Journal of Electrical Engineering and Automation (EEA) (2021)
Vol.03/ No.03
Pages: 214-229
https://www.irojournals.com/iroeea
DOI: https://doi.org/10.36548/jeea.2021.3.005

Automated Multimodal Fusion Technique for the Classification of Human Brain on Alzheimer's Disorder

B. Vivekanandam

Senior Lecturer, Faculty of Computer Science and Multimedia, Lincoln University College, Malaysia

Email: vivekanandam@lincoln.edu.my

Abstract

Alzheimer's Disorder (AD) may permanently impair memory cells, resulting in dementia. Researchers say that early Alzheimer's disease diagnosis is difficult. MRI is used to detect AD in clinical trials. It requires high discriminative MRI characteristics to accurately classify dementia stages. Due to the large extraction of features, improved deep CNN-based models have recently proven accurate. With fewer picture samples in the datasets, over-fitting issues arise, limiting the effectiveness of deep learning algorithms. This research article minimizes the overfitting error due to fusion techniques. This hybrid approach is used to classify Alzheimer's disease more accurately than other traditional approaches. Besides, the Convolutional Neural Network (CNN) provides more minute features of small changes in MRI scan images than any other algorithm. Therefore, the proposed algorithm provides great accuracy in the region of sagittal, coronal, and axial Mild Cognitive Impairments (MCI) in the brain segment classification. Moreover, this research article compares the proposed algorithm with previous research output that is used to help prove its superiority. The performance metrics uses Health Subject (HS), MCI, and Mini-Mental State Evaluation (MMSE) to evaluate the proposed research algorithm.

Keywords: Alzheimer disease, convolutional neural network, multimodal fusion, deep learning, batch normalization, group normalization, human brain classification

ISSN: 2582-3051
Submitted: 20.09.2021
Revised: 25.10.2021
Accepted: 07.11.2021
Published: 16.11.2021

Journal of Electrical Engineering and Automation (EEA) (2021)
Vol.03/ No.03
Pages: 214-229
https://www.irojournals.com/iroeea
DOI: https://doi.org/10.36548/jeea.2021.3.005

1. Introduction

Alzheimer's Disorder (AD) is a neurodegenerative illness that causes brain tissue to be lost and shrink or nerve cells to die, leading to memory loss and a decrease in the ability to do everyday functions like writing, speaking, and reading. Patients with Alzheimer's disease may have difficulty recognizing members of their own family at times. Alzheimer's disease patients in the early stages of the disease display aggressive behaviour, while those in the last stages of the disease suffer from heart failure and respiratory system malfunction [1-3].

Because of the incorrect prescription, it is impossible to make an early and reliable diagnosis of AD. However, early detection and treatment of Alzheimer's may enhance the patient's quality of life. In most cases, the symptoms of Alzheimer's disease (AD) appear gradually, but they get more severe over time as the brain problem progresses [4-7]. This illness affects a considerable number of individuals each year. AD is expected to affect one out of every 85 people in the globe by the year 2050. Dementia scales are generally based on the Global Deterioration Scale (GDS). The damaged or shrunk brain image is shown in the figure 1.

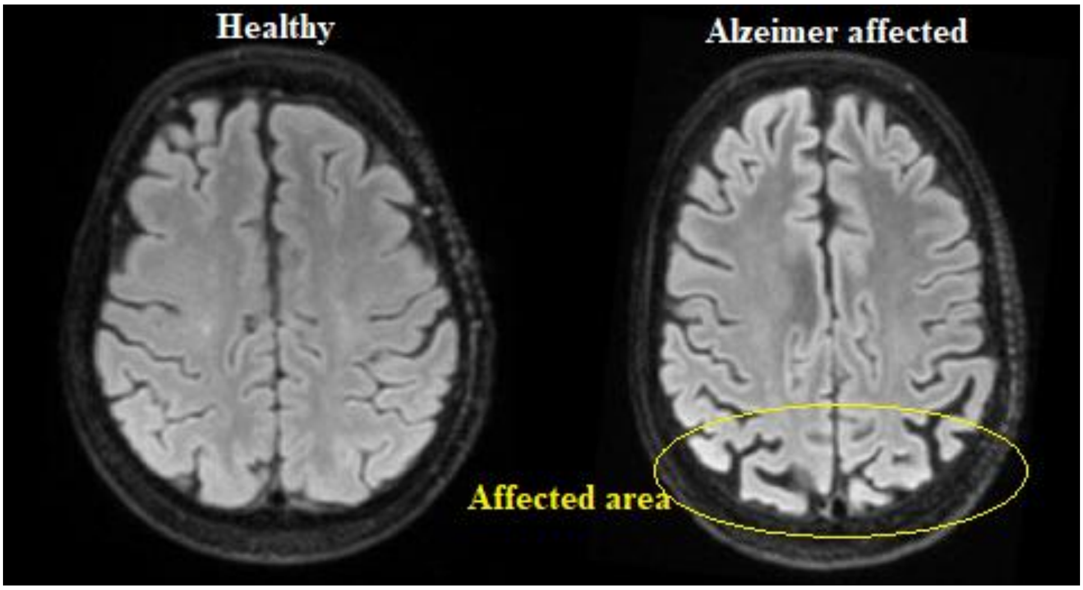

Figure 1. Alzheimer’s disease brain image

ISSN: 2582-3051
Submitted: 20.09.2021
Revised: 25.10.2021
Accepted: 07.11.2021
Published: 16.11.2021

Journal of Electrical Engineering and Automation (EEA) (2021)
Vol.03/ No.03
Pages: 214-229
https://www.irojournals.com/iroeea
DOI: https://doi.org/10.36548/jeea.2021.3.005

Magnetic Resonance Imaging (MRI) can distinguish between soft tissue and hard tissue, making it an ideal tool for studying the brain's structural features. MRI is believed to have less health concerns than other imaging modalities, such as CT and PET. Brain traumas and brain structure may now be studied using MRIs, which have made great strides in recent years [8-12].

Brain MRI segmentation is used in a number of clinical applications since it affects the findings of the overall study. The image segmentation for the medical images particularly grey and white samples through cerebellum spinal fluid has been detected through many machine learning approaches by heavy datasets. [12-14]. MRI may be used to segment aberrant brain tissue in Alzheimer's disease patients. It is necessary to use complex technical approaches and specialised skills to extract the image information needed for this segmentation [15].

Motivation of the research

For quantitative analysis of brain MRI, deep learning may be utilized to learn new characteristics that can be identified via self-learning of features. The computer vision based diagnosis depending on nodules and malignant of the tissues through deep learning has gained a lot of traction [11]. If these obstacles are addressed, the deep learning approach will be the sole option for brain MRI segmentation. Splitting an image into distinct areas is the primary goal of segmentation in brain MRI. Each region is composed of image pixels and its range of intensity through grey and white textures.

2. Structure of the Research Article

The following sections comprise this research article: Section 2 summarizes previous research and identifies research gaps. The third section describes a possible mechanism for detecting Alzheimer's disease using human brain categorization. Section 4 provides a test description for a variety of computer vision tasks. The last part summarizes the study findings and discusses possible future expansions.

ISSN: 2582-3051
Submitted: 20.09.2021
Revised: 25.10.2021
Accepted: 07.11.2021
Published: 16.11.2021

Journal of Electrical Engineering and Automation (EEA) (2021)
Vol.03/ No.03
Pages: 214-229
https://www.irojournals.com/iroeea
DOI: https://doi.org/10.36548/jeea.2021.3.005

3. Previous Research Work

In order to extract characteristics and execute various operations on AD MRI images, several machine learning-based models have been suggested in previous research works. A linear support vector machine on T1-weighted MRI images was used by Kloppel et al. to construct a dimensional reduction model for detecting AD patients [16].

Ahmed et al. used a patch-based classifier to create a simplified CNN model for AD multi-stage diagnosis. Improved accuracy and decreased processing cost were achieved using the model. The team used a three-view MRI picture to produce the patches and achieved an overall accuracy of 90.05 percent. However, when using machine learning models using handcrafted features, most research found that accuracy was dependent on how well the feature was described. To get the most out of this, professionals in the field are needed. Deep learning is a possible answer to this problem since it is widely known to be able to automatically collect arbitrary features and subsequently reach a high degree of accuracy [17].

Numerous Deep Learning-Based Models have been suggested to extract features directly from the input data and to conduct numerous operations on MRI images by using deep learning techniques. This kind of model is built on numerous layers and a hierarchical structure, which has significantly improved the capacity to represent features on a variety of datasets. Researchers Zeng et al. have used a Zero-Masking Technique (ZMT) to design a model that can avoid the greatest possible amount of data loss in magnetic resonance imaging (MRI) data [18 ,19].

Gupta and colleagues developed a sparse auto-encoder-based model for the categorization of three phases of Alzheimer's disease. For multi-classification on the (Alzheimer's Disease Neuroimaging Initiative) ADNI dataset, the combined accuracy attained is 95 percent, according to the results [20].

Dou et al. provided a better performance model for 3D CNN and 2D CNN techniques, which they called "the enhanced performance model". To identify brain micro bleeds, the

ISSN: 2582-3051
Submitted: 20.09.2021
Revised: 25.10.2021
Accepted: 07.11.2021
Published: 16.11.2021

Journal of Electrical Engineering and Automation (EEA) (2021)
Vol.03/ No.03
Pages: 214-229
https://www.irojournals.com/iroeea
DOI: https://doi.org/10.36548/jeea.2021.3.005

researchers employed a 3D CNN model. They carried out an extended experiment to evaluate the intended model and received a sensitivity result of 93.16 percent, which they used to validate the model [21].

An auto-encoder network was suggested by Suk et al. as a new approach for classifying AD and MCI converter stages using an auto-encoder network. Over the course of these MCI phases, they achieved an accuracy rate of 95.9 percent [22].

Its found that Long Short-Term Memory (LSTM) may link earlier knowledge about the patient to the present task in Hong et al. prediction of Alzheimer's disease. A three-layered approach is used to analyse time-series data, with each successive layer being composed of pre-connected cells and post-connected layers. Due to a dearth of data, the accuracy is still restricted when attempting to extract conventional characteristics from temporal information [23].

Jenkins et al. presented a deep learning model based on the inceptionV3 architecture for the early identification of Alzheimer's disease that would be tested on the ADNI dataset. In their analysis, they discovered that the accuracy rate for obtaining Receiver Operating Characteristics (ROC) was 95 percent and that the sensitivity rate was 100% [24].

Using intelligent data selection, a new approach was devised for the diagnosis and multi-classification of Alzheimer's disease using MRI images. For the ADNI database, they employed the popular (Visual Geometry Group) VGG CNN architecture. As a result of their use of transfer learning, they were able to achieve extremely high classification accuracy, such as 99.36 percent accuracy for AD against (Negative Cognition) NC, (Mild Cognitive Impairment) MCI versus NC, and overall 99.20 percent accuracy in multi-classification [25].

According to Gorji et al.'s research work, researchers developed an algorithm for predicting Early Mild Cognitive Impairment (EMCI) and Late Mild Cognitive Impairment (LMCI) based on a CNN-based model. The CNN may enhance outcomes in existing research employing deep learning for medical pictures and text categorization since it automatically

ISSN: 2582-3051
Submitted: 20.09.2021
Revised: 25.10.2021
Accepted: 07.11.2021
Published: 16.11.2021

Journal of Electrical Engineering and Automation (EEA) (2021)
Vol.03/ No.03
Pages: 214-229
https://www.irojournals.com/iroeea
DOI: https://doi.org/10.36548/jeea.2021.3.005

learns the properties of the given job. In contrast, CNN has a lower number of parameters, making it more suited for datasets with a limited number of variables [26, 27].

The review highlights the use of deep learning approaches to segregate these areas in brain scans. The tissue damage or shrinking effects through non uniformity segmentation is a bit difficult to solve.

4. Proposed Methodology

4.1 Fusion based design for AD classification

The data from the input is combined with the original image details in this technique. In this step, raw data or pre-extracted features are blended and stacked from several sources to provide a single input to the classifier. In the instance of Alzheimer's disease classification, the new feature vector becomes a single element with increased dimensionality and represents the single brain from several spaces. For example, if features are extracted from two distinct Region of Interests (ROIs) from the image that is used to concatenate the two vectors, it results in a single new vector domain. In addition, it includes deep learning architecture and intermediate and late fusion-based design [28, 29].

4.1.1 Fully Connection Layer (FCL)

As seen above, fusion may be used in a variety of ways by utilising three separate networks, each with its own visual projection. The three input images must be from the same topic and projection to properly feed the networks. However, in this section, the intermediate fusion is considered, which consists of a concatenation layer at the FC levels of the three networks [30-33]. The three projections are utilised as input for each network since there is a 3D-ROI representation of hippocampal region: sagittal, coronal, and axial.

ISSN: 2582-3051
Submitted: 20.09.2021
Revised: 25.10.2021
Accepted: 07.11.2021
Published: 16.11.2021

Journal of Electrical Engineering and Automation (EEA) (2021)
Vol.03/ No.03
Pages: 214-229
https://www.irojournals.com/iroeea
DOI: https://doi.org/10.36548/jeea.2021.3.005

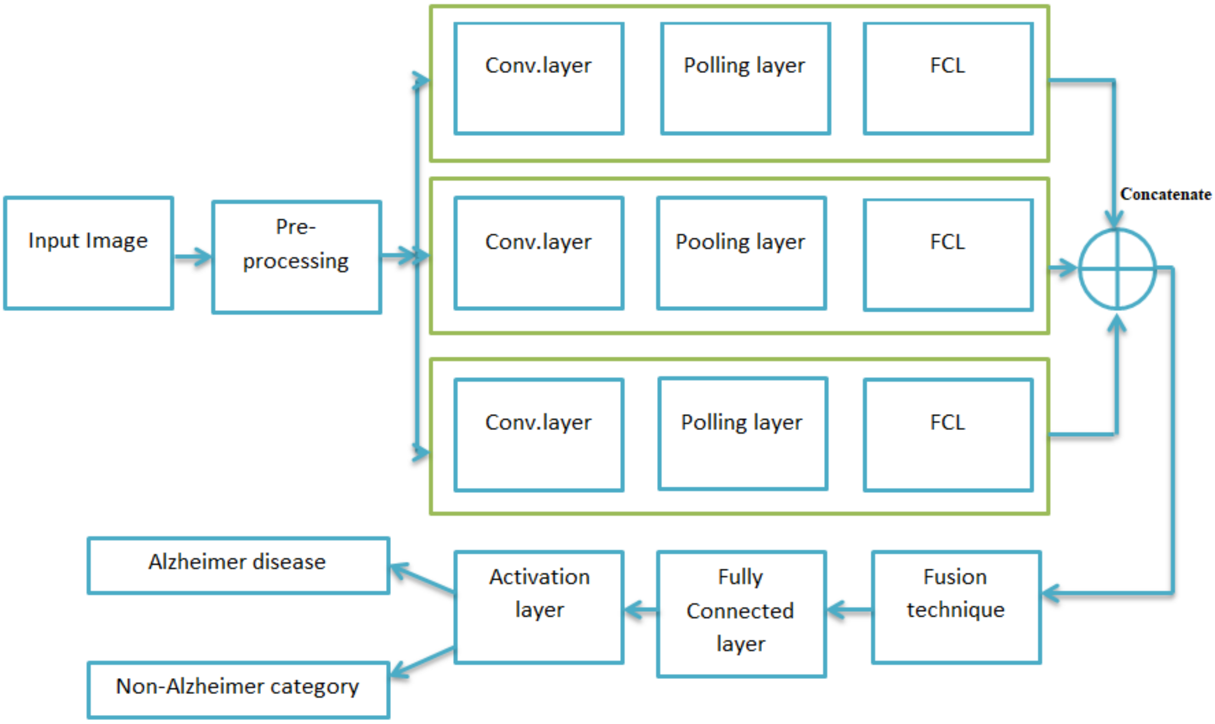

Figure 2. Overall proposed architecture

The networks are then united by concatenation of entirely linked layers via intermediary fusion. Then, to accomplish binary classification, an FC layer is generated that combines the three combined layers into two output scores. Figure 2 displays a high-level overview of the architecture. The same design is used to build each network for a single projection, which contains two convolutional layers, two pooling layers, and the ReLU activation function.

4.1.2 Intermediate fusion design

As previously stated, many fusion strategies concentrate on the classifiers themselves rather than their outputs. This paper demonstrates the ways to increase classification performance by advancing many classifiers in a single optimised structure. Indeed, each model is linked to its counterpart using a number of internal techniques to exchange features or scores

ISSN: 2582-3051
Submitted: 20.09.2021
Revised: 25.10.2021
Accepted: 07.11.2021
Published: 16.11.2021

Journal of Electrical Engineering and Automation (EEA) (2021)
Vol.03/ No.03
Pages: 214-229
https://www.irojournals.com/iroeea
DOI: https://doi.org/10.36548/jeea.2021.3.005

and enhance classification results [34-36]. Concatenation is a common intermediate approach used to consolidate models.

4.1.3 Late fusion design

Unlike the intermediate fusion approach, this technique is based on fusion inside models. Late fusion entails performing certain actions on the last layers of each network's outputs. It uses algebraic aggregation to provide outputs such as mean, median, and max, and then apply the softmax function to transform the scores to a probability choice.

4.2 Multi Modal based Fusion architecture

In this phase of the investigation, there employs the fusion approaches outlined above. It uses data from both MRI and Diffusion Tensor Imaging (DTI) modalities [37]. Rather than using three networks, the architecture of the model is enhanced by changing it to accept other data sources. The design is built by joining six networks of both modalities and all projections within them. The entire Siamese design built is shown in Figure 2.

It received three slices of each projection from left to right for both modalities (MRI and DTI-MD). The single branch network is then built and specified as described above. Finally, the fusion layer includes the two previously mentioned strategies: feature concatenation (the intermediate fusion) and aggregation functions, as well as the majority vote as the second application (the late fusion). Both approaches are used to the six networks.

In the initial design, the intermediate fusion discussed in this section is used, which has now been revised to operate in parallel over MRI and DTI data. The output of each network has been concatenated to feed an FC layer, as illustrated in Figure 2. This procedure employs the same strategy as stated above in the second implementation, which linked networks via late fusion. However, in this case, two approaches have been proposed for adapting multi-modal features:

ISSN: 2582-3051
Submitted: 20.09.2021
Revised: 25.10.2021
Accepted: 07.11.2021
Published: 16.11.2021

Journal of Electrical Engineering and Automation (EEA) (2021)
Vol.03/ No.03
Pages: 214-229
https://www.irojournals.com/iroeea
DOI: https://doi.org/10.36548/jeea.2021.3.005

1. Algebraic aggregation
2. Majority voting.

5. Results and Discussion

This section is dedicated to the development and testing of fusion algorithms for the MRI modality. The tests were conducted on a GPU-based high-performance computing platform outfitted with an Intel i7 CPU E5-2680 v2 @3.80GHz processor, 16GB of RAM, and single phase Nvidia graphics cards with 4GB dedicated memory. The networks were constructed from the ground up using stochastic gradient descent with Nester momentum. The following parameters were utilised during the training phase: 60 iterations resulted in around 100 epochs, the Learning rate was 0.0001, and the policy was fixed; Momentum was 0.9, and the batch size was 30.

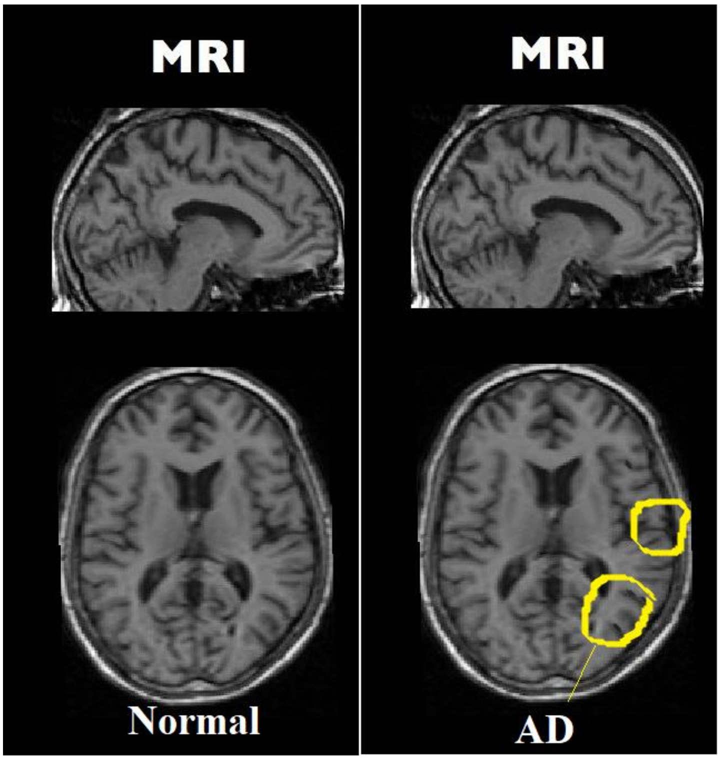

Figure 3. Results obtained by proposed algorithm

ISSN: 2582-3051
Submitted: 20.09.2021
Revised: 25.10.2021
Accepted: 07.11.2021
Published: 16.11.2021

Journal of Electrical Engineering and Automation (EEA) (2021)
Vol.03/ No.03
Pages: 214-229
https://www.irojournals.com/iroeea
DOI: https://doi.org/10.36548/jeea.2021.3.005

This approach identifies which projection is the most discriminative for the binary classification tasks in the first batch of trials. Three accuracies and loss curves in a single projection of Alzheimer's disorder features are shown in Figure 3. The sagittal projection produces somewhat higher accuracy after stabilisation than the coronal projection. It displays the results for the three predictions chosen after stabilisation at iteration with 60 values. It is found that the sagittal projection is the most discriminative after reviewing the results of numerous projections.

Table 1. Augmented subjects for training, testing dataset

Model	**MCI**		**HS**		**Detection Accuracy**	
	Training	**Testing**	**Training**	**Testing**	**Training**	**Testing**
SVM	209	41	209	41	72%	60%
CNN	201	40	210	40	82%	80%
Proposed Multimodal Fusion Technique	212	38	212	38	92%	91%

The AD/HS category delivers the greatest results when a majority vote is cast. This fundamental fusion strategy outperforms intermediate fusion on entirely connected layers; nonetheless, the improvement is small on average. Figure 4 shows the AD detection accuracy comparison.

It is quite useful in terms of the single sagittal projection. Max and mean fusion surpasses FC fusion and single sagittal in the HS/MCI classification, though the difference is small. With more data, traditional machine learning methods perform at a low level. HS/MCI training and testing comparison shown in the figure 5, exhibits the training and testing number of images from the dataset has computed for the solution.

ISSN: 2582-3051
Submitted: 20.09.2021
Revised: 25.10.2021
Accepted: 07.11.2021
Published: 16.11.2021

Journal of Electrical Engineering and Automation (EEA) (2021)
Vol.03/ No.03
Pages: 214-229
https://www.irojournals.com/iroeea
DOI: https://doi.org/10.36548/jeea.2021.3.005

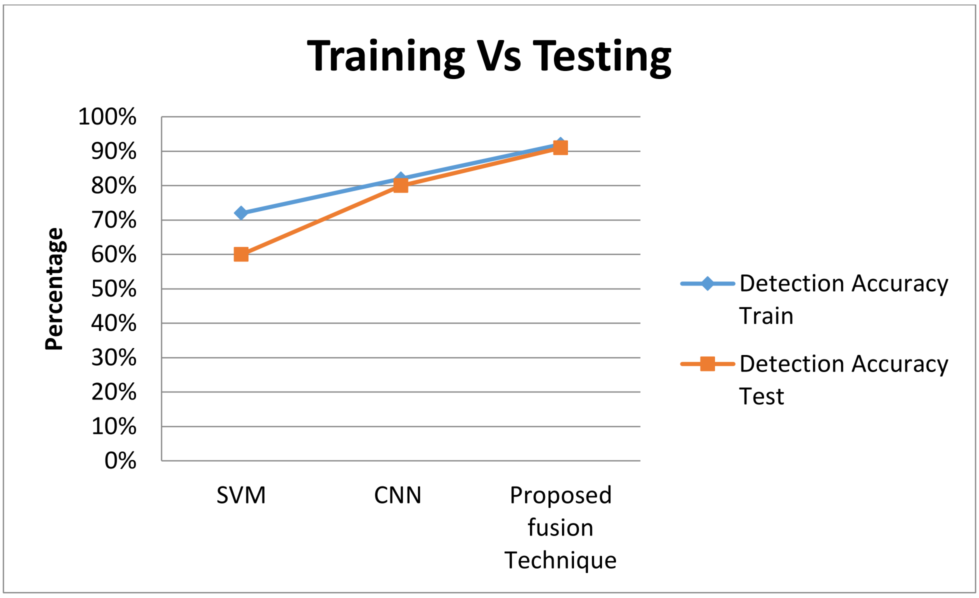

Figure 4. Detection accuracy comparison

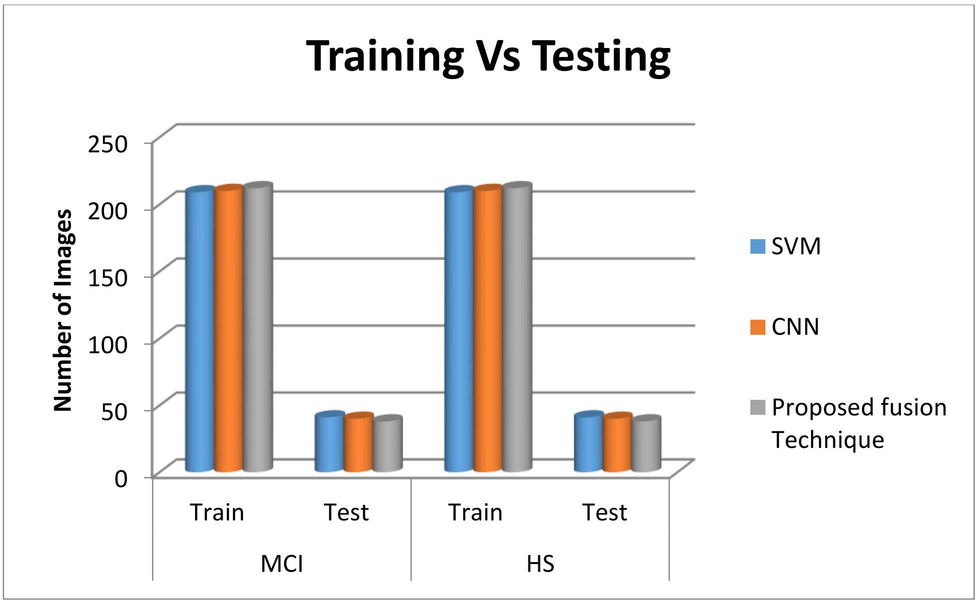

Figure 5. HS/MCI training vs testing comparison

Finding a solution to the automated segmentation of brain regions and appropriately detecting brain disorders might be difficult. Several variables contribute to these challenges,

ISSN: 2582-3051
Submitted: 20.09.2021
Revised: 25.10.2021
Accepted: 07.11.2021
Published: 16.11.2021

Journal of Electrical Engineering and Automation (EEA) (2021)
Vol.03/ No.03
Pages: 214-229
https://www.irojournals.com/iroeea
DOI: https://doi.org/10.36548/jeea.2021.3.005

including variations in the MCI acquisition settings, random categorization in the image section by nominal anatomical fixation in the brain segment by a MRI scan, and the use of a different MCI acquisition setting for each patient.

6. Conclusion

As a result, the study report includes a variety of experimental testings for the various methods of AD detection. The suggested approach performs best when combined with the HS, MCI and accuracy measures, as mentioned in Section 5 of this study article. In the future, it will be tested to see whether the same paradigm can be used for other computer-aided diagnostics. It also looks at the possibility of applying intelligent data splitting for classification. However, because of the poor contrast of the anatomical structure in MRI, it is very difficult to automatically classify AD. Numerous segmentation approaches with varying degrees of sophistication are available to address these issues. Because of its potential to offer effective results across a large data set and to learn and make judgments on their own, the deep learning techniques are used to classify the image category through brain segmentation. Complicated optimization approaches for huge data problems provide efficient solutions by creating fresh insights and tactics for optimization difficulties.

References

[1] Chen, Joy Iong Zong, and P. Hengjinda. "Early Prediction of Coronary Artery Disease (CAD) by Machine Learning Method-A Comparative Study." Journal of Artificial Intelligence 3, no. 01 (2021): 17-33.

[2] Shui-Hua Wang et al. “Classification of Alzheimer’s disease based on eight-layer convolutional neural network with leaky rectified linear unit and max pooling”. In: Journal of medical systems 42.5 (2018), p. 85.

ISSN: 2582-3051
Submitted: 20.09.2021
Revised: 25.10.2021
Accepted: 07.11.2021
Published: 16.11.2021

Journal of Electrical Engineering and Automation (EEA) (2021)
Vol.03/ No.03
Pages: 214-229
https://www.irojournals.com/iroeea
DOI: https://doi.org/10.36548/jeea.2021.3.005

[3] Balasubramaniam, Vivekanadam. "Artificial Intelligence Algorithm with SVM Classification using Dermascopic Images for Melanoma Diagnosis." Journal of Artificial Intelligence and Capsule Networks 3, no. 1 (2021): 34-42.

[4] Shuqiang Wang et al. “Automatic Recognition of Mild Cognitive Impairment from MRI Images Using Expedited Convolutional Neural Networks”. In: International Conference on Artificial Neural Networks. Springer. 2017, pp. 373–380.

[5] Tripathi, Milan. "Analysis of Convolutional Neural Network based Image Classification Techniques." Journal of Innovative Image Processing (JIIP) 3, no. 02 (2021): 100-117.

[6] Yan Wang et al. “A Novel Multimodal MRI Analysis for Alzheimer’s Disease Based on Convolutional Neural Network”. In: 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). IEEE. 2018, pp. 754–757.

[7] Manoharan, J. Samuel. "Study of Variants of Extreme Learning Machine (ELM) Brands and its Performance Measure on Classification Algorithm." Journal of Soft Computing Paradigm (JSCP) 3, no. 02 (2021): 83-95.

[8] Junhao Wen et al. “Convolutional neural networks for classification of Alzheimer’s disease: Overview and reproducible evaluation”. In: Medical image analysis 63 (2020), p. 101694.

[9] Sathesh, A., and Edriss Eisa Babikir Adam. "Hybrid Parallel Image Processing Algorithm for Binary Images with Image Thinning Technique." Journal of Artificial Intelligence 3, no. 03 (2021): 243-258.

[10] P. Qian, H. Friel, M. S. Traughber et al., “Transforming UTEmDixon MR abdomen-pelvis images into CT by jointly leveraging prior knowledge and partial supervision,” IEEE/ACM Transactions on Computational Biology and Bioinformatics, 2020.

[11] Tesfamikael, Hadish Habte, Adam Fray, Israel Mengsteab, Adonay Semere, and Zebib Amanuel. "Simulation of Eye Tracking Control based Electric Wheelchair Construction by Image Segmentation Algorithm." Journal of Innovative Image Processing (JIIP) 3, no. 01 (2021): 21-35.

ISSN: 2582-3051
Submitted: 20.09.2021
Revised: 25.10.2021
Accepted: 07.11.2021
Published: 16.11.2021

Journal of Electrical Engineering and Automation (EEA) (2021)
Vol.03/ No.03
Pages: 214-229
https://www.irojournals.com/iroeea
DOI: https://doi.org/10.36548/jeea.2021.3.005

[12] P. Qian, Y. Chen, J.-W. Kuo et al., “mDixon-Based Synthetic CT Generation for PET Attenuation Correction on Abdomen and Pelvis Jointly Using Transfer Fuzzy Clustering and Active Learning-Based Classification,” IEEE Transactions on Medical Imaging, vol. 39, no. 4, pp. 819–832, 2020.

[13] Vijayakumar, T. "Synthesis of Palm Print in Feature Fusion Techniques for Multimodal Biometric Recognition System Online Signature." Journal of Innovative Image Processing (JIIP) 3, no. 02 (2021): 131-143.

[14] Y. Jiang, K. Zhao, K. Xia et al., “A novel distributed multitask fuzzy clustering algorithm for automatic MR brain image segmentation,” Journal of Medical Systems, vol. 43, no. 5, pp. 118:1–118:9, 2019.

[15] Adam, Edriss Eisa Babikir, and A. Sathesh. "Construction of Accurate Crack Identification on Concrete Structure using Hybrid Deep Learning Approach." Journal of Innovative Image Processing (JIIP) 3, no. 02 (2021): 85-99.

[16] Klöppel, S.; Stonnington, C.M.; Chu, C.; Draganski, B.; Scahill, R.I.; Rohrer, J.D.; Fox, N.C.; Jack, C.R.; Ashburner, J.; Frackowiak, R.S.J. Automatic classification of MR scans in Alzheimer’s disease. Brain **2008**, 131, 681–689.

[17] Ahmed, S.; Choi, K.Y.; Lee, J.J.; Kim, B.C.; Kwon, G.R.; Lee, K.H.; Jung, H.Y. Ensembles of patch-based classifiers for diagnosis of Alzheimer diseases. IEEE Access **2019**, 7, 73373–73383.

[18] Zeng, K.; Yang, Y.; Xiao, G.; Chen, Z. A very deep densely connected network for compressed sensing MRI. IEEE Access **2019**, 7, 85430–85439.

[19] Zhang, Y.Y.; Dong, Z.; Phillips, P.;Wang, S.H.; Ji, G.; Yang, J.; Yuan, T.F.; Zhang, D.;Wang, Y.; Zhou, L.; et al. Ultrafast 3D ultrasound localization microscopy using a 32*32 matrix array. IEEE Trans. Med. Imaging **2015**, 38, 2005–2015.

[20] Gupta, A.; Ayhan, M.S.; Maida, A.S. Natural image bases to represent neuroimaging data. 30th Int. Conf. Mach. Learn. **2013**, 28, 2024–2031.

[21] Karthikeyan, C., J. Ramkumar, B. Devendar Rao, and J. Manikandan. "Medical Image Fusion Using Otsu’s Cluster Based Thresholding Relation." In International Conference

ISSN: 2582-3051
Submitted: 20.09.2021
Revised: 25.10.2021
Accepted: 07.11.2021
Published: 16.11.2021

Journal of Electrical Engineering and Automation (EEA) (2021)
Vol.03/ No.03
Pages: 214-229
https://www.irojournals.com/iroeea
DOI: https://doi.org/10.36548/jeea.2021.3.005

on Innovative Data Communication Technologies and Application, pp. 297-305. Springer, Cham, 2019.

[22] Dou, Q.; Member, S.; Chen, H.; Member, S.; Yu, L.; Zhao, L.; Qin, J. Automatic detection of cerebral microbleeds from MR images via 3D convolutional neural networks. IEEE **2016**, 35, 1182–1195.

[23] Suk, H.; Lee, S.; Shen, D. Deep ensemble learning of sparse regression models for brain disease diagnosis. Med. Image Anal. **2017**, 37, 101–113.

[24] Hong, X.; Lin, R.; Yang, C.; Zeng, N.; Cai, C.; Gou, J.; Yang, J. Predicting Alzheimer's disease using LSTM. IEEE Access **2019**, 7, 80893–80901.

[25] Jenkins, N.W.; Lituiev, M.S.D.; Timothy, P.; Aboian, M.P.P.M.S. A deep learning model to predict a diagnosis of Alzheimer disease by using 18 F-FDG PET of the brain. Radiology **2018**, 290, 456–464.

[26] Khan, N.M.; Abraham, N.; Hon, M. Transfer learning with intelligent training data selection for prediction of Alzheimer's disease. IEEE Access **2019**, 7, 72726–72735.

[27] Gorji, H.T.; Kaabouch, N. A deep learning approach for diagnosis of mild cognitive impairment based on mri images. Brain Sci. **2019**, 9, 217.

[28] Severyn, A.; Moschitti, A. UNITN: Training deep convolutional neural network for twitter sentiment classification. In Proceedings of the 9th International Workshop on Semantic Evaluation (SemEval 2015), Amsterdam, The Netherlands, 4–5 June 2015; pp. 464–469.

[29] Hamdan, Yasir Babiker. "Faultless Decision Making for False Information in Online: A Systematic Approach." Journal of Soft Computing Paradigm (JSCP) 2, no. 04 (2020): 226-235.

[30] S. Pereira, A. Pinto, V. Alves et al., "Deep convolutional neural networks for the segmentation of gliomas in multi-sequence MRI," in BrainLes 2015, pp. 131–143, Cham, Germany: Springer, 2015.

ISSN: 2582-3051
Submitted: 20.09.2021
Revised: 25.10.2021
Accepted: 07.11.2021
Published: 16.11.2021

Journal of Electrical Engineering and Automation (EEA) (2021)
Vol.03/ No.03
Pages: 214-229
https://www.irojournals.com/iroeea
DOI: https://doi.org/10.36548/jeea.2021.3.005

[31] Dhaya, R. "Analysis of Adaptive Image Retrieval by Transition Kalman Filter Approach based on Intensity Parameter." Journal of Innovative Image Processing (JIIP) 3, no. 01 (2021): 7-20.

[32] E. Shelhamer, J. Long, and T. Darrell, "Fully convolutional networks for semantic segmentation," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 39, no. 4, pp. 640–651, 2017.

[33] Kumar, Rahul, and Kapil Sharma. "Biometric System: Unimodal Versus Multibiometric Fusion and Its Current Applications." In Computer Networks and Inventive Communication Technologies, pp. 145-152. Springer, Singapore, 2021.

[34] Shanmuganathan, M., and C. Nalini. "The Problem of Rank Reversal in Combination with AHP and TOPSIS Applied to Image Fusion." In International Conference on Mobile Computing and Sustainable Informatics, pp. 401-414. Springer, Cham, 2020.

[35] M. Havaei, A. Davy, D. Warde-Farley et al., "Brain tumor segmentation with deep neural networks," Medical Image Analysis, vol. 35, pp. 18–31, 2017.

[36] Varshini, S. Amritha, and J. Aravinth. "Hybrid Level Fusion Schemes for Multimodal Biometric Authentication System Based on Matcher Performance." In Computational Vision and Bio-Inspired Computing, pp. 431-447. Springer, Singapore, 2021.

[37] Revathy, R., S. Venkata Achyuth Kumar, V. Vijay Bhaskar Reddy, and V. Bhavana. "Medical Image Registration Using Landmark Registration Technique and Fusion." In International Conference On Computational Vision and Bio Inspired Computing, pp. 402-412. Springer, Cham, 2019.

Author's biography

B. Vivekanadam is a senior lecturer in the Department of Computer Science and Multimedia at Lincoln University College in Malaysia. His major area of research are machine learning, neural network algorithms, image processing, video and signal processing, cloud computing, deep learning, artificial intelligence, object recognition, complex feature extraction and vision graphics.

ISSN: 2582-3051
Submitted: 20.09.2021
Revised: 25.10.2021
Accepted: 07.11.2021
Published: 16.11.2021