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# Automated Brain Tumor Identification in Biomedical Radiology Images: A Multi-Model Ensemble Deep Learning Approach

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**Abstract:** Brain tumors (BT) represent a severe and potentially life-threatening cancer. Failing to promptly diagnose these tumors can significantly shorten a person's life. Therefore, early and accurate detection of brain tumors is essential, allowing for appropriate treatment and improving the chances of a patient's survival. Due to the different characteristics and data limitations of brain tumors is challenging problems to classify the three different types of brain tumors. A convolutional neural networks (CNNs) learning algorithm integrated with data augmentation techniques was used to improve the model performance. CNNs have been extensively utilized in identifying brain tumors through the analysis of Magnetic Resonance Imaging (MRI) images The primary aim of this research is to propose a novel method that achieves exceptionally high accuracy in classifying the three distinct types of brain tumors. This paper proposed a novel Stack Ensemble Transfer Learning model called "SETL_BMRI", which can recognize brain tumors in MRI images with elevated accuracy. The SETL_BMRI model incorporates two pre-trained models, AlexNet and VGG19, to improve its ability to generalize. Stacking combined outputs from these models significantly improved the accuracy of brain tumor detection as compared to individual models. The model's effectiveness is evaluated using a public brain MRI dataset available on Kaggle, containing images of three types of brain tumors (meningioma, glioma, and pituitary). The experimental findings showcase the robustness of the SETL_BMRI model, achieving an overall classification accuracy of 98.70%. Additionally, it delivers an average precision, recall, and F1-score of 98.75%, 98.6%, and 98.75%, respectively. The evaluation metric values of the proposed solution indicate that it effectively contributed to previous research in terms of achieving high detection accuracy.

**Keywords:** brain tumor 1; MRI 2; CNN; AlexNet; ensemble model; transfer learning; data augmentation; biomedical imaging; deep learning

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## 1. Introduction

Over 350,000 people worldwide will have a primary brain tumor in 2021. According to World Health Organization (WHO) statistics, brain tumors are the tenth most common cause of death [1]. Brain tumors are unstable and may be harmful if not treated wisely. Tumors often begin to grow in the brain, likely spreading to other body regions over time. These tumors can change the structure of the brain. Brain damage can have a significant impact on the functionality of the body. Unrestricted and aberrant cell growth inside or around the brain is the cause of brain tumors. These tumors, which are categorized according to cell type and growth site as meningiomas, gliomas, and pituitary tumors, represent serious health hazards [2]. Figure 1 indicates the main types of brain tumors, i.e., meningiomas, gliomas, and pituitary tumors.

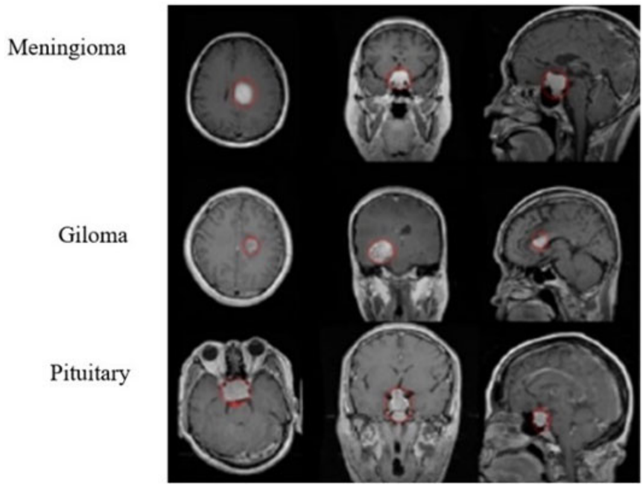



**Figure 1.** Different samples of brain tumors: meningioma, glioma, and pituitary.

Meningioma and glioma are deadly brain tumors if they are not diagnosed in their early stages. Patients typically do not survive for more than a year [3]. Therefore, early brain tumor detection is essential for carefully formulating treatment plans. Early BT diagnosis may increase the patient's probability of survival and help the medical practitioners to improve and plan suitable treatment utilizing MRI.

MRI and computer tomography (CT) are frequently employed in finding and evaluating brain tumors. These methods help medical practitioners identify the presence and location of indicators by thoroughly assessing information about the body's inside. MRIs produce a detailed image of the body using magnetic fields. It is the most widely used diagnostic tool among many imaging technologies for detecting various kinds of tumors. MRI is a painless medical imaging technique that produces high-quality pictures that provide 2D and 3D details images of brain tumors in different sizes [4]. However, reviewing these images manually is time-consuming and prone to mistakes. Furthermore, tumors can take on a variety of shapes, which further complicates the process of making an accurate diagnosis [5]. The development of efficient and computer-based procedures that are both automated and effective is the solution to this problem. This technique ought to result in cost savings. Deep learning and artificial intelligence (AI) have witnessed significant advancements in recent years, which have resulted in extraordinary progress in the field of medical research, notably in the accurate identification and categorization of brain tumors [6,7]. Recently, deep learning has garnered a lot of attention, particularly from researchers who are particularly interested in medicine. It has a substantial impact on a number of different aspects of illness research, including diagnosis [8], prognosis, and detection [9]. These approaches usually rely on picture content analysis, which is a key component of a wide variety of computer vision applications and is continuously undergoing technological advancement. Consequently, the advancement in deep learning and Internet of Things (IoT) in health sector are today considered to be the primary driving forces behind the development of health industry [10,11]. It has been noticed that the healthcare business is showing a growing interest in the identification of illnesses, with a special emphasis on the enhancement of the implementation of E-Health services [12].

The neurosurgical perspective is mainly used to diagnose the three forms of brain tumors early [13]. Different ML/DL models for brain tumor detection have been carried out, particularly the transfer learning model [14]. In the classification and scaling of medical imaging, the CNN model has expanded substantially in support of transfer learning. It is repeatedly used to interface with raw images and improve classification. In addition, the attainment of its features is dependent on a transfer learning model such as AlexNet, VGG19, and LeNet which is deliberate to classify images [15]. The research question for this investigation is RQ1: "How can an ensemble transfer learning system, combined with data augmentation techniques, precisely and effectively identify and classify various brain tumor diseases?".

The objective of this study was to create the composite ensemble model known as SETL_BMRI, which combines a data augmentation strategy with a deep stack ensemble technique to lower generalization errors and surge the accuracy of brain tumor classification. The model employed two well-known pre-trained CNN models (AlexNet and VGG19), which were concatenated using an augmentation technique. The experimental results demonstrated that the proposed technique yields more accurate and likely outcomes compared to single models and existing state-of-the-art methodologies.

The main contributions of our study are outlined below to highlight the significance of our work:

- The proposed unique stack ensemble transfer learning technique called SETL_BMRI uses CNN-based models like VGG19 and AlexNet to identify and classify tumors in an imbalance dataset of MRI brain tumor images, and furthermore, to reduce generalization errors and provide exact predictions for brain tumor classification.
- This work addresses the challenge of inadequate datasets, by incorporated data augmentation method to expands the size of a dataset.
- In this research work, a stack ensemble transfer learning model was used that incorporated data augmentation techniques to achieve high performance and accuracy.
- The performance of the recommended model was evaluated using the Kaggle dataset [16], which is open to the public. The model obtained a significant overall classification accuracy of 98.70% against several other baseline models. The performance parameters included accuracy, re-call, precision, and F1-Score.
- In the end, the suggested model produced good results, showing a low misclassification rate, and outperforming the functionality of existing techniques.

The following outline is included in the paper. In Section 2, the literature review is covered. Section 3 presents the methodology. Section 4 presents the implementation details, Section 5 presents the results, and Section 6 covers the discussion and limitations. The study's conclusion is presented in Section 7.

## 2. Literature Review

Timely identification and classification of brain tumors are crucial for a patient's treatment. The implementation of automated systems has enabled healthcare professionals to enhance patient care because of remarkable technological advancements. In artificial intelligence, deep learning has gained a lot of momentum and has made major advancements in a variety of fields, including natural language processing (NLP), autonomous cars, medicine, agriculture, and large language models (LLM) [17]. The arrival of new artificial intelligence and deep learning technologies has significantly influenced the field of medical image processing, particularly in the diagnosis of diseases. Recent studies have introduced several techniques employing machine learning (ML) and deep learning (DL) algorithms for the classification of brain tumors. This section reviews research on methodologies for classifying brain tumors using ML and DL-based algorithms [18].

Deep learning is one of the most effective techniques in artificial intelligence for instructing models to generate valuable decision-making skills from data [19]. The author discussed the steps involved in creating a deep learning project for radiology before providing an outline of some potential clinical use cases that would make use of these techniques [20]. The main objective was to investigate the opportunities and difficulties of future deep learning usage in radiology practices. To classify the brain tumor, various deep learning (DL) approaches have been proposed to achieve the goal of brain tumor classification such as convolutional neural networks (CNN) [21] and long short-term memory (LSTM) [22].

In the study authors [23] proposed a CNN-based learning method to identify brain tumors on MRI pictures. This model dataset contained 3263 pictures including 500 images without tumors, 937 images of meningiomas, 901 images of pituitary tumors, and 926 images of glioma tumors. The suggested model is the best at identifying different types of brain tumors and achieved 95.99% accuracy. However, it is recommended to modify the hyperparameters of the proposed model to enhance its accuracy.

A new CNN model called "BrainMRNet" was suggested by M. Toğaçar et al. [24]. The framework was created using a hyper-column method and attention segmentation. In the beginning, pre-processing was performed using BrainMRNet, an attention section that afterward carried out the approach of image augmentation, which allowed the retrieval of critical visual features subsequently transmitted to the convolutional network's layers. The dataset used for the research was composed of MRI images that are widely accessible. These images served as two labels. One showed an abnormal view, whereas the other showed a tumor. JPEG pictures were created from the original photographs. The proposed model compares with CNN models like AlexNet, VGG-16, and GoogleNet. Tumor identification using the BrainMRNet model was more accurate, with a 96.05% performed accuracy. However, the proposed model is not suitable for the multi-classification of brain tumors and can be improved and diversified.

The study [25] employed CNN, DNN, and KNN to diagnose brain tumors accurately and efficiently. The segmentation of the BRATS 2019 dataset served to exhibit the relative efficacy of several deep-learning algorithms. To choose the best features, the term "hybrid manta ray foraging optimization" was proposed. Tumor identification was performed using CNN. The three types of tumors in the dataset were benign tumors, malignant tumors, and typical images. A comparison of various machine learning models was undertaken, and the results were helpful in more effectively and accurately identifying brain tumors. In [26], P. Rajak et al. suggested developing a novel brain tumor detection and categorization system employing well-recognized deep transfer learning models, such as Dense-Net121, VGG16, MobileNet v2, and Xception. On a benchmark dataset, the suggested strategy's effectiveness is assessed in terms of accuracy and loss. DenseNet201 surpasses all other models in terms of accuracy, with a training accuracy of 97.48% and a validation accuracy of 96.42%. Similarly, S. U. Habiba et al. proposed in [27] a transfer learning approach using the InceptionV3 and DenseNet201 models to categorize brain tumors on a publicly accessible dataset. Data augmentation strategies can be employed to obtain accurate classification results by enhancing the dataset and mitigating overfitting. A deep convolutional neural network named "Brain-Deep Net" uses six closely coupled convolutional layers to retrieve information from thick layers. The proposed model was shown to have a classification accuracy of 96.3% for the three most popular types of brain tumors. glioma, meningioma, and pituitary.

In [28], Ishak Pacal1 et al. presented the most cutting-edge and powerful deep learning techniques. These techniques were separated into two groups: convolutional neural network (CNN) approaches and vision transformer (ViT) approaches. Both groups were ranked according to their effectiveness. Additionally, the study uses ensemble learning approaches to increase the accuracy of model outputs and data augmentation strategies to improve data variety. The performance of the models in terms of classification was enhanced by the discovery of high-performing models through the utilization of ensemble learning methodologies, which ultimately results in an accuracy of 91.76%.

In medical image analysis, small datasets are a widespread problem. Most computer vision works might benefit from extra data, and data augmentation is one method frequently employed to improve computer vision system performance. In [29], Y. LeCun et al. proposed the classification of the handwritten digit as one of the first uses of data augmentation. Data augmentation techniques on the ImageNet dataset improved picture classification. The proposed strategy aims to expand the dataset size. The authors conducted the studies by randomly cutting portions of the original photos, flipping them horizontally, and altering the pixel intensity. In [30] Parameshachari et al., proposed a model that could detect the tumor using a support vector machine (SVM) after image segmentation with Particle Swarm Optimization (PSO) and Watershed algorithms, Principal Component Analysis (PCA) and Discrete Wavelet Transform (DWT) approaches, and then feature extraction. This approach is more efficient for identifying the brain tumor MRI image data.

Following the emergence of numerous research projects utilizing various data augmentation approaches [31], we may divide them into two primary categories: (1) conventional transformations based on affine image transformation and color alteration and (2) Generative Adversarial Networks (GANs), a technology that relies on the unsupervised creation of fresh images while utilizing the min–max approach. In [32], researchers proposed a machine learning model to enhance the accuracy with which diseases like heart failure (HF) may be predicted. In [33] Begum, S.S. suggested a method with four unique stages: segmentation, classification, feature extraction, and feature selection brain MRI image noise is first removed, and then features are extracted using dominant run length and co-occurrence texture features as the primary preprocessing steps. To classify MRI scan images as tumor or non-tumors, the classification stage uses a Recurrent Neural Network (RNN) model. Although the suggested method yielded a 96.26% accuracy rate, it is considered inadequate.

We have provided a detailed comparison report among the different proposed methodologies in Table 1.

**Table 1.** Comparative analysis.

<table>
<tr><th>Year, Reference</th><th>Dataset</th><th>Model<br>Limitations</th></tr>
<tr><td>2023, [34]</td><td>Kaggle Brain Tumor</td><td>The proposed model is not suitable for pixel-level feature extraction. Data preparation necessitates more computing power.</td></tr>
<tr><td>2023, [35]</td><td>Figshare MRI Images</td><td>The proposed detection system applies only to binary classification of brain tumors and can be improved and diversified.</td></tr>
<tr><td>2023, [36]</td><td>Figshare MRI images</td><td>The accuracy still needs to be improved.</td></tr>
<tr><td>2023, [37]</td><td>Kaggle MRI</td><td>The model necessitates a vast amount of data.</td></tr>
<tr><td>2023, [38]</td><td>Kaggle and Figshare Dataset</td><td>More computation power is required for the proposed deep learning model as architecture.</td></tr>
<tr><td>2022, [39]</td><td>BraTs 2020 brain tumor MRI images</td><td>The accuracy still needs to be improved.</td></tr>
<tr><td>2022, [40]</td><td>Figshare and Harvard</td><td>The proposed models do not classify distinct types of brain tumors efficiently.</td></tr>
<tr><td>2023, [41]</td><td>BRATS, 2015</td><td rowspan="2">Both proposed models used a limited data set with binary classification of brain tumors.</td></tr>
<tr><td>2021, [42]</td><td>BR35H</td></tr>
</table>

The study's results highlight a common problem with current models: they are unable to classify brain tumors with greater accuracy due to a lack of generalization capacity. Therefore, there is a great problem in creating a reliable model with better classification accuracy. Inspired by this, we redirected our efforts to develop a robust and precise deep learning (DL) model to assist physicians in brain tumor diagnosis. Our innovative deep stacking ensemble model SETL_BMRI was developed for the three types of brain tumor classification, inspired by the success of ensemble learning models [43,44]. When compared to a single model, the proposed ensemble model shows much greater accuracy in diagnosing different kinds of brain tumors.

## 3. Proposed Research Methodology

This section discussed the methodology and details of the proposed model. The key aim is to automatically classify different types of brain tumors. AlexNet and VGG19 are used in an ensemble configuration in the innovative deep-stacked ensemble technique. This configuration is optimized for brain tumor diagnosis, with the goal of reducing detection errors and outperforming other models.

### 3.1. Convolutional Neural Networks (CNN)

The deep learning CNN technique distinguishes between various elements in an image by requiring and prioritizing several features in the images. CNN is a multilayered feedforward neural network and one of the key concepts in the deep learning approach. CNN needs much less pre-processing than other categorization methods [45]. Modest filtering techniques can also be effective with proper training [46]. The pixels around a convolution layer's neurons determine their features' output. The perceptron is the area of pixel density where a neuron's response might be affected [47].

A multi-layer convolutional neural network was designed in which a convolutional layer served as the start layer in the construction of an input MRI image, which uniforms the dimensions of every image. CNN model basic structure is shown in Figure 2. Convolution kernel entangled with the input layer was created after gathering every image in the same aspect [48]. It was possible to generate 32 convolutional filters with the assistance of three channel tensors, with each filter having a size of $3 \times 3$. The input layer, which is the top layer, has an image size of $224 \times 224$ pixels. It is a mathematical technique to modify a feature map by performing a dot product of two matrices. One matric represents the kernel, and the other displays the original image's pixel intensity values. The kernel is moved vertically and horizontally over the image to obtain attributes such as borders, areas, forms, etc., from the source image. The model starts to find better features using augmentation, such as blurring, sharpening, texturing, and gradient direction. In the CNN architecture, convolutional layers with a $2 \times 2$ kernel size are Equation (1), which explains the convolutional layers.

$$C(h,w) = \sum_x \sum_y i(h-x, w-y) f(x,y) \tag{1}$$

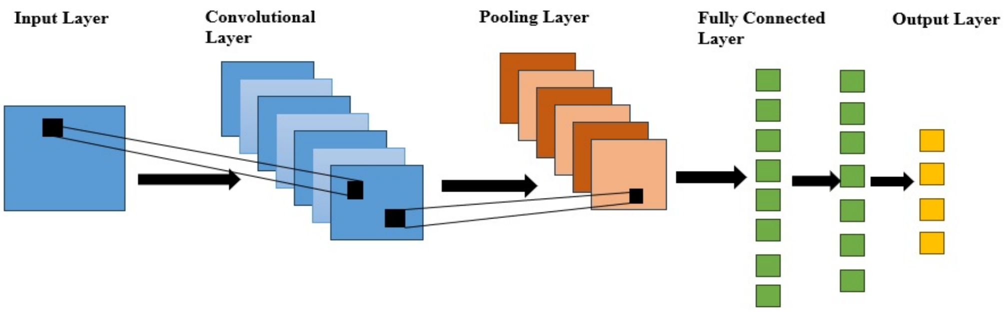



**Figure 2.** Basic architecture of CNN.

The dimension of the converted feature map is reduced in the following level, recognized as pooling layers. The CNN model offers a variety of pooling layers, including maximum, minimal, and average pools. To obtain the standout features from the altered feature map. We use max pooling, as shown in Equation (2).

$$f(z) = \max(0, z) \tag{2}$$

We have selected the Softmax function to serve as the activation function for the output layer of our proposed model.

$$\text{Softmax}(z)_j = \frac{\exp(z_j)}{\sum_{i=1}^{n} \exp(x_i)} \tag{3}$$

This function predicts a multinomial probability where the odds of each value are inversely correlated with their respective sizes in the vector. Equation (3) defines the outcome range s 0 to 3 for the Softmax activation function [49].

### 3.2. Visual Geometry Group-19 (VGG19)

The Visual Geometry Group (VGG) is based on the CNN model. It increases the neural network intensity such that it may achieve state-of-the-art precision on the ILSVRC [50] dataset in addition to applying it to additional image recognition databases. Nineteen convolutional layers and three fully linked layers make up the basic model VGG19′s 19 layers. It can classify the images into 1000 different item groups. One million photos arranged into a thousand categories comprise the ImageNet database, which was used to train VGG19. Because each convolutional layer employs numerous 3 × 3 filters, it is a particularly common technique for classifying pictures. The architecture of VGG19 is shown in Figure 3.

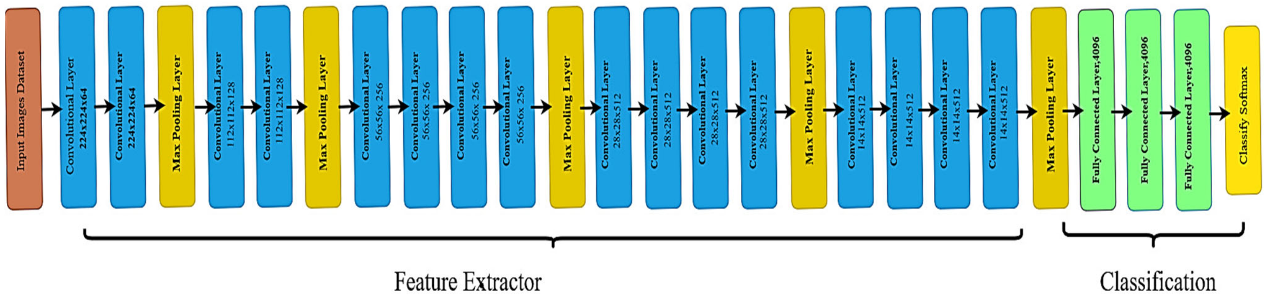



**Figure 3.** The basic architecture of VGG19.

### 3.3. AlexNet

The architecture of AlexNet is depicted in Figure 4, which is mainly made up of three max-pooling layers (3 × 3), three FC layers, and five convolutional layers (11 × 11, 5 × 5, 3 × 3, 3 × 3, 3 × 3). Following the first two convolutional layers in order, the first two max-pooling layers are applied. Convolutional layers three, four, and five are intimately related. After the fifth convolutional layer, the third max-pooling layer is added, and its output is supplied into a sequence of three FC layers. ReLU, stochastic gradient descent (SGD), dropout, and other methods are frequently cited as reasons for AlexNet's success.

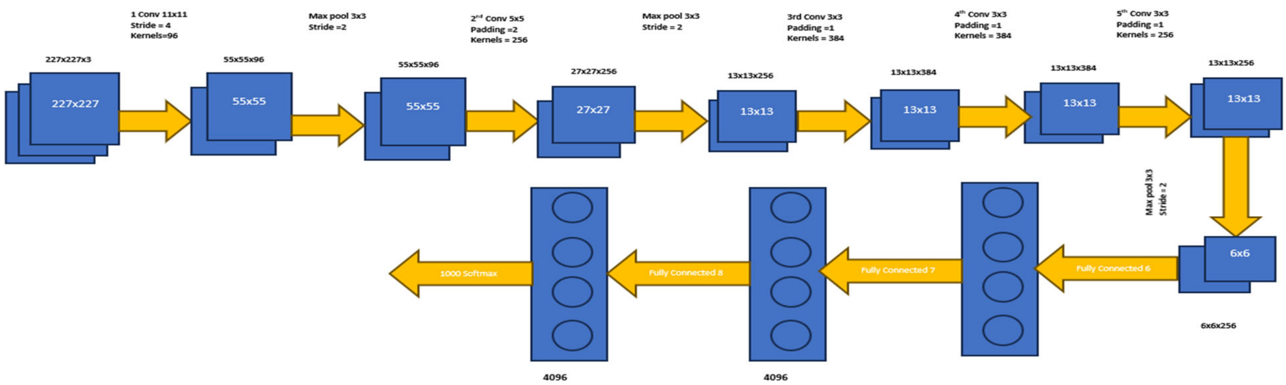



**Figure 4.** A block diagram of AlexNet's basic architecture.

The SGD technique is used to refine the overall cost function to retrieve the value of the convolutional kernel [51]. The overfitting issue in the first two FC layers is resolved using a dropout layer. The third FC layer, the SoftMax layer, is utilized to recognize various objects in a CNN [52].

### 3.4. Transfer Learning Approach

Transfer learning (TL) becomes especially important and advantageous in situations when training data are few or computational capacity is constrained. TL's core idea is to use pre-trained models on large benchmark datasets to enhance classification performance on smaller datasets. TL techniques have shown promise recently in a variety of medical imaging applications [53]. We used CNN architectures from the state of the art, including AlexNet, DenseNet201, VGG19, and ResNet50. These models have undergone significant improvements and have shown exceptional performance, especially when using the ImageNet dataset.

### 3.5. Ensemble Learning Model

Ensemble learning is a widely adopted technique in machine learning, particularly in supervised learning, aiming to enhance models' generalization capability. However, achieving high generalization ability is often challenging due to dataset nuances or model limitations, especially in critical domains like cancer tissue classification [54]. Ensemble learning addresses these challenges by combining predictions from multiple models into a unified model to enhance accuracy and generalizability. It is a dynamic method extensively used in the literature [55,56] categorized into basic techniques (like max-voting, averaging, and weighted average) and advanced methods (such as stacking, boosting, blending, and bagging). These approaches significantly improve prediction performance and offer diverse strategies to overcome inherent limitations in individual models. Ensemble learning seeks to enhance detection accuracy by employing multiple learning methods instead of relying on a single underperforming model. Factors like bias, overfitting, and variance significantly impact model performance. Ensembles effectively address these issues by capitalizing on the strengths of individual models. Stacking, a type of ensemble technique, combines diverse models to enhance classification efficiency. Typically, a base classifier initially categorizes the dataset, and then a meta-learner utilizes these predictions as features.

### 3.6. Dataset

In this study, we proposed an image classification model that would allow us to consider patient MRI pictures as input. For this investigation, a dataset [16] contains MRI brain tumor images presented in the train, test, and validation folders. These images are publicly available over the internet maintained in Section 1. There are three different types of brain tumors, namely, meningioma, glioma, pituitary, and no tumor. The total number of images is divided into four subfolders present inside the training, testing, and validation folders. The images in Figure 5 show the different types of brain tumors.

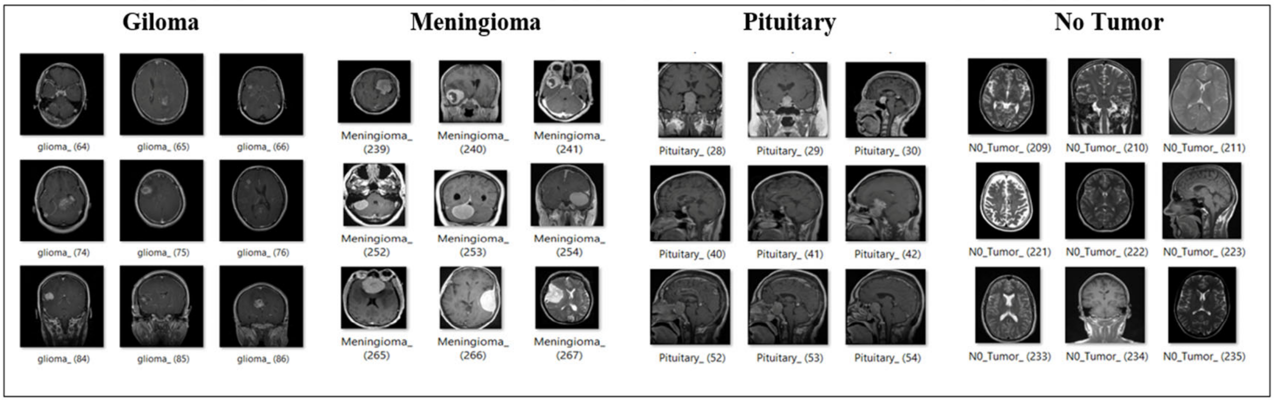



**Figure 5.** Brain tumor MRI Images.

### 3.7. Preprocessing and Image Classification

In the preprocessing phase, the MRI brain tumor dataset undergoes key actions. Images are collected, resized to 224 $\times$ 224 pixels, and stored as 'x_train' for machine learning or deep learning tasks. A crucial aspect is normalization, achieved by dividing pixel values by 255, which scales the data to the 0 to 1 range. This normalization aids deep learning models, especially neural networks, effective training, and convergence. Data generators are utilized to efficiently handle and preprocess data in batches, with data augmentation serving as a preventive measure against overfitting, especially valuable for large datasets. These generators are commonly employed alongside Keras models for image classification.

### 3.8. Data Augmentation

Data augmentation is used to increase the size of a dataset which helps the model's generalization capacity by lowering the danger of overfitting and being especially effective when the dataset is scarce. Different transformations can be used to improve image collection. These include flipping, rotation, and translation [57]. These transformations add more samples to the collection by altering the source images. Moving an image in a different direction (horizontally or vertically) helps produce new pieces by repositioning the object within the image [58]. In our case, we applied the changes using the flipping, rotation, and translation techniques as shown in Figure 6. The most popular methods include.

- Flipping: produces a mirror image of the original.
- Rotation: shifting an image at an angle concerning its central pixel.
- Translation: involves shifting the image along the X or Y direction or both.

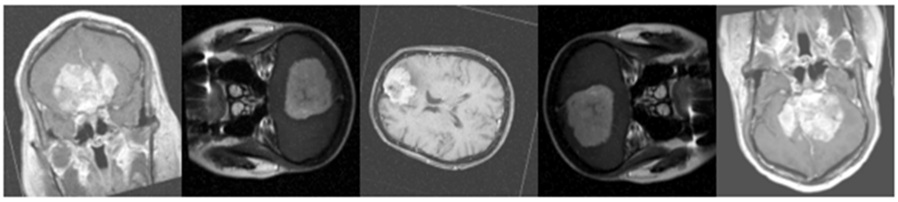


**Figure 6.** Brain tumor image after applying data augmentation approach.

The dataset of brain tumors utilized in the study includes 1908 images, as indicated in Table 2. The datasets are split into three categories: testing (220 images), validation (150 images), and training (1908 images). To create three times as many new photos, this dataset was expanded. Figure 7 and Algorithm 1 provide a detailed visual depiction of the architecture that our model proposes for the classification of brain tumors.

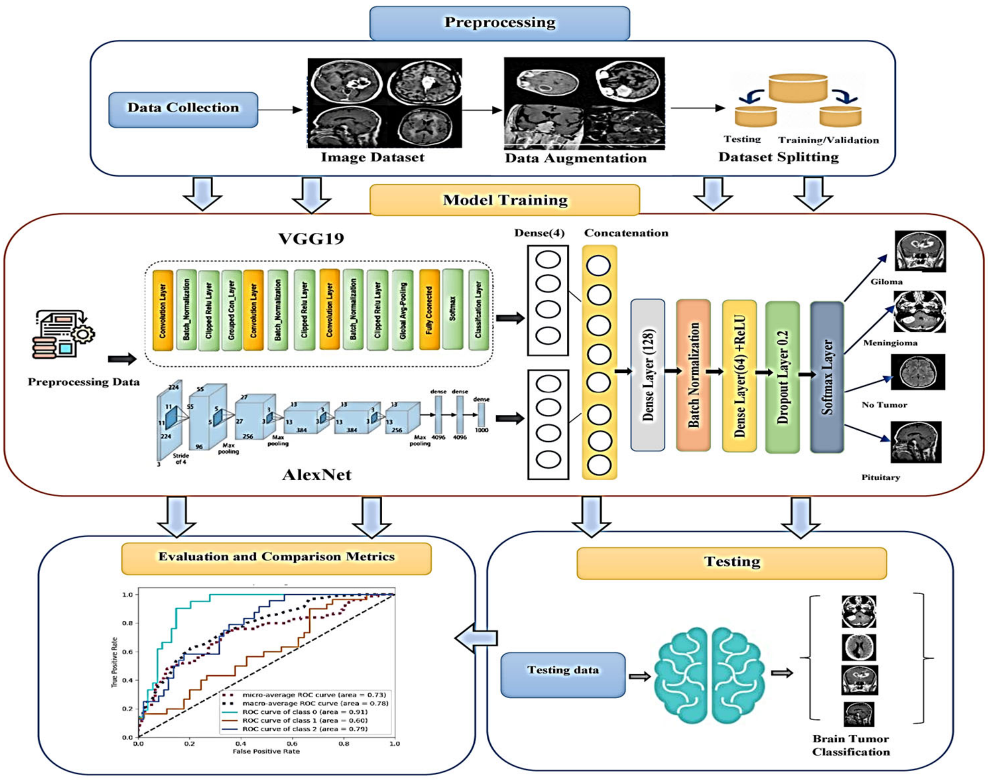



**Figure 7.** Proposed SETL_BMRI for multiclassification of brain tumor.

**Algorithm 1** Proposed Methodology

Input: Images Dataset (IDS)

Output: Evaluation metrics

1. Load IDS
2. Preprocessing IDS
3. Applying Data Augmentation (DA)
4. N ← Number of images in IDS
5. I ← 1
6. while I ≤ N
    a. Read images (IDS(I))
    b. Flip images
    c. Rotate images 90 degrees
    d. Translation Images
    e. I = I + 1
7. End
8. split dataset ()
9. load proposed learning model (LM)
10. for each epoch in epoch number
    a. y^ = model (features extract)
    b. loss = cross entropy (y, y^)
    c. ptimize (loss, accuracy)
11. return ()
12. print model evaluation
13. print accuracy curve, precision, recall, and F1-score
14. Classify brain tumors in MRI images

**Table 2.** MRI images dataset before and after augmentation.

| Dataset | Number of Images | After Augmentation |
|---|---|---|
| MRI images | 1908 | 5724 |
| Glioma Brain Tumor | 495 | 1485 |
| Meningioma Brain Tumor | 488 | 1464 |
| Pituitary | 395 | 1185 |
| No Tumor | 530 | 1590 |

The proposed model has been used by state-of-the-art CNN architectures AlexNet and VGG19 along with a data augmentation approach. The selection of these models stems from their remarkable performance in medical imaging tasks and their proven success in real-time applications. Notably, the pre-trained weights of both models were selected from the ImageNet dataset. The goal of reducing detection errors while simultaneously improving accuracy and resilience is the reason for using a deep ensemble model as opposed to a single CNN model.

This model uses the meta-learner that concatenated prediction vectors from all base learners as features. For multi-class classification at the second level, a brand-new fully connected neural architecture known as the meta-learner is used. The basis models are held frozen, while the meta-learner is taught using the training set. The pre-trained CNN and the suggested SETL_BMRI model for brain tumor prediction are covered in detail in the next sections. These models have performed well on the ImageNet dataset and have seen significant advances. To assess the efficacy of the model, it is recommended to split the dataset into distinct training, testing, and validation sets. Additionally, it is advisable to restrain the upper (classification) layers of the pre-trained VGG19 and AlexNet models before their integration. This precautionary measure ensures that the established layers remain unchanged upon loading. In the detection of brain tumors, it is imperative to craft distinctive classification layers for each model. Leveraging the preprocessed training dataset, both the VGG19 and AlexNet models will undergo comprehensive training. Subsequently, the performance of each model will be thoroughly assessed using the validation set. The efficiency of the models will be evaluated through the generation and analysis of predictions for the validation dataset, thus providing valuable insights into their respective capabilities. For the creation of a meta-classifier model, the predictions are combined to form a feature matrix, which shall serve as the input features for the meta classifier utilizing the associated class labels and the stacking predictions. Efficient feature extraction is crucial for MRI images, given their highly visual nature. The learning model's properties, such as weights and learning rate, are adjusted using an optimizer function.

## 4. Implementation Details

This section shows the quantitative results of the SETL_BMRI model that was suggested for brain tumor identification. Various critical indicators are used to analyze the individual performance of each subnetwork. A summary of the computing resources, the experimental dataset, and the measures used to assess performance are also included in this section. Moreover, a thorough comparison is carried out with many cutting-edge techniques on the same dataset to prove the effectiveness of the suggested model.

### *4.1. Environmental Setup*

For the experimental purpose, this study used the intel® Core i7-8700k for processing, 16 GB DDR4, NVIDIA GeForce 3080 graphics card, Windows 10 operating system, and Python programming language version 3.9.10. Additionally, the Keras and Tensorflow version 2.9.2 libraries are used for performing tasks.

### *4.2. Evaluation Metrics*

The following metrics have been used to examine the suggested model efficiency. The confusion matrix consists of four elements: false positive (FP), false negative (FN), true positive (TP), and true negative (TN).

Accuracy is a common metric used to evaluate classification models. The accuracy is calculated using the following Equation (4).

$$\text{Accuracy}(\%) = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \times 100 \tag{4}$$

Precision focuses on the percentage of accurately predicted positive samples (also known as true positives) among all positive predictions produced by the model. Equation (5) is used to calculate the precision.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{5}$$

The percentage of positive samples that were correctly predicted to be positive (true positives) relative to all other positive samples is known as recall, also known as sensitivity or true positive rate. Equation (6) is utilized to learn the recall.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{6}$$

Precision and recall are combined into a single metric called the F1 score. Equation (7) is used to determine the F1 score:

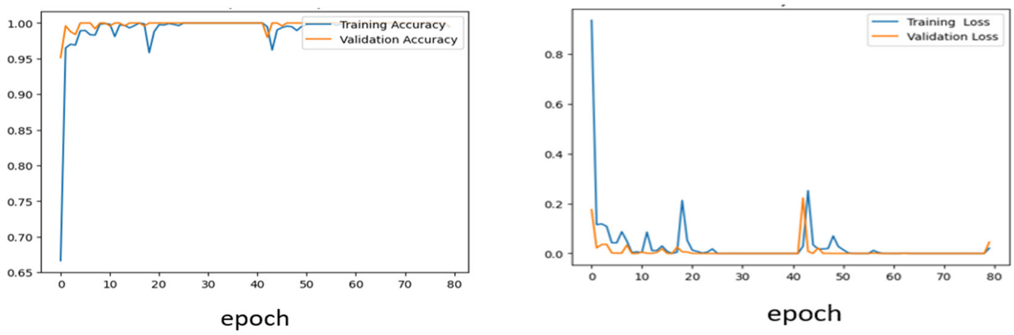
$$\text{F1} - \text{Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{7}$$

*4.3. Hyperparameters for Training and Evaluating Model*

The optimization of neural network performance is contingent upon several hyperparameters, such as batch size, learning rate, activation function, and optimization technique. Using a 50-epoch batch size, this work trains four pre-trained models. The Adam optimizer was used for fine-tuning, with learning rates set to 0.001, 0.0001, and 0.00001. All models were trained using categorical cross-entropy as the loss function, and overfitting was avoided by using a 0.3 dropout rate. The basic models fed feature vectors to the meta-learner's unique fully connected neural architecture. The Adam optimizer was chosen because it combines SGD and RMSPROP benefits. To prevent overfitting, L2 regularization of $1 \times 10^{-4}$ was applied during model training. The recommended SETL_BMRI-NET model's classification performance was assessed using these parameters.

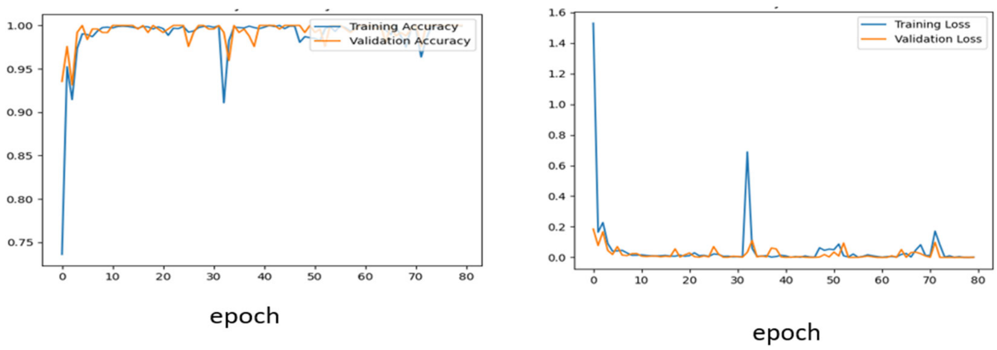
## 5. Results

This section presents the SETL_BMRI model's performance as well as important metrics for categorizing different kinds of brain tumors. The base models produced by VGG19 and AlexNet both have learning curves shown in Figures 8 and 9, respectively. The learning curves of the proposed model are presented in Figure 10, which shows the training accuracy rapidly improves with each epoch. The loss values notably show little variation, suggesting effective model convergence free from under- or overfitting.




(**a**) (**b**)

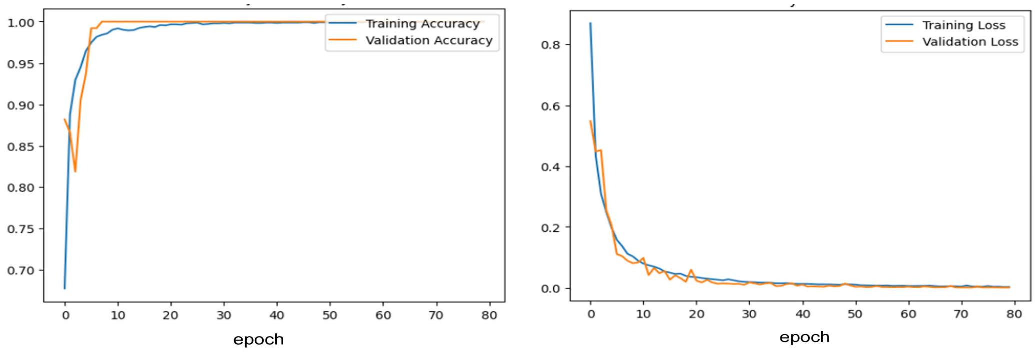
**Figure 8.** (**a**) Accuracy curve of AlexNet; (**b**) loss curve of AlexNet.




(**a**) (**b**)

**Figure 9.** (**a**) Accuracy curve of VGG19; (**b**) loss curve of VGG19.

To confirm effectiveness, we tested the proposed ensemble design with independently modified pre-trained models. The quantitative results of the suggested SETL_BMRI ensemble model are shown in Table 3, along with the specific performance metrics (accuracy, precision, recall, and F1-score) of each model that has been optimized for brain tumor prediction. The models were refined using Kaggle brain MRI data. The ResNet50 model performed poorly, with an accuracy of 92.40%. DenseNet201 had 97.20% precision, 98.30% recall, 98.20% F1-score, and 97.85% accuracy, but AlexNet only had 94.05%. VGG19 performed well with 97.02% accuracy, 97.30% recall, 95.70% precision, and 97.20 F1-Score. Table 3 clearly illustrates that the SETL_BMRI ensemble model outperformed individual models. SETL_BMRI outperformed all other models with 98.75% precision, 98.6% recall, 98.75% F1-Score, and 98.70% accuracy on the test dataset. Compared to other models, the proposed model showed a higher recall—important for medical image prediction models. The suggested model's improved generalization in comparison to other models is shown by the higher F1-score, which indicates superior predictive power.




(**a**) (**b**)

**Figure 10.** (**a**) Accuracy curve of proposed model; (**b**) loss curve of the proposed model.

**Table 3.** Class-wise comparison performance between the proposed SETL_BMRI model and other baseline deep learning models.

| Model | Class | Precision | Recall | F1-Score | Accuracy |
|---|---|---|---|---|---|
| ResNet50 | Glioma | 1.00 | 0.81 | 0.90 | 92.40 |
| | Meningioma | 0.62 | 1.00 | 0.77 | |
| | No Tumor | 0.97 | 1.00 | 0.98 | |
| | Pituitary | 1.00 | 0.99 | 0.99 | |
| AlexNet | Glioma | 1.00 | 0.95 | 0.97 | 94.05 |
| | Meningioma | 0.72 | 0.96 | 0.83 | |
| | No Tumor | 0.98 | 1.00 | 0.99 | |
| | Pituitary | 0.98 | 0.86 | 0.92 | |
| DenseNet201 | Glioma | 1.00 | 0.98 | 0.99 | 97.85 |
| | Meningioma | 0.89 | 1.00 | 0.94 | |
| | No Tumor | 0.99 | 1.00 | 1.00 | |
| | Pituitary | 1.00 | 0.94 | 0.97 | |
| VGG19 | Glioma | 1.00 | 0.99 | 0.99 | 97.02 |
| | Meningioma | 0.83 | 1.00 | 0.91 | |
| | No Tumor | 1.00 | 1.00 | 1.00 | |
| | Pituitary | 1.00 | 0.90 | 0.95 | |
| Proposed SETL_BMRI | Glioma | 1.00 | 0.97 | 0.99 | 98.70 |
| | Meningioma | 0.95 | 1.00 | 0.98 | |
| | No Tumor | 1.00 | 0.99 | 0.99 | |
| | Pituitary | 1.00 | 1.00 | 0.99 | |

Comparing the confusion matrices of the SETL_BMRI with the pre-trained models in Figure 11 shows that the proposed model (SETL_BMRI) classified accurately and reduced misclassifications. The training and validation accuracy and loss curve of AlexNet are shown in Figure 8a,b, respectively. The suggested model outperformed the others in terms of performance, with ensemble methods working well to reduce classification mistakes and produce better results overall. The classification performance of the suggested SETL_BMRI model for each kind of tumor is summarized in Table 3.

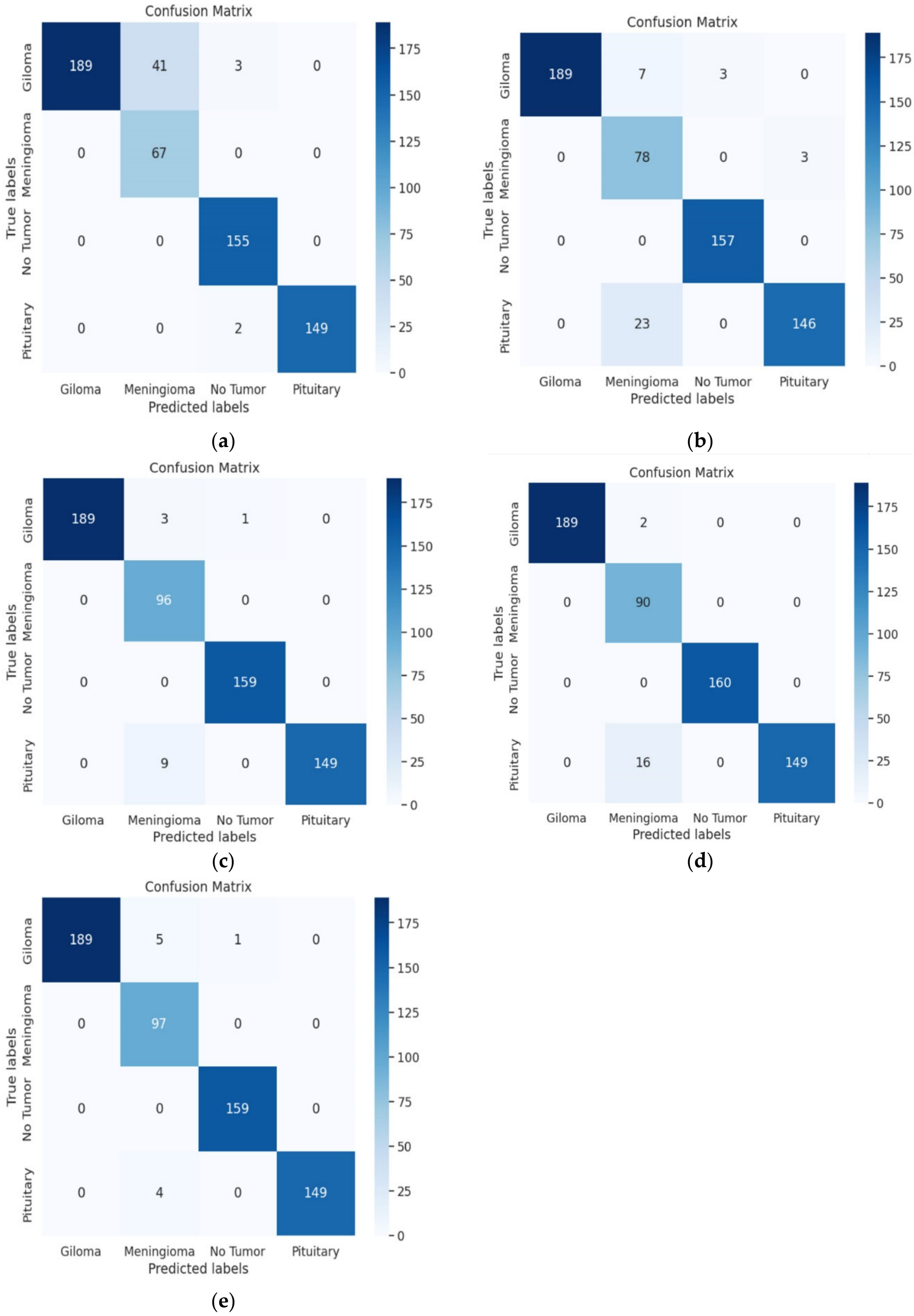



**Figure 11.** Confusion matrix of all deep learning models for classification of brain tumors: (**a**) ResNet50, (**b**) AlexNet, (**c**) DenseNet201, (**d**) VGG19, (**e**) Proposed SETL_BMRI ensemble model.

*Result Analysis*

The proposed SETL_BMRI model comprised of AlexNet, VGG19, and Ensemble transfer learning models, respectively, having performance metrics (Precision, Accuracy, Recall, and F1-Score) presented in Table 3.

The model's output is presented in Figure 12 which depicted the detection and classification of brain tumors. The proposed model performance metric is presented in Figure 13, which clearly elaborates on the high performance of SETL_BMRI model.

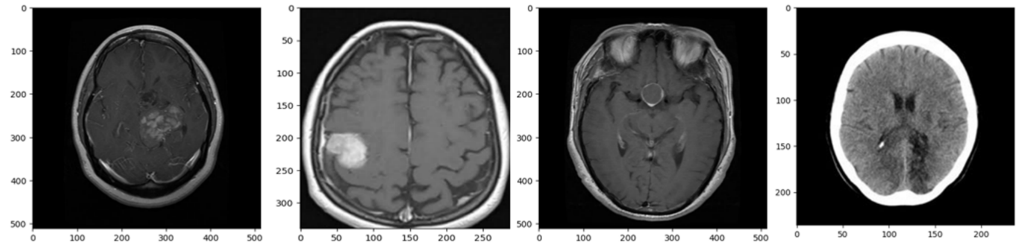


**Figure 12.** Test results of brain tumor classification: glioma, meningioma, pituitary, no tumor (left to right).

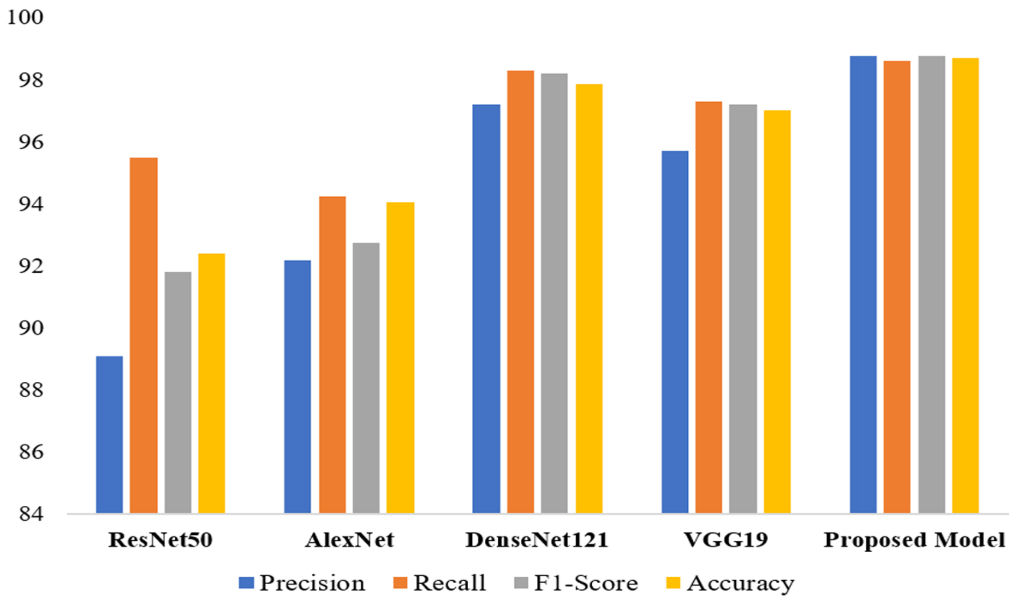



**Figure 13.** Comparison of the performance of the proposed model with pre-trained models.

## 6. Discussion

This section provides an extensive comparison between BMRINet and existing deep learning methods, highlighting the superior performance of our proposed SETL_BMRI ensemble model in diagnosing brain tumors using the same dataset. In Table 4, the first column represents a cited work, the second column shows the learning model, and the last column indicates an emphasis on dataset inclusion is crucial for contextualizing and interpreting the results effectively.

The remarkable performance of stacked SETL_BMRI model can be attributed to its sophisticated integration of two distinct CNN models coupled with a data augmentation technique. Data augmentation artificially increases the training dataset through transformations or modifications which improve the model's generalization capacity, mitigate class imbalance, and lower the risk of overfitting. Data augmentation is essential for healthcare applications because the model must require to handle variations in data and anomalies in image classes.

The proposed model used transfer learning, which is suitable in those situations when gathering a large amount of data is difficult. Transfer learning is the process of building a model on one activity and utilizing it as the foundation for another task. Transfer learning might be able to reduce the need for a lot of training data because it can use what it has learned from a source task that was trained on a lot of datasets, which stores common features and trends. The model needs fewer data to achieve adequate performance because it doesn't have to learn all of the features from scratch. Transfer learning is especially helpful in medical imaging since by utilizing pretrained models it may drastically lower the amount of training data needed. The SETL_BMRI model gains more discriminative power from the addition of a meta-learner with a dense layer. The batch normalization stabilizes and accelerates training, and dropout maintains the model from becoming overly dependent on any one set of features, which improves the model's capacity for generalization. Further, the effectiveness of transfer learning implementation can be greatly influenced by various factors, including the task complexities, the training data relevance and quality from the source model, the degree of similarity between the source and target tasks, and the minimal volume of training data that is necessary. An example in this study is when a model that was initially trained on a sizable dataset for object recognition can be refined to fit a particular object recognition task using a comparatively smaller dataset, since the essential attributes of images (such as edges, textures, and shapes) remain constant.

**Table 4.** We compare our proposed model with prior research to assess its effectiveness.

| Reference | Deep Learning Model | Model Accuracy |
|---|---|---|
| Ref. [40] | 2D CNN | 96.40% |
| Ref. [41] | Parallel DCNN | 97.33% |
| Ref. [42] | 25 Layers CNN | 86.23% |
| Ref. [43] | Deep CNN | 98.05% |
| Ref. [44] | One-Stage Deep Learning Model (YOLO) | 95.01% |
| Ref. [45] | Deep Convolutional Generative Adversarial Network (DCGAN) | 83.20% |
| Ref. [46] | VGG16 + CNN | 97.30% |
| Ref. [47] | AlexNet | 98.02% |
| Ref. [48] | CNN | 98.01% |
| Proposed Model SETL_BMRI | Stack Ensemble (AlexNet, VGG19) + Data Augmentation | 98.70% |

The SETL_BMRI model differs from traditional ensemble approaches in that it incorporates various methodologies and architectures to present a more reliable and accurate system for medical image classification. In conclusion, the discussion proposes to investigate substitute techniques to be considered as a future enhancement such as 3D CNNs, attention processes, or other inventive methods. For example, because 3D CNNs can handle volumetric data and offer a more thorough analysis than 2D CNNs, they can be very major in medical imaging. The most relevant portions of the image can be emphasized by models using attention processes (compatible with CNNs), which have been successfully used in natural language processing and medical imaging. Examining these and other methods may result in tools for diagnosis that are more successful and efficient.

*Limitation*

In this investigation, the identification of an appropriate dataset for classification is challenging due to the difficulty in obtaining/limited sample size. Imbalanced datasets can bias models by underrepresenting tumor types. Algorithms may improve at classifying common tumor types but struggle with minority classifications, lowering classification performance and reliability.

## 7. Conclusions and Future Work

This study used a stack ensemble deep transfer learning model with data augmentation approaches to develop a high-accuracy brain tumor classification system. The suggested model uses VGG19, AlexNet, and Ensemble transfer learning models to identify and classify tumors from brain images. The proposed study utilized Kaggle data sets divided into four classes: meningioma, glioma, pituitary, and no tumor. The dataset was split into three parts: training (70%), testing (20%) and validation (10%). The recommended model's training phase achieved a high success rate of 97–99%. The VGG19 test model achieved accuracy of 97.02%, compared to 94.05% for the AlexNet test model. The proposed model SETL_BMRI outperforms in terms of performance by achieving 98.70 accuracy. In future studies, several image segmentation methodologies will be utilized to provide the most accurate approximation of impacted brain areas, by distinguishing them from unaffected brain regions.

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## References

1. Anitha, V.; Murugavalli, S. Brain Tumour Classification Using Two-Tier Classifier with Adaptive Segmentation Technique. *IET Comput. Vis.* **2016**, *10*, 9–17. [CrossRef]
2. Badillo, S.; Banfai, B.; Birzele, F.; Davydov, I.I.; Hutchinson, L.; Kam-Thong, T.; Siebourg-Polster, J.; Steiert, B.; Zhang, J.D. An Introduction to Machine Learning. *Clin. Pharmacol. Ther.* **2020**, *107*, 871–885. [CrossRef] [PubMed]
3. Saddique, M.; Kazmi, J.H.; Qureshi, K. A Hybrid Approach of Using Symmetry Technique for Brain Tumor Segmentation. *Comput. Math. Methods Med.* **2014**, *2014*, 712783. [CrossRef] [PubMed]
4. Komninos, J.; Vlassopoulou, V.; Protopapa, D.; Korfias, S.; Kontogeorgos, G.; Sakas, D.E.; Thalassinos, N.C. Tumors Metastatic to the Pituitary Gland: Case Report and Literature Review. *J. Clin. Endocrinol. Metab.* **2004**, *89*, 574–580. [CrossRef] [PubMed]
5. Louis, D.N.; Perry, A.; Reifenberger, G.; Von Deimling, A.; Figarella-Branger, D.; Cavenee, W.K.; Ohgaki, H.; Wiestler, O.D.; Kleihues, P.; Ellison, D.W. The 2016 World Health Organization Classification of Tumors of the Central Nervous System: A Summary. *Acta Neuropathol.* **2016**, *131*, 803–820. [CrossRef]
6. Chahal, P.K.; Pandey, S.; Goel, S. A Survey on Brain Tumor Detection Techniques for MR Images. *Multimed. Tools Appl.* **2020**, *79*, 21771–21814. [CrossRef]
7. Sajjad, M.; Khan, S.; Muhammad, K.; Wu, W.; Ullah, A.; Baik, S.W. Multi-Grade Brain Tumor Classification Using Deep CNN with Extensive Data Augmentation. *J. Comput. Sci.* **2019**, *30*, 174–182. [CrossRef]
8. Rehman, A.; Naz, S.; Razzak, M.I.; Akram, F.; Imran, M. A Deep Learning-Based Framework for Automatic Brain Tumors Classification Using Transfer Learning. *Circuits Syst. Signal Process.* **2020**, *39*, 757–775. [CrossRef]
9. Wang, Y.; Zu, C.; Hu, G.; Luo, Y.; Ma, Z.; He, K.; Wu, X.; Zhou, J. Automatic Tumor Segmentation with Deep Convolutional Neural Networks for Radiotherapy Applications. *Neural Process. Lett.* **2018**, *48*, 1323–1334. [CrossRef]
10. Patil, R.B.; Ansingkar, N.; Deshmukh, P.D. Deep Learning Based Brain Tumor Segmentation: Recent Updates. In *Rising Threats in Expert Applications and Solutions*; Springer: Singapore, 2022; Volume 434, pp. 395–405.
11. Asad, R.; Rehman, S.U.; Imran, A.; Li, J.; Almuhaimeed, A.; Alzahrani, A. Computer-Aided Early Melanoma Brain-Tumor Detection Using Deep-Learning Approach. *Biomedicines* **2023**, *11*, 184. [CrossRef] [PubMed]
12. Özkaraca, O.; Bağrıaçık, O.İ.; Gürüler, H.; Khan, F.; Hussain, J.; Khan, J.; Laila, U.e. Multiple Brain Tumor Classification with Dense CNN Architecture Using Brain MRI Images. *Life* **2023**, *13*, 349. [CrossRef] [PubMed]
13. Meena, S.D.; Bulusu, S.V.; Siddharth, V.S.; Reddy, S.P.; Sheela, J. Brain Tumor Classification Using Transfer Learning. In *Brain Tumor Classification Using Transfer Learning*; CRC Press: Boca Raton, FL, USA, 2023; ISBN 978-1-00-326543-6.
14. Raza, A.; Ayub, H.; Khan, J.A.; Ahmad, I.; Salama, A.S.; Daradkeh, Y.I.; Javeed, D.; Ur Rehman, A.; Hamam, H. A Hybrid Deep Learning-Based Approach for Brain Tumor Classification. *Electronics* **2022**, *11*, 1146. [CrossRef]

15. Iman, M.; Arabnia, H.R.; Rasheed, K. A Review of Deep Transfer Learning and Recent Advancements. *Technologies* **2023**, *11*, 40. [CrossRef]
16. Kaggle Official Web Page. Brain Tumor MRI Dataset. Available online: https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset (accessed on 30 July 2023).
17. Karaman, A.; Pacal, I.; Basturk, A.; Akay, B.; Nalbantoglu, U.; Coskun, S.; Sahin, O.; Karaboga, D. Robust real-time polyp detection system design based on YOLO algorithms by optimizing activation functions and hyper-parameters with artificial bee colony (ABC). *Expert Syst. Appl.* **2023**, *221*, 11974. [CrossRef]
18. Anantharajan, S.; Gunasekaran, S.; Subramanian, T.; Venkatesh, R. MRI brain tumor detection using deep learning and machine learning approaches. *Meas. Sens.* **2024**, *31*, 101026. [CrossRef]
19. Albakri, A.; Alqahtani, Y.M. Internet of Medical Things with a Blockchain-Assisted Smart Healthcare System Using Metaheuristics with a Deep Learning Model. *Appl. Sci.* **2023**, *13*, 6108. [CrossRef]
20. Ahmad, S.; Ullah, T.; Ahmad, I.; Al-Sharabi, A.; Ullah, K.; Khan, R.A.; Rasheed, S.; Ullah, I.; Uddin, M.N.; Ali, M.S. A Novel Hybrid Deep Learning Model for Metastatic Cancer Detection. *Comput. Intell. Neurosci.* **2022**, *2022*, 8141530. [CrossRef]
21. Khan, H.A.; Jue, W.; Mushtaq, M.; Mushtaq, M.U. Brain tumor classification in MRI image using convolutional neural network. *Math. Biosci. Eng.* **2020**, *17*, 6203–6216. [CrossRef]
22. Amin, J.; Sharif, M.; Haldorai, A.; Yasmin, M.; Nayak, R.S. Brain Tumor Detection and Classification Using Machine Learning: A Comprehensive Survey. *Complex Intell. Syst.* **2021**, *8*, 3161–3183. [CrossRef]
23. Minarno, A.E.; Mandiri, M.H.C.; Munarko, Y.; Hariyady, H. Convolutional Neural Network with Hyperparameter Tuning for Brain Tumor Classification. *Kinet. Game Technol. Inf. Syst. Comput. Netw. Comput. Electron. Control* **2021**, *6*. [CrossRef]
24. Toğaçar, M.; Ergen, B.; Cömert, Z. BrainMRNet: Brain Tumor Detection Using Magnetic Resonance Images with a Novel Convolutional Neural Network Model. *Med. Hypotheses* **2020**, *134*, 109531. [CrossRef] [PubMed]
25. Sharif, M.; Amin, J.; Raza, M.; Yasmin, M.; Satapathy, S.C. An Integrated Design of Particle Swarm Optimization (PSO) with Fusion of Features for Detection of Brain Tumor. *Pattern Recognit. Lett.* **2020**, *129*, 150–157. [CrossRef]
26. Rajak, P.; Jangde, A.S.; Gupta, G.P. Towards Design of Brain Tumor Detection Framework Using Deep Transfer Learning Techniques. In *Convergence of Big Data Technologies and Computational Intelligent Techniques*; IGI Global: Hershey, PA, USA, 2023; pp. 90–103.
27. Habiba, S.U.; Islam, M.K.; Nahar, L.; Tasnim, F.; Hossain, M.S.; Andersson, K. Brain-DeepNet: A Deep Learning Based Classifier for Brain Tumor Detection and Classification. In Proceedings of the International Conference on Intelligent Computing & Optimization, Hua Hin, Thailand, 27–28 April 2022; Springer: Berlin/Heidelberg, Germany, 2022; pp. 550–560.
28. Pacal, I.; Serhat, K. Deep learning-based approaches for robust classification of cervical cancer. *Neural Comput. Appl.* **2023**, *35*, 18813–18828. [CrossRef]
29. LeCun, Y.; Bottou, L.; Bengio, Y.; Haffner, P. Gradient-Based Learning Applied to Document Recognition. *Proc. IEEE* **1998**, *86*, 2278–2324. [CrossRef]
30. Kiran; Parameshachari, B.D.; Sunil Kumar, D.S. SVM Based Brain Tumor Detection and Classification System. In Proceedings of the 2022 IEEE 2nd Mysore Sub Section International Conference (MysuruCon), Mysuru, India, 16–17 October 2022; pp. 1–4.
31. Engstrom, L.; Tran, B.; Tsipras, D.; Schmidt, L.; Madry, A. A Rotation and a Translation Suffice: Fooling CNNs with Simple Transformations. *arXiv* **2018**.
32. Goodfellow, I.; Pouget-Abadie, J.; Mirza, M.; Xu, B.; Warde-Farley, D.; Ozair, S.; Courville, A.; Bengio, Y. Generative Adversarial Nets. In Proceedings of the Advances in Neural Information Processing Systems 27, Montreal, QC, Canada, 8–13 December 2014.
33. Begum, S.S.; Lakshmi, D.R. Combining Optimal Wavelet Statistical Texture and Recurrent Neural Network for Tumour Detection and Classification over MRI. *Multimed. Tools Appl.* **2020**, *79*, 14009–14030. [CrossRef]
34. Saeedi, S.; Rezayi, S.; Keshavarz, H.; Niakan Kalhori, S.R. MRI-Based Brain Tumor Detection Using Convolutional Deep Learning Methods and Chosen Machine Learning Techniques. *BMC Med. Inform. Decis. Mak.* **2023**, *23*, 16. [CrossRef]
35. Rahman, T.; Islam, M.S. MRI Brain Tumor Detection and Classification Using Parallel Deep Convolutional Neural Networks. *Meas. Sens.* **2023**, *26*, 100694. [CrossRef]
36. Kumar, S.; Kumar, D. Human Brain Tumor Classification and Segmentation Using CNN. *Multimed. Tools Appl.* **2023**, *82*, 7599–7620. [CrossRef]
37. Kurdi, S.Z.; Ali, M.H.; Jaber, M.M.; Saba, T.; Rehman, A.; Damaševičius, R. Brain Tumor Classification Using Meta-Heuristic Optimized Convolutional Neural Networks. *J. Pers. Med.* **2023**, *13*, 181. [CrossRef] [PubMed]
38. Kalyani, B.J.D.; Meena, K.; Murali, E.; Jayakumar, L.; Saravanan, D. Analysis of MRI Brain Tumor Images Using Deep Learning Techniques. *Soft Comput.* **2023**, *27*, 7535–7542. [CrossRef]
39. Mukherkjee, D.; Saha, P.; Kaplun, D.; Sinitca, A.; Sarkar, R. Brain Tumor Image Generation Using an Aggregation of GAN Models with Style Transfer. *Sci. Rep.* **2022**, *12*, 9141. [CrossRef] [PubMed]
40. Khan, M.S.I.; Rahman, A.; Debnath, T.; Karim, M.R.; Nasir, M.K.; Band, S.S.; Mosavi, A.; Dehzangi, I. Accurate Brain Tumor Detection Using Deep Convolutional Neural Network. *Comput. Struct. Biotechnol. J.* **2022**, *20*, 4733–4745. [CrossRef] [PubMed]
41. Bairagi, V.K.; Gumaste, P.P.; Rajput, S.H.; Chethan, K.S. Automatic Brain Tumor Detection Using CNN Transfer Learning Approach. *Med. Biol. Eng. Comput.* **2023**, *61*, 1821–1836. [CrossRef]
42. Gunasekara, S.R.; Kaldera, H.; Dissanayake, M.B. A Systematic Approach for MRI Brain Tumor Localization and Segmentation Using Deep Learning and Active Contouring. *J. Healthc. Eng.* **2021**, *2021*, 6695108. [CrossRef] [PubMed]

43. Onan, A.; Serdar, K.; Hasan, B. Ensemble of keyword extraction methods and classifiers in text classification. *Expert Syst. Appl.* **2016**, *57*, 232–247. [CrossRef]
44. Onan, A.; Serdar, K.; Hasan, B. A hybrid ensemble pruning approach based on consensus clustering and multi-objective evolutionary algorithm for sentiment classification. *Inf. Process. Manag.* **2017**, *53*, 814–833. [CrossRef]
45. Zhou, D.-X. Theory of Deep Convolutional Neural Networks: Down sampling. *Neural Netw.* **2020**, *124*, 319–327. [CrossRef]
46. Wang, T.; Lu, C.; Yang, M.; Hong, F.; Liu, C. A Hybrid Method for Heartbeat Classification via Convolutional Neural Networks, Multilayer Perceptron, and Focal Loss. *PeerJ Comput. Sci.* **2020**, *6*, e324. [CrossRef]
47. Li, G.; Zhang, M.; Li, J.; Lv, F.; Tong, G. Efficient Densely Connected Convolutional Neural Networks. *Pattern Recognit.* **2021**, *109*, 107610. [CrossRef]
48. Palaz, D.; Magimai-Doss, M.; Collobert, R. End-to-End Acoustic Modeling Using Convolutional Neural Networks for HMM-Based Automatic Speech Recognition. *Speech Commun.* **2019**, *108*, 15–32. [CrossRef]
49. Scherer, D.; Müller, A.; Behnke, S. Evaluation of Pooling Operations in Convolutional Architectures for Object Recognition. In *Artificial Neural Networks—ICANN 2010, Proceedings of the 20th International Conference, Thessaloniki, Greece, 15–18 September 2010*; Springer: Berlin/Heidelberg, Germany, 2010; pp. 92–101.
50. Krizhevsky, A.; Sutskever, I.; Hinton, G.E. Imagenet classification with deep convolutional neural networks. *Commun. ACM* **2017**, *60*, 84–90. [CrossRef]
51. Han, X.; Zhong, Y.; Cao, L.; Zhang, L. Pre-Trained Alexnet Architecture with Pyramid Pooling and Supervision for High Spatial Resolution Remote Sensing Image Scene Classification. *Remote Sens.* **2017**, *9*, 848. [CrossRef]
52. Popuri, K.; Cobzas, D.; Murtha, A.; Jägersand, M. 3D Variational Brain Tumor Segmentation Using Dirichlet Priors on a Clustered Feature Set. *Int. J. Comput. Assist. Radiol. Surg.* **2012**, *7*, 493–506. [CrossRef] [PubMed]
53. Baltruschat, I.M.; Nickisch, H.; Grass, M.; Knopp, T.; Saalbach, A. Comparison of deep learning approaches for multi-label chest X-ray classification. *Sci. Rep.* **2019**, *9*, 6381. [CrossRef] [PubMed]
54. Laila, U.E.; Mahboob, K.; Khan, A.W.; Khan, F.; Taekeun, W. An Ensemble Approach to Predict Early-Stage Diabetes Risk Using Machine Learning: An Empirical Study. *Sensors* **2022**, *22*, 5247. [CrossRef] [PubMed]
55. Munshi, R.M.; Cascone, L.; Alturki, N.; Saidani, O.; Alshardan, A.; Umer, M. A novel approach for breast cancer detection using optimized ensemble learning framework and XAI. *Image Vis. Comput.* **2024**, *142*, 104910. [CrossRef]
56. Harish, P.; Baskar, S. *WITHDRAWN: MRI Based Detection and Classification of Brain Tumor Using Enhanced Faster R-CNN and Alex Net Model*; Elsevier: Amsterdam, The Netherlands, 2020.
57. Wong, S.C.; Gatt, A.; Stamatescu, V.; McDonnell, M.D. Understanding Data Augmentation for Classification: When to Warp? In Proceedings of the 2016 International Conference on Digital Image Computing: Techniques and Applications (DICTA), Gold Coast, QLD, Australia, 30 November 2016—2 December 2016; pp. 1–6.
58. Garcea, F.; Serra, A.; Lamberti, F.; Morra, L. Data augmentation for medical imaging: A systematic literature review. *Comput. Biol. Med.* **2023**, *152*, 106391. [CrossRef]