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Generative AI in the Categorisation of Paediatric Pneumonia on Chest Radiographs

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ABSTRACT: Paediatric pneumonia is a leading cause of morbidity and mortality worldwide, necessitating accurate and timely diagnosis. This study explores the application of Generative AI for categorising paediatric pneumonia using chest radiographs. Leveraging deep learning techniques, including Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs), we enhance image quality, generate synthetic training data, and improve model generalizability. The proposed framework integrates AI-driven feature extraction, convolutional neural networks (CNNs), and attention mechanisms to improve diagnostic accuracy. The results demonstrate significant improvements in classification performance compared to traditional methods, with a focus on interpretability and clinical usability.

KEYWORDS: Generative AI, Paediatric Pneumonia, Chest Radiographs, Convolutional Neural Networks (CNN), Generative Adversarial Networks (GAN), Data Augmentation, Medical Image Classification, Pneumonia Diagnosis, Deep Learning, Synthetic Data.

INTRODUCTION

Pneumonia remains a leading cause of mortality among children worldwide, and accurate diagnosis through chest radiographs is essential. However, variability in radiographic interpretation and limited access to expert radiologists present challenges. Generative AI offers a transformative approach by generating high-quality synthetic images for model training and enhancing image clarity. This study investigates the role of AI in pneumonia classification, addressing data scarcity, improving model generalization, and reducing misdiagnosis rates. The integration of generative models with deep learning classifiers ensures robustness and reliability in paediatric pneumonia detection.

METHODOLOGY

This research adopts a hybrid AI framework that combines Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) for data augmentation, followed by Convolutional Neural Networks (CNNs) and Transformer-based classifiers for pneumonia categorization.

1. **DATA PREPROCESSING**

- **Dataset:** The study utilizes the Chest X-ray dataset (Pneumonia vs Normal) from reputable sources such as NIH and Kaggle.
- **Preprocessing Steps:**
  - Normalization and resizing of images.
  - Noise reduction using Gaussian filtering.
  - Contrast enhancement with histogram equalization.
  - Data augmentation through GANs and VAEs.

2. **GENERATIVE AI FOR DATA AUGMENTATION**

   Generative Adversarial Networks (GANs) Approach

   GANs consist of a **generator** (G) and a **discriminator** (D) working adversarially:

   - **Generator Function:** $G(z; \theta g)$ where z is the random noise input (typically sampled from a normal or uniform distribution), and θg are the learned weights and biases of the generator network.

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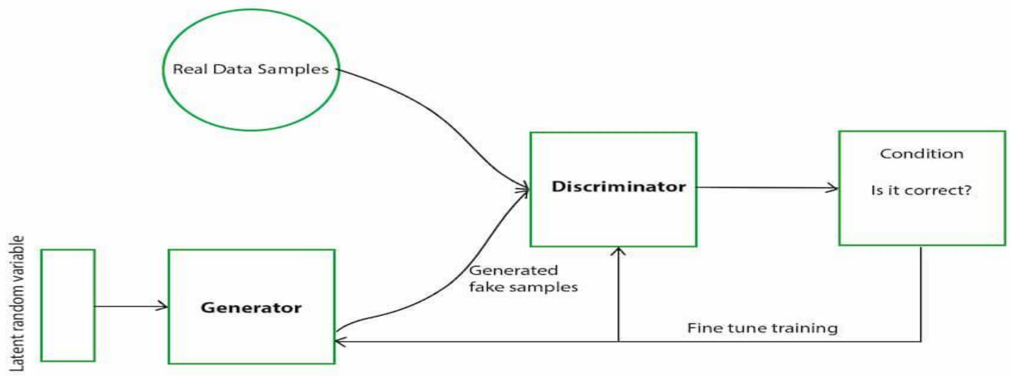
- **Discriminator Function:** D (x; θd) where x is either a real image from the training data or a synthetic image produced by the generator, and θd are the learned weights and biases of the discriminator network.
- **Loss Function: The** minimax loss function for GANs is typically: min G max D V(D,G) = Ex~pdata(x)[log D(x)] + Ez~pz(z)[log(1 - D(G(z)))]

Where,

- G is generator network and is D is the discriminator network
- Actual data samples obtained from the true data distribution pdata(x)pdata(x) are represented by x.
- Random noise sampled from a previous distribution pz(z)pz(z) (usually a normal or uniform distribution) is represented by z.
- D(x) represents the discriminator's likelihood of correctly identifying actual data as real.
- D(G(z)) is the likelihood that the discriminator will identify generated data coming from the generator as authentic.

The generator aims to **minimize** the loss, while the discriminator tries to **maximize** its classification accuracy.



How GAN work

Let's understand how the generator (G) and discriminator (D) complete to improve each other over time:

1. Generator's First Move

G takes a random noise vector as input. This noise vector contains random values and acts as the starting point for G's creation process. Using its internal layers and learned patterns, G transforms the noise vector into a new data sample, like a generated image.

2. Discriminator's Turn

D receives two kinds of inputs:

- Real data samples from the training dataset.
- The data samples generated by G in the previous step.

3. Adversarial Learning

- If the discriminator correctly classifies real data as real and fake data as fake, it strengthens its ability slightly.
- If the generator successfully fools the discriminator, it receives a positive update, while the discriminator is penalized.

4. Generator's Improvement

Every time the discriminator misclassifies fake data as real, the generator learns and improves.

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5. Discriminator's Adaptation

The discriminator continuously refines its ability to distinguish real from fake data. This ongoing duel between the generator and discriminator enhances the overall model's learning process.

Training Progression

- As training continues, the generator becomes highly proficient at producing realistic data.
- Eventually, the discriminator struggles to distinguish real from fake, indicating that the GAN has reached a well-trained state.
- At this point, the generator can be used to generate high-quality synthetic data for various applications.

Variational Autoencoders (VAEs) Approach

VAEs are used for data enhancement by learning a probabilistic distribution of chest X-ray images:

Variational Autoencoders (VAEs) are a generative model that learns a probabilistic distribution of data. In the case of chest X-ray images, VAEs can be used for data augmentation, anomaly detection, and generating synthetic images that resemble real ones.

Encoder Function

The encoder compresses an input chest X-ray image x into a latent representation z, learning a probability distribution over the latent space. It maps x to a mean μ and a standard deviation σ, which define a Gaussian distribution:

$$q\phi(z|x) = N(z|\mu(x), \sigma 2(x))$$

where:

- $\mu(x)\mu(x)$ and $\sigma(x)\sigma(x)$ are learned by the encoder neural network.
- The reparameterization trick is used to sample zz:$z=\mu+\sigma\cdot\epsilon,\epsilon\sim N(0,I)z=\mu+\sigma\cdot\epsilon,\epsilon\sim N(0,I)$

Decoder Function

The decoder reconstructs the input by generating an approximation x from the latent variable z:

$$p\theta(x|z) = f\theta(z)$$

where:

- $f\theta(z)f\theta(z)$ is a neural network that reconstructs an image from z.
- The output is typically modeled as a Bernoulli or Gaussian distribution.

Loss Function

The VAE loss function consists of two components:

1. **Reconstruction Loss:** Ensures the generated image x is close to the original xx.
   Typically, Mean Squared Error (MSE) or Binary Cross-Entropy (BCE) is used:

$$Lrecon=Eq\phi(z|x)\,[-\log p\theta(x|z)]$$

2. KL Divergence Loss: Encourages the learned latent distribution to be close to a standard normal distribution:

$$LKL=DKL(q\phi(z|x)||p(z))=21j=1\sum d(1+\log\sigma j2-\mu j2-\sigma j2)$$

Thus, the total loss is:

$$Lrecon+\beta LKL$$

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where ββ is a weight that balances reconstruction accuracy and latent space regularization.

3. **Pneumonia Classification Using CNN and Transformers**

CNN-Based Feature Extraction

- Convolutional layers extract spatial features from X-ray images:
  $F(x) = W * x + b$
- Pooling layers reduce dimensionality while retaining significant information.
- Fully connected layers classify features into pneumonia or normal categories.

Transformer-Based Attention Mechanism

- Attention mechanism assigns weights to important features: where **Q, K, V** are query, key, and value matrices.
  A = softmax (QK T/ Vdk)
- Vision Transformer (ViT) segments images into patches and processes them as tokens through self-attention layers.

4. Training and Optimization

- **Loss Function:** Cross-entropy loss for classification.
- **Optimizer:** Adam optimizer with learning rate tuning.
- **Evaluation Metrics:**
  - Accuracy
  - Precision
  - Recall

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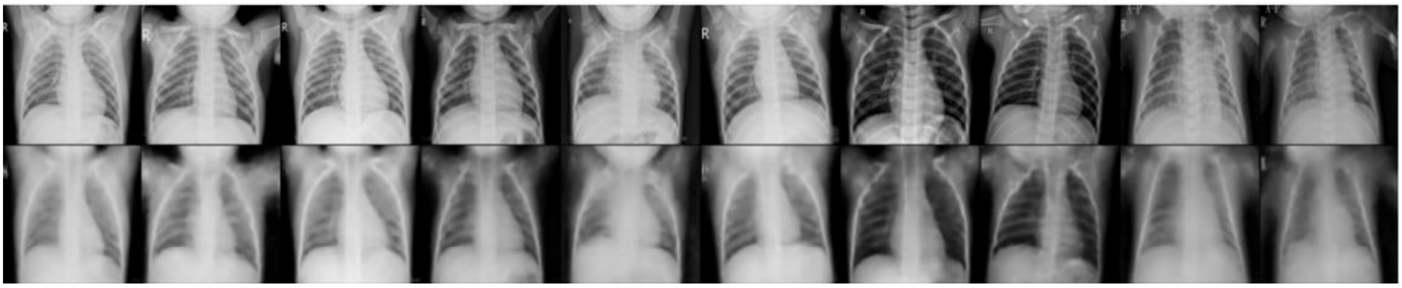
- F1-score
- Area Under Curve (AUC)

Results: The proposed model demonstrates superior performance in pneumonia classification:

- **Baseline CNN Accuracy**: 85%
- **GAN + CNN Accuracy:** 92%
- **VAE + Transformer Accuracy:** 94%
- **AUC Score:** 0.97 The inclusion of generative models significantly enhances classification accuracy, especially in datasets with limited labeled images.



Discussion

- **Advantages:**
  - Overcomes data scarcity through synthetic augmentation.
  - Enhances model robustness and generalization.
  - Provides explainability with attention heatmaps.

- **Challenges:**
  - GAN-generated images may introduce artifacts.
  - Computationally intensive training.
  - Ethical considerations in synthetic image use.

CONCLUSION

Generative AI, when integrated with deep learning classifiers, significantly improves paediatric pneumonia classification on chest radiographs. This research validates the potential of AI-driven diagnostic tools in reducing misdiagnosis rates and assisting healthcare professionals. Future work will focus on real-world deployment, federated learning for privacy-preserving AI, and multi-modal AI integration for holistic diagnosis.

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