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Wavelet Attention VGG19 and XGBOOST for Classification of Skin Disease

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Abstract: **This research paper introduces a novel framework for skin disease classification, combining Wavelet Attention VGG19 and XGBoost algorithms. Wavelet Attention VGG19 leverages the power of deep learning and wavelet attention mechanisms to extract discriminative features from skin lesion images, while XGBoost, a gradient boosting technique, complements the feature extraction capabilities with its ability to handle complex data relationships. The integration of these methodologies aims to improve accuracy and resilience in binary skin disease classification. The two goals of this study are to first improve feature learning and representation from skin lesion images by introducing wavelet attention into the VGG19 architecture, and second to improve classification performance by utilising XGBoost's ensemble and generalisation capabilities.**

Keywords: **Wavelet Attention, Xgboost, deep learning, convolutional neural network, skin disease classification, VGG19.**

I. INTRODUCTION

The skin is the largest organ of the human body, it covers all other organ of the body and serves the purpose of protecting the human body from harmful substance as well as prevent the flow of important nutrients from the human body [23], and is made up of the epidermis, dermis and hypodermis. The stratum corneum forms the top layer of the epidermis, with thick layers producing keratin that benefit the skin to protect the body [40]. [28] claims that there are three main types of skin diseases based on the causal factor; bacteria, fungal and viral diseases. [47] added parasitic pathogens, however,[34] claimed that animal pathogens are either viral, fungal or bacterial.

Accurate and timely diagnosis of skin diseases is critical in dermatology, as it has a substantial impact on patient treatment and outcomes. With the rapid advancement in artificial intelligence and machine learning, many studies have proposed the use of different ML and DL approaches for skin disease classification e.g. [31] [16] [39] etc. While many of these studies have improved on the state of the art on skin disease classification, the skin diseases classification still remains a challenge due to the inter-class similarity and intra-class variability of the skin diseases. Therefore, to advance the state of the art in skin disease classification, this study proposed a novel framework for skin disease classification, combining Wavelet Attention VGG19 and XGBoost algorithm. Existing research has shown the effectiveness of deep learning models like VGG19 in image recognition tasks, as well as wavelet attention methods in improving feature extraction from medical pictures. However, there is a scarcity of large-scale studies that look into the integration of various methodologies for skin disease classification.

Wavelet Attention VGG19 combines the capabilities of two powerful methodologies: the VGG19 architecture and wavelet attention mechanisms. VGG19 is a well-known convolutional neural network (CNN) that excels at image recognition tasks. Its deep architecture, which includes 19 convolutional layers, allows the model to learn hierarchical representations of features from input images. Wavelet attention, on the other hand, presents a unique attention mechanism based on wavelet theory, allowing the model to focus on significant spatial and frequency components in visual input. By combining the strengths of VGG19 with wavelet attention, this model can successfully extract discriminative features from skin lesion images and improve the interpretability of its conclusions.

XGBoost, a sophisticated gradient boosting technique, has exhibited remarkable performance in tabular data and classification tasks, complementing the feature extraction capabilities of Wavelet Attention VGG19. XGBoost is well-known for its ability to manage complex data relationships, missing values, and overfitting through regularization. By combining XGBoost and Wavelet Attention VGG19, we can take advantage of XGBoost's ensemble qualities and generalization abilities, resulting in a robust and accurate classification system for skin conditions.

As a result, the research objective is to develop and evaluate a new skin disease classification framework that combines the strengths of Wavelet Attention VGG19 and XGBoost in order to obtain accurate and reliable classification of skin diseases. The main goal is to improve feature learning and representation from skin lesion images by including a wavelet attention mechanism into the VGG19 architecture. In addition, the study intends to use XGBoost's ensemble and generalization capabilities to increase classification performance.

By tackling this research challenge, the study hopes to contribute to the area of dermatology by providing dermatologists and clinicians with a robust and interpretable tool for early detection and diagnosis of various skin illnesses. The proposed framework intends to overcome the limits of existing methodologies and increase the accuracy and efficiency of skin disease classification, resulting in improved patient outcomes and optimized dermatological healthcare services

II. RELATED WORKS

There have been several related works on skin disease classification using machine learning and deep learning methods. For instance, [23] developed a deep learning model to classify three types of skin diseases using dermoscopic images. The model used a convolutional neural network (CNN) with a customized structure to extract features from the images. The proposed model achieved high accuracy rates of over 90% in the classification of the three skin diseases, outperforming other machine learning algorithms. The study demonstrates the potential of deep learning models for accurate and efficient classification of skin diseases based on dermoscopic images. Similarly,[20] proposed a machine learning-based model for the classification of five types of skin diseases using dermoscopic images. The model used various features, such as texture and color, and achieved an accuracy rate of over 80%. The authors also conducted experiments to compare the performance of their model with other state-of-the-art methods and found that their model outperformed them in terms of accuracy. The proposed model could potentially help dermatologists in diagnosing skin diseases accurately and quickly.

Deep learning has also been used in skin cancer classification. [12] developed a deep learning model for the classification of melanoma, a type of skin cancer, using images. The model used a convolutional neural network (CNN) and achieved an accuracy rate of 95%, which was higher than that of the dermatologists who participated in the study. The study showed the potential of deep learning models in improving the accuracy of skin disease diagnosis. Additionally, [5] developed a deep learning model to classify skin lesions as benign or malignant using a large dataset of clinical and dermoscopic images. The model employed a multi-stage training approach with a convolutional neural network (CNN) and achieved a sensitivity of 97.4% and a specificity of 78.2%. The study demonstrated the potential of deep learning in assisting dermatologists in accurately diagnosing skin cancer. Other studies have explored the use of machine learning and deep learning for specific skin diseases. For instance, the work by [16] focused on psoriasis classification using a CNN-based approach. The model achieved an accuracy rate of 93%.

In the context of fungal skin disease classification, [21] proposed a deep learning model for the classification of six types of fungal skin diseases using dermoscopic images. The model utilized a convolutional neural network (CNN) architecture with transfer learning and achieved an accuracy rate of 87.7%. The authors evaluated the performance of the model on a dataset of 900 images, and the results showed that the model was effective in distinguishing between different types of fungal skin diseases. The study demonstrated the potential of deep learning models in the accurate classification of fungal skin diseases and could be useful in the development of computer-aided diagnosis systems. Meanwhile, [39] developed a deep learning-based approach for the classification of two types of fungal skin diseases using dermoscopic images. The model utilized a convolutional neural network (CNN) architecture and transfer learning to extract high-level features from the images. The study utilized a dataset of 616 images for model training and evaluation. The results showed that the proposed model achieved an accuracy rate of 89.4% in distinguishing between the two types of fungal skin diseases. The study demonstrated the potential of deep learning models in the accurate classification of fungal skin diseases and could be useful in the development of computer-aided diagnosis systems.

III. METHODOLOGY

DATA COLLECTION

The dataset used for this research were obtained from Kaggle, a total of 2506 images were collected. About 501 of the images were collected from healthy skin and 2005 from abnormal skin affected by acne rosacea, eczema, psoriasis, seborrheic dermatitis, lichen planus, and tinea capitis etc. Table 1 shows the number of images collected for each skin diseases. The anatomical sites include; abdomen, anterior torso, armpit, chin, ear, forehead, lateral face, lower back, lower extremity, nail, neck, periorbital region, posterior torso, scalp and upper extremity. Fig. 1 demonstrates sample of collected abnormal skin.

DATA PREPROCESSING

Image resizing, colour constancy, and data augmentation were performed before feeding the image to the deep learning network. All the images were resized to 180 x 180 pixels to match the input size of the VGG19 model. The shades of grey colour constancy algorithm were used in the pre-processing step to remove the colour bias of the clinical images. This was found to improve the classification accuracy of multisource images in literatures. The dataset was split into training (80%), validation (20%) prior to model training. Then data augmentation was applied to the training dataset by 90° rotation, horizontal and vertical image flipping to increase the number of datasets.

FIG. 1 SAMPLE IMAGE FROM THE SKIN DISEASES (A) ACNE VULGARIS, (B) ATOPIC DERMATITIS, (C) LICHEN PLANUS, (D) ONYCHOMYCOSIS, (E) TINEA CAPITIS AND (F) SEBORRHOEIC DERMATITIS

TABLE I. DATA COLLECTED

Disease	Number of images
Healthy	501
Acne and Rosacea Photos	600
Eczema	530
Psoriasis, Lichen Planus and related diseases	450
Tinea Ringworm Candidiasis and other fungal infection	526

WAVELET TRANSFORM INTEGRATION WITH VGG19

The Wavelet Attention VGG19 model is an advanced variant of the popular VGG19 architecture, enriched with wavelet attention mechanisms. It combines the power of VGG19's deep convolutional layers with wavelet attention to enhance its representational capacity and focus on essential visual features. The model aims to improve performance in image classification tasks, particularly in scenarios were capturing both local and global features is crucial.This integration enhances the model's ability to capture both local and global visual patterns in an image, making it more effective for challenging computer vision tasks.

The steps for integrating Wavelet Transform with VGG19 are as follows: Start with the original VGG19 architecture, which consists of 19 layers, including 16 convolutional layers and 3 fully connected layers. The VGG19 architecture uses small 3x3 filters for convolutions and max-pooling layers with a 2x2 window and a stride of 2 for down sampling. Use VGG19 for initial feature extraction from the input image. Apply convolutional and max-pooling layers to progressively extract hierarchical features from the image. Introduce wavelet filters to perform the Wavelet Transform on the intermediate feature maps obtained from VGG19's convolutional layers. The Wavelet Transform decomposes the feature maps into different frequency components at multiple scales, capturing both low-frequency and high-frequency visual patterns.

XGBoost is a powerful gradient boosting algorithm often used for multiclassification or binary classification tasks. In this case, it is employed to make binary predictions based on the features extracted by the VGG19 with Wavelet Attention. The enhanced feature representations from VGG19 with Wavelet Attention are used as input to the XGBoost classifier. XGBoost employs an ensemble of decision trees to these features, iteratively refining its predictions.

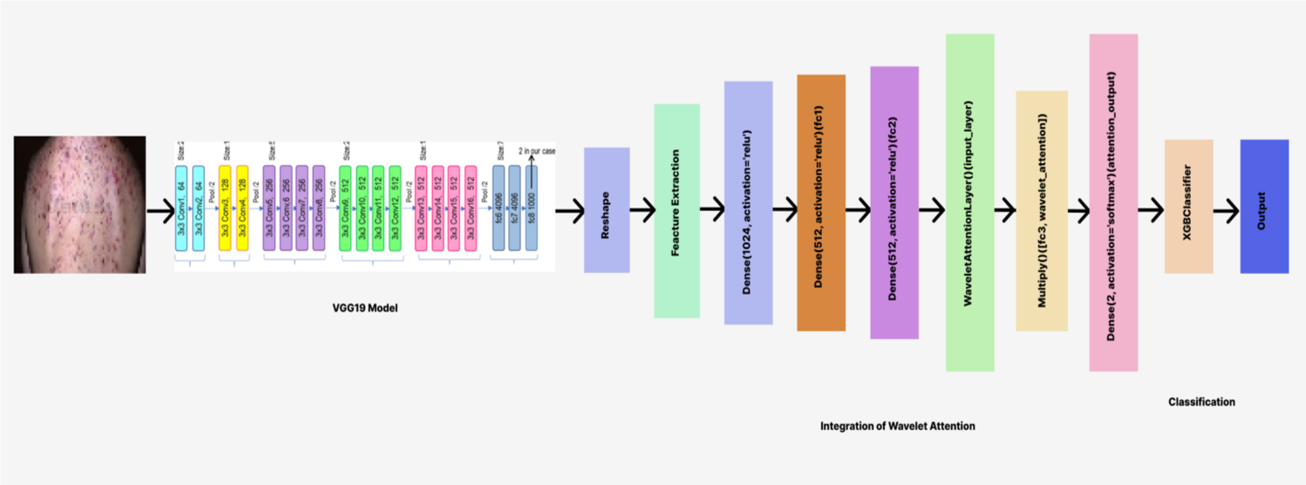

FIG.2 PROPOSED MODEL ARCHITECTURE

ALGORITHM IMPLEMENTATION

The VGG19 is used as our Feature Extraction Model. After preprocessing, we split our dataset into 80% train and 20% validation and then train our Wavelet Attention VGG19 model accordingly.

The integration of wavelet attention mechanism with the VGG19 architecture was done at after the convolutional layers, before the pooling layers. The wavelet attention layer takes the wavelet coefficients and feature maps as input and outputs the refined feature maps, which retain relevant information for classification.

IV. RESULT AND DISCUSSION

The balanced and scaled photos from the dataset were applied to learn the proposed model. Eighty percent of our training dataset is utilized for training, while the remaining twenty percent is used for validation. The models underwent 80 epochs of training. We evaluated the models' overall classification using the xgboost classifier. Below are the tables showing the result of the classification and training.

TABLE II. RESULTS SUMMARY OF THE PROPOSED MODELS

Accuracy		**Loss**	
Training Accuracy	**1.0000**	Training Loss	**1.0913e-04**
Validation Accuracy	**0.9726**	Validation Loss	**0.1155**

TABLE III. RESULTS SUMMARY OF THE PROPOSED MODELS

	Precision	**Recall**	**F1-score**	**Support**
micro avg	0.97	0.97	0.97	475
macro avg	0.98	0.96	0.97	475
weighted avg	0.97	0.97	0.97	475
samples avg	0.97	0.97	0.97	475

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From the TABLE II and TABLE III above, the overall classification report indicates that the XGBoost classifier is performing very well on the binary classification task, with high precision, recall, and F1-score values. These results suggest that the model is effectively distinguishing between the two classes in your dataset.

PERFORMANCE METRICS COMPARISON WITH STATE-OF-THE-ART APPROACHES

TABLE IV. PERFORMANCE METRICS COMPARISON WITH STATE-OF-THE-ART APPROACHES

Types of CNN Used	Sensitivity	Specificity	Precision	Accuracy
Inception V3	89%	93%	87%	91%
MobileNetV1	92%	89%	88%	92%
Wavelet Attention VGG19 and XGBOOST Model	**99%**	**94%**	**97%**	**98%**

The Deep Learning models was made using sensitivity, specificity, precision and accuracy. It shows that our proposed model **Wavelet Attention VGG19 and XGBOOST Model** performs better than InceptionV3 and MobileNetV1. Table 4 demonstrates the result. Sensitivity, specificity, precision, and accuracy were used to create the Deep Learning models. It demonstrates that **Wavelet Attention VGG19 and XGBOOST Model,** our suggested model, outperforms InceptionV3 and MobileNetV1. The figure below demonstrates the result.

FIG. 3 PERFORMANCE OF OUR PROPOSED MODEL

VISUALIZATION OF LEARNED FEATURES AND ATTENTION MECHANISM

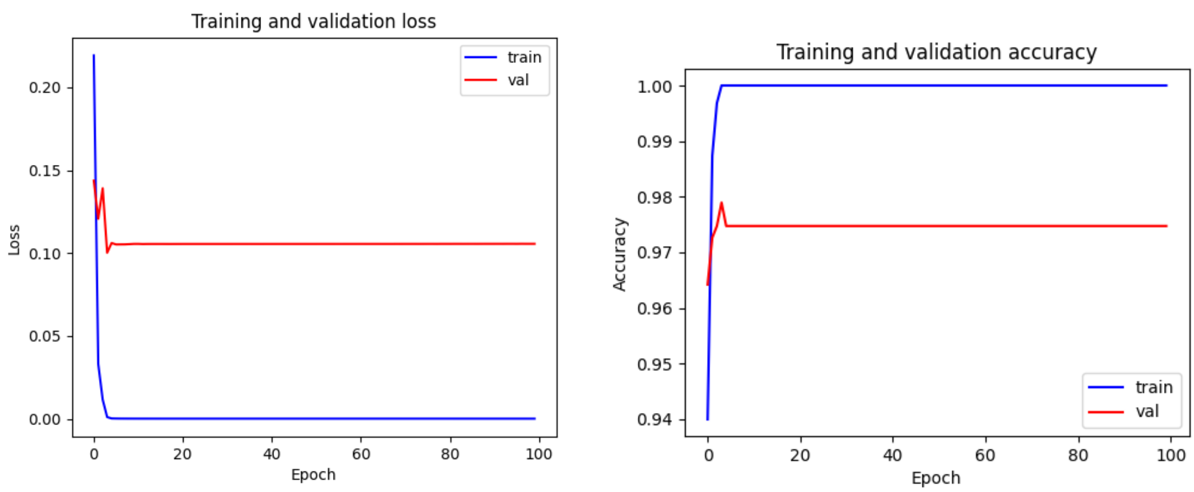

FIG. 4 LOSS AND ACCURACY GRAPH OF WAVELET ATTENTION VGG19 AND XGBOOST MODEL

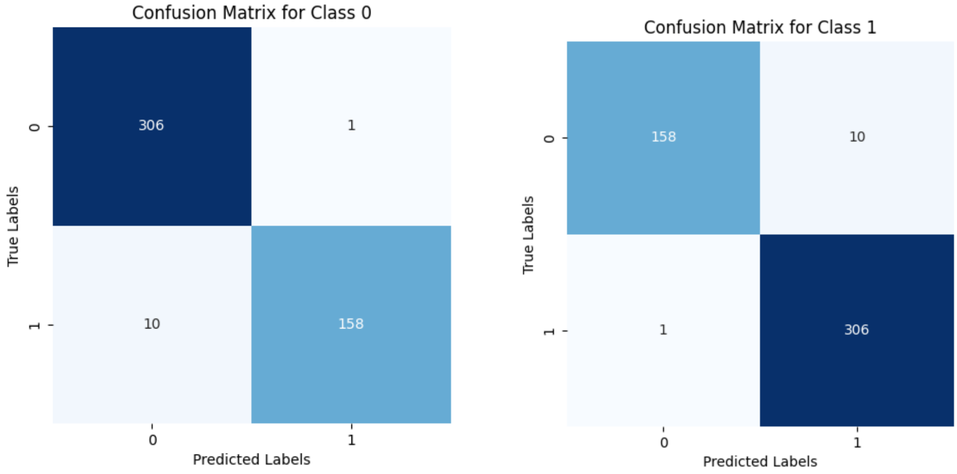

FIG 5. CONFUSION MATRIX OF OUR PROPOSED MODEL

INTERPRETATION OF EXPERIMENTAL RESULTS

Initial training loss, training accuracy, validation accuracy, and validation loss were all 0.20, 0.93, 0.97, and 0.11 respectively after 20 epochs. After 60 epochs, we achieved 98% training accuracy and 97% validation accuracy. The loss of the model was progressively decreasing. Training and validation losses were 0.15 and 0.12 respectively in the end. Table 4 shows how well our proposed model performs.

The training and validation accuracy of the proposed model is shown in Fig. 2 The training and validation loss is also displayed.

The XGBoost classifier was trained and evaluated using extracted features from the Wavelet Attention VGG19 model. The *objective*='binary:logistic' was used for binary classification, *n_estimators*=100 is the number of trees, *max_depth*=6 is maximum tree depth, *learning_rate*=0.1 is learning rate and *random_state*=42 is the random seed for reproducibility.

COMPARATIVE ANALYSIS OF DIFFERENT CNN ARCHITECTURES

The values are evaluated on repeated execution of the proposed model with a varied training level. The performance of the proposed model is compared against a Convolutional Neural Network (CNN), Deep CNN model, InceptionV3, and MobileNet V2 and LSTM models. In evaluating the proposed model's performance, the experimentation is repeatedly executed over the auxiliary computer on repeated execution of the model. The evaluations are done in concern to the number of times the proposed model accurately classifies the skin disorder that is considered the True Positive and correctly identifies that the image is not of that particular skin category as True Negative.

TABLE V. COMPARATIVE RESULT BETWEEN OUR WORK AND OTHER WORK

Work Done	Object (s) Dealt with	Size of Dataset	Approach	Accuracy
Viswanatha Reddy Allugunti [45]	skin disease classification using CNN	552	CNN	88.83%
Arora et al. [2]	Detect Eczema and non-Eczema	500	InceptionV3	97.5%
EczemaNet [43]	Classify different Eczema	2500	Deep CNN	96.2%
Parvathaneni Naga S. et al. [31]	skin disease classification	10,000	MobileNet V2 and LSTM	85.34%
Hussain et al. [16]	Skin disease classification	2000	CNN approach	93%
Yuan et al. [39]	Skin disease binary classification	616	Deep learning approach	89.4%
Our Work	**Skin disease classification**	**2506**	**Wavelet Attention VGG19 and XGBOOST Model**	**98%**

V. CONCLUSION

In this extensive research, we examined the integration of the Wavelet Attention mechanism with the powerful VGG19 architecture for skin disease categorization. This integration is a concentrated attempt to utilize the benefits of both techniques - wavelet transform's analysis, convolutional neural networks' deep feature learning capabilities and xgboost classifier. By integrating these techniques, we want to improve the model's accuracy, interpretability, and robustness in classifying different skin disorders from medical images.

ADVANTAGES OF THE PROPOSED APPROACH

1. **Enhanced Feature Extraction:** The combination of wavelet transforms and VGG19 improves feature extraction. The wavelet transform enables the model to capture both high-frequency and low-frequency information in images, which could be useful for detecting complicated patterns in skin diseases.

2. **Multi-Resolution Analysis:** Wavelet transform provides a multi-resolution analysis of images. This can help the model focus on both global and local features, potentially improving its ability to detect lesions, textures, and anomalies in various skin conditions.

3. **Improved Discriminative Features:** The combination of VGG19's deep convolutional layers and wavelet-transformed inputs has the potential to improve discriminative feature extraction. This is especially crucial for distinguishing between skin conditions that appear cosmetically identical.

LIMITATIONS OF THE PROPOSED APPROACH

1. **Complexity of Computation:** The integration of wavelet transform and deep learning can increase the computational complexity of the model, thereby affecting training time and resource requirements.

2. **Data Dependence:** The effectiveness of wavelet transform might be influenced by the characteristics of the dataset. If the dataset doesn't have enough texture variation, the benefits might be limited.

3. **Hyperparameter Tuning:** Integration introduces additional hyperparameters to tune, such as wavelet filter choice, levels of decomposition, and fusion mechanisms. Finding optimal settings can be challenging.

Finally, our findings highlight the potential of combining the Wavelet Attention mechanism with the VGG19 design as a possible path for improving skin disease classification. The integrated approach captures subtle patterns, textures, and anomalies in medical images by combining wavelet-attention analysis with deep feature extraction. While the approach offers significant benefits in terms of improved accuracy, it also acknowledges limitations such as higher computational complexity and hyperparameter adjustment.

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