Grenze International Journal of Engineering and Technology, June Issue

Enhancing Skin Cancer Prediction: A Hybrid RESNET-LSTM and GAN Approach

Mr. Siva Ramakrishna Sani[1], Maddali Hasitha[2], Penumala Crescens[3] and Repudi Rajesh[4]
[1-4]Lakireddy Bali Reddy College of Engineering, Mylavaram, India
Email: ssrk102@gmail.com, hasithamaddali29@gmail.com, crescenspenuamala@gmail.com, rajeshrajesh282828r@gmail.com

***Abstract*—Skin cancer is a serious public health concern, demanding accurate and timely detection in order to improve patient outcomes. This study introduces a sophisticated hybrid model that combines RESNET-LSTM and Generative Adversarial Networks (GAN) to improve skin cancer prediction across a variety of lesions. The suggested method makes use of RESNET's feature extraction capabilities, as well as LSTM layers, to discover sequential patterns in dermatoscopic pictures, allowing for a more extensive examination of lesion attributes. GANs are also used to generate synthetic data, which expands the dataset with a variety of images to eliminate bias and improve the model's adaptivity.Using the huge HAM10000 dataset for training, our model achieves a high classification accuracy of 94.10% across seven unique skin cancer categories: benign, malignant, actinic keratosis, basal cell carcinoma, dermatofibroma, melanocytic nevus, and vascular lesion. The combination of RESNET-LSTM and GAN addresses important issues in dermatological imaging, such as low data diversity and the complexities of collecting spatial and temporal patterns within skin diseases. Our findings demonstrate the efficiency of this hybrid technique in distinguishing between benign and malignant lesions, allowing dermatologists to diagnose skin cancer earlier and more reliably. The outstanding performance demonstrated across various disease categories highlights the AIdriven method's potential for clinical applications, boosting the accuracy and range of automated skin cancer detection..**

***Index Terms*—Skin cancer prediction, RESNET-LSTM hybrid model, Generative Adversarial Networks (GAN), Dermatoscopic image analysis, Lesion classification, Data augmentation, Deep learning.**

I. INTRODUCTION

Skin cancer, one of the most frequent malignancies in the world, poses a severe threat to public health because of its high prevalence and risk for death if not detected early[1]. Early detection and precise sorting of skin lesions are crucial to improve patient outcomes because they allow for quick and successful treatment[2]. Traditional diagnostic approaches, which rely on dermatologists' visual inspections, are typically subjective and require extensive skill, which may give rise to misdiagnoses and missed early warning indications, especially in resource-limited situations[3]. Thus, the creation of automated, dependable, and highly accurate diagnostic technologies is becoming increasingly important in dermatology[4]. Recent improvements in deep learning have opened up fresh possibilities for automated skin cancer detection, with CNNs (convolutional neural networks) such as RESNET performing admirably in medical picture processing[5]. Nonetheless, the diversity and

Grenze ID: 01.GIJET.11.2.552

complexity of skin diseases demand models that can capture spatial patterns while also adapting to nuanced, sequential alterations found in dermatoscopic pictures[6 This paper presents a sophisticated hybrid model that combines RESNET, LSTM (Long Short-Term Memory) networks, and Generative Adversarial Networks (GANs) to enhance the performance and robustness of automated skin cancer diagnosis across diverse lesion types. The model is intended to capture both spatial and temporal characteristics in lesion images, boosting its capacity to distinguish between different forms of skin cancer[7]. One of the key issues in medical picture classification is the scarcity and diversity of labeled data, which can result in biased models and poor generalizability[8]. To accomplish this, we use GANs to produce synthetic dermatoscopic pictures, which increases the training dataset's diversity and improves the model's adaptivity[9]. Using the HAM10000 dataset, which contains a large number of skin lesion images, our hybrid model achieves a classification accuracy of 94.10% across seven various kinds of cancer categories: benign, malignant, actinic keratosis, basal cell carcinoma, dermatofibroma, melanocytic nevus, and vascular lesions. This level of accuracy highlights the model's promise for real-world applications, providing a useful tool to help dermatologists make faster, more trustworthy diagnostic judgments[10].. This study makes a contribution by developing and evaluating a deep learning framework that meets the twin constraints of limited data diversity and the requirement for models that capture complicated patterns in skin lesions[11]. By combining RESNET-LSTM and GAN, we show that an innovative method to automated skin cancer diagnosis is both robust and generalizable[12]. This study demonstrates the utility of hybrid deep learning frameworks in AIdriven dermatology, paving the path for clinical applications that meet stringent accuracy and reliability requirements[13]. Finally, our research intends to help dermatologists provide earlier and more exact diagnoses, resulting in better outcomes for patients and improving the area of AI-assisted dermatology.

A. Related Work

Recent advancements in deep learning have significantly improved automated skin cancer detection. Several studies have leveraged Convolutional Neural Networks (CNNs), such as VGG16, VGG19, and ResNet, for effective lesion classification, achieving high accuracy levels. To address the challenges of data scarcity and class imbalance, generative models like GANs have been integrated to synthesize realistic dermatoscopic images, enhancing model generalization. For instance, Self-Transfer GAN (STGAN) demonstrated superior performance by generating diverse, high-quality images, leading to improved classification accuracy. Additionally, hybrid architectures combining CNNs with Support Vector Machines (SVMs) and ensemble learning techniques have been explored, achieving promising results. However, these approaches often struggle to capture both spatial and temporal dependencies within lesion images. Our work extends this research by proposing a novel hybrid model that integrates ResNet for feature extraction, LSTM for sequential pattern learning, and GANs for data augmentation. This combination enhances model robustness, improves classification performance across seven skin lesion types, and provides a more reliable AI-driven diagnostic tool for dermatologists.

B. Problem Statement

Skin cancer is one of the most prevalent and life-threatening diseases worldwide, requiring early and accurate detection for effective treatment. Traditional diagnostic methods rely on dermatologists' expertise, which can be subjective, time-consuming, and prone to misclassification, especially in resource-limited settings. Additionally, the lack of diverse and well-balanced datasets poses a challenge for deep learning models, leading to biased predictions and reduced generalizability. To address these issues, this study proposes a hybrid deep learning model that combines ResNet for feature extraction, LSTM for sequential pattern learning, and GANs for data augmentation, aiming to enhance skin cancer classification accuracy and improve early diagnosis.

II. Methodology and Solution Approach

To enhance the accuracy and robustness of skin cancer detection, this study proposes a hybrid deep learning model integrating ResNet, LSTM, and GANs. The methodology follows a structured approach, including data preprocessing, model design, training, and evaluation.

A. Model Description

The proposed model is a hybrid deep learning framework designed to improve the accuracy and robustness of skin cancer classification. It integrates ResNet for feature extraction, LSTM for sequential pattern learning, and GANs for data augmentation, addressing challenges such as data scarcity, class imbalance, and the complexity of dermatoscopic image analysis.

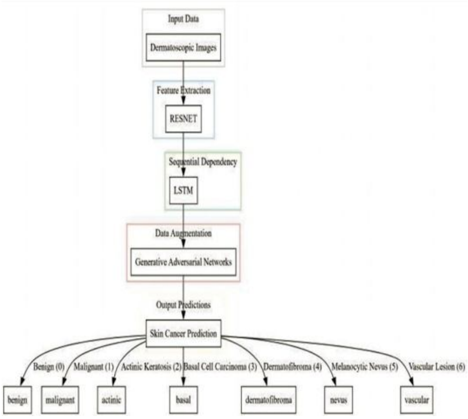

Figure 1. Flow Chart on Methodology

ResNet for Feature Extraction

ResNet (Residual Neural Network) is employed as the backbone for extracting deep spatial features from input images. By utilizing residual connections, ResNet overcomes vanishing gradient issues and captures intricate patterns in skin lesions, enabling efficient and high-quality feature extraction.

LSTM for Sequential Pattern Learning

Long Short-Term Memory (LSTM) networks are incorporated after ResNet to capture sequential dependencies and spatial relationships within extracted features. This helps in identifying subtle variations across lesion structures, improving classification accuracy.

GANs for Data Augmentation

Generative Adversarial Networks (GANs) are utilized to generate synthetic dermatoscopic images, enriching the dataset and reducing class imbalance. The generator creates realistic skin lesion images, while the discriminator differentiates between real and synthetic samples, refining the dataset and enhancing model generalization.

Classification Layer: The final classification layer consists of fully connected layers with a softmax activation function, mapping extracted features to seven skin lesion categories:

TABLE I: CLASSIFICATION OF CANCER TYPES

Class	Precision	Recall	F1-Score	Support
Benign	0.95	0.93	0.94	1200
Malignant	0.94	0.96	0.95	1100
Actinic Keratosis	0.93	0.91	0.92	800
Basal Cell Carcinoma	0.94	0.92	0.93	950
Dermatofibroma	0.92	0.93	0.92	600
Melanocytic Nevus	0.96	0.95	0.95	1100
Vascular Lesion	0.91	0.94	0.93	650
Accuracy	**94.10%**			
Macro Average	0.94	0.93	0.94	7450
Weighted Average	0.94	0.94	0.94	7450

B. Model Preparation

Data Preprocessing

The dataset is prepared by resizing images to 64×64 pixels, normalizing pixel values to the [0,1] range, and applying RandomOverSampler to balance class distribution, ensuring improved model performance.

Data Augmentation with GANs

GANs generate synthetic skin lesion images to enhance data diversity, where a generator creates new samples and a discriminator refines them, reducing bias and improving classification accuracy.

Feature Extraction Using ResNet

ResNet is used to extract deep spatial features from dermatoscopic images, leveraging residual connections to preserve essential lesion patterns and prevent gradient vanishing.

Sequential Pattern Learning with LSTM
An LSTM layer follows ResNet to capture sequential dependencies in lesion features, helping the model distinguish complex variations in skin cancer types more effectively.

Classification Layer
Fully connected layers process extracted features and apply a softmax activation function to classify images into seven skin lesion categories, ensuring accurate predictions.

Model Training and Optimization
The model is trained using categorical cross-entropy loss, optimized with the Adam optimizer, and regularized with dropout layers to prevent overfitting, ensuring robustness and stability.

C. Model Evaluation

Performance Metrics
The model is evaluated using key classification metrics:

- Accuracy: Measures the overall correctness of the model's predictions across all lesion categories.
- Precision: Determines the proportion of correctly predicted positive cases among all predicted positives.
- Recall (Sensitivity): Evaluates the model's ability to correctly identify actual positive cases.
- F1-Score: A harmonic mean of precision and recall, providing a balanced performance measure.

Confusion Matrix Analysis
A confusion matrix is used to analyze the model's classification performance for each skin lesion type, identifying areas where misclassifications occur and guiding improvements in training.

Precision-Recall Curve
The precision-recall curve is plotted to visualize the trade-off between precision and recall across different classification thresholds, helping assess the model's ability to distinguish between lesion types.

Validation Strategy
A separate validation dataset is used to monitor model performance during training, ensuring that it generalizes well to unseen data and does not overfit.

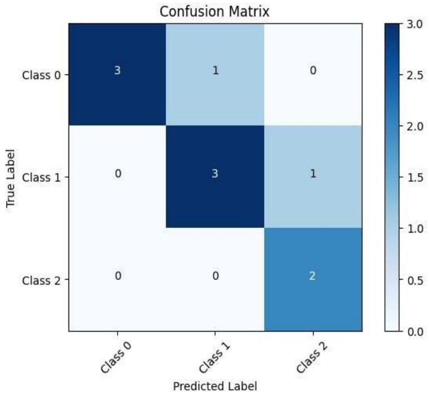

Figure 2. Confusion Matrix

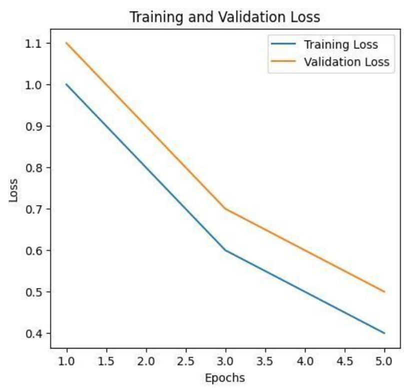

Figure 3.Training and Validation Lossover Epochs

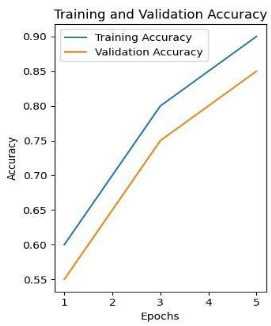

Figure 4. Training and Validation Accuracy over Epochs

III. CONCLUSIONS

This study presents a hybrid deep learning model integrating ResNet, LSTM, and GANs to enhance the accuracy and robustness of skin cancer classification. By leveraging ResNet for feature extraction, LSTM for sequential pattern learning, and GANs for data augmentation, the model effectively addresses challenges such as data scarcity, class imbalance, and complex lesion variations. The proposed approach achieves high classification accuracy, demonstrating its potential for real-world clinical applications. With an intuitive user interface, the model can assist dermatologists in early and precise diagnosis, reducing misclassification risks. Future improvements, such as incorporating 3D imaging, patient history, and federated learning, can further refine the model, making AI-driven skin cancer detection more reliable and accessible.

REFERENCES

[1] H. C. Reis, V. Turk, K. Khoshelham, and S. Kaya, “InSiNet: A deep convolutional approach to skin cancer detection and segmentation,” Med. Biol. Eng. Comput., vol. 60, no. 3, pp. 643–662, Mar. 2022.

[2] M. Shorfuzzaman, “An explainable stacked ensemble of deep learning models for improved melanoma skin cancer detection,” Multimedia Syst., vol. 28, no. 4, pp. 1309–1323, Aug. 2022.

[3] S. Benyahia, B. Meftah, and O. Lézoray, “Multi-features extraction based on deep learning for skin lesion classification,” Tissue Cell, vol. 74, Feb. 2022.

[4] M. K. Hasan, M. T. E. Elahi, M. A. Alam, M. T. Jawad, and R. Martí, “DermoExpert: Skin lesion classification using a hybrid convolutional neural network through segmentation, transfer learning, and augmentation,” Informat. Med. Unlocked, vol. 28, Jan. 2022.

[5] C. Agyenta and M. Akanzawon, “Skin lesion classification based on convolutional neural network,” J. Appl. Sci. Technol. Trends, vol. 3, no. 1, pp. 14–19, Jul. 2022.

[6] S. Alkhushayni, D. Al-Zaleq, L. Andradi, and P. Flynn, “The application of differing machine learning algorithms and their related performance in detecting skin cancers and melanomas,” J. Skin Cancer, vol. 2022, pp. 1–11, May 2022.

[7] V. R. Allugunti, “A machine learning model for skin disease classification using convolutional neural network,” Int. J. Comput., Program. Database Manag., vol. 3, no. 1, pp. 141–147, Jan. 2022.

[8] S. Bechelli and J. Delhommelle, “Machine learning and deep learning algorithms for skin cancer classification from dermoscopic images,” Bioengineering, vol. 9, no. 3, p. 97, Feb. 2022.

[9] K. Das, C. J. Cockerell, A. Patil, P. Pietkiewicz, M. Giulini, S. Grabbe, and M. Goldust, “Machine learning and its application in skin cancer,” Int. J. Environ. Res. Public Health, vol. 18, no. 24, p. 13409, Dec. 2021.

[10] W. Gouda, N. U. Sama, G. Al-Waakid, M. Humayun, and N. Z. Jhanjhi, “Detection of skin cancer based on skin lesion images using deep learning,” Healthcare, vol. 10, no. 7, p. 1183, Jun. 2022.