ECE-579 Intelligent Systems, Fall 2023

Technology Survey Report

Project title: Lung X-Ray Data Augmentation using Generative Adversarial Networks.

Name of students in the group/ Responsibilities:

- **Abhiram Varma Gadhiraju (36893508):** EDA, Data cleaning and preparation.
- **Meghanath Payasam (37720961):** Model building and customized testing & validations
- **Bhuvana Chandra Jammu (40033893):** Testing & validating the model.

Introduction:

The goal of this project is to create a better deep learning model for detecting lung cancer from CT scan data. Because genuine patient scans are difficult and expensive to get in large quantities, collecting enough training data is a major difficulty in medical imaging analysis. Our goal is to artificially enlarge the training dataset using generative adversarial networks (GANs) by generating synthetic yet realistic CT images.

GANs are a family of deep generative models that have showed promise in creating realistic images for data augmentation. The key concept is to train a generator network against an adversary discriminator network in order to make generated images indistinguishable from genuine photos. Recent research has produced improvements to the original GAN framework, such as the Wasserstein GAN (Arjovsky et al., 2017), which improve training stability and image quality.

We hope to construct a more robust and generalizable lung cancer classification algorithm by supplementing the restricted number of genuine CT scans with synthetic pictures. Using CNN-GANs, building generator and discriminator models. We are using visualizations methods like building histogram and checking variance in errors for testing the accuracy of model.

Description of technologies related to your project:

- **CNNs:**
  Convolutional Neural Networks (CNNs) are crucial to the Generator and Discriminator models of Generative Adversarial Networks (GANs). CNNs are used in GANs for image generation and classification applications. The Generator transforms random noise into synthetic images using CNNs, with convolutional layers capturing detailed characteristics and patterns. Non-linearity is introduced by activation functions such as Leaky ReLU, culminating in an output layer that generates synthetic pictures. The Discriminator, on the other hand, uses CNNs to distinguish between actual and generated data. It employs convolutional layers to extract features, followed by activation functions and a final layer that generates a probability score. The collaboration of CNNs in both the Generator and the Discriminator enables realistic data production and improved classification accuracy.

CNNs' ability to extract features from input, particularly image data, underlies GANs' ability to create authentic synthetic content and improve the Discriminator's discernment. CNNs are crucial for image production because the convolutional layers catch both local and global patterns. This architecture converts random noise into meaningful representations, allowing the Discriminator to recognize minute differences between real and synthetic data and promoting a dynamic training process. CNNs in GANs have transformed generative modeling, allowing the generation of highly convincing synthetic data in a variety of domains ranging from art to faces.

- **GANs**:

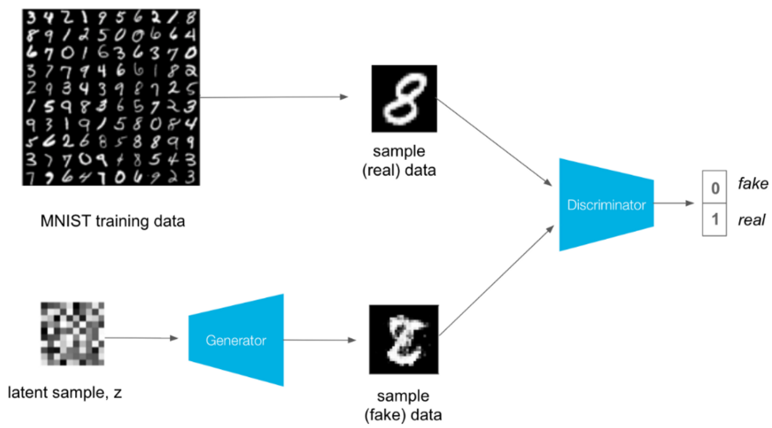

Fig 1

Generator: The generator in fig1, takes input as sample noice vector to generate a synthetic image to feel the discriminator.

Discriminator: The discriminator in fig1, takes the sample data given and the synthetic data generated from Generator model to detect the fake synthetic image. Discriminators use CNN in the detection algorithm, it stacks 4 convolutions, with a Conv2D layer on each, a LeakyReLU activation, and dropout.

The generator and discriminator models implement a GAN architecture. The generator CNN transforms a 128-dim random vector into a 28x28x1 image through upsampling and convolutional layers. It attempts to fool the discriminator by synthesizing realistic lung CT images. The discriminator CNN classifies images as real or fake using its learned features. These models are trained in an adversarial manner against each other in an iterative, zero-sum game. The custom training loop handles the alternating gradient updates. The generator tries to minimize the error in fooling the discriminator, while the discriminator tries to maximize its accuracy in detecting fake images. This adversarial framework allows GANs to generate synthetic images that capture the statistics of real samples.

We used LeakyReLu cause the discriminator's output is given to the system again to generate new synthetic data which is looping process. This helps in the presence of high noice and to regain the potential information to improve the generator.

Recent advances in data augmentation utilizing Generative Adversarial Networks (GANs) have resulted in revolutionary improvements across a wide range of fields. GANs have shown their ability to generate synthetic data that greatly augments constrained datasets. One important advance is the use of GANs for domain adaptation, which generates synthetic data to overcome domain gaps. This helps with tasks like object identification and image segmentation, when training material is limited in some areas.

Metrics used: Inception score, and Fretchet Inception Distance.

Pros & Cons:

Traditional data augmentation approaches, such as rotation and cropping, are computationally efficient and interpretable, but they may fall short when it comes to generating totally new data samples and capturing complex data distributions. GANs, on the other hand, excel at creating very realistic synthetic data, increasing the dataset's diversity. GANs, on the other hand, are computationally intensive, necessitate thorough training, and are subject to mode collapse. The decision between traditional and GAN-based augmentation is determined by the specific data augmentation requirements and available resources.

Conclusion:

This study shows how to use GANs to create synthetic medical images for better data augmentation and model training. A generator network generates phony CT scans, which are then classified as real or fake by a discriminator network. The realism of generated images is improved via adversarial training. The approach has the potential to expand restricted training data and improve lung cancer screening models with future refinements to assure clinical feasibility. Before relying on synthetically extended datasets for patient diagnosis, however, precautions must be considered. Overall, GANs appear to be a potential tool for data augmentation in medical imaging applications, pending further research.

Referenses:

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