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DeepTumorNet: A CNN-Based Multi-Class Brain Tumor Detection Approach Using MRI Scans and Segmentation of Data

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Abstract

Health is fundamental to human well-being, with brain health particularly critical for cognitive functions. Magnetic resonance imaging (MRI) serves as a cornerstone in diagnosing brain health issues, providing essential data for healthcare decisions. The Brain tumors have been noted as among the most life-threatening forms of cancer whereby accurate and timely diagnosis would be very important in terms of patient survival and proper treatment response. This paper presents an analysis and a comparison of the performance of three different models of deep learning, such as Multi-Layer Perceptron (MLP), AlexNet, and InceptionV3, on brain tumor multi-class classification using magnetic resonance imaging (MRI) scans. With the help of a publicly available data that contained labeled MRI images of four categories such as glioma, meningioma, pituitary tumors, and normal (non-tumorous) cases, we also trained all the models to evaluate the performance. The data also feature segmentation data that makes the model perform better in terms of targeting the appropriate areas in the brain scan. Among the models, the MLP serves as a fundamental baseline for performance comparison. However, the convolutional neural network (CNN)-based architectures, specifically AlexNet and InceptionV3, demonstrated significantly superior results. Notably, InceptionV3, which incorporates deep and wide convolutional layers along with transfer learning capabilities, achieved the best overall accuracy at 88.57%. These findings underscore the importance of using advanced CNN models and pre-trained architectures for improving diagnostic accuracy in medical imaging tasks. By leveraging transfer learning and efficient model design, this research contributes to the development of automated systems that can assist medical professionals in detecting and classifying brain tumors more reliably and quickly.

Keywords: Brain tumor, Segmentation, ResNet, Deep neural network, CNN, Healthcare, Prediction models.
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INTRODUCTION

The majority of primary brain tumors are life-threatening. Whereas other types of brain malignancies metastasize from some other part of the body to the brain, primary brain tumors form within the brain. Accurate imaging plays a crucial role in diagnosing these tumors. Imaging plays an essential role in the evaluation of these tumors [1, 2]. MRI, CT and PET scans are among the most frequent high-resolution methods applied. Among them, MRI is particularly important for the investigation of the internal structure of the brain and is instrumental in identifying and evaluating brain tumors [3, 4]. Primary brain cancer is distinguished from secondary one which starts from elsewhere in the body and then spreads to the brain. This is because MRI is a non-invasive modality and therefore is widely used in imaging of the brain and in diagnosis [5, 6]. MRI equipment uses waves and electronic signals to capture the various body parts. To explain the appearance of a movable bed, this is a part of the cylindrical frame within which the

MRI is located, and all its sides are surrounded by magnets. This is a magnetic tunnel in which the patient is on a bed, then slides to the scanner for the MRI scan. To the patient inside, a steep magnetic field that orients the protons in hydrogen atoms is used [7, 8]. These protons which are put into the body together with radio waves give signals that MRI converts to images. The common idea in MRI is to utilize a favorable magnetic field and radio signals to form images which show alterations of the body's growth processes. Image segmentation on the other hand is the process of segmenting a picture as widely as possible at its basic form or elements such as the pixel [9, 10].

This technique divides the pixels of a region into groups meeting recognized criteria such as color, intensity, and texture intensity [11, 12]. This leads to the achievement of good quality images which can enhance view for enhanced viewing in case of slight changes in body structure. MRI in biomedicine helps see tiny organs and tissues with vivid details. It assists in detecting variations in tissues and is believed to better than different imaging types. Traditionally, radiologists spent much time sifting through MRI pictures to find out whether there were brain tumors or not [13, 14]. Over the past few decades, there has been extensive research on image segmentation, with numerous studies conducted [15]. However, there is a lack of comprehensive comparisons between different segmentation methods, highlighting that segmentation remains a challenging and active research area.

The objective is to precisely segment brain tissue and tumors in 2D MRI data. To achieve this, excellent methods that clearly define tumor boundaries utilizing MATLAB and other tools are used. Segmentation methods are generally classified into three types: manual, semi-automatic, and fully automatic. Manual segmentation involves radiologists using both MRI images and their expertise, but this method is time-consuming and prone to errors, leading to its reduced use. Semi-automatic methods require user input for tasks like labeling and adjustment, which, while less tedious, still face challenges with consistency [17- 21].

$$\boldsymbol{Dice} = \frac{\boldsymbol{2/X \cap Y/}}{\boldsymbol{/X/+/Y/}} \qquad \text{Eq (1)}$$

Where:

- X=point cloud of pixels in the triumphant segmentation
- Y = element of pixels in ground truth segmentation
- |X∩Y| = number of overlapping pixels between the two sets
- |X| and |Y| = number of pixels in each set, respectively

Recent research focuses predominantly on fully automatic methods designed to handle image variability more effectively. Neural networks, unlike traditional computers, process data similarly to the human brain [22]. They use many interconnected units (neurons) to solve problems by learning from examples rather than following strict algorithms. While deep learning methods have demonstrated encouraging results in automatic segmentation, high accuracy requires well-prepared training datasets [23-26]. The primary objective of this research is to create reliable, effective, and optimal CNN-based tumor detection methods. Traditional methods for segmenting brain tumors from pre-surgery MRI scans, done by neuroradiologists, are often difficult due to the tumor's varying shape, unclear edges, and image distortions. This makes the process time-consuming and more complex [27, 28].

$$Loss = CrossEntropy(y, \hat{y}) \qquad \text{Eq (2)}$$

In the medical field, "automatic tumor segmentation" using deep learning techniques has produced excellent outcomes. Convolutional Neural Nets (CNNs): Consisting of multiple hidden layers for convolution and activation, CNNs have shown remarkable efficacy in the identification of various diseases, including skin cancer [29], brain tumor [30] and breast cancer [31-33].

This study investigated the effects of applying various CNN-based deep learning models for brain tumor detection and classification using MRI scans. While earlier studies have explored the impact of CNNs in general tumor detection tasks, they have not explicitly addressed their influence on multi-class brain tumor classification through a direct comparison of different CNN architectures using segmentation data. We fill that gap in this work by thoroughly examining the efficacy and accuracy of widely-used brain tumor segmentation techniques. Our objective is to evaluate the effectiveness and reliability of three widely used deep learning models—Multi-Layer Perceptron (MLP), AlexNet, and InceptionV3—for the task of multi-class brain tumor classification using MRI scans. The objective of this research is to determine the method of automation that provides maximum accuracy in segmenting the brain tumor. Below figure 1 shows APT MRI Images with high grade Tumor. These techniques come in handy with neurosurgeons and oncologists since it provide the right information that may be useful when issuing diagnoses, when planning for treatment, and even increasing the likelihood that the patient will survive.

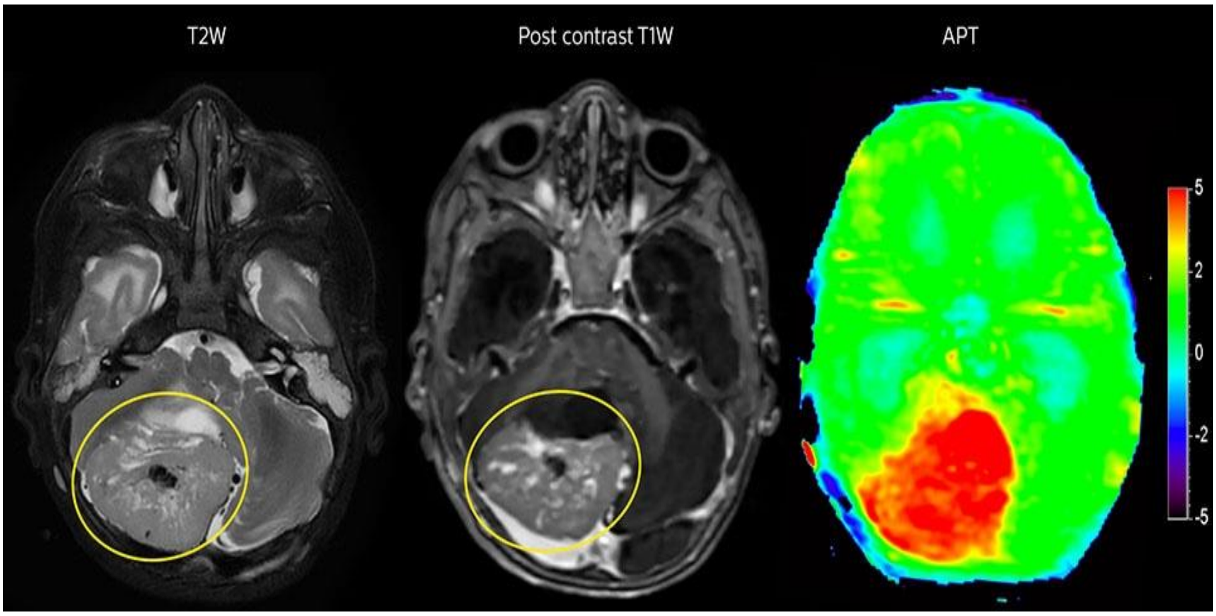

Figure 1.
APT MRI Images with high grade Tumor [34]

RELATED WORK

Based on the above discussion, current studies related to deep learning for the identification of brain illnesses are discussed in this section with a focus on CNN-based approaches for automatic segmentation of brain tumors from MRI scans. Many works have presented approaches based on CNNs for segmenting brain tumors. For instance, Urban proposed a 3D CNN model in the context of multimodal MRI glioma segmentation, which correctly predicts tissue classes with the 3D patches as input [35-38]. Zikic developed an approach to transfer 4D data into the 2D patches, enabling the use of 2D-CNN designs for segmentation of brain tumors [40, 41]. In the previous works, different architectures of CNNs were used for the segmentation of the brain tumor. For instance, [42, 43]. Table 1 shows the Comparative Analysis of Methods used for MRI Images. Proposed two-stage training strategies to overcome the problem of class imbalance and designed a CNN to predict a restricted network configuration for component classification of a multi-level data model. To obtain the features from each MRI modality image, Rao used four different CNNs and fixed several planes across each pixel [44, 45].

Table 1.
Comparative Analysis of Methods used for MRI Images

Ref	Method/Model Used	Dataset	Result/Contribution
[46, 47]	3D U-Net (CNN)	BRATS MRI Dataset	Improved brain tumor segmentation accuracy.
[48, 49]	Hybrid Traditional + Deep Learning Model	Brain MRI	Enhanced brain tumor classification.
[50, 51]	CNN using multi-channel MRI images	Private MRI Dataset	Better diagnosis using T1, T2, and FLAIR sequences.
[52, 53]	CNN for Real-Time Detection	MRI Dataset (Custom)	Reduced latency for faster tumor detection.
[54, 55]	Deep Learning Review	General Medical Imaging	Identified challenges such as data privacy issues.
[56, 57]	CNN and IoMT Integration	Clinical Datasets (Review)	Proposed improvements in healthcare outcomes.
[58, 59]	Deep Learning Autoencoder	MRI + Breath Sample Analysis	Achieved 97.8% precision for tumor detection.
[60, 61]	CNN-DWT-LSTM Hybrid Model	Brain MRI Dataset	Enhanced classification accuracy and robustness.
[62, 63]	CNN-based CAD System	MRI Images (Clinic Collection)	Developed remote diagnosis support system.
[64, 65]	VGG19 and CNN Comparative Study	Brain MRI Scans	98.31% accuracy in tumor detection.

More recently, CNN architectures have been proposed to segment brain tumors. As an example, [66] constructed a CNN model that has two pathways capable of understanding the coarse information of the brain tissue and the fine information of the brain MRI. In [67] the efficiency of the use of smaller 3x3 estimated channels in convolutional stages in brain tumor segmentation was compared, and three different glioma segmentation methods using CNN were proposed in [68].

Some alternative methods have been considered too, including brain tumor segmentation and classification using multi-view knowledge-based collaborative deep learning [69] and hybrid CNN-DWT-LSTM techniques. Convolutional neural networks (CNNs), one type of deep learning technique, have become more and more common in medical imaging over the last ten years [70].

Several investigations have demonstrated their efficacy in detecting anomalies, including cancers, in different human organs. [71] Introduced a system that uses wearable IoMT sensors for data gathering and deep learning algorithms for real-time health monitoring. These studies demonstrate the use of deep learning techniques for segmenting and identify different types of brain diseases. Our goal in this paper is to present a thorough analysis of brain illness detection with different CNN approaches or methodologies.

Deep Learning

The concept of deep learning traces its origins to early artificial neural networks (ANNs) research, starting with perceptron models in the 1960s. In [72] created the perceptron, a linear classifier, was created, marking the beginning of learning algorithms. However, due to limitations, particularly in handling non-linear data, neural networks faced skepticism for years. Over time, advances in computing power, larger datasets, and improved training methods led to deeper neural networks, giving rise to modern "deep learning." "This branch of machine learning employs multi-layered neural networks to automatically extract features from data, progressing from simple to complex patterns." The two most popular architectures are Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). CNNs are revolutionizing tasks such as image and video recognition by modeling the structure of the visual cortex [73].

$$\boldsymbol{z = \sum_{i=1}^{n} w_i x_i + b} \quad \text{Eq (3)}$$

Where:

- w = weight,
- x = input feature,
- b = bias,
- z = linear combination before activation

Convolutional Neural Network

Convolutional Neural Networks (CNNs) are based on research into how mammals' visual cortex's function. The design of CNNs mimics how neurons in the brain process visual information by recognizing different levels of spatial patterns. The term "convolutional" in Convolutional Neural Networks (CNNs) refers to the main mathematical process that allows the network to use shared weights, focus on local areas, and maintain spatial consistency [74] While neural networks have been studied for visual tasks since the 1980s, Kate and Shukla's LeNet-5 model for handwritten number detection was the first to successfully employ CNNs [75]. This model introduced gradient-based learning, which was crucial for document recognition and led to major advances in the field. CNNs do particularly well when processing data having a grid-like structure, such as photographs, this is equivalent to a 2D pixel grid.

The uses of neural networks in medical diagnostics were the main emphasis of this literature review, which also examined the basic ideas and sophisticated structures of neural networks. It traced these networks' development from biological models to contemporary uses, emphasizing convolutional neural networks (CNNs) because of their groundbreaking work in the field of medical image analysis [76]. The review discussed important challenges such as the need for large labeled datasets and improving model interpretability, while also highlighting how neural networks have significantly enhanced diagnostic accuracy [77].

$$\boldsymbol{ReLU(x) = max(0, x)} \quad \text{Eq (4)}$$

To advance brain disease detection using deep learning techniques, several research gaps need addressing:

(a) There is a lack of focus on improving MRI image quality and applying these enhancements to CNN-based methods.

(b) Technology is rapidly evolving, and improvements in computer programs are crucial for early disease detection, potentially preventing patient deaths.

(c) Employing effective feature extraction and reduction methods can accelerate detection processes and increase accuracy.

(d) A significant challenge is the precise identification of tumor locations, as variations in tumor size and shape make it difficult for doctors to pinpoint exact locations. We need models that can quickly address tumor localization.

Brain MRI Classification

A CNN-based Classification created by researchers integrates the comprehension of broad brain tissue context information and specific brain MRI accuracy. The segmentation of brain tumors benefits from using three different CNN-based glioma approaches with 3x3 estimated channels during their convolutional phases [78]. Different scientists investigated the combination of multi-view knowledge-based collaborative deep learning with hybrid CNN-DWT-LSTM approaches to segment and classify brain tumors. CNNs have experienced tremendous growth in the past decade as a preferred deep-learning technique for medical imaging activities. The ability of CNNs to detect medical anomalies like cancers in different human organs has been confirmed through numerous research studies [79, 80]. The research field of segmentation stays active because evaluation systems need full completion for different methods. The main purpose of 2D MRI data analysis involves the accurate division of brain tissues together with tumor differentiation. The definition of tumor boundaries reaches its best success through MATLAB software methods working together with additional hardware solutions [81, 82].

Segmentation approaches consist of manual and half-automatic and completely automatic methods among their three main categories. Manual segmentation techniques have decreased as radiologists now analyze MRI images with expert opinions for their work but this process requires long durations and produces possible errors. Users are required to supply input information during semi-automatic method execution for labeling activities yet the methodology delivers inconsistent results [83, 84]. Multiple brain disease detection and segmentation processes are shown through research studies that adopt deep learning methods. The research investigates deep examination of CNN methodology designs that detect brain diseases [85]. The inception of artificial neural network investigations leads to deep learning research by developing perceptron models in the first place [86].

Neural networks perform automatic data feature extraction because it is a machine learning technique that uses different layered models to recognize patterns starting from basic to advanced. CNNs along with RNNs represent the most ubiquitous choices from existing neural network frameworks. Image and video recognition change because CNNs duplicate the visual cortex's organizational design [87, 88]. Below Figure 2 shows the brain Tumor Types and the application of medical imaging techniques. Traditional computers function differently than neural networks because they imitate brain processing methods. Many interconnected units (neurons) in neural networks employ examples for problem-solving rather than following strict programming algorithms.

The Volumetric Convolutional Network (V-Net) focuses on helping medical classification systems by detecting brain tumors from diverse MRI scan data through its image analysis features. The V-Net system has two operational units, with the encoder segment placed on the left side and the decoder unit located on the right side. The encoder compresses the signals, while the decoder decompresses them to their original size. Through its processing, V-Net maintains multiple spatial map resolutions and spatial relationship awareness [90, 91]. The developed system reaches high performance and establishes an accurate geographical location because lateral connections transfer information between the encoder and decoder. The

Parametric Rectified Linear Unit (PReLU) helps V-net recognize patterns in the input data through which it can detect outlines according to known designs. An existing pre-built 2D V-Net model received HGG BraTS2020 dataset training to evaluate study results against alternative models [92, 93].

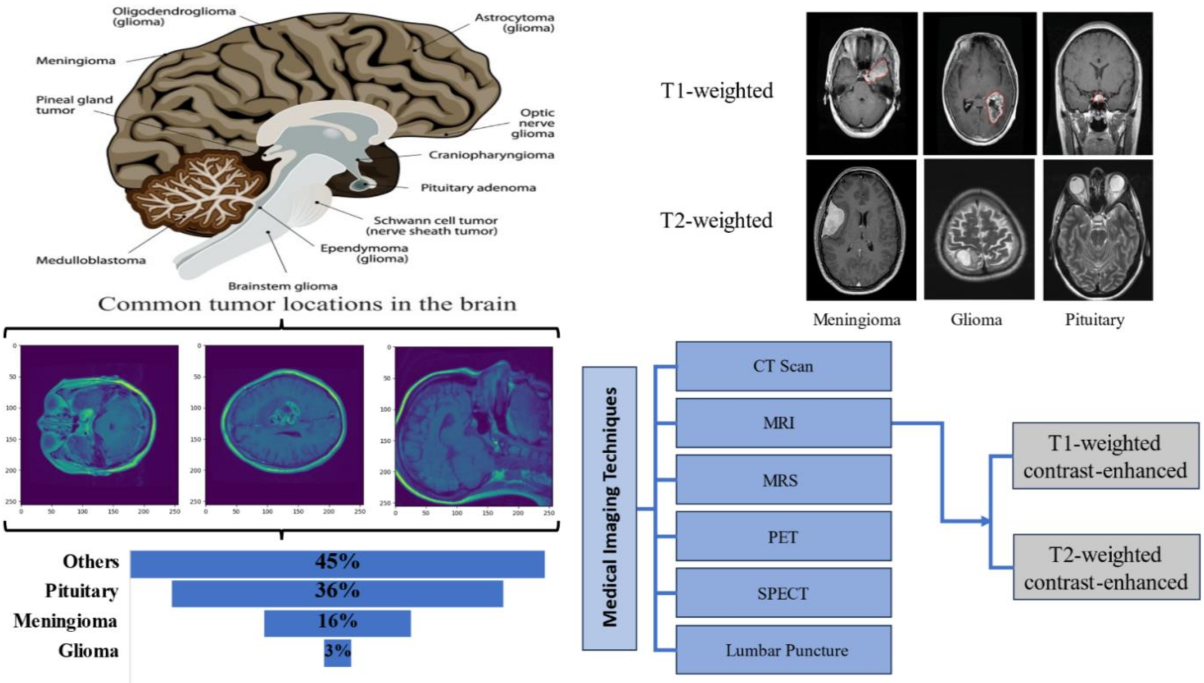

Figure 2.
Brain Tumor Types and the application of medical imaging techniques [89]

METHOD & MATERIALS

Today, even despite significant development in the use of deep learning and MRI, it is extremely challenging to identify and separate brain tumors from the data stream. To the CNNs, which have shown great potential in image processing, there are several issues that still remain open. These are for instance; the need to look for the right and better approach to improving the MRI picture quality, the prediction models will always need to be adjusted in an attempt to correspond with the growing and enhancing technology tendency, and again the need for gaining and improving the techniques involved in feature extraction and dimensionality reduction processes. Furthermore, the identification of the tumor locations is still challenging because they are irregular in size and shape. To fix these issues and improve diagnosis, this research will compare different CNN-based techniques for segmenting, detection and classification of brain tumors in MRI scans.

PROPOSED SOLUTION

Data Collection

MRI brain scans were sourced from a publicly available dataset including four tumor classes: glioma, meningioma, pituitary, and no tumor.

Image Preprocessing: Pixel values were **normalized** using mean (μ) and standard deviation (σ):

$$\mathbf{x} = \frac{\mathbf{x} - \boldsymbol{\mu}}{\boldsymbol{\sigma}} \qquad \text{Eq (5)}$$

Where:

- x = pixel value,
- μ = mean,
- σ = standard deviation.
- Data augmentation techniques like random rotation, flipping, and zoom were applied to reduce overfitting and improve generalization.

Model Development:

- Three models were implemented: MLP, AlexNet, and InceptionV3 (pre-trained on ImageNet).
- Development was done using Python (v3.x) with Tensor Flow (v2.x) and Keras libraries.

Training Configuration:

- Loss Function: Categorical Cross entropy
- Optimizer: Adam (learning rate = 0.001)
- Batch Size: 32
- Epochs: 25
- Validation Split: 10% of training data used for validation
- Early Stopping and Model Check pointing were used to prevent overfitting.

Dataset Split:

- 80% of the data was used for training
- 20% used for final testing
- Class distribution was preserved using stratified sampling

Evaluation:

- The accuracy, loss and confusion matrix was used to test models on test data.
- Additional optional metrics were precision, recall, and F1-score which determined model fairness in multiple classes.

This paper will compare 3 deep learning architectures-Multi-Layer Perception (MLP), AlexNet and Inception3 - in the classification of brain tumor adoption of MRI scans. All of those models are trained with the same data, and preprocessing of data is applied in the same form, so the comparison is fair. They are then evaluated on a standard test against which the most precise and dependable solution in classifying multi-class tumors using MRI can be established.

$$\boldsymbol{Accuracy} = \frac{\boldsymbol{TP+TN}}{\boldsymbol{TP+TN+FP+FN}} \qquad \text{Eq (6)}$$

Where:

- TP= True Positives (correctly predicted tumor class)
- TN = True Negatives (correctly predicted non-tumor class)
- FP = False Positives (incorrectly predicted tumor class)
- FN= False Negatives (missed tumor cases)

The local objective function of the i-th client is denoted by fi(t) while x represents the current model parameter and ξ indicates the data point sampled for local training In these assumptions LOF represents local and SOF demonstrates second-order function smoothness and LH stands for Lipschitz convexity. Lastly, SCOF and COF express objective function convexity while $f(x1) \geq f(x2)+(x1 - x2)T\nabla f(x2)$ indicates the coercive property and CF denotes the existence of a global minimum. BG, BV along BGD determine conditions required to prove convergence. The function characteristics of convexity in MOG are described by two properties: first SCOF and COF while second f (x1) ≥ f (x2)+(x1 −x2)T∇f (x2) establishes the rules of convexity and the coerciveness of f (x) follows a pattern of lim x →∞ f (x) → ∞. When CF applies it guarantees the existence of a worldwide minimum for the objective function. Figure 3 represents the Framework for Skull Segmentation using Convolution Neural Network (CNN). The properties of gradients are captured through BG, BV, and BGD. This situation emphasizes the need to combine technological expertise with legal and ethical considerations when approaching such problems. The Proposed Technique relies on the following algorithm.

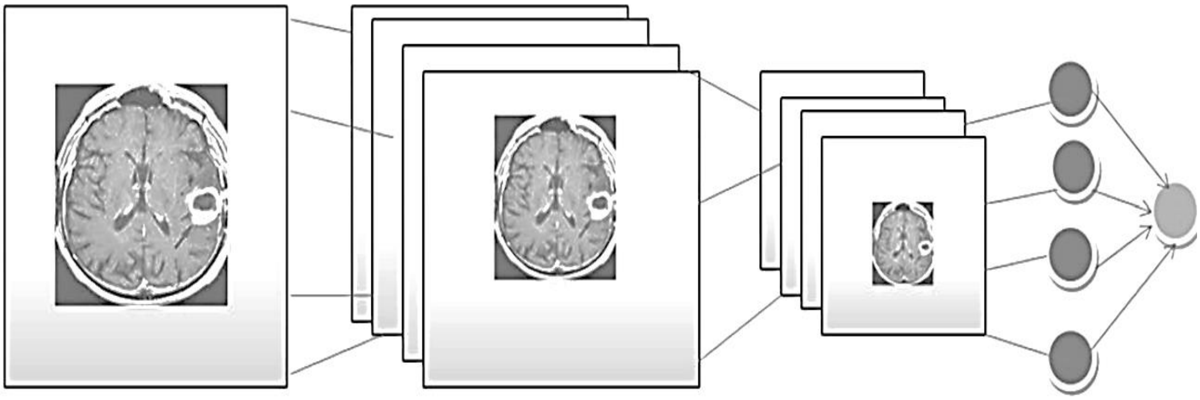

Figure 3.
Framework for Skull Segmentation using Convolution Neural Network (CNN)

Data Description

This study aims at designing, comparing, and assessing deep learning models in multi-class tumor brain classification on MRI scans. The following deep learning structures constitute the study: Multi-Layer Perceptron (MLP), AlexNet and InceptionV3. All the models are then developed, trained and tested to classify MRI images as one of the four classes: glioma tumor, meningioma tumor, pituitary tumor and no tumor.

MLP (Multi-Layer Perceptron): Baseline model without spatial feature extraction.

MLP is a type of feedforward neural network composed entirely of fully connected (dense) layers.

- **Input Layer:** Accepts the flattened 150×150 image input (22,500 nodes).
- **Hidden Layers:** Two dense layers with 128 and 64 neurons, respectively. Each is followed by a ReLU activation function and dropout (rate = 0.3) for regularization.
- **Output Layer:** 4 neurons with softmax activation for multi-class prediction.

Although MLPs are simple and easy to implement, they lack the ability to exploit spatial hierarchies in image data.

- x = input vector, W = weight matrix
- b = bias vector, σ(z)= activation function (example: ReLU, sigmoid, etc.)

Overall MLP operation:

$\boldsymbol{a^{(l)}}$**=** $\boldsymbol{\sigma\ (W^{(l)}(l-1)+b^{(l)})}$

Where l is the layer number.

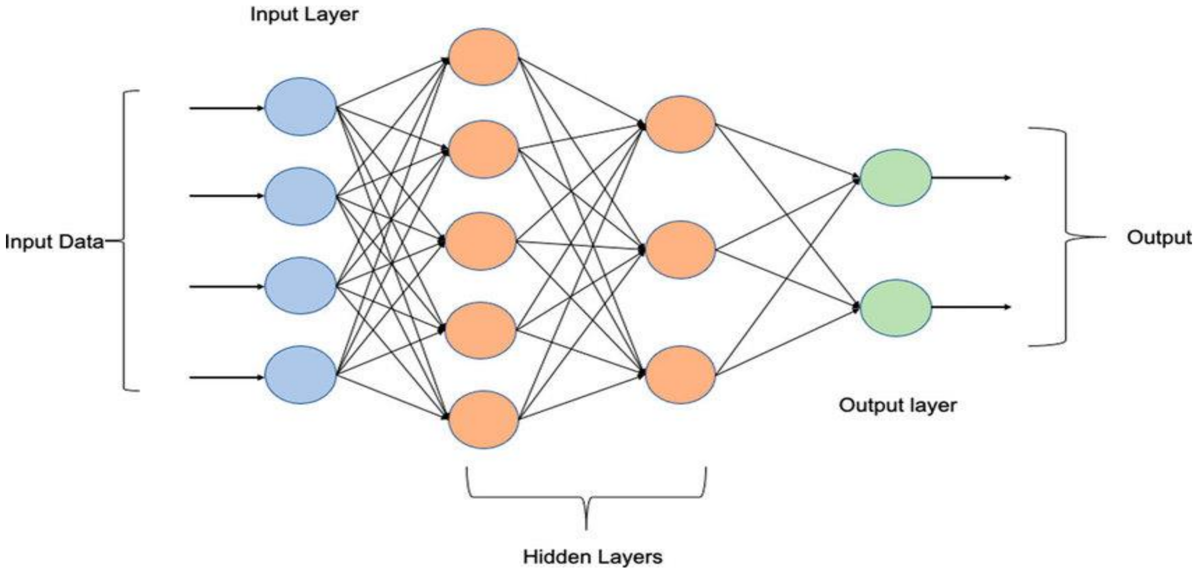

Figure 5.
MLP Architecture used for MRI Images

AlexNet: Early CNN architecture capable of capturing spatial hierarchies.

AlexNet is one of the earliest deep CNN architectures that showed breakthrough performance on image classification tasks.

- Convolutional Layers: 5 convolutional layers with increasing filter sizes and ReLU activations.
- Max-Pooling Layers: Follow specific convolutional layers to down sample feature maps.
- Fully Connected Layers: 3 dense layers with decreasing neuron counts (4096 → 1024 → 512), each followed by dropout to reduce overfitting.
- Output Layer: 4 neurons with softmax activation.

AlexNet benefits from depth and feature hierarchy but may struggle compared to modern architectures in capturing fine-grained features in medical images.

Convolution operation

S(i,j)=m∑n∑(m,n)×K(i−m,j−n) Eq (7)

- X = input image, K = kernel (filter), ∗ = convolution operator, S(i,j) = output feature map at position (i,j)

After convolution

- Activation: ReLU(x)=max(0,x)
- Max Pooling: y=$max_{i,j\in pool}\ (x_{i,j})$

InceptionV3: Advanced CNN utilizing multi-scale feature extraction.

InceptionV3 is a state-of-the-art CNN model that uses inception modules, enabling the network to learn both fine and coarse features simultaneously.

- Base Model: Pre-trained on ImageNet and loaded without the top classification layer.
- Custom Top Layers:
- Global Average Pooling
- Dense Layer with 256 neurons (ReLU activation)
- Dropout for regularization
- Output Layer: 4 neurons with SoftMax activation
- Training Strategy: Initially, base layers are frozen to preserve ImageNet-learned features. Later, selected layers are unfrozen and fine-tuned on the MRI dataset using a lower learning rate.

Basic convolution inside inception block:

$\boldsymbol{O} = \boldsymbol{\sigma}(\boldsymbol{W} \times \boldsymbol{X} + \boldsymbol{b})$ Eq (8)

Factorized convolution (e.g., 1×3 followed by 3×1):

$\boldsymbol{O} = \boldsymbol{\sigma}(\boldsymbol{W_1} \times (\boldsymbol{W_2} \times \boldsymbol{X}) + \boldsymbol{b})$Auxiliary classifier (loss function used during training):

$\boldsymbol{L_{aux}} = -\boldsymbol{i}\sum \boldsymbol{Y_i} \boldsymbol{log}(\boldsymbol{\hat{y}_i})$ Eq (9)

Models Training

All three models were compiled and trained using:

- Loss Function: Categorical Cross entropy (suitable for multi-class classification).
- Optimizer: Adam optimizer with a learning rate of 0.001.
- Evaluation Metric: Accuracy with Batch Size: 32 and Epochs: 25
- Callbacks: Early stopping and model checkpointing were used to avoid overfitting and retain the best model weights. All models were implemented using Python with TensorFlow and Keras libraries. Training was conducted on a system with [GPU type, RAM].

Individual Model PerformanceTo evaluate and compare model performance, the following metrics were used:

- Accuracy: Measures the proportion of correct predictions.
- Loss: Evaluated using categorical cross entropy on both training and validation sets.
- Confusion Matrix: Provides a detailed view of true vs. predicted classes, useful in identifying patterns of misclassification.
- Precision, Recall, F1-Score (optional extension): Could also be calculated to assess class-wise performance and balance.

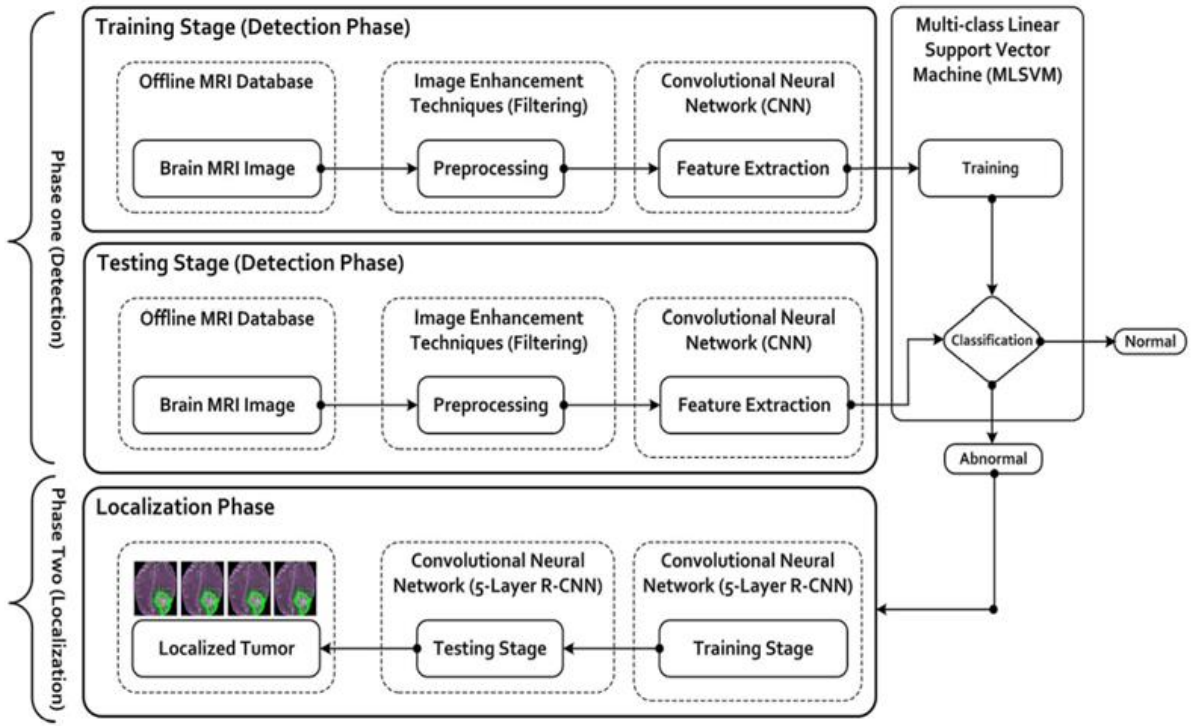

Figure 4.
CNN based Proposed Model

Multi-Layer Perceptron (MLP)

As it can be seen in figure 8, The MLP was utilized as the baseline in this work. It comprised the fully connected layers which were capable of handling flattened data of MRI images. The MLP achieved mediocre results though it was simple because it failed to represent the complicated image spatial hierarchy, a characteristic of MRI images. The model was trained during a specified number of epochs although it did not satisfy the accuracy level which implies that it cannot manage the task of classification of the images when there are no convolutional layers.

$$\boldsymbol{z} = \boldsymbol{W}\boldsymbol{x} + \boldsymbol{b} \qquad \text{Eq (10)}$$

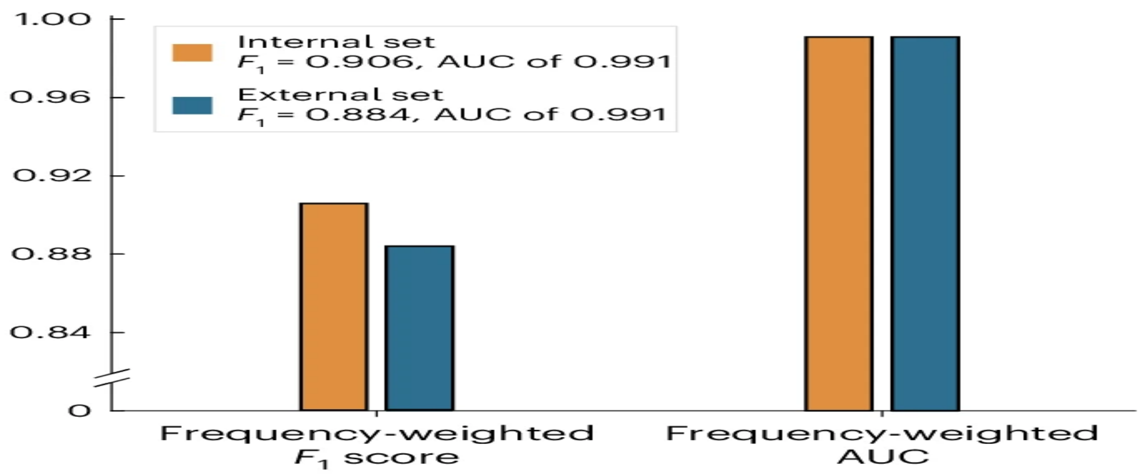

Figure 6.
F-1 and AUC over multiple data streams Score

AlexNet-CNN

In Figure 9, deeper architecture of convolutional neural network known as AlexNet, was used to improve capturing of spatial information of the MRI images. The model included several convolutional and pooling layers which were followed with fully connected layers. AlexNet trained to a specified set of epochs illustrated better results, contrasting the MLP, with greater accuracy and lesser loss. Nonetheless, even though it was compared to more advanced architectures, it was still lacking thus indicating the possibility of greater improvement.

$$\boldsymbol{f}'(\boldsymbol{x}) = \boldsymbol{g}(\boldsymbol{f}(\boldsymbol{x}; \boldsymbol{\theta}_{pretrained}); \boldsymbol{\theta}_{new} \quad \text{Eq (11)}$$

Where:

- x = input MRI image
- f(x; $\boldsymbol{\theta}_{pretrained}$) = feature extraction using the pre-trained convolutional base (from ImageNet)
- g(·;$\boldsymbol{\theta}_{new}$) = new fully connected layers adapted for MRI classification (with newly learned weights)
- f'(x) = final result (predicted tumor setup)

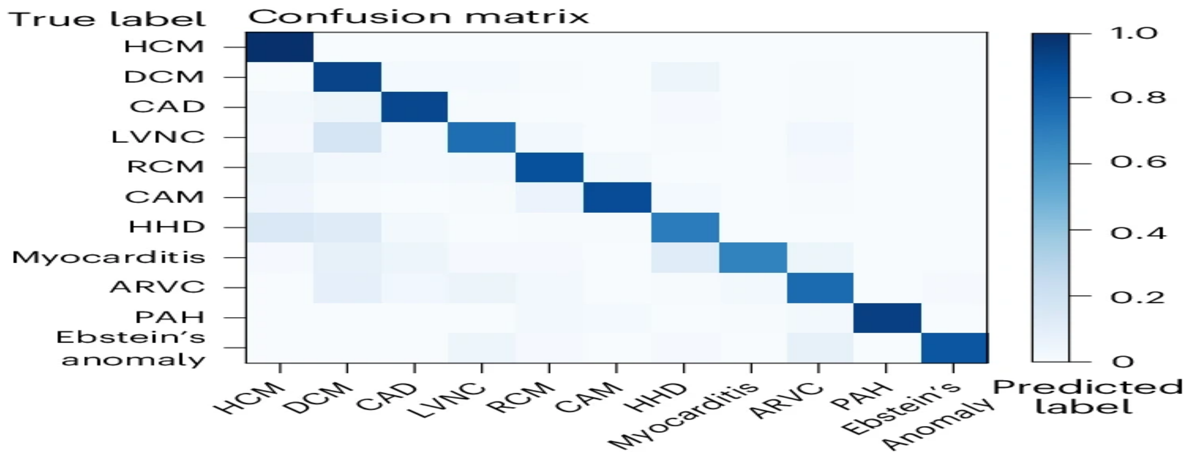

Figure 7.
Confusion Matrix labeled over multiple parameters

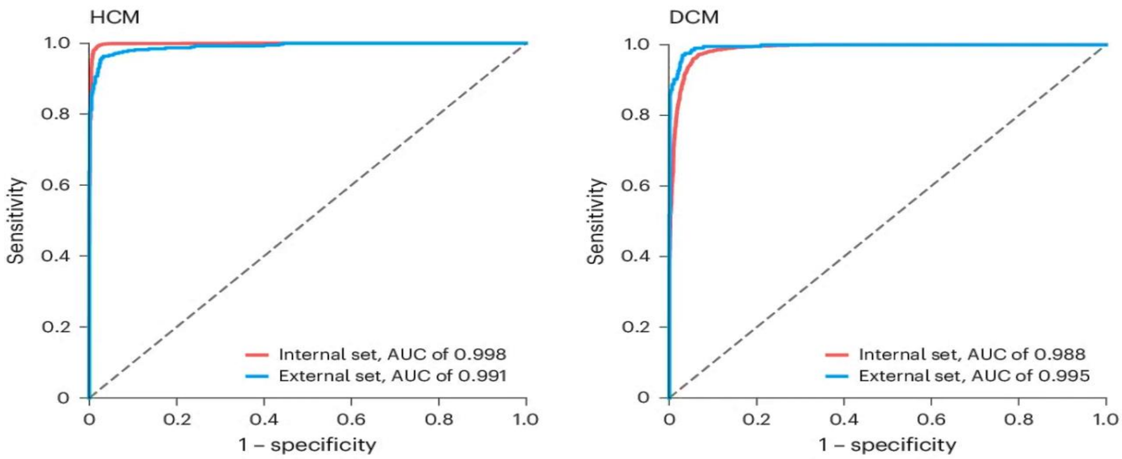

Figure 8.
(a) Sensitivity vs specificity for HCM and DCM

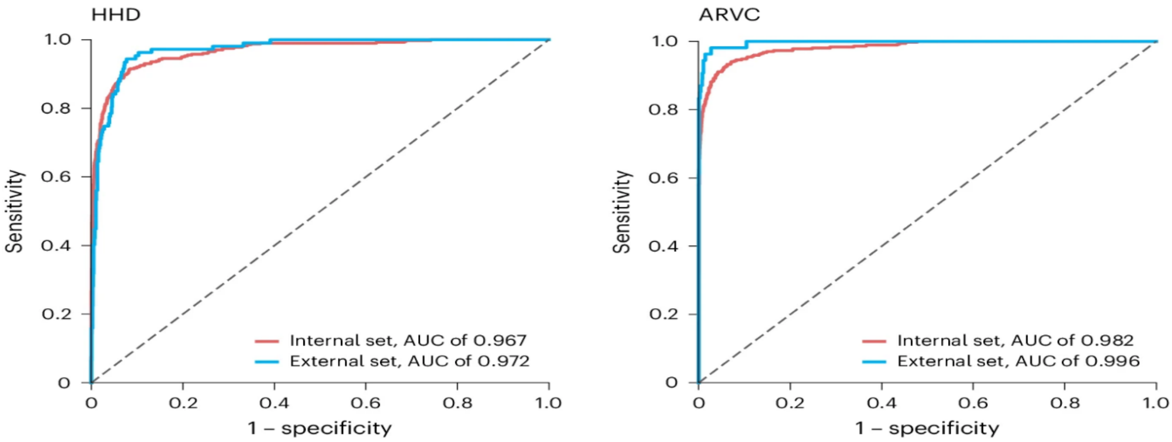

Figure 9.
(a) Sensitivity vs specificity for HHD and ARVC

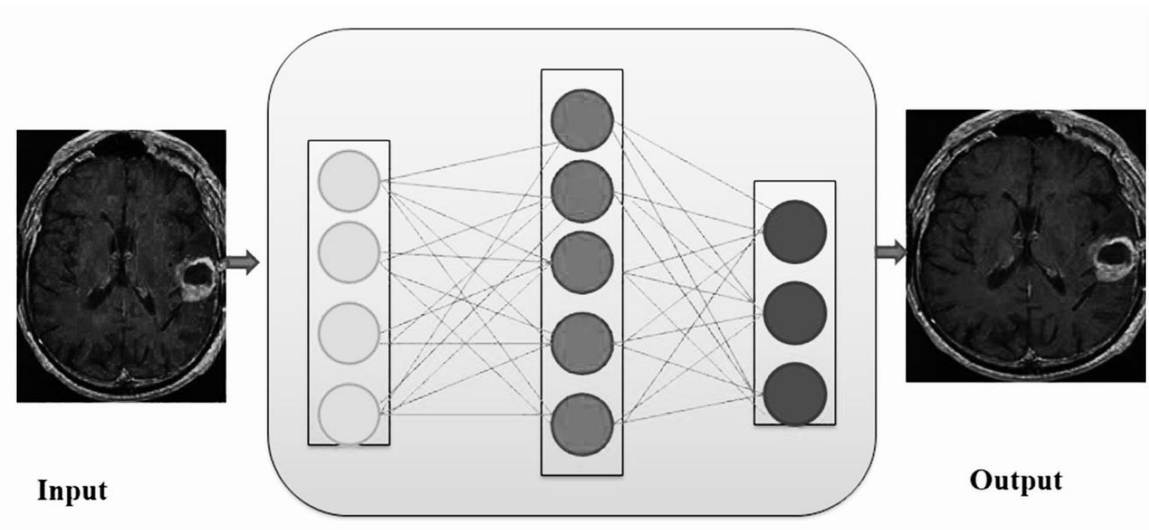

Figure 10.
Tumor Identification Using Convolution Neural Network (CNN)

$$d_{AHD}(X,Y) = \left(\frac{1}{X}\sum_{x\varepsilon X}\frac{min}{y\varepsilon Y}d(x,y) + \frac{1}{Y}\sum_{y\varepsilon Y}\frac{min}{\epsilon Xd}d(x,y)\right)/2 \quad \text{Eq (12)}$$

$$d_{AHD}(2,31) = \left(\frac{1}{2}\sum_{x\varepsilon X}\frac{min}{y\varepsilon Y}d(2,31) + \frac{1}{31}\sum_{y\varepsilon Y}\frac{min}{\epsilon Xd}d(2,31)\right)/2 \quad \text{Eq (13)}$$

$$d_{AHD}(4,41) = \left(\frac{1}{4}\sum_{x\varepsilon X}\frac{min}{y\varepsilon Y}d(4,41) + \frac{1}{41}\sum_{y\varepsilon Y}\frac{min}{\epsilon Xd}d(4,41)\right)/2 \quad \text{Eq (14)}$$

$$d_{AHD}(2,n) = \left(\frac{1}{2}\sum_{x\varepsilon X}\frac{min}{y\varepsilon Y}d(2,n) + \frac{1}{n}\sum_{y\varepsilon Y}\frac{min}{\epsilon Xd}d(2,n)\right)/2 \quad \text{Eq (15)}$$

The Average Hausdorff Distance (AHD) is another statistic that defines the shift of two sets of points and is often used to assess a segmentation method, for example, CNN-based Brain Tumor Segmentation.

$$\rho_c = \frac{2a_{12}}{(\mu_1 - \mu_2)^2 + \sigma_1^2 + \sigma_2^2} \quad \text{Eq (16)}$$

The formula for Cohen's d calculates the impact magnitude in a two-sample t-test, useful for comparing two CNN models' segmentation performance for brain tumors.

μ_1 and μ_2: Mean performance metrics of two models (e.g., Dice score, accuracy).

σ_1 and σ_2: Standard deviations of the performance metrics.

σ_{12}: Covariance between the models' performances.

A higher effect size indicates a more significant performance difference, while zero means no difference. In brain tumor segmentation, Cohen's d helps quantify the magnitude of performance differences between CNN models. Gaussian statistics are used to demonstrate the correlation between these two-reference strategies (variable 1) and alternative techniques (variable 2). The means (μ_1 and μ_2), typical deviations (σ_1 and σ_2), and covariance (σ_{12}) of these variables define them.

$$\mathrm{R}^2 = 1 - \frac{\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2}{\sum_{i=1}^{n}(Y_1 - \bar{Y})^2} \quad \text{Eq (17)}$$

The measure of prediction success by a CNN model for brain tumor segmentation is determined through the R-squared value calculation.

Y_i: Shows the actual segmentation outcome for the i-th MRI scan. The CNN model generates its predicted segmentation output Y_hat_i from an earlier provided scan. Y_bar: The average of all actual segmentation results. A higher value of R-squared indicates that the model provides accurate predictions of actual segmentation results. A value of R-squared at 1 indicates complete accuracy in predicting segmented areas. The model completely misses every pattern that contributes to the segmentation outcomes when R-squared equals 0. The model shows the relationship to the segmentation results between 0 and 1. During CNN model evaluation for brain tumor segmentation R-squared proves useful for identifying the right model and represents how well the data is reflected through its value strength. The predictive formula uses Y_i as the reference value Yˆ_i . as the projected value and Yˉ as the average actual value.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2} \quad \text{Eq (18)}$$

The formula represents one important parameter for evaluating the precision of brain tumor segmentation models is the Root Mean Squared Error (RMSE).

Y_I: The actual label for a voxel in the MRI scan (tumor = 1, non-tumor = 0).

Ŷ_i: The predicted label for the voxel from the segmentation model.

n: The total count of voxels within the MRI scan.

The Mean squared error calculates the average value of squared differences between a true object label and a predicted label through an operation that divides the squared label difference by the total number of image Voxel and divides this outcome by the number of scanned images. The division of clustering components reduces the RMSE value below actual values thus allowing the model to generate an enhanced tumor subdivision. CNN-based brain-tumor segmentation networks achieve optimal segmentation using the model that exhibits the lowest RMSE value for performance assessment among models. Y_i represents reference values while Y<_(i) shows projected values in this formula which uses the value of n for data points.

$$\mathrm{TDI} = \sqrt{(\Delta C)^2 + (\Delta \sigma)^2} \qquad \text{Eq (19)}$$

The Total Distance Index (TDI) formula evaluates the accuracy of brain tumor segmentation:

TDI: Measures the distinction between the CNN-segmented tumor and the ground truth.

ΔC: Difference in centroid locations of the segmented tumor versus the ground truth.

Δσ: Difference in standard deviations, reflecting tumor spread.

A lower TDI indicates better segmentation accuracy and helps compare and improve CNN models. The combined results of the two sets of studies provide insightful information about which strategy most closely resembles the reference technique, enabling a reliable and accurate segmentation decision.

$$JSC = \frac{|X \cap Y|}{|X \cup Y|} \qquad \text{Eq (20)}$$

Jacquard Measures of the Similarity Coefficient measure the similarity among the predicted tumor boundaries and the reference outlines. Where Y is the reference outline and X is the expected tumor boundary.

$$\mathrm{BDE} = \frac{1}{|\mathrm{Y}|} * \sum (\mathrm{D}(\mathrm{x}, \mathrm{Y})) \qquad \text{Eq (21)}$$

Boundary Displacement Error measures the average distance between the predicted tumor boundary and the reference outline. Where: x is a point on the predicted tumor boundary, Y is the reference outline, where the distance between x and the closest point on Y is expressed as d(x, Y). The accuracy measures the proportion of the correctly classified instances both true positives and true negatives out of all instances. *TP:* True positives which malicious queries are correctly classified as malicious. *TN:* True Negative which benign queries correctly classified as benign. *FP:* False positive which benign queries incorrectly classified as malicious. *FN:* False Negatives which malicious queries are incorrectly classified. The accuracy, precision, and Recall is defined below:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad \text{Eq (22)}$$

Sunway Medical Centre uses multimodal MR imaging as its main diagnostic tool for detecting brain tumors. The technique stands as both simple and strong and contributed to the development of radiomics which extracts quantifiable features from MR images. The accuracy of these attributes depends largely on how well tumors get distinguished from their surrounding image area.

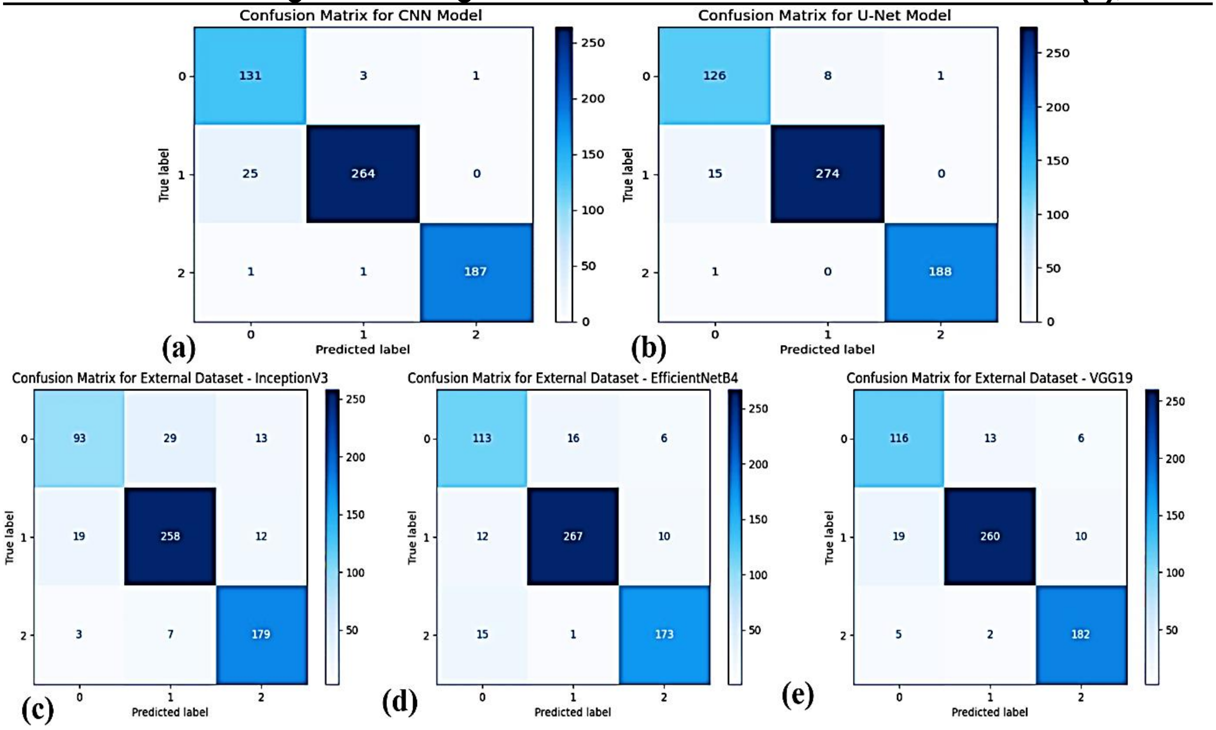

Figure 8.
Confusion Matrix of Brain MRI Segmentation for cross-dataset validation.

Research has developed plenty of deep learning approaches for brain tumor segmentation yet a complete evaluation of their performance remains unsettled. The research evaluated several common brain tumor segmentation methods to determine which one delivered optimal results. Our findings are clear. We applied CaPTk, 2DVNet EnsembleUNets and ResNet50 to the BraTS2021 dataset's 1251 samples of T1, T2, T1ce and FLAIR mpMRI images that used an expert-radiologist generated pre-segmented reference image as baseline.

The use of Pyradiomics for post-segmentation produced 4852 features from each examined subject. EnsembleUNets maintained the prime position as the best performer among different statistical metrics through outstanding results across direct tumor segmentation and radiomic feature extraction tasks. The method achieved success because it brings together three unique models (U-Net (3D), MI-U-Net (3D), and MI-U-Net (3D+2D)) using both 3D and 2D image types for precise segmentation. EnsembleUNets shows excellent performance in tumor segmentation which enables better clinical diagnosis and specific tumor classifications and optimized treatment planning, especially for radiation therapy requiring precise tumor outline definition. By being effective the approach could facilitate the connection between radiometric characteristics and genetic information and establish groundwork for developing individualized treatment strategies in disease management research.

Table 2.
Comparative Analysis of Proposed and Current Techniques

Classifier	Model	Number of layers	Kernel sizes	Activation functions	Optimization	parameters
NBB	3-Layer CNN	3 Conv + 1 Dense	3 × 3	ReLU	Adam	~ 300 K
E-CNN	U-Net	Encoder-Decoder (+ 10 Layers)	3 × 3	ReLU	Adam	~ 31 M
SVM	VGG19	19	3 × 3	ReLU	SGD + Momentum	~ 20 M

RNN	InceptionV3	42	1 × 1, 3 × 3, 5 × 5	ReLU + Soft max	RMSProp	~ 23 M
Proposed	EfficientNetB4	55	varied (3 × 3, 5 × 5)	Swish + Soft max	Adam	~ 19 M

Table 2.
Comparative Analysis of various parameters

Classifier	Model	Computation Time	JC	Dice Score	Sensitivity	Accuracy	Specificity	Precision	F-Score
NBB	3-Layer CNN	$K = 30$	0.6486	0.7442	0.6486	0.6415	0.6437	0.6435	0.6483
E-CNN	U-Net	$K = 30$	0.7484	0.6433	0.6486	0.5245	0.6485	0.5245	0.6485
SVM	VGG19	$K = 30$	0.8432	0.8444	0.6485	0.7627	0.6486	0.7627	0.6486
RNN	InceptionV3	$K = 30$	0.612	0.5245	0.6485	0.6486	0.7442	0.7442	0.6487
Proposed CNN	EfficientNetB4	$K = 30$	0.6222	0.7627	0.6486	0.7484	0.6433	0.6433	0.6487

CONCLUSION AND RECOMMENDATIONS

This paper evaluates CNN-based algorithms that perform identification work in addition to segmentation and clustering tasks for glioma medical treatment preparation from MRI pictures. The authors state they found novel results about how segmentation performance measures link to radiomic descriptors of tumor areas since no studies tackled this relationship to date. All performance assessment metrics unanimously indicate that EnsembleUNets represents the best solution compared to alternative methods. EnsembleUNets provides an appropriate solution for researchers and clinical institutions who want precise and fast tumor identification. The development of methods should improve EnsembleUNets' tumor detection precision because accurate segmentation forms the base for medical decisions in patient care.

EnsembleUNets demonstrates superiority among all proposed solutions for multivariate brain tumor detection and segmentation tasks using MRI images. It has been recently observed that the classification performance of deep learning models in detecting brain tumors relies heavily on their complexity in structure as well as on their capacity to use the spatial characteristics. The results gathered by us are conclusive and show that the phenomenon can be attributed to the combination of transfer learning and deep convolutional layers rather than just a number of neurons or just a number of layers.

Although the MLP model was not effective in learning spatial pattern, the AlexNet was moderate. However, it was the pre-trained InceptionV3 that achieved the highest classification accuracy of 88.57%, indicating its superior ability to generalize across multi-class tumor data. These findings indicate the significance of the higher-order CNN models, segmentation-minded infeed, and transfer learning, as the parameters that enhance medical image classification. Additional research can be more advantageous by investigating more effective models and incorporating larger data in terms of developing superior generalization and diagnostic assistance.

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REFERENCES

01/Arjun_Panesar_Machine_Learning_and_AI_for_Health-iedu.us_.pdf,

Abdullah, M. M., Khan, H., Farhan, M., & Khadim, F. (2024). An Advance Machine Learning (ML) Approaches for Anomaly Detection based on Network Traffic. Spectrum of engineering sciences, 2(3), 502-527.

Ahmad, I., Nasim, F., Khawaja, M. F., Naqvi, S. A. A., & Khan, H. (2025). Enhancing IoT Security and Services based on Generative Artificial Intelligence Techniques: A Systematic Analysis based on Emerging Threats, Challenges and future Directions. Spectrum of engineering sciences, 3(2), 1-25.

Ahmad, J., Salman, W., Amin, M., Ali, Z., & Shokat, S. (2024). A Survey on Enhanced Approaches for Cyber Security Challenges Based on Deep Fake Technology in Computing Networks. Spectrum of Engineering Sciences, 2(4), 133-149.

Akmal, I., Khan, H., Khushnood, A., Zulfiqar, F., & Shahbaz, E. (2024). An Efficient Artificial Intelligence (AI) and Blockchain-Based Security Strategies for Enhancing the Protection of Low-Power IoT Devices in 5G Networks. Spectrum of engineering sciences, 2(3), 528-586.

Ali, I., Saleem, M. U., Khan, A. A., Naz, A., Nawaz, M., & Khan, H. (2025). An Enhanced Artificial Intelligence Generated Virtual Influencer Framework: Examining the Effects of Emotional Display on User Engagement based on Convolutional Neural Networks (CNNs). Annual Methodological Archive Research Review, 3(4), 184-209.

Ali, M. S. et al. Alzheimer's disease detection using m-random forest algorithm with optimum features extraction. In 2021 1st International Conference on Artificial Intelligence and Data Analytics (CAIDA) (ed. Ali, M. S.) 1–6 (IEEE, 2021).

Ali, M., Khan, H., Rana, M. T. A., Ali, A., Baig, M. Z., Rehman, S. U., & Alsaawy, Y. (2024). A Machine Learning Approach to Reduce Latency in Edge Computing for IoT Devices. Engineering, Technology & Applied Science Research, 14(5), 16751-16756.

Ali, R., Khan, H., Arif, M. W., Tariq, M. I., Din, I. U., Afzal, A., & Khan, M. A. Authentication of User Data for Enhancing Privacy in Cloud Computing Using Security Algorithms. In Securing the Digital Realm (pp. 187-200). CRC Press.

Analytics Vidhya, Commonly used machine learning algorithms (with python and R codes), 2021, Analytics Vidhya. Available at: https://www.analyticsvidhya. com/blog/2017/09/common-machine-learning-algorithms Maneerat, Y., Prasongsukarn, K., Benjathummarak, S., Dechkhajorn,

Asghar, M. A., Aslam, A., Bakhet, S., Saleem, M. U., Ahmad, M., Gohar, A., & Khan, H. (2025). An Efficient Integration of Artificial Intelligence-based Mobile Robots in Critical Frames for the Internet of Medical Things (IoMTs) Using (ADP2S) and Convolutional Neural Networks (CNNs). Annual Methodological Archive Research Review, 3(4), 160-183.

Aslam, I., Tariq, W., Nasim, F., Khan, H., Khawaja, M. F., Ahmad, A., & Nawaz, M. S. (2025). A Robust Hybrid Machine Learning based Implications and Preventions of Social Media Blackmailing and Cyber bullying: A Systematic Approach.

Ayub, N., Anwer, M. A., Iqbal, A., Rizwan, S. M., Shahbaz, A., Abid, M. H., & Rafi, S. (2025). Enhanced ML Framework based on Artificial Neural Network for countermeasures of Data Protection and Network Vulnerabilities Detection in Industrial Internet of Things. Annual Methodological Archive Research Review, 3(5), 410-431.

Ayub, N., Ejaz, A., Hassan, B., Hussain, M. Z., Nadeem, M., Sabir, L., & Fatima, S. (2025). AN EFFICIENT MACHINE LEARNING AND DEEP LEARNING BASED DEEP PACKET SECURITY FRAMEWORK FOR DETECTION OF COMPUTING NETWORK FAULTS IN THE IOTS. Spectrum of Engineering Sciences, 3(5), 659-674.

Ayub, N., Habib, Z., Bakhet, S., Riaz, S., Rizwan, S. M., Abid, M., ... & Khan, H. (2025). AN OPTIMAL AI & DEEP LEARNING MECHANISM FOR MITIGATING HACKING THREAT IDENTIFICATION USING SECURE NETWORK INFRASTRUCTURE BASED ON LINUX AND SOFTWARE-DEFINED NETWORK (SDN). Spectrum of Engineering Sciences, 3(5), 675-687.

Ayub, N., Imtiaz, M. A., Ali, E., Alqahtani, A. M., Ali, A., Ashurov, M., ... & Law, F. L. (2025). A Decision Framework for Intra Task Fixed Priority INTEL PXA270 Distributed Architecture for Soft RT-Applications Based on Deep Learning. Engineering, Technology & Applied Science Research, 15(3), 23553-23558.

Ayub, N., Iqbal, M. W., Saleem, M. U., Amin, M. N., Imran, O., & Khan, H. (2025). Efficient ML Technique for Brain Tumor Segmentation, and Detection, based on MRI Scans Using Convolutional Neural Networks (CNNs). Spectrum of Engineering Sciences, 3(3), 186-213.

Ayub, N., Sarwar, N., Ali, A., Khan, H., Din, I., Alqahtani, A. M., ... & Ali, A. (2025). Forecasting Multi-Level Deep Learning Autoencoder Architecture (MDLAA) for Parametric Prediction based on Convolutional Neural Networks. Engineering, Technology & Applied Science Research, 15(2), 21279-21283.

Ayub, N., Waheed, A., Ahmad, S., Akbar, M. H. A., Fuzail, M. Z., & Hashmi, A. H. (2025). Strengthening Network Security: An Efficient DL Enabled Data Protection and Privacy Framework for Threat Mitigation and Vulnerabilities Detection in IoT Network. Annual Methodological Archive Research Review, 3(6), 1-25.

Ayub, N., Waheed, A., Ahmad, S., Akbar, M. H. A., Fuzail, M. Z., & Hashmi, A. H. (2025). Strengthening Network Security: An Efficient DL Enabled Data Protection and Privacy Framework for Threat Mitigation and Vulnerabilities Detection in IoT Network. Annual Methodological Archive Research Review, 3(6), 1-25.

B. Nithya, V. Ilango, Predictive analytics in health care using machine learning tools and techniques, in: 2017 International Conference on Intelligent Computing and Control Systems (ICICCS), IEEE, 2017, pp. 492–499.

Chung, J., Gulcehre, C., Cho, K. & Bengio, Y. Empirical evaluation of gated recurrent neural networks on sequence modeling. Preprint at arXiv: 1412. 3555 (2014).

Dosovitskiy, A. et al. An image is worth 16x16 words: Transformers for image recognition at scale. Preprint at arXiv: 2010. 11929 (2020).

Fakhar, M. H., Baig, M. Z., Ali, A., Rana, M. T. A., Khan, H., Afzal, W., ... & Albouq, S. (2024). A Deep Learning-based Architecture for Diabetes Detection, Prediction, and Classification. Engineering, Technology & Applied Science Research, 14(5), 17501-17506.

Fatima, M., Ali, A., Ahmad, M., Nisa, F. U., Khan, H., & Raheem, M. A. U. ENHANCING THE RESILIENCE OF IOT NETWORKS: STRATEGIES AND MEASURES FOR MITIGATING DDOS ATTACKS. Cont.& Math. Sci., Vol.-19, No.-10, 129-152, October 2024 https://jmcms.s3.amazonaws.com/wp-content/uploads/2024/10/10072102/jmcms-2410025-ENHANCING-THE-RESILIENCE-OF-IOT-NETWORKS-MF-HK.pdf

Fawy, K. F., Rodriguez-Ortiz, G., Ali, A., Jadeja, Y., Khan, H., Pathak, P. K., ... & Rahman, J. U. (2025). Catalytic exploration metallic and nonmetallic nano-catalysts, properties, role in photoelectrochemistry for sustainable applications. Reviews in Inorganic Chemistry, (0).

Gordon, T. & Kannel, W. B. Multiple risk functions for predicting coronary heart disease: The concept, accuracy, and application.Am. Heart J. 103, 1031–1039 (1982).

Gordon, T. Diabetes, blood lipids, and the role of obesity in coronary heart disease risk for women. Ann. Intern. Med. 87, 393 (1977).

H. Khan, I. Uddin, A. Ali, M. Husain, "An Optimal DPM Based Energy-Aware Task Scheduling for Performance Enhancement in Embedded MPSoC", Computers, Materials & Continua., vol. 74, no. 1, pp. 2097-2113, Sep. 2023

H. Khan, M. U. Hashmi, Z. Khan, R. Ahmad, "Offline Earliest Deadline first Scheduling based Technique for Optimization of Energy using STORM in Homogeneous Multi-core Systems", IJCSNS Int. J. Comput. Sci. Netw. Secur., vol. 18, no. 12, pp. 125-130, Dec. 2018

H. Khan, M. U. Hashmi, Z. Khan, R. Ahmad, A. Saleem, "Performance Evaluation for Secure DES-Algorithm Based Authentication & Counter Measures for Internet Mobile Host Protocol", IJCSNS Int. J. Comput. Sci. Netw. Secur., vol. 18, no. 12, pp. 181-185, July. 2018

Hashmi, U., & ZeeshanNajam, S. A. (2023). Thermal-Aware Real-Time Task Schedulabilty test for Energy and Power System Optimization using Homogeneous Cache Hierarchy of Multi-core Systems. Journal of Mechanics of Continua and Mathematical Sciences, 14(4), 442-452.

Hassan, A., Khan, H., Ali, A., Sajid, A., Husain, M., Ali, M., ... & Fakhar, H. (2024). An Enhanced Lung Cancer Identification and Classification Based on Advanced Deep Learning and Convolutional Neural Network. Bulletin of Business and Economics (BBE), 13(2), 136-141.

Hassan, H. Khan, I. Uddin, A. Sajid, "Optimal Emerging trends of Deep Learning Technique for Detection based on Convolutional Neural Network", Bulletin of Business and Economics (BBE)., vol. 12, no. 4, pp. 264-273, Nov. 2023

Hossain, M. M. et al. Cardiovascular disease identification using a hybrid cnn-lstm model with explainable AI. Inf. Med. Unlocked 42, 101370 (2023).

Hussain, M., Ahmed, H. A., Babar, M. Z., Ali, A., Shahzad, H. M., Rehman, S. U., ... & Alshahrani, A. M. (2025). An Enhanced Convolutional Neural Network (CNN) based P-EDR Mechanism for Diagnosis of Diabetic Retinopathy (DR) using Machine Learning. Engineering, Technology and Applied Science Research, 15(1), 19062-19067.

Hussain, S., Sarwar, N., Ali, A., Khan, H., Din, I., Alqahtani, A. M., ... & Ali, A. (2025). An Enhanced Random Forest (ERF)-based Machine Learning Framework for Resampling, Prediction, and Classification of Mobile Applications using Textual Features. Engineering, Technology & Applied Science Research, 15(1), 19776-19781.

Islam, M. K. et al. Melanoma skin lesions classification using deep convolutional neural network with transfer learning. In 2021 1st International Conference on Artificial Intelligence and Data Analytics (CAIDA) (ed. Islam, M. K.) 48–53 (IEEE, 2021).

Islam, M. K., Rahman, M. M., Ali, M. S., Mahim, S. & Miah, M. S. Enhancing lung abnormalities diagnosis using hybrid dcnnvit- gru model with explainable ai: A deep learning approach. Image Vis. Comput. 142, 104918 (2024).

Islam, M. K., Rahman, M. M., Ali, M. S., Mahim, S. & Miah, M. S. Enhancing lung abnormalities diagnosis using hybrid dcnnvit- gru model with explainable ai: A deep learning approach. Image Vis. Comput. 142, 104918 (2024).

J. McPadden, T.J. Durant, D.R. Bunch, A. Coppi, N. Price, K. Rodgerson, C.J. Torre Jr., W. Byron, A.L. Hsiao, H.M. Krumholz, W.L. Schulz, Health care and precision medicine research: analysis of a scalable data science platform, J. Med Internet Res. 21 (4) (2019) e13043–e13045.

Jabeen, T., Mehmood, Y., Khan, H., Nasim, M. F., & Naqvi, S. A. A. (2025). Identity Theft and Data Breaches How Stolen Data Circulates on the Dark Web: A Systematic Approach. Spectrum of engineering sciences, 3(1), 143-161.

Javed, M. A., Anjum, M., Ahmed, H. A., Ali, A., Shahzad, H. M., Khan, H., & Alshahrani, A. M. (2024). Leveraging Convolutional Neural Network (CNN)-based Auto Encoders for Enhanced Anomaly Detection in High-Dimensional Datasets. Engineering, Technology & Applied Science Research, 14(6), 17894-17899.

Khan, A. Ali, S. Alshmrany, "Energy-Efficient Scheduling Based on Task Migration Policy Using DPM for Homogeneous MPSoCs", Computers, Materials & Continua., vol. 74, no. 1, pp. 965-981, Apr. 2023

Khan, A. K., Bakhet, S., Javed, A., Rizwan, S. M., & Khan, H. (2025). Framework for Predicting Customer Sentiment Aware Queries and Results in Search Using Oracle and Machine Learning. Spectrum of Engineering Sciences, 3(2), 588-617.

Khan, A. Yasmeen, S. Jan, U. Hashmi, "Enhanced Resource Leveling Indynamic Power Management Techniqueof Improvement In Performance For Multi-Core Processors" ,Journal of Mechanics of Continua and Mathematical Sciences., vol. 6, no. 14, pp 956-972, Sep. 2019

Khan, H., Ali, A., & Alshmrany, S. (2023). Energy-Efficient Scheduling Based on Task Migration Policy Using DPM for Homogeneous MPSoCs. Computers, Materials & Continua, 75(1).

Khan, H., Imtiaz, M. A., Siddique, H., Rana, M. T. A., Ali, A., Baig, M. Z., ... & Alsaawy, Y. (2025). An Enhanced Task Migration Technique Based on Convolutional Neural Network in Machine Learning Framework.

Khan, H., Usman, R., Ahmed, B., Hashimi, U., Najam, Z., & Ahmad, S. (2019). Thermal-aware real-time task schedulabilty test for energy and power system optimization using homogeneous cache hierarchy of multi-core systems. Journal of Mechanics of Continua and Mathematical Sciences, 14(4), 442-452.

Khan, I. Ullah, M. U. Rahman, H. Khan, A. B. Shah, R. H. Althomali, M. M. Rahman, "Inorganic-polymer composite electrolytes: basics, fabrications, challenges and future perspectives", Reviews in Inorganic Chemistry., vol. 44, no. 3, pp. 1-2, Jan. 2024

Khan, K. Janjua, A. Sikandar, M. W. Qazi, Z. Hameed, "An Efficient Scheduling based cloud computing technique using virtual Machine Resource Allocation for efficient resource utilization of Servers", In 2020 International Conference on Engineering and Emerging Technologies (ICEET), IEEE., pp. 1-7, Apr. 2020

Khan, M. U. Hashmi, Z. Khan, R. Ahmad, "Offline Earliest Deadline first Scheduling based Technique for Optimization of Energy using STORM in Homogeneous Multi-core Systems", IJCSNS Int. J. Comput. Sci. Netw. Secur., vol. 18, no. 12, pp. 125-130, Oct. 2018

Khan, Q. Bashir, M. U. Hashmi, "Scheduling based energy optimization technique in multiprocessor embedded systems", In 2018 International Conference on Engineering and Emerging Technologies (ICEET), IEEE., pp. 1-8, Sep. 2018

Khan, S. Ahmad, N. Saleem, M. U. Hashmi, Q. Bashir, "Scheduling Based Dynamic Power Management Technique for offline Optimization of Energy in Multi Core Processors", Int. J. Sci. Eng. Res., vol. 9, no. 12, pp. 6-10, Dec. 2018

Khan, S., Ullah, I., Khan, H., Rahman, F. U., Rahman, M. U., Saleem, M. A., ... & Ullah, A. (2024). Green synthesis of AgNPs from leaves extract of Saliva Sclarea, their characterization, antibacterial activity, and catalytic reduction ability. Zeitschrift für Physikalische Chemie, 238(5), 931-947.

Khawar, M. W., Salman, W., Shaheen, S., Shakil, A., Iftikhar, F., & Faisal, K. M. I. (2024). Investigating the most effective AI/ML-based strategies for predictive network maintenance to minimize downtime and enhance service reliability. Spectrum of Engineering Sciences, 2(4), 115-132.

Lee, J.h., Chae, J.-w. & Cho, H.-c. Improved classification of different brain tumors in mri scans using patterned-gridmask. IEEE Access (2024).

Liaqat, M. S., Sharif, N., Ali, A., Khan, H., Ahmed, H. N., & Khan, H. (2024). An Optimal Analysis of Cloud-based Secure Web Applications: A Systematic Exploration based on Emerging Threats, Pitfalls and Countermeasures. Spectrum of engineering sciences, 2(5), 427-457.

Mudda, M., Manjunath, R. & Krishnamurthy, N. Brain tumor classification using enhanced statistical texture features. IETE J. Res. 68, 3695–3706 (2022).

Mumtaz, J., Rehman, A. U., Khan, H., Din, I. U., & Tariq, I. Security and Performance Comparison of Window and Linux: A Systematic Literature Review. Securing the Digital Realm, 272-280.
Mumtaz, J., Rehman, A. U., Khan, H., Din, I. U., & Tariq, I. Security and Performance Comparison of Window and Linux: A Systematic Literature Review. Securing the Digital Realm, 272-280.
Mustafa, M., Ali, M., Javed, M. A., Khan, H., Iqbal, M. W., & Ruk, S. A. (2024). Berries of Low-Cost Smart Irrigation Systems for Water Management an IoT Approach. Bulletin of Business and Economics (BBE), 13(3), 508-514.

Nakashima, T. et al. Prognostic impact of spontaneous coronary artery dissection in young female patients with acute myocardial infarction: A report from the Angina Pectoris-Myocardial Infarction Multicenter Investigators in Japan. Int. J. Cardiol. 207, 341–348 (2016).

Nasir, M. S., Khan, H., Qureshi, A., Rafiq, A., & Rasheed, T. (2024). Ethical Aspects In Cyber Security Maintaining Data Integrity and Protection: A Review. Spectrum of engineering sciences, 2(3), 420-454.

Nasir, M. S., Khan, H., Qureshi, A., Rafiq, A., & Rasheed, T. (2024). Ethical Aspects In Cyber Security Maintaining Data Integrity and Protection: A Review. Spectrum of engineering sciences, 2(3), 420-454.
Naveed, A., Khan, H., Imtiaz, Z., Hassan, W., & Fareed, U. (2024). Application and Ethical Aspects of Machine Learning Techniques in Networking: A Review. Spectrum of engineering sciences, 2(3), 455-501.
Naz, H. Khan, I. Ud Din, A. Ali, and M. Husain, "An Efficient Optimization System for Early Breast Cancer Diagnosis based on Internet of Medical Things and Deep Learning", Eng. Technol. Appl. Sci. Res., vol. 14, no. 4, pp. 15957–15962, Aug. 2024
Noor, H., Khan, H., Din, I. U., Tarq, M. I., Amin, M. N., & Fatima, M. (2025). 12 Virtual Memory Management. Securing the Digital Realm: Advances in Hardware and Software Security, Communication, and Forensics, 126.
oi=fnd&pg=PP1&dq=application+of+python+programming+language+in+ health+care+sectors&ots=BJz0Qe_09q&sig=Bhv_iaxOuZoKJu-WVEKPDr6B9y0, BelItSoft, Python in healthcare, BelItSoft (2017) Available at: https: //belitsoft.com/custom-application-development-services/healthcare-softwaredevelopment/ python-healthcare, [Accessed on 5th March, 2021].
P. Guleria, M. Sood, Intelligent learning analytics in healthcare sector using machine learning, in: Machine Learning with Health Care Perspective, Springer, Cham, 2020, pp. 39–55.
P. Mathur, Overview of machine learning in healthcare, in: Machine Learning Applications using Python, A Press, Berkeley, CA, 2019, pp. 1–11.
Rahman, M. U., Khan, S., Khan, H., Ali, A., & Sarwar, F. (2024). Computational chemistry unveiled: a critical analysis of theoretical coordination chemistry and nanostructured materials. Chemical Product and Process Modeling, 19(4), 473-515.
Ramzan, M. S., Nasim, F., Ahmed, H. N., Farooq, U., Nawaz, M. S., Bukhari, S. K. H., & Khan, H. (2025). An Innovative Machine Learning based end-to-end Data Security Framework in Emerging Cloud Computing Databases and Integrated Paradigms: Analysis on Taxonomy, challenges, and Opportunities. Spectrum of engineering sciences, 3(2), 90-125.
S. Khan, I. Ullah, H. Khan, F. U. Rahman, M. U. Rahman, M. A. Saleem, A. Ullah, "Green synthesis of AgNPs from leaves extract of Salvia Sclarea, their characterization, antibacterial activity, and catalytic reduction ability", Zeitschrift für Physikalische Chemie., vol. 238, no. 5, pp. 931-947, May. 2024
Salvi, M., Acharya, U. R., Molinari, F. & Meiburger, K. M. The impact of pre-and post-image processing techniques on deep learning frameworks: A comprehensive review for digital pathology image analysis. Comput. Biol. Med. 128, 104129 (2021).
Sarwar, H. Khan, I. Uddin, R. Waleed, S. Tariq, "An Efficient E-Commerce Web Platform Based on Deep Integration of MEAN Stack Technologies", Bulletin of Business and Economics (BBE)., vol. 12, no. 4, pp. 447-453, Jun. 2023
Shah, S. Ahmed, K. Saeed, M. Junaid, H. Khan, "Penetration testing active reconnaissance phase–optimized port scanning with nmap tool", In 2019 2nd International Conference on Computing, Mathematics and Engineering Technologies (iCoMET), IEEE., pp. 1-6, Nov. 2019
Spieker, V. et al. Deep learning for retrospective motion correction in MRI: A comprehensive review. IEEE Trans. Med. Imaging (2023).
Sultan, H., Rahman, S. U., Munir, F., Ali, A., Younas, S., & Khan, H. (2025). Institutional dynamics, innovation, and environmental outcomes: a panel NARDL analysis of BRICS nations. Environment, Development and Sustainability, 1-43.
T. Davenport, R. Kalakota, The potential for artificial intelligence in healthcare, Future Healthcare J. 6 (2) (2019) 94.
U. Hashmi, S. A. ZeeshanNajam, "Thermal-Aware Real-Time Task Schedulabilty test for Energy and Power System Optimization using Homogeneous Cache Hierarchy of Multi-core Systems", Journal of Mechanics of Continua and Mathematical Sciences., vol. 14, no. 4, pp. 442-452, Mar. 2023

V.V. Kumar, Healthcare Analytics Made Simple: Techniques in Healthcare Computing using Machine Learning and Python, Packt Publishing Ltd., 2018, Available at: https://books.google.com/books?hl=en&lr=&id=nwZnDwAAQBAJ&

W. & Chaisri, U. Intersected genes in hyperlipidemia and coronary bypass patients: Feasible biomarkers for coronary heart disease. Atherosclerosis 252, e186–e184 (2016).

Wilson, P. W. F. et al. Prediction of coronary heart disease using risk factor categories. Circulation 97, 1837–1847 (1998).

Y. A. Khan, "A GSM based Resource Allocation technique to control Autonomous Robotic Glove for Spinal Cord Implant paralysed Patients using Flex Sensors", Sukkur IBA Journal of Emerging Technologies., vol. 3, no. 2, pp. 13-23, Feb. 2020

Y. A. Khan, "A high state of modular transistor on a 105 kW HVPS for X-rays tomography Applications", Sukkur IBA Journal of Emerging Technologies., vol. 2, no. 2, pp. 1-6, Jun. 2019

Y. A. Khan, "Enhancing Energy Efficiency in Temperature Controlled Dynamic Scheduling Technique for Multi Processing System on Chip", Sukkur IBA Journal of Emerging Technologies., vol. 2, no. 2, pp. 46-53, Jan. 2019

Y. A. Khan, F. Khan, H. Khan, S. Ahmed, M. Ahmad, "Design and Analysis of Maximum Power Point Tracking (MPPT) Controller for PV System", Journal of Mechanics of Continua and Mathematical Sciences., vol. 14, no. 1, pp. 276-288, May. 2019

Y. A. Khan, M. Ibrahim, M. Ali, H. Khan, E. Mustafa, "Cost Benefit Based Analytical Study of Automatic Meter Reading (AMR) and Blind Meter Reading (BMR) used by PESCO (WAPDA)", In 2020 3rd International Conference on Computing, Mathematics and Engineering Technologies (iCoMET), IEEE., pp. 1-7, Aug. 2020

Y. A. Khan, U. Khalil, H. Khan, A. Uddin, S. Ahmed, "Power flow control by unified power flow controller",Engineering, Technology & Applied Science Research., vol. 9, no. 2, pp. 3900-3904, Feb. 2019

Yang, Y. et al. Early detection of brain tumors: Harnessing the power of gru networks and hybrid dwarf mongoose optimization algorithm. Biomed. Signal Process. Control 91, 106093 (2024)..

Yousaf, M., Khalid, F., Saleem, M. U., Din, M. U., Shahid, A. K., & Khan, H. (2025). A Deep Learning-Based Enhanced Sentiment Classification and Consistency Analysis of Queries and Results in Search Using Oracle Hybrid Feature Extraction. Spectrum of Engineering Sciences, 3(3), 99-121.

Zaheer, M., Azeem, M. H., Afzal, Z., & Karim, H. (2024). Critical Evaluation of Data Privacy and Security Threats in Federated Learning: Issues and Challenges Related to Privacy and Security in IoT. Spectrum of Engineering Sciences, 2(5), 458-479.

Zebrack, J. S. et al. Usefulness of high-sensitivity C-Reactive protein in predicting long-term risk of death or acute myocardial infarction in patients with unstable or stable angina pectoris or acute myocardial infarction. Am. J. Cardiol. 89, 145–149 (2002).

A. Panesar, Machine Learning and AI for Healthcare (1–73), Apress, Coventry, UK, 2019, Available at https://iedu.us/wp-content/uploads/edd/2020/

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