DC-Al GAN: Pseudoprogression and True Tumor Progression of Glioblastoma multiforme Image Classification Based On DCGAN and Alexnet

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Abstract—Glioblastoma multiforme (GBM) is a kind of head tumor with an extraordinarily complex treatment process. The survival period is typically 14-16 months, and the 2 year survival rate is approximately 26%-33%. This is true even in cases where the patient undergoes surgical resection with concurrent radiotherapy and chemotherapy. The clinical treatment strategies for the pseudoprogression (PsP) and true tumor progression (TTP) of GBM are different, so accurately distinguishing these two conditions is particularly significant. A misdiagnosis can lead to missed opportunities in terms of treatment. As PsP and TTP of GBM are similar in shape and other characteristics, it is hard to distinguish these two forms with precision. In order to differentiate them accurately, this paper introduces a feature learning method based on a generative adversarial network: DC-Al GAN. GAN consists of two architectures: generator and discriminator. Alexnet is used as the discriminator in this work. Owing to the adversarial and competitive relationship between generator and discriminator, the latter extracts highly concise features during training. In DC-Al GAN, features are extracted from Alexnet in the final classification phase, and the highly nature of them contributes positively to the classification accuracy. Compared with non-overlapping pooling, the overlapping in Alexnet leads to more original information and a higher classification accuracy. The generator in DC-Al GAN is modified by the deep convolutional generative adversarial network (DCGAN) by adding three convolutional layers. This effectively generates higher resolution sample images. Appropriate deepening of the layers improves the ability of the generator to create images, while the discriminator's discernment ability improves simultaneously. Feature fusion is used to combine high layer features with low layer features, allowing for the creation and use of more precise features for classification. The experimental results confirm that DC-Al GAN achieves high accuracy on GBM datasets for PsP and TTP image classification, which is superior to other state-of-the-art methods.

Index Terms: glioblastoma multiforme, pseudoprogression, generative adversarial network (GAN), DCGAN, Alexnet

I. INTRODUCTION

Glioblastoma multiforme(GBM) is one of the most common brain tumors, and is primarily caused by the canceration of glial cells in the brain and spinal cord. At present, the treatment of GBM includes surgery, radiotherapy, chemotherapy, targeted therapy and so on [1]. Specific treatment should take into account the patient's physical condition, the expected conditions of treatment, the location of the brain tumor, as well as the pseudoprogression (PsP) and true tumor progression (TTP) of GBM. Among patients who have received routine treatment, the probability of GBM being PsP is about 20% [2]. PsP mimics TTP at the tumor site or resection margins, but subsequently regresses or remains stable [3] [4]. The clinical treatment strategies for these two conditions are different, so it is necessary to distinguish between them. Accurate differentiation contributes to suitable treatment methods for patient's differing conditions. However, it is difficult to distinguish PsP and TTP using only MRI output. This is because these two entities have very similar shapes and characteristics. At present, the most common method used to distinguish PsP and TTP is based on changes in the lesion area that is visible on the MRI. Unfortunately, the time required for this analysis is too long, sometimes taking several months. This delays the patient's optimal treatment time, and has a detrimental effect on the outcome. Although it is vital to distinguish these two conditions of GBM, biopsy testing of brain tumors is not a widely recommended treatment. This is partly due to the invasiveness of the process, but it also carries
an increased risk for later treatment. In summary, it is essential to find a better method to distinguish between PsP and TTP of GBM.

Over the past decade, researchers have devoted considerable effort to explore methods for differentiating PsP and TTP of GBM. The focus has been on analyzing genetic and molecular markers, as well as image features, to achieve this goal [5]-[8]. The results of this research warrant further study, and the possibility of these methods being clinically realized needs to be discussed [2][9][10][11]. Functional MRI can reflect the information of human health conditions and the functional changes caused by pathological diversification. Functional MRI includes diffusion weighted imaging (DWI) and perfusion weighted imaging (PWI). DWI is capable of showing the diffusion of water molecules in tissues, and PWI can reflect the blood perfusion function of tissues by calculating specific parameters. In addition, diffusion tensor imaging (DTI) can be performed on the basis of DWI. It is mapped based on the directional movement of water molecules, and reveals how brain tumors affect nerve cell connections. [12]-[16] The methods to this point are used to identify useful data in the region of interest, and further to select attributes that distinguish PsP and TTP of GBM. However, these methods have achieved limited success for several reasons. Firstly, the manual division of the lesion area based on experience is problematic because of subjectivity bias, as well as the high cost in terms of manpower and time. Next, the analysis of basic image features cannot adequately capture the nuances of PsP and TTP in the GBM dataset. It is also worth noting that these studies have focused on using different attributes to evaluate various MRIs, rather than developing an objective and automatic classification system for the two conditions.

With the development of deep learning, researchers have gradually discovered its potential for use in the field of image recognition [17]-[23]. Significant progress has been made using deep learning-based methods, especially deep convolutional neural networks (CNN). This approach has greatly promoted the development of image classification and segmentation systems [24]-[26]. Compared with traditional pattern recognition methods, the greatest advantage of CNN for image classification is that it can learn image features automatically. This important advancement eliminates the complicated feature-engineering part of the traditional approach. Specifically, it is not necessary to study the local or global features while searching for what aspects best describe the characteristics of the image itself. Some approaches [27]-[31] based on CNN have achieved success in image classification tasks, but deep convolutional neural networks often confront a severe problem known as overfitting. Overfitting occurs because machine learning methods are required to train many learnable parameters, which in turn requires a large number of training samples. This issue becomes particularly tricky when the number of training samples is limited. In this domain the problem is exemplified because medical images are difficult to obtain in large quantities due to both limited access and the inherent confidentiality of the subject matter. If there is an insufficient number of training samples, the deep model is often over-trained. Consequently the model performs well during the training phase, but relatively poorly during the subsequent testing phase. Therefore, it is important to carry out a new and effective training strategy for deep learning models that solves the problem of overfitting.

Generative adversarial networks (GANs) [32] are deep neural networks that can be regarded as a regularization method, and can greatly alleviate the overfitting phenomenon. GAN models consist of two parts: generator and discriminator. The generator produces synthetic images by imitating the original data distribution, whereas the discriminator is used to distinguish samples and classify them as real or generated [33]-[39]. In the learning stage of GAN [40], it is necessary to train the discriminator, D, to efficiently discern the source of input data as either genuine or fake. Simultaneously, the aim of the generator, G, is to create samples that are increasingly similar to the real images. Through the adversarial and competitive relationship between these two networks, when a limited number of training samples is used, the process of training the discriminator will not immediately succumb to overfitting. With the help of GAN, deep CNN achieves better performance in classification accuracy, and furthermore the problem of
overfitting can be greatly alleviated [38][41][42]. Although GAN has performed well in many fields, the adversarial nature of the method leads to problems of instability. In order to solve this, myriad techniques have been used to stabilize the training process. It has been discovered that a deep convolutional generative adversarial network plays an important role in eliminating instability problems.

The deep convolutional generative adversarial network (DCGAN), whose discriminator and generator are built on CNNs, has achieved a high level of performance in image synthesis tasks [41]. Generator G, which takes a uniform noise distribution as input, can be reshaped into a multidimensional tensor. Discriminator D replaces pooling layers with stride convolutions on the basis of common CNNs, and the activation functions are the leaky rectified linear unit [43]. DCGAN shows potential in automatically learning data distribution characteristics, and it effectively alleviates the instability that comes with GAN training.

In this research, Alexnet [44] was chosen as the discriminator, and it was used to identify the features used for final classification. Alexnet is an architecture based on CNN that has proven success in scene classification tasks. It is recognized as an excellent basic level, automatic scene classification technology [45]-[47]. The typical pooling process is non-overlapping, although this is a distinction with Alexnet where it is, indeed, overlapping. This contributes to a higher classification accuracy because more original information is retained. Suppose the kernel sizes are $z \times z$ and the stride is $s$ in each of the convolutional and deconvolutional layers. Upon setting $s = z$, traditional local pooling, as commonly employed in CNNs, is obtained. If $s < z$ is set, overlapping pooling is obtained [42]. Models with overlapping pooling are slightly more resistant to overfitting during training. In addition, feature fusion has been employed to combine high layer features with low layer features. This results in a more robust feature, which improves the final classification accuracy to some extent.

GAN is a promising unsupervised learning method, but so far, it has rarely been applied in the classification of PsP and TTP of GBM. We assert that for this kind of classification task, GAN is an excellent choice because it is an unsupervised learning method that is dependent on the generator to provide for a shortage of training data. Thus, in this paper, we propose a model DC-Al GAN, which combines DCGAN with Alexnet to learn the representation of GBM images.

The contributions of this paper are the following:

1. The classification of PsP and TTP in GBM datasets is a novel application for GAN.
2. The features extracted from the discriminator are used for classification. The benefit of the antagonism and competition between discriminator and generator leads to the extraction of highly refined features during training. Ultimately, the classification is more precise.
3. Alexnet is employed as the discriminator in this work, and the extracted features are used during the final classification. The typical pooling process is non-overlapping, while it is overlapping in Alexnet. This contributes to a higher classification accuracy because more original information is retained.
4. Feature fusion was implemented such that it combines features from both high and low layers, leading to features that are more precise. The result is an improvement in the final classification accuracy.

The framework of the proposed DC-Al GAN model is shown in Fig. 1.
II. PRELIMINARIES

Section A introduces the principle of Generative adversarial networks and summarizes the training procedure involving generator and discriminator. Section B shows the Alexnet architecture.

A. Generative Adversarial Networks

A generative adversarial network is a deep learning framework that is trained using an adversarial system. Synthetic data that adheres to the original distribution is generated to assist in the process of training. Unlike other deep learning models, the GAN consists of two parts: generator and discriminator. The generator synthesizes images by imitating the original data distribution, whereas the purpose of the discriminator is to distinguish a sample as either genuine or fake.

In GANs, the generator and discriminator perform training iteratively in separate, alternating rounds based on the minimax game playing algorithm. First, the generator produces fake samples from random noise, which can initially fool the discriminator. Then the discriminator is supplied with both genuine and fake images, and learns to distinguish them. Throughout the process the two parts update simultaneously, and this continues until the Nash equilibrium is satisfied.

The minimax game rules that both generator and discriminator obey are as follows:

$$\min_G \max_D V(D,G) = \mathbb{E}_{p_{data}(x)} [\log D(x, G(x))] + \mathbb{E}_{p_z} [\log (1 - D(G(z), z))]$$

(1)

$D(x)$ represents the probability that x belongs to the class of real images, rather than fake samples. The primary goal of the discriminator is to calculate the probability at close to 1 when the input data is that of real images. When fake samples are considered, the purpose of the discriminator is to judge the data and learn what distinguishes them. Simultaneously, as $D(G(z))$ is close to 0, the generator aims to approach 1. This is essentially a minimax-style game between generator and discriminator.

In essence, during the learning phase for GANs, the aim is to train model $D$ such that it is able to effectively and efficiently discriminate the source of input as either real or fake. Simultaneously, model $G$ aims to generate samples that are increasingly closer to real images.
B. Alexnet Architecture

Alexnet is an architecture based on CNN that achieves convincing success in scene classification tasks, and has proven to be an excellent basic level, automatic scene classification technology. Alexnet contains five convolutional layers and three fully-connected layers. Local response normalization is incorporated within Alexnet, which improves network generalization performance. As the fully-connected layers require standardized input (image size), the images are all adjusted to be 227 × 227 pixels.

Assume that the input sample \( X_i \in \mathbb{R}^n \) denotes the input data, and \( y_i \in \{1, \ldots, K\} \) expresses the corresponding ground truth label for Xi. Further, suppose that the AlexNet model includes N layers, the weight combinations for the AlexNet architecture are \( W = (W(1), \ldots, W(N)) \), and in this architecture the relationships between the weight parameters and the filters are respectively shown in Equations (2) and (3)

\[
\begin{align*}
    P^{(n)} &= f(C^{(n)}) \quad (2) \\
    C^{(n)} &= W^{(n)} * p^{(n-1)} \quad (3)
\end{align*}
\]

In Equations (2) and (3), \( C(n) \) refers to the convolved responses on the previous feature map; \( f() \) is the pooling function on \( C \). \( P(W) \) refers to the output objective, which is defined in Equation (4)

\[
P(W) = \|w^{(out)}\|^2 + L(W,w^{(out)})
\]

where \( \|w^{(out)}\|^2 \) and \( L(W,w^{(out)}) \) are respectively the margin and squared hinge loss of the support vector machine (SVM) classifier. The overall loss of the output layer \( L(W_w^{(out)}) \) is shown in Equation (5)

\[
L(W_w^{(out)}) = \sum [1 - f(w^{(out)}, x)_y - f(p^{(n)}, y)_y]
\]

Equation (5) represents the squared hinge loss of the prediction error. From the above description it can be understood that, in Equation (5), the AlexNet architecture learns the convolutional kernels \( W \). It is able to predict the label and give a strong push to having discriminative and sensible features at each layer. In this way, the overall goal of producing a good classification result at the output layer can be achieved.

The Alexnet architecture is shown in Fig. 2.

III. DC-AL GAN ARCHITECTURE

In this section, the network architecture of the proposed model, DC-AL GAN, is described.

A. Discriminator

Alexnet was utilized as the discriminator in this work. It contains five convolutional layers, and each of these follows a ReLU activation function. The extracted features mentioned in this work refer to output features from the discriminator’s convolutional layer. Once training of the discriminator is complete, the output of the final layer in the discriminator model is regarded as the representation of the input image. The concept of feature fusion, which combines features from the different convolutional layers, has a positive effect on the final classification accuracy. The reason for the improvement is that more precise features are created during the fusion process. All of the convolution layers in the discriminator are subject to the ReLU activation function, and the slope is set to 0.2. A stochastic gradient descent algorithm is used during training, where the batch size is set at 64. The Adam optimizer is used in the network, with the learning rate set to 0.0002, and momentum \( \beta_1 \) as 0.5. The input images were scaled to [-1,1] before training the network. This is done in order to avoid any bias that is created by very large or very small numerical values. Another advantage is that it curbs numerical complexity during computation.

When the discriminator is trained, the parameters of the generator are fixed. Optimizing the discriminator means maximization of the discriminate accuracy – therefore maximizing \( V_D \) in equation (6)

\[
V_D = E_{x,z \sim p_{data}(x,z)}[\log D(x,z)] + E_{z \sim p_z(z)}[\log (1 - D(x,z))]
\]

Obviously, when optimizing the discriminator, it is assumed that the generator has created fake samples. Optimizing the first item of equation (6) means that the output of the discriminator is maximized when inputting real images. This is because the prediction results of real images are expected to be close to 1.

As for fake samples, optimization results should be minimized because the values are ideally close to 0. That is to say, the smaller the \( D(G(z)) \) is, the better the performance of the optimizer is. However, it is contradictory that when the first item is increasing, the second item decreasing. Therefore, we adapt the second item for \( 1-D(G(z)) \).

Given sufficient ability for the discriminator and generator to learn, GANs will have a global optimum. The optimum can be obtained by simple analysis. First, the discriminator can reach an optimum when the generator is fixed. Based on this value, an optimal function of the generator can be derived. It can be proven that the optimal function reaches a global minimum when generated distribution coincides with the actual data distribution.

When the generator is fixed, in order to achieve an optimal discriminator, the discriminator must be trained such that \( V(G,D) \) is maximized, as shown in the following equation:

![Fig. 2. Architecture of Alexnet. The ReLU activation function is applied to every convolutional layer.](image-url)
\[ V(D, G) = \mathbb{E}_{D\sim\mathcal{D}}[\log D(x, G_z(x))] \\
+ \mathbb{E}_{z\sim\mathcal{Z}}[\log (1 - D(G(z), z))] \\
= \int p_{\text{data}}(x) \log D(x) \, dx \\
+ \int p(z) p(x|z) \log (1 - D(x)) \, dx \, dz \]

(7)

As we know, \( p(x) = \int p(y)p(x|y) \, dy \), therefore the equation can be expressed as follows:

\[ V(D, G) = \int p_{\text{data}}(x) \log D(x) \, dx + \int p(x) \log (1 - D(x)) \, dx \\
= \int p_{\text{data}}(x) \log D(x) \\
+ p(x) \log (1 - D(x)) \, dx \]

(8)

For any \((a, b) \in \mathbb{R}^2 \setminus \{0, 0\}\), the function \( y = a \log(y) + b \log(1 - y) \) achieves maximization at the point \( \frac{a}{a+b} \) and the result follows after applying this function to equation (9)

\[ D_G^*(x) = \frac{p_{\text{data}}(x)}{p_{\text{data}}(x) + p(x)} \]

(9)

That is, the optimal discriminator is as shown in equation (9) when the generator is fixed.

Jensen-Shannon (JS) divergence is a method based on Kullback-Leibler (KL) divergence that measures the similarity between two probability distributions. It has a symmetrical structure and a limited range of values. The definition for JS divergence is shown in equation (10)

\[ \text{JSD}(P||Q) = \frac{1}{2} D_{\text{KL}}(P||M) + \frac{1}{2} D_{\text{KL}}(Q||M) \]

(10)

In the above formula, \( M = \frac{1}{2} (P + Q) \), \( P \) and \( Q \) represent probability distributions, respectively.

KL divergence is a method to measure how a probability distribution deviates from the standard probability distribution, as shown in equation (11)

\[ D_{\text{KL}}(P||Q) = \int_{-\infty}^{\infty} p(x) \log \frac{p(x)}{q(x)} \, dx \]

(11)

\( p \) and \( q \) represent the density of probability distributions, respectively.

When \( p(x) = p_{\text{data}}(x) \), it is clear that \( D_G^*(x) = \frac{1}{2} \), applying equation (8) to (9), it follows that:

\[ V(D^*_G, G) = \int p_{\text{data}}(x) \log \left( \frac{p_{\text{data}}(x)}{p_{\text{data}}(x) + p(x)} \right) \\
+ p(x) \log \left( \frac{p_{\text{data}}(x) + p(x)}{p(x)} \right) \, dx \\
= \int p_{\text{data}}(x) \log \left( \frac{p_{\text{data}}(x)}{p_{\text{data}}(x) + p(x)} \right) \\
+ p(x) \log \left( \frac{p_{\text{data}}(x) + p(x)}{p(x)} \right) \, dx - \log 4 \\
+ \log 4 \int p(x) \, dx \\
= \int p_{\text{data}}(x) \log \left( \frac{2p_{\text{data}}(x)}{2p_{\text{data}}(x) + p(x)} \right) \\
+ p(x) \log \left( \frac{2p_{\text{data}}(x) + p(x)}{2p(x)} \right) \, dx - \log 4 \\
= D_{\text{KL}} \left( \frac{p_{\text{data}}(x)}{2} \right) \\
+ D_{\text{KL}} \left( \frac{p(x)}{2} \right) - \log 4 \\
= 2 \cdot \text{JSD}(p_{\text{data}}(x)||p(x)) - \log 4 \]

(12)

The value of the JS divergence between two distributions is always non-negative. Also, JS is zero when \( p(x) = p_{\text{data}}(x) \). Therefore, the global minimum is \( V(D^*_G, G) = - \log(4) \). To clarify, when the generative distribution coincides with real data distribution, the function reaches a global minimum.

In the process of training the discriminator, \( d_{\text{loss real}} \) corresponds to the loss of real images. The output of the discriminator is expected to be as close to 1 as possible. This is because the result increases in accordance with the performance of the discriminator. The \( d_{\text{loss real}} \) is

\[ d_{\text{loss real}} = \mathbb{E}_{x\sim\mathcal{D}}[\log D(x, z)] \]

(13)

The \( d_{\text{loss fake}} \) matches the loss of generated samples. The output should be as small as possible because an ideal discriminator will label fake samples as 0. The \( d_{\text{loss fake}} \) is

\[ d_{\text{loss fake}} = \mathbb{E}_{z\sim\mathcal{Z}}[\log (1 - D(x, z))] \]

(14)

The discriminator loss (\( d_{\text{loss}} \)) is comprised of \( d_{\text{loss real}} \) and \( d_{\text{loss fake}} \)

\[ d_{\text{loss}} = d_{\text{loss real}} + d_{\text{loss fake}} \]

(15)

The architecture of the discriminator is shown in Fig. 3.

Fig. 3. Alexnet is used as the discriminator, which also extracts more precise features by using feature fusion for the final classification. The feature fusion layer learns to combine coarse, high layer features with fine, low layer features. F1 represents
the features from the last convolutional layer, F2 combines features from the last two convolutional layers, and F3 includes features from the last three convolutional layers. In this approach, it allows the resulting features to contain finer details while retaining high-level classification accuracy. The red, blue, and green lines represent the characteristics of the output of the final layer, the second last layer, and the third last layer, respectively.

B. Generator

The generator is an improved network that is based on DCGAN. While the generator creates samples that are similar to the original data, the discriminator can learn more precise features from the input samples. This competitive process has the effect of each promoting the other. The input of the generator is a 100 dimensional uniform tensor, which is then converted into a four dimensional tensor. DC-Al GAN has three more convolutional layers than DCGAN. The seven convolutional layers are used to generate images of 512×512 pixels in size. The ReLU activation function is applied to all of the layers in the generator, in addition to the tanh function, which is used in the output layer. Batch normalization is employed in both generator and discriminator.

With respect to the generator and the mutual competition with the discriminator, it expects the output of generated samples to approach 1 after being evaluated. The parameters of the discriminator are fixed when the generator is in the training phase. The purpose of training the generator is to boost the score of the synthetic samples, bringing them as close to 1 as possible. This means that D(G(z)) is increased, which affects VG in equation (16). In order to bring equation (16) into line with 1-D(G(z)), we adapt equation (16) to equation(17). In other words, optimizing the generator is to realize minimizing 1-D(G(z)), that is, minimizing VG:

\[
V_G = \mathbb{E}_{x \sim p_d(x, z)}[\log(D(x, z))] \\
V_G = \mathbb{E}_{x \sim p_d(x, z)}[1 - \log(D(x, z))] \tag{16} \\
\]

In the process of training GANs, the generator loss (g_loss) is comprised of g_loss_r and g_loss_f. The g_loss_r represents the deviation between the generated samples and the real images, as shown in equation (18). Reducing g_loss_r by continuously training the network and adjusting parameters will enhance the generated images, bringing them closer to the real ones.

\[
g_{\text{loss}_r} = \mathbb{E}_{x \sim p_d(x, z)}[1 - \log(D(x, z))] \tag{18} \\
\]

The g_loss_r describes the deviation between the output of the generator and that of the feature fusion layer. The greater the similarity between these, the more genuine the images appear.

Here, we set f(x) as the activation function in the discriminator. Both the convolutional layer and the pooling layer will possess a bias, and be activated such that the nonlinear characteristics can be better captured.

The formula of g_loss_f is shown in equation (19). Samples \{x_1, x_2, ..., x_m\} come from the GBM dataset, whereas samples \{z_1, z_2, ..., z_m\} originate from the random noise tensor, and w represents the convolutional kernel.

\[
g_{\text{loss}_f} = \|f(\sum_{i=1}^{m} w \cdot x^{(i)} + \text{bias}) - f(\sum_{i=1}^{m} w \cdot G(z^{(i)}) + \text{bias})\| \tag{19} \\
\]

As aforementioned, the generator’s loss contains two parts: g_loss_r and g_loss_f. The combination of these two kinds of loss increases the precision of the network during training. Consequently, the sample image produced by the generator is increasingly similar to the real image. In turn, the discriminator can extract more accurate features, and it improves the final classification accuracy. The functional expression of g_loss is shown in equation (20).

\[
g_{\text{loss}} = g_{\text{loss}_r} + g_{\text{loss}_f} \tag{20} \\
\]

The architecture used for the generator is shown in Fig. 4.

Fig. 4. The generator is a modified network founded on deep convolutional generative adversarial networks. It contains seven convolutional layers, and can transform a 100 dimensional uniform tensor into 512×512 pixel images.

C. Classification using SVM algorithm

The Support Vector Machine (SVM) was first proposed by Cortes and Vapnik in 1995. It has many unique advantages in solving pattern recognition problems that are nonlinear, high-dimensional, and have a small sample size. The architecture can be extended to other machine learning problems such as function fitting. A linear SVM will create a situation where not all of the data will be partitioned; however, the majority of the data be correctly classified.

Tenfold cross-validation is used with the regular linear classifier L2-SVM for classification in DC-Al GAN. The features extracted from the discriminator are regarded as the input to the SVM for classification.

IV. EXPERIMENTS

In this section, three sets of experiments are described. The purpose is to evaluate and compare the results of our method, DC-Al GAN, to other state of the art methods. In the first experiment, the results of DC-Al GAN are compared with four related classification systems, including DCGAN, Resnet,
Densenet, and VGG. The second experiment involves the analysis of classification results between sets of layers. Specifically, the last convolutional layer, the last two convolutional layers, and the last three convolutional layers, represented as F1, F2 and F3, respectively. In the final experiment, the best-performing combination from the second experiment (i.e., the features from the last two convolutional layers) is chosen and used for classification. In the final experiment, variations in k-fold cross-validation are compared with values k=5, 10 and 20, respectively.

In DC-Al GAN, tenfold cross-validation and regular linear classifier L2-SVM are used. This model uses TensorLayer, which is a library to facilitate deep learning (DL) and reinforcement learning (RL). It is an extension of Google TensorFlow. TensorLayer provides popular DL and RL modules that can be easily customized and assembled for tackling real-world machine learning problems.

A. Comparison with other models

To analyze the classification performance of DC-Al GAN (DCAL), it is compared with DCGAN, Resnet, Densenet, and VGG. All of these are used in differentiating PsP and TTP of GBM. DC-Al GAN, DCGAN, Resnet, Densenet, and VGG reached an overall accuracy of 0.92, 0.844, 0.877, 0.873, and 0.862, respectively. Boxplots of the classification accuracy for each of the five models are shown in Fig. 5.

It can be seen that among the five methods, the median of DCAL is much higher than the others. This means that classification using DCAL is relatively stable. Because the average value is heavily influenced by extremes, it is sometimes unreasonable to use it as a measure. Rather, the median is a better choice because it is less likely to be affected by very high or very low values.

By examining the length of the boxplots, it shows that the classification accuracy of DCAL is relatively centralized and stable. In contrast, Densenet is the worst performer. It can be concluded that the DC-Al GAN model proposed in this paper achieves higher classification accuracy when compared with the previous methods for the task at hand.

Fig. 6 shows 96 feature maps that were learned by the first convolutional layer using the 512×512×1 input images. It appears that the first convolutional layer is focused primarily on color and edge information.

The sample images produced by the generator at different epochs are shown in Fig. 7. The last image in the figure consists of real samples, whereas the first seven images are the samples produced by the generator at different epochs. It is obvious that as the number of epochs increases, the generated samples gradually improve, becoming more like the genuine data. The result is a well-trained combination of G and D using only unlabeled samples. Also, D has learned the features from the data, which is beneficial for classification in the next steps.

B. Comparison of classification results using features extracted from different convolutional layer sets

In this research, Alexnet has been used as the discriminator, which is also responsible for extracting the features used in the final classification. In addition, feature fusion has been employed to combine coarse, high layer features with fine, low layer features. The intention is to ensure that the network contains features with fine detail, yet retain high-level classification accuracy. Ultimately, the discriminator extracts features from the fusion layer. F1 represents the features from the final convolutional layer, F2 shows features from the last two layers, and F3 contains features from the last three layers.

The results of DC-Al GAN are illustrated in Fig. 8. The curves represent the accuracy for each of the feature sets. The overall accuracy obtained for each of F1, F2, and F3 is 0.893, 0.92 and 0.867, respectively. It is clear that the performance
using set F2 is superior to that of the others. This means the combination of the last two convolutional layers results in the best combination. Post-analysis has shown that F3 underperforms because the features are less refined, and do not usefully contribute to the predictive power of the model.

Fig. 8. The classification accuracy of DC-Al GAN with features F1, F2, and F3.

Table 1 contains additional statistics with respect the classification performance. The calculations are as follows: Sensitivity = TP/(TP + FN). Specificity = TN/(FP + TN). Precision = TP/(TP + FP), and Recall = Sensitivity. Where TP, FP, FN, and TN refer to true positive, false positive, false negative, and true negative, respectively.

Table 1 : Comparison of classification performance using different features

| Methods          | Classification Performance |
|------------------|----------------------------|
|                  | Sensitivity    | Specificity | Precision |
| DC-Al GAN_F1     | 0.912          | 0.747       | 0.881     |
| DC-Al GAN_F2     | 0.976          | 0.883       | 0.945     |
| DC-Al GAN_F3     | 0.929          | 0.833       | 0.920     |

Fig. 9 shows the confusion matrix for each of the three experiments. As seen in previous charts and tables, the model created using F2 is clearly the top performer.

Fig. 9. (a)–(c) correspond to the confusion matrix of DC–AL GAN with features F1, F2, and F3, respectively.

Fig. 10(a), shows that the average accuracies were 0.902, 0.918, and 0.916 when CV=5, 10, and 20, respectively. These results indicate that this approach has a promising differentiation capability. The respective values for the AUC are 0.886, 0.945, and 0.929. In addition, as shown in Fig. 10 (b), the p-values for different CV values are all greater than 0.05. Therefore, the difference in performance is insignificant and allows us to conclude that the classification system is stable. Fig. 10(c) and Fig. 10 (d) are boxplot representations of accuracy and AUC of ROC, respectively.

In this section, the performance of different cross validation values is compared through the receiver operating characteristic curves. The ROC curves correspond to 5, 10, and 20 CV repetitions, as shown in Fig. 11. The results show that this method achieves the best performance with 10 CV repetitions. In a reasonable range, appropriately increasing the multiple of cross validation can improve the generalization ability of the model and make the model have better output performance, however, the computational load should also be considered simultaneously. For example, when CV is increased from 5 to 10, the performance of the model is obviously improved. When CV is increased from 10 to 20, the output results do not change significantly, but the calculation amount is doubled. So in this paper, we adopt 10 CV repetitions. In Fig. 11 (a)–(c), the areas under the ROC curves are close to 1, and the TPR values are greater than 0.8. The areas under the ROC curves of the 5 and 20 CV repetition are smaller than 10. Consequently, the experimental results confirm that this method has a better generalization
capability.

Fig. 11. ROC curves of these methods with 5, 10 and 20 CV repetitions.

V. CONCLUSION AND FUTURE WORK

This paper introduces an unsupervised representation learning algorithm called DC-Al GAN. It is capable of learning interpretable representations, even from challenging GBM datasets. Alexnet is an integral component in the architecture where it is used as a discriminator to extract features. The results show that the discriminator is able to extract features that work effectively for classification. It does so by observing and analyzing the sample images created by the generator. In addition, DC-Al GAN utilizes feature fusion by combining coarse, high layer features with fine, low layer features. This has shown to be beneficial in terms of classification performance. In summary, the experimental results have confirmed that DC-Al GAN achieves high accuracy on GBM datasets for PsP and TTP classification. Other possible future improvements to the work proposed in this paper include: optimizing the architecture of generator to produce high-quality samples of images and classifying images in a semi-supervised manner to lower the demand for label data.