

Enhancing Pneumonia Image Classification Accuracy for GAN-Generated Data Using DSITL of Customized VGG19 Features with Hybrid Dimensionality Reduction (DSITL-HDR)

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Pneumonia Classification, GAN, DSITL, Customized VGG19, Feature Extraction.

ABSTRACT

Pneumonia is a serious respiratory infection and a global health concern. Deep Learning (DL) models, especially Convolutional Neural Networks (CNNs), have improved pneumonia diagnosis using chest X-ray (CXR) images. However, classifying imbalance dataset remains challenging due to overfitting. The proposed study overcome this issue by generating synthetic images using Generative Adversarial Networks (GANs). The Domain-Specific Inductive Transfer Learning (DSITL) of a customized VGG19 features reduced by dimensionality reduction the reduced features are fed in Random Forest (RF) classifier. The results show improved classification accuracy, highlighting the potential of DSITL- hybrid feature for medical imaging.

1. Introduction

Pneumonia diagnosis relies on accurate CXR analysis, and DL has significantly improved this process. GANs generate synthetic images to supplement real data, but differences between real and synthetic images create classification challenges.

The proposed model integrates real and GAN-generated images to improve classification accuracy. Three datasets (D1, D2, and D3) containing both real and synthetic images are used. Data augmentation techniques like flipping, rotation, and contrast adjustment enhance image diversity. The standard VGG19 model is modified by removing one convolutional block to speed up training and adding two dropout layers to reduce overfitting. To further refine feature extraction, DSITL is applied, which improves training efficiency on synthetic datasets. Domain-specific layers enhance the model's ability to process GAN-generated images, while Hybrid Dimensionality Reduction (HDR) techniques help remove noise and focus on relevant features.

Performance evaluation includes accuracy, precision, recall, F1-score, and confusion matrix analysis. This study demonstrates how DSITL and customized VGG19 can bridge domain gaps and improve pneumonia classification.

2. Literature Review

Several studies have explored pneumonia classification using DL models. Pneumonia Classification existing studies focus on transfer learning using standard architectures like VGG19, ResNet, and Inception for pneumonia classification. However, these models often struggle with synthetic data due to domain discrepancies. **Mehta et al.**, proposed Conditional Generative Adversarial Network(cGAN) model, a generator and discriminator network, generates images based on class labels, fine-tunes TL models, and achieves maximum accuracy of 98.2%, 94.21%, and 93.67%, demonstrating its potential for cost-effective, reliable, and accessible testing.

(Patil et al., 2023), proposed Attention Mechanisms based Cycle-Consistent GAN (AMCGAN) enhances medical image analysis accuracy and reliability, particularly for CXR data. It uses GAN and attention mechanisms to create realistic images, enhancing disease classification models. Experiments

on CXR images of COVID-19, pneumonia, and normal cases showed high precision (98.15% accuracy). **Khalifa et al.**, presented a pneumonia CXR detection method using GAN and Deep Transfer Learning (DTL) on a limited dataset. The model uses 5863 X-ray images, with a 10% training dataset and 90% generated using GAN. DTL models AlexNet, GoogLeNet, Squeezenet, and Resnet18 are selected based on their small architectures. The combination of GAN and DTL is shown to be efficient in testing accuracy measurement. Resnet18 is the most suitable deep transfer model, achieving 99% accuracy in precision, recall, and F1 score. The research outperforms related work in terms of testing accuracy. **Sharma et al.**, proclaimed a two-phase oversampling approach called SMOTIFIED-GAN, which uses knowledge transfer to transform unrealistic SMOTE samples into realistic distributions. The approach improves minority class sample quality and performance by up to 9% compared to other algorithms, with a reasonable time complexity.

Patel et al., was analysed three TL methods for efficiently diagnosing pneumonia. VGG16 (96.7%) and VGG19 (95.6%) performed similarly, with VGG16 slightly better. ResNet model had the lowest accuracy (88.14%). **Shazia et al.**, explored the use of CXR-based Computer-Aided Diagnostic (CAD) techniques for early-stage diagnosis of respiratory diseases like Covid-19, lung opacity, viral pneumonia, and normal healthy lungs. The study uses three architectures: VGG16, VGG19, and MobileNet, combining transfer learning and custom models. The results show an accuracy of 98%. **Loey et al.**, focused on using synthetic data generated by GAN to categorize CXR images as normal and abnormal. The model classifies pneumonia 170 and normal 170 with 84% accuracy, compared to existing methods. The accuracy can be increased by taking large data samples. **Ali et al.**, proposed an automated Computer-Aided Diagnosis (CAD) system for diagnosing pneumonia using the Chest X-Ray8 dataset, which is skewed and lacks diversity in X-ray capturing setups and human subjects. The system generates samples for the minority class and uses Random Under-Sampling for the majority class and accuracy obtained this model ResNet50- 89.14%, VGG16- 97.86%, Xception- 99.47%. However, the study acknowledges limitations, such as reliance on a single source dataset and validation for different imaging modalities. **Srivastav et al.**, proposed model achieved 94.5% accuracy in classifying pneumonia based on chest X-ray images. A comparison was conducted between a naïve CNN model and a CNN model based on VGG16 without GAN based synthetic image generation. The model showed significant improvement in performance due to dataset oversampling and the use of GANs to populate minority class samples. Hyperparameters were fine-tuned using grid search. **Putri et al.**, showed that the integration of Deep Convolutional Generative Adversarial Networks (DCGANs) and Genetic Algorithms (GAs) improves the accuracy of pneumonia detection in X-ray images. The DCGAN generates synthetic images, while GAs enhance the model's hyperparameters, resulting in a 95.50% accuracy and 94.75% F1-Score. This approach addresses challenges in limited data scenarios and enhances the diagnostic capabilities of deep learning models in medical imaging applications.

These studies highlight the potential of GAN-generated data in medical imaging but also show the need for improved adaptation techniques like DSITL.

3. Proposed Methodology

This study proposes a **DSITL-HDR model** combining DSITL, a customized VGG19 model, and Hybrid-Dimensionality Reduction (HDR) techniques for pneumonia classification. Figure 1 depicts the framework of DSITL-HDR model. This model describes the integration of customized VGG19-based feature extraction with hybrid (Principal Component Analysis (PCA) and Canonical Correlation Analysis (CCA)) features for classification. These features improve classification performance by minimizing feature redundancy and computational complexity. PCA transforms features into a new set of uncorrelated features (PC) that retain maximum variance in the features. CCA finds feature with the maximum correlation (CF). The hybrid (PCA+CCA) combined both the features. The RF classifier is used for classify the label of unlabeled CXR images.

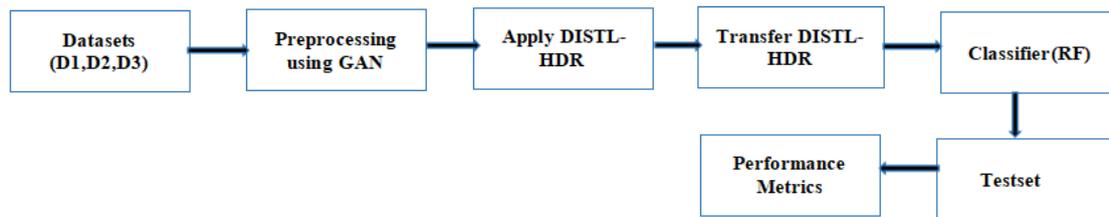


Figure1: Framework of DSITL-HDR model

Three imbalanced CXR (D1, D2, D3) image datasets [12,13,14] are used in this study. The imbalanced dataset is balanced using GANs. The original dataset and balanced dataset are presented in Table 1. The images of balanced dataset are preprocessed with data augmentation techniques like flipping, rotation, and contrast adjustment to improve diversity. The model has been customized with a convolutional block removed and two dropout layers added in VGG19 architecture. The reduced features are extracted from last fully connected layer of the customized CNN model before the output layer of customized CNN. A RF Classifier is an ensemble learning method that builds multiple decision trees and combines their outputs for classification, improving accuracy and reducing overfitting. It takes input features (X) and labels (Y) and trains multiple decision trees. Parameters like number of trees, minimum leaf size, and number of features per split. This study uses RF with number of trees are 100, The performance metrics such as confusion matrix, accuracy, precision, recall, and F1-score are recorded. The algorithm for the proposed study DSITL-HDR is presented as follows

Algorithm DSITL-HDR

Input: D1, D2, D3 Source, Target Dataset

Output: Performance Metrics

BEGIN

1. Load dataset using Image Datastore.
2. Preprocess images with custom read function.
3. Split dataset into source (training) and target (testing) datasets.
4. Define CNN architecture using layer Graph (Add convolutional, ReLU, pooling, dropout, fully connected, and SoftMax layers).
5. Connect layers appropriately.
6. Set training options with Adam optimizer and tuning parameters.
7. Train the network on the source dataset.
8. Fit the trained classifier to the extracted FC features from the source dataset using `fitcecoc`.
9. Predict labels for the target dataset using the trained classifier.
10. Rf1 = PCA-transformed features from the source dataset.
11. Rf2 = CCA-transformed features from the source dataset.
12. Rf = Combine (Rf1, Rf2)
13. [C11, C12, C13] = Train RF (Rf1, Rf2, Rf)
- // Predict Labels
14. Predict _ labels = predict (transformed target dataset) using Cij where (i=1,2,3 and j=1,2,3).
15. Compute Performance Metrics

16. Display Performance Metrics

END

4. Results

The proposed DSITL-HDR model uses input image of 224x224 and trained on training and test data set. The number of features extracted from fully connected layer of training set is 4096 features. From those features PCA and CCA are performed. Thousand features from each dimensionality reduction are combined. The combined feature is applied to RF classifier. TL is a technique that allows models to apply previously acquired knowledge to new, related tasks. The features learned from one source/ data are transferred to another source/ target. The trained models from D1, D2, and D3 extract features using TL and are tested in D1 to D2, D1 to D3, D2 to D1, D2 to D3, D3 to D1 and D3 to D2. The performance of test data set is evaluated. The better results of Performance Metrics of DSITL-Hybrid for balanced datasets are presented in Table 2.

Table 1: Dataset used

Original Dataset			GAN Generated Synthetic Dataset		Balanced Dataset		
Pneumonia	Normal	Total	Pneumonia	Normal	Pneumonia	Normal	Total
3875	1341	5216 (D1)	-	2534	3875	3875	7750 (B1)
2973	1104	4077 (D2)	-	1869	2973	2973	5946 (B2)
107	77	177 (D3)	-	30	107	107	214 (B3)

DSITL-HDR(D3-D1)				DSITL-HDR(D3-D2)				DSITL-HDR(D1-D3)			
TARGET \ OUTPUT	Pneumonia	Normal	SUM	TARGET \ OUTPUT	Pneumonia	Normal	SUM	TARGET \ OUTPUT	Pneumonia	Normal	SUM
Pneumonia	2020 65.16%	13 0.42%	2033 99.36% 0.64%	Pneumonia	2290 96.30%	0 0.00%	2290 100.00% 0.00%	Pneumonia	82 95.35%	0 0.00%	82 100.00% 0.00%
Normal	17 0.55%	1050 33.37%	1067 98.41% 1.59%	Normal	3 0.13%	85 3.57%	88 96.59% 3.41%	Normal	1 1.15%	3 3.49%	4 75.00% 25.00%
SUM	2037 99.17% 0.83%	1063 98.78% 1.22%	3100 99.63% 0.97%	SUM	2293 99.87% 0.13%	85 100.00% 0.00%	2378 99.87% 0.13%	SUM	83 98.60% 1.29%	3 100.00% 3.00%	86 98.84% 1.16%

Figure 2: Confusion Matrix of DSITL-HDR for balanced dataset

Table 2: Performance Metrics of DSITL-Hybrid for balanced datasets with TL

Datasets	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
D3 → D1	99.03	99.36	99.17	99.26
D3 → D2	99.87	100.00	99.87	99.93
D1 → D3	98.84	100.00	98.80	99.33

Table 3: Comparison of Proposed Study with Existing Study

Datasets	Accuracy (%)	
	Existing study	Proposed study
D1 → D1	(Without TL) 92.63 [15]	99.02
	(With TL) 92.80 [16]	
	(With TL) 91.78 [17]	
D3 → D1	-	99.03
D3 → D2	-	99.87
D1 → D3	-	98.84

The **DSITL framework** improved classification accuracy across all datasets, demonstrating its ability to adapt to synthetic data.

5. Conclusion

A DSITL-Hybrid framework that improves pneumonia classification accuracy on GAN-generated CXR images is shown in this paper. Domain disparities are decreased by the customized VGG19 models efficient adaptation to synthetic datasets. Future Work will focus on investigating new domain adaption strategies and expanding DSITL to other medical imaging tasks.

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