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Feature Extraction Using Markov Random Field (MRF) On Improving CNN Classification Results For Alzheimer's Disease Diagnosis

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Abstract

Alzheimer's disease is a degenerative neurological disorder that significantly affects patients' cognitive functions and social lives. It is a leading form of dementia, characterized by the progressive death of brain cells. One widely adopted diagnostic approach involves magnetic resonance imaging (MRI) to evaluate brain structures. Recent advances in machine learning have enabled automated image analysis, with Convolutional Neural Networks (CNNs) commonly used for image feature extraction and classification. However, CNNs face a major limitation in maintaining consistency during image segmentation, which results in reduced classification accuracy. This issue arises from CNNs' limited ability to preserve local pixel-level consistency during feature extraction. To address this, we propose integrating a Markov Random Field (MRF)-based layer into the CNN architecture, which has been shown to enhance segmentation consistency. This study utilizes publicly available MRI datasets of Alzheimer's patients and employs a k-fold cross-validation scheme for evaluation. The results show that the CNN-MRF model improves classification accuracy to 63%, compared to 61% with the standard CNN. Furthermore, the loss value is reduced from 0.80 to 0.74. Although the improvement in accuracy is incremental, a paired t-test confirms that the difference is statistically significant ($p < 0.05$). This method has proven effective in enhancing the reliability of image-based diagnostic systems for early detection of Alzheimer's disease.

Keywords— *Alzheimer's, CNN, Markov Random Filed*

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1. INTRODUCTION

The brain is one of the most important and most complex organs in the human body. In addition, the brain has a vital function, namely processing information, problem solving, thinking, decision making, imagining and remembering [1], [2]. Stored memories can be processed into information that can affect a person's character or identity. Memory loss caused by dementia is one of the most frightening things. Alzheimer's is one of the most common diseases of dementia. As a person ages, Alzheimer's becomes a scary specter for most people. Alzheimer's gradually kills cells in the brain which causes someone with Alzheimer's to lose all memories, the ability to recognize family members, the ability to follow simple instructions, even Alzheimer's sufferers can lose the ability to swallow, cough and the most severe lose the ability to breathe [3]. [4], [5] It is estimated that around 50 million people in the world suffer from dementia with treatment costs equivalent to the world's 18th largest economy [2]. then in 2050 dementia sufferers are estimated to reach 152 cases. Diagnosing Alzheimer's dementia becomes complicated and difficult because there are similarities with aging or vascular dementia[6], [7], [8]. Accurate diagnosis of Alzheimer's dementia plays a major role in prevention and treatment through monitoring its development. [9], [10], [11], [12]. Some research in the process of detecting Alzheimer's disease is the use of MRI brain images, this tool can measure the number of cells in the brain, in addition the MRI tool is also able to measure the structure of the parietal lobe [13].

Imaging plays an important role in many scientific fields, in this case medical imaging has become a powerful tool for understanding brain function, imaging such as Magnetic Resonance (MRI)[14], [15], has been used in the medical diagnostic process in evaluating brain structure and brain function in identifying signs and symptoms of Alzheimer's [3]. With the

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development of technology and the growth of imaging data, machine learning (ML) and deep learning (DL) play an important role in creating information extraction results and making prediction results more accurate [16].

Several machine-learning methods have been widely applied in the Alzheimer's classification process [17], [18] and have shown quite good performance [17]. In general, CNN has a multi-layer architecture that has advantages in the deep learning process that resembles the human brain and is able to represent images well [1]. However, CNN has problems in the image separation process so that there is the potential for segmentation errors in an image that have an impact on poor classification results [19].

In this study we propose the addition of MRF as an additional layer in the CNN architecture. The addition is intended to maintain local spatial consistency in the segmentation process, by considering the relationship between adjacent pixels, from the addition of this layer it is expected that the results of brain image feature extraction will be more accurate, so that in the end it can improve classification performance in detecting Alzheimer's disease. The main focus of this study is to improve the reliability of segmentation in the process of classifying brain MRI images with CNN, which leads to increased classification accuracy in supporting the development of a more accurate and consistent diagnostic automation system.

Therefore, this study we proposes the integration of a Markov Random Field (MRF) into the CNN framework to enhance segmentation consistency and improve classification performance in Alzheimer's diagnosis.

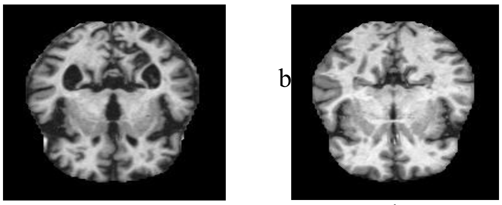
2. RESEARCH METHODS

In this section, we present some supporting literature in the analysis and interpretation of the results, including several theories that are relevant to the topic being studied by examining various research sources and supporting data in the research context.

2.1. Alzheimer

Alzheimer's is a neurodegenerative disease or a disease of neuron loss in brain tissue which is characterized by a significant decline in a person's cognitive abilities [20], this disease is one of the causes of dementia.

Alzheimer's is also one of the most common diseases suffered by people in the world [3] this is caused by several factors including aging, which is impossible to avoid. However, the severity of Alzheimer's can be minimized by conducting early screening, through brain imaging for proper care and treatment [13]



a b

Figure 1. Comparison of brain images with Alzheimer a) and Normal Brain b)

The process of identifying brain images of Alzheimer's sufferers requires further in-depth research to determine the level of severity and damage to the cell system in the brain.[20]

2.2. CNN

Convlutional Neural network (CNN) is an algorithm that is commonly used for processing data in the form of images. This algorithm is quite effective in recognizing and detecting objects in an image. CNN is specifically designed to process data with a grid structure [21], [22]

CNN is an important component in the field of computer vision and image processing. CNN is an image processing algorithm that was first introduced in the 80s. However, in the 2010s, CNN was widely used in image processing along with advances in hardware technology[23], [24]. The key to CNN is the architecture of the Convolution layer that forms the structure of the CNN algorithm itself. CNN often contains a pooling layer to help handle overfitting and increase efficiency in the computing process. CNN also has a fully connected layer that functions to represent features from previous learning results.[25]

CNN has been widely used in several applications in fields such as Health, automated agriculture and so on. This ability of CNN in handling the process of automatic feature extraction from visual data and being able to handle large and complex problems places CNN as one of the powerful algorithms.

The architecture of CNN is similar to Artificial Neural Networks (ANN) in general[1]. CNN architecture consists of a collection of

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neurons that form a layer. Each neuron has a weight, bias and activation function. This is different from ANN which describes a collection of one-dimensional neuron layers vertically, the layers in CNN are arranged in three dimensions, this causes the CNN architecture to have width, height and depth. In Figure 2. A general depiction of the CNN architecture can be seen.

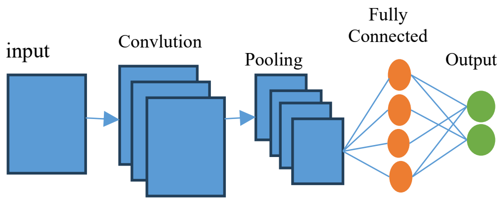

Figure 2. CNN architecture

In CNN, the classification process is carried out on the fully connected layer, which is an artificial neural network, where each neuron will be connected and arranged to form a layer. So that the input can be processed on the fully connected layer. The feature map generated from the convolution layer is converted into a long vector, then enters the fully connected layer to carry out the classification process.

The research stages were carried out to improve the classification results by adding new layers to the CNN architecture. In Figure 3, the new CNN-MRF architecture can be seen.

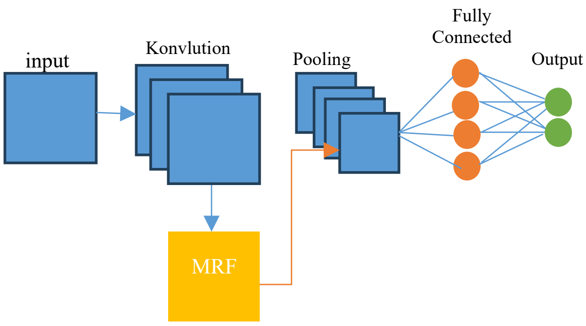

Figure 3. CNN-MRF architecture

The addition of layers to this convolution layer aims to obtain the best features by optimizing the feature extraction process in the image, to reduce inconsistencies in the feature extraction process, so that the classification results can be improved.

2.2. Markov Random Field

MRF is a multivariate stochastic process, capable of describing a random variable field with its local spatial dependencies. Unlike Markov Chains, a category of univariate stochastic processes, random fields consist of multiple dimensions, usually interpreted as space or space-time components. The so-called Markov property, often investigated in time series applications, is extended to the local neighborhood of nodes in the corresponding undirected graph. Applications of MRF models include image processing, computer vision and geostatistics. In the context of image analysis, MRFs can be used for low-level image transformations and filtering, as well as for high-level tasks, such as object or texture classification [26]. MRF introduces a spatially dependent structure, where the label of a pixel depends on the labels of its neighboring pixels. This helps maintain spatial consistency in the segmented image, resulting in smoother and less noisy segmentation[27].

In this study, MRF is added to the CNN layer to segment brain images. In helping to refine the segmentation results by considering the relationship between adjacent pixels, this method allows the classification results to be better in identifying the diagnosis of Alzheimer's disease.

3. RESULTS

In this section we will present the research results systematically, the addition will start from the identification of the problem which is the main element in the formulation of the objectives and scope of the research. Next we will discuss the results we obtained from this study including the main findings that contribute to further understanding related to the research topic being studied. We will analyze these findings comprehensively in identifying the implications and significance of related research. Thus, this section aims to provide a comprehensive overview of the research that has been conducted. The details of the sub-chapters that will be discussed in this section are as follows.

4. DISCUSSION

Convolutional Neural Network (CNN) is one of the deep learning architectures specifically designed for hierarchical image processing. CNN is capable of automatically extracting features through convolutional layers that mimic the functionality of the human visual system—starting from simple features such as edges to more complex patterns like textures or structural forms of the brain.

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However, CNN has a known limitation in preserving local pixel consistency during the segmentation process. This limitation becomes particularly critical when dealing with brain MRI images for Alzheimer's diagnosis, where the difference between stages such as *MildDemented* and *VeryMildDemented* is subtle and requires highly precise segmentation. As observed in our experimental results, CNN frequently failed to distinguish between the *MildDemented* and *VeryMildDemented* classes, resulting in misclassifications due to the visually similar features between these categories. This phenomenon is consistent with previous studies that have reported CNN's limited capability in distinguishing class boundaries with low contrast. To address this issue, we propose integrating a Markov Random Field (MRF) layer into the CNN architecture. MRF incorporates spatial pixel context, helping to reinforce segmentation by maintaining consistency among neighboring pixels that are likely to belong to the same class.

4.1. Data Processing

The dataset used in this study was obtained from a public repository on Kaggle.com. The images were categorized into four primary classes with the following distributions MildDemented 896 images, ModerateDemented 64 images, NonDemented 3200 images, VeryMildDemented 1792 images.

As observed, the dataset is highly imbalanced, which can lead to biased model performance favoring the majority classes. To address this issue, we implemented several preprocessing and balancing strategies, including Resizing all images to 128×128 pixels, Normalizing pixel values to a range of [0, 1].

Data augmentation applied specifically to the minority classes (*MildDemented* and *ModerateDemented*) using: Random rotation (±15 degrees), Horizontal flipping, Zooming and shifting. These techniques were applied to increase sample diversity and reduce overfitting. Subsequently, the dataset was split into training and testing sets using a stratified split with an 80:20 ratio to maintain proportional class distributions.

This setup was then used for training the model and evaluating its performance. Further details of the data processing pipeline can be seen in Figure 3.

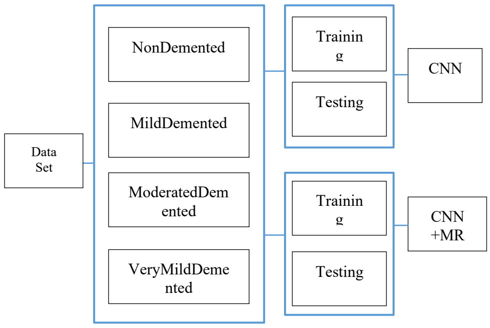

Figure 4. Data processing flow

4.2. Research Results

In this section, we present the results of our study based on the analysis that has been conducted. Several key findings are presented in the form of tables and figures to provide a clearer understanding of the implications derived from the study.

1. Test Results

In this section, we present the results of our study based on the analysis that has been conducted. Several key findings are presented in the form of tables and figures to provide a clearer understanding of the implications derived from the study. Both the CNN and CNN+MRF models were trained for 50 epochs with 35 steps per epoch. The performance evaluation was carried out using the following metrics: accuracy, loss, precision, recall, and F1-score. The main results are summarized in Table 1. In addition to the table, the results are also presented in graphical form, as shown in Figures 5 and 6, to further illustrate the performance comparison between the models.

Model	**Akurasi(%)**	**Loss**
CNN	61%	0,80
CNN + MRF	63%	0.74

Tabel 1. Result comparsion CNN vs CNN+ MRF

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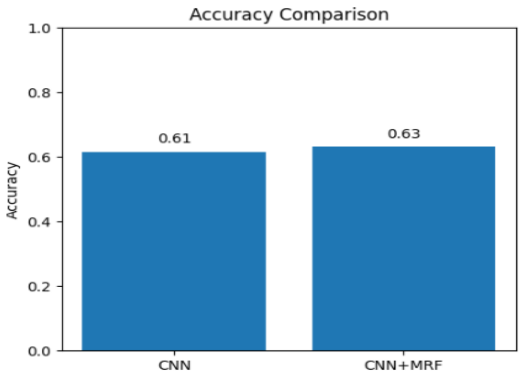

Figure 5. Comparison of CNN and CNN+MRF Algorithm Evaluation Results

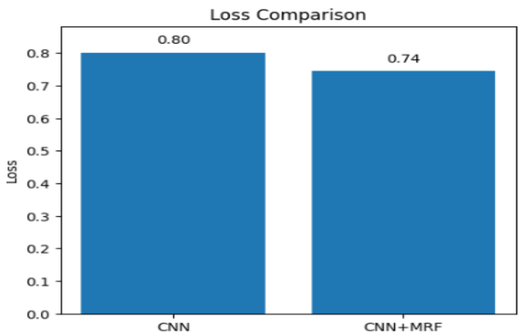

Figure 6. Loss comparison between CNN and CNN+MRF

Although the accuracy improvement is only 2%, the paired t-test indicates that the difference is statistically significant ($p < 0.05$). Furthermore, the lower loss value suggests that the CNN+MRF model is more stable during the learning process. The detailed per-class evaluation results are presented in Table 2

Class	Precision (CNN)	F1-Score (CNN)
NonDemented	0.78	0.79
VeryMildDemented	0.63	0.61
MildDemented	0.57	0.55
ModerateDemented	0.40	0.37
	Precision (CNN+MRF)	**F1-Score (CNN+MRF)**
VeryMildDemented	0.80	0.80
MildDemented	0.68	0.66
ModerateDemented	0.60	0.59
NonDemented	0.42	0.38

Tabel 2. Evaluation Result Per Class

Table 2 shows that CNN+MRF yields an improvement in F1-score across all classes, particularly for *VeryMildDemented* and *MildDemented*, which were previously prone to misclassification by the standard CNN model. This demonstrates that the integration of MRF effectively enhances segmentation and classification performance, especially in cases involving subtle inter-class feature differences.

5. CONCLUSION

Based on the test results by comparing the model performance on the two graphs shown in Figure 5 and Figure 6, it can be concluded that the addition of Markov Random Field (MRF) to the Convolutional Neural Network (CNN) model has a fairly positive impact on model performance. In terms of accuracy, the pure CNN model has a value of 0.61, while the model combined with MRF increases the accuracy value to 0.63. Although this increase is relatively small, it shows that the CNN + MRF model approach is able to provide better prediction results compared to pure CNN

From the loss side, we can see that the CNN model has a value of 0.80, while for CNN + MRF the loss decreased to 0.74. This decrease indicates that the model with MRF is able to reduce prediction errors and is more stable in the learning process. Thus, it can be concluded that the implementation of MRF on CNN not only increases accuracy but also optimizes the training process by reducing the loss value. However, because the increase in accuracy is still relatively small, further analysis is needed to determine whether this difference is significant and useful in other cases.

6. SUGGESTION

This study is still limited to the use of publicly available datasets, to increase validity there needs to be a comparison dataset from the primary dataset, for further research it is expected to use a broader and more diverse dataset covering data sources from various institutions, as well as consideration of the diversity of imaging conditions. In the configuration study on the Markov Random Field is fixed, therefore further research is expected to explore parameters to optimize in increasing consistency in segmentation, at the evaluation stage we are limited to only measuring the level of accuracy, in further research it is expected to include additional metrics such as precision, recall, F1-score, and area under the curve (AUC), so that the classification ability of the model can be evaluated more comprehensively.

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