Computer-Aided Diagnosis to recognize Alzheimer Disease based on DECOC algorithm

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Summary
Recent innovations in technology related to medical fields are widely wished to enhance prevention, diagnosis, and treatment. Seen that Alzheimer's Disease (AD) is hard to be identified at an earlier stage, many approaches and techniques are proposed. Detecting the AD-based in Magnetic Resonance Images (MRI) presents a great challenge. The recognition of AD helps to slow the effects of the disease when using an early treatment. An automated tool called Computer-Aided Diagnosis (CAD) is well invited to recognize and to identify AD. The motivation behind this work is to assess the features of how much explicit highlights the AD. The Gyrification index, the cortical thickness, and the Alzheimer's Disease Assessment Scale (ADAS) are studied in this paper. Many classifiers are implemented to highlight the best one. In this paper, we propose to use the classifier Data-driven Error Correcting Output Code (DECOC) prepared with Gyrification index, cortical thickness, and ADAS psychological grades. The proposed CAD framework identifies AD more accurately than others done by alternative classifiers. The outcomes prove that the cortical thickness and the ADAS psychological grades provide accurate identification of the AD instead of other features.

Key words:
Alzheimer's disease, Cortical thickness, ADAS, Gyrification index, kNN, SVM, DECOC

1. Introduction

The need of accurate CAD frameworks to help doctors in precisely diagnosing is increasing in many fields [1][2]. Alzheimer's sickness is a neurodegenerative issue that influences a huge populace. This disease corrupts the memory, judgment, and conduct related to patient. Detect AD at early-stage helps doctor to plan the treatment which decrease the propagation of the Alzheimer. Unfortunately, there are few CAD frameworks that attempt to identify accurately the AD early. For sure, early discovery of AD by MRI is of incredible assistance to doctors and patients since it is a moderately minimal effort, a non-intrusive system that can bolster target analysis, keeping away from human distortion. Different CAD frameworks were proposed dependent on examination of MRI pictures of the human mind. For example, approaches dependent on thickness maps used to portray disseminations of white issue and dark issue were considered in [3] and cortical thickness based methodologies were involved in [4]. Different works [5] depended on the explicit locale of interests, for example, average worldly projection, hippocampus, entorhinal cortex, and average transient flap decay. Notwithstanding CAD frameworks dependent on the investigation of basic MRI of the cerebrum to identify AD, different examinations concentrated on the examination pictures acquired as discussed in [6] [7] [8]. While trying to improve CAD frameworks' precision, authors in [9] attempted to remove highlights presented in images and they proposed a multi-modular frameworks. For sure, King et al., [10] utilized a 3D square tallying triangle crossing point calculation. The proposed method stored the fractal measurement. In this manner, they recommended that the fractal measurement of cortical is small in comparison between AD and healthy person [10].
Some investigations utilized fractal examination for structuring CAD frameworks for pathology location dependent on MRI of the mind [11], investigation of dendritic arborization [12], walk portrayal [13], investigation of neuronal movement [14], and intricacy coordinating during syncopated social coordination [15]. We plan to research the limit of various neighborhood fractal measurement measures acquired from areas of premiums on improving the precision of AI classifiers inside the setting of AD identification. This is planning a productive CAD framework which accomplishes precise analysis.
A recent study involved by Lahmari et al., [16] attempts to find the best combination of data types to identify AD based on MRI. The authors try to manage six data types using four classifiers techniques (LDA, KNN, NB, and SVM). They found that using the SVM classifier with the ADAS and cortical metrics achieves the best recognition of the AD according to the accuracy, sensitivity, and specificity. The method proposed by Lahmari et al., obtains accurate recognition due to ADAS features. This method is semi-automated because ADAS grades are not automated and could be influenced or worth interpreted.
Liu et al., [17] attempted to recognize AD using a new approach based on machine learning. The authors applied a deep convolutional neural networks (deep-CNN) to

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identify the disease. Identify the AD at earlier stage is too important because such disease is irreversible. The deep-CNN is performed to Hippocampus because it is considered as the first affected region in brain. The authors attempted to identify the disease through the shape and the volume features read by the MRI picture. The achieved accuracy is around 92%.
In light of this brief discussion of the used technique to recognize AD, we propose a full automated AD recognition. We attempt to find a more significant feature to identify the AD based on powerful classifiers. For this, we propose to apply the DECOC classifier to identify the AD. Then, the achieved results are compared with cases that use other classifiers as SVM and the kNN. To this end, we use information from [10] and contrast our outcomes with the cutting edge achievement rate.

2. Materials and Methods

The proposed CAD tool is performed according to designs utilized in [10]. Lord et al. [10] use the Alzheimer's Disease Neuroimaging Initiative (ADNI) database [18]. Authors considered 70 images from which 35 pictures associated with gentle Alzheimer's ailment and 35 pictures associated with control subjects. They utilized the Free Surfer programming to fragment the dark issue from the white issue dependent on force contrasts and geometric auxiliary contrasts. At that point, the pial and dark/white issue limit surfaces were evaluated. Cortical thickness values are considered when the process of the segmentation and surface generation is done. Besides, the Gyrification index of every side of the equator was dictated by the Free Surfer programming. At long last, a three-dimensional (3D) 3D shape tallying calculation was utilized to gauge the 3D fractal measurement (FD) of the cortical surfaces. The cortical measurements incorporate the cortical thickness and the gyrification index. Extra subtleties on the information, picture division, processing of fractals, and cortical measurements can be found in [10].
Many intelligent systems in literature used DECOC classifier are applied to recognize objects such as handwritten [19], fingerprint [20], suspicious behavior [21]. Results achieved by these studies prove a high accuracy. This pushes us to perform the DECOC classifier in the case of the identification of AD.
This paper uses the DECOC algorithm to recognize AD from a health person through the MRI. The DECOC classifier is performed according to confidence score and separability criteria [20].

Separability Criterion

$$S(G)=\left\{ \frac{2}{|G|^2-|G|0} \sum_{j\neq k, c_j c_k \in G} d(c_j, c_k) \qquad |G|\neq 1 \ and \ |G|\neq K-1 \right. \tag{1}$$

Confidence Score

$$C(f)=\left\{ \frac{S(G_{+/-}(f))}{S(G_+(f))+S(G_-(f))}; |G_+|\neq 1 \ and |G_+|\neq K-1 \right. \tag{2}$$

The DECOC classifier could be summarized by the following code:

// Compute the inter-class distance

```
def Inter_class_distance (T)
    for x in range(0,L,10):
        for y in range (0,C,10):
            for xm in range(0,10):
                for ym in range(0,10):
                    Dist=Hamming(T[xm][ym],T[xm+10][ym])
    return (Dist)
```

// Compute the separability criteria

```
def Separability_criteria (Dist)
    for x in range(0,len(Dist)):
        sum[x]+=Dist[i]
    for x in range(0,len(Dist)):
        if (condition 1):
            SC[G1][i]=Separability_Factor * sum[i]
        if (condition 2):
            SC[G2][i]=Separability_Factor * sum[i]
        if (condition 3):
            SC[G3][i]=Separability_Factor * sum[i]
    return (SC)
```

// Compute and sort the confidence score

```
def confidence_score (SC)
    for x in range(0,len(SC)):
        CS[i]= SC[G1][i]/(SC[G2][i]+SC[G3][i])
    return CS
def Sort_CS (CS)
    CS_Max=CS[sort(CS)]
    Pos_xy=Pos[CS_Max]
    return (Pos_xy)
```

// Compute the Hamming distance

```
def Hamming_distance (TD, TS)
    for x in range(vli,vli+10):
        for y in range(vci,vci+10):
            Dist_TD_TS[i]= Hamming(TD[i][j],TS[i][j])
    return (Dist_TD_TS)
```

Based on MRI pictures (AD patients and healthy persons), we perform the recognition using three classifiers: DECOC (described below), k-nearest neighbors algorithm (kNN) [22], and bolster vector machine (SVM) [23]. The kNN algorithm is performed according to the similarity of the nearest neighbours clusters. To consider only the closest pattern, we set the k parameter to one. The SVM algorithm differentiates between classes according to the structural risk minimization theory [24].
These classifiers are applied to recognize the AD according to three features: Gyrification index, cortical thickness, and ADAS. Achieved results are evaluated by performing three main metrics: accuracy, sensitivity, and specificity. Figure 1 shows all combinations between features and AI classifiers.

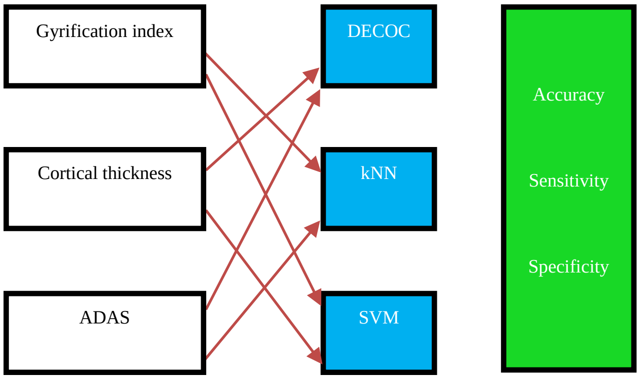

Fig. 1 Block diagram of data types for AD recognition

This paper has performed 9 combinations to highlight the adequate feature and the best classifier. Each feature applied separately the kNN classifier, the SVM classifier, and the DECOC classifier.

3. Results

This section shows the achieved performance metrics issued from all combinations presented in figure 1. Table 1 gives grouping results to each sort of AI classifier when prepared with a given kind of information: Gyrification index, cortical thickness, and ADAS.

Table 1: Classification results

Features	Metrics	kNN	SVM	DECOC
Gyrification index	Accuracy	68%	68%	**71%**
	Sensitivity	**70%**	**70%**	69%
	Specificity	66%	64%	**68%**
Cortical Thickness	Accuracy	75%	81%	**93%**
	Sensitivity	78%	76%	**85%**
	Specificity	73%	86%	**89%**
ADAS	Accuracy	96%	**97%**	**97%**
	Sensitivity	94%	**97%**	**97%**
	Specificity	97%	**97%**	**97%**

For Gyrification index, the DECOC method accomplished the best measurement accuracy (71%) and specificity (68%). The kNN and the SVM had the best sensitivity measure (70%). For cortical thickness achievements, The DECOC also brought the competition by accomplishing the following results: accuracy (93%), sensitivity (85%), and specificity (89%). For the ADAS test, the SVM and the DECOC are best classifiers by providing 97% for each metric.
In synopsis, the test results show that the DECOC works best as far as exactness for all sorts of examples considered. Figure 3 shows the average of found values of accuracy, sensitivity, and specificity of all used classifiers.

As appeared in Figure 3, the outcomes show that cortical thickness measurements convey more data than Gyrification index for the arrangement of AD patients and control subjects: 83% accuracy against 69%, 80% sensitivity against 70%, and 83% specificity against 66%. The ADAS method achieved the best recognition results compared with other features (97% accuracy, 96% sensitivity, and 97% specificity).

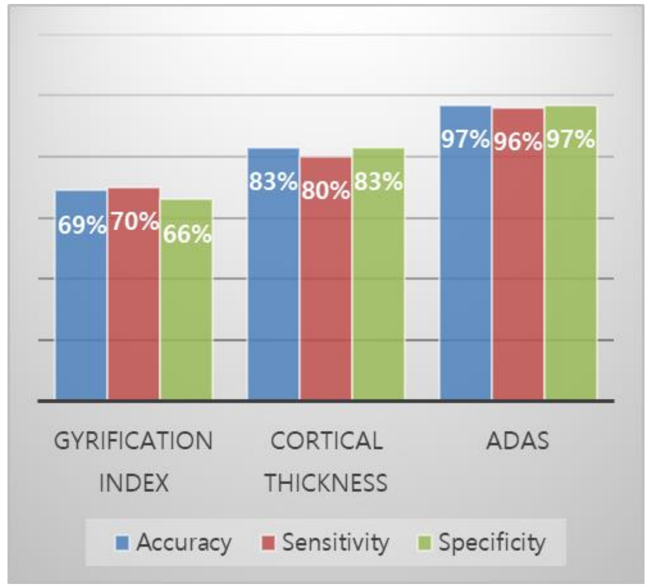

Fig. 2 Average results computed by all classifiers

4. Discussion

According to the analysis done for the cortical thickness and their blends presented in the study [10], we prove that the CAD tool could recognize the AD subjects through this feature. We additionally assessed the exhibition of a few AI techniques right now. Our outcomes show that kNN, SVM, and DECOC classifiers considered in our study achieve a good result when using the cortical thickness and the ADAS features.
As presented in the previous section, it is not useful to recognize the AD according to gyrification index because its accuracy was minim (about 70%). The CAD tool could not rely on only the gyrification index to recognize AD. The ADAS assessment is the best one but it is challenged by two problems: (1) The assessment is based on feedback answers which did not provide automated recognition, (2) This method could not be used in the case of deaf and dumb persons. The cortical thickness feature achieves an acceptable accuracy especially when using the DECOC classifier. Relying on this feature, the CAD tool could be considered as an automated framework. Enhancing the recognition of the AD through the cortical thickness feature can be the target of a future work.

Our outcomes especially when using DECOC classifier provides an accurate result. The DECOC applied for the cortical thickness is more automated then results that occurred from the ADAS which is based on psychological questions. The proposed framework based on detecting AD person using cortical thickness is the objective of this paper. As it were, to develop a powerful CAD framework for precisely ordering AD patients and control subjects, it is prescribed to utilize both ADAS and cortical thickness features.

At the light of this discussion, we can prove that the CAD tool based only on the cortical thickness is sufficient to detect the AD at early-stage.

5. Conclusion

Provide an accurate CAD to detect AD is the subject of many researches. We apply three different AI classifiers (kNN, SVM, and DECOC) to extract the best one according to three main features (Gyrification index, cortical thickness, and ADAS).

We found that all classifiers considered right now better with ADAS assessment. The DECOC algorithm provides high performance. It achieves an accuracy around 93%, a sensitivity about 85% and a specificity around 89%. The cortical thickness measurements issued from the MRI pictures are improved by applying the DECOC classifier. Therefore, the CAD framework could rely on the cortical thickness feature which achieves an accurate result. Relying on this feature instead the ADAS is important because the first one is an automated recognition but the second one is based on a psychological test in which the error can exist. The proposed CAD framework could be enhanced by applying a deep learning algorithm as the CNN to achieve an accuracy near the 100%. We presume that the combination of neuroanatomical highlights and intellectual tests accomplishes the highest performance for successful recognizing AD.

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