Special Topics of Artificial intelligence

Exploring GAN Variants for Balancing Imbalanced Datasets

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Problem Statement

Class imbalance is a common problem in machine learning where some classes have a lot of data and other classes have very little data. When this happens, the model usually learns the majority classes better and performs poorly on the minority class. This is a problem because the model may give good overall accuracy but still fail on the class that actually matters.

The purpose of this project is to see if Generative Adversarial Networks (GANs) can be used to help solve the class imbalance problem. GANs can generate new data that looks similar to real data. By generating extra samples for the minority class, the classifier may learn better and improve its performance. In this project, different GAN models are tested to see how effective they are.

Description of Dataset and Imbalance Analysis

The MNIST dataset was used for this project. The dataset contains grayscale images of handwritten digits from 0 to 9, and each image has a size of 28×28 pixels. MNIST is a well-known dataset and is commonly used for image classification experiments.

To create an imbalanced dataset, digit 9 was chosen as the minority class. The number of digit 9 images was reduced, while the images for the other digits were kept the same. This caused digit 9 to have much fewer samples compared to the other classes. A class distribution plot was created to clearly show the imbalance in the dataset and confirm that digit 9 was the minority class.

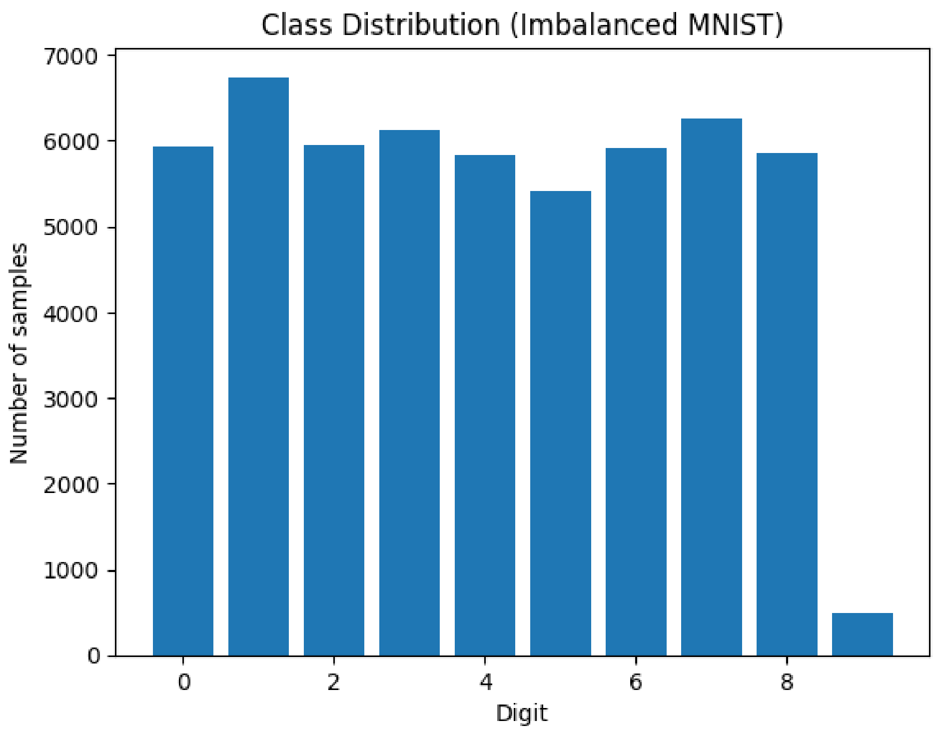

Figure 1 **Class distribution**

Details of GAN Architectures and Training

In this project, two GAN models were implemented: a Vanilla GAN and a DCGAN.

The Vanilla GAN is made up of two networks, a generator and a discriminator. The generator tries to create fake images that look like real images of the minority class, while the discriminator tries to tell real images apart from fake ones. The Vanilla GAN was trained using only the minority class data. After training, it was able to generate digit images that looked similar to real handwritten digits.

DCGAN was also implemented as a more advanced GAN model. It uses convolutional layers instead of fully connected layers. Even though DCGAN is more powerful, it was harder to train in this project because there were not many minority class samples. As a result, the generated images were less clear and more unstable compared to the Vanilla GAN. This shows that advanced GAN models usually need more data and careful training.

Classifier Setup and Evaluation

A Convolutional Neural Network (CNN) classifier was used to evaluate the effect of GAN-based data augmentation. The same classifier model was used in all experiments to make sure the comparison was fair.

First, the classifier was trained on the imbalanced dataset without any generated data. After that, the classifier was trained again using the dataset augmented with GAN-generated images. The performance was evaluated using precision, recall, and F1-score. Special attention was given to the results of the minority class since that was the main focus of the project.

All experiments were conducted using Google Colab. The same classifier architecture and training settings were used across all experiments to ensure a fair comparison. Hyperparameters were kept consistent, and performance was evaluated using standard classification metrics.

Results and Comparisons

When the classifier was trained on the imbalanced dataset, it performed poorly on the minority class. The recall and F1-score for digit 9 were low, which showed that the classifier struggled to recognize that class.

After adding synthetic samples generated by the Vanilla GAN, the classification performance improved significantly. The F1-score for digit 9 increased to 0.99, which shows that GAN-based data augmentation was very effective in this case. When DCGAN-generated samples were used, the improvement was smaller and less consistent. This is mainly due to the difficulty of training DCGAN with limited data.

Dataset Version	Precision (9)	Recall (9)	F1-score (9)
Imbalanced	**0.85**	**0.60**	**0.70**
Vanilla GAN	**1.00**	**0.99**	**0.99**
DCGAN	**0.92**	**0.88**	**0.90**

Table 1 **Classification performance comparison for the minority class (digit 9)**

Observations and Conclusions

Based on the results, it can be seen that GAN-based data augmentation can help solve the class imbalance problem. The Vanilla GAN worked well and was able to generate useful samples that improved the classifier's performance on the minority class.

Although DCGAN is a more advanced model, it did not perform as well in this project because it requires more data and stable training conditions. Overall, this project shows that GANs are a useful approach for handling imbalanced datasets, especially when simpler models are used.

References

1. Goodfellow, I. et al. "Generative Adversarial Networks."
2. LeCun, Y. et al. "Gradient-Based Learning Applied to Document Recognition."