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WASSERSTEIN GAN-GRADIENT PENALTY WITH DEEP TRANSFER LEARNING FOR 3D MRI ALZHEIMER DISEASE CLASSIFICATION

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Abstract—**MRI scans for Alzheimer's disease (AD) detection are popular. Recent computer vision (CV) and deep learning (DL) models help construct effective computer assisted diagnosis (CAD) models for AD detection and categorization. Due to their dependence on huge training datasets and effective hyper parameter tuning procedures, most models failed. Transfer learning adjusts the final fully linked layers to use trained DL models on smaller datasets. It handles picture categorization problems well. This research introduces a Wasserstein GAN-Gradient Penalty with Deep Transfer Learning (WGANGP-DTL)-based AD classification model on 3D MRI data. WGANGP-DTL aims to accurately identify and classify AD. WGANGP increases dataset size. The WGANGP-DTL model pre-processes MRI images using image enhancement and segments them using 3DS-FCM. Feature extraction uses ant lion optimizer (ALO) with Inception v3 model. For classifying AD, deep belief network (DBN) model is used. The WGANGP-DTL model is experimentally validated using benchmark 3D MRI datasets. WGANGP-DTL outperformed recent methods in experiments.**

Keywords—**3D MRI scans, Alzheimer's disease, Deep learning, Generative Adversarial Network, Ant lion optimizer.**

I. INTRODUCTION

Using current economy and openly available technologies, Alzheimer's disease (AD) characteristics could be analysed to create more efficient and precise tools [1]. Neuroimaging [2], emotion analysis, and cognitive tests and methodologies can be used to diagnose AD early on. Few behavioural scrutiny methods use sensors in the patient's home to detect odd responses to everyday concerns [3]. Alzheimer's specialists struggle because there is no effective treatment for AD [4]. Neuroimaging is the most promising field for early AD detection since brain degeneration might appear as substantial cerebral shrinking in magnetic resonance imaging (MRI). Brain MRI allows non-invasive in vivo AD-related brain changes [5]. To avoid rising AD care costs for patients, Computer Aided System (CAD) is used for accurate and early AD detection [6]. Conventional machine learning (ML) approaches used voxel- and ROI-related characteristics for AD prognosis [7]. Deep learning, especially convolutional neural networks (CNNs), can solve these problems [8]. No treatment can cure or stop AD's aetiology [9]. MCI diagnosis is crucial for efficient administration and care programmes, improving novel medications, and preventing illness progression [10]. This research introduces a Wasserstein GAN-Gradient Penalty with Deep Transfer Learning (WGANGP-DTL)-based AD classification model for 3D MRI data. The WGANGP-DTL model expands the dataset size. Picture improvement with 3DS-FCM-based image segmentation is also used. Feature extraction uses ant lion optimizer (ALO) with Inception v3 model. DBN is also used to classify AD. The WGANGP-DTL model is experimentally validated using benchmark 3D MRI datasets.

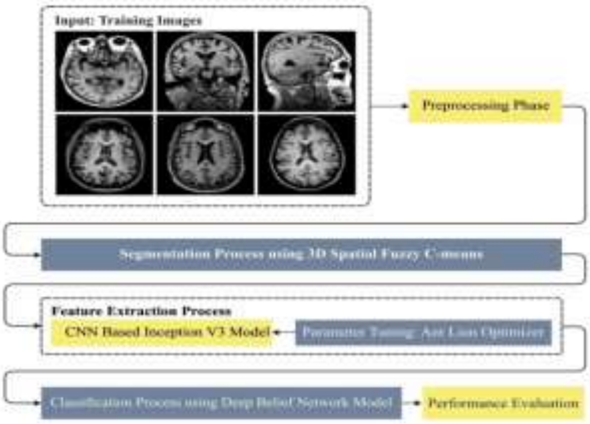

Fig. 1. Overall process of WGANGP-DTL Approach

II. LITURATURE SURVEY

PET and MRI results imply a two-stage DL structure for AD prognosis by Pan et al. [11]. Fan et al. [12] propose a U-net AD prognosis system using 3D T1-weighted magnetic resonance imaging (MRI). Blending with deep management improved model results. Zhang et al. [13] proposed a novel computer-aided AD diagnosis technique using an inexplicable 3D Residual Attention Deep Neural Network (DNN) (3D ResAttNet) for endwise learning from sMRI scans. Liu et al. [14] propose a CNN-based multi-model deep learning structure for programmed hippocampal segmentation and AD classification using structural MRI data. Bäckström et al. [15] propose a smaller three-dimensional convolutional network (3D ConvNet) infrastructure that can improve AD recognition on large datasets. This study tested an innovative brain imaging approach to improve AD diagnosis [16]. 3D-CNNs used MRI for binary and ternary illness categorization.

III. THE PROPOSED MODEL

This paper introduces WGANGP-DTL for 3D MRI AD detection and classification. At first, the WGANGP-DTL model used data augmentation, image pre-processing, and 3DS-FCM-based segmentation. Then, the ALO with Inception v3 model is used to extract features and tweak its hyper parameters. Finally, the DBN model is used to classify AD. Fig.1 shows the WGANGP-DTL procedure.

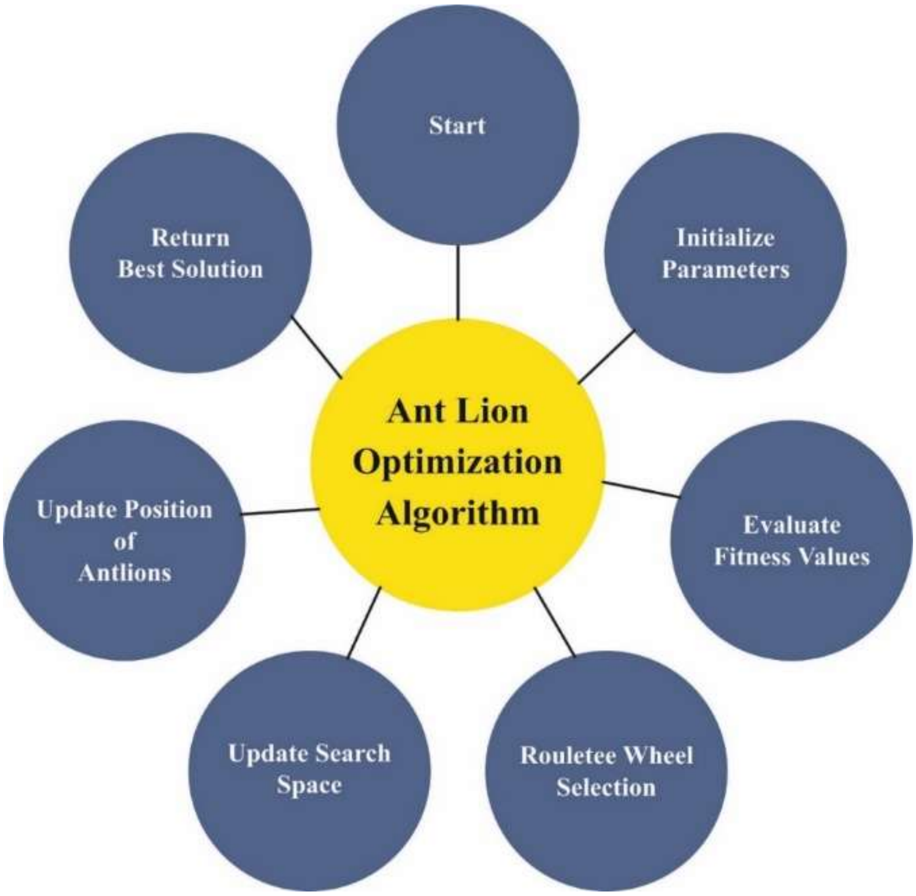

Fig. 2. Steps involved in ALO

Following fig.2 depicts the steps involved in ALO algorithm . The ALO system grows a FF for gaining classifier efficiency. It solves a positive integer for signifying the better efficiency of candidate result.

IV. RESULT AND DISCUSSION

The performance validation of the WGANGP-DTL model is tested using a dataset (available at https://adni.loni.usc.edu/) comprising 138 MRI scans. The dataset holds MRI scans under distinct classes such as Normal Control (NC), Significant Memory Concern (SMC), Mild Cognitive Impairment (MCI), Early MCI (EMCI), Late MCI (LMCI), and Alzheimer's Dementia (AD). The number of images on original dataset is 1000 and it increases up to 2250 images after data augmentation process using the WGANGP model. Fig. 3 showcases the sample images. Table 1 depicts the described dataset's details.

Fig. 4 reports a brief set of confusion matrices formed by the WGANGP-DTL model on AD classification. With 80% of training (TR) data, the WGANGP-DTL model has recognized

1750, 1738, 1754, 1793, 1823, and 1791 samples under NC, SMC, MCI, EMCI, LMCI, and AD classes respectively. Meanwhile, with 20% of testing (TS) data, the WGANGP-DTL system has recognized 450, 445, 483, 438, 413, and 438 samples under NC, SMC, MCI, EMCI, LMCI, and AD classes correspondingly. Eventually, with 70% of TR data, the WGANGP-DTL approach has recognized 1539, 1564, 1561, 1549, 1592, and 1563 samples under NC, SMC, MCI, EMCI, LMCI, and AD classes correspondingly.

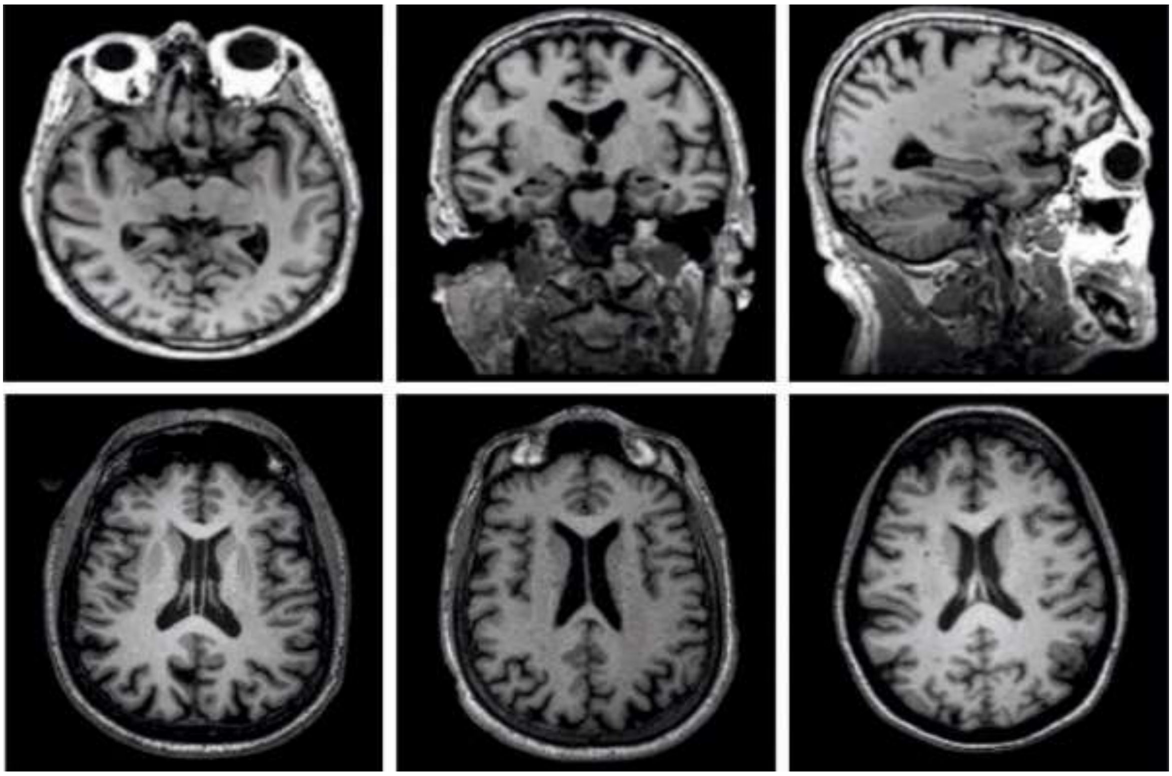

Fig. 3. Sample images

The training accuracy (TA) and validation accuracy (VA) attained by the WGANGP-DTL system on test dataset is demonstrated in Fig. 5. The experimental outcome implied that the WGANGP-DTL approach has gained maximum values of TA and VA. In specific, the VA seemed to be superior to TA. The training loss (TL) and validation loss (VL) achieved by the WGANGP-DTL approach on test dataset are established in Fig. 6. The experimental outcome inferred that the WGANGP-DTL system has been able least values of TL and VL. In specific, the VL seemed to be lower than TL. Fig. 7 offers a brief examination of the WGANGP-DTL model with recent models. The figure indicated that the ResNet-Softmax, AlexNet-SVM, and esNet50-RF models have obtained lower values of 88.14%, 89.17%, and 90.96% respectively. At the same time, the VGG16, CNN, Deep 3D CNN, and Modified ResNet18 models have accomplished certainly increased values of 92.20%, 92.17%, 91.28%, and 92.11% respectively. Though the Graph CNN model has accomplished reasonably value of 93.38%, the WGANGP-DTL model has depicted maximum of 99.09%.

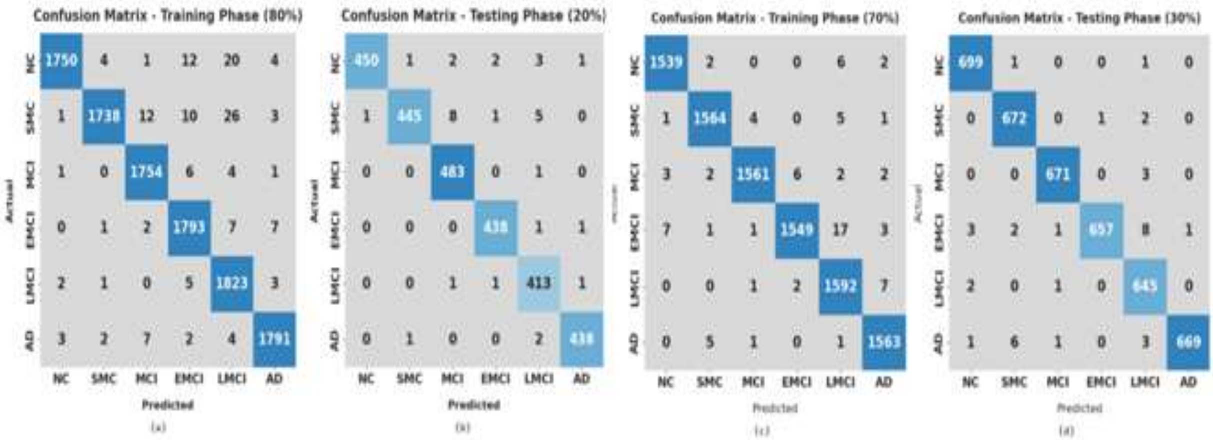

Fig. 4. Confusion matrices of WGANGP-DTL technique (a) 80% of TR data, (b) 20% of TS data, (c) 70% of TR data, and (d) 30% of TS data

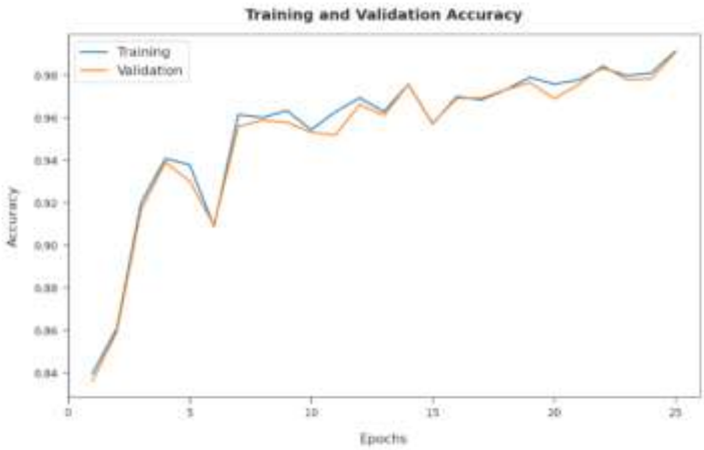

Fig. 5. TL and VL analysis of WGANGP-DTL technique

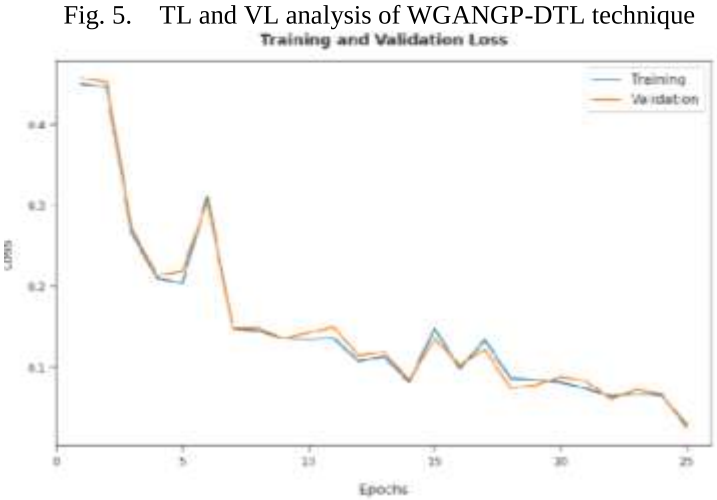

Fig. 6. TA and VA analysis of WGANGP-DTL technique

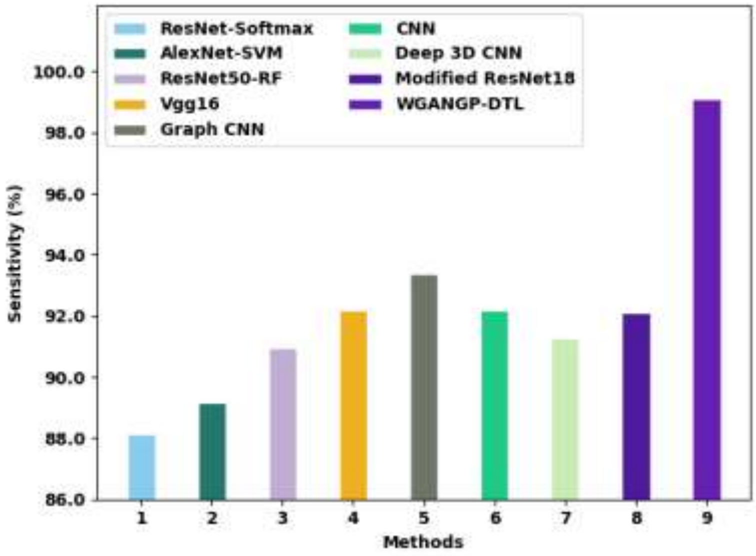

Fig. 7. $Sens_y$ analysis of WGANGP-DTL technique with existing algorithms

Fig.8 provides a brief examination of the WGANGP-DTL approach with recent models. The figure revealed that the ResNet-Softmax, AlexNet-SVM, and esNet50-RF models have obtained minimal values of 88.25%, 89.18%, and 89.22% correspondingly. Concurrently, the VGG16, CNN, Deep 3D CNN, and Modified ResNet18 methodologies have accomplished certainly increased values of 88.64%, 90.15%, 88.55%, and 91.52% correspondingly. But, the Graph CNN methodology has accomplished reasonably value of 88.20%, the WGANGP-DTL approach has portrayed maximal of 99.82%.

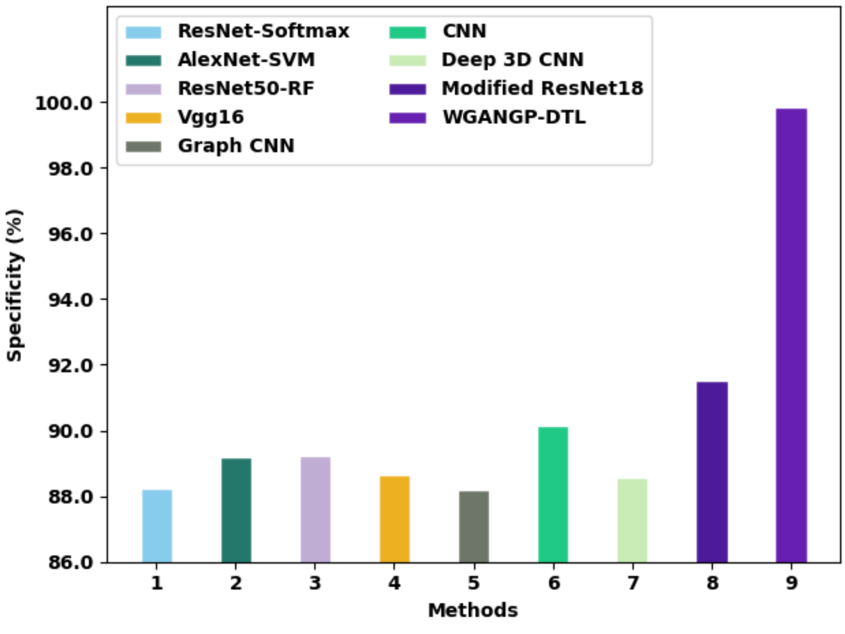

Fig. 8. $Spec_y$ analysis of WGANGP-DTL technique with existing algorithms

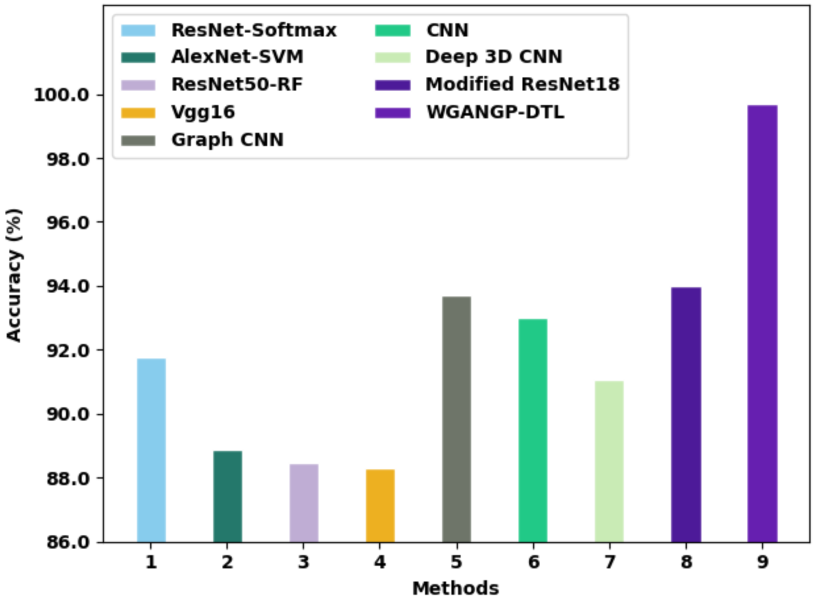

Fig. 9. Accu$_y$ analysis of WGANGP-DTL technique with existing algorithms

Fig.9 offers a brief examination of the WGANGP-DTL system with recent algorithms. The figure exposed that the ResNet-Softmax, AlexNet-SVM, and esNet50-RF models have reached lesser values of 91.77%, 88.86%, and 88.45% correspondingly. Followed by, the VGG16, CNN, Deep 3D CNN, and Modified ResNet18 approaches have accomplished certainly maximal values of 88.28%, 92.99%, 91.08%, and 93.99% correspondingly. CNN algorithm has accomplished reasonably value of 93.70%, the WGANGP-DTL model has showcases higher of 99.70%. By observing the above tables and figures, it is assured that the WGANGP-DTL model has been employed for AD detection and classification on 3D MRI images.

V. CONCLUSIONS

In this study, a new WGANGP-DTL approach was introduced for the recognition and classification of AD using 3D MRI scans. The presented WGANGP-DTL model has employed WGANGP based data augmentation, image pre-processing, and 3DS-FCM based segmentation at the initial stages. Followed by, the ALO with Inception v3 model is exploited to extract features in which the ALO algorithm is applied to tune the hyper parameters related to the Inception v3 model. At last, the DBN technique is exploited for the identification of AD into distinct classes. The result analysis of the WGANGP-DTL model is performed against benchmark 3D MRI dataset and outcomes were scrutinized under numerous aspects. The experimental outcomes stated the superior outcomes of the WGANGP-DTL model over recent approaches. In future, deep instance segmentation techniques can be employed for improving the classification accuracy of the presented method.

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