Intelligent Systems with Applications 22 (2024) 200388

Contents lists available at ScienceDirect

Intelligent Systems with Applications

journal homepage: www.journals.elsevier.com/intelligent-systems-with-applications

Classification of Vascular Dementia on magnetic resonance imaging using deep learning architectures

Hina Tufail [a,1], Abdul Ahad [a,b,c,1], Mustahsan Hammad Naqvi [a,1], Rahman Maqsood [a,1], Ivan Miguel Pires [d,*,1]

[a] Knowledge Unit of Systems and Technology, University of Management and Technology, Sialkot, Pakistan
[b] School of Software, Northwestern Polytechnical University, Xian, Shaanxi, 710072, PR China
[c] Department of Electronics and Communication Engineering, Istanbul Technical University (ITU), 34467, Turkey
[d] Instituto de Telecomunicações, Escola Superior de Tecnologia e Gestão de Águeda, Universidade de Aveiro, 3750-127, Águeda, Portugal

ARTICLE INFO

Keywords:
Convolutional neural network
Densely connected convolutional network
Magnetic resonance imaging
Vascular dementia
Visual geometry group

ABSTRACT

Vascular Dementia is a severe disease that results from dead nerve cells' accumulation in blood vessels. This affects the blood flow and impairs memory and decision-making abilities. Machine learning and deep learning have been used in detecting this disease. Nevertheless, their accuracy has been inconsistent, explaining why their utilization in diagnosing patients has led to poor performance. We developed several transfer learning architectures that improve classification accuracy and diagnosis performance in assessing vascular dementia. The process first entails the preprocessing of the dataset where a random selection ensures data representation is balanced. We used a dataset containing resting-state fMRI scans to split training, testing, and validation into 80%, 10%, and 10%. We employ different Convolutional Neural Network architectures such as VGG16, VGG19, DenseNet121, and InceptionResNetV2 to enhance classification. To, enhance these, we incorporated Rectified Linear Unit and leaky activation functions for the training phase to counteract problems associated with vanishing gradient common in deep learning tasks. Our methodology ensures effective information flow throughout different layers, which is essential for a divergent information hierarchy in medical information. As such, the specifics show that our approach achieved 84.67% in accuracy in the multi-classification, which is better than the current state-of-the-art research in the same field. Therefore, the result shows that transfer learning-based approaches are suitable when combined with strategic pre-processing and activation functions in improving the diagnosis of vascular dementia using MRI images.

1. Introduction

Healthcare is undergoing a profound transformation, transitioning from traditional methods to advanced approaches. Central to this evolution is cutting-edge communication technologies like 5G and beyond 5G (B5G), alongside the integration of machine learning and deep learning algorithms (Ahad et al., 2024; Butt, Ahad, Wasim, Madeira, & Chamran, 2023). These technologies play pivotal roles in enabling smart healthcare systems and revolutionizing how medical services are delivered, monitored, and optimized. With 5G/B5G's ultra-fast speeds, low latency, and high capacity, healthcare professionals can leverage real-time data transmission for remote consultations, surgical procedures, and patient monitoring, irrespective of geographical constraints (Ahad et al., 2023). Machine learning and deep learning further enhance this paradigm shift by analyzing vast datasets to predict diseases, personalize treatments, and streamline administrative tasks (Butt, Ahad, Wasim, Shayea et al., 2023).

In recent years, unprecedented progress in the field of biomedical image analysis and artificial intelligence has led to a new understanding of and method for diagnosing many pathologies. Cancer remains a difficult issue in the global medical field. Dementia is defined as a progressive decline in cognitive function that interferes with a person's ability to learn new information and recall previously learned information (Iadecola, 2013; Román, 2002). Among the types of the enigmatic pathology, Vascular Dementia is the second most prevalent, after Alzheimer's disease . According to research, VD affects approximately 15% to 20% of patients with another dementia in Europe and the United States and even more in Asian countries — up to 30% (Liu, Yao, Liu, & Sato, 2019). Etiologically, just like AD, the incidence of VD

* Corresponding author.
E-mail addresses: ahad9388@gmail.com (A. Ahad), impires@ua.pt (I.M. Pires).
[1] All authors contributed equally to the manuscript.

https://doi.org/10.1016/j.iswa.2024.200388
Received 27 February 2024; Received in revised form 22 April 2024; Accepted 16 May 2024
Available online 18 May 2024

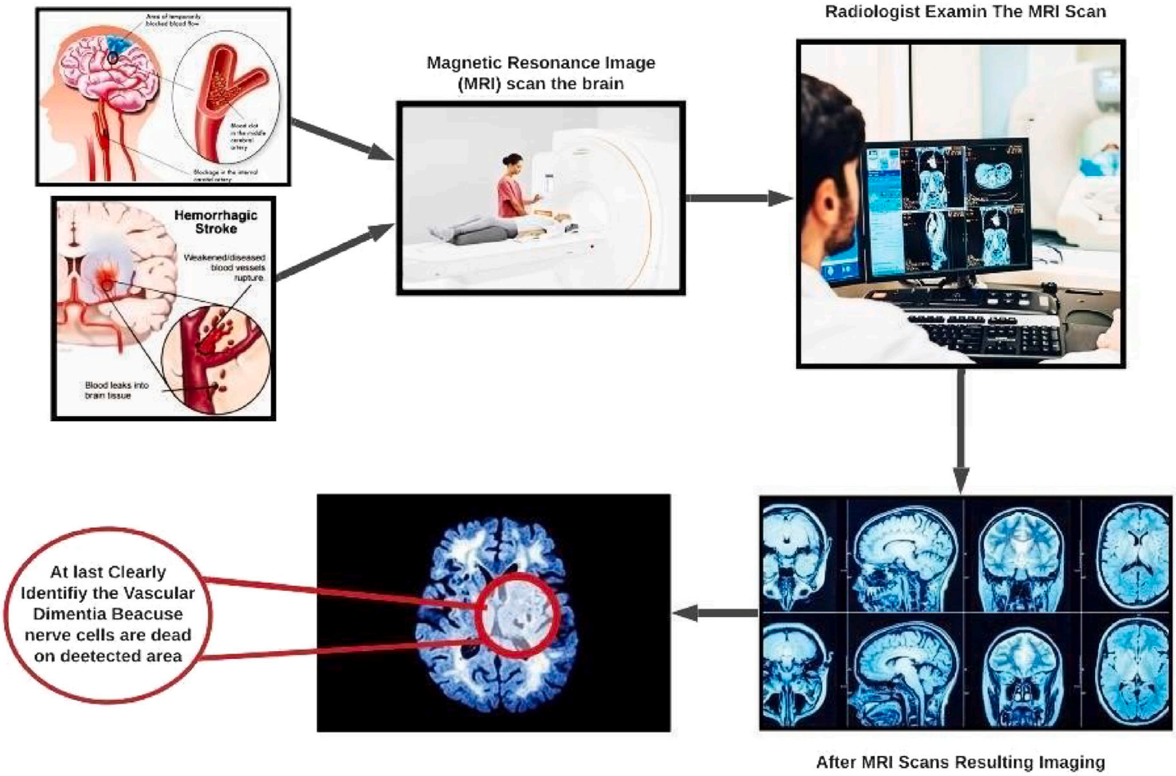

Fig. 1. A general way to identify the disease.

increases with age; therefore, this issue is of special relevance in aging populations worldwide. Vascular dementia is a broad term for cognitive impairment due to brain tissue damage from major artery strokes, vessel narrowing, and other vascular lesions. VD presents many clinical challenges given its high prevalence and poor treatment response (Li, Hsu, & Rudzicz, 2019). VD is both a critical and a preventable diagnosis. Therefore, accounting for its high tendency and morbidity is essential. However, low incidence should also be accounted for given the high contrast between potential therapies and outcomes in those diagnosed and untreated. Advanced techniques such as Diffusion Tensor Imaging (DTI) and resting-state functional magnetic resonance imaging (rs-fMRI) have significantly expanded the potential to study changes in the brain function and structure typical of dementia (Braaten, Parsons, McCue, Sellers, & Burns, 2006; T. O'Brien & Thomas, 2015). As a result, they can be extensively employed for diagnosis and classification. Deep learning is a form of artificial intelligence that has revolutionized several fascinating areas lately: DNA analysis, computer vision, natural language processing, and brain circuitry. A general way to identify the VD is illustrated in Fig. 1.

Deep learning algorithms are well-suited for learning complex patterns and representations from data. In many modern applications, they are the most effective tool to achieve the desired results. It is particularly relevant in medical image analysis (He, Gao, Sabnis, & Sun, 2023; Morton, St. John, & Tyas, 2019). Despite this fact, in the study of Vascular Dementia, there is still no effective way to detect and classify VD with high accuracy and efficiency. The novel deep-learning approach to the application of deep-learning architectures on rs-fMRI datasets will improve the performance of detection for early detection of VD. Such a tool will also enable the multi-classification of VD cases, which is currently impossible due to the classification gap (Shankle, Mani, Pazzani, & Smyth, 1997; Wang, Xu, Zhao, & Lou, 2019). Thus, the primary goals of the research are:

- To analyze the characteristics and applicability of deep-learning architectures in early detection of VD based on the rs-fMRI data.
- To assess the feasibility of discovering multiple phenomena of VD and creating a divided and advanced classification system.
- Get insights on deep learning-based methodologies: advantages and limitations for VD diagnosis and classification.
- Develop a framework to help neurosurgeons and radiologists more efficiently recognize and classify VD cases to improve treatment procedures for patients.

The research on deep learning's role in VD diagnosis and classification could make a substantial contribution to neuroimaging and dementia research. It could have a significant impact on patient outcomes and treatment approaches. Ultimately, different classifiers are used to distribute the data equally in two classes for binary classification. The number of output neurons can be increased to classify the results into multiple forms (multi-classification) . The most common approach used for training a model is the backpropagation approach. This research reviewed recent literature and found one of the best methodologies for detecting VD and its classification. It also represents the methodology for detecting the VD early and multi-classifying them using different deep learning-based architectures with highly normalized datasets (Charidimou, Jäger, & Werring, 2012). A general model that finds the best results is illustrated in Fig. 2.

Around 17% of people affected with Dementia will have VD. Estimations showed that the 65 age group has an excessive effect on this disease. On the Other hand, in terms of detection and classification, no vacant accuracies exist with a machine learning algorithm that proves the person has VD 100%. Existing Machine learning-based architectures cannot classify VD into Multiple divisions. Hence, these are the main factors to conduct this research study.

1.1. *Contribution and organization of the paper*

The present study's main value is that it thoroughly analyzes the rs-fMRI dataset using a range of deep learning architectures. We sought to identify the best-performing model for early-stage VD detection by

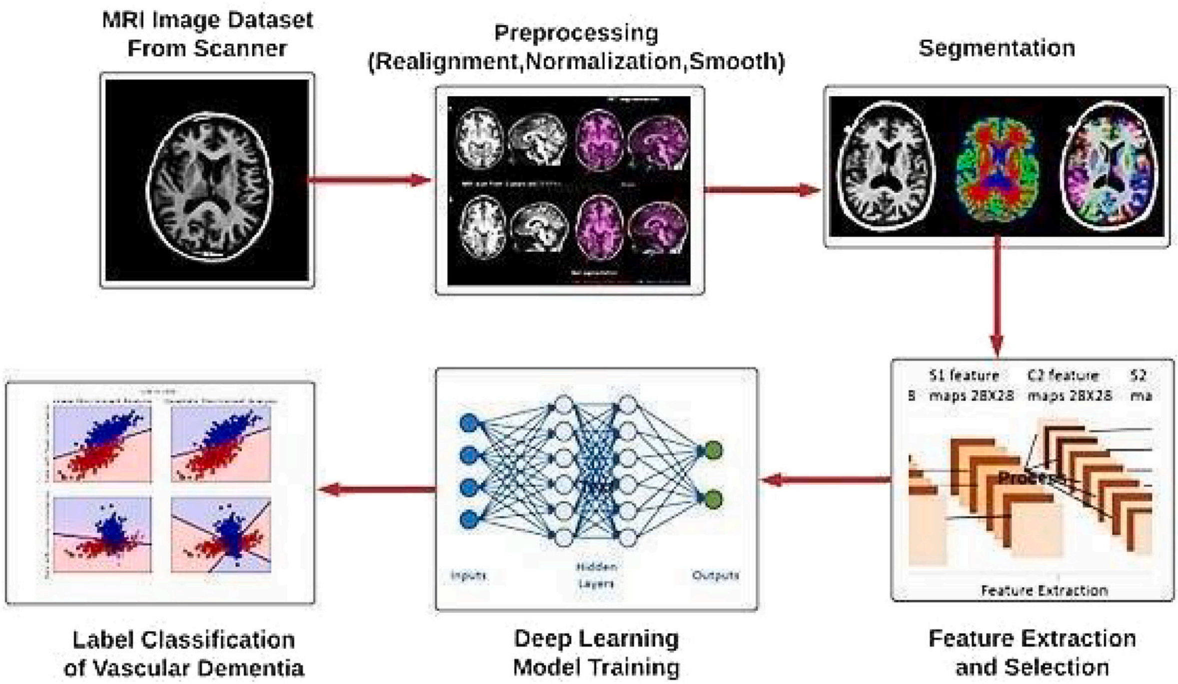

Fig. 2. Block diagram of Deep Learning Architectures to classify MRI-based vascular Dementia.

comparing and contrasting the architectures' capabilities. The solutions developed in this study do not have novel characteristics. In turn, they contribute to the development of future research on deep learning architecture-based VD detection, and likely Alzheimer's Disease detection. Our experimental outcomes show that this solution was successful.

The manuscript is organized as follows: Section 2 elaborates on the literature review. The following Section 3 illustrates the proposed methodology. Furthermore, Section 4 focuses on the result discussion of the experimental outcomes and conclusion drawn in Section 5, respectively.

2. Literature review

In this section, the context research has been identified. On the detection and classification of Vascular Dementia related to medical image analysis, highlight the techniques and algorithms working based on recent year studies. Machine learning and deep learning architectures can leave the paradigm change for detecting different diseases in medical image analysis. MRI and CT scans help us to determine and evaluate disease detection.

Castellazzi et al. (2020) explored machine learning algorithms to differentiate vascular Dementia from Alzheimer's disease. The collection of subjects is 77 for MRI scans that are further extended to DTI and rs-fMRI analysis, which could engender the three dataset classes. The first is the DTI dataset, extracted from VD patients. GT dataset is extracted from AD, and GT+DTI datasets are extracted from MXD dementia patients. Three types of algorithms, Artificial Neural Network (ANN), Support Vector Machine (SVM), and Adaptive Neuro-fuzzy inference system, were used for detection purposes. Two models of ANN are used. The first is a Multilayer perceptron (MLP), and the other is the Radial Basis Function Network (RBFN). The MLP model implemented in MATLAB is composed of three layers. It comprises n inputs, 8 neurons in the hidden layer, and one in the output layer. The sigmoid function is used as an activation function. For model training, the Bayesian regularization backpropagation approach is used. The variant of RBFN three-layer feed-forward network is used with Gaussian function. The new rbe function is used in MATLAB to set the equal 0.1 for the RB layer.

Wang et al. (2019) proposed the detection of vascular Dementia with Electroencephalography techniques and then classification using SVM classifiers. By using electroencephalogram (EEG) features through 3 supervised machine learning approaches, i.e., linear discriminant analysis (LDA), backpropagation neural network (BP), and support vector machine (SVM) as classifiers to discriminate early vascular dementia patients. With EEG connectivity patterns as features and machine learning methods as classifiers, classifier performance is assessed, then feature selection and cross-validation (LOOCV) are combined. Feature selection was performed within LOOCV to select the relevant classification features. The classification was executed using MATLAB and LIBSVM toolbox. An EEG uses small metal discs attached to the scalp to capture brain cell signals' electrical impulses. Electrical signals are used by the nerve cells for interaction with each other. Wavy lines will surface on an EEG recording due to this brain operation. Target stimuli (green circles) and no target stimuli (red circles) were noted for a clearer understanding of how differential functions. Each stimulus appeared randomly in the middle of the display, and its diameter was measured.

Ford et al. (2019) compared machine learning algorithms with epidemiological approaches to detect Dementia for initial care patients. The data on dementia patients was collected over five years. It was designed with the same split sets between each model. This data is divided into a training set (80%) and a test set (20%). The primary step is to use the baseline statics model and logistic regression with the least absolute selection and shrinkage operator (LASSO) implementations. This data is used for binary classification, and LASSO implements help prioritize the data and evaluate the weight features. This model can be compared with four machine learning algorithms: the random forest, naive Bayes, support vector machine, and neural network. All the values or data can then be analyzed with e1071, PROC, ROCR, and Python, which can be used for implementation. When the data is tuned with several model parameters, there is no improvement because the model is over-simple. Each model is accessed for capability for classification vs. controls under the Receiver Operating Characteristics Curve (AUROC). The feature can be retained with a logistic regression model. After analysis, the total curve is about 0.74, and the precision is 0.31. Overall results show that logistic regression with the random forest benefits support vector and neural networks because they produce interpret feature weights. The main limitation is that binary features can lose the information, and the correct dataset can replicate the novel data sets. Another limitation is that the variables can represent the same features as the multi-level model.

Gill et al. (2020) explored two kinds of machine learning algorithms. The first can deal with predicting future abnormalities vs. normal impairments. The second can deal with three types of classification to evaluate the normal, mild, and restricted diagnosis using basis features. Both experiments can test clinical and brain cognitive features and could be combined to check the performance of algorithms. For cross-validation, they used the Monto Carlo 10-fold cross-validation approach that divides the trained data into 10 parts, in which the 9 parts were considered for training and 1 for further testing. It can generate the datasets of 100 samples and apply the 10 times iterations. In the end, the confidence level increased. An estimated clean and clear transparency is 95%. The absolute difference is noted. It followed 83 participants affected in the early stages, 112 in the mild stage, and 145 in the restricted stage. The author compared both types of features, predicting better features than a lonely combination. The approach gives the ROC range of 0.87 scores and 0.73 scores as well. When predicting the second experiment, they achieved the 7 features overall on separating with an accuracy of 58.8%. In the second-class experiment, the machine learning algorithm can achieve the 2 features from differential ordinary to mild. The third-class machine learning algorithm can show a low accuracy, estimated at 58.8% lower when we compared it with the second class. The overall classification shows that it is much more challenging to classify these stages from one another. Combining results of the previous state-of-the-art methods estimation shows that previously used methods can only focus on the modality of single-image datasets.

Sobhaninia, Rezaei, Karimi, Emami, and Samavi (2020) described the expanded MRI image dataset for enlarging datasets classification by pairwise GAN. Most datasets currently available are relatively moderate in scale and are frequently followed by incomplete MRIs in various modalities. The authors increased the number of brain MRI images in the training dataset using a pairwise Generative Adversarial Network (GAN) model to solve the problems of inadequately big datasets and insufficient picture modality for deep Learning. The pairwise GAN will generate synthetic MRIs in several modalities. A post-processing method for achieving the patient-level diagnostic outcome by integrating the slice-level glioma subtype classification findings is plurality voting. A two-stage training technique is proposed to learn glioma features using GAN-augmented MRIs accompanied by real MRIs. The effectiveness of the suggested scheme, isocitrate dehydrogenase 1 (IDH1) modification, and IDH1 wild-type mutation has been tested on a dataset to characterize glioma molecular subtypes. Experimental studies on the dataset have yielded positive outcomes (with a test accuracy of 88.82 percent). Parallels with other state-of-the-art approaches were included.

Meenakshi and Revathy (2020) explored the Evolution channel selection algorithm with the EEG signal to differentiate the VD from Stroke-related patients. This paper shows the number of different techniques to detect VD patients. The first and primary technique is Savitzky Golay filters that are used for the denoising part. The second most reliable technique is RC dispersion entropy, which extracts the datasets on the other end. The differential evolution feature selection (DEFS) algorithm was used to detect the signal more precisely. The composition of three techniques for detection was given the best localization. The SVM classifier used the input and output stages with the leading DEFS algorithm for classification. The results showed that the 6 channels could improve classification outcomes with a working memory load. The overall result concludes that SVM with the DEFS algorithm can show precise results with a destination of 89 Rehman, Naz, Razzak, Akram, and Imran (2020) explored the machine learning algorithm to tackle the challenge of precisely identifying Dementia. In this study, they reviewed the quality measures of the previous methods. They set the background analysis to train the model and extracted the parameters. The study is concentric, just like wavelength. The steps are to use the raw datasets, preprocess the data, feature extraction, and vector calculation, use the classifier, and then organize the prediction measures. On the other end, the same wavelength is used for testing the parameters with the distinction of parameters. From a clinical perspective, the methodology for previous detections does not find relevant results for clinicians. Machine learning methods to discriminate the healthy controls from AD are better. The study indicates that the machine learning techniques for detecting dementia-related patients do not fulfill the precise needs. However, the collaboration process between the clinicians is a better approach. A better machine learning algorithm requires better disciplinary processes.

Balasooriya and Nawarathna (2017) proposed the EEG technique with K Nearest Neighbor (KNN) and SVM classifiers and the infirmity of a fuzzy neighborhood analyzer. In this study, data can be collected from five vascular dementia patients. Fifteen are mildly affected by strokes, and fifteen are those who are in the stage of recovery. The analysis proceeds in two folds. First is the discrimination of VD, mild stroke patients, and recovery stage patients using the fuzzy neighborhood preserve analyzer with the enhancement of QR decomposition. It aims to expand and observe the spectral features that discriminate mild-stroke patients from control subjects. However, there are 19th channels that are analyzed using ICA wavelet analysis. The ratio can be calculated to show the VD and mild Stroke patients to analyze the dominion frequency relative power. The nonlinear features like permutation En and FD were used to calculate the regulation, which can be less in VD and stroke patients. The SVM classifier and k nearest neighbor classifier can detect the recovery base patients. The result showed that the SVM and KNN estimated accuracy is 89%. The Decomposition technique showed 67% accuracy.

The study indicates that the machine learning techniques for detecting dementia-related patients do not fulfill the precise needs. Still, the collaboration process between the clinicians is better to approach the better machine learning algorithm, which requires better disciplinary processes.

3. Proposed methodology

A convolutional neural network (CNN) is a form of artificial neural network used to analyze pixel input, which is used in image recognition and processing. A CNN employs a system similar to a multilayer perceptron, which is already optimized for low processing requirements, including input, hidden, and output layers. The hidden layer can contain different convolutional layers, average pooling, fully connected convolutional layers, and normalization layers.

Gradient vanishing is a challenging problem in tuning deep learning models, especially when the network has more layers. The value of derivatives decreases with each layer in backpropagation, causing a gradient vanishing problem. This problem typically arises when the sigmoid function is used as an activation function in the neural network model. This problem is tackled in the proposed research using ReLU and Leaky ReLU activation functions wherever needed. A detail pictorial description of proposed model is shown in Fig. 2.

3.1. Dataset details

The dataset used in the proposed experimentation for detecting and classifying vascular Dementia is resting-state functional magnetic resonance imaging (rs-fMRI) (Perry, Parvizi, & Pinheiro-Chagas, 2021). It is a multi-class dataset with five classes named Binswanger Dementia, hemorrhagic Dementia, Multi-Infarct Dementia, Strategical Dementia, and Subcortical Dementia, as shown in Table 1. The first class of dataset is Binswanger dementia, also called subcortical vascular Dementia,

Table 1
Rs-fMRI Dataset.

	Dataset classes	Actual image count	Random selection
		(Unbalanced)	(Balanced)
rs-fMRI Dataset	Binswanger Dementia	4608	4400
	hemorrhagic Dementia	4608	4400
	Multi-Infarct Dementia	7080	4400
	Strategical Dementia	4608	4400
	Subcortical Dementia	4608	4400

which is a type of Dementia caused by widespread, microscopic areas of damage to the deep layers of white matter in the brain. A characteristic pattern of BD-damaged brain tissue can be seen with modern brain imaging techniques such as CT scans or magnetic resonance imaging (MRI). The second dataset class is hemorrhagic Dementia, in which blood accumulates and compresses surrounding areas of brain tissues. The third class is multi-infarct Dementia, most commonly known as vascular Dementia, which is caused by multiple strokes or disruption of blood flow to the brain. The fourth class of the dataset is strategic Dementia. The last class listed in the dataset is subcortical Dementia, a clinical syndrome characterized by slow mental processing, forgetfulness, impaired cognition, apathy, and depression. All these classes have different numbers of the image dataset. To make a dataset balanced, up-sampling and down-sampling techniques are typically used to represent each class in the dataset equally. In the preprocessing step of the proposed methodology, we make our dataset balanced by these known techniques of up-sampling and downsampling.

The novelty of this research lies in the fact that it multi-classifies the rs-fMRI dataset to determine the cause of Dementia by classifying it into one of the 5 classes mentioned above. Previously, only binary classification was done with a dataset reported and compared within the results section.

We will use this dataset with transfer learning models such as VGGNET16, VGGNET19, DenseNet121, and InceptionResNetV2 in the proposed method. The total count of images in each class is unbalanced. We need to balance the dataset for better performance. After balancing the number of images in each dataset class by subsampling and upsampling, we get 22 000 images with 4400 images in each class. Different dataset split ratios calculate results. The first split is 80% for training and 20% for validation and testing. The second split is 70% for training and 30% for validation and testing. The third split is 28% training and 72% validation and testing dataset. Then, we apply multiple powerful CNN models on all these dataset distributions to detect vascular Dementia and analyze the performance of the abovementioned deep learning architectures.

3.2. Dataset acquisition

Data were acquired at the Stanford University Richard M. Lucas Center for Imaging on a 3T General Electric SIGNA Premier scanner using a 48-channel head coil (GE Healthcare, Milwaukee, WI, USA). Blood oxygenation level-dependent (BOLD) functional MRI data were acquired using a simultaneous multislice gradient-echo echo-planar pulse sequence. Sequence parameters were similar to those used as part of the Human Connectome Project: TR 1000 ms, TE 30 ms, flip angle 64°, 2.4 mm isotropic voxels, matrix 88 × 88 × 65, multislice 5× acceleration. The signal dropout was minimized by visually selecting a slice plane approximately 25° from the anterior–posterior commissural plane towards the coronal plane. A T1-weighted anatomical scan was acquired in each session using a 3DFSPGR three-dimensional sequence: TR 1891 ms, TE 1.172 ms, TI 400 ms, flip angle 11°, $1.0 \times 1.0 \times 1.2$ mm voxels, matrix 256 × 192 × 132. A gradient-echo B0 field map was acquired to correct for spatial distortions: TE 6.5, 8.5 ms with slice prescription/spatial resolution matched to the BOLD sequence (Perry et al., 2021).

Data collected during a visual fixation task were used for functional connectivity analysis. The patient fixated on a black '+' symbol at the center of a light gray screen. The patient was asked to remain as still as possible, awake and focused throughout each run. In between runs, the patient was asked if he could successfully stay still during the previous run to reinforce the expectation that this should be closely monitored. Each run lasted 7 m 2 s, and three functional runs were collected (Perry et al., 2021).

3.3. Dataset preprocessing by random selection

In our research on diagnosing vascular dementia using deep learning, preprocessing plays a pivotal role in shaping the performance and reliability of our models. A key aspect of preprocessing is data sampling, which involves the careful selection and manipulation of the dataset to ensure balanced representation across different classes.

3.3.1. Balancing the dataset

One of the primary challenges in working with medical datasets, including those related to vascular dementia, is the imbalance between classes. For instance, certain classes may have significantly more samples than others, leading to biases in model training and reduced generalization capability. To address this issue, we employ random selection methods guided by human observation to balance the dataset. Subsampling or up-sampling is a preprocessing step to balance an unbalanced dataset, as the unbalanced dataset affects the model's overall accuracy. In this proposed research, we choose a random selection method by human observation to limit the number of images in each class. This method balances the overall number of images in each class. Table 1 shows rs-fMRI Dataset.

4. CNN transfer learning models

4.1. Visual geometry group (VGGNET16-19)

The name VGGNET, abbreviated Visual Geometry Group, is given by the science and engineering department of Oxford University. The main aim is to analyze the depth and power of the convolutional neural network that determines how many effects on accuracy and large image dataset classification. The deep dense 16 CNN admitted to deeper network layers and overcame more parameters; a minimal 3*3 convolutional filter is embedded in all layers. Suppose we talk about the overall general representation of the model, including a list of 5 convolutional layers, which can lead with the MaxPool. Another significant difference is that more cascade Convolutional layers are embedded in 5 sets. The diagram shows the overall network structure.

4.2. Visual geometry group (VGGNET19)

The only difference between VGG16 and VGG19 is that one acing uses 16 layers, and the other can use 19. The last three fully connected layers are the same in both architectures.

4.3. Densely connected convolutional network (DenseNet121)

Among the most recent developments in deep Learning for image classification is DenseNet. DenseNet is quite identical to ResNet with few key distinctions. DenseNet convolves (.) the result of the preceding stage with the result of the upcoming layer. In contrast, ResNet employs an additive technique (+) that combines the lower layer (identity) with either the upcoming layer. DenseNet was created to address the diminishing gradient's effect on the performance of high-level neural networks. DenseNet comes in various variants, such as DenseNet121, DenseNet160, and DenseNet201. The numbers indicate how many layers there are in the algorithm.

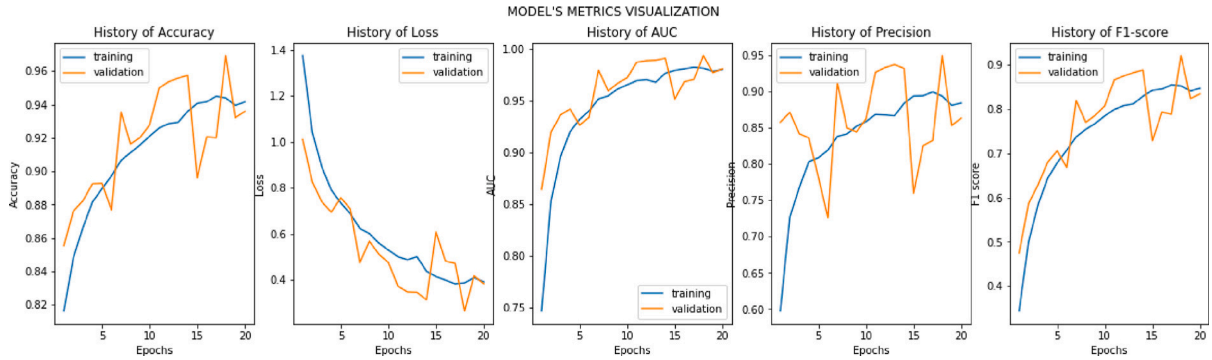

Fig. 3. VGGNET16 experimental result with 80–20 dataset distribution.

Table 2
Rs-fMRI Dataset distribution.

	72-28 Dataset split		80-20 Dataset split
	Validation 28%	Training 72%	Training 80%
	1232	3168	3520
	1232	3168	3520
rs-fMRI Dataset Distribution	1232	3168	3520
	1232	3168	3520
	1232	3168	3520

4.4. Inception ResNet V2

The Inception-ResNet-v2 framework is a variant including its Inception V3 framework. It is more detailed than the preceding Inception V3, which is a specific variant of almost the same structure with the repetitive residual blocks compacted. The inception frames have been streamlined in this version with fewer concurrent towers than in the prior Inception V3. An Inception-ResNet-v2 structure outperforms prior state-of-the-art algorithms in terms of accuracy.

4.5. Generalization ability of Deep learning models

The deep learning models we used in our research have different levels of generalization ability. DenseNet121 and InceptionResNetV2 are known for their strong generalization, meaning they can perform well on new, unseen data beyond what they were trained on. VGG16 and VGG19, while simpler, still show decent generalization and can recognize patterns in new data. Each model has its strengths and tradeoffs, with more complex models generally offering better generalization but requiring more resources for training.

5. Results discussion and recommendations

As we see in the above analysis, the CNN model named DenseNet with 121 layers performs well in predicting the classes of Vascular Dementia. Its classification accuracy is higher than that of other CNN models. We split 20 random samples from the test data set before training. The DenseNet model correctly identifies and classifies the results.

The overall results show that increasing the complexity of the model may increase the classification performance. The prediction analysis is based on 80%–20% dataset distribution, details provided in Table 2, because this split has good accuracy and an F1 score. Our experimental model performed well compared to the state-of-the-art model. Table 3 shows the comparison of the proposed method with state-of-the-art (Alizadeh et al., 2022; Hu, Ju, Shen, Zhou, & Li, 2016) (See Figs. 3–5).

The traditional technique, which depends on the skill of radiotherapists to evaluate and examine the components of the MRI, has been utilized for detecting and categorizing Vascular Dementia. Operator-assisted classification techniques are non-reproducible and are less suitable for big datasets. Manual processing of huge datasets is a time-consuming operation. Computer-aided diagnostic techniques are required to process a large amount of data efficiently to tackle such difficulties. The best-performing approaches for such challenges follow a similar pattern (Balasooriya & Nawarathna, 2017; Ford et al., 2019; Zhao et al., 2018). Instead of training a singular deep CNN model, many deep CNN models are trained and merged to determine the final results. To make maximum use of diverse aspects of the available data, the models utilized vary in terms of network topologies, inherent complexity, and loss functions. It is a community observation network that achieves significantly better results than its components, but it is not desirable for some applications due to neural network architecture complexity. In this case, we use more complex models with accurate results and satisfactory prediction results. We applied different models for better accuracy and performance. Accuracy is still low. The F1 score is comparatively less satisfactory. DensNET121 predicted VD better than other models. This model could be used for better prediction by changing the layer's structure.

At some points, other models overfit; therefore, this is the best model for larger datasets, especially when data images in different classes are unbalanced. Finally, combining actual and unbalanced training datasets, comparisons with several current techniques have demonstrated that the proposed methodology has achieved the best performance to the state-of-the-art while being based on distinct datasets. finally, the DenseNet model with 121 layers stands out in our analysis, showcasing superior performance in predicting classes related to Vascular Dementia. Its classification accuracy surpasses that of other CNN models, as evidenced by the correct identification and classification of results from a test dataset split into 20 random samples before training. Our findings suggest that increasing the model's complexity may lead to enhanced classification performance.

While VGGNET16 exhibited high accuracy and performance, its prediction results were comparatively lower due to model complexity. This limitation prompts consideration for employing more complex models in future experiments, as discussed earlier. Our conclusion from this investigation is that DenseNet121 excels in accuracy classification and prediction results, showcasing promise for advancing diagnostic capabilities in Vascular Dementia.

6. Conclusion and future work

The study investigated the power of CNN models, which are used in a very invasive way. In our study, the rs-fMRI-based dataset is used. The primary step of the proposed methodology is to split the dataset into three models. Firstly, the data images split on the training set into 80%, 70%, and 28%, respectively. Second is the validation set split into 10%, 15%, and 72%, respectively. However, the remaining images are settled for the test dataset for further prediction on unseen data after training.

Table 3
Results comparison of the proposed method with state-of-the-art.

Proposed model	Modality	Datasets	Dataset distribution	Used methodology	Classification mode	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)
Differentiate the Vascular Dementia from Alzheimer's disease (Castellazzi et al., 2020)	MRI	rs-fMRI dataset	80% Distribution	Radial Basis Function Network	Binary Classification	55.75	55.5	56	55.78
				Multilayer Perceptron	Binary Classification	58.25	55.5	61	58.73
				Support Vector Machine with Radial Basis Function (Kernel)	Binary Classification	81	93.5	68.5	74.8
				Support Vector Machine with MLP sigmoid kernel	Binary Classification	78.25	81	75.5	76.78
				Adaptive Neuro-Fuzzy Inference System	Binary Classification	82.75	73.5	92	90.18
Proposed Methodology			Validation = 28% Training = 72%	VGG16	Multi-Classification	90.6	67.07	91.14	82.65
				VGG19		88.92	59.72	89.82	79.8
				DenseNet121		82.4	100	83.43	81.13
				InceptionResNetV2		84.96	61.21	92.69	62.69
			Training = 80% Validation = 10% Testing = 10%	VGG16	Multi-Classification	94.15	81.43	94.2	88.39
				VGG19		92.38	74.74	92.83	85.32
				DenseNet121		84.67	78.97	97.22	79.89
				InceptionResNetV2		88.92	71.55	94.94	72.64
			Training = 70% Validation = 15% Testing = 15%	VGG16	Multi-Classification	94	80.7	94.01	88.3
				VGG19		92.21	73.97	92.59	85.14
				InceptionResNetV2		88.58	70.62	94.96	71.81

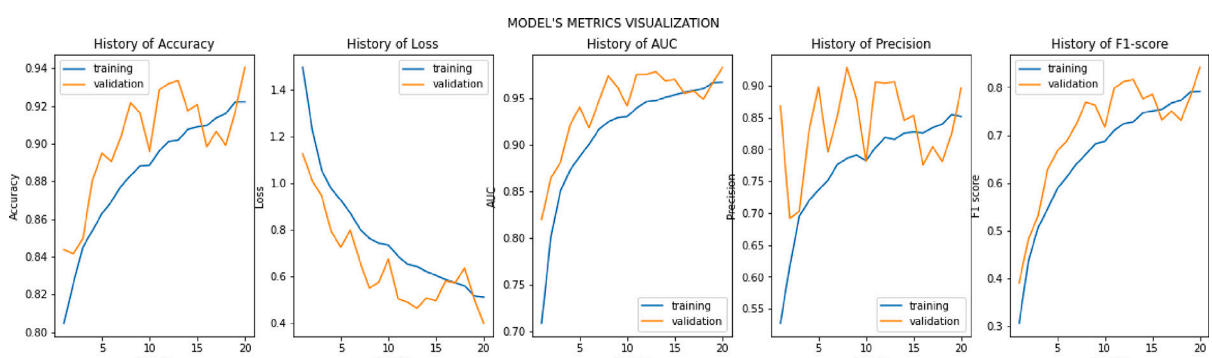

Fig. 4. VGGNET19 experimental result with 80–20 dataset distribution.

Fig. 5. DenseNet121 experimental result with 80–20 dataset distribution.

The distribution is applied to advanced CNN models VGG16, VGG19, DensNET121, and InceptionResNETV2. By comparing the results of all these models, we achieved greater accuracy with DenseNET121. The limitation of using VGGNET16 is that the accuracy and performance results are high, but the prediction results are low. The main reason for lower prediction results with VGGNET16 is the complexity of the model. We may apply more complex models in future experiments, as discussed above. We concluded that the DensNET121 performs well on accuracy classification and prediction results.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

This work is funded by FCT/MEC through national funds and, when applicable, co-funded by the FEDER-PT2020 partnership agreement under the project UIDB/50008/2020.

References

Ahad, A., Ali, Z., Mateen, A., Tahir, M., Hannan, A., Garcia, N. M., et al. (2023). A comprehensive review on 5G-based smart healthcare network security: taxonomy, issues, solutions and future research directions. *Array*, Article 100290.

Ahad, A., Jiangbina, Z., Tahir, M., Shayea, I., Sheikh, M. A., & Rasheed, F. (2024). 6G and intelligent healthcare: Taxonomy, technologies, open issues and future research directions. *Internet of Things*, Article 101068.

Alizadeh, F., Homayoun, H., Batouli, S. A. H., Noroozian, M., Sodaie, F., Salari, H. M., et al. (2022). Differential diagnosis among alzheimer's disease, mild cognitive impairment, and normal subjects using resting-state fMRI data extracted from multi-subject dictionary learning atlas: A deep learning-based study. *Frontiers in Biomedical Technologies*.

Balasooriya, N. M., & Nawarathna, R. D. (2017). A sophisticated convolutional neural network model for brain tumor classification. In *2017 IEEE international conference on industrial and information systems* (pp. 1–5). IEEE.

Braaten, A. J., Parsons, T. D., McCue, R., Sellers, A., & Burns, W. J. (2006). Neurocognitive differential diagnosis of dementing diseases: Alzheimer's dementia, vascular dementia, frontotemporal dementia, and major depressive disorder. *International Journal of Neuroscience*, *116*(11), 1271–1293.

Butt, H. A., Ahad, A., Wasim, M., Madeira, F., & Chamran, M. K. (2023). 5G and IoT for intelligent healthcare: AI and machine learning approaches—A review. In *International conference on smart objects and technologies for social good* (pp. 107–123). Springer.

Butt, H. A., Ahad, A., Wasim, M., Shayea, I., Coelho, P. J., Pires, I. M., et al. (2023). Federated machine learning in 5G smart healthcare: a security perspective review. *Procedia Computer Science*, *224*, 580–586.

Castellazzi, G., Cuzzoni, M. G., Cotta Ramusino, M., Martinelli, D., Denaro, F., Ricciardi, A., et al. (2020). A machine learning approach for the differential diagnosis of alzheimer and vascular dementia fed by MRI selected features. *Frontiers in Neuroinformatics*, 25.

Charidimou, A., Jäger, H. R., & Werring, D. J. (2012). Cerebral microbleed detection and mapping: principles, methodological aspects and rationale in vascular dementia. *Experimental Gerontology*, *47*(11), 843–852.

Ford, E., Rooney, P., Oliver, S., Hoile, R., Hurley, P., Banerjee, S., et al. (2019). Identifying undetected dementia in UK primary care patients: a retrospective case-control study comparing machine-learning and standard epidemiological approaches. *BMC Medical Informatics and Decision Making*, *19*(1), 1–9.

Gill, S., Mouches, P., Hu, S., Rajashekar, D., MacMaster, F. P., Smith, E. E., et al. (2020). Using machine learning to predict dementia from neuropsychiatric symptom and neuroimaging data. *Journal of Alzheimer's Disease*, *75*(1), 277–288.

He, S., Gao, B., Sabnis, R., & Sun, Q. (2023). RNAdegformer: accurate prediction of mRNA degradation at nucleotide resolution with deep learning. *Briefings in Bioinformatics*, *24*(1), bbac581.

Hu, C., Ju, R., Shen, Y., Zhou, P., & Li, Q. (2016). Clinical decision support for alzheimer's disease based on deep learning and brain network. In *2016 IEEE international conference on communications* (pp. 1–6). IEEE.

Iadecola, C. (2013). The pathobiology of vascular dementia. *Neuron*, *80*(4), 844–866.

Li, B., Hsu, Y.-T., & Rudzicz, F. (2019). Detecting dementia in mandarin Chinese using transfer learning from a parallel corpus. arXiv preprint arXiv:1903.00933.

Liu, K., Yao, Y., Liu, Z., & Sato, R. (2019). Design concepts of electronic medical tools for dementia early detection and assessment. In *2019 IEEE 1st global conference on life sciences and technologies (lifeTech)* (pp. 31–33). IEEE.

Meenakshi, A., & Revathy, S. (2020). An efficient model for predicting brain tumor using deep learning techniques. In *2020 5th international conference on communication and electronics systems* (pp. 1000–1007). IEEE.

Morton, R. E., St. John, P. D., & Tyas, S. L. (2019). Migraine and the risk of all-cause dementia, alzheimer's disease, and vascular dementia: A prospective cohort study in community-dwelling older adults. *International Journal of Geriatric Psychiatry*, *34*(11), 1667–1676.

Perry, C., Parvizi, J., & Pinheiro-Chagas, P. (2021). *fMRIdata.figshare Dataset*. Milwaukee, WI, USA: GE Healthcare, Stanford University Richard M. Lucas Center for Imaging, http://dx.doi.org/10.6084/m9.figshare.14675505.v1, [Online].Available:.

Rehman, A., Naz, S., Razzak, M. I., Akram, F., & Imran, M. (2020). A deep learning-based framework for automatic brain tumors classification using transfer learning. *Circuits, Systems, and Signal Processing*, *39*, 757–775.

Román, G. C. (2002). Vascular dementia may be the most common form of dementia in the elderly. *Journal of the Neurological Sciences*, *203*, 7–10.

Shankle, W. R., Mani, S., Pazzani, M. J., & Smyth, P. (1997). Detecting very early stages of dementia from normal aging with machine learning methods. In *Artificial intelligence in medicine: 6th conference on artificial intelligence in medicine europe, aIME'97 grenoble, France, March 23–26, 1997 proceedings 6* (pp. 71–85). Springer.

Sobhaninia, Z., Rezaei, S., Karimi, N., Emami, A., & Samavi, S. (2020). Brain tumor segmentation by cascaded deep neural networks using multiple image scales. In *2020 28th Iranian conference on electrical engineering* (pp. 1–4). IEEE.

T. O'Brien, J., & Thomas, A. (2015). Vascular dementia. *The Lancet*, *386*(10004), 1698–1706.

Wang, C., Xu, J., Zhao, S., & Lou, W. (2019). Identification of early vascular dementia patients with EEG signal. *IEEE Access*, *7*, 68618–68627.

Zhao, X., Wu, Y., Song, G., Li, Z., Zhang, Y., & Fan, Y. (2018). A deep learning model integrating FCNNs and CRFs for brain tumor segmentation. *Medical Image Analysis*, *43*, 98–111.