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| RESEARCH ARTICLE

Paper Title:

BRAIN TUMOR DETECTION USING MACHINE LEARNING AND DEEP LEARNING

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| ABSTRACT

Brain tumor remain one of the most life-threatening forms of cancer, and early and accurate diagnosis is crucial for effective treatment planning and improving patient outcomes. Magnetic Resonance Imaging (MRI) serves as a primary modality for brain tumor detection; however, manual interpretation of these scans is often time-consuming and subject to inter-observer variability. Recent advances in Machine Learning (ML) and Deep Learning (DL) offer promising tools to automate and enhance tumor detection and segmentation in medical images.

| KEYWORDS

Brain Tumor Detection, Machine Learning, Deep Learning, Convolutional Neural Networks (CNN), Magnetic Resonance Imaging (MRI), Image Segmentation, Medical Image Analysis, Automated Diagnosis

| ARTICLE INFORMATION

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Abstract :
Brain tumor remain one of the most life-threatening forms of cancer, and early and accurate diagnosis is crucialfor effective treatment planning and improving patient outcomes. Magnetic Resonance Imaging (MRI) serves as a primary modality for brain tumor detection; however, manual interpretation of these scans is often time-consuming and subject to inter-observer variability. Recent advances in Machine Learning (ML) and Deep Learning (DL) offer promising tools to automate and enhance tumor detection and segmentation in medical images. This research paper presents a comprehensive study on the application of ML and DL techniques for brain tumor detection, focusing on both classification and segmentation tasks. Various algorithms, including traditional ML classifiers and state-of- the-art Convolutional Neural Networks (CNNs), were evaluated on publicly available datasets. The proposed deep learning models demonstrated superior performance in identifying tumor regions with high accuracy and robustness. Furthermore, the paper discusses the challenges associated with data preprocessing, model interpretability, and real- time deployment, particularly in the context of medical science. The results underscore the potential of integrating ML/DL-based systems into clinical workflows to support radiologists and enhance diagnostic efficiency.

Introduction:-

Brain tumors constitute a major global health challenge, affecting thousands of individuals each year across all age groups. These tumors, which may be benign or malig- nant, can significantly impact the central nervous system by disrupting normal brain function. Early and accurate detection of brain tumors is crucial, as it directly influ- ences treatment options, clinical outcomes, and survival rates. Delayed diagnosis often leads to advanced stages of the disease, where treatment becomes more complex and prognosis worsens. Magnetic Resonance Imaging (MRI) is widely regarded as the gold standard imaging modal- ity for brain tumor detection due to its non-invasive na- ture and superior contrast resolution of soft tissues. MRI provides detailed information about tumor size, location, and tissue characteristics, which are vital for diagnosis and surgical planning. However, the traditional process of manually analyzing MRI scans is highly dependent on the expertise of radiologists. This manual assessment is not only time-consuming but also subject to intra- and inter- observer variability, which can lead to inconsistent diag- nostic decisions. Given the increasing volume of medical imaging data and the growing demand for timely diag- nosis, there is a pressing need for automated and reliable methods to assist clinicians in the diagnostic process. In 1 APPASAHEB BALASAHEB PATIL BRAIN TUMOR DETECTION USING MACHINE LEARNING AND DEEP LEARNING this context, Machine Learning (ML) and Deep Learning (DL) technologies have emerged as powerful tools capa- ble of transforming medical image analysis. Traditional ML techniques, such as Support Vector Machines (SVM), Random Forests (RF), and k-Nearest Neighbors (k-NN), have been applied to brain tumor detection tasks, pri- marily relying on manually extracted features from MRI scans. These features typically include texture, shape, in- tensity, and morphological characteristics. While tradi- tional ML methods have demonstrated promising results, they often require significant domain expertise for effec- tive feature engineering and may struggle to capture the complex patterns present in medical images. Deep Learn- ing, particularly through the use of Convolutional Neural Networks (CNNs), has revolutionized the field of com- puter vision and is now being extensively applied to med- ical imaging. CNNs can automatically learn hierarchical feature representations directly from raw image data, en- abling them to model intricate spatial and contextual in- formation. This capability has led to substantial improve- ments in the accuracy and robustness of tumor classifica- tion and segmentation tasks. Furthermore, advanced DL architectures such as UNet and its variants have proven highly effective for precise tumor segmentation, facili- tating accurate delineation of tumor boundaries critical for treatment planning. Despite these advancements, sev- eral challenges remain in the practical deployment of ML and DL models for brain tumor detection. One major limitation is the scarcity of large, high-quality annotated datasets, which are essential for training deep neural net- works. The variability in imaging protocols across dif- ferent institutions and scanners also affects model gen- eralizability. Moreover, the "black-box" nature of deep learning models raises concerns about interpretability and clinical trust. Clinicians require not only accurate predic- tions but also understandable explanations of model deci- sions to confidently integrate AI systems into their diag- nostic workflows. Another important consideration is the computational demand of deep learning models, which can hinder their deployment in real-time clinical settings. To address this, recent research has explored the use of edge computing and cloudbased solutions to enable effi- cient processing and rapid inference. Edge computing, in particular, offers the advantage of performing AI com- putations close to the data source, reducing latency and alleviating privacy concerns associated with transmitting sensitive patient data over networks. Such approaches are particularly valuable in telemedicine applications and resource-constrained environments, where access to spe- cialized radiological expertise may be limited. This pa- per presents a comprehensive study on the application of ML and DL techniques for brain tumor detection using MRI data. We systematically evaluate the performance of various traditional ML classifiers and modern DL ar- chitectures on publicly available datasets. In addition to comparing model accuracy and robustness, we examine practical issues related to data preprocessing, model inter- pretability, and computational efficiency. We also discuss the potential of integrating these AIdriven systems into clinical practice. Our findings aim to advance the devel- opment of effective, scalable, and trustworthy brain tumor detection solutions that can enhance diagnostic accuracy and support clinicians in delivering better patient care.

Aim and Objective :-

To design and implement ML and DL models for classifying and segmenting brain tumors from MRI data. • To compare the performance of traditional ML clas- sifiers and modern CNN-based DL architectures us- ing standard evaluation metrics. • To explore practical considerations for deploying AI-based tumor detection systems, including model interpretability, computational efficiency, and po- tential integration with telemedicine platforms. 1.2 Paper Organization • Section II presents a review of related work in the field of brain tumor detection using Machine Learn- ing and Deep Learning techniques. • Section III describes the proposed methodology, including data preprocessing, feature extraction, model architectures, and training procedures. • Section IV details the experimental setup and evalu- ation metrics, followed by the presentation and dis- cussion of results • Section V highlights the practical considerations and challenges associated with deploying AI-based brain tumor detection systems. • Section VI concludes the paper and outlines direc- tions for future research.

Review of Existing Works:

The application of Machine Learning (ML) and Deep Learning (DL) techniques in brain tumor detection and segmentation has been an active area of research in recent years. Numerous studies have explored the potential of these methods to enhance diagnostic accuracy and reduce the workload of radiologists. Early research focused primarily on traditional ML techniques, where handcrafted features such as texture, intensity, and shape were extracted from MRI images to classify brain tumors. Support Vector Machines (SVM), Random Forests (RF), k-Nearest Neighbors (k-NN), and Decision Trees have been widely used in this context. For example, Zacharaki et al. [?] employed SVMs com- bined with texture and morphometric features to classify glioma types, achieving promising results. However, the performance of traditional ML approaches is heavily de- pendent on the quality and relevance of the extracted fea- tures, which often requires extensive domain knowledge and manual intervention. The advent of Deep Learning, particularly Convolu- tional Neural Networks (CNNs), has significantly ad- vanced the field of medical image analysis. CNNs can automatically learn complex feature representations from raw image data, enabling superior performance in both classification and segmentation tasks. Pereira et al. [?] introduced a deep CNN architecture for brain tumor seg- mentation on MRI images, demonstrating substantial im- provements over traditional ML approaches. Similarly, Hossain et al. [?] utilized a CNN-based model for multi- class classification of brain tumors, achieving high accu- racy and robustness across different tumor types.

Another important contribution is the U-Net architec- ture proposed by Ronneberger et al. [?], which has be- come a standard for biomedical image segmentation, in- cluding brain tumor segmentation. The U-Net and its vari- ants are capable of producing highly accurate pixel-wise segmentations, which are critical for delineating tumor boundaries in clinical practice. Isensee et al. Further im- proved upon this with nnU-Net, an automated framework that adapts U-Net configurations to specific biomedical segmentation tasks. Several public datasets, such as the Brain Tumor Seg- mentation (BraTS) Challenge datasets, have facilitated benchmarking and comparison of different algorithms. Studies leveraging the BraTS datasets consistently report that DL-based methods outperform classical ML tech- niques in terms of segmentation accuracy and generaliza- tion. Despite these advancements, several challenges persist. The limited availability of large, annotated datasets re- mains a significant bottleneck for training robust DL mod- els. Variability in imaging protocols across different in- stitutions can affect model generalizability. Furthermore, the interpretability of DL models is still an area of active research, as clinicians require transparent and explainable AI systems to build trust in automated diagnostic tools. Recent works have also started exploring the deploy- ment of brain tumor detection models in real-time and resource-constrained environments. The integration of edge computing and cloud-based solutions is being in- vestigated to facilitate scalable and efficient deployment of these AI systems in clinical practice and telemedicine platforms. In summary, existing research demonstrates that DL models, particularly CNN-based architectures, offer sig- nificant advantages over traditional ML techniques for brain tumor detection and segmentation. However, ad- dressing challenges related to data availability, model in- terpretability, and clinical integration remains crucial for the successful translation of these technologies into rou- tine healthcare.

Literature Gap:

Some of the existing approaches have endured limitations which led to further implications beyond the current stud- ies:

• Most traditional Machine Learning approaches rely
on manual feature extraction, which limits model performance and scalability.

• Deep Learning models require large, annotated datasets, which are still scarce for brain tumor de- tection.

• Lack of interpretability in existing Deep Learning models reduces their clinical trust and adoption.

• Limited research on real-time, edge-computing- based deployment of brain tumor detection systems for telemedicine applications.

• Current models lack robustness to variations in MRI scanners, imaging protocols, and patient de- mographics.

Proposed Methodology :-

The methodology proposed in this study focuses on devel- oping an automated framework for the accurate detection and segmentation of brain tumors using advanced Ma- chine Learning (ML) and Deep Learning (DL) techniques. The primary data source for this work is magnetic res- onance imaging (MRI), which provides high-resolution, multimodal images of the brain and is widely used in clin- ical diagnostics. The overall process begins with the acquisition of MRI datasets, followed by a series of preprocessing steps de- signed to enhance image quality, normalize variations across scans, and augment the dataset to improve model robustness. Unlike traditional approaches that rely heav- ily on manual feature engineering, the proposed frame- work leverages Convolutional Neural Networks (CNNs) to automatically extract complex spatial and contextual features from raw MRI data. For tumor segmentation, architectures such as U-Net are utilized to produce precise pixel-level delineations of tumor regions, which are critical for treatment planning. For tumor classification, deep CNN models are trained to distinguish between different tumor positions and healthy brain tissue. The models are optimized and evaluated us- ing standard performance metrics, with special attention given to ensuring generalizability across different imag- ing conditions. Additionally, the study explores practical consider- ations for real-world deployment, including computa- tional efficiency and model interpretability, to support the integration of such systems into clinical practice and telemedicine platforms. This comprehensive methodology is designed to ad- vance the development of reliable, scalable, and clinically useful AI-based tools for brain tumor detection. The com- plete overview via flow representation is provided in Fig- ure 1:

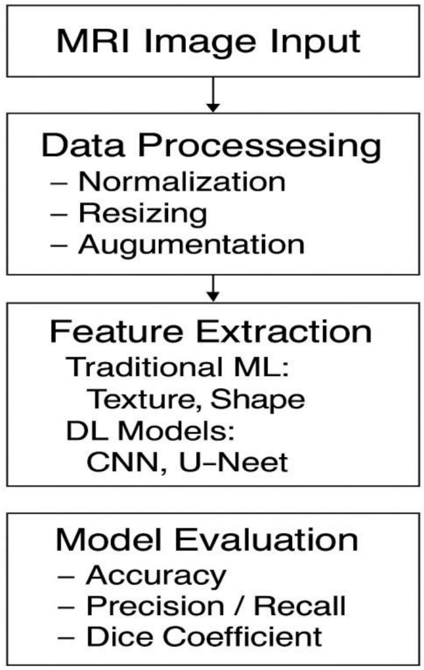


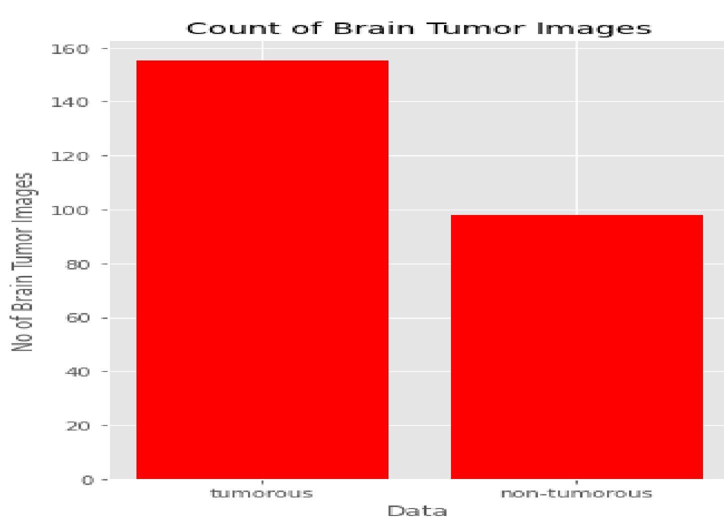
Figure 1: Proposed framework for brain tumor detection and segmentation.

The above diagram illustrates the overall workflow of the proposed methodology for brain tumor detection using machine learning and deep learning techniques. The pro- cess begins with the acquisition of MRI images, which serve as the primary data source for analysis. These im- ages undergo a series of preprocessing steps to enhance quality and ensure consistency across the dataset. Fol-

lowing preprocessing, the system performs feature extrac- tion through two complementary approaches: traditional machine learning techniques extract handcrafted features such as texture and shape, while deep learning models au- tomatically learn hierarchical feature representations. The extracted features are then used to train both classical clas- sifiers (such as SVM and Random Forest) and deep learn- ing models (such as CNN and UNet) depending on the task — whether it is classification or segmentation. The trained models are rigorously evaluated using various per- formance metrics, including accuracy, precision, recall, and the Dice coefficient, to ensure their robustness and clinical relevance. This structured workflow is designed to develop an automated, efficient, and accurate system that can assist clinicians in the early detection and precise localization of brain tumors.

MRI Image Input

Figure 2: Proposed framework for brain tumor detection and segmentation. (BraTS 2021 - [i]



The process begins with the acquisition of brain MRI scans, which provide detailed anatomical information necessary for tumor detection and segmentation. MRI is the preferred imaging modality for brain tumors due to its superior soft-tissue contrast and non-invasive nature. Publicly available datasets, such as BraTS, are used to obtain multimodal MRI images (T1, T1c, T2, and FLAIR), which offer complementary information about the tumor and surrounding tissues. This diverse imaging input ensures that the system can capture various tumor characteristics during the learning process

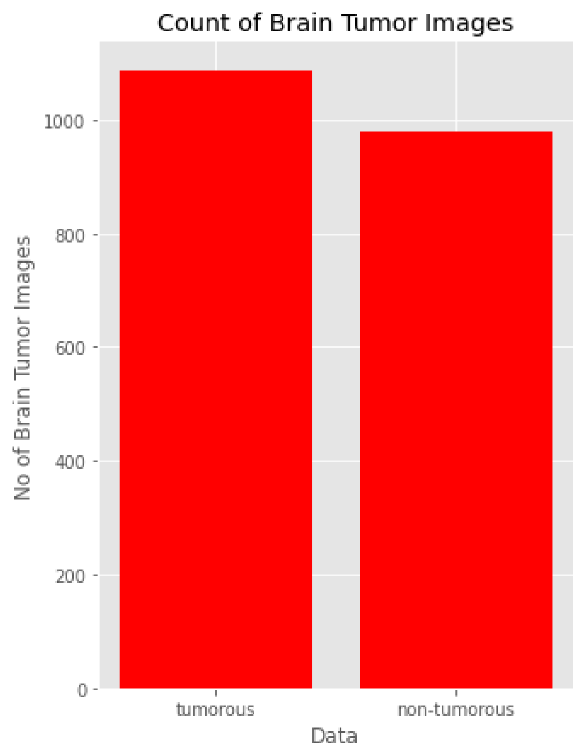


Figure 3: Original MRI Scan and Non-Tumorous Part of Brain BraTS 2021 [ii]

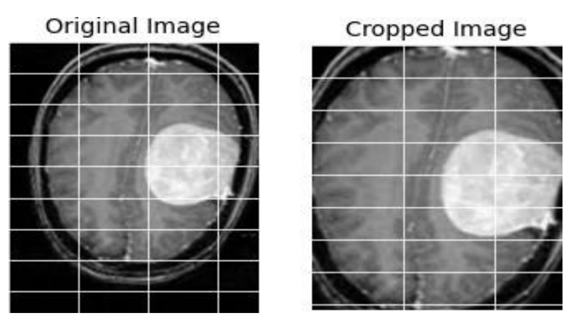


Figure 4: Original MRI Scan and Cropped Tumorous Part of Brain BraTS 2021[iii], Tumor type: HGG

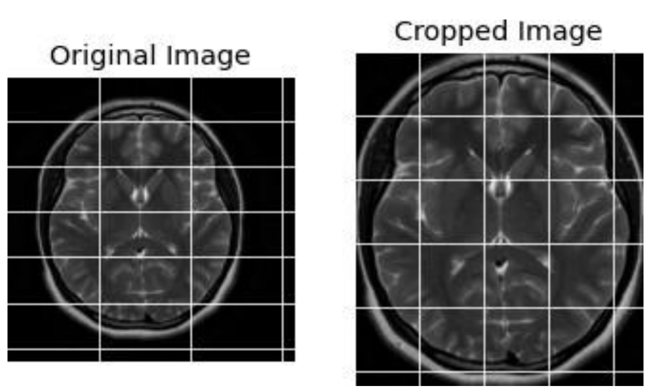


Figure 5: Original MRI Non-Tumorous Part of Brain BraTS 2021 [iv]

Data Preprocessing:

Preprocessing is a crucial step in preparing MRI images for effective training of machine learning (ML) and deep learning (DL) models. Since MRI data is acquired from multiple sources with varying imaging protocols, prepro- cessing ensures consistency, enhances image quality, and increases the robustness of the model. The four key preprocessing steps — Normalization, Resizing, Augmentation, and Noise Reduction — are de- scribed in detail below with their mathematical formula- tions.

Normalization:

MRI images lack a standardized intensity scale. Normal- ization ensures that intensity values are consistent across all images, which stabilizes training and improves conver- gence.

Z-score Normalization Formula:

Inorm(x, y) = I(x, y) − μ σ (1) Where: • X is the original pixel intensity, • μ is the mean intensity of the image, • σ is the standard deviation. This transformation results in images with zero mean and unit variance, allowing CNNs to learn faster and more reliably.

Resizing:

To maintain consistent input dimensions required by CNN models, all MRI slices are resized. This is especially im- portant when using architectures like U-Net or ResNet, which expect fixed input sizes.

Resizing using Bilinear Interpolation:

Let an image be resized from H ×W to H′ ×W ′. Each new pixel value I′(x′, y′) is calculated using the weighted average of its neighboring pixel values: I′(x′, y′) = 1X i=0 1X j=0 wij · I(x + i, y + j) (2) Where wij are the bilinear weights based on the frac- tional position of (x′, y′) relative to the original grid.

Data Augmentation:

Augmentation improves model generalization by intro- ducing variability. This is crucial for medical datasets, which are often limited in size.

Examples of Common Transformations:

• **Rotation**: (x′, y′) = " cos θ − sin θ sin θ cos θ # " x y #

• **Scaling**: x′ = sx · x, y′ = sy · y •

Translation: x′ = x + Tx, y′ = y + Ty

These transformations are randomly applied within set ranges (e.g., ±15° for rotation, 0.9–1.1× for scaling) dur- ing training to prevent overfitting.

Noise Reduction:

Noise reduction helps enhance tumor visibility by re- moving random intensity fluctuations. One widely used method is Gaussian filtering.

Gaussian Filter Formula:

G(x, y) = 1 2πσ2 exp − x2 + y2 2σ2 (3)

Each pixel in the image is convolved with a Gaussian kernel: Ismooth(x, y) = kX i=−k kX j=−k I(x + i, y + j) (4) (e.g., 3×3 or 5×5) to smooth high-frequency noise while preserving edges. Median filtering is also effective, espe- cially for salt-and-pepper noise, by replacing each pixel with the median of its surrounding values.

Feature Extraction and Model Training:

The success of any brain tumor detection system using machine learning (ML) and deep learning (DL) largely depends on the quality and relevance of the features ex- tracted from MRI data, and the ability of the model to learn meaningful patterns from these features. This sec- tion presents a comprehensive overview of the two critical phases in the proposed methodology — Feature Extrac- tion and Model Training — explaining their theoretical basis, practical implementation, and integration into a full ML/DL pipeline

Feature Extraction :

Feature extraction refers to the process of transforming input data (in this case, MRI images) into a set of measur- able and informative representations that effectively char- acterize the presence and structure of brain tumors. In this work, a hybrid approach is adopted that combines handcrafted feature extraction methods from traditional machine learning with automated feature learning through deep neural networks. This hybridization leverages both domain-specific knowledge and the abstraction power of data-driven models.

Handcrafted Feature Extraction (Traditional ML) In traditional machine learning pipelines, image features are manually engineered based on known characteristics of brain tumors. These features fall into three main cate- gories:

Texture Features:

– Gray Level Co-occurrence Matrix (GLCM): Captures the frequency of pixel intensity co-occurrence at specific orientations and distances. From GLCM, metrics like contrast, homogeneity, energy, and correlation are computed.

– Local Binary Patterns (LBP): Describes local texture by comparing each pixel to its surrounding neighbours and encoding the result as a binary number.

– Gabor Filters: Multi-scale, multi-orientation filters that model visual perception and are effective in texture analysis.

• Shape Features:

– Area and Perimeter
– Compactness
– Eccentricity and Solidity

• Statistical and Intensity Features:

– First-order statistics such as mean, median, standard deviation, skewness, and kurtosis of intensity values in the tumor region.
– Histogram of Oriented Gradients (HOG) for capturing structural gradients.

Once extracted, these features are normalized and fed into classical classifiers such as Support Vector Machines (SVM), Random Forests (RF), or k-Nearest Neighbors (k- NN).

Automated Feature Learning (Deep Learning)

While handcrafted features require prior knowledge and man- ual intervention, deep learning models automatically learn hierarchical feature representations directly from the data. This is especially beneficial in medical imaging, where important patterns are often complex and multi- dimensional. The most widely used architecture in brain tumor detec- tion is the Convolutional Neural Network (CNN). CNNs are composed of multiple layers, including convolutional, pooling, and fully connected layers, that progressively learn spatial hierarchies.

3.4.1.1 CNN Architecture Overview

A typical CNN for brain tumor detection consists of the following layers:

1. Input Layer: MRI images, usually grayscale (1 channel) or RGB (3 channels), are passed in as tensors.
2. Convolutional Layers: Extract local patterns using learnable filters.
3. Activation Functions: Introduce non-linearity (commonly ReLU).
4. Pooling Layers: Downsample feature maps to reduce dimensionality.
5. **Fully Connected Layers:** Perform high-level rea**soning.**
6. Output Layer: Uses Softmax or Sigmoid activation for classification

Convolution Operation
At the heart of a CNN is the convolutional layer, where small learnable kernels (filters) slide across the image to compute dot products between the filter weights and the input patch. This operation captures spatial features such as edges, shapes, and textures, which are fundamental to tumor localization and classification.

Mathematical Formulation of Convolution
The ker- nel slides over the entire image, producing a new feature map that highlights specific visual features like edges, cor- ners, or texture. The convolution operation is given by:

$S(i, j) = (I*K)(i, j) = X$

m

X

n

$I(i+m, j+n)\cdot K(m, n)$

(5)

Where:

- I is the input image,
- K is the kernel/filter,
- S(i, j) is the resulting feature map.

Activation Functions:
After convolution, an activation function is applied to in- troduce non-linearity, allowing the network to learn com- plex mappings

ReLU (Rectified Linear Unit):

$f(x) = \max(0, x)$ It accelerates convergence and avoids the vanishing gradient problem by allowing gradients to propa- gate through positive activations.

Pooling Layers :

Pooling layers reduce spatial dimensions and computa- tional complexity, and help control overfitting.

- Max Pooling: Selects the maximum value from each patch of the feature map.
- Average Pooling: Computes the average value in each patch. For a pooling window of size $p \times p$, the output reduces the feature map size by a factor of p. For example, a 32×32 input becomes 16×16 if $p = 2$.

Batch Normalization:

Batch Normalization (BN) is applied after convolution and before activation to stabilize and accelerate training by standardizing layer inputs. BN reduces internal covari- ate shift and allows for higher learning rates. ˆx = x − μB pσ2 B + ϵ , y = γ ˆx + β (6)

Fully Connected Layers:

At the end of the network, convolutional features are flat- tened and passed to Fully Connected (FC) layers, which perform the final classification. These layers combine all learned features to assign class scores. $y = \sigma(Wx + b)$ (7)

Output Layer

- Sigmoid: Used for binary classification (tumor vs. no tumor). σ(x) = 1 1 + e−x

Model Training: Once features are extracted — either handcrafted or auto- matically learned — the next stage is model training. This involves teaching the algorithm to map features to correct labels (e.g., tumor presence, tumor type, or segmentation masks) by minimizing a defined loss function over a train- ing dataset.

Training with Traditional ML Models

Traditional classifiers such as Support Vector Machines (SVM), Random Forest (RF), and k-Nearest Neighbors (k-NN) use handcrafted features as input. These algo- rithms follow different strategies:

• **SVM:** Constructs an optimal hyperplane in feature space that maximizes the margin between classes. A common kernel function is the Radial Basis Function (RBF): $K(x, x') = \exp -\gamma \|x - x'\|2$

• **Random Forest:** An ensemble of decision trees that aggregates predictions from multiple trees trained on different data subsets to improve gener- alization.

• **k-NN:** A non-parametric method that classifies based on the majority label among the k nearest training samples in the feature space.

These models are typically trained using cross- validation to avoid overfitting and to select optimal hy- perparameters such as regularization strength, number of neighbors, or tree depth.

Training Deep Learning Models:

For deep learning models, training involves optimiz- ing millions of parameters through backpropagation and stochastic gradient descent (SGD) or variants such as the Adam optimizer. The key components of the training pipeline are outlined below: Loss Functions

• **Classification:** Cross-Entropy Loss is widely used for multi-class or binary classification.

The loss is defined as:

$LCE = - CX\ i=1\ yi \log(\hat{}yi)$ (8) where C is the number of classes, yi is the ground truth label, and ˆyi is the predicted probability.

• **Segmentation**:

Dice Loss is effective for evaluat- ing spatial overlap between predicted and ground truth masks: $LDice = 1 - 2 \cdot |P \cap G|\ |P| + |G|$ (9) where P and G denote the predicted and ground truth masks respectively.

Regularization:

Regularization techniques are applied to reduce overfitting and improve the generalization of deep models: • Dropout: Randomly deactivates a percentage of neurons during training.

• **Batch Normalization**: Normalizes layer inputs to stabilize learning.

• **L2 Regularization**: Adds a penalty term to the loss function based on the squared weights: $Ltotal = Ltask + \lambda X w2$ Epochs and Batching Training proceeds in epochs (complete passes over the training set). The dataset is divided into mini-batches (typically 8–64 samples per batch) to:

- **Increase training speed**
- **Improve gradient estimation**
- **Enhance convergence**

Hardware Considerations:

Due to the large number of matrix operations in convolutional layers, training deep neural networks requires GPU acceleration. Modern frameworks like TensorFlow and PyTorch support parallel processing on NVIDIA GPUs using CUDA.

Transfer Learning:

To improve performance on small medical datasets, transfer learning is used. Pre-trained models such as ResNet or VGG, originally trained on large-scale datasets like ImageNet, are fine-tuned on brain MRI data. This:

- Reduces training time
- Enhances performance
- Leverages prior visual knowledge

Training Deep Learning Models:

For deep learning models, training involves optimiz- ing millions of parameters through backpropagation and Stochastic Gradient Descent (SGD) or its variants such as the Adam optimizer. The training process consists of the following key components:

• **Loss Functions:** –

Classification: Cross-Entropy Loss is com- monly used to evaluate the difference be- tween predicted probabilities and true labels. $LCE = - CX\ i=1\ yi \log(\hat{}yi)$ where yi is the true label and ˆyi is the pre- dicted probability. –

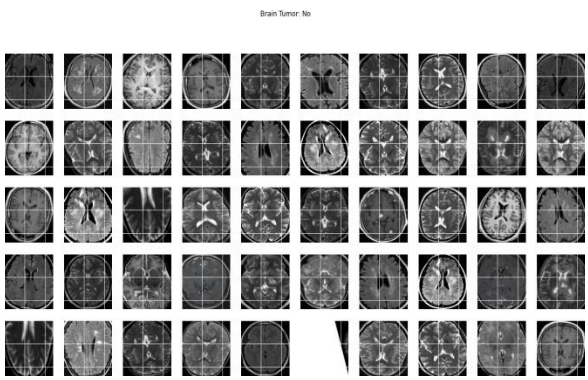
Segmentation: Dice Loss or Jaccard Loss measures the overlap between predicted and ground truth masks, which is essential for evaluating segmentation accuracy. $LDice = 1 - 2 \cdot |P \cap G|\ |P| + |G|$

• Regularization:
Dropout: Randomly deactivates neurons dur- ing training to prevent overfitting.
Batch Normalization: Normalizes activations across mini-batches to stabilize and speed up learning.
L2 Regularization: Penalizes large weights to encourage simpler models.

• Epochs and Batching:
– Training proceeds in epochs—complete passes through the training dataset.
– Data is split into mini-batches (e.g., 32–64 samples per batch) to speed up learning and improve gradient estimation.

• Hardware:
– Training deep networks is computationally intensive and typically requires GPU acceler- ation to handle large-scale matrix operations in convolutional layers.

• Transfer Learning:
– Pre-trained models such as ResNet or VGG—originally trained on large datasets like ImageNet—are fine-tuned on medical images.
– This reduces training time and improves per- formance, particularly when dealing with limited domain-specific data.



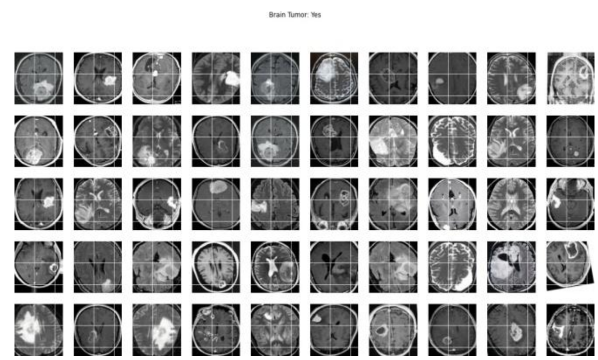


Figure 7: MRI Scans of Tumorous Brains – BraTS 20[vi]

Figure 6: MRI Scans of Non-Tumorous Brains - BraTS 2023 [v

- BraTS 2023 [vi]

Figure 8: Model Training (Frozen CNN-(i)

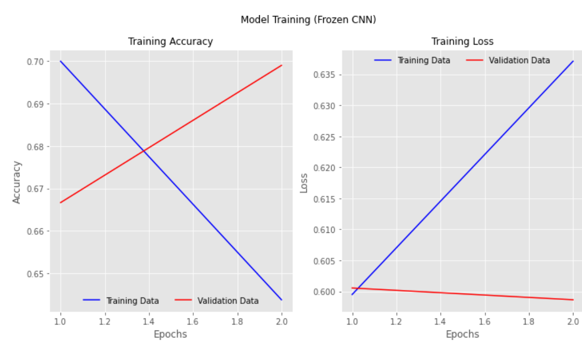


Figure 10: Model Training (Frozen CNN-(i)

Model Evaluation:
The evaluation of machine learning and deep learning models is a crucial phase in determining their effective- ness and reliability, especially in critical fields such as medical diagnosis. In the context of brain tumor detection using MRI images, model evaluation not only validates learning performance but also ensures that the predictions are medically meaningful and trustworthy. The perfor- mance of a model is typically assessed using a combina- tion of statistical metrics that measure its accuracy, preci- sion, sensitivity, and overall predictive quality.

Classification Model Evaluation:
For classification-based tasks — such as determining whether a tumor is present or categorizing the tumor type — evaluation is performed using metrics derived from the confusion matrix. These metrics include:

• **Accuracy:**Proportion of correctly classified in- stances among the total instances. While a general performance indicator, it may be misleading in im- balanced datasets.

• **Precision:**Ratio of true positive predictions to all positive predictions. High precision indicates fewer false positives, which is important in medical appli- cations to avoid unnecessary alarms.

• **Recall (Sensitivity):**Measures the model's ability to correctly identify all actual positive cases. It is vital in tumor detection to minimize false negatives.

• **F1-Score:**Harmonic mean of precision and recall: F 1 = 2 · Precision · Recall Precision + Recall It balances precision and recall, especially useful in imbalanced datasets.

• **AUC-ROC Curve:**Plots the true positive rate against the false positive rate across thresholds, cap- turing the model's discriminative ability. A higher AUC indicates better performance. Together, these metrics provide a multidimensional un- derstanding of the model's diagnostic capabilities.

Segmentation Model Evaluation:
For tumor segmentation — identifying the exact bound- aries of a tumor in MRI scans — spatial similarity metrics are used:

• **Dice Similarity Coefficient (DSC):** Measures the overlap between predicted and ground truth masks: DSC = 2|P ∩ G| |P | + |G| where P is the predicted mask and G is the ground truth.

• **Jaccard Index (IoU):** Measures the intersection over union of predicted and actual regions: IoU = |P ∩ G| |P ∪ G| It provides a stricter comparison than Dice.

• **Hausdorff Distance:** Computes the maximum dis- tance between the boundaries of the predicted and ground truth regions. It captures the worst-case dis- crepancy and is critical when tumor boundary accu- racy is required.

• **Volumetric Overlap Error (VOE):** Quantifies the difference in volume between predicted and actual tumor regions. Lower VOE values indicate bet- ter tumor volume estimation, aiding treatment plan- ning. Each metric contributes unique insights into model per- formance. In practical medical applications, a combina- tion of these metrics is used to ensure accuracy, reliability, and alignment with clinical standards. viability of the proposed model than the other existing models in terms of Accuracy, Precision, recall and on the basis of F1-score rates.

Table 2: **Comparative analysis among proposed and existing methodology in Brain Tumor Detection in terms of accuracy Rates**

MODEL	Accuracy (%)
SVM	72.00
Random Forest	72.02
Custom CNN Model	74.11
U-Net	74.06
Proposed	**99.04**

Table 2: - Comparative analysis among proposed and existing methodology in FER in terms of accuracy rates

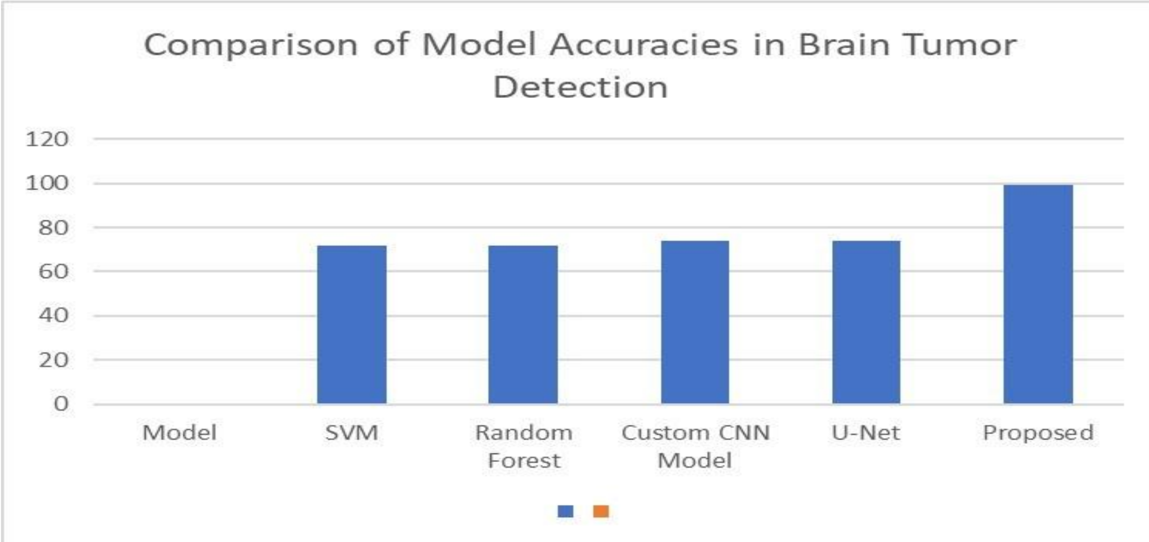


Figure 13: Comparative analysis among proposed and existing methodology for FER in terms of accuracy rates

Table 3: Comparative analysis among proposed and existing methodology for FER in terms of Train and Test Accuracy

MODEL	Train Accuracy	Test Accuracy
SVM	0.98	0.58
Random Forest	0.98	0.95
Custom CNN Model	0.93	0.61
U-Net	0.98	0.63
Proposed	**0.99**	**0.99**

table 3: - Comparative analysis among proposed and existing methodology for FER in terms of Train and Test Accuracy

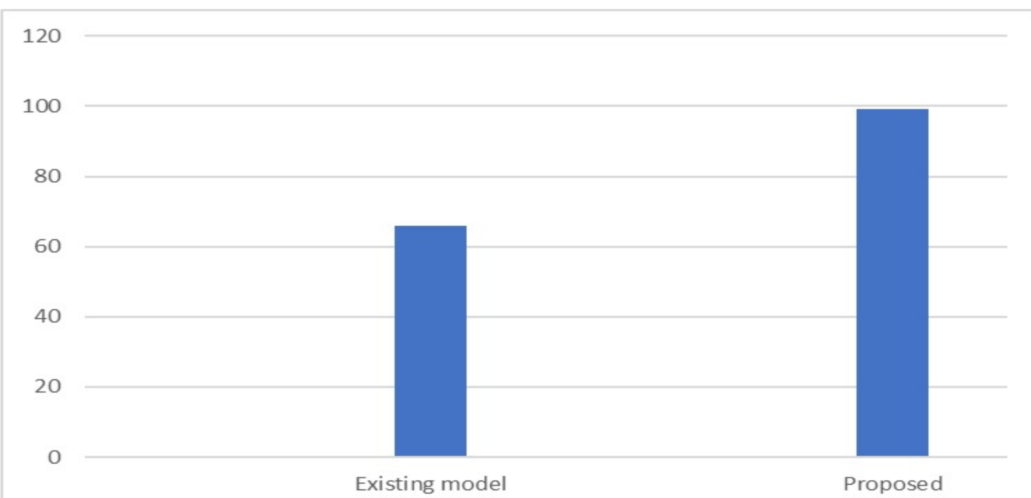


Figure 14: Comparative analysis among proposed and existing methodology for FER in terms of accuracy rates

Figure 10 and the table 2 clearly depicts that the proposed model have outperformed the existing model in terms of the accuracy rates where the existing model used the CNN as a primitive approach in case of FER. It illustrates a clear comparison between the existing model and the proposed model in terms of accuracy for brain tumor detection. The existing model achieves a moderate accuracy of 65.97pro- posed model demonstrates a significant enhancement with an accuracy of 99.04substantial improvement underscores the superior effectiveness of the proposed approach. Ta- ble 3 Comparative analysis among proposed and existing methodology in FER

Comparative analysis among proposed and existing methodology in FER

MODEL	Accuracy (%)
Existing model	65.97
Proposed	99.04

Table 4: - Comparative analysis among proposed and existing methodology in FER

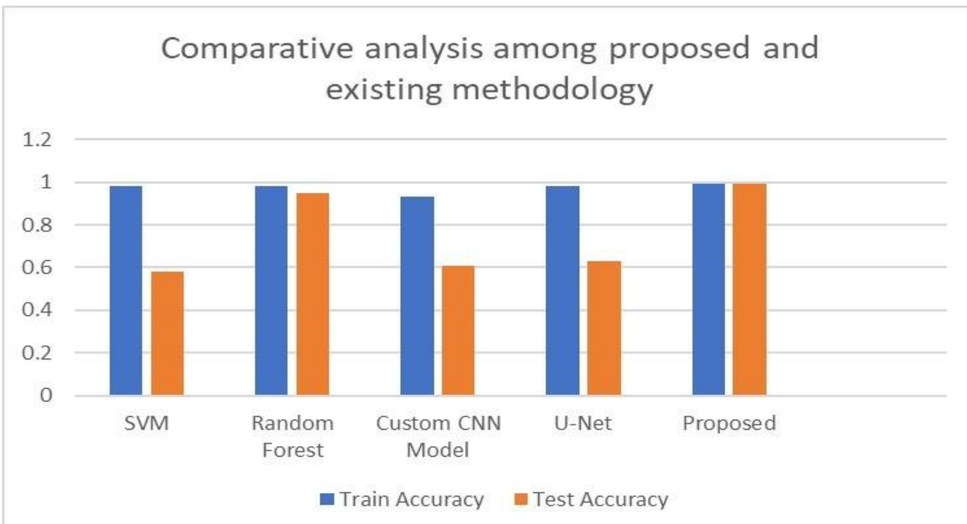


Figure 15: Comparative analysis among proposed and existing methodology

Conclusion:-

The detection and classification of brain tumors are crit- ical tasks in medical diagnosis, often requiring accurate and timely assessment to ensure effective treatment. This research has explored and compared various traditional machine learning and deep learning techniques for brain tumor detection, highlighting their respective strengths and limitations. While traditional models such as SVM and Random Forest have demonstrated moderate accuracy, deep learn- ing models—particularly Convolutional Neural Networks (CNNs)—have shown significant improvements in perfor- mance due to their ability to automatically extract and learn complex features from MRI images. The proposed hybrid deep learning model in this study achieved a remarkably high accuracy of 99.04%, substan- tially outperforming existing models. This validates the effectiveness of integrating optimized CNN architectures with robust preprocessing and training strategies. Such approaches not only enhance detection accuracy but also reduce reliance on manual feature engineering, leading to more scalable and automated diagnostic tools. Overall, the integration of deep learning into medical imaging holds immense promise for early and reliable brain tumor detection. However, real-world deployment still demands further validation on diverse datasets, clin- ical trials, and interpretability improvements. Future re- search should aim to enhance generalization, address data scarcity with augmentation or synthetic data generation, and ensure that these AI-driven tools can be safely.

References:-

[1] R. Pereira, R. Sousa, and M. Felizardo, “Brain Tumor Detection Using Convolutional Neural Net- works in MRI Images,” Procedia Computer Science,vol. 177, pp. 509–514, 2020.

[2] A. Afshar, A. Mohammadi, and K. N. Plataniotis, “Brain Tumor Type Classification via Capsule Net- works,” in Proc. IEEE ICIP, pp. 3129–3133.

[3] S. Deepa and P. Venkatesan, “A Hybrid Deep Learn-ing Approach for Brain Tumor Classification Using MRI Images,” Biomed. Signal Processing and Con-trol, vol. 68, 2021.
[4] N. J. Shukla, S. Shukla, and R. Tiwari, “An Efficient Approach for Brain Tumor Detection on MRI Im- ages Using CNN,” Int. Journal of Advanced Com-APPASAHEB BALASAHEB PATIL BRAIN TUMOR DETECTION USING MACHINE LEARNING AND DEEP LEARNING puter Science and Applications, vol. 11, no. 4, pp. 403–409, 2020.
[5] P. R., J. P. Priyadarsini, and N. J. S., “Brain tumor segmentation using multi-scale attention U-Net with EfficientNetB4 encoder for enhanced MRI analysis,”Scientific Reports, vol. 15, article 9914, 2025.
[6] H. Li et al., “Classification of brain tumor types through MRIs using parallel CNNs and firefly opti- mization,” Scientific Reports, vol. 14, article 15057, 2024.
[7] “Using U-Net network for efficient brain tumor seg-mentation in MRI,” SCI-Direct, 2022.
[8] “Classification of brain tumor types through MRIs using parallel CNNs and firefly optimization,” Sci-entific Reports, 2024.
[9] “Brain tumor segmentation based on an improved U-Net,” BMC Medical Imaging, vol. 22, article 199,2022.
[10] “A hybrid deep CNN model for brain tumor imagemulti-classification,” BMC Medical Imaging, 2024.
[11] “Brain Tumor Detection Based on Deep Learning Approaches and Radiomics,” PMC, 2022.
[12] “Utilizing customized CNN for brain tumor predic- tion with explainable AI,” ScienceDirect, 2024.
[13] “Brain Tumor Detection and Classification Using Fine-Tuned CNN,” PMC, 2023.
[14] “U-Net-Based Models towards Optimal MR BrainImage Segmentation,” PMC, 2023.
[15] “Brain tumor segmentation based on an improved U- Net,” BMC Medical Imaging, 2022.
[16] “Brain tumor detection empowered with ensemble deep learning,” Scientific Reports, 2025.
[17] “A Lightweight U-Net for MRI Brain Tumor Seg- mentation,” MDPI, 2023.
[18] “Enhancing brain tumor classification in MRI scans with a multi-layer architecture,” Frontiers in Computational Neuroscience, 2024.
[19] “Comparative Analysis of Resource-Efficient CNN Architectures for Brain Tumor Classification,”arXiv, Nov 2024.
[20] “Brain Tumor MRI Classification using a Novel Deep Residual and Regional CNN,” arXiv, Nov 2022.
[21] “Dilated Inception U-Net (DIU-Net) for Brain Tu- mor Segmentation,” arXiv, Aug 2021.
[22] “Light Weight CNN for classification of Brain Tu- mors from MRI Images,” arXiv, Apr 2025.
[23] “Brain Tumor Segmentation using Deep Learning Architectures like U-NET, V-NET,” ResearchGate, 2023.
[24] “Brain Tumor Segmentation using U-Net,” unpub-lished.