Soumia Benbakreti[1], Samir Benbakreti[2], Kadda Benyahia[3], Abdelkader Khobzaoui[1]

Laboratory of Mathematic, University of Djillali Liabes, Sidi Bel Abbes, Algeria (1),
Ecole Nationale des Telecommunications et des Technologies de l'Information et de la Communication (ENSTTIC), Department of speciality, Oran, Algeria (2),
LTC Laboratory, University of Tahar Moulay, Saida, Algéria (3).

doi:10.15199/48.2024.05.24

Pretrained models for classification of dementia degree and treatment of Alzheimer's disease

Abstract. *The early diagnosis of Alzheimer's disease poses a significant challenge in the health sector, and the integration of deep learning and artificial intelligence (AI) holds promising potential for enhancing early detection through the classification of dementia levels, enabling more effective disease treatment. Deep neural networks have the capacity to autonomously learn and identify discriminative characteristics associated with this pathology. In this study, three pre-trained CNN-based models are employed to classfify MRI images of Alzheimer's patients, with ResNet18 yielding excellent results and achieving an accuracy rate of 97.3%.*

Streszczenie. *Wczesna diagnoza choroby Alzheimera stanowi poważne wyzwanie w sektorze zdrowia, a integracja głębokiego uczenia się i sztucznej inteligencji (AI) niesie obiecujący potencjał w zakresie poprawy wczesnego wykrywania poprzez klasyfikację poziomów demencji, umożliwiając skuteczniejsze leczenie chorób. Głębokie sieci neuronowe mają zdolność autonomicznego uczenia się i identyfikowania cech dyskryminacyjnych związanych z tą patologią. W tym badaniu do klasyfikacji obrazów MRI pacjentów z chorobą Alzheimera wykorzystano trzy wstępnie wyszkolone modele oparte na CNN, przy czym ResNet18 zapewnia doskonałe wyniki i osiąga współczynnik dokładności wynoszący 97,3%.**(Wstępnie wytrenowane modele do klasyfikacji stopnia demencji i leczenia choroby Alzheimera)***

Keywords: Alzheimer disease, dementia, images classification, convolutionel neural network evolutionary algorithms
Słowa kluczowe: Choroba Alzheimera, otępienie, klasyfikacja obrazów, algorytmy ewolucyjne splotowych sieci neuronowych

Introduction

The integration of artificial intelligence (AI) in medicine holds significant opportunities for early disease diagnosis through machine learning algorithms analyzing diverse medical data. This includes radiographic images and scans, enabling timely detection and improving treatment prospects. Additionally, AI systems aiding clinical decision-making offer recommendations to healthcare professionals, streamlining the decision process through in-depth data analysis [1].
Alzheimer's disease represents a significant burden on public health globally. According to the World Health Organization (WHO), approximately 50 million people worldwide are currently living with dementia, with the vast majority suffering from Alzheimer's disease [2]. This figure is expected to rise alarmingly as the global population ages, with estimates suggesting that the number of people with dementia could reach 152 million by 2050 if preventive measures and effective treatments are not developed [3]. Furthermore, Alzheimer's disease has a significant economic impact. According to the Alzheimer's Association, in the United States alone, the costs of care and support for individuals with Alzheimer's reached approximately 355 billion dollars in 2021 [4]. These numbers underscore the urgency of research and intervention in the fight against this debilitating disease.

Alzheimer's disease (AD) is a gradually advancing systemic condition that impacts the brain [5], blood vessels within the brain [6], peripheral tissues [7], in addition to red blood cells (RBC) [8], platelets [9], and white blood cells (leukocytes) [10]. It is characterized by a gradual decline in cognitive abilities, including memory impairment, typically observed in the elderly. In 95% to 98% of cases, AD develops sporadically, and statistics on this form of dementia indicate that approximately 50% of individuals aged 80 or older are affected [11]. The degree of dementia is closely linked to Alzheimer's disease, as Alzheimer's disease is one of the primary causes of dementia [12]. Dementia is a general term that describes a set of cognitive and behavioral symptoms that significantly interfere with a person's ability to function in daily life. Alzheimer's disease is the most common form of dementia, accounting for a large proportion of dementia cases in older individuals. The relationship between the degree of dementia and Alzheimer's disease is as follows:

- **Alzheimer's disease is a major cause of dementia:** In many cases, Alzheimer's disease is the primary underlying cause of dementia. It is characterized by a progressive loss of memory, cognitive abilities, and daily functioning.
- **The severity of dementia increases with the progression of Alzheimer's disease:** As Alzheimer's disease advances, the symptoms of dementia worsen. Individuals affected may experience increasing difficulties in remembering recent events, communicating, making decisions, moving, and performing basic activities of daily living.
- **Stages of Alzheimer's disease:** Alzheimer's disease is typically divided into several stages, ranging from mild to severe. The mild stage may be associated with subtle memory and concentration problems, while the severe stage is characterized by complete dependence on care, loss of the ability to speak, and loss of mobility.
  Detecting the degree of dementia is crucial for the appropriate management and treatment of individuals with dementia, including Alzheimer's disease. Here's how the detection of the degree of dementia can impact treatment:
  – **Early Diagnosis:** Early detection of the degree of dementia can facilitate an early diagnosis of Alzheimer's disease or other forms of dementia. Early diagnosis offers several advantages, including the possibility of starting treatment sooner, which can slow down the progression of the disease in some cases.
  – **Treatment Choices:** The severity of dementia often influences treatment choices. In the early stages of Alzheimer's disease, specific medications approved by health authorities may be prescribed to help alleviate symptoms and improve the quality of life. In more advanced stages, other approaches to symptom management and support are often preferred.

Furthermore, some medications used to treat the symptoms of Alzheimer's disease may have limited or less beneficial effects when the degree of dementia is more advanced, such as Cholinesterase inhibitors (donepezil, rivastigmine, galantamine). They aim to increase levels of acetylcholine, a neurotransmitter involved in memory and cognitive function. However, their effectiveness may be more limited as the disease progresses to more advanced stages. It's important to understand that these medications do not cure Alzheimer's disease but aim to alleviate symptoms and slow down the progression of the disease in its early stages.

Related Work

The paper [13] discusses Alzheimer's disease (AD) and its devastating effects on brain regions like the hippocampus, leading to cognitive and functional impairments. It introduces a Siamese Convolutional Neural Network (SCNN) with triplet-loss function to represent MRI images as k-dimensional embeddings for early disease diagnosis. Both pretrained and non-pretrained CNNs are utilized for this purpose. The model achieved high accuracy, scoring 91.83% on ADNI and 93.85% on OASIS datasets. It also compares favorably with similar methods in existing literature.

In [14], the authors tackle Alzheimer's disease classification, highlighting the limitations of current methods due to inconsistencies and low sensitivity. It introduces a Convolutional Neural Network (CNN) model for precise Alzheimer's disease detection from MRI images, offering detailed disease probability maps and clear risk visualizations. Addressing class imbalance, the DEMentia NETwork (DEMNET) achieves an impressive accuracy of 95.23% in dementia stage detection.

The paper [15] presents a data processing pipeline for identifying structural brain changes, particularly hemispheric asymmetry, using MRI data from the Alzheimer's Disease Neuroimaging Initiative (ADNI). The approach utilizes machine learning algorithms and convolutional neural networks to distinguish between normal cognition (NC), early mild cognitive impairment (EMCI), and Alzheimer's Disease (AD) with promising results, achieving accuracy rates of 92.5% and 75.0% for NC vs. EMCI, and 93.0% and 90.5% for NC vs. AD, respectively.

In [16], the task involves analyzing acoustically pre-processed speech data to classify Alzheimer's Disease (AD) and predict Mental Mini State Exam scores. The study focuses on textual transcripts from spontaneous speech, comparing various models including SVMs, GBDT, CRFs, and Transformer-based models. The top-performing models are TF-IDF vectorization with SVM and a pre-trained Transformer model (DistilBERT) used as an embedding layer in linear models. Results show high classification accuracy (0.81-0.82) and a Root Mean Square Error (RMSE) of 4.58 for regression.

Proposed Model and Dataset used

Traditional and modern computer vision models differ significantly in terms of their approach, performance, and complexity. In the past, human expertise was required for feature extraction from images, which was not easily scalable. One of the most effective deep learning models is the CNN, which has proven successful in tasks such as classification and detection [21]. CNN-based models revolutionized computer vision by enhancing feature extraction from images. However, they have limitations in terms of generalization and interpretation.

1 **AlexNet:** Developed by Alex Krizhevsky in 2012, it was the first CNN to win the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) [17]. It popularized the use of deep convolutional layers. AlexNet used an asymmetric architecture, meaning that the convolutional layers were not all of the same depth. This allowed it to learn features at different levels of abstraction.

2 **GoogLeNet (Inception):** This model, developed by Google, introduced the concept of Inception modules, which use different sizes of convolutional filters to extract features at various scales [18]. The Inception architecture of GoogleNet has been praised for its efficiency in extracting features at various spatial scales while keeping a relatively low number of parameters. This approach enabled GoogleNet to achieve excellent performance in image classification while remaining relatively lightweight compared to other architectures.

3 **ResNet18 (Residual Network):** A convolutional neural network with a depth of 18 layers, was developed and trained by Microsoft in 2015 as part of Deep Residual Learning for Image Recognition [19]. To tackle the challenge of vanishing gradient in neural networks, ResNet architectures introduced residual layers and skip connections, enhancing the training process and enabling deeper networks with improved performance. The model was trained on over a million images from the ImageNet dataset, utilizing colored images with a resolution of 224x224 pixels, and demonstrating the capability to classify up to 1000 objects.

Figure 1 provides an overview of the proposed model.

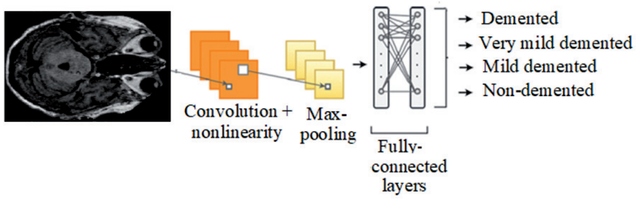

Fig. 1. The proposed pretrained model.

The dataset employed is the OASIS MRI dataset, containing a vast collection of 80,000 brain MRI images. These images have been categorized into four groups, representing various stages of Alzheimer's progression (see Table 1). The dataset serves as a valuable resource for the analysis and early detection of Alzheimer's disease indicators.

In the neural network training process, 2D images were utilized as input data. Brain images were segmented along the z-axis into 256 sections, with selections made from slices numbered between 100 and 160 in each patient's data. This approach resulted in the creation of a comprehensive dataset suitable for in-depth analysis.

The classification of patients was carried out based on provided metadata and Clinical Dementia Rating (CDR) values, leading to the formation of four distinct classes: demented, very mild demented, mild demented, and non-demented. These classes facilitate the identification and exploration of different stages in the progression of Alzheimer's disease.

- **Feature extraction with pretrained model:** You can use a each architecture, to extract features from the input images. The convolutional layers the model are highly effective at capturing local image features, such as edges, textures, and patterns.
- **Dimension reduction:** Once you have extracted the features with CNN variant, you can use a dimension reduction layer, such as a global pooling layer, to aggregate spatial information and reduce the dimensionality of the extracted features.

We refrained from employing data augmentation tech-

Table 1. The used dataset details

Level of dementia	Number of images
Mild Dementia	5002
Moderate Dementia	448
Non demented	62700
Very mild Dementia	13700

Table 2. The training parameters of the pretrained models.

Parameter	Value
Initial learning rate	0.001
Optimizer	SGDM
Max epoch	5
Mini batch size	20
Activation function	Softmax
Validation frequency	10

niques, as recent studies, such as [20], have shown that these methods do not necessarily ensure the success of the model.

Experiments and results

To evaluate the performance of our models, we used the following metrics:

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1 - score = \frac{2 * Precision * Recall}{Precision + Recall} \tag{4}$$

Where:

- TP (True Positive): It represents the number of correctly predicted positive samples by the model. This means that the model has correctly identified these samples as positive.
- TN (True Negative): It represents the number of correctly predicted negative samples by the model. This means that the model has correctly identified these samples as negative.
- FP (False Positive): It represents the number of negative samples incorrectly predicted as positive by the model. This means that the model has identified these samples as positive when they are actually negative.
- FN (False Negative): It represents the number of positive samples incorrectly predicted as negative by the model. This means that the model has identified these samples as negative when they are actually positive.

The initial parameters of the tree architectures are mentioned in Table 2 and the results obtained are shown in Table 3. The figures 2 and 3 illustrate the accuracy curves, the loss function and the confusion matrix of the best model respectively.

Table 3. The obtained results

Models	The used metrics			
	Accuracy (%)	**Precision** (%)	**Recall** (%)	**F1-score** (%)
AlexeNet	91.9	87.15	84.57	84.85
ResNet18	**97.3**	**97.4**	**96.8**	**97.07**
GoogleNet	94.8	88.54	83.78	86.08

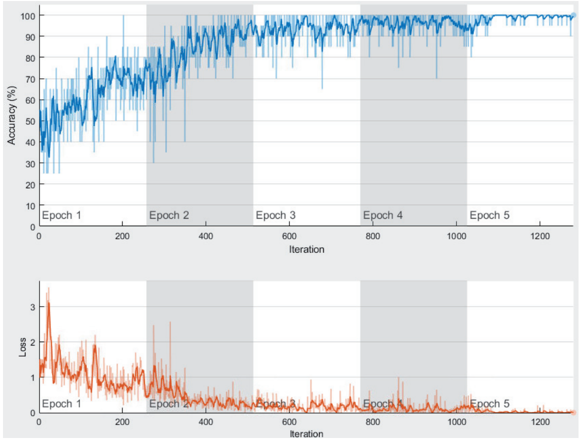

Fig. 2. Accuracy and loss curves for ResNet18.

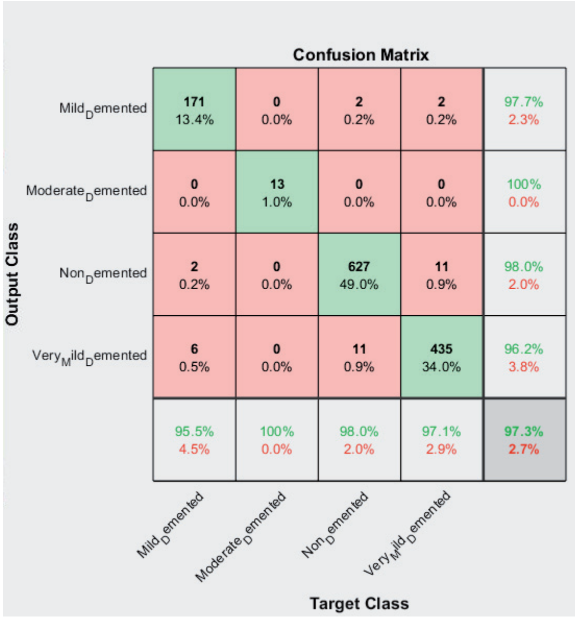

Fig. 3. The confusion matrix of ResNet18.

These high recognition rates can be explained by the fact that the residual connections introduced by ResNet18 facilitate the training of deep networks by allowing layer skipping, thereby addressing the vanishing gradient problem. This architecture enables the model to learn complex and hierarchical features from images, which is crucial for accurate classification, especially in medical fields with magnetic resonance images. Furthermore, ResNet18's relative compactness compared to other ResNet variants provides high performance while reducing computational load. Its ability to leverage knowledge transfer from pretrained models on extensive databases like ImageNet enhances its efficiency for specific tasks, such as medical image classification.
We conducted a comparison between the outcomes achieved by ResNet18 and those of state-of-the-art approaches, revealing that ResNet18 demonstrated superior performance (See Figure 4).

Conclusion

In this paper, we have elucidated the significance of an efficient and early classification system for determining the degree of dementia in Alzheimer's disease, which, in turn, enhances treatment efficacy and decelerates the disease's progression. The remarkable performance of the ResNet18

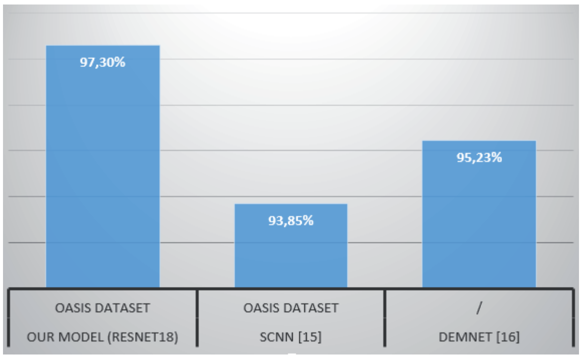

Fig. 4. The comparison with related work.

model in image classification, achieving the highest classification rates at 97.3%, particularly in the realm of early disease diagnosis like Alzheimer's, can be attributed to several pivotal features embedded in its architecture.

In essence, the innovative design of ResNet18 positions it as a robust choice for computer-aided diagnostic applications rooted in deep learning. As part of our future endeavors, we plan to delve into other deep learning methodologies, including variants of the Vision Transformer, and integrate them with the previously pretrained models.

Authors:
Dr. Benbakreti Soumia, Laboratory of Mathematic, University of Djillali Liabes, Sidi Bel Abbes, Algeria, E-mail: souben2223@gmail.com
Dr. Benbakreti Samir, Ecole Nationale des Telecommunications et des Technologies de l'Information et de la Communication (ENSTTIC), Department of speciality, Oran, Algeria, E-mail: samir.benbakreti@ensttic.dz.com
Dr. Benyahia Kadda, LTC Laboratory, University of Tahar Moulay, Saida, Algéria, E-mail: benyahiak@gmail.com
Dr. Khobzaoui Abdelkader, Laboratory of Mathematic, University of Djillali Liabes, Sidi Bel Abbes, Algeria, E-mail: akhobzaoui@yahoo.fr

REFERENCES

[1] Ghassan Ahmad, I.: Machine Learning to Diagnose Breast Cancer, PRZEGLĄD ELEKTROTECHNICZNY,20232(1), pp. 10–12, 2023.
[2] Gauthier S., Rosa-Neto P., Morais J.A., Webster C.: World Alzheimer Report 2021: Journey through the Diagnosis of Dementia; Alzheimer's Disease International: London, UK, 2021. [web page] `https://www.alzint.org/resource/world-alzheimer-report-2021/`
[3] Guerchet M., Prince M., Prina M.: Numbers of people with dementia worldwide: An update to the estimates in the World Alzheimer Report 2015, 2020.
[4] Wong W.: Economic burden of Alzheimer disease and managed care considerations, The American journal of managed care, 26(8 Suppl), pp. S177-S183, 2020.
[5] Chitradevi D., Prabha S.: Analysis of brain sub regions using optimization techniques and deep learning method in Alzheimer disease, Applied Soft Computing, 86, pp. 105857, 2020.
[6] Greenberg S. M., Bacskai B. J., Hernandez-Guillamon M., Pruzin J., Sperling R., Van Veluw S. J.: Cerebral amyloid angiopathy and Alzheimer disease—one peptide, two pathways, Nature Reviews Neurology, 16(1), pp. 30-42, 2020.
[7] De Felice F.G., Gonçalves R.A., Ferreira S.T.: Impaired insulin signalling and allostatic load in Alzheimer disease, Nature Reviews Neuroscience, 23(4), pp. 215-230, 2022.
[8] Baldacci F., Daniele S., Piccarducci R., Giampietri L., Pietrobono D., Giorgi F.S., Nicoletti V., Frosini D., Libertini P., Lo Gerfo A., Petrozzi L.: Potential diagnostic value of red blood cells α-synuclein heteroaggregates in Alzheimer's disease, Molecular Neurobiology, 56, pp. 6451-6459, 2019.
[9] Wu T., Chen L., Zhou L., Xu J., Guo K.: Platelets transport β-amyloid from the peripheral blood into the brain by destroying the blood-brain barrier to accelerate the process of Alzheimer's disease in mouse models, Aging (Albany NY), 13(5), pp. 7644, 2021.
[10] Bahado-Singh R.O., Vishweswaraiah S., Aydas B., Yilmaz A., Metpally R.P., Carey D.J., Crist R.C., Berrettini W.H., Wilson G.D., Imam K., Maddens M.: Artificial intelligence and leukocyte epigenomics: Evaluation and prediction of late-onset Alzheimer's disease, PloS one, 16(3), pp. e0248375, 2021.
[11] Zaudig M., Mittelhammer J., Hiller W., Pauls A., Thora C., Morinigo A., Mombour W.: SIDAM - A Structured Interview for the diagnosis of Dementia of the Alzheimer type, Multi-infarct dementia and dementias of other aetiology according to ICD-10 and DSM-III-R, Psychological Medicine, 21(1), pp. 225-236, 1991, doi:10.1017/S0033291700014811.
[12] Zeisel J., Bennett K., Fleming R.: World Alzheimer Report 2020: Design, dignity, dementia: Dementia-related design and the built environment, Alzheimer's Disease International, 2020. [web page] `https://www.alzint.org/resource/world-alzheimer-report-2020/`
[13] Hajamohideen F., Shaffi N., Mahmud M., Subramanian K., Al Sariri A., Vimbi V., Abdesselam A.: Four-way classification of Alzheimer's disease using deep Siamese convolutional neural network with triplet-loss function, Brain Informatics, 10(1), pp. 5, 2023.
[14] Murugan S., Venkatesan C., Sumithra M. G., Gao X.Z., Elakkiya B., Akila M., Manoharan S.: DEMNET: a deep learning model for early diagnosis of Alzheimer diseases and dementia from MR images, Ieee Access, 9, pp. 90319-90329, 2021.
[15] Herzog N.J., Magoulas G.D.: Brain asymmetry detection and machine learning classification for diagnosis of early dementia, Sensors, 21(3), pp. 778, 2021.
[16] Searle T., Ibrahim Z., Dobson R.: Comparing natural language processing techniques for Alzheimer's dementia prediction in spontaneous speech, arXiv preprint arXiv:2006.07358, 2020.
[17] Krizhevsky A., Sutskever I., Hinton G.E.: Imagenet classification with deep convolutional neural networks, Advances in neural information processing systems, 25, 2012.
[18] Szegedy C., Liu W., Jia Y., Sermanet P., Reed S., Anguelov D., Erhan D., Vanhoucke V., Rabinovich A.: Going deeper with convolutions, In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 1-9, 2015.
[19] He K., Zhang X., Ren S., Sun J.: Deep residual learning for image recognition, In: Proceedings o of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 770-778, 2016.
[20] Benbakreti, S., Benouis, M., Roumane, A. et al.: Impact of the data augmentation on the detection of brain tumor from MRI images based on CNN and pretrained models, In: Multimed Tools Appl,2023.
[21] Maciej, G., Stanisław O.: Classical versus deep learning methods for anomaly detection in ECG using wavelet transformation, PRZEGLĄD ELEKTROTECHNICZNY,2021(6), pp. 72–76, 2022.