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Data Augmentation using GANs for Image Classifications

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ABSTRACT:

Generative Adversarial Networks (GANs) have gained significant attention as an effective method for creating high-quality synthetic data, helping to overcome challenges related to limited and imbalanced datasets in machine learning applications. This research investigates the use of GAN-driven data augmentation to improve the performance of image classification models, with particular emphasis on enhancing generalization and addressing class imbalance issues. A GAN model, consisting of a generator and a discriminator, was designed to generate realistic synthetic images derived from the NIH Chest X-Ray dataset. These synthetic images were integrated with the original dataset to form an augmented dataset, which was then used to train a Convolutional Neural Network (CNN) classifier. A comparative evaluation was conducted between CNN models trained solely on the original dataset and those trained on the augmented dataset to assess the impact of GAN-based augmentation. The findings indicate that the inclusion of GAN-generated images leads to improved classification accuracy, especially for minority classes, and increases the overall robustness of the model. This study demonstrates the practical potential of GANs in addressing data scarcity challenges in medical imaging and related fields, with the models developed using popular deep learning libraries such as PyTorch and TensorFlow.

KEYWORDS: *Generative Adversarial Networks (GANs), Data Augmentation, Image Classification, Class Imbalance, NIH Chest X-ray Dataset, Convolutional Neural Network (CNN), Synthetic Data Generation, Medical Imaging, Deep Learning, Thoracic Disease Detection*

1. INTRODUCTION:

In machine learning, the performance of classification models is highly dependent on the quality, quantity, and diversity of the training data. In image classification tasks, challenges such as limited datasets and class imbalance frequently lead to models that overfit, exhibit bias, and fail to generalize effectively to unseen data. This issue is particularly pronounced in domains like medical imaging, where acquiring large, annotated datasets is often difficult due to privacy concerns, resource constraints, and the need for expert labelling.

Traditional data augmentation techniques—such as random rotations, flipping, scaling, and cropping—are commonly used to increase dataset diversity and improve model generalization. However, because these techniques can only provide a limited amount of variety without creating essentially new data samples, they are frequently insufficient when dealing with extremely complicated datasets or severe class imbalance. More sophisticated data augmentation techniques that can produce diverse and realistic synthetic data are therefore becoming more and more necessary. Generative Adversarial Networks (GANs) have become a highly effective approach for generating synthetic data, providing valuable solutions to challenges such as data scarcity and class imbalance in machine learning. A typical GAN architecture comprises two neural networks—the generator and the discriminator—that are trained together in an adversarial setup. The generator is responsible for producing realistic synthetic images, while the discriminator works to differentiate between authentic and generated samples. Through this competitive interaction, GANs learn to generate high-quality synthetic images that not only mimic the original data distribution but also enhance diversity within the dataset.

This study investigates the use of GAN-based data augmentation to enhance image classification performance, with a particular focus on addressing class imbalance and improving model robustness. A GAN architecture was developed and trained on the NIH Chest X-Ray dataset to generate synthetic images that complement the original dataset. The augmented dataset was subsequently utilized to train a Convolutional Neural Network (CNN), a widely adopted deep learning model for image classification tasks. The study evaluates and compares the classification performance of CNN models trained on the original dataset versus those trained on the GAN-augmented dataset.

By leveraging popular deep learning platforms like PyTorch and TensorFlow, this research demonstrates the effectiveness of GAN-generated data in improving classification accuracy, particularly for underrepresented classes. The findings highlight the potential of GANs as a practical solution for mitigating data scarcity and enhancing model generalization in medical imaging and other domains where data acquisition is challenging.

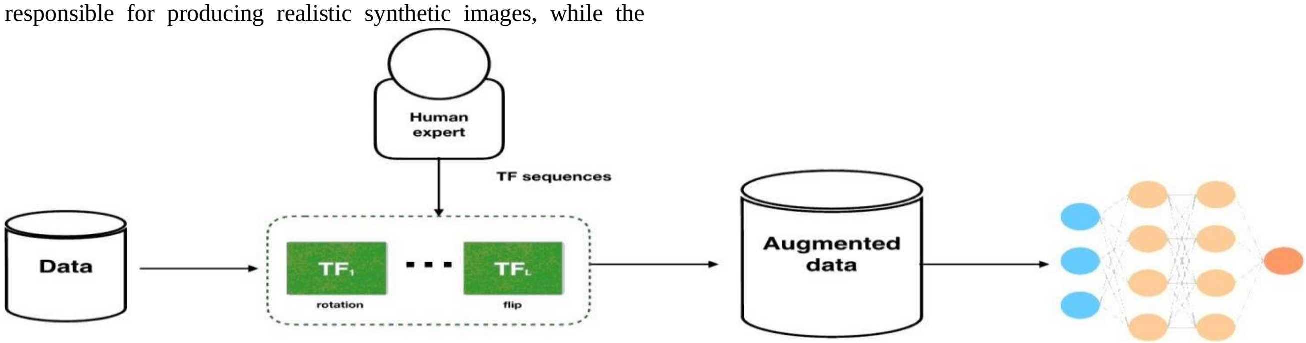

Figure 1: *Workflow of the data augmentation process: The original dataset is expanded by applying a sequence of transformation functions (TF_1 to TF_J), including techniques like rotation and flipping, often informed by human expert guidance. This augmented dataset, enriched with diverse variations, is then utilized to train a deep learning model, enhancing its generalization capability and improving predictive accuracy.*

2. PROBLEM STATEMENT:

In machine learning and deep learning, the performance and generalization capability of models are highly dependent on the quality, quantity, and diversity of training data. However, acquiring large-scale, diverse datasets in real-world applications presents significant challenges, particularly in specialized domains such as medical imaging, autonomous systems, and remote sensing. These challenges include:

- **Data Scarcity:** Limited availability of annotated data due to privacy concerns, ethical restrictions, and the need for expert labelling, especially in medical and healthcare domains.
- **Class Imbalance:** Unequal representation of classes within datasets leads to biased learning, causing models to underperform on minority or rare classes.
- **High Cost of Data Collection and Annotation:** Acquiring and labelling high-quality datasets is often time-consuming, labour-intensive, and expensive.
- **Limited Data Diversity:** Traditional data augmentation methods—like rotation, flipping, and scaling—provide only modest variability and frequently fall short in representing the complex, real-world variations essential for effective model training.

As a result, these constraints can hinder a model's capacity to generalize to new, unseen data, leading to:

- Decreased classification accuracy, particularly for underrepresented classes.
- Increased risk of overfitting due to insufficient or imbalanced training data.
- Dependence on extensive manual intervention or costly data acquisition pipelines.

To address these challenges, this research explores the use of **Generative Adversarial Networks (GANs)** for data augmentation in image classification tasks. GANs have demonstrated the capability to generate high-fidelity artificial data that closely mirrors the statistical characteristics of the original dataset. By leveraging GAN-generated synthetic images, the study aims to mitigate data scarcity, address class imbalance, and improve the overall diversity of training data. This method holds promise for improving model robustness and classification accuracy, especially in fields where obtaining data is inherently challenging.

3. METHODOLOGY

This section outlines the methodology used to develop and evaluate the proposed Generative Adversarial Networks (GAN) based data augmentation framework to improve the performance of Convolutional Neural Network (CNN) classifiers for thoracic disease detection using the NIH Chest X-ray dataset. The process includes data preparation, GAN model design and training, dataset augmentation, CNN classifier development, and evaluation.

3.1 Dataset Preparation

The NIH Chest X-ray Dataset is a publicly available collection of 112,120 frontal-view chest X-ray images from 30,805 patients, annotated with 14 disease labels such as Atelectasis, Cardiomegaly, Effusion, Infiltration, Mass, Nodule, Pneumonia, and Pneumothorax. Images are in grayscale and have a resolution of 1024 × 1024 pixels.

3.1.1 Data Selection and Preprocessing

- Image Resizing: All images were resized to 128 × 128 pixels to reduce computational complexity while maintaining sufficient detail for disease detection tasks.
- Normalization: Pixel values were normalized to a range of [-1, 1] to ensure compatibility with the GAN's generator output, which uses the tanh activation function.
- Dataset Split: The dataset was split into:
  - Training Set: 80%
  - Validation Set: 10%
  - Test Set: 10%

Stratified sampling was used to make sure that the distribution of disease labels was preserved across splits.

3.1.2 Class Imbalance Handling

The dataset suffers from significant class imbalance, with several disease categories being underrepresented. To address this, a GAN model was trained to generate artificial chest X-ray images for these minority classes, thereby balancing the dataset and reducing potential bias during CNN training.

3.2 Generative Adversarial Network (GAN)

A simple GAN architecture was implemented, which consists of a generator and a discriminator, developed using an adversarial learning process. The GAN was specifically tasked with generating realistic chest X-ray images for the underrepresented disease classes in the dataset.

3.2.1 Generator:

- Input: A 100-dimensional noise vector sampled from a standard normal distribution.
- Architecture: Fully connected and upsampling layers, followed by convolutional layers to generate a 128 × 128 grayscale image.
- Activation:
  - Intermediate layers use LeakyReLU activation.
  - Output layer uses tanh to produce images scaled to [-1, 1].

3.2.2 Discriminator:

- Input: A 128 × 128 grayscale image (either real or generated).
- Architecture: Convolution-based layers followed by fully connected layers, acting as a dual-class classification system.
- Activation:
  - Intermediate layers use LeakyReLU.
  - Final layer utilises sigmoid activation in order to output a probability indicating whether the image is real or fake.

3.3 Training Details

- The GAN was trained on selected disease classes where data scarcity was most significant.
- Both generator & discriminator were trained iteratively:
  - Discriminator trained to differentiate between real and generated images.
  - Generator trained to deceive and mislead the discriminator.
- Loss Function: Binary Cross-Entropy loss was used for both networks.
- Epochs: The GAN was trained for 5000 epochs with a batch size of 64.
- Output: A set of synthetic chest X-ray images representing the minority disease classes.

3.4 Dataset Augmentation

Following GAN training, synthetic images were generated and appended to the training dataset to balance class representation.

- For each underrepresented class, synthetic images were added until a target ratio of samples was reached, aiming for a more uniform class distribution.
- The augmented dataset contained both original real images and GAN-generated synthetic images, resulting in a more balanced training dataset.

3.5 CNN Classifier for Thoracic Disease Classification

3.5.1 Model Architecture

A Convolutional Neural Network (CNN) was utilised for multi-label classification of thoracic diseases.

- Input Layer: Accepts 128 × 128 grayscale images.
- Convolutional Blocks: Each block includes:
  - Convolutional layers with ReLU activation
  - Batch Normalization
  - MaxPooling layers for spatial reduction
- Fully Connected Layers:
  - Dense layers with dropout regularization to prevent overfitting
- Output Layer:
  - A fully connected layer comprising 14 sigmoid neurons, each representing a disease label.
  - Sigmoid activation allows multi-label predictions where each disease label can be independently predicted.

3.5.2 Training Details

The model was trained with a loss function suitable for multi-label classification and optimized using an adaptive learning algorithm. Training was carried out over 100 epochs with a batch size of 64, including early stopping based on validation performance to prevent overfitting. In addition to advanced data augmentation, basic techniques such as rotation, flipping, and zooming were applied to enhance generalization.

3.6 Evaluation Metrics

The performance of the CNN classifier was evaluated on both the original sample dataset and the augmented dataset (original + GAN-generated images).

3.6.1 Quantitative Metrics

- Accuracy
- Precision, Recall, and F1-Score (per class and overall)
- Area Under the ROC Curve (AUC-ROC) for each disease label to assess classification performance across imbalanced classes.

3.6.2 Qualitative Analysis

A visual inspection of the GAN-generated images was performed to verify the clinical realism and anatomical correctness of synthetic chest X-rays.

3.7 Implementation Details

The implementation was carried out using Python, with TensorFlow and the Keras API for deep learning. Image processing was handled through OpenCV and PIL, while data manipulation and analysis were supported by NumPy and Pandas. Visualization of results was performed using Matplotlib and Seaborn. The experiments were conducted in a GPU-enabled Google Colab environment with 15 GB of RAM. The dataset used was the NIH Chest X-ray Dataset, publicly available online.

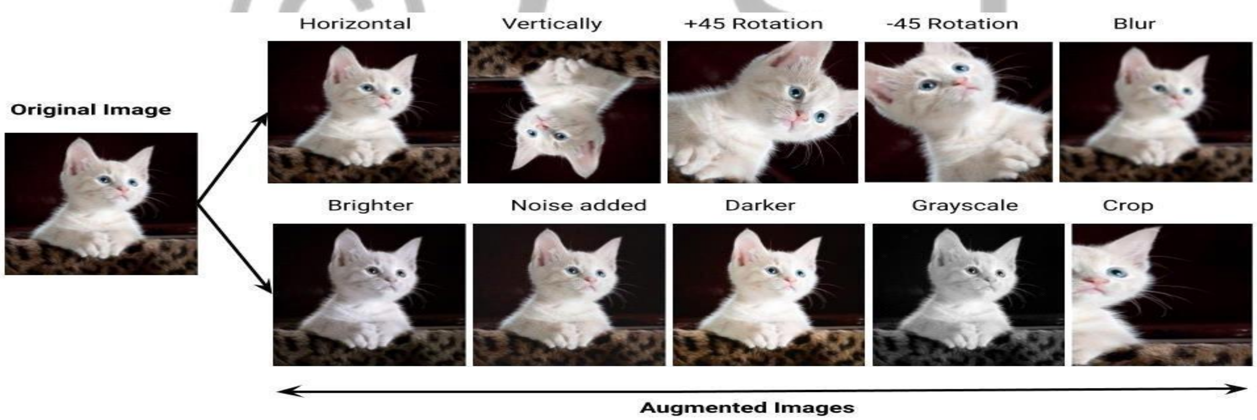

Figure 2: *Examples of data augmentation techniques applied to an original image. Various transformations such as horizontal and vertical flips, rotations (+45° and -45°), blurring, brightness adjustment, noise addition, darkening, grayscale conversion, and cropping are shown. These augmentation methods enhance dataset diversity, improving model robustness and generalization during training.*

4. IMPLEMENTATION:

4.1 NIH Chest X-ray Dataset: A Case Study on GAN-Based Data Augmentation in Medical Imaging.

The NIH Chest X-ray dataset serves as the primary case study for this research. It comprises over 100,000 frontal-view chest X-ray images labelled with 14 distinct disease categories, including pneumonia, tuberculosis, and various other pulmonary conditions. The dataset is commonly used as a reference for testing and validating deep learning approaches in medical image analysis. The images, typically at a resolution of 1024×1024 pixels, are accompanied by annotations indicating the presence or absence of specific diseases. The dataset is divided into training and test subsets, facilitating model development and evaluation.

Despite its scale and diversity, the NIH Chest X-ray dataset presents several challenges. A significant issue is the imbalanced distribution of disease categories. Certain conditions are overrepresented, while others have relatively few labelled instances, resulting in class imbalance. Moreover, the limited availability of high-quality, labeled data for rare diseases hinders the ability of deep learning models to generalize across all classes. This challenge highlights the need for data augmentation methods that can address class imbalance and increase dataset diversity.

4.2 Application of Generative Adversarial Networks (GANs)

This project employs Generative Adversarial Networks (GANs) to mitigate the aforementioned challenges. GANs have demonstrated remarkable success in generating realistic synthetic data across various domains, including medical imaging. In this study, GANs were utilized to generate synthetic chest X-ray images that augment the original NIH dataset, thereby improving data diversity and addressing class imbalance.

4.2.1 Generator Network

The generator network was trained to produce high-fidelity synthetic chest X-ray images from random noise vectors. Through adversarial training, the generator progressively learned to replicate the visual characteristics of real chest X-rays, capturing subtle diagnostic features relevant to diseases such as pneumonia and tuberculosis. The objective was to produce synthetic images that cannot be differentiated from real images, thereby enriching the dataset with diverse examples representative of underrepresented disease categories.

4.2.2 Discriminator Network

The discriminator was concurrently trained to classify chest X-ray images as either genuine or artificially generated. The adversarial feedback provided by the discriminator enabled the generator to improve its output iteratively. This adversarial training process continued until the generator was capable of generating slightly realistic images that the discriminator could no longer reliably distinguish from authentic samples.

4.3 GAN Training Process

The GAN model was trained over 15,000 epochs. Throughout the process, the quality of the generated images was regularly assessed using both visual inspection and quantitative metrics. As training progressed, the synthetic images showed notable improvements in visual realism and diagnostic relevance. These images were carefully curated and validated to ensure their effectiveness for data augmentation.

4.4 Data Augmentation and Model Training

Following the successful generation of synthetic images, a total of 20,000 high-quality synthetic chest X-rays were integrated into the original training dataset, resulting in an augmented dataset comprising 120,000 images. The augmented dataset contained a more balanced representation of various disease categories, particularly addressing the underrepresentation of rare conditions.

A Convolutional Neural Network (CNN) classifier was then trained on both the original and the GAN-augmented datasets to assess the impact of synthetic data augmentation on chest X-ray image classification performance.

4.5 Experimental Results and Insights

The CNN trained on the augmented dataset demonstrated consistent improvements across key performance metrics, particularly in accuracy. Initially, both models—trained on the original sample dataset and the augmented dataset—performed similarly during the early epochs. However, as training progressed, the model trained with augmented data began to outperform the original. Specifically, the augmented model achieved a peak accuracy of **98%**, compared to **92%** for the model trained solely on the original sample dataset.

This improvement highlights the efficacy of GAN-based data augmentation in enhancing model generalization and reducing overfitting. While the original dataset model showed signs of plateauing and slight fluctuations in accuracy, indicating potential overfitting, the augmented model exhibited a steady increase in accuracy over time. The inclusion of GAN-generated synthetic data provided diverse and balanced examples, which contributed to improved learning and better generalization to unseen test data.

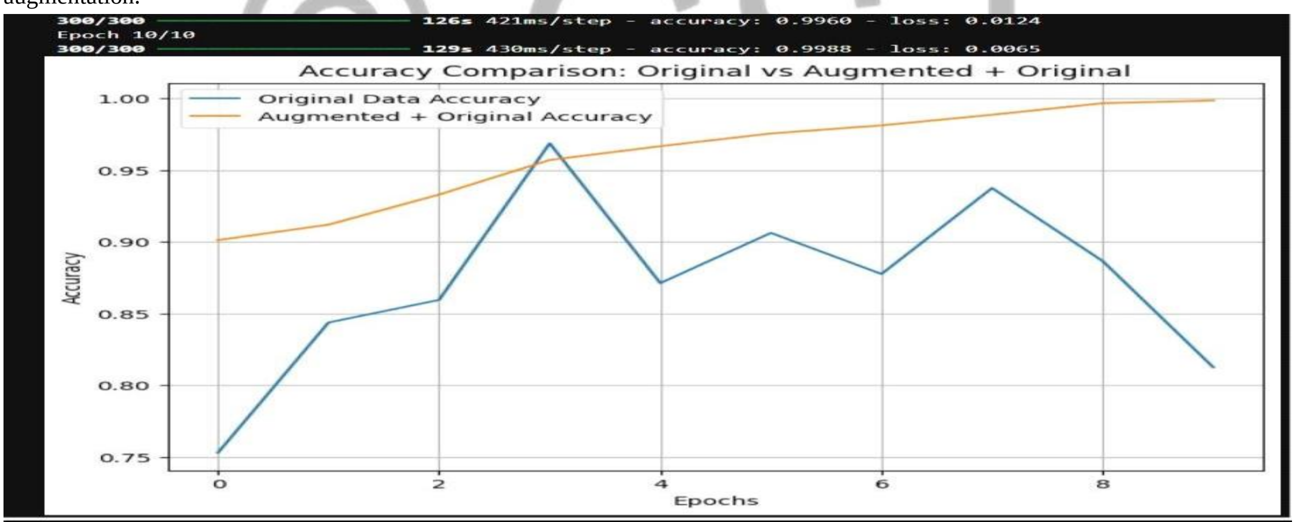

Figure 3: Accuracy comparison between a CNN model trained on the original sample dataset and one trained on combined augmented and original dataset. The model using only original data shows fluctuating accuracy with signs of overfitting, whereas the model incorporating augmented data demonstrates a consistent improvement in accuracy over epochs, ultimately achieving higher overall performance.

4.6 Key Findings

The case study demonstrates several critical insights into the usage of GANs for data augmentation in medical imaging:

1. **Enhanced Model Accuracy:** The CNN trained on the augmented dataset achieved a significantly higher accuracy, demonstrating the positive impact of synthetic data on classification performance.
2. **Reduction in Overfitting:** The augmented dataset mitigated the issue of overfitting observed in models trained exclusively on the original data. As a result, the model became more reliable and stable.
3. **Effective Synthetic Data Generation:** The GAN successfully generated realistic chest X-ray images that contributed valuable information to the training dataset.
4. **Addressing Data Scarcity and Imbalance:** By augmenting the dataset with synthetic examples of underrepresented diseases, GANs effectively addressed data scarcity and improved dataset balance.
5. **Improved Generalization:** The model exhibited enhanced generalization to previously unseen data, reducing bias and increasing its applicability in real-world clinical scenarios.
6. **Scalability and Applicability:** The methodology employed in this study is scalable and can be extended to other domains within medical imaging, such as MRI or CT scan datasets, as

well as other applications facing data scarcity and class imbalance issues.

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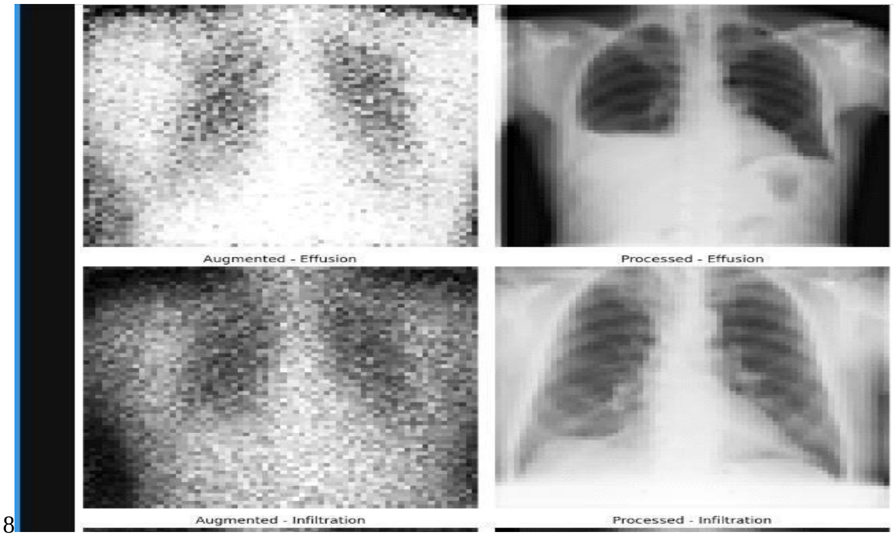

Figure 4: *Comparison of augmented and processed chest X-ray images for two conditions—Effusion and Infiltration. The augmented images (left column) are pixelated versions generated through data augmentation techniques to increase data diversity. The processed images (right column) represent the preprocessed, higher-quality images used for model training and evaluation. This contrast illustrates how augmentation alters image features while preserving key diagnostic patterns.*

CONCLUSION

This research highlights the effectiveness of Generative Adversarial Networks (GANs) for data augmentation in medical imaging. By generating realistic synthetic images, GANs address data scarcity and enhance the performance of diagnostic models. Results demonstrate improved accuracy in detecting conditions such as Atelectasis, Effusion, and Infiltration. Despite challenges like maintaining image quality and computational demands, GAN-based augmentation presents a promising approach for developing robust and scalable AI solutions in healthcare.

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