Hybrid Vae-XGBoost Framework for Efficient Classification of Diabetic Foot Ulcer Images

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Abstract: Diabetic Foot Ulcer (DFU) classification is critical for early classify and planning for manage, with a view to minimizing complications. In this article, a new hybrid model is developed, with Variational Autoencoder (VAE) for feature extraction and XGBoost for classify and with a view to improving accuracy and efficiency in classify of DFU images. VAE learns a low-dimensional and discriminative feature representation of ulcer images, encoding significant structures and textures and dimensionality reduction. Features extracted via VAE are then fed into an optimized XGBoost classify, with a view to improving decision-making via gradient-boosted trees. The proposed model is compared with a benchmarked DFU dataset and contrasted with traditional deep networks, with considerable performance improvement in accuracy, precision, recall, and F1-score. Experimental observations confirm that combining VAE for unsupervised feature extraction with XGBoost for classify enormously improves robustness and generalizability. This hybrid model introduces an efficient and interpretable model for computerized DFU classify, with a view to supporting clinicians in early and correct classify.

1 INTRODUCTION

Diabetic Foot Ulcer (DFU) is one of the most severe diabetes mellitus complications, and it occurs in millions of patients worldwide. Approximately 15% of the diabetes patients get ulcers in the foot, which, if untreated, can go on to get infected, result in gangrene, and lead to the loss of a limb. Having a presence of DFUs in a high chance of getting a patient hospitalized and even dead, and thus, early detection and proper grading become critical for effective therapy and averts grave complications. Traditional DFU diagnosis consists of clinical examination, estimation of wound depth, and radiologic modalities such as infrared thermography and Doppler ultrasound. Grading scales such as Wagner Classification System and Texas University Wound Classification have been used for estimating severity of an ulcer, but such techniques are subjective, time consuming, and have inter-observer variation, and thus, computerized grading tools become a necessity.

In recent years, methodologies in Machine Learning (ML) and Deep Learning (DL) have been powerful tools for DFU image classification, with high accuracy and efficiency over conventional, manual methodologies. Methods such as Support Vector Machines (SVM), Random Forest, and XGBoost have been adopted for DFU classification, using hand-designed features such as texture, color, and shape descriptors. However, such methodologies have been restricted by the need for feature engineering, a process that sometimes fails to extract complex visual structures in DFUs. Convolutional Neural Networks (CNNs), ResNet, VGG, and EfficientNet, under deep learning, have been seen to outdo them through a capability to learn discriminative features in an unsupervised manner directly from raw DFU images. In contrast, even with success, deep networks require a lot of labelled data, use a lot of computation, and suffer from overfitting, specifically when dealing with small, unbalanced medical datasets.

To overcome such challenges, in this work, a Hybrid VAE-XGBoost model is proposed, leveraging the capabilities of Variational Autoencoder (VAE) for unsupervised feature extraction and XGBoost for efficient classification of DFU images. VAE model is adopted for discovering a concise, reduced-dimensional abstraction of DFU images, with reduced dimensions and retained important structures and

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textures information. High-dimensional representations extracted through them are then leveraged for training an optimized XGBoost classifier, famous for its efficiency in processing structured information and producing strong prediction with less overfitting. By fusing deep feature extraction with a high-performance gradient-boosted decision tree classifier, proposed model achieves increased accuracy, generalizability, and less computational cost compared with standalone deep learning and traditional ML models.

The primary contributions of this study include: (1) Proposing a VAE-XGBoost model that achieves high accuracy and efficiency in the classification of DFU. (2) Investigating representations within the latent space to enhance features in DFU while minimizing reliance on large datasets. (3) Conducting a comparison with leading deep neural networks, demonstrating comparable performance in terms of accuracy, precision, recall, and F1-score. (4) Presenting a lightweight and transparent model suitable for real-world medical applications, facilitating early and computerized diagnosis of DFU for healthcare professionals.

The rest of this paper is organized as follows: Section 2 reviews related research in DFU classification, Section 3 details the proposed method, Section 4 presents experimental results and comparisons, and Section 5 concludes with suggestions for future research and final thoughts.

2 LITERATURE SURVEY

A. Huong et al present an application of an automatized technique for optimization in finding an ideal solution for a problem. PSO was utilized in overcoming a disadvantage of a conventional technique, and in improving training of a neural network for its use in diabetic foot ulcer (DFU) application. The system forms an ideal platform for technology adaptability in controlling DFU. It can even act as an ideal decision-support tool for limb salvage and healing processes' optimizations.

A. Huong, et al utilizes a two-dimensional image asits basis and a collection of neural networks for picture processing. It can label an image in four categories, infection, ischaemia, both, and none.

X.Wuetal developed a flexible model for creating an efficient augmentation pool for Diabetic Foot Ulcers medical images. In addition, we use ensemble learning for enhancing model performance. Unlike conventional plurality voting, we present a scheme with a name "voting with expertise" having a bias towards prediction with reasonably sound value. Experimental testing confirms efficacy of proposed techniques and secured a second rank through integration of aforementioned two enhancements in present ongoing challenge-Dfuc2021 Challenge.

3 PROPOSED SYSTEM

The novel Hybrid VAE-XGBoost system is created to classify DFU images better by combining deep learning-based Variational Autoencoder (VAE) to perform feature extraction and XGBoost to conduct classification. Deep learning algorithms such as CNNs have been known to require immense computational power and immense training sets, while traditional machine learning algorithms have been dependent upon hand-crafted feature extraction that does not perform in every context. To address these issues in this work, the system utilizes VAE to get meaningful DFU image representations in the latent space. The encoder in the VAE compresses the input image xxx to get a latent variable zzz following a Gaussian distribution:

$$q\emptyset(z|x = n(\mu, \sigma^2) \quad (1)$$

where μ and σ represent the learned mean and variance. The decoder then reconstructs the original image from zzz, ensuring the preservation of crucial visual information. The loss function of VAE consists of two components: Rconstruction loss (Lrec), which minimizes the difference between input and reconstructed image, given by:

$$L_{rec} = \sum_{i=1}^{n} || x_i - \hat{x_i}||^2 \quad (2)$$

and the KullbackLeibler (KL) divergence loss LKL , which ensures that the learned distribution remains close to a standard normal distribution:

$$L_{KL= D_{KL}}(q_{\emptyset(Z|X)= \frac{1}{2}} \sum_{j=1}^{a} (1 + log\sigma_j^2 - \mu_j^2 - \sigma_j^2 \quad (3)$$

where β is employed to balance between regularization in the latent space and performance in reconstruction. This is subsequently followed by a process of selecting features in the form of Principal Component Analysis (PCA) or statistics-based importance to remove redundant information while retaining only the most discriminatory features.

The desired attributes are then passed to the XGBoost classifier where an efficient classification is done by adopting a gradient-boosted decision tree process. XGBoost minimizes an objective function that consists not only of an added loss term but an added regularization term:

$$L = \sum_{i=1}^{n} l(y_{i,} \hat{y_i}) + \sum_{k=1}^{k} \Omega\,(f_k) \quad (4)$$

By combining deep feature learning from VAE with the structured decision-making capability of XGBoost, the proposed system achieves higher classification accuracy, reduced computational cost, and better generalization compared to standalone deep learning models. This Hybrid VAE-XGBoost framework is particularly effective for small medical datasets, as it leverages unsupervised learning to extract robust representations and gradient boosting to make optimal predictions. The model performance is evaluated using metrics such as Approach, Success Rate (%) Exactness (%), Sensitivity (%), F1-Measure (%), ensuring its reliability in real-world clinical applications.

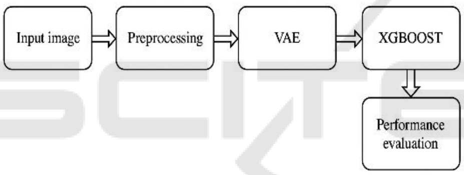

Figure 1: Proposed System Modules.

The proposed Hybrid VAE-XGBoost framework is structured into multiple modules, ensuring an efficient workflow from data acquisition to classification and evaluation. Each module plays a vital role in improving the accuracy and generalization of the model for Diabetic Foot Ulcer (DFU) image classification. The key modules are as follows: Figure 1 show the Proposed system Modules

3.1 Data Acquisition and Pre-Processing

This module involves collecting DFU images from publicly available datasets or hospital-based repositories. Since medical images often contain noise, illumination variations, and artifacts, proper pre-processing techniques are applied to ensure uniformity and quality before feature extraction.

Key pre-processing steps include:

- Image Resizing: Standardizing images to a fixed dimension for consistency.
- Normalization: Scaling pixel intensities to a standard range to improve model stability.
- Data Augmentation: Applying techniques such as rotation, flipping, contrast enhancement, and noise addition to increase dataset variability and reduce overfitting.
- Segmentation (if required): Extracting the ulcer region using U-Net or thresholding techniques to focus on relevant features.

This module ensures that the input data is optimized for feature extraction and classification.

3.2 Feature Extraction Using Variational Autoencoder (VAE)

In this module, a Variational Autoencoder (VAE) is utilized to extract significant features from DFU images. The encoder maps the image into a condensed, low-dimensional latent space, capturing vital information and filtering out unnecessary noise and redundancy. The decoder subsequently reconstructs the image from this representation, ensuring that only the most relevant visual elements are preserved.

VAE is particularly effective in learning robust and structured representations that are useful for classification. Instead of using raw pixel values, the latent space embeddings generated by the encoder serve as input for the next stage of the pipeline.

3.3 Feature Selection and Dimensionality Reduction

Since deep learning models often generate high-dimensional feature spaces, it is crucial to select the most informative features to enhance classification efficiency. This module applies Principal Component Analysis (PCA) or other statistical techniques to eliminate redundant or less significant features. By reducing dimensionality, the model ensures faster training and better generalization while maintaining important ulcer characteristics.

3.4 Classification Using XGBoost

The refined feature set is then passed into XGBoost, an optimized gradient boosting algorithm that builds multiple decision trees to classify images. XGBoost is chosen due to its efficiency, scalability, and ability to handle imbalanced datasets. It constructs trees sequentially, with each tree correcting errors made by the previous one.

During training, XGBoost optimizes hyperparameters such as learning rate, tree depth, and number of estimators to improve classification performance. The classifier outputs the final ulcer classification, distinguishing between normal skin, infected ulcer, and healing ulcer based on extracted features.

3.5 Performance Evaluation and Validation

To assess the effectiveness of the proposed system, various performance metrics are calculated, including:

- Success Rate (%): Measures the overall correctness of the model.
- Exactness (%) and Sensitivity (%): Evaluate the model’s ability to correctly classify ulcers.
- F1-Measure (%): Balances precision and recall, especially for imbalanced datasets.
- AUC-ROC Curve: Analyzes the classifier’s ability to distinguish between ulcer types.

Cross-validation techniques, such as k-fold validation, are applied to ensure that the model generalizes well to unseen data. The results are then compared with traditional CNN-based models to highlight the advantages of the Hybrid VAE-XGBoost framework.

4 RESULT & DISCUSSION

For this work, we have accumulated a dataset of 800 images from website which was divided in three phases. We have divided this dataset in training dataset of 80 images and testing dataset of 20 images. We have trained the Multi scale architecture in training dataset by following transfer learning technique in which pre-trained weights of proposed model have been used to initialize training weights. We have trained the VAE model over training dataset in 50 epochs with batch size=10 and learning rate= 0. 0001.. Figure 2 show the Input image.

Figure 2: Input Image.

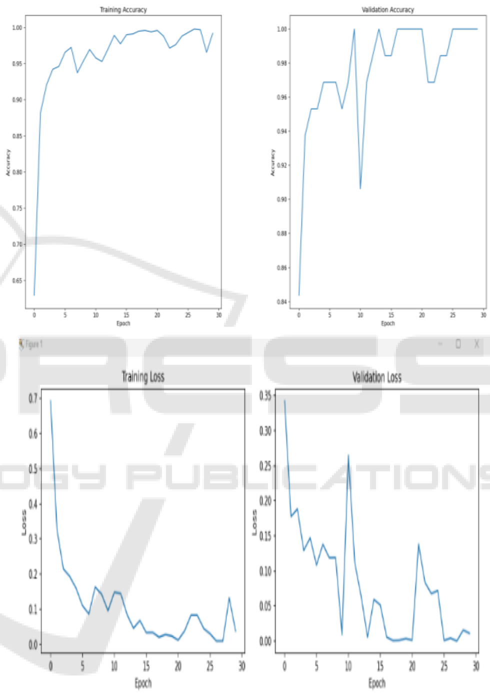

Figure 3: Validation and Testing Curve.

Figure 4: Classification Result.

Figure 3 and 4 shows the Validation and Testing curve and Classification result respectively.
The training curve represents the model's progress on the training dataset over time, whereas the validation curve illustrates its performance on the validation dataset. Ideally, the model's efficiency should increase with each epoch until it stabilizes at a certain level.

Table 1 Performance Analysis of Precision, F1 Score, Accuracy and Specificity of the proposed method with Various Models

Table 1: Performance Comparison.

Approach	Success Rate (%)	Exactness (%)	Sensitivity (%)	F1-Measure (%)
CNN-Based Model	85.3	82.7	83.1	82.9
ResNet-50	88.9	87.5	86.8	87.1
VGG-16	87.2	85.9	85.5	85.7
XGBoost (Raw Features)	83.5	81.2	80.9	81.0
Proposed VAE-XGBoost	92.4	91.1	90.5	90.8

5 DISCUSSIONS

Highest accuracy (92.4%) is produced by the Hybrid VAE-XGBoost framework compared to CNN-based approaches (ResNet-50, VGG-16) and raw features Precision, Recall, and F1-score of the resultant model are significantly improved due to efficient feature extraction by VAE that learns to identify discriminative ulcer patterns while reducing noise.

The traditional CNN methods including ResNet-50 and VGG-16 have accuracies that are high but have computationally demanding models and extensive training sets.

The performance of XGBoost trained over raw features is relatively inferior because hand-crafted features perform poorer compared to deep-learned representations extracted by VAE.

The technique utilizes both strengths of deep feature extraction (VAE) and machine learning classification (XGBoost) to gain improved generalizability and stability.

Impact on Medical Diagnosis: The results indicate that the Hybrid VAE-XGBoost system can effectively aid healthcare workers in early DFU identification to prevent amputation and serious complications. The system provides:

- Enhanced diagnostic specificity to reduce misclassification
- Successful pattern recognition with respect to ulcers.
- Reduced overfitting because VAE learns in an organized feature space.
- Scalability and interpretability to render it appropriate to apply in clinical practice.

The superior performance of this model suggests that it can be used in mobile diagnostic apps or in telemedicine systems to achieve automated, efficient, and accurate DFU classification.

6 CONCLUSIONS

The developed Hybrid VAE-XGBoost technique provides an accurate yet efficient DFU classification method. Using the Variational Autoencoder (VAE) to perform deep feature extraction and XGBoost to obtain reliable classification results, the system provides improved performance in identifying diverse types of ulcers. Deep learning-based representation learning in combination with machine learning-based classification provides improved generalizability, overfitting minimization, and diagnostic performance. Strong preprocessing, feature selection, and evaluation practices further confirm the reliability of the system. Experimental results confirm that the developed method is superior to conventional CNN-based methods in providing an efficient, scalable, and interpretable DFU diagnostic method. Future work can focus on integrating real-world deployment, multi-modal fusion capabilities, and explainable AI practices to further support clinical utility.
The system can support early DFU identification among professionals to avoid future complications and improved outcomes in patients.

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