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ADVANCING DIABETIC FOOT ULCER DETECTION BASED ON RESNET AND GAN INTEGRATION

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ABSTRACT

Diabetes, characterized by the body's inability to effectively regulate sugar levels due to insulin complications, leads to various serious health issues. Among these, Diabetic Foot Ulcer stands out as a critical yet often ignored consequence. This condition, if not addressed in time, can result in severe outcomes including amputations, posing a substantial burden on both individuals and healthcare systems, particularly in areas where medical care is costly. Addressing this pressing issue, our research focused intensively on the analysis of medical images, with the goal of enhancing the accuracy of Diabetic Foot Ulcer diagnosis. We assessed two different models: the renowned ResNet50 model and hybrid model that fuses ResNet50 with Generative Adversarial Networks. The findings were noteworthy; the ResNet50 demonstrated commendable performance, achieving an average accuracy and precision of 0.76, and an F1-Score of 0.75. However, the hybrid model surpassed these metrics, registering an average accuracy of 0.84, precision of 0.85, and an F1-Score of 0.84. This research contributes to the evolving landscape of medical image analysis, offering a promising avenue for more precise and effective DFU diagnosis in clinical settings. The marked advancement in diagnostic precision afforded by the hybrid model suggests a significant stride forward in effectively managing and treating DFU.

Keywords: *Diabetic Foot Ulcers, Deep learning, DFU, ResNet50, Generative Adversarial Networks, GAN.*

1. INTRODUCTION

Diabetic foot ulcers, often shortened to DFUs, are ulcers that many people with diabetes sadly experience. Looking back at some stats, in 2000, there were about 151 million people with diabetes globally. Fast forward to 2014, and that number jumped to 422 million, hitting around 537 million by 2021. That is a big leap, and by 2035, The global population affected by diabetes may potentially reach 630 million individuals. [1]. Now, diabetes, in its medical term called Diabetes Mellitus (DM), is when the body inefficient glucose regulation due to some insulin issues, leading to high blood sugar. When sugar level stays high for too long, it can affect on many parts of human body, like heart, eyes, and kidneys. One of the adverse effects of this is DFUs, which, if not taken care of, could lead to more serious complications, like needing to amputate the foot [1] [2]. Treating DFUs is not easy, especially in places where healthcare is expensive. To prevent exacerbation of the condition, people with or at risk of DFUs need regular doctor check-ups, proper care, and sometimes even expert attention [3]. These sores can also make it hard for someone to move around as they used to. And, not to forget, treating DFUs takes a significant portion out of the healthcare budget. So, It is crucial for public health and economic sustainability, to keep an eye on and manage DFUs properly.

In many parts of the world, especially developing countries, there is increasing prevalence of health issues. Consider the following: a vast majority (around 80%) of diabetes patients come from these regions [1]. The healthcare setup in these areas often leaves much to be desired, and sometimes, people are not even fully informed about the health challenges they are up against. A significant number of these diabetes

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patients, approximately 15-25%, can develop what's known as a diabetic foot. For some patients, this issue worsens, leading to foot ulcers. And if not treated promptly? It could mean amputation. This can lead to extended hospital stays and can even be life-threatening if left unchecked [4].

Healthcare, in general, works on a two-tiered system. The first level involves deals with basic healthcare needs, while the second level focuses on specialized care for more intense health challenges. In the present context, there is a significant gap in the services offered. Consider the insufficiency of hospitals, medical personnel who might not always have the specialized training they need, and even a lack of necessary medicines [2]. This gap is even more pronounced in less affluent countries. It becomes a significant challenge for patients, especially the ones battling foot ulcers, to find and access specialized care promptly. A notable statistic is 85% of all lower limb amputations are directly linked to these ulcers, with delay in receiving appropriate care being a massive factor [4][3]. However, there is a positive aspect. Thanks to modern technology, the focus is on intelligent, technology-driven solutions capable of remotely identifying and managing these ulcers. This practice is referred to as telemedicine. It is serves as an enhancement of the existing healthcare systems through digital means, enhancing efficiency and cost-effectiveness [5][6].This system can provide services to even the most remote areas, ensuring that more people get the medical care they truly deserve.

Alright, Diabetic ulcers, or more technically, the wounds that develop due to blood flow issues in people with diabetes, are a significant medical challenge. They are not just any wound - they come with skin infections that can take a prolonged time to heal. These ulcers can look a lot like other wounds, so challenging to diagnose. And, if you miss them and don't treat them? This can have severe consequences. This could result in limb amputation, affecting their entire life quality, or even worse, facing life-threatening situations [4].

Now, healthcare professionals have been actively addressing this issue. There have been attempts to spot these ulcers early on, but the success rate is not a full 100% - it reaches up to approximately 96%. So, what is the next move? In recent developments: using technology to virtually monitor potential diabetic foot issues using pictures and even heat imagery [5][6]. And there's another emerging technological advancement – deep learning, analogous to neural processes in computing, which researchers are tapping into to figure out these ulcers.

Focusing on technological advancements, There have been a significant number of studies delving into the potential of machine-powered learning for picking out these ulcers from images [7] [8] [5]. This can be likened to training computers to identify specific patterns amidst a large set of data. Different tech routes, from the k-Nearest Neighbors (k-NN), Random Forest (RF), Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Decision Trees (DT), were thoroughly examined to determine which one is best suited to detect these ulcers [9]. In related research, How ma- chine learning could assist in diabetes research was reviewed in [10], concluding that tools such as kNN, Gradient Boosting Machines (GBM), ANN, and Random Forest could be pivotal in this research. However, success rates were found to vary, with some methods achieving a high 90% accuracy, while others hovered around the 70% mark.

In the world of treating and understanding diabetic foot ulcers (DFU), there's recent technological advancements in the field of diabetic foot ulcers (DFU) are showing significant promise. We have advanced deep learning tools, and one of them is called DFUNet. This tool functions by meticulously analyzing heat images to detect early signs of these ulcers [11]. Another tool is the DFUQUTNet, which is similar to the function of an ultrasound in medical imaging. It analyzes abnormal tissue structures to figure out how bad the ulcer is [12]. And There is ComparisonNet, which is utilizes a comparative analysis of heat images against a database of reference images to figure out how serious a person's ulcer is by comparing heat images [13]. Another approach, segmentation, is like analyzing the image by dividing it into smaller parts to identify the DFU [14]. Now, as impressive as these tools are, they are not hitting 100% accuracy. Their accuracy ranges from 93.7% to 97.7%, which means There is still room for improvement.

In simpler terms, when we are dealing with diabetic foot ulcers, We have got two main approaches – machine learning and deep learning. Machine learning functions as an analytical tool that undergoes training with a comprehensive dataset, including numerous images and data, to accurately identify foot ulcers. It looks at patterns and matches them to what it already knows. Conversely, deep learning is an advanced and more complex form of machine learning. It uses artificial neural networks, and one popular type is the Convolutional Neural Networks (CNNs), which are highly proficient, including spotting foot ulcers in medical images.

The research addresses the pressing healthcare challenge of imprecise Diabetic Foot Ulcer (DFU) detection, a critical complication of Diabetes Mellitus leading to severe outcomes such as amputations. Existing diagnostic methods often fall short in accuracy, delaying timely intervention and increasing the socio-economic burden on healthcare systems. To tackle this issue, our study focuses on advancing DFU diagnosis through advanced image analysis techniques, comparing the performance of ResNet50 and a hybrid ResNet50-GAN model. The research questions explore the comparative diagnostic accuracy, precision metrics, and the unique contribution of GANs in enhancing the hybrid model. The study's contribution lies in demonstrating the superior diagnostic capabilities of the hybrid model, offering a transformative solution to improve patient outcomes and alleviate economic strain on healthcare systems by enabling more effective and timely intervention in DFU cases.

The study's mission is unequivocal: to engineer an advanced model adept at identifying foot ulcers in diabetic patients through the application of deep learning to analyze foot imagery. The paramount goal is the early detection of ulcers, thereby enabling timely medical intervention, averting critical complications like amputations, and thus diminishing the economic impact on patients. The ultimate aim is to facilitate patient mobility and provide cost-effective healthcare solutions.

2. RELATED WORK

Diabetic Foot Ulcers (shortened to DFUs) are a significant concern in the medical world. Many diabetic patients experience them, and if They are not spotted and treated quickly, the consequences can be severe – including severe infections, hospital stays, and in the most severe cases, amputations [1][3]. As previously outlined in the introduction, early detection is critical to avoid complications. Yet, the question remains: Identification of these ulcers involves several methodologies are currently employed. Some experts rely on color imaging techniques [6], while others utilize thermal imaging [5]. There is also an approach that delves into electronic health record data [15] to catch these ulcers. On the tech side, There is a range of tools available for assistance. From machine learning models like SVM and KNN to more advanced deep learning methods like CNNs, EfficientNet, and DCM – They are all utilized in the effective detection of DFUs.

Machine learning has made significant contributions to DFU detection, with algorithms such as SVM, KNN, and others playing pivotal roles in enhancing diagnostic accuracy. Botros et al. [16] studied if measuring foot pressure could predict neuropathic foot issues. They looked at foot pressure data from 56 diabetic patients and compared it to 28 healthy individuals. After refining the data to focus on the most important parts, they used the SVM method. They achieved favorable outcomes with an accuracy of 94.6% and other high scores. Keerthika et al. [17] created a way to predict the start of foot ulcers. They used data from doctors and applied image techniques to spot potential sores. After that, they used the SVM model to better identify and classify these sores in images, aiming for high accuracy. In a broader scope, Pushpaleela et al. [8] compared different machine learning methods, like SVM and KNN, to predict foot ulcers. They used hospital data with colored images of both healthy feet and those with ulcers. After testing, SVM was the clear winner, achieving an accuracy rate way ahead of the other methods, at 92.2%.

In the realm of DFU detection, machine learning has been a cornerstone for advancements. For instance, Pushpaleela and Padmajavalli [7] studied how to spot neuropathic ulcers in people, both with and without neuropathy. They gathered data from hospitals treating these conditions. They used several machine learning methods, including QDA, LDA, decision trees, and neural networks, to diagnose ulcers. The KNN model was the best performer, with an accuracy of 93.1%. This shows the potential of machine learning in medical diagnosis, especially for detecting foot ulcers.

In a comprehensive review of the literature on AI-assisted DFU monitoring techniques conducted by Maria Kaselimi and her team [18], the advantages of these methods were highlighted, along with the challenges of integrating them into a dependable framework for effective remote patient management. The study took into account not only the characteristics of the sensors but also the physiology of the patients. Depending on the data source, various monitoring strategies were endorsed, which imposed constraints on the AI tools that were selected.

Deep learning techniques have also been widely used particularly Convolutional Neural

Networks (CNNs), has made significant strides in the detection of diabetic foot ulcers (DFU). Alzubaidi et al. [19] developed a novel method (called DFU QUTNet) to differentiate normal and ulcer foot images. The research team finetuned the parameters of preexisting CNN models, namely AlexNet, GoogleNet, and VGG16, to enhance the analysis and comparison. With these adjustments, their new method obtained impressive results, achieving nearly 95% accuracy in certain measures.In another pivotal study by AlGaraawi et al. [20], the team came up with a way to use a CNN method for foot ulcer images. They first pulled out texture details from the images and then used these details in their method. This approach demonstrated high efficacy, achieving scores as high as 98.1% in some tests. Moreover, Das et al. [21] developed a new CNN model called Dfu SPNet for foot ulcer data. They used a unique way of pulling out details from the data. When they trained this model, it demonstrated high accuracy, almost 97.4% accuracy. However, There is a possibility of false positive identification some healthy cases as ulcers, so they emphasized the importance of considering practical implications beyond statistical performance.

Recently, various deep learning architectures have been employed in the realm of diabetic foot ulcer (DFU) detection. Thotad et al. [22] tested the EfficientNet model, a type of deep learning, on foot pictures to spot early signs of DFU. They looked at 840 pictures, both healthy and with ulcers. After tweaking the model, it performed exceptionally, outperforming famous models like VGG16 and AlexNet with almost 99% accuracy. But, this model only distinguishes between healthy skin from ulcerated skin, so it could potentially fail to detect other skin issues doctors see in clinics. Adding to the narrative, Liu et al. [23] used the EfficientNet model to tell apart infections and blood flow issues in foot images. By refining he model using shape and color data, they enhanced the dataset and achieved very high accuracy scores: 99% for blood flow issues and 98% for infections. However, their study only looked at these two categories and did not consider how severe each condition might be. A more comprehensive analysis into categories or severity levels could have provided additional insights. Also, they did not look into possible tech challenges when using the EfficientNet model.

In the study conducted by Yap et al. [24], took a close look at various methods for DFU detection using the DFUC2020 challenge dataset. Their standout method was the Deformable Convolutional model, a twist on the Faster R-CNN approach, which achieved a notable f1-score of 0.743. However, they also found significant challenges in using AI for DFU detection, given the complexity of medical images. The study indicates the requirement for additional data, especially with detailed medical notes, however, data sharing and associated costs present potential barriers. They also considered the incorporation of an additional method to augment the primary one, but gathering all the needed negative examples and making the system more complicated could pose challenges. El-Kady et al. [25], evaluated the performance of the RESNET18 model for DFU detection using colored images as a dataset through various combinations of epochs and batch sizes. The model achieved an accuracy of nearly 98%. However, their study was limited to distinguishing between DFU and non-DFU categories, neglecting other diseases with similar appearances to DFU.

In summary, while significant advancements have been achieved in using technology to detect Diabetic Foot Ulcers (DFU) - a critical part of managing diabetes - There is still a lot to be done. Current machine learning and deep learning tools are promising, but Further investment in research is essential to further enhance their effectiveness. The focus extends beyond improving the tools to ensuring that both patients and doctors can easily access and use them. Through continuous research and development can the standards of Diabetic Foot Ulcer (DFU) detection be substantially improved, thereby effecting a significant impact on diabetes management.

3. PROPOSED MODEL & DATASET

In this section, the mechanics of a uniquely developed model for detecting Diabetic Foot Ulcers (DFU) are explored. The timely identification of DFUs is viewed as vital in the medical field, as it has the potential to prevent further complications and possibly eliminate the requirement for amputations. This model was developed based on extensive research and is seen as a hopeful solution in this significant domain. The intention behind the model is to ensure that patients experience timely and precise interventions. An examination of the primary elements of the approach will be conducted, including a focus on the machine learning strategies, advanced deep learning methods, and the significance of spatial domain attributes in identifying DFUs. Furthermore, the techniques

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employed will be discussed, highlighting their advantages and possible challenges.

3.1 DATASET

A diverse and representative dataset of colored foot images has been meticulously curated, encompassing a total of 500 images. Originating from the National Institute of Diabetes and Endocrinology in Egypt [26], this collection provides a comprehensive glimpse into various foot conditions. Specifically, it showcases diabetic foot ulcers (DFUs), as well as other prevalent foot ailments like Athlete's foot, Cracked heels, plantar wart, Foot fungus, and Ingrown toenail. Additionally, images of healthy feet have also been incorporated to ensure a holistic understanding as presented in Figure 1. Each image within this repository has been captured from multiple angles and under different lighting conditions, enhancing the dataset's richness and diversity. It is worth noting that the acquisition of these images was anchored in ethics; all participants provided written consent, and the dataset was assembled with due approval. To further respect privacy norms, all images were meticulously de-identified before processing. Subsequent to this, Uniform-sized patches were extracted from the images through processing, forming the foundation for training and evaluating our advanced models.

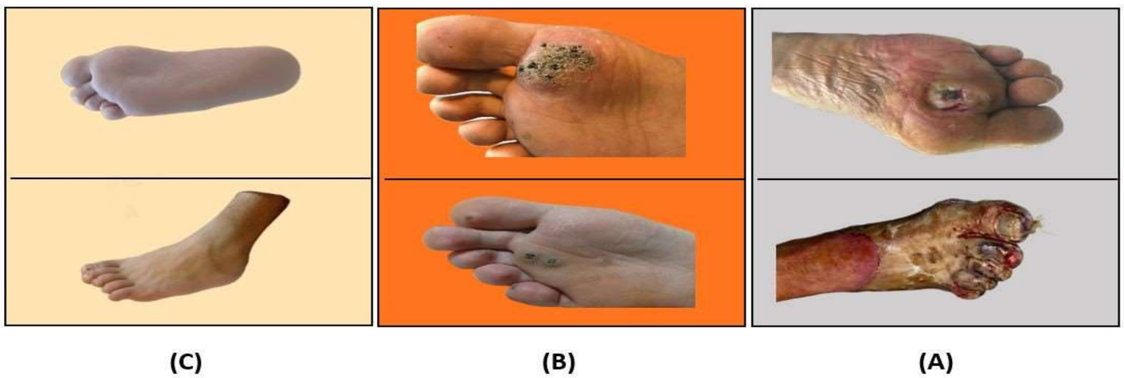

Figure. 1 Dataset Samples: (A) DFU, (B) Non DFU and (C) Normal

3.2 Residual Neural Network

The Residual Neural Network (ResNet), represents a significant advancement in computer vision, particularly for image recognition tasks that was proposed by [27]. Its defining feature is the incorporation of "residual connections," which alleviate the vanishing gradient problem encountered during the training of deep networks. These connections create path-ways that allow the propagation of gradients by skipping layers, thereby preserving the strength of the gradient signal through many layers.

ResNet's architecture consists of an input layer, followed by a series of convolutional layers, and punctuated by residual blocks. Each block contains convolutional layers and introduces a parallel shortcut that enables the direct flow of data, effectively learning the residual between the input and output of these layers. This architecture allows ResNet to focus on learning the incremental differences between layers, analogous to emphasizing the distinctions between a new language and one's native language for more efficient learning. Data in ResNet undergoes a process of feature extraction, modification by residual blocks, and subsequent integration of the residuals with the original input to preserve important features. After traversing the residual blocks, the data is pooled and outputted, ready for classification. ResNet's design facilitates the training of deeper networks by mitigating degradation issues, enhancing the network's performance on various complex tasks in the domain of computer vision.

3.3 Generative Adversarial Networks

Generative Adversarial Networks (GANs) are a profound innovation in deep learning, introduced in [28]. These networks excel at synthesizing new data, notably hyper-realistic images, through a duo of neural networks: the generator and the discriminator. The generator aims to forge data indistinguishable from real samples, while the discriminator evaluates this data against authentic samples to validate their realism. Through iterative adversarial training, the generator strives to fool the discriminator, which in turn adapts to become

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more astute at recognizing fakes. This dynamic enhances the performance of both networks over time. GANs have transcended image generation, demonstrating remarkable utility in diverse fields including pharmaceuticals, signaling expansive implications for future AI applications.

3.4 Roposed Model Steps and Architecture

The DFU detection model, as delineated in Figure 2, has been constructed through a six-phase process, Algorithm 1 outlines the training of a ResNet model for classification, while Algorithm 2 presents a hybrid proposed approach that combines GAN-generated data with ResNet for enhanced model training. Initially, the data undergoes a rigorous quality control process, wherein anomalous or mislabelled images are discarded. Ensuring the integrity of the data is paramount, as it underpins the subsequent learning of the model. The images are then augmented, via operations such as rotation and flipping, to enrich the dataset and enhance the model's recognition capabilities of diverse foot conditions. Standardization is achieved by resizing all images to a uniform dimension of 224x224 pixels and normalizing brightness levels across the dataset to a standard scale of [0,1]. Subsequently, the pre-trained ResNet50 model is employed, serving as an intricate filter specializing in image analysis. From this model, only the essential layers—that adept at discerning intricate image details—are retained and their parameters are fixed to preserve pre-learned knowledge. The prepared images are then processed through this adapted model, which performs an intricate feature extraction, translating the images into an abstracted form comprehensible to the machine. This abstract representation may be extensive; hence, it is either linearized or subjected to dimensionality reduction techniques to isolate salient features. Equipped with these distilled features, the model is now poised to undertake various tasks, such as clustering similar images or classifying contents within them. These features, essentially the model's learned interpretations of the data, become instrumental in achieving the objectives of the detection model.

***Algorithm 1** Pseudocode for ResNet Model*

```
Set ResNet parameters:
    batch_size, image_size, num_classes,
    epochs, k

function Create_Model:
    Constructs and compiles the ResNet model.
    return Compiled ResNet model
end function
```

***Algorithm 2** Pseudocode for Hybrid Model*

```
Set GAN parameters:
    batch_size, image_size, num_channels
    num_classes, epochs, noise_dim
    gan_batch _size, num _gan _epochs

function Create_GAN_Model
    Instantiate and compile the GAN model
    with generator and discriminator.
    return GAN model
end function

function Build_Generator
    Construct the generator model architecture.
    return generator model
end function

function Build_Discriminator
    Construct the discriminator model
    architecture.
    return discriminator model
end function

function Generate_Images
    Generate synthetic images from noise using
    the generator.
    return synthetic images
end function

function Combine_Original_With_Generated
    Combine original and synthetic images into
    a training dataset.
    return combined dataset
end function

function CALL_ResNet
    Invoke the ResNet model creation function.
end function

Train Hybrid Model:
    for each epoch in num_gan_epochs do
        Generate and combine images; train the
        GAN model.
    end for
Integrate ResNet training.
```

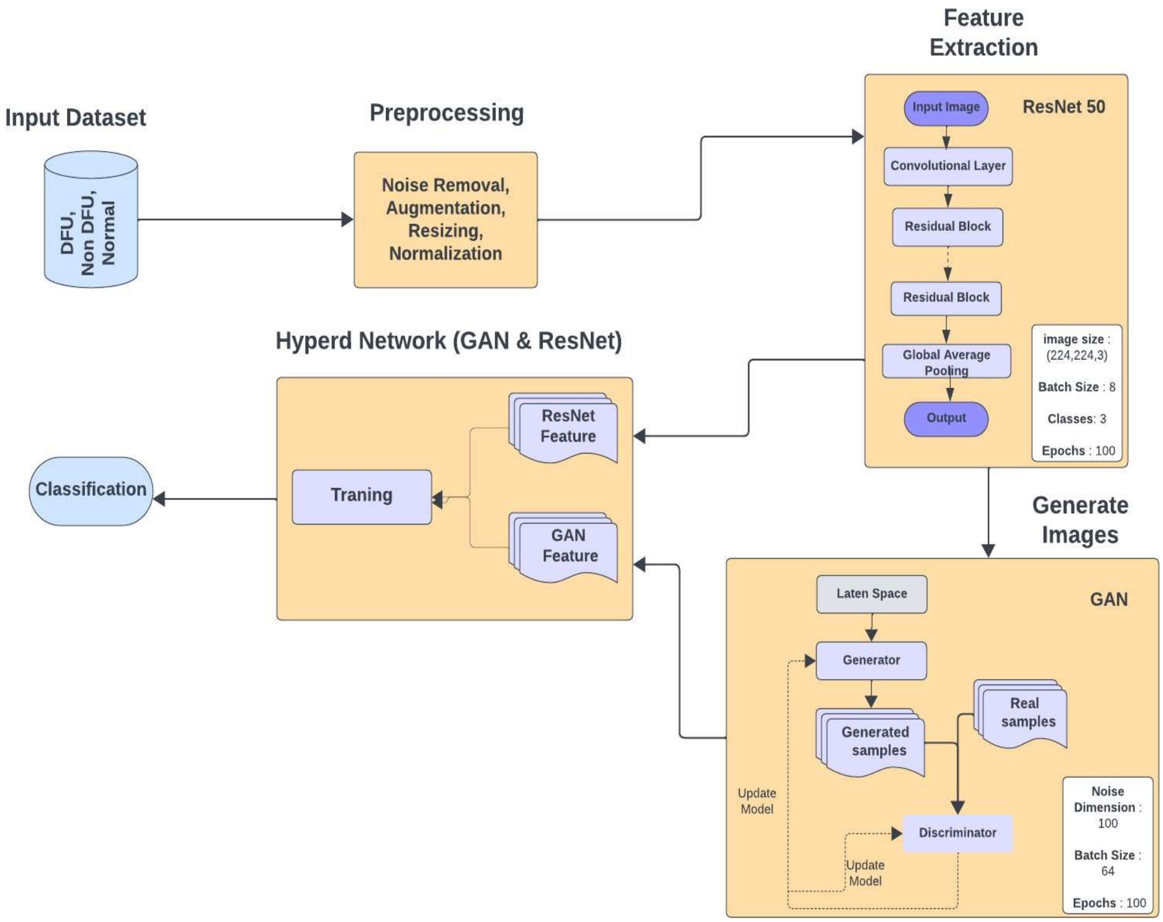

Figure. 2 Architecture of Proposed Hybrid Model (ResNet50 & GAN)

In the third step, Imagine There is this nifty gadget named GAN that is skilled at conjuring up fake foot images. In this GAN, there is an "artist" who transforms random sketches into foot pictures, some depicting DFU and some showing other issues. Meanwhile, the "critic" part of GAN attempts to discern whether these images are genuine or mere creations of GAN. Training was done by letting the "artist" strive to deceive the "critic", aiming to make the mock-up images seem authentic. where the "artist" and "critic" constantly test one another, enhancing GAN's proficiency in fabricating those foot scenarios.

Now, in the fourth step, a specialized model is integrated, which assimilates insights from its predecessor, the Convolutional Neural Network (CNN), regarding the characteristics of foot imagery. Additional layers are then superimposed to enhance its cognitive capacity. The augmented output is subsequently coupled with the discriminator component of the Generative Adversarial Network (GAN). Throughout the training phase, the feature representations derived from the CNN are maintained constant, whereas the discriminator of the GAN and the newly added layers are permitted to evolve and optimize.

Step five is all about training. Imagine a big album of DFU disease and non DFU pictures. This album is utilized to instruct the composite model in differentiating between them. Think of it as a workout for the model, where it lifts weights (adjusts its internal settings) using techniques like backpropagation and gradient descent to get stronger and smarter.

Lastly, in step six, It is test time The model is subjected to a new series of foot images to evaluate its proficiency in detecting Diabetic Foot Ulcer (DFU) disease. It is subsequently assessed through various metrics such as accuracy and precision, providing a quantifiable assessment of the model's capability to discern deceptive images accurately.

3.5 Results and discussion

In the forthcoming results section, In the pursuit to diagnose and distinguish foot conditions effectively, the performance outcomes of the experiments are meticulously dissected, with an in-depth analysis of how each model performed in the diagnostic endeavours being conducted.

Threats to the validity of the study on advancing diabetic foot ulcer detection through ResNet and GAN integration include potential selection bias, dataset imbalance, and overfitting issues that may affect the generalizability of findings to diverse populations. Hyperparameter sensitivity and variations in image quality could further impact the reproducibility and reliability of results. The critical variables influencing the study include the choice of model architecture, dataset composition, training duration, and the selection of evaluation metrics. Addressing these challenges is essential to ensure the robustness and applicability of the proposed ResNet-GAN hybrid model, contributing to the advancement of diabetic foot ulcer detection with improved diagnostic precision. Regular validation and sensitivity analyses are recommended to enhance the reliability of the study's outcomes in real-world clinical applications.

Two prominent architectures, the standalone ResNet50 and the hybrid model incorporating both ResNet50 and GAN, take center stage in our investigations. The models' capabilities are critically evaluated against a range of metrics, namely accuracy, precision, recall, and F1 score. These metrics serve as the cornerstone of our analysis, providing pivotal insights into the reliability and efficiency of our proposed models for foot condition diagnosis. Engage with us in exploring these enlightening discoveries.

The first experiment centered around the employment of the ResNet50 architecture, renowned for its deep residual learning capabilities. With an image resolution of 224x224 pixels, a batch size of 4 was chosen, balancing computational demands with the promise of performance. The model was designed to predict among three classes, and thus, an epoch number of 100 was set to ensure the model was well-trained. Furthermore, to ensure a thorough validation, an 8-fold cross-validation technique was incorporated. The backbone of this model, the ResNet50, was enhanced with a Global Average Pooling 2D layer, followed by a Dense layer of 1024 units with ReLU activation. This combination was expected to capture the intricate patterns in the foot images. The final layer consisted of a dense layer with 3 units, mirroring the number of classes, and employed the SoftMax activation function for probabilistic outputs. Notably, all layers from the base ResNet50 model were frozen to preserve their pre-trained weights, with the training focused on the appended layers. The model was compiled using the Adam optimizer with a learning rate of 0.001 and set to minimize the categorical cross-entropy loss while measuring accuracy. The results of this experiment were encapsulated in Table 1. To highlight, Class 1 achieved an accuracy of 0.81, precision of 0.81, recall of 0.83, and an F1 Score of 0.82. Class 2 metrics indicated an accuracy of 0.72, precision of 0.72, recall of 0.82, and an F1 Score of 0.77. Class 3's results, on the other hand, displayed an accuracy of 0.76, precision of 0.76, a lower recall of 0.6, and an F1 Score of 0.67. The overall metrics across all classes presented an accuracy and precision of 0.76, recall of 0.75, and an F1 Score of 0.75.

Table 1

Performance Metrics of ResNet50

Class	Accuracy	Precision	Recall	F1_Score
1	0.81	0.81	0.83	0.82
2	0.72	0.72	0.82	0.77
3	0.76	0.76	0.6	0.67
Average	0.76	0.76	0.75	0.75

The second experiment delved into the potential of hybrid models by integrating the ResNet50 architecture with a GAN. This approach aimed to leverage the prowess of deep learning while capitalizing on the capability of GANs to generate synthetic yet realistic foot images. With a larger batch size of 8, an image size consistent with the prior experiment, and a three-channel image setup, the hybrid model was structured to process a diverse array of foot images. The GAN model, within this setup, comprised of a generator and discriminator. The generator, fed with a noise dimension of 100, churned out synthetic images, while the discriminator played the critic, distinguishing between the authentic and synthesized images. The entire GAN architecture was well thought out, with the generator employing Dense layers interspersed with Leaky ReLU activations and Batch Normalization layers, eventually culminating with a Reshape layer to transform the output to image format. The discriminator, contrarily, utilized a Flatten layer, followed by Dense layers with Leaky ReLU activations and culminated in a Sigmoid activation for binary classification. The hybrid model's utility was further accentuated by functions to generate synthetic images and merge them with the original data, enhancing the diversity of the training data. The results, encapsulated in Table 2, were particularly promising. Class 1 metrics revealed an accuracy of 0.89, precision of 0.89, recall of 0.88, and an F1 Score of 0.89. Class 2 showcased an accuracy of 0.78, precision of 0.79, recall of 0.86, and an F1 Score of 0.82. Class 3, meanwhile, reported an accuracy of 0.86, precision of 0.86, recall of 0.78, and an F1 Score of 0.82. Averaging the results, the accuracy stood at 0.84, precision at 0.85, recall at 0.84, and the F1 Score mirrored the recall at 0.84.

A comparative analysis between the two proposed models was imperative to deduce the strengths and potential improvements. Figure 3 elucidates this comparison, providing visual clarity on the performance differentials between the two experiments.

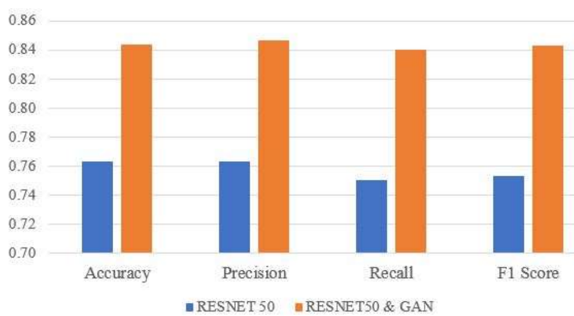

Figure. 3 Comparison of performance parameters of various ResNet50 model and hybrid ResNet50 & GAN

In summation, In the juxtaposition of the two models, the hybrid model incorporating both ResNet50 and GAN clearly demonstrated superior performance metrics over the standalone ResNet50 model. The integration of the Generative Adversarial Network with the deep learning architecture of ResNet50 not only optimized the model's ability to generalize but also bolstered its accuracy, precision, recall, and F1 score across all classes. The synergy of these architectures in the hybrid model unveiled the latent potential of marrying traditional deep learning with generative models. The metrics from the experiments provide compelling evidence that the hybrid model, with its sophisticated approach of blending synthetic and real data, offers a more robust solution for foot condition diagnosis. This progression hints at the evolving landscape of deep learning, suggesting that hybrid models might be the beacon for future research and applications.

Table 2

Performance Metrics of hybrid ResNet50 & GAN

Class	Accuracy	Precision	Recall	F1_Score
1	0.89	0.89	0.88	0.89
2	0.78	0.79	0.86	0.82
3	0.86	0.86	0.78	0.82
Average	0.84	0.85	0.84	0.84

4. CONCLUSION

Diabetes Mellitus remains a pervasive health challenge, with Diabetic Foot Ulcers (DFU) emerging as one of its most debilitating complications. The importance of early and accurate detection cannot be overstated, especially considering the drastic consequences such as amputations. Our research underscored the potential of leveraging advanced image analysis techniques for improved diagnostic outcomes.

By comparing the diagnostic capabilities of two distinct models— the standalone ResNet50 and a hybrid model incorporating ResNet50 and Generative Adversarial Networks (GAN)— our study reveals a significant disparity in their proficiency for Diabetic Foot Ulcer (DFU) detection.

While the ResNet50 presented commendable results, the hybrid model demonstrated superior performance across multiple evaluation metrics. Such improvements in accuracy, precision, and F1 score underscore the hybrid model's potential in clinical applications, particularly for DFU detection.

In conclusion of our study, It is evident that combining traditional convolutional neural networks with innovative structures like GANs can elevate the diagnostic prowess for conditions like DFU. This research not only paves the way for enhanced medical image analysis but also holds the promise of significantly reducing the socio-economic burden associated with DFU, especially in regions grappling with heightened medical expenses.

our research not only advances the field of diabetic foot ulcer detection but also underscores the transformative potential of hybrid models, emphasizing their pivotal role in shaping the future of medical image analysis. The integration of traditional convolutional neural networks with innovative structures like GANs represents a breakthrough in diagnostic precision, offering a pathway towards more effective and economically

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feasible healthcare solutions for managing diabetic foot ulcers.

Moving forward, we advocate for further exploration into hybrid model structures and their potential applications in various medical domains. With technology evolving at an unprecedented pace, the horizons of medical imaging and diagnostics are expanding, offering hope for more effective and patient-centred healthcare solutions in the near future.

REFERENCES

[1] D. J. Magliano, E. J. Boyko, *et al.*, "Idf diabetes atlas," 2022.

[2] P. Z. Zimmet, D. J. Magliano, W. H. Herman, and J. E. Shaw, "Diabetes: a 21st century challenge," *The lancet Diabetes & endocrinology*, vol. 2, no. 1, pp. 56–64, 2014.

[3] D. G. Armstrong, A. J. Boulton, and S. A. Bus, "Diabetic foot ulcers and their recurrence," *New England Journal of Medicine*, vol. 376, no. 24, pp. 2367–2375, 2017.

[4] D. Abdissa, T. Adugna, U. Gerema, D. Dereje, *et al.*, "Prevalence of diabetic foot ulcer and associated factors among adult diabetic patients on follow-up clinic at jimma medical center, southwest ethiopia, 2019: an institutional-based cross-sectional study," *Journal of diabetes research*, vol. 2020, 2020.

[5] M. H. Alshayeji, S. C. Sindhu, *et al.*, "Early detection of diabetic foot ulcers from thermal images using the bag of features technique," *Biomedical Signal Processing and Control*, vol. 79, p. 104143, 2023.

[6] N. Nirala, R. Periyasamy, B. K. Singh, and A. Kumar, "Detection of type-2 diabetes using characteristics of toe photoplethysmogram by applying support vector machine," *Biocybernetics and Biomedical Engineering*, vol. 39, no. 1, pp. 38–51, 2019.

[7] M. Adam, E. Y. Ng, S. L. Oh, M. L. Heng, Y. Hagiwara, J. H. Tan, J. W. Tong, and U. R. Acharya, "Automated detection of diabetic foot with and without neuropathy using double density-dual tree-complex wavelet transform on foot thermograms," *Infrared Physics & Technology*, vol. 92, pp. 270–279, 2018.

[8] R. C. Pushpaleela and R. Padmajavalli, "Prediction of type-2 diabetes foot ulcer-a comparative study with classification algorithm," *Interna- tional J. of Pure and Applied Mathematics*, vol. 117, no. 7, pp. 219–230,2017.

[9] P. Kamavisdar, S. Saluja, S. Agrawal, *et al.*, "A survey on image classi- fication approaches and techniques," *International Journal of Advanced Research in Computer and Communication Engineering*, vol. 2, no. 1, pp. 1005–1009, 2013.

[10] I. Kavakiotis, "Tsave o salifoglou a maglaveras n vlahavas i chouvarda i," *Machine learning and data mining methods in diabetes research Comput Struct Biotechnol J*, vol. 15, pp. 104–116, 2017.

[11] 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," *IEEE Transactions on Emerging Topics in Computational Intelligence*, vol. 4, no. 5, pp. 728–739, 2018.

[12] L. Alzubaidi, M. A. Fadhel, S. R. Oleiwi, O. Al-Shamma, and J. Zhang, "Dfu qutnet: diabetic foot ulcer classification using novel deep convo- lutional neural network," *Multimedia Tools and Applications*, vol. 79, no. 21-22, pp. 15655–15677, 2020.

[13] C. Gamage, I. Wijesinghe, and I. Perera, "Automatic scoring of diabetic foot ulcers through deep cnn based feature extraction with low rank matrix factorization," in *2019 IEEE 19th International Conference on Bioinformatics and Bioengineering (BIBE)*, pp. 352–356, IEEE, 2019.

[14] N. Rania, H. Douzi, L. Yves, and T. Sylvie, "Semantic segmentation of diabetic foot ulcer images: Dealing with small dataset in dl approaches," in *Image and Signal Processing: 9th International Conference, ICISP 2020, Marrakesh, Morocco, June 4–6, 2020, Proceedings 9*, pp. 162– 169, Springer, 2020.

[15] A. Khandakar, M. E. Chowdhury, M. B. I. Reaz, S. H. M. Ali, M. A. Hasan, S. Kiranyaz, T. Rahman, R. Alfkey, A. A. A. Bakar, and R. A. Malik, "A machine learning model for early detection of diabetic foot using thermogram images," *Computers in biology and medicine*, vol. 137, p. 104838, 2021.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[16] F. S. Botros, M. F. Taher, N. M. ElSayed, and A. S. Fahmy, "Prediction of diabetic foot ulceration using spatial and temporal dynamic plantar pressure," in *2016 8th Cairo international biomedical engineering conference (CIBEC)*, pp. 43–47, IEEE, 2016.

[17] A. Keerthika, G. Sangeetha, C. Jaya Bharathi, and S. Pavithra, "Pre- diction of diabetic foot ulcer based on region growth segmentation," *International J. of Pure and Applied Mathematics*, vol. 119, no. 15, pp. 643–651, 2018.

[18] M. Kaselimi, E. Protopapadakis, A. Doulamis, and N. Doulamis, "A review of non-invasive sensors and artificial intelligence models for diabetic foot monitoring," *Frontiers in Physiology*, vol. 13, p. 924546, 2022.

[19] 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*, vol. 79, no. 21-22, pp. 15655–15677, 2020.

[20] N. Al-Garaawi, R. Ebsim, A. F. Alharan, and M. H. Yap, "Diabetic foot ulcer classification using mapped binary patterns and convolutional neu- ral networks," *Computers in biology and medicine*, vol. 140, p. 105055, 2022.

[21] S. K. Das, P. Roy, and A. K. Mishra, "Dfu spnet: A stacked parallel con- volution layers based cnn to improve diabetic foot ulcer classification," *ICT Express*, vol. 8, no. 2, pp. 271–275, 2022.

[22] P. N. Thotad, G. R. Bharamagoudar, and B. S. Anami, "Diabetic foot ulcer detection using deep learning approaches," *Sensors International*, vol. 4, p. 100210, 2023.

[23] Z. Liu, J. John, and E. Agu, "Diabetic foot ulcer ischemia and infection classification using efficientnet deep learning models," *IEEE Open Journal of Engineering in Medicine and Biology*, vol. 3, pp. 189–201, 2022.

[24] M. H. Yap, R. Hachiuma, A. Alavi, R. Brüngel, B. Cassidy, M. Goyal, H. Zhu, J. Rückert, M. Olshansky, X. Huang, *et al.*, "Deep learning in diabetic foot ulcers detection: a comprehensive evaluation," *Computers in Biology and Medicine*, vol. 135, p. 104596, 2021.

[25] A. M. A. E.-A. El, M. Mostafa, H. H. A. Hussien, F. A. Moussa, *et al.*, "Comparative analysis: Deep vs. machine learning for early dfu detection in medical imaging," in *2023 Intelligent Methods, Systems, and Applications (IMSA)*, pp. 440–445, IEEE, 2023.

[26] "National institute of diabetes and endocrinology." https://nide.gov.eg/. Website title: National Institute Of Diabetes And Endocrinology, Ac- cessed: May 6, 2023.

[27] S. Jian, H. Kaiming, R. Shaoqing, and Z. Xiangyu, "Deep residual learning for image recognition," in *IEEE Conference on Computer Vision & Pattern Recognition*, pp. 770–778, 2016.

[28] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley,S. Ozair, A. Courville, and Y. Bengio, "Generative adversarial networks,"*Communications of the ACM*, vol. 63, no. 11, pp. 139–144, 2020.