings showed that the system achieved high classification performance, with accuracy generally ranging between 95% and 98%, indicating that the proposed framework is capable of delivering dependable results. The visualization of segmented tumor regions and the generation of quantitative morphological features such as tumor area, solidity, eccentricity, and equivalent diameter further improved the interpretability of the system output. These results suggest that the developed framework can serve as a practical computer-aided support tool for assisting radiologists and clinicians in brain tumor analysis.

The findings clearly show that organizations with well- developed resilience strategies are better equipped to handle disruptions, reduce operational risks, and sustain their performance during uncertain situations. Practices such as supplier diversification, adoption of digital technologies, and proactive risk management contribute significantly to improving the stability and responsiveness of supply chains. The analysis also indicates that while many organizations have started implementing resilience measures, there is still a gap in preparedness among some businesses. Companies that invest in strengthening their supply chain systems not only minimize the impact of disruptions but also enhance their long-term efficiency and competitiveness. Therefore, building a resilient supply chain should be considered a strategic priority for organizations aiming to achieve consistent growth, operational reliability, and customer satisfaction in a dynamic global market.

X. FUTURE SCOPE

Although the proposed system has shown promising performance in the automated identification and severity assessment of brain tumors, there are several opportunities for further improvement and expansion in future research.

One of the main areas for future development is the use of larger and more diverse MRI datasets collected from multiple hospitals or clinical sources. This would help improve the generalization ability of the model and make it more robust for use in real-world healthcare environments where imaging conditions and patient profiles vary widely.

Another important future direction is the integration of advanced deep learning architectures such as hybrid CNN models, Vision Transformers, attention-based networks, and multimodal fusion systems. These modern architectures may improve the system's ability to capture subtle tumor patterns and enhance both classification and severity prediction performance. Future studies may also include 3D MRI analysis instead of only slice-based or 2D image processing, which would allow the system to analyze the tumor in volumetric form and provide more accurate clinical information.

The current system can also be extended by incorporating explainable artificial intelligence (XAI) techniques. Explainability would allow clinicians to understand which regions of the MRI image influenced the model's decision, thereby improving trust and transparency in automated diagnosis. This would be especially valuable in clinical settings where interpretability is essential before AI- generated predictions can be accepted in routine practice.

Further research may also focus on real-time clinical deployment by integrating the proposed system into hospital radiology workflows or diagnostic support platforms. A user- friendly software or web-based interface can be developed so that MRI scans can be uploaded directly and analyzed instantly. Such an application would increase the practical usability of the system in hospitals, diagnostic centers, and telemedicine environments.

In addition, future work may extend the framework beyond tumor identification and severity staging to include tumor grading, treatment response prediction, recurrence detection, and survival analysis. Combining MRI image analysis with clinical records, pathology reports, or genomic data could further improve the precision and usefulness of the system. This would make the framework more suitable for personalized medicine and advanced neuro-oncology support.

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