M.Tech Dissertation Preliminary

Presentation On

GENERATIVE ADVERSARIAL NETWORKS - BASED DATA AUGMENTATION FOR ROBUST DEEP LEARNING MODELS IN MEDICAL IMAGES

Submitted By :

Ms. Tejal Khade

P23CS019

Guided By :

Dr. Chandra Prakash

Assistant Professor, DoCSE, SVNIT

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INDEX

Introduction

Generative Adversarial Networks (GANs), introduced by Ian Goodfellow in 2014, have transformed machine learning by enabling two neural networks—the Generator and Discriminator—to compete and improve iteratively. Recognized as a groundbreaking innovation by experts like Yann LeCun, GANs have been extensively applied in medical imaging for tasks like data augmentation, classification, and segmentation. They are particularly effective in addressing challenges of limited and imbalanced datasets by generating high-quality, diverse synthetic data. In the context of diabetic foot ulcers (DFUs), a serious complication of diabetes that can lead to limb amputation if untreated, GANs provide a robust solution. By augmenting DFU datasets with realistic and diverse synthetic images and integrating them with Convolutional Neural Networks (CNNs), GANs enhance model performance for accurate DFU classification. This approach not only improves early detection and diagnosis but also addresses critical challenges in medical imaging datasets.

Why GANs?

- There are many traditional data augmentation techniques, such as rotation, flipping, translation, Gaussian noise, and color jitter, which rely solely on variations of the original dataset, which limits the diversity of generated data.
- These methods are constrained in addressing the challenge of imbalanced datasets, particularly for underrepresented classes, and may fail to capture the complex variations necessary for robust model training.
- GANs are used in data augmentation, image synthesis, image-to-image translation, segmentation and localization, image deblurring, etc.
- In medical applications, GANs have proven to be addressing data insufficiency and imbalance, particularly in diabetic foot ulcer (DFU) classification.
- Considering, DFU, a severe complication of diabetes, can lead to limb amputation if untreated. Effective diagnosis is critical but hindered by limited and imbalanced datasets.
- This research work proposes a GAN-based augmentation strategy to generate diverse and realistic DFU images, integrated with Convolutional Neural Networks (CNNs) for accurate classification. By enriching datasets and preserving medical image realism, this approach aims to improve classification performance, offering a robust solution for early DFU detection and treatment.

Types of Generative Adversarial Networks(GANs)

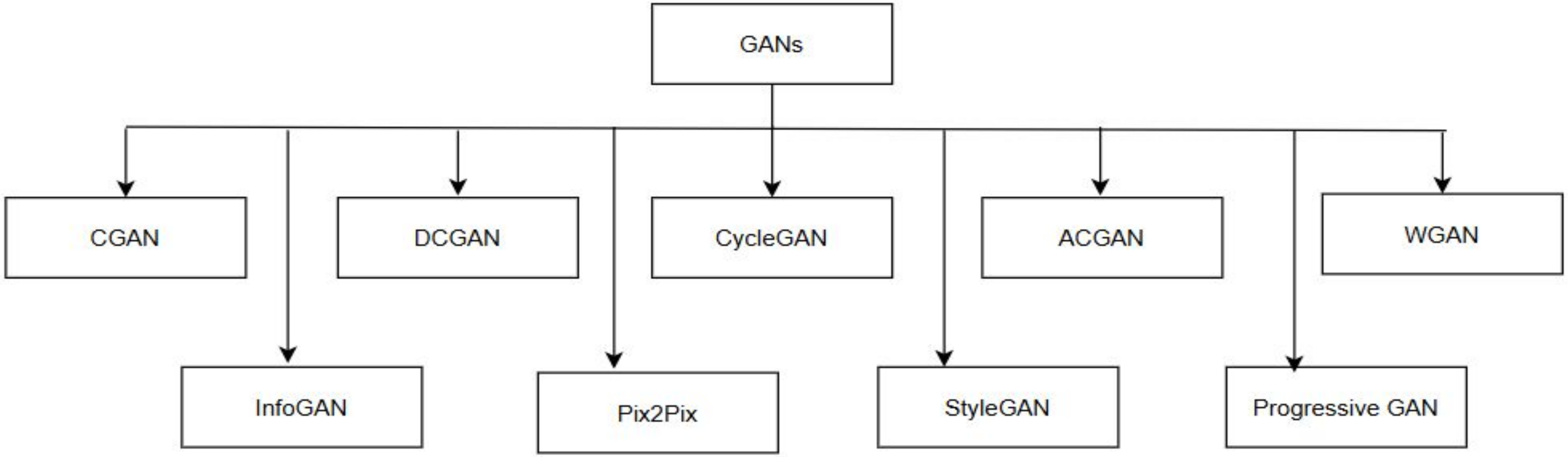

Fig 1: Types of GAN

This represents a hierarchical categorization of various types of Generative Adversarial Networks (GANs), showcasing the diversity of GAN architectures designed for medical imaging tasks.

Applications of GAN

Generative Adversarial Networks (GANs) have emerged as powerful tools in deep learning, enabling innovative solutions across various domains.

1. **Medical Imaging:** GANs have revolutionized medical image analysis by addressing challenges such as data scarcity, class imbalance, and noise reduction.
2. **Image Synthesis and Data Generation**:GANs are widely used to create high-quality synthetic images for training and simulation purposes.
3. **Video and Audio Applications**:GANs are used to create, enhance, and modify video and audio content.
4. **Text-to-Image Synthesis**: GANs like DALL-E and others can convert textual descriptions into high-quality images, aiding industries such as advertising, education, and content creation.
5. **Security and Surveillance:** GANs help improve facial recognition accuracy by generating diverse facial datasets.

Problem Description

Medical image analysis plays a critical role in diagnosing and treating various conditions, where accurate classification is essential for effective clinical decision-making. However, the scarcity of annotated medical images and imbalanced class distribution in available datasets present significant challenges to the performance and reliability of deep learning models in this domain. This research explores the use of GAN-powered data augmentation to address these issues. For instance, in the context of diabetic foot ulcers (DFUs), GANs can mitigate data insufficiency and imbalance, facilitating early diagnosis and effective treatment. The proposed approach integrates GAN based data augmentation with deep learning models, aiming to develop reliable and effective solutions for medical image classification. This research seeks to advance the field of medical image analysis by leveraging GANs to build robust models better equipped to handle real-world medical datasets. This research aims to advance DFU diagnosis by leveraging GANs to build robust deep learning models that are better equipped to handle real-world medical image datasets.

Literature Survey

Year	Paper	Techniques/Approach	Evaluation Parameters	Dataset	Limitations
[1] 2024	Dfootnet: A domain adaptive classification frame- work for diabetic foot ulcers using dense neural network architecture	1. A deep neural architecture is proposed for the classification of diabetic foot ulcers(DFUs), addressing the unique challenges posed by DFU imaging data 2. The architecture integrates convolutional neural networks (CNNs) with residual blocks and feature fusion layers to enhance feature extraction and representation. 3. Natural Data Augmentation-rotation, flipping, Gaussian noise, shearing, and translation. 4. Results: Accuracy of 98.87%, precision of 99.01%, recall of 98.73%, F1-score of 98.86%, and an AUC-ROC of 98.13%	1. Accuracy 2. Precision 3. Recall 4. F1-Score 5. AUC-ROC Curve	DFU2020 and MICCAI DFUs	1. Need for more diverse datasets, 2. Required better hyperparameter fine-tuning 3. Evaluation across different clinical scenarios to improve real-world applicability.
[2] 2024	Medical image synthesis via conditional gans: Application to segmenting brain tumours.	1. Two novel frameworks based on conditional Generative Adversarial Networks (cGANs) to enhance the segmentation accuracy of brain tumors in magnetic resonance imaging (MRI). 2. Enhancement and Segmentation GAN (ESGAN), Enhancement GAN (EnhGAN) are used to ensure separability between classes. 3. ESGAN achieves competitive performance on small datasets, EnhGAN improves segmentation results for complex tumor regions.	1. Probability Density Function (PDF) 2. AUC-ROC Curve	BraTS'13 and BraTS'18 datasets	1. CGANs fail in enhancing tumor segmentation effectively. 2. Further improvements in MRI-based medical image analysis

Literature Survey Continued..

Year	Paper	Techniques/Approach	Evaluation Parameters	Dataset	Limitations
[3] 2023	Self-supervised augmentation of quality data based on classification-reinforced gan	1. CLS-R GAN, a Classification-Reinforced GAN, is used to improve both the quality and diversity of augmented data using a novel self-training framework. 2. In CLS-R GAN, an independent classifier helps guide the generator to self-train by classifying fake data and enhancing real data in an unsupervised way. 3. Experiments are performed including liver ultrasound image augmentation, demonstrated the effectiveness of CLS-R GAN in enhancing data quality and diversity.	1. Accuracy 2. Precision 3. Recall 4. F1-Score 5. AUC-ROC Curve	DFUC2020 dataset	1. Difficulties are faced in acquiring enough realistic data 2. Data is imbalanced
[4] 2023	Dfu-siam: A novel diabetic foot ulcer classifi-cation with deep learning	1. Ensemble of Convolutional Neural Networks (CNN) and Vision Transformers (ViT) was proposed for diabetic foot ulcer (DFU) classification. 2. Siamese Neural Network (SNN) with a k-Nearest Neighbors (kNN) classifier for enhanced performance. 3. Natural Data Augmentation-rotation, flipping, Gaussian noise, shearing, and translation.	1. Accuracy	DFUC2021 Challenge dataset	1. class imbalance 2. Could not explore ensemble modeling or more computationally intensive variations to further enhance results.

Literature Survey Continued..

Year	Paper	Techniques/Approach	Evaluation Parameters	Dataset	Limitations
[5] 2023	The use of generative adversarial networks in medical image augmentation	1. Reviews the application of Generative Adversarial Networks (GANs) for medical image augmentation. 2. Paper examines 52 peer-reviewed studies (2018–2022) to identify popular GAN architectures, Common Medical Modalities and Target Organs, Downstream Tasks like Classification and segmentation of medical images, evaluation metrics.	1. qualitative methods 2. quantitative direct methods (FID, SSIM) 3. Quantitative indirect methods		1. Insufficient datasets 2. imbalanced class distributions in medical imaging
[6] 2022	Efficient multi-model vision transformer based on feature fusion for classification of dfuc2021 challenge	1. Addresses the growing challenge of Diabetic Foot Ulcers (DFUs), particularly those with ischemia and infection, emphasizing the need for early detection. 2. They used Pre-trained transformer models, fine-tuned on the DFUC-21 dataset, for multi-class DFU classification 3. A Multi-Model approach was proposed, where features from parallel trained transformers were fused from the last layers.	1. macro-average F1-Score 2. Weighted cross-entropy	DFUC2021 Challenge dataset	1. class imbalance 2. Need for combining CNNs with transformer architectures for future improvements in DFU classification.

Literature Survey Continued..

Year	Paper	Techniques/Approach	Evaluation Parameters	Dataset	Limitations
[7] 2021	Deep learning in diabetic foot ulcers detection: A comprehensive evaluation	1. Advanced models were explored for DFU detection, including EfficientDet, Cascade R-CNN integrated with DetNet, and Faster R-CNN with deformable convolution layers. 2. Data augmentation techniques such as random rotation and shear transformations to enhance the robustness of the models.	1. Accuracy 2. Precision 3. Recall	Benchmark datasets, including the MS-COCO dataset and the Diabetic Foot Ulcers Grand Challenge (DFUC2020) dataset	1. CNNs fail to perform good for remote monitoring applications. 2. Need for reducing false positives caused by difficulties in distinguishing ulcers from other skin conditions.
[8] 2021	Analysis towards classification of infection and ischaemia of diabetic foot ulcers	1. Pretrained models from ImageNet and data augmentation strategies were employed to enhance model performance. For example, ischaemia images underwent eight augmentation techniques, while infection and ischaemia classes were augmented with three techniques, significantly increasing data samples. 2. DenseNet121 and EfficientNetB0 emerged as top performers.	1. per-class 2. F1-Score, 3. micro-average 4. F1-Score 5. macro-average s of Precision, Recall, F1-Score, and AUC.	DFUC2021 Challenge dataset	1. class imbalance 2. Accurately detecting infection and co-occurrence of ischaemia and infection continues to be difficult, especially in the "both" category. 3. Need of advanced augmentation techniques like GAN.

Literature Survey Continued..

Year	Paper	Techniques/Approach	Evaluation Parameters	Dataset	Limitations
[9] 2022	Dfuc 2020: Analysis towards diabetic foot ulcer detection	1. This study evaluates the performance of multiple deep learning models for diabetic foot ulcer (DFU) detection 2. The models include EfficientDet, which leverages EfficientNet as a backbone and BiFPN for feature fusion, YOLOv5, known for real-time object detection with single-pass processing, and Faster R-CNN, featuring a three-stage architecture for robust region proposals and detection 3. Data augmentation techniques such as scaling, color adjustments, and mosaic augmentation were applied to enhance diversity.	1. F1-score and 2. mean average precision (MAP)	Dataset consisting of 640x480 pixel images annotated with LabelImg and VGG Image Annotator.	1. CNNs fail to perform good for remote monitoring applications. 2. Need for reducing false positives caused by difficulties in distinguishing ulcers from other skin conditions.
[10] 2021	Comparison of hybrid convolutional neural networks models for diabetic foot ulcer classification	1. The study presents the design of four hybrid CNN models for DFU classification, with an empirical comparison of different architectures featuring varying numbers of branches. 2. The models utilized feature aggregation techniques, including a Global Average Pooling layer and fully connected layers with dropout for enhanced classification performance.	1. per-class 2. F1-Score, 3. micro-average 4. F1-Score 5. macro-averages of Precision, Recall, F1-Score, and AUC.	Dataset used consisted of 754 images of patients' feet, with two categories: abnormal (DFU) and normal (healthy skin).	1. Class imbalance 2. Inability to improve performance by increasing network width. 3. Small size of the dataset, and the model's current focus on only two classes (normal vs. abnormal)

Literature Survey Continued..

Year	Paper	Techniques/Approach	Evaluation Parameters	Dataset	Limitations
[11] 2022	Covidgan: Data augmentation using auxiliary classifier gan for improved covid-19 detection	1. The study explores the use of deep learning, particularly Convolutional Neural Networks (CNNs), for detecting COVID-19 using chest X-rays (CXR). 2. Used VGG16 CNN model 3. Auxiliary Classifier Generative Adversarial Network (ACGAN)-based approach called CovidGAN. 4. Data augmentation techniques : CovidGAN which generates these synthetic images to increase the performance of CNNs for COVID-19 detection, increasing classification accuracy from 85% to 95% .	1. F1-score 2. precision 3. Accuracy 4. Recall	Chest X-ray images dataset.	1. Unavailability of large dataset. 2. Class imbalance
[12] 2021	Recognition of ischaemia and infection in diabetic foot ulcers: Dataset and techniques	1. Ensemble CNN model was compared against handcrafted machine learning algorithms for diabetic foot ulcer (DFU) classification tasks. 2. The study focused on binary classification tasks, specifically differentiating between Ischaemia vs. Non-Ischaemia and Infection vs. Non-Infection. 3. Suggested to Improve model performance by optimizing hyperparameters for both traditional machine learning algorithms and CNN models	1. Accuracy 2. F1-Score 3. Precision, Recall, and AUC.	Dataset consisted of 1459 DFU images collected from the Lancashire Teaching Hospitals,	1. The study highlighted challenges such as high visual intra-class dissimilarities and inter-class similarities. 2. Imbalanced dataset, and limited data quality. infection in DFU images may not always present clear visual indicators, which complicates the classification task. 3. Need of advanced augmentation techniques like GAN.

Literature Survey Continued..

Year	Paper	Techniques/Approach	Evaluation Parameters	Dataset	Limitations
[13]2019	Dfu_qutnet: Diabetic foot ulcer classification using novel deep convolutional neural network	1. A novel CNN model named DFU_QUTNet was proposed for diabetic foot ulcer (DFU) classification and compared with top-performing CNN architectures like GoogleNet, AlexNet, and VGG16 after fine-tuning. 2. The features extracted by DFU_QUTNet were used to train both SVM and KNN classifiers,with the SVM classifier showing the highest precision, recall, and F1-Score	1. precision 2. recal 3. F1-Score	Dataset of 754 foot images from DFU patents, with each image's region of interest (ROI) resized to 224x224.	1. Small dataset of only 754 images, lack of generalization to other tasks like skin cancer classification, and no clinical validation or comparison with expert clinicians.
[14] 2017	Dfunet: Convolutional neural networks for diabetic foot ulcer classification	1. DFUNet, specifically designed to process input data more effectively and efficiently than other state-of-the-art CNN architectures. 2. 10-fold cross-validation, DFUNet achieved an impressive AUC score of 0.961, outperforming all tested machine learning and deep learning classifiers 3. CNN architectures such as LeNet, AlexNet, and GoogLeNet were also employed. 4. DFUNet demonstrated superior accuracy and sensitivity compared to GoogLeNet and AlexNet. 5. Data augmentation techniques like rotation, flipping, contrast enhancement, color space variations, and random scaling were applied.	1. Accuracy 2. F1-Score 3. AUC	Dataset consists of classifying ulcer and non-ulcer images.	1. Class imbalance 2. Inability to improve performance by increasing network width. 3. While data augmentation techniques like rotation, flipping, contrast enhancement, color space variations, and random scaling were applied, they did not significantly improve overall performance. 4. Need of advanced augmentation techniques like GAN.

Research Challenges

The challenges outlined in the studies, particularly in the context of diabetic foot ulcer (DFU) classification, include:

1. **Dataset Size and Diversity:** Small and non-diverse datasets restrict model generalization to varied real-world scenarios. Limited datasets hinder the ability to learn comprehensive problem representations, leading to suboptimal performance.
2. **Class Imbalance:** Certain classes are underrepresented, causing biased models that struggle to identify rare or infrequent classes accurately.
3. **Limitations of Traditional Data Augmentation:** Techniques like rotation, flipping, and noise addition often fail to significantly improve performance, especially in complex classification tasks. These methods may not adequately capture the diversity required for robust model training.
4. **Generalization Issues:** Models perform well on specific datasets but often fail to generalize to unseen or varied clinical and real-world settings.
5. **Focus on Binary Classification:** Many studies address binary classification tasks, neglecting the complexities of multiclass or hierarchical classification. This limits the ability to handle nuanced real-world scenarios.

Proposed Methodology

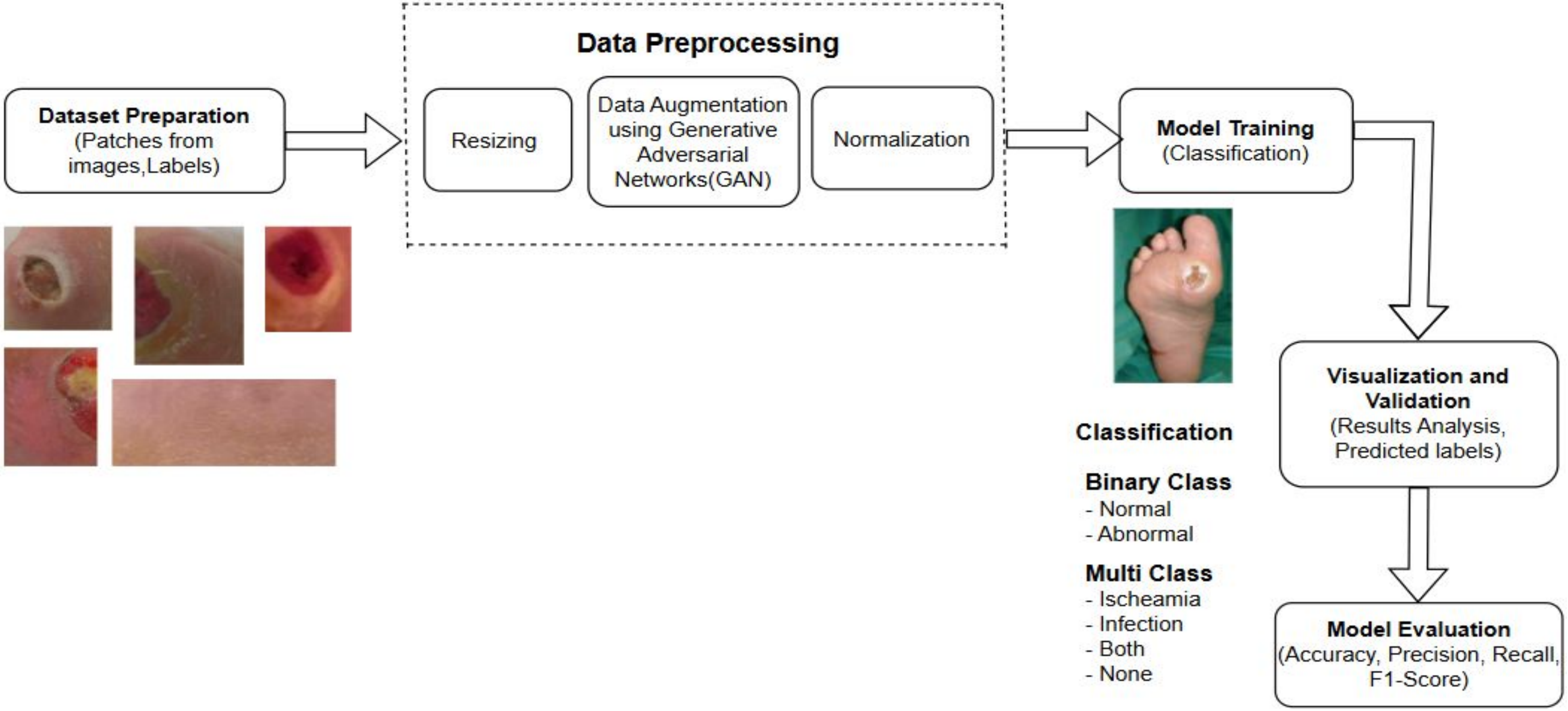

Fig 2: Workflow of proposed methodology

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Proposed Methodology Continued..

This section consists of five parts: (i) our dataset with samples of diabetic foot ulcers from diverse patients (ii) labeling process of our dataset into normal skin and abnormal patched skin categories (iii) preprocessing of training patches through resizing, normalization and data augmentation using GANs to improve model accuracy (iv) fine-tuning CNN architectures as the base architecture integrated with GAN principles to enhance DFU classification. Our proposed model employs GAN-based data augmentation to address class imbalance and increase data diversity while using its CNN module to extract robust features for accurate classification, achieving improved performance compared to pre-trained models.

1. Dataset Preparation
2. Ground Truth Annotation
3. Data Preprocessing
4. Model Training
5. Visualization and Validation
6. Model Evaluation

Dataset

Data Type	Internal Subdivision	Sample Count	Dimension
DFUC2021_train	Images	5955	224x224
DFUC2021_test	Images	5734	224x224
PartA_DFU_Dataset	Abnormal	1038	Variable
	Normal	641	Variable
PartB_DFU_Dataset	Infection	5890	256x256
	Ischaemia	9890	256x256

Table 1: DFUC DATASET

The dataset is designed to aid in the classification and analysis of Diabetic Foot Ulcers (DFUs) and consists of multiple subdivisions and data types to cater to various diagnostic needs.

Challenges of Dataset

1. **Image Dimensions**: While most images are resized to standard resolutions like 224x224 or 256x256 pixels, some subsets in Part A have variable dimensions.
2. **Class Imbalance**: Certain subsets exhibit a disparity in class distribution, such as a higher number of images in the Ischaemia class compared to Infection.
3. **Applications**: The dataset is well-suited for tasks like binary classification, multi-class classification, and model evaluation, addressing challenges in DFU detection and classification.

Description of Workflow Design Architecture

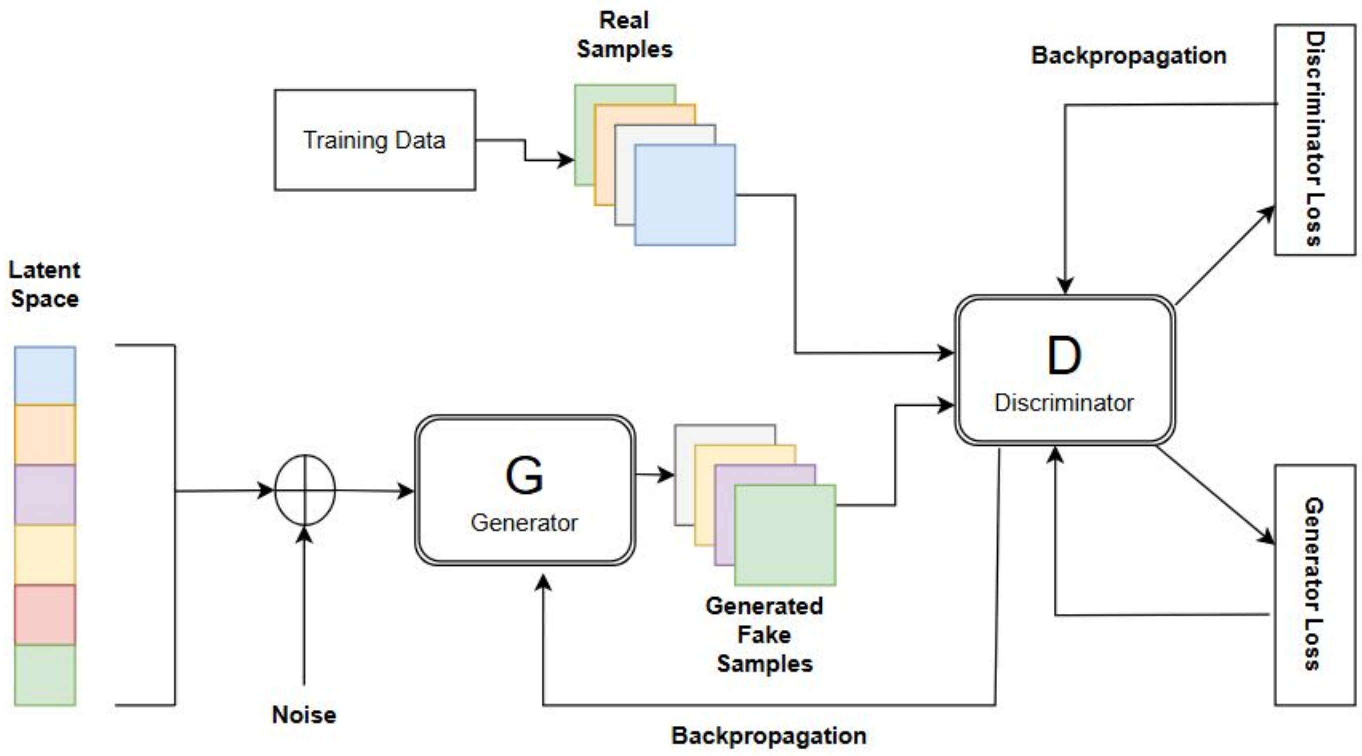

Fig 3: Basic GAN Architecture

Description of Workflow Design Architecture

Role of GAN in the architecture:

- A Generative Adversarial Network (GAN) is a deep learning model comprising two neural networks: the Generator and the Discriminator, trained in a competitive framework. The Generator creates synthetic samples, often referred to as fake data, starting from random noise, while the Discriminator evaluates and differentiates between real and generated data. This iterative process enhances the Generator's ability to produce realistic outputs and improves the Discriminator's capacity to identify fake samples, eventually achieving a balanced state .
- Over time, various GAN architectures have been developed and widely adopted for tasks like medical image synthesis and augmentation. Popular GAN variants include Conditional GAN (cGAN), Deep Convolutional GAN (DCGAN), Cycle-Consistent GAN (CycleGAN), Auxiliary Classifier GAN (ACGAN), Pix2Pix and many more. Among these, studies have identified cGAN as one of the most frequently used architectures for basic augmentation tasks [5]. Although I have not yet experimented with these architectures for my specific use case, the proposed methodology will incorporate one of these well-established architectures for data augmentation. The choice will be based on its ability to generate high-quality synthetic images and address class imbalance challenges in diabetic foot ulcer (DFU) datasets, ultimately improving classification accuracy.

Workflow Continued..

Role of CNN in the architecture:

- Convolutional Neural Networks (CNNs) has achieved state-of-the-art performance in medical image generation when trained on sufficient labeled data. However, due to their large number of parameters, CNNs are prone to overfitting on small datasets, making generalization highly dependent on the dataset’s size and diversity. This poses a significant challenge in the medical imaging domain, where labeled data is often limited.
- The Convolutional Neural Network (CNN) acts as the backbone for the classification task, processing the DFU images to extract meaningful features like texture, color variations, shape irregularities with computational efficiency. By incorporating a dense architecture with deep convolutional layers, skip connections, and bottleneck layers, the CNN captures both low-level and high-level features, crucial for distinguishing between normal and abnormal skin patches, infection and ischaemia classes.

Workflow Continued..

- **Integration of GAN and CNN:**

The synergy between GAN and CNN is a key aspect of the proposed architecture. While the GAN focuses on improving the quality and quantity of training data, the CNN leverages this augmented dataset to enhance classification performance. This integration ensures:

- Robust feature extraction from diverse and balanced datasets.
- Improved model accuracy and generalization.
- Reduction of overfitting due to enriched training data.

Therefore, we will first use GAN architectures for producing high quality Diabetic foot ulcers images/patches. We aim to present a novel architecture using one variant of GAN for Diabetic foot ulcers classification using CNN. To enhance classification performance, the GAN is integrated with a Convolutional Neural Network (CNN). We believe that our hybrid architecture proves to be efficient solution for DFU classification and ensures a comprehensive approach to handle challenges like limited data, class imbalance, and complex feature variability.

Conclusion

Data scarcity in medical imaging remains a critical challenge specifically in diabetes management, requiring timely diagnosis and effective treatment strategies. This study presented a robust approach to DFU classification, integrating advanced deep learning techniques and GAN-based data augmentation to address challenges like class imbalance and limited data diversity. The proposed deep neural network aims to demonstrate improved classification performance by leveraging synthetic images, enabling the extraction of meaningful features for accurate DFU classification. By employing GANs for high-quality data augmentation and leveraging pre-trained CNNs for robust feature extraction, the approach ensures enhanced classification accuracy and generalization. The synergy between GANs and CNNs will not only enriches the training dataset but also reduces overfitting, enabling the model to perform effectively on diverse and unseen data.

Future Scope

- Future objectives include the development of a mobile application designed to help in the detection of diabetic foot ulcers (DFUs) from the comfort of a patient's home. This application aims to support patients and their families in identifying and tracking ulcers, thereby minimizing the need for frequent hospital visits. Additionally, the app has the potential to alleviate the burden on healthcare systems by facilitating accessible care for patients in remote areas, ensuring safer and more efficient DFU management.
- Other goals include expanding the dataset, validating the model in real-world clinical environments for addressing other diseases, and incorporating it into diagnostic tools for broader use in managing diabetic foot conditions, ultimately improving patient outcomes and supporting clinicians in making more informed decisions.
- Integrating explainable AI techniques will provide clinicians with insights into the prediction of model, fostering trust and facilitating adoption in clinical practice.

References

[1] A. V. Nishu Bansal, “Dfootnet: A domain adaptive classification framework for diabetic foot ulcers using dense neural network architecture,” Springer Science+Business Media, LLC, part of Springer Nature, vol. 16, 2024.

[2] A. L. S. MohammadHamghalama, b, “Medical image synthesis via conditional gans:application to segmenting brain tumours.” ELSEVIER, 2024.

[3] S. Kim and S. Lee, “Self-supervised augmentation of quality data based on classification-reinforced gan,” in Proceedings of the 17th International Conference on Ubiquitous Information Management and Communication (IMCOM). IEEE, 2023, corresponding Author: Sukhan Lee (lsh1@skku.edu).

[4] M. S. A. Toofanee, S. Dowlut, M. Hamroun, K. Tamine, V. Petit, A. K. Duong, and D. Sauveron, “Dfu-siam: A novel diabetic foot ulcer classification with deep learning,” IEEE Access, 2023, author et al.: Preparation of Papers for IEEE TRANSACTIONS and JOURNALS. [5] A. Makhlouf, M. Maayah, N. Abughanam, and C. Catal, “The use of generative adversarial networks in medical image augmentation,” vol. 35. Springer, 2023.

References Continued..

[6] A. Qayyum, A. Benzinou, M. Mazher, and F. M. deau, “Efficient multi-model vision transformer based on feature fusion for classification of dfuc2021 challenge,” in Proceedings of the DFUC2021 Challenge. Springer, 2022, dOI: 10.1007/978-3-030-94907-55.

[7] M. H. Yapa, R. Hachiuma, A. Alavi, R. Brüngeld, B. Cassidy, M. Goyal, H. Zhu, J. Rückert, M. Olshansky, X. Huang, H. Saito, S. Hassanpoure, C. M. Friedrich, D. B. Ascher, A. Song, H. Kajita, D. Gillespie, N. D. Reeves, J. M. Pappachani, C. O’Shea, and E. Frank, “Deep learning in diabetic foot ulcers detection: A comprehensive evaluation,” Computers in Biology and Medicine, vol. 135, 2021.

[8] M. H. Yap, B. Cassidy, J. M. Pappachan, C. O’Shea, D. Gillespie, and N. D. Reeves, “Analysis towards classification of infection and ischaemia of diabetic foot ulcers,” arXiv:2104.03068v2 [cs.CV], 2021, published: 21 June 2021.

[9] B. Cassidy, N. D. Reeves, J. M. Pappachan, D. Gillespie, C. O’Shea, S. Rajbhandari, A. G. Maiya, E. Frank, A. J. M. Boulton, D. G. Armstrong, B. Naja, J. Wu, and M. H. Yap, “Dfuc 2020: Analysis towards diabetic foot ulcer detection,” arXiv:2004.11853v3 [cs.CV], 2021, arXiv preprint, 24 M

References Continued..

[10] L. Alzubaidi, A. A. Abbood, M. A. Fadhel, O. Al-Shamma, and J. Zhang, "Comparison of hybrid convolutional neural networks models for diabetic foot ulcer classification," Journal of Engineering Science and Technology, vol. 16, 2021.

[11] A. Waheed, M. Goyal, F. Al-Turjman, D. Gupta, A. Khanna, and P. R. Pinheiro, "Covidgan: Data augmentation using auxiliary classifier gan for improved covid-19 detection," in Special Section on Emerging Deep Learning Theories and Methods for Biomedical Engineering. IEEE, 2020.

[12] M. Goyala, N. D. Reeves, S. Rajbhandari, N. Ahmad, C. Wang, and M. H. Yap, "Recognition of ischaemia and infection in diabetic foot ulcers: Dataset and techniques," Computers in Biology and Medicine, 2020.

[13] L. Alzubaidi, M. A. Fadhel, S. R. Oleiwi, O. Al-Shamma, and J. Zhang, "Dfu_qutnet: Diabetic foot ulcer classification using novel deep convolutional neural network," Multimedia Tools and Applications, 2019.

[14] M. Goyal, N. D. Reeves, A. K. Davison, S. Rajbhandari, J. Spragg, and M. H. Yap, "Dfunet: Convolutional neural networks for diabetic foot ulcer classification," arXiv:1711.10448v2 [cs.CV], 2017, published: 10 December 2017.

Internship Report

Internship at Intel, Bangalore At Intel Bangalore, the internship involved working on different projects and tasks alongside experienced professionals, learning about the company's services and cutting-edge technologies. As part of the NPU AI Frameworks team, I focused on gaining hands-on experience with Intel's Neural Processing Units (NPUs) and their integration with AI frameworks. This included working with tools like OpenVINO, ONNX Runtime, and optimizing inferencing workloads. The internship provided an in-depth understanding of how Intel's hardware accelerates AI computations, helping to improve performance and scalability in real-world AI applications. I also had the opportunity to collaborate with experts in the field, further enhancing my skills in deploying efficient AI solutions. Through collaboration and learning, I deepened my understanding of Intel's role in advancing artificial intelligence, enhancing my skills in deploying scalable, efficient AI models.

THANKYOU