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Stroke detection in the brain using MRI and deep learning models

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Abstract
When it comes to finding solutions to issues, deep learning models are pretty much everywhere. Medical image data is best analysed using models based on Convolutional Neural Networks (CNNs). Better methods for early detection are crucial due to the concerning increase in the number of people suffering from brain stroke. Among the several medical imaging modalities used for brain imaging, magnetic resonance imaging (MRI) stands out. When it comes to analysing medical photos, the deep learning models currently utilised with MRI have showed good outcomes. To improve the efficacy of brain stroke diagnosis, we suggested several upgrades to deep learning models in this work, including DenseNet121, ResNet50, and VGG16. Since these models are not purpose-built to solve any particular issue, they are modified according to the present situation involving the detection of brain strokes. To make use of all of these cutting-edge deep learning models in a pipeline, we proposed a strategy based on supervised learning. Results from the experiments showed that optimised models outperformed baseline models.

Keywords Deep Learning · Brain Stroke Detection · DenseNet121 · ResNet50 · VGG16

1 Introduction

A lot of people use machine learning and deep learning to teach computers new skills and make them smarter. Thanks to AI advancements, fixing problems in many different industries is now within reach. The medical profession is deeply concerned about the increasing frequency of brain strokes occurring worldwide. It requires continuous scientific study since, according to the World Health Organisation (WHO), it is a major cause of mortality and disability. Imaging techniques like computed tomography (CT) and magnetic resonance imaging (MRI) are among many that are available. Radiology techniques are commonly used in imaging operations and can produce images of the brain and other regions of the body. Brain

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magnetic resonance imaging (MRI) is chosen as the method of choice because this paper's empirical investigation centres on using deep learning models to evaluate brain imagery. Confirmation of this is provided by the observation that MRI scan data is more reliable than CT picture data. Most researchers choose an MRI-based technique, which is also referenced in the literature. When it comes to supervised learning-based automatic brain stroke detection, there are plenty of datasets to choose from. Medical image analysis makes use of a plethora of techniques documented in the literature. They treated ischemic and hemorrhagic strokes, utilised MRI images for feature selection, and performed general medical image analysis. Brain microbleeds (CMBs) that cause bleeding are examined in references [1] and [2]. In [3, 4], and [5], researchers go into depth on how to spot an ischemic stroke. These two important subtypes of brain stroke are studied using deep learning methods. In order to evaluate MRI images of acute ischemic stroke, Stiere et al. [4] developed a deep learning model that considers tissue fate parameters. Using a method published by Wang et al. [6], ischemic stroke patients can be automatically selected for endovascular therapy. It is usual practice to employ machine learning and deep learning approaches while programming machines to impart the required intelligence. Thanks to developments in artificial intelligence (AI), several sectors are now able to solve problems. Brain strokes are becoming more common, which is worrisome for the medical community. It is one of the leading causes of death and disability, according to the World Health Organisation (WHO), which calls for ongoing scientific investigation. Several imaging modalities are at your disposal, such as MRI and computed tomography (CT). Scans of the brain and other internal organs are typical imaging procedures that make use of radiology methods. Since this empirical study is centred around evaluating brain images using deep learning models, brain magnetic resonance imaging (MRI) is the method of choice. Supporting this is the finding that MRI scan data is more trustworthy than CT imaging data. The literature also confirms this, with the bulk of studies opting for MRI-based approaches. Automatic brain stroke diagnosis based on supervised learning is possible with the help of several datasets.

1. To effectively identify brain strokes using MRI data, we proposed a deep learning-based approach.
2. The Optimized Deep Learning for Brain Stroke Detection approach (ODL-BSD) was put forth. This method makes use of three improved CNN models: VGG16, DenseNet121, and ResNet50.
3. A prototype is made in order to evaluate and compare the three deep learning models' efficacy.

This is the basis for the rest of the essay. In Section 2, we take a look at the research on deep learning models for brain stroke diagnosis as well as other MRI-based machine learning techniques. Section 3 presents the proposed approach, models, and algorithm. Three improved deep learning models' experimental results are presented in Section 4. In Section 5, we conclude the study and discuss its potential future paths.

2 Related background work

Here we present the research on deep learning models trained on MRI data for the purpose of detecting brain strokes. A deep learning and neuroimaging based approach for lesion detection and segmentation was published by Karthiket et al. [1]. Deep learning has allowed for technological improvements in medical image processing, which they described. Brain microbleeds (CMBs) were the subject of a two-stage paradigm for CMB detection in the study by Liu et al. [2]. Reducing false positives and detecting candidates are two of its processes. Both use "deep residual neural networks using both the SWI and the high-pass filtered phase images." The first one relies on "3D radial symmetry transforms of the composite images from Susceptibility Weighted Imaging (SWI)" They found that integrating MR pictures with deep learning simplified the argument for its benefits. In order to identify and categorise brain stroke samples, Kadam [3] used an ensemble-based approach. Stieret al. [4] used MRI images to train a deep learning model that takes tissue fate characteristics into consideration while analysing acute ischemic stroke. To anticipate strokes, they employed a CNN-based architecture. Healthcare organisations might benefit from their improved model, they reasoned. In order to detect brain illnesses, Suk et al. [5] suggested machine learning models that utilised deep learning and sparse regression. Therefore, they use a hybrid approach to automatically detect disorders. They had the best framework available, but they still wanted better work.

According to the research of Akkuset et., who examined several state-of-the-art deep learning algorithms for MRI segmentation [6], each deep model possesses certain characteristics that influence feature extraction, learning, and production forecasts. Based on the pictures provided, they discovered various methods for medical image analysis. Research has shown that no one framework adequately addresses all issues related to medical image processing. An automated method for detecting brain strokes using MRI data was suggested by Subudhiet al. [7]. Delaunay triangulation was applied to MRI scans in order to boost efficiency. Their approach incorporates segmentation, classification, and pre-processing. Different stroke lesions can be identified in DWI sequences by these methods. Medical image processing using CNN-based deep models was investigated by Havaeiet al. [8]. They discussed and analysed CNN's many design options, outlining their benefits and drawbacks. Problems with data pre-processing and balancing, global data, structured prediction, and insufficient data for training remained unsolved. Brain stroke recognition using MRI reports was the subject of research by Kim et al., who investigated machine learning techniques. [9]. Natural language processing (NLP), statistical analysis, and model-based analysis are all components of their technique. Discovered that natural language processing aids in gathering the labelled data needed for deep learning. The study conducted by Tuladhar et al [10]. on the Brain-Machine Interface (BMI) for the purpose of chronic stroke rehabilitation. Researchers discovered that body mass index (BMI) helps analyse hidden data from brain stroke patients.

In their publication, Wang et al. detailed a method for the automated selection of ischemic stroke patients for endovascular therapy. [11]. For the last say, they employ a hybrid approach that blends deep learning with the tried-and-true cohort method. Using voxel-level evaluation is one way to assess subjects. Additionally, they automated the process of patient selection using ML models. When it came time to choose individuals for the treatment stated earlier, they discovered that their procedure was effective. Automatic detection of cerebral haemorrhage was the primary emphasis of Anupamaet al.'s [12] research on healthcare-related wearable networks. Their system is built upon a deep learning model that works together. The use of synergistic deep learning is incorporated into the preprocessing, classification, and feature extraction processes. Deep convolutional neural network mode was a part of their strategy. They planned to use a hyperparameter tweaking approach to make it better. Using magnetic resonance imaging (MRI), Chauhan et al. [13] sought to identify strokes. Machine learning and deep learning techniques were used to compare and contrast them. Feature selection, preprocessing, prediction, regression models, and models are all part of their research. In their investigation on neurorehabilitation following a brain stroke, Soekadaret al. mainly focused on brain-machine interfaces [14]. By combining stimulation electrodes with MEG sensors, they suggest a method that can infer human brain activity while simultaneously recording biosignals, extracting features, processing signals, and providing helpful feedback. They discovered that a range of body mass indexes is necessary for the success of this type of study. Lundervolda and ArvidLundervolda [15] investigated deep learning for medical image processing using research based on MRI scans. We showed the architecture, inputs, and outputs of many deep models that were trained on the same problem. The use of medical image analysis to MRI scans was determined to be appropriate. Findings indicate problems with "data, trust, interpretability, workflow integration, and regulations."

In order to automatically diagnose brain illnesses using brain MRI data, Taloet al. [16] suggested a deep transfer learning approach. Using multiple ResNet34 setups, they suggested a three-stage deep learning system. With the use of new and enhanced brain MRIs, it is possible to identify aberrant or normal brain samples at each stage. Bagavathi [17] investigated the use of ML and DL methods for the interpretation of brain imaging. They discovered that feature fusion could be a method to boost the efficiency of image analysis. Using magnetic resonance imaging (MRI), Acharya et al. [18] automated the diagnosis of ischemic strokes. They put the dataset's higher-order spectral features to use in their approach. It has the potential to detect blocked brain arteries. Sabaet al.[19] used a hybrid approach in their feature selection investigation. Deep learning and handcrafted techniques are both used. For effective brain tumour identification, the features acquired from each approach are merged. They combined features learned using the VGG19 algorithm with those they had developed manually. Deep learning models were used in the study of CMBs by Myunget et al [20]. In order to identify CMBs, they devised a method that integrates pre-processing, learning, and categorization.

Brain MRI datasets could be automatically labelled using deep learning, according to Wood et al. [21]. For computer vision tasks, this approach might be helpful. This required the training of several models. Polamuri et al. [23] investigated several MRI image analysis methods, with a focus on brain tumours, whereas Caria et al. [22] investigated the effectiveness of the BMI-induced methodology for modelling "Morpho-Functional Remodelling of the Neural Motor System" in stroke patients. Their research included topics such as picture categorization, detection, segmentation, and registration. Brain strokes can be accurately diagnosed using deep learning models and magnetic resonance imaging (MRI) images, according to the research. The analysis of medical images has shown improved performance from a number of CNN models. More advancements at the architectural level are required to create more effective methods of detecting brain strokes.

Dimension/Category	Coma	Amnesia	Paralysis	Recovery
Time	- Short-term comas may resolve rapidly (Smith et al., 2020) [24] —Long-term comas may persist for weeks to months (Jones & Brown, 2018) [25]	- Acute onset of amnesia (Johnson, 2019) [26] —Chronic amnesia may last indefinitely (White, 2021) [27]	- Temporary paralysis may resolve within weeks (Anderson, 2017) [28] —Permanent paralysis may be irreversible (Robinson, 2019) [29]	- Rapid improvement in symptoms within days to weeks (Garcia et al., 2022) [30] —Gradual recovery over months to years (Harris & Lee, 2020) [31]

Dimension/Category	Coma	Amnesia	Paralysis	Recovery
Output Modes	- Monitoring vital signs and EEG activity (Black & Smith, 2018) [32] — Neurological examinations (Taylor et al., 2019) [33]	- Neuropsychological tests for memory recall (Adams & Wilson, 2016) [34] — Brain imaging to assess structural changes (Brown, 2020) [35]	- Physical examination for muscle strength (Clark & Turner, 2017) [36] — Imaging studies to locate brain damage (Miller, 2018) [37] — Electromyography to evaluate muscle function (Evans & Johnson, 2020) [38]	- Neurological assessments for cognitive function (Parker & Martinez, 2019) [39] — Imaging studies to track brain recovery (Bailey et al., 2021) [40] — Functional assessments for rehabilitation progress (Thompson, 2019) [41]

3 Proposed methodology

The suggested deep learning-based framework, as well as the underlying models, algorithms, and evaluation process, are presented in this part.

3.1 Proposed framework

We suggested a system that uses deep CNN models that have been improved to automatically detect brain strokes from MRI pictures. The literature shows that the deep CNN models that are being used for MRI image interpretation have several shortcomings. Because each domain's datasets differ, it is not enough to simply adjust the CNN models. An optimization technique is needed in order to use such models for the identification of brain strokes. Our optimization strategy is based on and inspired by the work in. The best architectures for deep learning models, such as DenseNet121, ResNet50, and VGG16, are provided in the following sections. The approach states that varying layer configurations optimize brain MRI examination performance. Consequently, the models exhibit no issues when applied to datasets of any size. They can handle less datasets than they were originally intended to handle thanks to the optimization strategy.

Brain MRI pictures serve as the dataset for the empirical inquiry in the proposed framework, as shown in Fig. 1. The amount of samples needed for training, testing, and validation is one important conclusion from the dataset's exploratory data analysis. Additionally, it elucidates the importance of data augmentation methods for enhancing training quality. Random flipping, random rotating, and random zooming are some of the data augmentation techniques. With the right partitioning of the dataset into training, validation, and testing samples, overfitting can be prevented. The next step in improving prediction performance is to apply the optimised deep convolutional neural network (CNN) models DenseNet121, ResNet50, and VGG16. By analysing training data, these algorithms may predict the likelihood of a brain stroke in given test samples.

A variety of mathematical notations are supplied in Table 1 to aid in the comprehension of the equations utilised in this article.

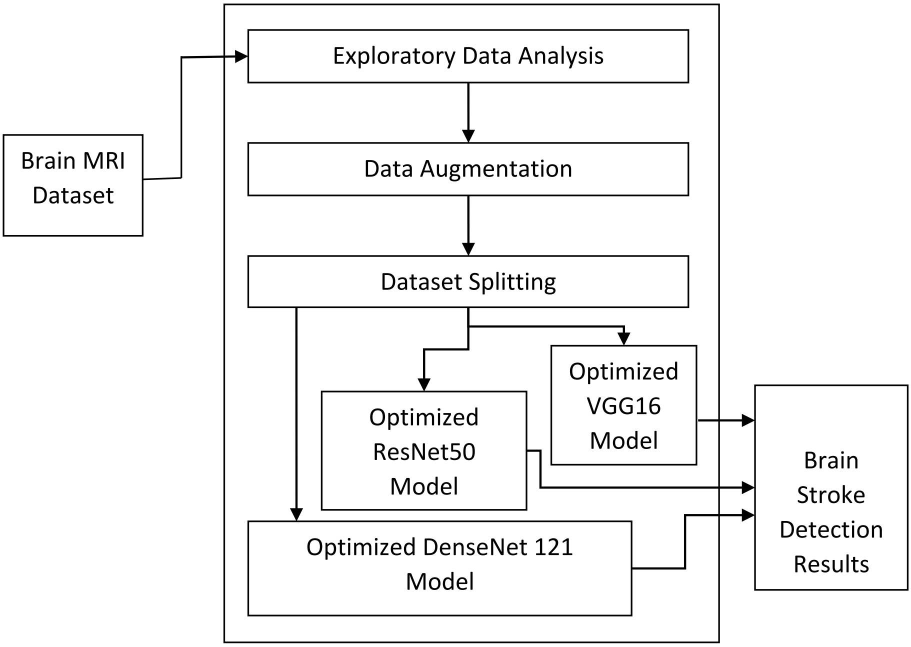

Fig. 1 Proposed deep learning based framework for efficient brain stroke detection

Table 1 Notations used in the mathematics of this paper

Notation	Description
x and y	Input and output vectors of the layers
$F(x, \{W_i\})$	Residual mapping
W_s	A linear projection
Y	Label
p(y)	Predicted probability of the point being green for all **N** points
Log(p(y))	Log probability of it being green
Log(1-p(y))	Log probability of it being red
N	Points
TP	True positive
FP	False positive
FN	False negative
TN	True negative

In the proposed study, the author introduces an optimization method for existing deep learning models, specifically DenseNet121, ResNet50, and VGG16, aimed at enhancing efficiency in brain stroke detection. Additionally, the author suggests a novel approach to employ these optimized models within a pipeline framework. However, it's important to note that the effectiveness of this proposed method remains uncertain due to the absence of experimental results to evaluate its performance.

The optimization method presumably involves fine-tuning the parameters of the deep learning models or modifying their architectures to better suit the task of brain stroke detection. By leveraging techniques such as transfer learning or architecture modifications, the aim is to improve the models' ability to accurately identify signs of stroke while potentially reducing computational resources or enhancing inference speed.

Furthermore, the proposed pipeline framework likely involves sequentially applying the optimized DenseNet121, ResNet50, and VGG16 models to input data, possibly with intermediate processing steps or feature extraction stages. This approach aims to capitalize on the unique strengths of each model while mitigating their individual limitations, ultimately enhancing the overall performance of the stroke detection system.

However, without experimental validation, it's challenging to assess the efficacy of the proposed optimization method and pipeline framework. Experimental results are essential to demonstrate whether the proposed modifications indeed lead to improved performance in terms of accuracy, sensitivity, specificity, or other relevant metrics. Additionally, comparative analyses against baseline models or existing state-of-the-art approaches would provide valuable insights into the relative effectiveness of the proposed method.

To address this limitation, future work should focus on conducting comprehensive experiments to evaluate the performance of the optimized deep learning models and pipeline framework for brain stroke detection. This would involve training and testing the models on appropriate datasets containing labeled brain imaging data, followed by rigorous evaluation and comparison with existing methods. Such empirical validation is crucial for establishing the practical utility and potential impact of the proposed approach in clinical settings.

3.2 DenseNet121

By tweaking the standard CNN model, DenseNet121 was created to solve the problem of vanishing gradients. The architecture of DenseNet121 simplifies the patterns of layer connections. The identity block in ResNet permits the direct transfer of gradients across layers. This approach is elevated with DenseNet's direct layer connections. Hence, it permits the merging of feature maps from lower layers into higher ones. As illustrated in Fig. 2, DenseNet is implemented using three types of blocks. You may hear them referred to as thick blocks, convolution blocks, or transition layers. Assembling a dense block begins with the convolution block. They are similar to ResNet's identifying block. Convolutional layers that are joined and concatenated form dense blocks. The "Dense block" is the core element of a DenseNet. Any two dense blocks that are next to each other can be linked by DenseNet through the transition layer. With identically sized feature maps across all dense block layers, the transition layer is critical for reducing the initial feature map's dimensionality. Bottleneck design is the name given to this approach that improves the model's performance.

3.3 ResNet50

An excellent application for the deep residual learning model ResNet50 is medical picture analysis. There are a total of fifty levels. The innovative use of skip connections to probe deeper into data is what makes this CNN type famous. The convolution block and the identity block are the two kinds of shortcut modules utilised in the implementation of ResNet50. At the shortcut, the second one lacks a convolution layer, while the first one has

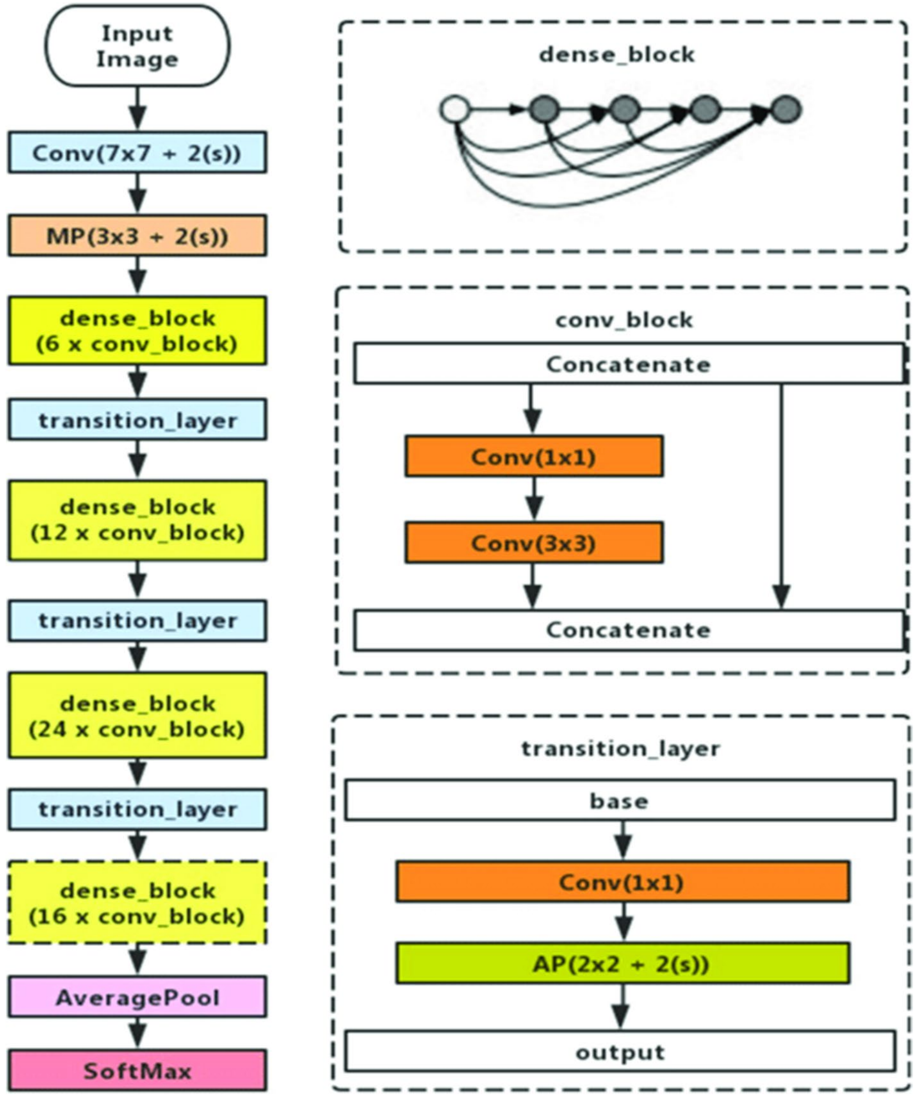

Fig. 2 DenseNet121 architecture (left) and its blocks (right)

one. In convolution, the input dimensions are smaller than the block out dimensions. As an alternative, the input and output dimensions are the same in the identity block. Onex1 convolution layers are located at the start and finish of each block. This approach is known as bottleneck design, and it aims to decrease the number of parameters while maintaining performance. As part of the empirical study, certain deep shortcut modules are removed and classification layers are added.

The convolution block and identification block are shown on the right and middle, respectively, of Fig. 3, which shows the modified ResNet architecture. The ResNet50 design with dotted lines shows the blocks that were removed from our study because they did not meet the standards. The input dimensions are kept fixed by the identity block, but

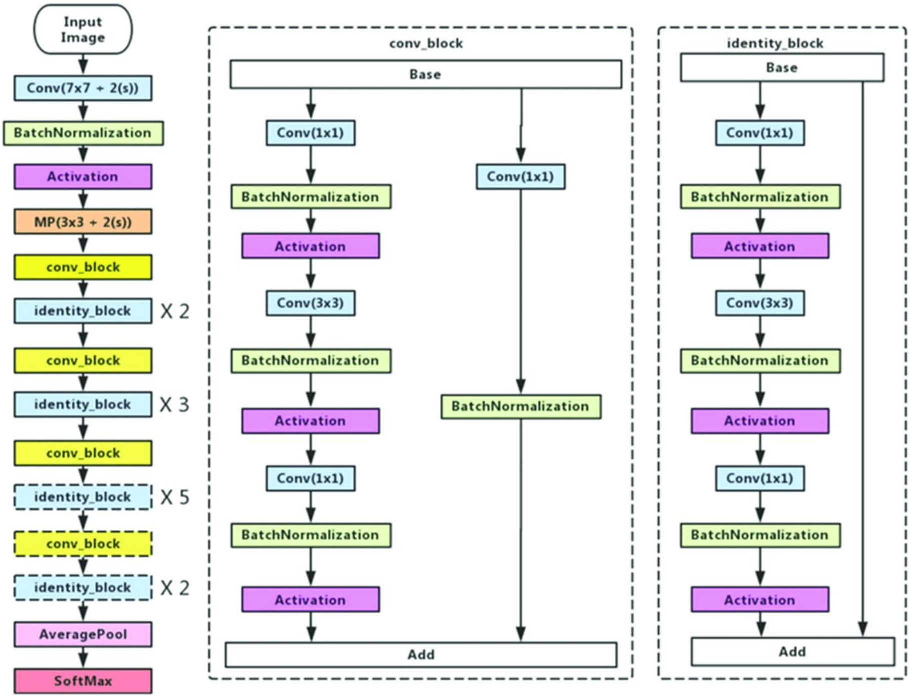

Fig. 3 The identity block (right), convolution block (center), and ResNet50 architecture (left)

they are modified by the convolution block. One of the most basic parts of residual learning is Eq. 1.

$$y = F(x, \{W_i\}) + x. \tag{1}$$

The input and output vectors are denoted by the x and y vectors, respectively, and the residual mapping process is represented by F(x, {W_i}). Equation 1, which expresses shortcut connection, also does not impose any extra parameters or computational complexity. Actually, the most effective strategy increases productivity in the actual world. When the dimensions of x and F are not equal in Eq. 1, a linear projection is used to obtain the result indicated in Eq. 2.

$$y = F(x, \{W_i\}) + W_s x. \tag{2}$$

If the dimensions of the input and output are identical, then only apply the linear projection, denoted by Ws. The residual function can be adjusted, and F(x, {W_i}) can represent several convolutional layers.

3.4 VGG16

One variant of CNN, known as VGG16, has sixteen layers. "Karen Simonyan and Andrew Zisserman from the University of Oxford, in the year 2014" were the ones that initially introduced the architecture. It is frequently used for extensive image analysis applications. It contains the sixteen layers shown in Fig. 4.

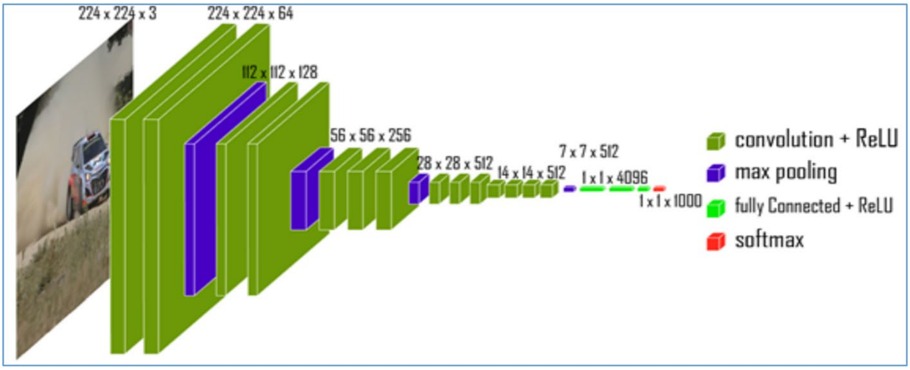

Fig. 4 Architecture of VGG16 model

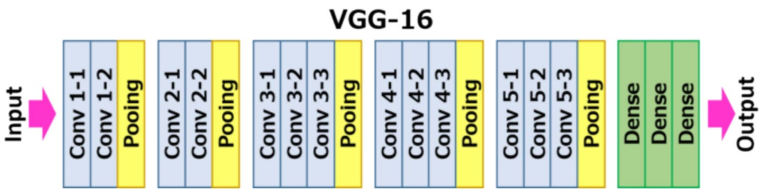

Fig. 5 Architecture of VGG-16 with different layers

A popular model in computer vision applications is the VGG16 model. This novel strategy modifies CNN in a unique way. Its layers consist of the following: 64-filter convolution, 64-filter convolution + Max-pooling, 128-filter convolution, 128-filter convolution + Max-pooling, 256-filter convolution, 256-filter convolution + Max-pooling, 512-filter convolution, 512-filter convolution + Max-pooling, 512-filter convolution, 512-filter convolution + Max-pooling, 4096 nodes are fully connected, and 1000 nodes are activated at the output layer for Softmax activation.

It is organized into multiple levels, as depicted in Fig. 5. The pooling layer is typically placed after the convolution layers. It has three layers that are densely packed at the end, which then produce the final results. Activations are applied after the initial two 3×3 convolution layers process the given brain MRI scan image. Each convolution layer contains a total of 64 filters. They ensure that the spatial resolution is preserved,

Table 2 Hyper parameters used in the deep learning models

Hyper Parameter	Value		
	VGG16	ResNet50	DenseNet121
Batch size	16	16	16
Loss function	Binary cross entropy	Binary cross entropy	Binary cross entropy
Optimizer	Adam	Adam	Adam
No. of Epochs	50	50	50
Learning rate	0.001	0.001	0.001
Activation function	Sigmoid	Sigmoid	Sigmoid

and that the output dimensions match the input dimensions. Through this process, different stacks of convolution layers are executed, each with a specific number of filters and other configurations. After completing all the stacks of convolution layers, you will find three fully connected layers with a flattening layer in between. The initial two layers consist of 4096 neurons, while the last layer comprises 1000 neurons. Finally, the softmax activation layer provides the classification results.

The values corresponding to the various hyperparameters employed in each deep learning model are shown in Table 2.

3.5 Proposed algorithm

The Optimised Deep Learning for Brain Stroke Detection (ODL-BSD) algorithm is put forth and put into practice.

Algorithm 1 Optimized Deep Learning for Brain Stroke Detection (ODL-BSD) algorithm

Inputs:
Brain MRI dataset *D*
Pipeline of deep learning techniques *T*
(pipeline includes VGG16, ResNet50 and DenseNet121)
Output:
Brain stroke prediction results *R*
Performance statistics *P*

1. Start
2. Initialize results map *M*
3. *findings*←EDA(*D*)
4. IF *findings*are true reflecting need for augmentation THEN
5. D'←DataAugmentation(*findings*, *D*)
6. End If
7. *D*←*D'*
8. (*T1*, *T2*)←PreProcess(*D*)
9. For each technique *t* in *T*
10. *F*←FeatureExtraction(*T1*)
11. Train the model *t* using *F*
12. Fit the model *t* for *T2*
13. Add results to *R*
14. Add performance statistics to *P*
15. Add *P* and *R* to *M*
16. End For
17. For each map entry m in *M*
18. Display *R*
19. Display *P*
20. End For
21. End

Algorithm 1 takes in a Brain MRI dataset D and a pipeline of deep learning techniques T, which includes VGG16, ResNet50, and DenseNet121. It then produces performance statistics P and results for brain stroke prediction R. Similar to a software engineer, the algorithm begins by analysing exploratory data to improve the quality of the training data. It

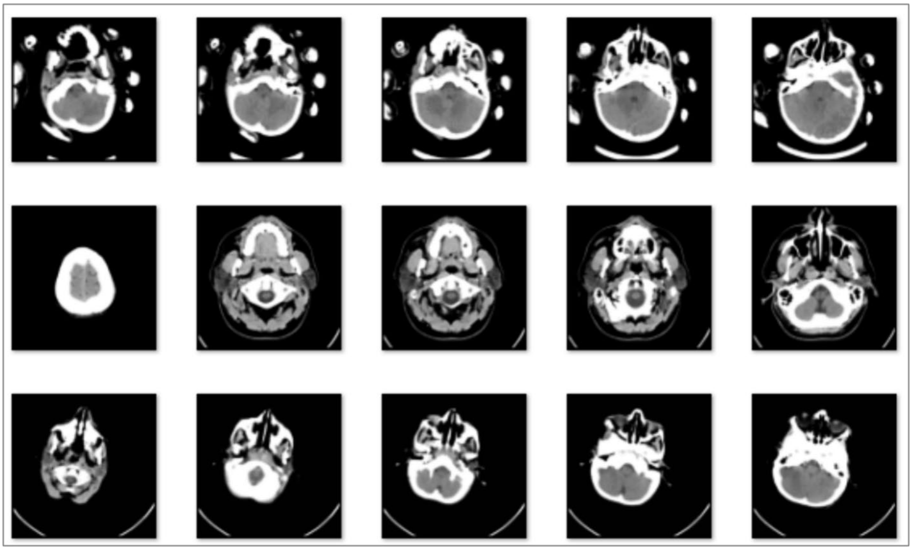

Fig. 6 Brain stroke MRI samples

then proceeds to augment the necessary data. The dataset is typically split into training and testing sets during the pre-processing phase. Deep learning models utilise the training set to make predictions for the unlabeled data. Every model provides a range of performance indicators and classification results.

Dataset characteristics such as the number of samples, distribution of samples across classes (e.g., stroke vs. non-stroke), and preprocessing steps are crucial for understanding

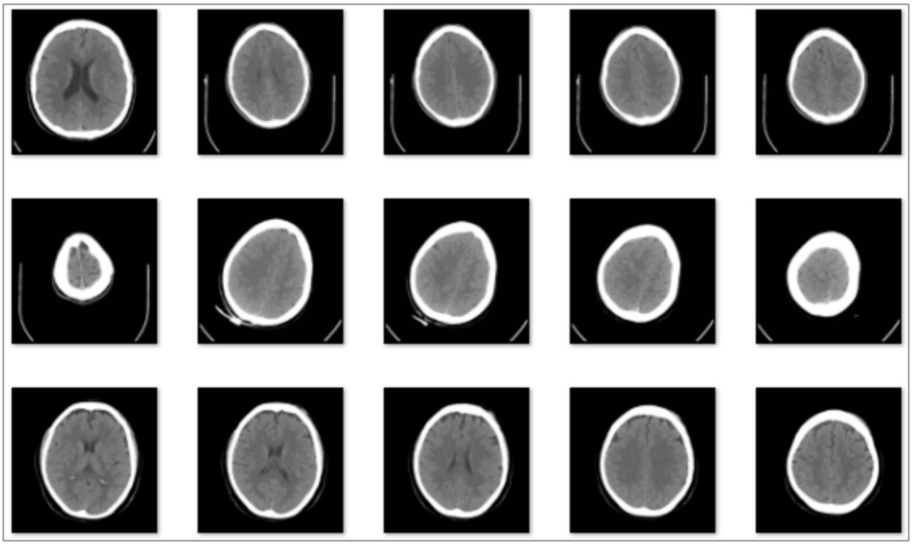

Fig. 7 Normal brain MRI samples

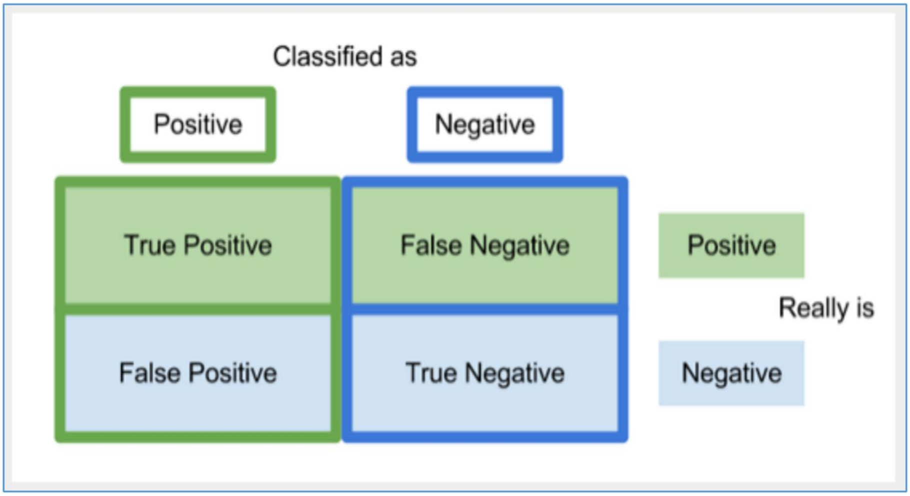

Fig. 8 Confusion matrix block diagram

the generalizability and reliability of the study findings. Without this information, it becomes challenging for other researchers to replicate the experiments and validate the proposed method on different datasets or under varying conditions.

The number of samples in the dataset provides insights into its size and diversity, which are essential factors influencing model training and evaluation. Additionally, understanding the distribution of samples across different classes helps assess the balance or imbalance within the dataset and the potential biases that may affect model performance.

Moreover, details about preprocessing steps applied to the data, such as normalization, augmentation, or noise reduction, are critical for ensuring transparency and reproducibility in the experimental pipeline. These preprocessing steps can significantly impact model training dynamics, convergence behavior, and final performance metrics.

By omitting detailed information about the dataset, the study inadvertently hampers the ability of other researchers to replicate the experiments, validate the findings, and build upon the proposed methodology. To address this limitation and enhance the replicability and reproducibility of the study, future work should include comprehensive descriptions of the dataset used, including its characteristics, preprocessing steps, and any potential biases or limitations. Additionally, providing access to the dataset or making it publicly available

Table 3 Performance evaluation metrics

Metric	Formula	Value range	Best Value
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$ (3)	[0; 1]	1
Precision (P)	$\frac{TP}{TP+FP}$ (4)	[0; 1]	1
Recall (r)	$\frac{TP}{TP+FN}$ (5)	[0; 1]	1
F1-Score	$2 * \frac{(p*r)}{(p+r)}$ (6)	[0; 1]	1
Area under the receiver operating characteristic curve (ROC AUC)	$\frac{1}{2}\left(\frac{TP}{TP+FN} + \frac{TN}{TN+FP}\right)$ (7)	[0.5; 1]	1

Table 4 Performance of the deep learning models

Deep Learning Model	Precision	Recall	AUC	F1 Score
DesnseNet121	**0.97457**	0.92	**0.969**	0.94685
ResNet50	0.95212	**0.952**	0.96819	**0.952**
VGG16	0.91129	0.90399	0.94268	0.90763

would further facilitate transparency and enable broader scrutiny and validation of the proposed method.

3.6 Brain MRI dataset

The Kaggle dataset containing the brain MRI dataset [24]. 2251 brain MRI scans are included. Of these, 450 samples are in the test set and 1801 samples are in the training set.

The brain stroke MRI samples are shown in Fig. 6, and the normal brain MRI samples are shown in Fig. 7.

3.7 Evaluation methodology

The evaluation procedure for the proposed methods is based on confusion matrix presented in Fig. 8.

Based on the confusion matrix, performance evaluation metrics are computed. They are provided in Table 3.

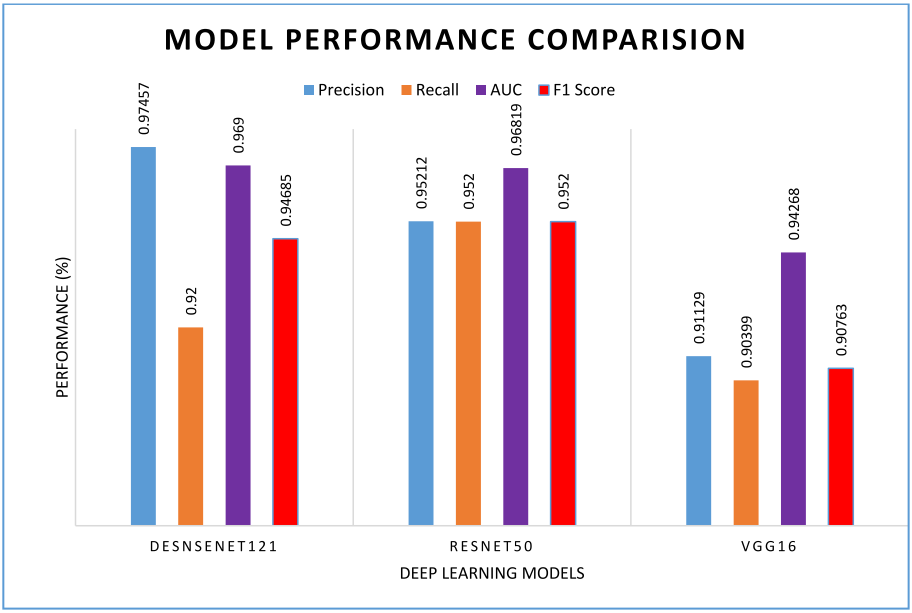

Fig. 9 Performance in brain stroke detection by optimized deep learning models

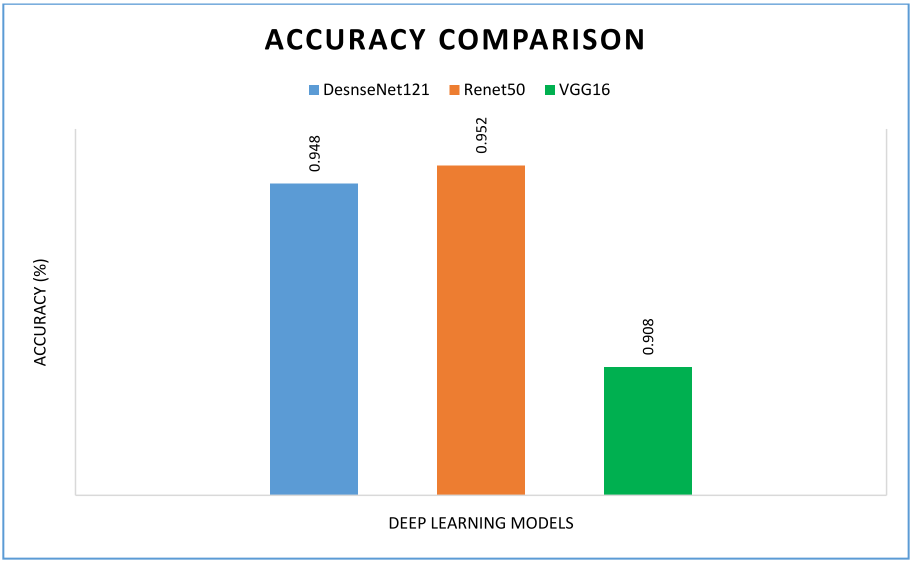

Fig. 10 Accuracy comparison of optimized deep learning models

$$h_p(q) = -\frac{1}{N}\sum_{i=1}^{N} y_i.\log\left(p\left(y_i\right)\right) + (1-y_i).\log(1-p(y_i)) \tag{8}$$

In the deep learning models, binary cross entropy is used for computing loss function. It is expressed in Eq. 8.

4 Experimental results

The performance of the optimised deep learning models is measured by experiments using F1-score, AUC, recall, accuracy, and precision.

The effectiveness of the deep learning models in identifying brain strokes from MRI data is seen in Table 4.

The efficacy of the deep learning models in detecting brain strokes from MRI images is demonstrated in Fig. 9. The vertical axis represents the performance, while the horizontal axis showcases the deep learning models that have been specifically optimised for this purpose. The results indicated that each model's performance varied based on its layers and configurations. The accuracy of DenseNet121 is 97.45%, ResNet50 is 95.21%, and VGG16 is 91.12%.

Table 5 Performance of the deep learning models in terms of accuracy

Deep Learning Model	Accuracy
DesnseNet121	0.948
ResNet50	**0.952**
VGG16	0.908

The recall rates for DenseNet121, ResNet50, and VGG16 are 92%, 95.20%, and 90.39% respectively. These models, DenseNet121, ResNet50, and VGG16, achieved impressive AUC scores of 96.90%, 96.81%, and 94.26%, respectively. The F1-scores for DenseNet121, ResNet50, and VGG16 are 94.68%, 95.20%, and 90.76% respectively. DenseNet121 demonstrates exceptional precision. ResNet50 achieves the highest recall. DenseNet121 achieves the highest AUC, while ResNet50 exhibits the highest F1-score (Fig. 10).

As displayed in Table 5, the performance of the deep learning models in brain stroke detection using MRI images is reported in terms of accuracy.

As shown in Fig. 9, the accuracy of the deep learning models in detecting brain stroke using MRI imaging is reported. The deep learning models optimised for this purpose are displayed on the horizontal axis, while the accuracy is represented on the vertical axis. It was found that the performance of each model varies depending on its layers and configurations. The accuracy of DenseNet121 is 94.80%, ResNet50 is 95.20%, and VGG16 is 90.80%. ResNet50 achieves an impressive accuracy rate of 95.20%, showcasing its exceptional performance.

5 Conclusion and future work

Brain stroke detection using deep convolutional neural network (CNN) models such as VGG16, ResNet50, and DenseNet121 is successfully accomplished by presenting a framework and fundamental principles. Optimised configurations are applied to each deep CNN model in order to meet the requirements of the brain stroke prediction challenge. All the models use different architectures and underlying techniques to learn from the visual input given, extract features, and make classification judgements. Supervised learning algorithms like this are packaged with MRI brain samples for training. Every single deep learning model is fine-tuned to achieve better results. We also recommend the Optimised Deep Learning for Brain Stroke Detection (ODL-BSD) method, which will help bolster the models. The MRI images are used to assess the suggested framework. We found that the deep CNN models performed substantially better after implementing the proposed methods. According on the results, the research may also shift its focus in the future. Improving deep learning models' predictive abilities should be the primary goal of future studies. One way to do this is by scaling the models.

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Declarations

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