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Early Diagnose Alzheimer's Disease by Convolution Neural Network-based Histogram Features Extracting and Canny Edge

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Abstract

Alzheimer's disease (AD) increasingly affects the elderly and is a major killer of those 65 and over. Different deep-learning methods are used for automatic diagnosis, yet they have some limitations. Deep Learning is one of the modern methods that were used to detect and classify a medical image because of the ability of deep Learning to extract the features of images automatically. However, there are still limitations to using deep learning to accurately classify medical images because extracting the fine edges of medical images is sometimes considered difficult, and some distortion in the images. Therefore, this research aims to develop A Computer-Aided Brain Diagnosis (CABD) system that can tell if a brain scan exhibits indications of Alzheimer's disease. The system employs MRI and feature extraction methods to categorize images. This paper adopts the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset includes functional MRI and Positron-Version Tomography scans for Alzheimer's patient identification, which were produced for people with Alzheimer's as well as typical individuals. The proposed technique uses MRI brain scans to discover and categorize traits utilizing the Histogram Features Extraction (HFE) technique to be combined with the Canny edge to representing the input image of the Convolutional Neural Networks (CNN) classification. This strategy keeps track of their instances of gradient orientation in an image. The experimental result provided an accuracy of 97.7% for classifying ADNI images.

Keywords: ADNI, Canny Edge, CNN, Early Diagnosis, Feature extraction, Histogram features, Precise Edge.

Introduction

Brain tissue and cerebral cortex are smaller due to AD, and ventricles expand in the brain; based on these effects, The course of the disease can be foreseen [1]. MR scans can show this phenomenon when Alzheimer's disease is advanced. The area and network of brain tissue in this disorder that control cognition, memory, planning, and judgment are affected. The images showing the stages of Alzheimer's disease: Non-demented HC, very mild demented MCI, Mild demented MC, and Moderate demented AD [2] are shown in Figure 1.

However, several markers discovered in AD imaging data are also seen in standard imaging data [3]. The visual distinction between AD data and images of older people with traditional aging effects requires in-depth information and knowledge. Clinical diagnosis based on MRI images needs to be revised because changes in the brain tissue are minimal and often unnoticeable [4]. Therefore, categorizing MRI-based imaging data is needed; extracting image characteristics that help to classify brain disease data from healthy people has always required some tool or algorithm. Strong computational intelligence techniques, such as deep Learning, can aid in the early classification of Alzheimer's disease, assisting researchers and clinicians in diagnosing [5, 6].

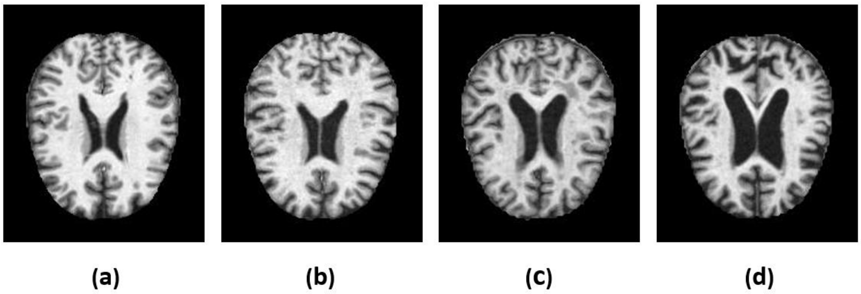

Figure 1. ADNI database showing the stages of Alzheimer's disease. (a) HC; (b) MCI; (c) MC; (d) AD.

Previous studies have used many machine learning algorithms applied to structural MRI to classify individuals with AD into different groups. Compared to more traditional approaches to machine learning, deep learning algorithms have significant advantages. For example, the most informative features can be automatically extracted from raw images without time-consuming preprocessing [7]. That means that processes will take less time, be more objective, and be less prone to bias. Based on what was discussed, deep-learning algorithms work well for large-scale, high-dimensional medical image analysis [8]. According to the research, Convolutional Neural Networks (CNNs), which belong to the family of deep-learning techniques, outperform other machine-learning approaches [9]. A typical CNN consists of three layers: as shown in Fig.2 a convolution layer, a merge layer, and a fully connected layer.

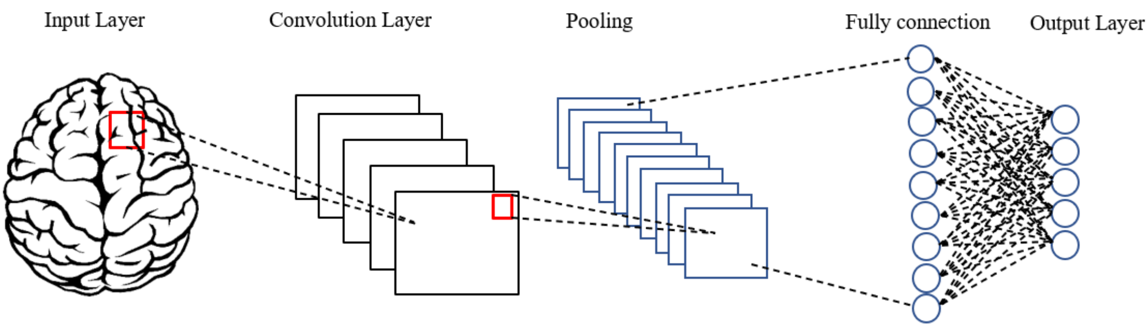

Figure 2. Typical Convolution Neural Network for image processing.

Clinicians face challenges in diagnosing Alzheimer's disease primarily due to the nuanced modifications observed in the cerebral cortex [10]. Several issues accompany the disease finding, including the data type, rotation, and scaling. Several researchers have resorted to voxel-based morphometry for analyzing MRI images (VBM) [11]. Raw data is analyzed to extract meaningful patterns and then classified based on their distinctive features. Remarkable imaging technology advancements have spawned numerous image classification applications [12]. Brain classification is important and can be a fundamental basis for diagnosing Alzheimer's. By employing deep Learning (DL) techniques, semantic classification methods can accurately predict brain volume in individuals affected by Alzheimer's [13].

This research paper proposes a comprehensive methodology for predicting the presence and severity of Alzheimer's disease using a convolutional neural network (CNN) and advanced computer imaging techniques. The process encompasses data analysis, image feature extraction, and MRI scan classification. The proposed framework achieves state-of-the-art results with a novel feature selection method that combines Canny edge detection and Histogram Features Extraction (CHFE).

- Histogram feature extraction with Canny edge detection is a novel feature selection method that combines two powerful techniques to improve feature selection accuracy.
- Histogram feature extraction provides a better understanding of the data distribution, which is essential for effective feature selection.
- The analysis provides a novel feature selection method for Alzheimer's diagnosis by combining histogram feature extraction and volumetric analysis of structural MRI images.

Related Works

Early diagnosis of Alzheimer's disease is notoriously challenging [14]. Several methods for working with brain imaging data, including deep learning-based methods, machine learning, and deep convolutional neural networks [15]. Diagnosing Alzheimer's disease in clinical studies relies heavily on magnetic resonance imaging (MRI), which can serve as the foundation for various tasks, including feature extraction and more. Deep Learning is the latest iteration of machine learning-based approaches since 2000 [16]. To attain high accuracy and high achievement, machine learning models work best when paired with features carefully created by domain experts. Newer, deeper model designs have been more popular, notably in medical image processing, since 2013. Several deep-learning methods have been employed to diagnose AD patients, including Random Forest (RF) classifiers and Support Vector Machines (SVM) on weighted MRI images for multimodal classification [17]. The categorization of Alzheimer's disease has been approached using deep learning architectures including CNN, recurrent neural networks, and deep neural networks.

Hong et al. [18] proposed an extended short-term memory LSTM network constructed with activation layers and wholly linked to record the interim relationship between stage of Alzheimer's Disease and the features. Experiments demonstrate that our model outperforms most current models. They achieved an overall performance of 82.05% for the multi-classification of Alzheimer's disease patients.

Taheri Gorji and Kaabouch N. [19] proposed a deep learning technique, one of the most influential fields of machine learning, may differentiate between healthy individuals and two kinds of MCI based on MRI findings. They employed a CNN with an efficient architecture to extract high-quality MRI features to categorize individuals as healthy, EMCI, or LMCI. This research randomly picked 70% of the data for training and 30% for testing our model. The findings indicated that the sagittal view provided the most accurate categorization between the CN and LMCI groups, with an accuracy of 94.54%.

Sarraf and Tofighi [20] using CNN algorithms with deep Learning, these researchers reveal that the most effective strategy to distinguish between safe fMRI and clinical data is to look for invariant shift and scale properties. LeNet-5 architecture and the CNN differentiated Alzheimer's functional MRI data from conventional controls, where the test findings were 96% accurate.

Kalavathi et al. [21] proposed two steps: firstly, the skull is removed from the brain image using a

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contour-based brain segmentation method (CBSM). Then a clustering method called Fast Fuzzy C Means (FFCM) is used to segment brain tissues such as white matter (WM) and gray matter (GM). In the second step, similarity indices such as Jaccard and Dice are used to identify segmented WM and GM for the presence of Alzheimer's disease on MR images of the brain.

Duaa AlSaeed and Samar Fouad [22], evaluating the effectiveness of automatic feature extraction by CNN to classification Alzheimer Disease. The model's performance was evaluated between the fully connected layers of a CNN-based model trained with three different classifiers (SoftMax, SVM, and RF) for diagnosing Alzheimer's disease using an MRI image.

Materials and Methods

The multi-site Alzheimer's Disease Neuroimaging Initiative (ADNI) project will improve clinical trials for the prevention and treatment of Alzheimer's disease (AD) [23]. This collaborative project brings together the expertise and resources of business and the public sector to survey AD participants, those at risk of developing AD, and individuals who show no signs of cognitive decline. Researchers at 63 locations in the United States and Canada use neuroimaging, biochemical, genetic, and biological markers to monitor the course of AD in the human brain. This understanding contributes to developing more effective clinical trials for preventing and treating AD [24]. ADNI has had a global influence in two ways: by producing a set of standardized procedures that enables the comparison of findings from other centers and by adopting a data-sharing policy that makes all data accessible to qualified researchers worldwide without restriction. Over 1,000 scientific articles have cited ADNI data. Fig.3 shows a sample of ADNI.

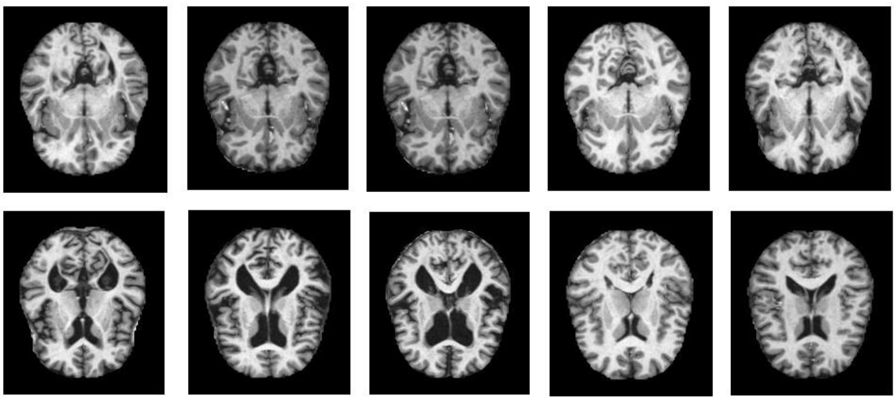

Figure 3. Samples of MRI dataset ADNI [25].

Deep Learning

The field of medical image processing, like every other area of IT, has been revolutionized by AI. Deep Learning is the most prevalent in medical image processing because of its ability to extract image features automatically, which contributes to increasing classification accuracy [26, 27]. In our work, deep Learning is used because it can find methods for eliciting a high degree of abstraction by analyzing an extensive data set [28].

Convolutional-based techniques for imaging and analysis, such as image registration, segmentation, and object identification, have gained popularity in recent years. Numerous concerns include employing functions [29], which may be successfully addressed by defining a solid collection of features utilizing deep learning approaches. This section discusses the advancements in image recognition made possible by deep learning architectures [30]; MRI image registration, segmentation, and identification are all strategies utilized to enhance image quality [31].

Numerous standard techniques (algorithms) of supervised learning have caught academic researchers' attention and successfully used

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different aspects [32, 33]. These algorithms include, but are not limited to, ANN, Decision Trees, Naive Bayes, KNN, Rule Learners, SVM, Random Forest, and Bayesian Networks [34, 35].

This paper proposes a comprehensive framework for classifying Alzheimer's based on CNN. The framework's three main stages as shown in Fig.4; each layer has stages and algorithms. The frame layers are (1) data collection and pre-processing and (2) the application of deep Learning using CNN. (3) Extracting the features of images and classification, (4) Performance evaluation. The main contributions of this framework are extracting the edges of images using three algorithms and classifying a new edge image using CNN's deep Learning.

The methodology employed in this paper consists of several sequential steps: data collection, pre-processing, feature extraction, deep learning classification, and validation [36]. The initial step involves obtaining images from the Alzheimer's Disease Neuroimaging Initiative (ADNI) and applying pre-processing techniques. Subsequently, the pre-processed data feeds into CNNs, enabling the extraction of features and the classification of various stages of Alzheimer's disease [37]. The proposed method was divided into distinct parts: data collection, extracting the features of the images using CHFE, classifying the data using CNN two time for the original images firstly and for a new feature extraction image secondly, finally the performance evaluation stage.

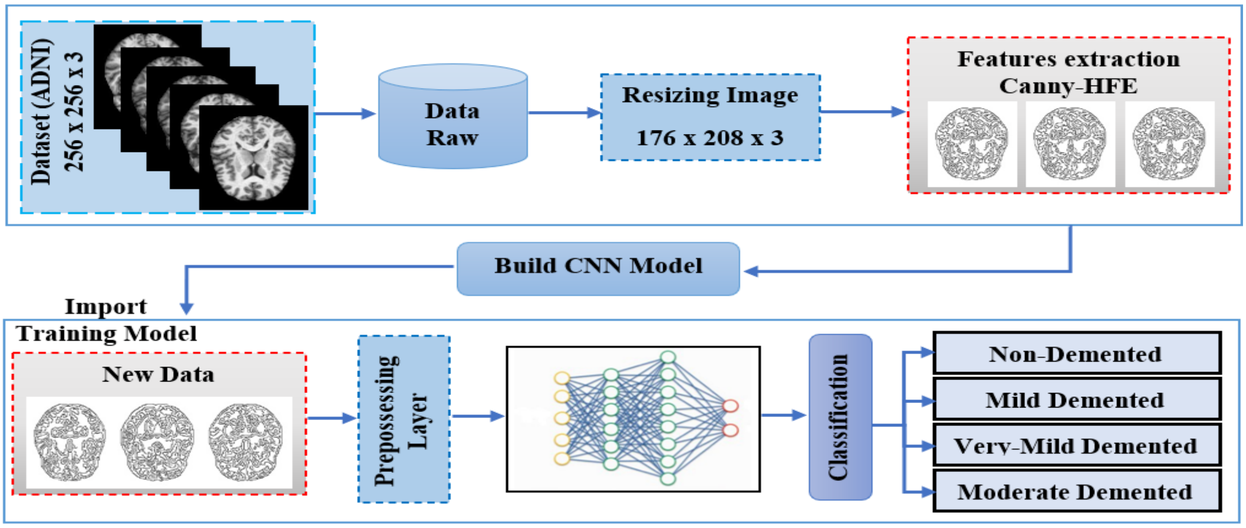

Figure 4. Structure of the proposed method for extracting features and classification.

Data collection is one of the key stages where the correct image type is selected and analyzed for viable images. First, data is configured and stored by categories to be classified. This research collected data from the Alzheimer's Neuroimaging Initiative, which provides a dataset for research purposes [38]. It is then applied to Pre-processing data. At this stage, the Histogram feature extraction is used to obtain the characteristics of the magnetic resonance images, which assists in achieving high accuracy throughout the testing process.

The ADNI data undergo analysis and are translated into 2D images during the pre-processing stage. This process results in the creation of a dataset suitable for training phases with deep neural networks. Concurrently, the characteristics of the pre-processed phase are listed in Table 1.

Table 1. Data used for training and testing.

Group	No. of Image Training	No. of image Testing
Non-Demantra	2560	640
very mild dementia	1792	448
mild dementia	717	179
moderate dementia	52	12

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Results and Discussion

Data collection and pre-processing was the first step in the proposed model. After that, the features were extracted using three different methods to obtain the most accurate method at the classification stage.

Feature Extraction method

For improved results in the classification step of ADNI image, three distinct feature extraction techniques were applied to detect image edges. The performance of fMRI edge extraction and its integration into deep learning-based classification were subsequently compared. The analysis revealed that the most accurate results were achieved when employing canny and histogram-based feature extraction, as opposed to using histogram, canny methods for edge detection. Within the edge extraction methods, it was observed that the histogram method, when within certain limits, yielded lower accuracy, and the canny method resulted in the loss of some edges. On the contrary, the CHFE method exhibited higher accuracy with precise edges, capturing all edges of the image. This advanced preprocessing method was adopted for deep learning-based classification. An example of an image with extracted edges using this method is presented in Fig. 5.

(a) (b) (c)

Figure 5. Sample of the methods applied to detect the edges of images. (a) Canny edge; (b) Histogram edge; (c) Canny-Histogram feature extraction.

Canny-Histogram Feature Extraction (CHFE)

In this study, a method has been devised for extracting image features based on the information derived from edges of various orientations. Various engineering techniques are available for eliminating image features, including Histogram feature extraction [39] and the Scale-Invariant Feature Transform (SIFT) [40]. Convolution is utilized to identify edges within an image. As explained in previous sections detailing the convolution process, convolving an image with appropriate horizontal and vertical kernels generates image gradients, with significant pixel values indicating strong edge content in specific directions. To determine the edge content in each orientation, the image is convolved with the corresponding kernel, a rectified linear unit (ReLU) is applied to eliminate negative entries, and the remaining positive pixel values are summed. Fig. 6 illustrates an example of how edges are extracted from an image using this approach.

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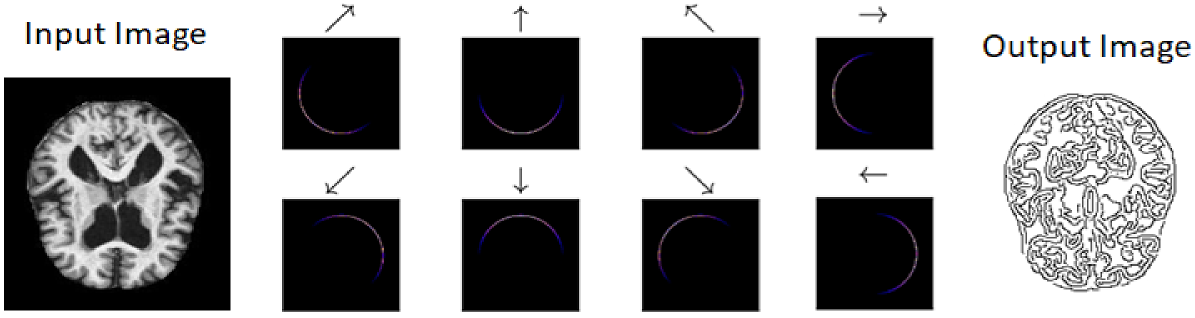

Figure 6. A CHFE edge detection result.

CHFE is computed by splitting the image into cells and then grouping the cells into blocks. Eq. 1 and Eq.2 determine each pixel's gradient magnitude and orientation inside the block. Data features entered were obtained after the application, whereas Fig.7 shows brain images after applying edge detection with the histogram feature extraction.

$$m(x,y) = \sqrt{d_x(x,y)^2 + d_y(x,y)^2} \quad (1)$$

$$\theta = arctan \frac{d_y(x,y)}{d_x(x,y)} \quad (2)$$

Figure 7. Edge detection by Canny-Histogram feature extraction.

CNN model Application and classification

Each convolutional neuron analyzes data only in its receptive field. This is analogous to the response of neurons in the visual brain to a particular stimulus. Fully connected feedforward neural networks can be used for feature learning and data classification but are not optimal for both tasks [41]. Due to the vast input size of images, where each pixel represents a vital input characteristic, even a shallow design would need many neurons. In addition, CNN are appropriate for data having a grid-like architecture (such as images) since spatial relationships between individual features are considered during convolution and pooling [42]. Fig.8 shows the convolution neural network architecture in the proposed method.

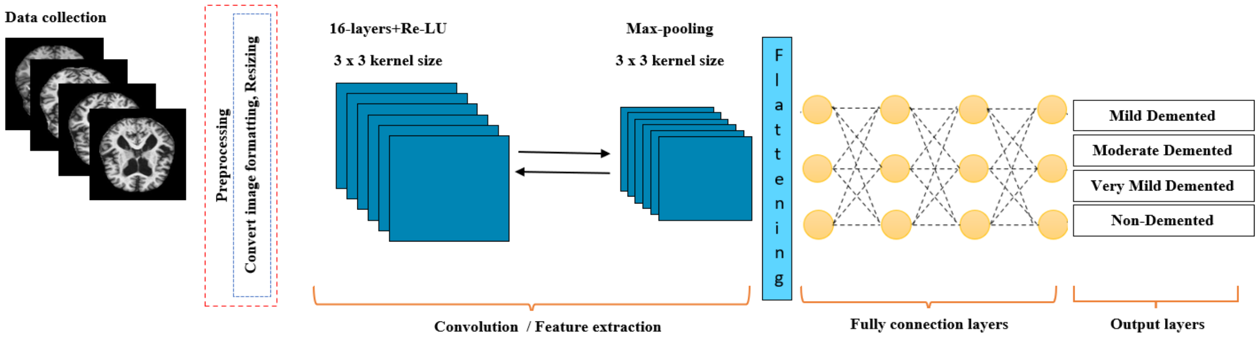

Figure 8. Convolution Neural Network in the proposed method.

Performance Evaluation

Evaluation criteria are a key element in the evaluation of a classification method [43] and guide the development and refinement of a classification model. All measurements are derived from the values of these four factors: true positive (TP), true negative (TN), false positive (FP) and false negative (FN). See Table 2. Definition of the measuring parameters.

The following standardized scales are most commonly used in the field of classification. True positives, true negatives, false positives, and false negatives are referred to as TP, TN, FP, and FN. The indicators used to assess classification accuracy are summarized below:

$$Accuracy = \frac{\text{TP+TN}}{\text{TP+FP+FN+TN}} \quad (3)$$

Table 2. Definition of the measuring parameters.

Parameter	Definition
TP	The pattern is correctly classified as positive.
FN	The pattern was mistakenly classified as negative.
FP	The pattern was incorrectly classified as positive.
TN	The pattern is correctly classified as negative.

In this investigation of Alzheimer's disease, it's observed that the deep learning model employing CNNs exhibited superior performance compared to conventional machine learning techniques for AD classification. Notably, the most accurate results were achieved when utilizing images generated through the CHFE method, as illustrated in Table 3. Our simulation outcomes suggest that our recommended framework attains exceptional classification accuracy in contrast to alternative approaches. The experimental findings confirmed an accuracy rate of 97.7%. The accuracy of the proposed approach can be found in Table 4, alongside a comparison with prior studies.

Table 3. Description the accuracy of deep learning classification based on feature extraction methods.

Training extracted images	Accuracy %
Canny edge + CNN	89.8
Histogram + CNN	91.4
CNN	96.4
CHFE + CNN	**97.7**

Table 4. Comparison of previous methods for Alzheimer's classification with proposed method.

Authors	Method	Accuracy
Richhariya et al., [11]	USVM-RFE	87.89%
Hedayati et al., [44]	CAED	94%
Hong et al., [18]	LSTM	82.05%
Gorji et al., [19]	CNN	94.54%
Duaa AlSaeed and Samar Fouad [22]	CNN	99%
Yousry Abdul Azeem et al., [45]	ADAM +CNN	97.5
Proposed method	**CHFE+CNN**	**97.7%**

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Conclusion

This paper presents a comprehensive framework to develop A Computer-Aided Brain Diagnosis (CABD) system for Alzheimer's disease (AD) classification based on CNN. The framework comprises four main components:

- Data Collection and Pre-processing: The first step involves collecting and pre-processing the data.
- Deep Learning with CNN: The second component employs CNN for deep learning.
- Feature Extraction from Images: The third stage focuses on extracting features from images and organizing them into groups.
- Performance Evaluation: The final step involves evaluating the performance of the proposed method.

This approach is centered on extracting features from MRI images using Canny and Histogram Feature Extraction (CHFE), offering enhanced insights into the data. In the analysis of Alzheimer's disease, the deep learning model employing CNN demonstrated superior performance compared to traditional machine learning methods for AD classification. Furthermore, a method for extracting features from MRI images was introduced during the pre-processing phase. The study illustrates the CNN model's practicality for training and testing, showcasing its applicability in real-world scenarios.

Simulation results indicate that our suggested framework achieves superior classification accuracy compared to other approaches. Specifically, the experimental results yielded an accuracy of 97.7%, precision of 91.3%, sensitivity of 98.1%, and specificity of 93.64% using the MRI dataset from ADNI.

Authors’ Declaration

- Conflicts of Interest: None.
- We hereby confirm that all the Figures and Tables in the manuscript are ours. Besides, the Figures and images, which are not ours, have been given the permission for republication attached with the manuscript.
- Authors sign on ethical consideration’s approval
- Ethical Clearance: The project was approved by the local ethical committee from ADNI (https://adni.loni.usc.edu/data-samples/data-types/mri/).

Authors' contributions statement:

Conception, design and drafting the manuscript, K.A.K.; acquisition of data and analysis, F.M.; interpretation, revision and proofreading, G.A.S; formal analysis, F.H.N. All authors have read and agreed to the published version of the manuscript.

References

1. Fjell AM, McEvoy L, Holland D, Dale AM, Walhovd KB, Initiative AsDN. What is normal in normal aging? Effects of aging, amyloid and Alzheimer's disease on the cerebral cortex and the hippocampus. Prog. Neurobiol. PROG NEUROBIOL. 2014;117:20-40. https://doi.org/10.1016/j.pneurobio.2014.02.004.
2. Therriault J, Zimmer ER, Benedet AL, Pascoal TA, Gauthier S, Rosa-Neto P. Staging of Alzheimer’s disease: past, present, and future perspectives. Trends. Mol. Med. . 2022. https://doi.org/10.1016/j.molmed.2022.05.008.
3. Janghel R, Rathore Y. Deep convolution neural network based system for early diagnosis of Alzheimer's disease. Irbm. 2021;42(4):258-67. https://doi.org/10.1016/j.irbm.2020.06.006.
4. Sathiyamoorthi V, Ilavarasi A, Murugeswari K, Ahmed ST, Devi BA, Kalipindi M. A deep convolutional neural network based computer aided diagnosis system for the prediction of Alzheimer's disease in MRI images. Measurement. 2021;171:108838. https://doi.org/10.1016/j.measurement.2020.108838.

5. Al-Khuzaie FE, Bayat O, Duru AD. Diagnosis of Alzheimer disease using 2D MRI slices by convolutional neural network. Appl Bionics Biomech .2021. https://doi.org/10.1155/2023/9762945.
6. Ai R, Jin X, Tang B, Yang G, Niu Z, Fang EF. Ageing and Alzheimer's Disease: Application of Artificial Intelligence in Mechanistic Studies, Diagnosis, and Drug Development. Artif Intell Med. .2021; p. 1-16. https://doi.org/10.1007/978-3-030-58080-3_74-1.
7. Vieira S, Pinaya WH, Mechelli A. Using deep learning to investigate the neuroimaging correlates of psychiatric and neurological disorders: Methods and applications. Neurosci Biobehav Rev. .2017;74:58-75. https://doi.org/10.1016/j.neubiorev.2017.01.002.
8. Khodatars M, Shoeibi A, Sadeghi D, Ghaasemi N, Jafari M, Moridian P, et al. Deep learning for neuroimaging-based diagnosis and rehabilitation of autism spectrum disorder: a review. Comput. Biol. Med. . 2021;139:104949. https://doi.org/10.1016/j.compbiomed.2021.104949.
9. Janiesch C, Zschech P, Heinrich K. Machine learning and deep learning. EM. 2021;31(3):685-95. https://doi.org/10.1007/s12525-021-00475-2.
10. Association As. Alzheimer's disease facts and figures. Alzheimer's & Dementia. 2018;14(3):367-429. https://doi.org/10.1016/j.jalz.2018.02.001.
11. Richhariya B, Tanveer M, Rashid A, Initiative AsDN. Diagnosis of Alzheimer's disease using universum support vector machine based recursive feature elimination (USVM-RFE). Biomed. Signal Process. Control. . 2020;59:101903. https://doi.org/10.1016/j.bspc.2020.101903.
12. Mahmud M, Kaiser MS, Hussain A, Vassanelli S. Applications of deep learning and reinforcement learning to biological data. IEEE Trans. Neural Netw. Learn. Syst. . 2018;29(6):2063-79. https://doi.org/10.1109/TNNLS.2018.2790388.
13. Schwarz CG, Gunter JL, Wiste HJ, Przybelski SA, Weigand SD, Ward CP, et al. A large-scale comparison of cortical thickness and volume methods for measuring Alzheimer's disease severity. NeuroImage: Clin. . 2016;11:802-12. https://doi.org/10.1016/j.nicl.2016.05.017.
14. Porsteinsson A, Isaacson R, Knox S, Sabbagh M, Rubino I. Diagnosis of early alzheimer's disease: Clinical practice in 2021. The JPAD. 2021;8(3):371-86. https://doi.org/10.14283/jpad.2021.23.
15. Sui J, Jiang R, Bustillo J, Calhoun V. Neuroimaging-based individualized prediction of cognition and behavior for mental disorders and health: methods and promises. Biol. Psychiatry. 2020;88(11):818-28. https://doi.org/10.1016/j.biopsych.2020.02.016.
16. Afrasiabi M, Mohammadi M, Rastegar M, Afrasiabi S. Advanced deep learning approach for probabilistic wind speed forecasting. IEEE Transactions on Industrial Informatics. 2020;17(1):720-7. https://doi.org/10.1109/TII.2020.3004436.
17. Yamanakkanavar N, Choi JY, Lee B. MRI segmentation and classification of human brain using deep learning for diagnosis of Alzheimer's disease: a survey. Sensors. 2020;20(11):3243. https://doi.org/10.3390/s20113243.
18. Hong X, Lin R, Yang C, Zeng N, Cai C, Gou J, et al. Predicting Alzheimer's disease using LSTM. Ieee Access. 2019;7:80893-901. https://doi.org/10.1109/ACCESS.2019.2919385.
19. Taheri Gorji H, Kaabouch N. A deep learning approach for diagnosis of mild cognitive impairment based on MRI images. Brain Sci. . 2019;9(9):217. https://doi.org/10.3390/brainsci9090217.
20. Sarraf S, Tofighi G. Classification of alzheimer's disease using fmri data and deep learning convolutional neural networks. arXiv preprint arXiv:160308631. 2016. https://doi.org/10.48550/arXiv.1603.08631.
21. Kalavathi P, Christy A, Priya T. Detection of Alzheimer disease in MR brain images using FFCM method. Computational methods, communication techniques and informatics. 2017:140-4.
22. AlSaeed D, Omar SF. Brain MRI Analysis for Alzheimer's Disease Diagnosis Using CNN-Based Feature Extraction and Machine Learning. Sensors. 2022;22(8):2911. https://doi.org/10.3390/s22082911.
23. Jack Jr CR, Bernstein MA, Fox NC, Thompson P, Alexander G, Harvey D, et al. The Alzheimer's disease neuroimaging initiative (ADNI): MRI methods. J. Magn. Reson. Imaging. 2008;27(4):685-91. https://doi.org/10.1002/jmri.21049.
24. Noella R, Priyadarshini J. Diagnosis of Alzheimer's, Parkinson's disease and frontotemporal dementia using a generative adversarial deep convolutional neural network. Neural. Comput. Appl. NEURAL COMPUT. 2022:1-10. https://doi.org/10.1007/s00521-022-07750-z.
25. Mueller SG, Weiner MW, Thal LJ, Petersen RC, Jack C, Jagust W, et al. The Alzheimer's disease neuroimaging initiative. Neuroimaging Clin. N. Am. . 2005;15(4):869-77. https://doi.org/10.1016/j.nic.2005.09.008.
26. Abdou MA. Literature review: Efficient deep neural networks techniques for medical image analysis. Neural. Comput. Appl. NEURAL COMPUT. 2022:1-22. https://doi.org/10.1007/s00521-022-06960-9.
27. Hasan AM, Qasim AF, Jalab HA, Ibrahim RW. Breast cancer MRI classification based on fractional entropy image enhancement and deep feature extraction. Baghdad Sci. J. . 2023;20(1):0221. https://dx.doi.org/10.21123/bsj.2022.6782.
28. Kazemzadeh M, Hisey CL, Zargar-Shoshtari K, Xu W, Broderick NG. Deep convolutional neural networks as a unified solution for Raman spectroscopy-based classification in biomedical

applications. Opt. Commun. . 2022;510:127977. https://doi.org/10.1016/j.optcom.2022.127977.
29. Sahai E, Astsaturov I, Cukierman E, DeNardo DG, Egeblad M, Evans RM, et al. A framework for advancing our understanding of cancer-associated fibroblasts. Nat. Rev. Cancer. 2020;20(3):174-86. https://doi.org/10.1038/s41568-019-0238-1.
30. Lane ND, Bhattacharya S, Mathur A, Georgiev P, Forlivesi C, Kawsar F. Squeezing deep learning into mobile and embedded devices. IEEE Pervasive Computing. 2017;16(3):82-8. https://doi.org/10.1109/MPRV.2017.2940968.
31. Guo Z, Li X, Huang H, Guo N, Li Q. Deep learning-based image segmentation on multimodal medical imaging. IEEE Transactions on Radiation and Plasma Medical Sciences. 2019;3(2):162-9. https://doi.org/10.1109/TRPMS.2018.2890359.
32. Van Engelen JE, Hoos HH. A survey on semi-supervised learning. Machine Learning. 2020;109(2):373-440. https://doi.org/10.1007/s10994-019-05855-6.
33. Kadhim KA, Mohamed F, Khudhair ZN, Alkawaz MH, editors. Classification and predictive diagnosis earlier Alzheimer's disease using MRI brain images. 2020 IEEE Conference on Big Data and Analytics (ICBDA); 2020: IEEE. https://doi.org/10.1109/ICBDA50157.2020.9289829.
34. Alasker H, Alharkan S, Alharkan W, Zaki A, Riza LS, editors. Detection of kidney disease using various intelligent classifiers. 2017 3rd international conference on science in information technology (ICSITech); 2017: IEEE. https://doi.org/10.1109/ICSITech.2017.8257199.
35. Alnedawe SM, Aljobouri HK. A New Model Design for Combating COVID-19 Pandemic Based on SVM and CNN Approaches. Baghdad Sci. J. 2023. https://doi.org/10.21123/bsj.2023.7403.
36. Padmasini N, Umamaheswari R, Kalpana R, Sikkandar MY. Comparative study of iris and retinal images for early detection of diabetic mellitus. JMIHI. 2020;10(2):316-25. https://doi.org/10.1166/jmihi.2020.2973.
37. Ramzan F, Khan MUG, Rehmat A, Iqbal S, Saba T, Rehman A, et al. A deep learning approach for automated diagnosis and multi-class classification of Alzheimer's disease stages using resting-state fMRI and residual neural networks. J. Med. Syst. . 2020;44(2):1-16. https://doi.org/10.1007/s10916-019-1475-2.
38. Thompson RF, Iadanza MG, Hesketh EL, Rawson S, Ranson NA. Collection, pre-processing and on-the-fly analysis of data for high-resolution, single-particle cryo-electron microscopy. Nat. Protoc. 2019;14(1):100-18. https://doi.org/10.1038/s41596-018-0084-8.
39. Najjar FH, Khudhair KT, Khaleq AHA, Kadhim ON, Abedi F, Al-Kharsan IH, editors. Histogram Features Extraction for Edge Detection Approach. 2022 5th International Conference on Engineering Technology and its Applications (IICETA); 2022: IEEE. https://doi.org/10.1109/IICETA54559.2022.9888697.
40. Dinu A, Manju R, editors. A Novel Modelling Technique for Early Recognition and Classification of Alzheimer's disease. 2021 3rd International Conference on Signal Processing and Communication (ICPSC); 2021: IEEE. https://doi.org/10.1109/ICSPC51351.2021.9451803.
41. Eskandari H, Imani M, Moghaddam MP. Convolutional and recurrent neural network based model for short-term load forecasting. Electr. Power Syst. Res. ELECTR POW. 2021;195:107173. https://doi.org/10.1016/j.epsr.2021.107173.
42. Andresini G, Appice A, Malerba D. Nearest cluster-based intrusion detection through convolutional neural networks. KBS. 2021;216:106798. https://doi.org/10.1016/j.knosys.2021.106798.
43. Santra G, Martin JM, editors. Some observations on the performance of the most recent exchange-correlation functionals for the large and chemically diverse GMTKN55 benchmark. AIP Conference Proceedings; 2019: AIP Publishing LLC.2019. https://doi.org/10.1063/1.5137915.
44. Hedayati R, Khedmati M, Taghipour-Gorjikolaie M. Deep feature extraction method based on ensemble of convolutional auto encoders: Application to Alzheimer's disease diagnosis. Biomed. Signal Process. Control. 2021;66:102397. https://doi.org/10.1016/j.bspc.2020.102397.
45. AbdulAzeem Y, Bahgat WM, Badawy M. A CNN based framework for classification of Alzheimer's disease. Neural. Comput. Appl. NEURAL COMPUT. 2021;33(16):10415-28. https://doi.org/10.1007/s00521-021-05799-w.

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التشخيص المبكر لمرض الزهايمر عن طريق استخراج مميزات الصور بالرسم البياني واكتشاف حافة كاني باستخدام الشبكة العصبية التلافيفية

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الخلاصة

يؤثر مرض الزهايمر (AD) بشكل متزايد على كبار السن ويعتبر أحد الامراض الرئيسية التي تؤدي الى الموت لأولئك الذين يبلغون من العمر 65 عامًا وأكثر. يتم استخدام طرق مختلفة للتعلم العميق للتشخيص التلقائي لهذا المرض، إلا أنها احيانا قد تحتوي على بعض القيود. يعد التعلم العميق من الطرق الحديثة التي تم استخدامها لكشف وتصنيف الصورة الطبية بسبب قدرته على استخراج ميزات الصور بشكل تلقائي. ومع ذلك، لا تزال هناك بعض القيود على استخدام التعلم العميق لتصنيف الصور الطبية بدقة عالية لأنه في بعض الأحيان لا يمكن استخراج الحواف الدقيقة، وقد يكون هناك بعض التشويه في الصور. يهدف هذا البحث إلى تطوير نظام تشخيص الدماغ بمساعدة الحاسوب (CABD) الذي يمكنه معرفة ما إذا كان فحص الدماغ يظهر مؤشرات على مرض الزهايمر ام لا. يستخدم النظام المقترح التصوير بالرنين المغناطيسي وطرق استخراج الميزات لتصنيف الصور الطبية. تستهدف هذه الورقة مجموعة بيانات مبادرة التصوير العصبي لمرض الزهايمر (ADNI) التي تتضمن التصوير بالرنين المغناطيسي الوظيفي والتصوير المقطعي بالإصدار البوزيتروني لتحديد مريض الزهايمر، والتي تم إنتاجها للأشخاص المصابين بمرض الزهايمر بالإضافة إلى الاشخاص غير المصابين. تستخدم التقنية المقترحة فحوصات الدماغ بالرنين المغناطيسي لاكتشاف وتصنيف السمات باستخدام تقنية استخراج ميزات الرسم البياني (HFE) ليتم دمجها مع اكتشاف حواف Canny الذي يمثل الصورة المدخلة ليتم ادخالها في الشبكة العصبية التلافيفية لغرض تصنيفها. تقوم هذه الإستراتيجية بتتبع حالات الاتجاه المتدرج في الصورة. حيث قدمت هذه التقنية المقترحة نتيجة تجريبية بلغت دقتها 97.7% لتصنيف صور الرنين المغناطيسي لمرض الزهايمر.

الكلمات المفتاحية: مبادرة التصوير العصبي لمرض الزهايمر (ADNI)، حافة كاني، الشبكة العصبية التلافيفية، التشخيص المبكر، استخراج مميزات الصور، ميزات الرسم البياني، الحافة الدقيقة.