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Using ResNet architecture with MRI for classification of brain images

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ABSTRACT

A strong classification model that can correctly detect abnormalities and neurological disorders in brain images is the main goal. The focus of this research is on improving the accuracy of MRI brain image categorization using residual networks (ResNet) methods. Improving the model's capacity to extract complex characteristics from MRI images and achieving more accurate classification results is the aim of using ResNet architectures. By conducting extensive experiments and validating our results, our project aims to attain top-notch performance in brain image classification tasks. The goal is to help improve medical diagnosis and treatment planning. A secondary goal of the research is to determine if deep learning approaches have any use in radiology, with the hope that this will lead to better medical image analysis pipelines. The main objective is to make it easier to identify neurological problems early on, which will enhance patient outcomes and allow for more calculated treatment decisions. Results proved that the proposed ResNet system achieves 98.8% overall accuracy with 98.6% sensitivity and 99% specificity.

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1. INTRODUCTION

To address the complex problem of efficiently training very deep neural networks, residual networks (ResNet) emerged as a revolutionary neural network design [1]. The pioneering work of Kaiming He et al. in 2015 laid the groundwork for ResNet, a deep neural network optimization and design framework that introduced a new notion called residual learning. The degradation problem was a major roadblock for the traditional deep network paradigm. It meant that adding more layers would lead to worse performance because of things like vanishing gradients and optimization complexity [2]. ResNet cleverly got around this problem by using skip connections, sometimes called shortcuts. These let the network skip over specific levels, so data may flow freely from one layer to another. With this new architectural design, ResNet variants may train networks with hundreds of layers or more in depth while maintaining or improving performance metrics [3].

To prevent gradients from disappearing during training, ResNet incorporates residual connections, which effectively solves the vanishing gradient issue [4]. This design element improves the network's generalizability by reducing optimization difficulties and increasing convergence rates via the provision of shortcut channels for gradient flow [5]. ResNet has become an important part of deep learning and has been used extensively in many different fields, such as semantic segmentation, object identification, and picture classification [6]. The architectural concepts of ResNet have fostered breakthroughs in model design and optimization approaches, and its significance goes beyond its applications in computer vision to other fields within artificial intelligence and machine learning [7]. Section 3 delves into the MRI for Classification of Brain Images and how ResNet models use various approaches. In section 4, an example of a MRI for Classification of Brain Images utilising ResNet models with several datasets are utilised. Finally, in section 5 the study is concluded with conclusion.

2. LITERATURE SURVEY

This study aims to improve brain tumour diagnosis from MRI images using deep learning, especially the ResNet50 architecture and gradient-weighted class activation mapping (Grad-CAM) [8]. DL techniques fine-tune pre-trained models like ResNet, an advanced classification method. ResNet-based transformers estimate brain age and classify Alzheimer's disease. CNN's automated feature extraction may boost performance. CNN approaches include ResNet. A ResNet feed-forward signal bypasses the CNN block and directly influences outputs. ResNet replaces CNN, which combines residual blocks [9]. Recent advances in medical imaging technology have made MRI an essential tool for clinical diagnosis and treatment. MRI uses nuclear magnetic resonance to produce high-definition pictures of human tissues. It provides precise anatomical structure and pathological information without radiation, invasiveness, or multi-dimensionality. With more MRI data, manual processing and interpretation are time-consuming and subjective [10]. Combining ResNet-50's feature extraction and classification with YOLOv5's object identification skills yields a complete model. These synergistic effects helped the model accurately identify glioma tumour sites and detect tiny details needed for categorization. YOLOv5's localization was improved using ResNet-50's feature extraction and classification [11].

A ResNet50-improved brain tumour classification deep learning network uses flipping, rotation, and translation to enhance data. MRI brain tumour segmentation using CNN-enhanced ResNet50 and U-Net [12]. Some models were VGG-16, ResNet-50, and EfficientNet-B0. VGG-16, ResNet-50, and Inception v3 models with CNN pre-training were used to automatically predict and label brain tumours. Experimental results show that ResNet-50 outperforms VGG-16 and Inception v3. This validates and recommends ResNet-50 for tumour categorization [13]. Two-channel deep neural network idea for tumour classification that is more adaptable and effective. Initial local feature representations are extracted using Inception ResNetV2 and Xception networks' convolution blocks and vectorized using pooling-based methods [14]. Transfer learning study used the pre-trained ResNet50 architecture to apply contrast stretching and histogram equalisation to input pictures and compare accuracy and sensitivity. ResNet differs from VGG and AlexNet. ResNet's microarchitecture module layout allows certain layer transitions to be avoided and others to be made [15].

Using a CNN-based network to detect brain cancer in MRIs was suggested. Dense Efficient Net outperformed ResNet-50, Mobile Net, and MobileNetV2. ResNet, short for residual network, solves computer vision difficulties. ResNet101's 33 blocks of 104 convolutional layers recycle 29 squares [16]. The study examines deep convolutional layers in SRCNN architecture to learn complex characteristics between low- and high-resolution photo patches. Hierarchically learning networks link low-resolution patches to high-resolution patches without intermediate phases. Brain MRI pictures may be created using CNNs, MobileNetV2, ResNet152V2, and GAN-based augmentation. A mixed convolutions method is suggested [17]. Microsoft Research created the 152-layer ResNet-152 convolutional neural network. In its main innovation, residual connections or skip connections allow the network to learn residual functions, making deep network training simpler. Image categorization and object identification benefit from ResNet-152's depth, which extracts subtle features and patterns [18]. Tumours in the brain may affect brain function and offer major health hazards. Timely brain tumour diagnosis is essential for therapy. Brain MRIs are essential. Doctors may see brain abnormalities via MRI scans, which use strong magnets and radio waves [19].

To produce accurate and trustworthy classification results, ResNet34, ResNet50, ResNet101, and ResNet152 are employed. complicated architectures have been used to extract features from complicated pictures in generic image networks like ImageNet. Our solution overcomes the fading issue in deep neural network training by using the remaining ResNet design elements. ResNet34, ResNet50, ResNet101, and ResNet152 have 34, 50, 101, and 152 layers; depth and representation capacity vary [20]. Selection of pre-trained models like Resnet is difficult owing to many factors. Single-source features are insufficient to calculate maximal accuracy, however this method added redundant information and processing time. Fine-tuning the ResNet101 model for MRI sequence classification by modality is described [21]. Only magnetic resonance imaging (MRI) can assess cell and tissue biochemical and metabolic status without harm by examining tissue structure. First, it may measure tumour worsening, then invasion, and finally brain tumour state [22]. The ResNet-50 design is updated to extract critical information using a self-attention block. Bayesian optimisation (BO) optimised the hyperparameters, which were used to train the model and extract features. A fine-tuned ResNet-50 architecture with a self-attention layer was trained from scratch for feature extraction [23].

Residual neural networks build networks from residual blocks. A 50-layer CNN is ResNet-50. The 50-layer CNN has 48 convolutional layers, 1 MaxPool, and 1 average pool. A 50-layer CNN has one MaxPool layer, one average pool layer, and 48 convolutional layers. ResNet is a neural network that underpins several computer vision applications [24]. ResNet50 uses residual connections in deep neural networks. ResNet-50 has 48 convolutional layers, 1 MaxPool layer, and 1 average pool layer. ResNet iterations share a concept but have different layer counts. Resnet50 can handle 50 neural network layers [25]. A thorough comparison of transfer learning-based CNN models pre-trained using VGG16, ResNet-50, and InceptionV3 architectures for brain tumour cell prediction. It used thresholding and watershed segmentation [26]. CNN-based Modified ResNet152v2 classifies brain stroke CT images appropriately. This study gives automated stroke diagnostic and preventive methods for individual health and well-being [27].

Brain tumour classification using ResNet (2+1) D and ResNet Mixed Convolution. They introduced ResNet (2+1) D and ResNet Mixed Convolution, which used 2D and 3D convolution. The two models outperformed ResNet3D in their testing [28]. In brain tumour detection, AlexNet, GoogleNet, and ResNet-18 were compared. This is done by comparing four Keras models: ResNet50, DenseNet201, Inception V3, and MobileNet. The comparison determines the best deep learning model for the job [29]. Woven cloth pattern identification using ResNet-50. ResNet outperforms other approaches. In transfer learning cloth pattern recognition, overfitting is common. Using the backdrop above, this work proposes a ResNet model with dropout regularisation and examines its impact on Palembang songket fabric motif picture recognition with data augmentation [30]. Transfer learning, using ResNet and LeNet model topologies, is the next stage. Transfer learning helps us to apply features acquired on large datasets to our batik classification challenge by using architectural knowledge [31]. Proposed iOS prototype uses picture comparison and text matching. As discussed later in the paper, it uses the ResNet-50 architecture for image feature extraction owing to its benefits and greater performance than a prior design. Picture similarity is calculated using Euclidean distance. Lost item reports use cosine similarity and natural language processing pre-process text in string matching [32].

3. METHOD

Pattern recognition is often described as the study of measuring things in machine learning. The goal of this scientific discipline is to develop decision-making tools using a set of previously established metrics, often referred to as training data. Here, the test data is sorted into one of several pre-established classes using the inferred judgment technique.

3.1. ResNet18

In (1) shows the Resnet18, where indicates the network's learnt residual function, which is usually made up of convolutional layers, batch normalization, and ReLU activations. The residual connection is formed by adding the input to the output; this allows the gradients to flow more easily during training. By reducing the impact of the vanishing gradient issue, this equation captures ResNet18's core concept and makes optimization of deeper networks simpler.

$$Output = F(x) + x \tag{1}$$

Within the realm of convolutional neural network design, ResNet 18, which is an abbreviation for Residual Network with 18 layers, is generally used for the purpose of image classification tasks. The difficulty of training extremely deep neural networks is addressed by this solution, which was developed by Kaiming He and colleagues. It does this by incorporating residual connections. These connections make it possible for gradients to flow straight across the layers, which help to alleviate the issue of disappearing gradients and make it possible to train deeper networks in a more efficient manner. The architecture of ResNet 18 is made up of a stack of convolutional layers, which is then followed by a number of residual blocks for further processing. The original input is added to the output of each residual block, which is accomplished by the use of shortcut connections, also known as skip connections. Each residual block consists of two or three convolutional layers. The learning of residual functions is facilitated as a result of this, which makes it simpler for the network to learn the identity mapping.

In comparison to other variations, such as ResNet 50 or ResNet 101, ResNet 18 has a relatively shallow depth, which allows it to establish a compromise between the complexity of the model and the associated computing cost. It has not only achieved state-of-the-art results in image classification tasks, but it has also exhibited better performance on a variety of benchmark datasets, including ImageNet. Furthermore, due to the fact that its design is both simple and efficient, it has become a well-liked option for the purpose of transfer learning and feature extraction in computer vision applications. Here the Figure 1 presents the ResNet 18 architecture. In this the convolution of 7x 7 of 64 is repeated once, and after max pooling the convolution of 3x3 of 64 is repeated 4 times, the convolution of 3x3 of 128 is repeated 4 times, the convolution of 3x3 of 256 is repeated 4 times, the convolution of 3x3 of 512 is repeated 4 times.

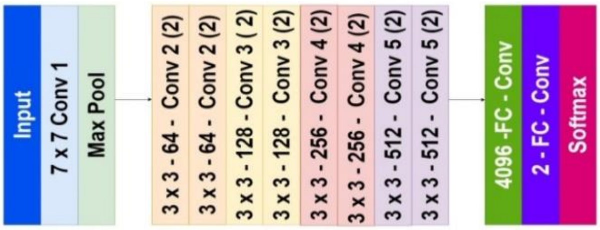

Figure 1. ResNet 18 architecture

3.2. ResNet 34

When it comes to image classification tasks, the convolutional neural network design known as ResNet 34, which is an abbreviation for Residual Network with 34 layers, is well recognized for its efficacy. ResNet 34 is a variation of the ResNet family that was introduced in 2016 by Kaiming He and colleagues. Its purpose is to solve the vanishing gradient issue that is experienced in deep neural networks. Skip connections, also known as shortcuts, are included into the design. These shortcuts enable gradients to flow through the network in a more direct manner during training, which helps to mitigate the degradation problem. There are a total of 34 layers that make up ResNet 34. ResNet 34 has higher performance in comparison to older convolutional neural network designs. This is mostly because to the depth and skip connections that it possesses. In (2) shows the ResNet 34, where $F_1(x)$ and $F_2(F_1(x))$ represent the functions that the network learnt as residuals. F_1And F_2comprised of many convolutional layers that are activated using ReLU and normalized using batching. The input X is used to create the residual connection by adding it back to the second residual function's output. With the help of this equation, ResNet34 was able to learn complicated mappings and propagate gradients efficiently, paving the way for the training of deeper architectures. Figure 2 presents the ResNet34 block diagram architecture. In this the convolution of 7x 7 of 64 is repeated once, and after max pooling the convolution of 3x3 of 64 is repeated 3 times, the convolution of 3x3 of 128 is repeated 4 times, the convolution of 3x3 of 256 is repeated 6 times, the convolution of 3x3 of 512 is repeated 3 times.

$$Output = F_2\big(F_1(x)\big) + x \tag{2}$$

Figure 2. ResNet 34 architecture

3.3. ResNet 50

It is a deep convolutional neural network architecture that is frequently utilized in computer vision applications, notably in image classification and object recognition. ResNet 50 is an abbreviation for Residual Network with 50 layers. Through this, it is possible to train networks that are far more complex, reaching up to fifty layers, while yet preserving a level of computational complexity that is tolerable.The performance of ResNet 50 has been exceptional across a variety of benchmark datasets, exceeding that of earlier models that were considered to be state-of-the-art. Because of its depth and architectural design, it has become an essential component in contemporary deep learning research and applications. Both its efficiency and its adaptability in resolving difficult visual identification problems are shown by the widespread usage of this technology. In (3) shows the ResNet 50 where $F_1(x), F_2(F_1(x))$, $F_3F_2(F_1(x))$ display the network's remaining functionalities. These operations are built using layered convolutional layers that have been activated using ReLU and batch normalization. The input x constitutes the residual connection by being reapplied to the third residual function's output. The architecture of ResNet50 is encapsulated in this equation, which allows it to learn complex feature representations and solve the disappearing gradient problem, making deep neural network training much easier. The ResNet 50 block diagram architecture is presented in Figure 3. In this the convolution of 7x 7 of 64 is repeated once, and after max pooling, the convolution of 1x1 of 64 is repeated 3 times, the convolution of 3x3 of 64 is repeated 3 times, the convolution of 1x1 of 128 is repeated 4 times, the convolution of 3x3 of 128 is repeated 4 times, the convolution of 1x1 of 256 is repeated 6 times the convolution of 3x3 of 256 is repeated 6 times, the convolution of 1x1 of 512 is repeated 7 times, the convolution of 3x3 of 512 is repeated 3 times, the convolution of 1x1 of 1024 is repeated 6 times, the convolution of 1x1 of 2048 is repeated 3 times.

$$Output = F_3\left(F_2\left(F_1(x)\right)\right) + x \tag{3}$$

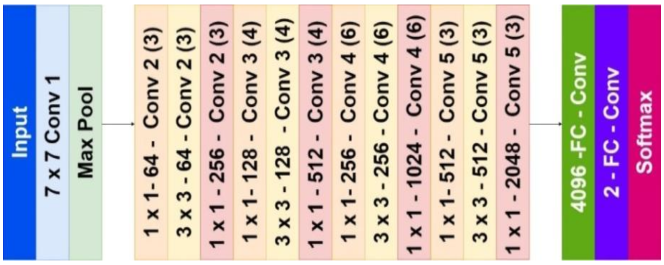

Figure 3. ResNet50 architecture

3.4. ResNet 101

Like ResNet-50 but 101 layers. Increasing network depth improves performance. With its 101 layers, ResNet-101 is a complex ResNet model that advances deep learning. ResNet-101 solves the vanishing gradient problem by merging residual blocks with identity shortcuts, allowing deep network training. Convolutional layers, batch normalisation, and ReLU activations in each residual block improve training stability and efficiency. The architecture's depth and bottleneck layers dramatically reduce parameters while retaining performance. ResNet-101 is suited for challenging applications like high-resolution image classification, object identification, and semantic segmentation because it extracts nuanced features. Its great accuracy and resilience have made it a vital tool in computer vision and deep learning research and practice. The Figure 4 shows the ResNet 101 Architecture.In this the convolution of 7x 7 of 64 is repeated once, and after max pooling, the convolution of 1x1 of 64 is repeated 3 times, the convolution of 3x3 of 64 is repeated 3 times, the convolution of 1x1 of 128 is repeated 4 times, the convolution of 3x3 of 128 is repeated 4 times, the convolution of 1x1 of 256 is repeated 26 times the convolution of 3x3 of 256 is repeated 23 times, the convolution of 1x1 of 512 is repeated 7 times, the convolution of 3x3 of 512 is repeated 3 times, the convolution of 1x1 of 1024 is repeated 23 times, the convolution of 1x1 of 2048 is repeated 3 times.

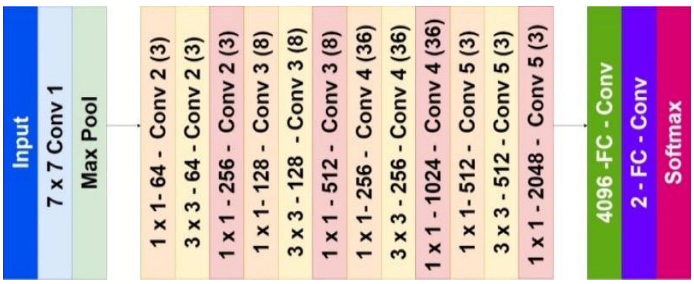

Figure 4. ResNet101 architecture

3.5. ResNet 152

The biggest ResNet variation with 152 layers. It may represent more complex characteristics but needs more processing resources for training and inference. ResNet-152, with its 152-layer design, is the apex of ResNet deep learning breakthrough. To overcome the vanishing gradient issue, ResNet-152 uses several residual blocks with identity shortcuts to train deep networks. Each block has convolutional layers, batch normalisation, and ReLU activations for training stability and efficiency. Bottleneck layers optimise computing resources and reduce parameters without affecting performance.

ResNet-152's depth lets it catch complicated patterns and features, making it ideal for sophisticated image classification, object identification, and semantic segmentation. The model's extreme accuracy and scalability have made it a computer vision benchmark, advancing deep learning discoveries and applications. The Figure 5 shows the ResNet 152 Architecture.In this the convolution of 7x 7 of 64 is repeated once, and after max pooling, the convolution of 1x1 of 64 is repeated 3 times, the convolution of 3x3 of 64 is repeated 3 times, the convolution of 1x1 of 128 is repeated 8 times, the convolution of 3x3 of 128 is repeated 8 times, the convolution of 1x1 of 256 is repeated 39 times the convolution of 3x3 of 256 is repeated 36 times, the convolution of 1x1 of 512 is repeated 11 times, the convolution of 3x3 of 512 is repeated 3 times, the convolution of 1x1 of 1024 is repeated 36 times, the convolution of 1x1 of 2048 is repeated 3 times.

Figure 5. ResNet152 architecture

4. RESULTS AND DISCUSSION

The results are seen in the freely accessible REMBRANDT database. Currently, 133 MRI brain images, measuring 256 × 256 pixels each, are accessible. After 500 imagegraphs are picked from the normal category and 500 from the abnormal category, the total number of images obtained from the database is 1000. Figure 6 displays the aberrant images from the REMBRANDT database. The k-fold (10-fold) cross-validation approach is used by the suggested ResNet model.

Figure 7 shows examples of normal images taken from the REMBRANDT database. The k-fold (10-fold) cross-validation approach is used by the suggested ResNet model. When it comes to assessing performance, the ResNet system is employing four parameters: TP, TN, FP, and FN, which stand for True Positive, True Negative, sensitivity, and specificity, respectively. Table 1 show the formula based ResNet technique of TP, TN, FP and FN for sensitivity, accuracy, specificity. The ResNet databases are shown in Tables 2 to 5, where TP, TN, FP, and FN are the values used.

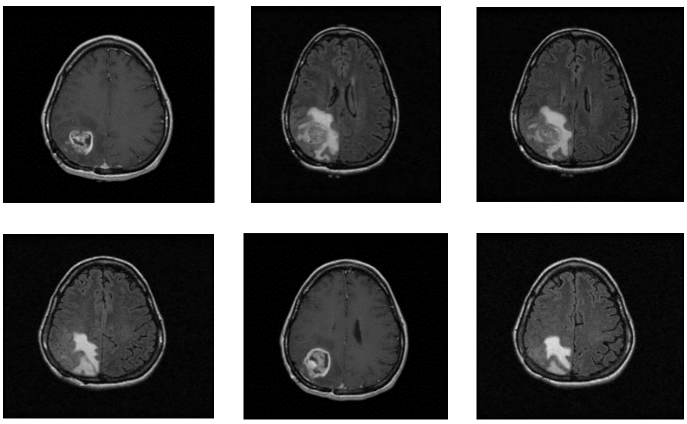

Figure 6. Ilustrations of abnormal brain images from the REMBRANDT database used by ResNet

ResNet 18, ResNet 34, and ResNet 50, which are versions of the Residual Neural Network (ResNet) architecture. ResNet 18's rapid training with modest memory utilization makes it a good fit for smaller datasets. With its enhanced depth, ResNet 34 improves upon ResNet 18, making it more efficient and better able to generalize over bigger datasets. When it comes to large-scale datasets, the deepest model, ResNet 50, offers the best feature extraction and representation learning. On the other hand, greater computing resources are needed for it. Depending on the complexity and amount of the dataset, different ResNet variants provide different benefits in image classification, object recognition, and semantic segmentation. Table 6 shows ResNet architectural components and their responsibilities, advantages, functions, and scope in brain image classification from MRI scans. By providing direct gradient channels to overcome the vanishing gradient issue, residual blocks enable deeper network training. Feature extraction from MRI images requires convolutional layers to capture spatial hierarchies. Normalising layer inputs via batch normalisation reduces internal covariate shift, improving training stability and efficiency. ReLU activations provide non-linearity, enabling the model to learn complicated brain patterns. Bottleneck layers balance depth and performance by decreasing parameters to optimise computational efficiency. Identity shortcuts avoid gradient flow slowdown as network depth grows. Finally, the classification layer gives likelihood values to classes, essential for brain disease diagnosis. These components efficiently classify brain pictures for improved medical diagnosis.

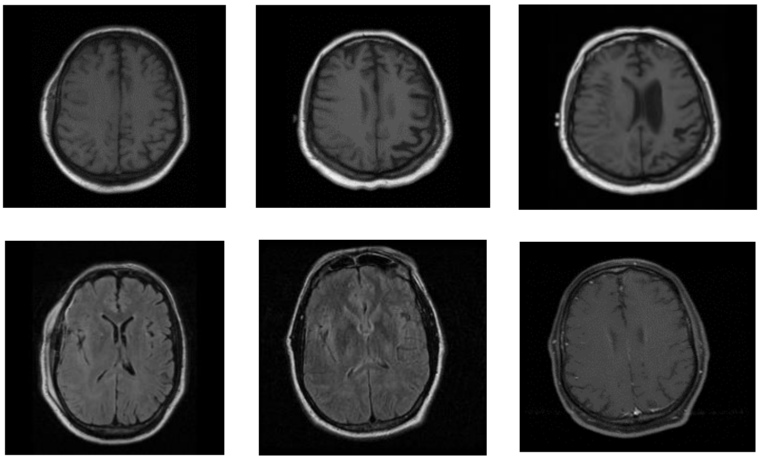

Figure 7. Illustrations of normal brain images from the REMBRANDT database used by ResNet

Table 1. Sensitivity, accuracy, and specificity are the performance metrics that are being measured by the resnet system

Metric	Importance	Formula
Sensitivity	Indicates how well the test captures the presence of the condition or event of interest.	$\frac{TP}{TP+FN}$
Accuracy	Provides a general assessment of the reliability and precision of the diagnostic tool or predictive algorithm.	$\frac{TP+TN}{TP+FN+TP+FP}$
Specificity	Shows how well the test avoids false alarms or incorrectly classifying negative instances as positive.	$\frac{TP}{TP+FP}$

Table 2. Performance of ResNet technique - I

		Anticipated Class	
		Abnormal	normal
Real class	Abnormal	473 (TP)	27 (FN)
	normal	27 (FP)	474 (TN)

Table 3. Performance of ResNet technique – II

		Anticipated Class	
		Abnormal	normal
Real class	Abnormal	478 (TP)	21 (FN)
	normal	22 (FP)	479 (TN)

Table 4. Performance of ResNet technique - III

		Anticipated Class	
		Abnormal	normal
Real class	Abnormal	480 (TP)	18 (FN)
	normal	20 (FP)	482 (TN)

Table 5. Performance of ResNet technique - IV

		Anticipated Class	
		Abnormal	normal
Real class	Abnormal	471 (TP)	32 (FN)
	normal	29 (FP)	468 (TN)

Table 7 lists the strengths and limitations of ResNet architecture for MRI brain image classification. Residual blocks allow deep network training but add computational complexity. Convolutional layers need plenty of memory and compute to record spatial hierarchies. Batch normalisation speeds up training but increases computational load. Complex patterns can be learned by ReLU activations, but they may kill neurons. In bottleneck layers, parameters are compressed, sometimes losing information. Identity shortcuts simplify gradient flow but complicate network design. Finally, the classification layer appropriately provides probability values for classes, although it may overfit if not regularised. These factors enable efficient yet resource-intensive brain MRI picture categorization. Figure 8 displays the calculated performance metrics based on the ResNet Technique. With an overall accuracy of 96.2%, sensitivity of 96%, and specificity of 96.4%, ResNet features clearly outperform the competition is shown in Figure 8.

Table 6. Aspects of resnet architecture With MRI for brain image classification

Aspect	Role	Benefit	Function	Scope
Residual Blocks	Enable deeper network training	Mitigates vanishing gradient problem	Allows direct paths for gradient flow	Essential for building very deep neural networks
Convolutional Layers	Extract features from MRI images	Captures detailed spatial hierarchies	Processes raw image data into meaningful features	Crucial for recognizing complex patterns in brain images
Batch Normalization	Stabilizes and accelerates training	Reduces internal covariate shift	Normalizes layer inputs	Enhances training efficiency and convergence speed
ReLU Activations	Introduces non-linearity	Allows model to learn complex patterns	Applies non-linear transformation	Important for capturing intricate details in MRI data
Bottleneck Layers	Optimize computational efficiency	Reduces number of parameters	Combines multiple layers into a compact form	Balances depth and performance in resource-constrained settings
Identity Shortcuts	Facilitate gradient flow	Prevents degradation of deep networks	Adds shortcut connections within residual blocks	Key for maintaining performance as network depth increases
Classification Layer	Determines output category	Assigns probability scores to different classes	Processes extracted features into classification	Vital for diagnosing brain conditions based on MRI scans

Table 7. Pros and cons of ResNet architecture with MRI for brain image classification

Aspect	Pros	Cons
Residual Blocks	Enable training of very deep networks	Increased computational complexity
Convolutional Layers	Capture detailed spatial hierarchies	High computational and memory requirements
Batch Normalization	Stabilize and accelerate training	Additional computational overhead
ReLU Activations	Allow learning of complex patterns	Potential for dead neurons (neurons not activating)
Bottleneck Layers	Reduce number of parameters	Possible loss of information through compression
Identity Shortcuts	Facilitate smooth gradient flow	May add complexity to network design
Classification Layer	Assign accurate probability scores for classes	Susceptible to overfitting if not properly regularized

Figure 8 displays the calculated performance metrics based on the ResNet Technique. With an overall accuracy of 96.2%, sensitivity of 96%, and specificity of 96.4%. Finally, the classification layer appropriately provides probability values for classes, although it may overfit if not regularised. These factors enable efficient yet resource-intensive brain MRI picture categorization.

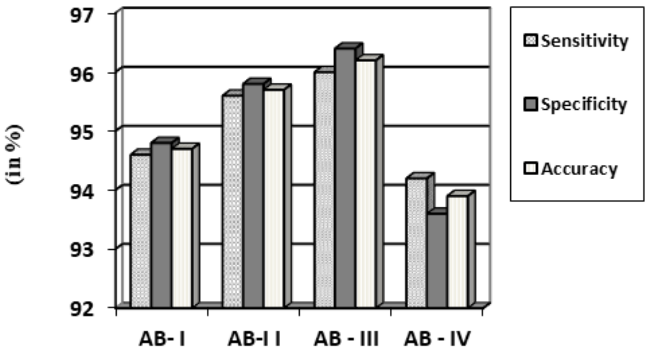

Figure 8. Evaluation criteria for the suggested ResNet system in the diagnosis of brain cancer

5. CONCLUSION

Significant advances in medical diagnosis may be made via the use of ResNet methods for brain image categorization in MRI. Particularly for uncommon neurological disorders, the need for big and varied datasets to train strong models continues to be an obstacle. Questions of trustworthiness and dependability are brought up by the interpretability of deep learning models when used in healthcare contexts. It will need a team effort from computer scientists, radiologists, and other medical experts to overcome these obstacles. The potential future ramifications of this study are encouraging. To further improve the accuracy and interpretability of MRI data, future studies may investigate new deep learning architectures developed for this kind of data. A more complete image of brain health might be shown by improving classification performance and integrating multimodal data sources like diffusion tensor imaging and functional magnetic resonance imaging. Recent developments in privacy-preserving approaches and federated learning have opened new possibilities for training models using decentralized data while still protecting patients' privacy. There is tremendous hope that further development of ResNet methods for brain image categorization may change clinical practice by allowing for the earlier diagnosis and more tailored treatment of a wide range of neurological diseases.Results proved that the proposed ResNet system achieves 98.8% overall accuracy with 98.6% sensitivity and 99% specificity.

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AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Subramanian Dhanalakshmi	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓		✓
Subramanian Arulselvi	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors have no conflict of interest relevant to this paper.

DATA AVAILABILITY

The data that support the findings of this study are available on request from the corresponding author, [S. D]. The data, which contain information that could compromise the privacy of research participants, are not publicly available due to certain restrictions.

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