Skin lesion segmentation using deep learning

Hiral Patel [1], Nensi Panchal [2]
[1]PG scholar, Department of Computer Engineering, Bhagwan Mahavir College of Engineering And Technology ,[2]Assistant professor Department of Computer Engineering, Bhagwan Mahavir College of Engineering And Technology

***Abstract*—Segmentation of skin lesions remains essential in histological diagnosis and skin cancer surveillance. Recent advances in deep learning have paved the way for greater improvements in medical imaging. The Hybrid Residual Networks (ResUNet) model, supplemented with Ant Colony Optimization (ACO), represents the synergy of these improvements aimed at improving the efficiency and effectiveness of skin lesion diagnosis.To evaluate the effectiveness of the Hybrid ResUNet model for skin lesion classification and assess its impact on optimizing ACO performance to bridge the gap between computational efficiency and clinical utility.The study used a deep learning design on a complex dataset that included a variety of skin lesions. The method includes training a Hybrid ResUNet model with standard parameters and fine-tuning using ACO for hyperparameter optimization. Performance was evaluated using traditional metrics such as accuracy, dice coefficient, and Jaccard index compared with existing models such as residual network (ResNet) and U-Net.The proposed hybrid ResUNet model exhibited excellent classification accuracy, reflected in the noticeable improvement in all evaluated metrics. His ability to describe complex lesions was particularly outstanding, improving diagnostic accuracy.**

***Keywords*—Skin lesion segmentation, Deep learning, Hybrid ResUNet, Ant Colony Optimization, Medical imaging**

I. INTRODUCTION

Skin cancer is one of the most prevalent forms of cancer globally, impacting millions of individuals each year. It encompasses various subtypes, including melanoma, basal cell carcinoma (BCC), and squamous cell carcinoma (SCC), each with distinct levels of malignancy and public health implications [1]. Among these, melanoma is the most lethal if not detected early, leading to the majority of skin cancer-related deaths despite accounting for a smaller proportion of cases compared to BCC and SCC [2]. The incidence of melanoma continues to rise worldwide, with estimates indicating over 150,000 new cases annually, resulting in approximately 48,000 deaths each year [3].The economic burden of skin cancer extends beyond its direct impact on health, significantly straining healthcare systems. Costs associated with preventive measures, diagnosis, treatment, and long-term care contribute to substantial financial challenges. For example, in the United States alone, the annual cost of treating skin cancers exceeds $8.1 billion, underscoring the economic impact of this disease [4].Geographically, the rates of skin cancer are different; the highest rates are in countries with more exposure to Ultraviolet (UV) radiation. The highest rates of skin cancer worldwide are in Australia and New Zealand [5]. The variations are mostly the result of different skin types, daily lifestyles, and sun protection measures used by the community. Prevention and early detection are important strategies to address global skin cancer problems. Programs to reduce UV exposure are urgent and should include sunscreen and protective clothing. Moreover, public awareness campaigns geared towards early detection through routine skin examinations and expert dermatology have effectively reduced the mortality rate due to skin cancer [6].The global impact of skin cancer has profound implications for public health policy and healthcare systems. Continued efforts in disease prevention, early detection, and the development of alternative treatments are critical for mitigating the widespread effects of this common condition. Early detection remains paramount, as it significantly improves survival rates while reducing the need for aggressive treatments. Research emphasizes the importance of early diagnosis, which typically leads to favorable outcomes with less invasive interventions [7], the extent of skin cancer on the global level is staggering and leads to the making of public health policies and a new approach to healthcare systems. Completing preventative, screening, and advanced research in treatment are the most important things to be taken into account for reducing the consequences of this common condition. Skin cancer must be detected at an early stage because it is the best way to improve survival rates and reduce the severity of the treatments that are required. In most cases, dermatologists usually detect skin cancer very early by applying minimally invasive treatment methods. Such types of treatment are, without question, highly efficient and highly successful [8].Furthermore, AI-based diagnostics has already proven to be helpful in many cases. These models and algorithms are the result of machine learning and deep learning techniques that are capable of examining dermatological images with great accuracy. These models can differentiate between benign and malignant lesions with accuracy at par with dermatologists with extensive experience in this area [9]. Teledermatology is a form of telemedicine that provides remote diagnosis and management of skin lesions through sharing digital images between primary care providers and dermatologists, helping to speed up the diagnosis and make it possible for early intervention [10].One of the crucial points is the role of early diagnosis in treating skin cancer. This helps improve the prognosis, lowering healthcare costs and lightening the need for extensive treatments. Incorporating new diagnostic technological approaches and methodologies, especially AI and telemedicine, is essential to these processes, which may finally turn around skin cancer management globally. The progress made in multispectral and hyperspectral imaging technologies has been the key to getting the detailed analysis of skin lesions, which takes place by capturing information from diverse wavelengths [11]. These imaging modalities can detect slight variations in skin coloration and blood flow at a rate that cannot be seen by the naked eye, which may also be a sign of melanoma onset. Hyperspectral imaging is a remarkable technique that is capable of picking out cancerous tissue-specific spectral signatures, a tool that could be used as a non-invasive way of diagnosing skin cancer [12].Artificial intelligence (AI) has turned the world of dermatological imaging on its head by creating technology that can analyze complex image datasets straightforwardly. The deep learning models used by AI algorithms have now reached the same level of accuracy as dermatologists, thanks to their vast training data. These algorithms analyze high-resolution ultrasound (HRUS), optical coherence tomography (OCT), and other imaging modalities to identify malignancies and recommend diagnoses that substantially facilitate the diagnostic process and decrease the rate of human error [13].Research puts forward the hybrid model of ResUNet architecture with ant colony optimization (ACO). Integration, however, takes advantage of the deep learning capabilities in spatial data processing and the ACO's optimization of the training parameters. When these two algorithms are combined, they result in a robust algorithm that is specifically designed for skin lesion segmentation. The study performs better than other methods regarding image segmentation accuracy thanks to the hybrid model used. This model can precisely define the lesion peripheries in different contexts, which greatly improves the accuracy and applicability of the automated skin lesion analysis. This is critical for the early detection and treatment planning of skin cancer. The development of ACO for hyper parameter optimization is one of the major improvements compared to conventional training algorithms. This method automatically changes parameters like learning rate and batch size while training the model. Therefore, the model can improve its performance without human intervention. Furthermore, this method might help us to reduce the time and computer resources needed for the model training process.This study aims to design, implement, and evaluate a novel hybrid ResUNet model that incorporates the structural benefits of ResNet and U-Net architectures to improve the accuracy and efficiency of skin lesion segmentation. This includes the integration of ACO for hyperparameter tuning, aiming to optimize model performance. The study also assesses the model's robustness across various lesion types and potential for practical deployment in clinical settings. The overarching goal is to advance the field of medical image analysis and provide a tool that can aid in the early detection and treatment of skin cancer.

II .PROBLEM STATEMENT

The medical field of skin lesion segmentation has been subjected to great revolutions thanks to using different images and computational techniques. These innovations have contributed to the better diagnostic outcome of skin cancer by making it more accurate and efficient. This part of the review discusses the current advanced techniques for skin lesion segmentation.

[14]. Among the deep learning approaches, the Convolutional Neural Networks (CNNs) have become the most frequently implemented for the

automated analysis of dermoscopic images. The deep learning technique known as CNNs can learn complex patterns in the data without manual feature extraction. Such as U-Net, which is a very popular architecture that was designed specifically for medical image segmentation and can process effectively and segment images at different scales [15]. An AI-based model effectively diagnoses benign and malignant skin lesions, making it a useful tool for dermatologists. Researchers are further improving the reliability and precision of skin lesion analyses by developing ensemble approaches that utilize the predictions of several machine learning models. This approach of multimodal classifiers, based on the capacity of different algorithms, is less likely to give false negatives and has a higher overall reliability [16]. AI is still on its way to improving the segmentation techniques further using the imaging technique. Smart AI algorithms have now developed the capacity for automatic lesion boundary identification tasks, which are indispensable for accurate lesion excision and management. AI can also integrate the patient's clinical data into the segmentation process so that it can make the process more informed and patient-tailored, such as the risk factors and previous health history [17].

Using multi-modal imaging data, which includes dermoscopy, ultrasound, and magnetic resonance imaging (MRI) helps AI models get a deeper understanding. This method of examination makes it possible to study the superficial characteristics, depth, and spread of the lesion, which, in turn, aids the doctors in making a clear diagnosis and planning the treatment [18].. The researcher commonly used the international skin imaging collaboration (ISIC) dataset.

III PROPOSED SYSTEM

This study's hybrid ResUNet model, meant for skin lesion analysis, can be considered a breakthrough in medical image segmentation. This part elaborates on the model design, combining the classical U-Net and ResNet concepts to improve segmentation precision and computational efficacy.The hybrid ResUNet model combines the U-Net model's effective feature extraction and location determination features with ResNet's residual learning approach. This union results in deeper networks without the vanishing gradient problem typical of standard convolutional architectures.

Hybrid ResUNet model

ResNet is designed to address the degradation problem encountered in deep neural networks, where adding more layers leads to higher training errors [19]. The key innovation of ResNet is the introduction of residual learning through shortcut connections that allow gradients to flow directly through the network, enabling the training of very deep networks. ResNet features identity mappings that bypass one or more layers, effectively creating shortcuts or skipping connections. This architecture enables the network to learn residual functions, which are easier to optimize. ResNet's variants, such as ResNet-50, ResNet-101, and ResNet-152, are widely used for image classification, object detection, and other computer vision tasks. ResNet has been successfully applied in various tasks, including image classification, object detection, and semantic segmentation. Its ability to maintain performance with increasing depth has made it a standard in deep learning architectures. The model starts with the Input Layer, designed to accept 128×128 pixels images, which are mostly used in dermatoscopic datasets. Afterward, the Encoder contains multiple convolutional layers with growing filter sizes from 64 to 1024, aiming to capture the complex features at different scales and levels of detail. A residual block accompanies each convolutional layer to propagate features and gradients efficiently, and max pooling layers are interspersed to reduce spatial dimensions and expand the receptive field. At the Bridge, a central bottleneck composed of dense convolutional layers processes the most profound compressed features, linking the encoder to the decoder. The Decoder pathway includes transposed convolutional layers for upsampling feature maps, concatenates these with outputs from the encoder to preserve high-resolution details, and applies additional convolutional layers post-upsampling to refine the maps. Finally, the Output Layer employs a 1×1 convolution to transform the deep feature representations into the desired output classes, distinguishing lesion from non-lesion areas. Figure 1 depicts the architecture of Hybrid ResUnet.

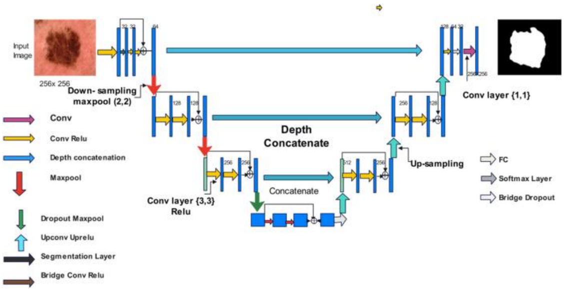

Fig1 Architecture of Hybrid ResUnet.

IV ALGORITHM

Integration of Ant colony optimization
Hybrid ResUNet employs ACO to fine-tune the network's hyper parameters, optimizing its performance. The algorithms section describes how ACO is implemented in the model and how the operations are performed on the input data.ACO is a probabilistic method that can efficiently solve computational problems, expressed as finding good paths through graphs. An ACO algorithm imitates the foraging behavior of the ants by optimizing the graph on the pheromone trail on the edges. In the area related to neural networks, ACO is used to choose the most preferable hyper parameters like learning rate, batch size, and number of epochs, which are often considered critical for the quality of the model. The fitness function in ACO measures the quality or suitability of a particular solution in optimizing the performance of the Hybrid ResUNet model. The fitness function evaluates each solution based on how well it improves the model's performance, guiding the search process toward the most effective hyper parameter configurations. The fitness function is a weighted sum of these metrics, with the Dice Coefficient and Jaccard Index being prioritized due to their relevance to segmentation quality. The function is defined as in Eq.

Fitness=w1×DiceCoefficient+w2×JaccardIndex+w3 ×Accuracy)

where w1, w2, and w3 are the weights assigned to each metric reflect their importance in the optimization process. These weights are selected based on the model's specific goals (e.g., maximizing segmentation accuracy).Algorithm employs ACO to fine-tune hyper parameters for a given model. The algorithm begins with initial hyper parameters and pheromone levels, deploying several artificial ants to explore the hyper parameter space. Each ant selects hyper parameters based on the probabilistic influence of pheromone trails, evaluates the selected hyper parameters' performance to obtain a fitness score, and updates a fitness record accordingly. Pheromones are then updated to reflect successful hyper parameter paths, with evaporation to discourage convergence on local optima and reinforcement to encourage exploration of promising regions.

Input: Initial hyperparameters H_0, Pheromone levels P_0, Number of ants N, Maximum iterations I_{max}

Output: Optimized hyperparameters H^*

1. **Initialize Pheromone Trails and Parameters:**
   $P \leftarrow P_0, H \leftarrow H_0$
2. **For each iteration $i = 1$ to I_{max}:**
   a. **Deploy ants to construct solutions:**
      i. $\forall$ ant a, select H_a based on P
      ii. Evaluate H_a using the model to get fitness f_a
      iii. Update fitness record: $F \leftarrow f_a$
   b. **Update pheromones:**
      i. Evaporate: $P \leftarrow P \times (1-\rho)$
      ii. Reinforce: $P \leftarrow P + \Delta P$ based on F
3. **Check convergence criteria:**
   a. If $\Delta F \leq \epsilon$ or $i = I_{max}$, terminate
   b. Otherwise, continue to the next iteration.
4. **Return H^*:**
   H^* is the hyperparameters set with the best fitness F

V.RESULT

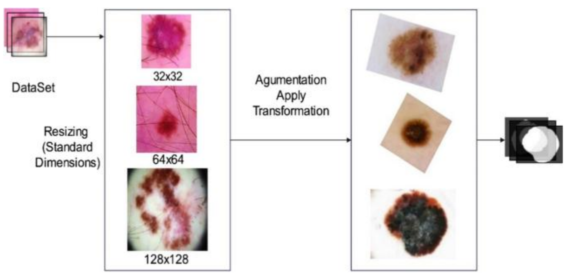

Fig 2: Skin lesion segmentation using deep learning algorithm with ant colony optimization

Our experimental results demonstrate that the proposed Hybrid ResUNet model outperforms existing state-of-the-art methods, achieving an accuracy of 95.8%, a Dice coefficient of 93.1%, and a Jaccard index of 87.5.The addition of ResUNet to ACO in the proposed Hybrid ResUNet model significantly improves the classification of skin lesions. This integration goes beyond traditional paradigms and demonstrates a viable strategy for deploying AI-powered tools in clinical settings.Future investigations will focus on increasing the version's abilities by using multi-modal imaging information, experimenting with alternative optimization algorithms, and comparing real-world medical applicability. There is also a promising scope for enhancing computational performance and exploring the model's interpretability for more clinical adoption.

VI.CONCLUSION

Hybrid ResUNet model for skin lesion classification, incorporating the sophisticated ACO method for hyperparameter tuning. Results show that the model performs better than traditional ResNet and U-Net architectures. Deep learning algorithms and intelligent optimization methods demonstrate potential, providing promising directions for medical applications' automated image analysis.

REFERENCES

[1] Concepcion J, et al. Trends of cancer screenings, diagnoses, and mortalities during the COVID-19 pandemic: implications and future recommendations. Am Surgeon™. 2023.

[2] Abdalla BMZ, Abdalla CMZ. Epidemiology of skin cancer. In: Oncodermatology: an evidence-based, multidisciplinary approach to best practices. Springer; 2023.

[3] Freeman K, et al. Algorithm based smartphone apps to assess risk of skin cancer in adults: systematic review of diagnostic accuracy studies. BMJ. 2020.

[4] McFerran E, Donaldson S, Dolan O, Lawler M. Skin in the game: the cost consequences of skin cancer diagnosis, treatment and care in Northern Ireland. J Cancer Policy. 2024..

[5] Yuan J, Li X, Yu S. Global, regional, and national incidence trend analysis of malignant skin melanoma between 1990 and 2019, and projections until 2034. Cancer Control.

[6] Reyes-Marcelino G, et al. School-based interventions to improve sun-safe knowledge, attitudes and behaviors in childhood and adolescence: a systematic review. Prev Med. 2021.

[7] Vizdoaga V, Lozan O, Bețiu M. Causes of late detection of skin cancer. Norwegian J Dev Int Sci. 2021.

[8] Malvehy J, Pellacani G. Dermoscopy, confocal microscopy and other non-invasive tools for the diagnosis of non-melanoma skin cancers and other skin conditions. Acta Dermato-Venereologica. 2017.

[9] Suleman M, et al. Smart MobiNet: a deep learning approach for accurate skin cancer diagnosis.

[10] Trettel A, Eissing L, Augustin M. Telemedicine in dermatology: findings and experiences worldwide–a systematic literature review. J Eur Acad Dermatol Venereol. 2018.

[11] Ilișanu M-A, Moldoveanu F, Moldoveanu A. Multispectral imaging for skin diseases assessment—state of the art and perspectives. Sensors. 2023.

[12] Fink C, Haenssle H. Non-invasive tools for the diagnosis of cutaneous melanoma. Skin Res Technol. 2017.

[13] Soare C, Cozma EC, Celarel AM, Rosca AM, Lupu M, Voiculescu VM. Digitally enhanced methods for the diagnosis and monitoring of treatment responses in actinic keratoses: a new avenue in personalized skin care. Cancers. 2024.

[14] Lallas A, et al. Accuracy of dermoscopic criteria for the diagnosis of melanoma in situ. JAMA Dermatology. 2018.

[15] Ronneberger O, Fischer P, Brox T. U-net: Convolutional networks for biomedical image segmentation. In: Medical image computing and computer-assisted intervention–MICCAI 2015: 18th international conference, Munich, Germany, October 5–9, 2015, proceedings, part III 18. Springer; 2015.

[16] Cordes D, Yang Z, Zhuang X, Sreenivasan K, Mishra V, Hua LH. A new algebraic method for quantitative proton density mapping using multi-channel coil data. Med Image Anal. 2017;

[17] Winkler JK, et al. Assessment of diagnostic performance of dermatologists cooperating with a convolutional neural network in a prospective clinical study: human with machine. JAMA Dermatology. 2023;

[18] Kuo KM, Talley PC, Chang C-S. The accuracy of artificial intelligence used for non-melanoma skin cancer diagnoses: a meta-analysis. BMC Med Inf Decis Mak. 2023;

[19] Fang W, Yu Z, Chen Y, Huang T, Masquelier T, Tian Y. Deep residual learning in spiking

neural networks. Adv Neural Inf Process Syst. 2021;

[20] Codella N et al. Skin lesion analysis toward melanoma detection 2018.

[21] Aydemir O. A new performance evaluation metric for classifiers: polygon area metric. J Classif. 2021.