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Metaheuristic-Assisted Hybrid Deep Learning Framework for Skin Cancer Detection, Segmentation, Classification, and Severity Prediction

Punam R. Patil[1], Ritu Tandon[2], Rajesh Kumar Nagar[3], Bhushan V. Patil[4]

[1,2] Department of Computer Science & Engineering, SAGE University, Indore, Madhya Pradesh.

[3] Department of Electronics & Communication Engineering, SAGE University, Indore, Madhya Pradesh.

[4]Assistant Professor, Department of Electronics & Telecommunication Engineering, R. C. Patel Institute of Technology, Shirpur, Maharashtra.

punam.patil@sageuniversity.in (https://orcid.org/0000-0001-5021-3547), ritu.tondon@sageuniversity.in (https://orcid.org/0000-0001-9248-8397), errajesh973@gmail.com (https://orcid.org/0000-0002-7805-4426), patilbhushan007@gmail.com (https://orcid.org/0000-0002-3346-2119)

Abstract. Skin cancer constitutes the most prevalent form of carcinoma, posing a significant threat to public health, with melanoma recognised for its particularly high mortality rate. The timely recognition of this pathology is crucial for the enactment of effective treatment modalities; nevertheless, traditional diagnostic techniques often face challenges due to deficiencies in image clarity and the complexities inherent in visual discrimination. This study introduces an advanced deep learning approach designed to achieve superior segmentation and categorisation of cutaneous neoplasms, with a distinct focus on the assessment of severity. Furthermore, the research includes a comprehensive analysis of the severity classifications of the identified cancers. Altogether, the potential of advanced deep learning methodologies to transform the landscape of skin cancer diagnostics is apparent, offering an integrative approach that enhances early detection, improves classification accuracy, and supports severity assessment, ultimately contributing to superior patient management and outcomes.

Keywords: Skin Disease Detection; Classification; Preprocessing; Dermoscopic images; Deep Learning.

1. INTRODUCTION

Cancer is a significant medical emergency characterised by the unrestrained proliferation of atypical cells within the human biological system. Melanoma is the most violent type of skin cancer. The best way of treating the melanoma disease is by detecting it early, as it can be cured easily before spreading to other parts of the body [1] [2]. The dermoscopic image is used to detect suspected skin lesions or melanoma due to its non-invasive nature. Several clinical measures, such as classical pattern analysis, a seven-point checklist, and ABCD rules, are used to detect melanoma in dermoscopic images based on local colour and texture patterns [3] [4]. Still, dermatologists struggle to distinguish various skin lesion types due to the similarities of intrinsic visual features among the skin lesion types. Recently, the researchers used an automated learning system to achieve performance equivalent to that of qualified dermatologists, which indicates the outlook for automated skin lesion analysis [5][6]. The skin lesion classification is the most complex issue in the recent research accomplishments due to the reasons like (i) The pigment areas of skin lesion images share strong visual similarities in various skin diseases types (ii) different visual patterns are observed in the same skin lesions (iii) more complex skin conditions like inconsistency of the color and the disturbing items including color marks, other artifacts veins, and hairs in the skin lesion images are also observed [7] [8]. Moreover, the dermatologists need to focus on the details of subtlety from the benign ones for distinguishing the malignant cases; however, the high intra-class variations and large inter-class similarities become difficult [9] [10]. Furthermore, the noisy items are introduced by the existence of a difficult skin condition, which affects the texture description and colour of the obtained image. This condition depreciates the classification performance [11]. Higher intra-class variation and strong inter-class visual similarity among different skin lesions are observed, which also makes diagnosis more difficult, even for experienced dermatologists. For improving the recent machine learning (ML) models, many research works are performed to support the skin lesions diagnosis [12] [13]. The Euclidean distances among the intra-class and inter-class samples are given as the extracted features to ResNet.

Several methods are used before the classification task for executing the skin lesion segmentation that provides the ROI region or boundary information for assisting the succeeding classification tasks [14]. Different skin lesion segmentation approaches, such as the deep CNN models, active contour models, region-merging-based methods and thresholding-based models, are used for this purpose. In recent times, the CNN-based models have attained more attention for the image classification task with superior performance. The neural network is initialised with pretrained weights from the same task for faster training and better performance [15] [16]. Therefore, the existing models used the most perceptive approach and a good starting point, and then they transformed the skin lesion classification task of the NN (neural networks) via fine-tuning parameters. Many techniques, such as test augmentation and ensemble, are used to boost the simulation outcomes of the skin lesion classification [17]. Thus, the multi-task structure is implemented for the skin lesion analysis that trains both the classification task and the segmentation tasks at the same time.

- **Motivation**

Skin cancer poses a major global health threat, with melanoma being the deadliest type. Early detection is crucial for effective treatment, while late-stage diagnosis drastically reduces survival rates. Although dermatologists use imaging tools for diagnosis, ordinary cameras often yield poor-quality images. Dermoscopy offers clearer visuals, improving lesion detection. Deep learning and convolutional neural networks enhance accuracy in skin cancer segmentation and classification. This study develops an efficient DL framework emphasising severity analysis in order to get around conventional computational and diagnostic restrictions.

- **Problem Statement:**

Melanoma in particular, which has a high death rate when discovered at an advanced stage, is still a serious global health concern. Conventional diagnostic techniques that use images from a conventional camera often yield poor-quality findings, making it difficult to detect and classify problems accurately. Even though dermoscopic imaging enhances vision, differences in lesion size, shape, and texture make segmentation and classification difficult. Current deep learning models lack severity analysis, are computationally costly, and are ineffective in classifying different forms of skin cancer. Therefore, to facilitate early identification and enhance patient outcomes, an effective deep learning-based framework is required that precisely segments, categorises, and analyses the severity of skin cancer.

- **Objectives:**

The primary objectives of this research are as follows:

1. To develop an enhanced feature extraction module for skin cancer classification by employing a Two-phase Self-Attention based Hierarchical Capsule Network (TSHCaps) that effectively captures spatial and contextual relationships within dermoscopic images.
2. To integrate the Tent Chaotic Walrus Optimisation Algorithm (TCWOA) into the detection framework to achieve optimal feature selection, reduce computational complexity, and enhance classification efficiency.
3. To design an efficient skin cancer segmentation approach using a Progressive Attention-based Hierarchical Residual Swin Transformer (PA-HRST) that accurately delineates lesion boundaries across multiple scales.
4. To propose a Global Attention-based Multilevel Semantic Knowledge Alignment Distillation Network (GA-MSKAD) for precise and robust skin cancer classification through effective feature alignment and semantic knowledge transfer.
5. To introduce a Residual Lasso Logistic Regression (RLLR) model for predicting the severity level of skin cancer based on extracted deep features and optimised parameters.

2. LITERATURE REVIEW

A survey of various related techniques for skin cancer segmentation and classification is described below.

A study [18] implemented a shape-based segmentation approach in order to precisely locate skin lesions using a combination of Active Contour Segmentation, ResNet50, Capsule Network, and SGD efficiency. The representation demonstrated high performance with 98% accuracy and an AUC-ROC of 97.3%, proving its robustness in feature extraction and lesion boundary detection. In [19], a FrCN-DGCA model was proposed employing a Dynamic Graph Cut Algorithm along with transferring models and FrCN architecture for skin lesion segmentation. The system achieved 97.986% accuracy and 94.335% precision, indicating effective pixel-level segmentation and classification capability. In [20], a GHO-DCaNN model integrating GHO-Capsule Neural Network, SSFO, and a Hybrid GHO optimiser was designed to enhance skin cancer detection with 99.06% accuracy, 97.83% specificity, and 99.50% sensitivity, signifying superior detection precision.

A hybrid framework [21] integrating GNN with a Capsule Network and Tiny Pyramid ViG was developed to enhance skin cancer classification. This architecture achieved 95.52% accuracy after 75 epochs of training, confirming the effectiveness of mixing graph-based and capsule-based representations. An optimised Convolutional Neural Network (CNN) approach [22] was applied for early detection of dermal lesions, using the DICE metric, which achieved 98.66% accuracy, indicating its capability for early-stage lesion identification. In [23], a Coot Search Optimisation Algorithm was applied utilising a Capsule Network to enhance the process of segmentation. The proposed method attained an impressive 99.26% accuracy, highlighting its superior segmentation efficiency. A fuzzy-GLCM-based technique [24] employing CapsNet, dynamic routine mechanisms, and F-CapsNet architecture was developed to reduce contrast distortions in dermoscopic images. This model achieved 99.16% accuracy on the 2017 ISBI dataset, 99.45% on the 2019 ISBI dataset, and 98.42% on the PH2 dataset, showcasing exceptional consistency. The MICaps model [25], developed using UNet and Capsule Network, was designed for recognising multiple object instances. It improved diagnostic performance by up to 3.27%, indicating effective multi-object feature recognition. A CBAM-integrated FixCaps model [26] was employed to minimise spatial information loss. FixCaps, CBAM, and Capsule Network combined achieved 96.49% accuracy, confirming improved spatial feature retention. The study [27] that utilised Convolutional Blocks with Capsule Networks addressed complex lesion classification challenges, achieving 98.93% accuracy, 98.52% specificity, 95.7% recall, and 98.87% F1 score, demonstrating well-rounded and sturdy performance. A CNN-CapsNet hybrid approach [28] was implemented for recognising cuticle integuments, attaining 98.9% accuracy, emphasising its reliability. In [29], an AI-based diagnostic system was developed using five transfer learning models, optimisation techniques, and an Inception-ResNet architecture for detecting the Monkeypox virus. In the [30] study, Metaheuristic Optimisers were incorporated with various AI-based classifiers for skin disease diagnosis, reaching 87.30% accuracy, signifying potential for future optimisation-based frameworks. A study [31] employed image processing techniques and dermatological screening using Support Vector Machines (SVM), achieving 90.8% accuracy for effective skin disease detection. The incorporation of ICSO, Derm-CDSM, and MSSO methods [32] formed a deep learning hybrid method that showed excellent accuracy in skin cancer classification and segmentation.

A CNN-based approach [33] was used for image feature extraction and classification, incorporating machine learning and Softmax algorithms, yielding high accuracy and strong feature discrimination capabilities. Study [34] focused on deep learning (DL) with a robust dataset for skin disease detection, to achieve an optimal model performance with high accuracy. In [35], a hybrid model combining Deep Neural Network (DNN) and Random Forest (RF) was developed to enhance performance, achieving 96.8% accuracy. A mobile-based study [36] implemented MobileNet and CNN to design an AI-powered mobile application for epidermal disease detection, achieving approximately 85% accuracy, suitable for real-time screening. The transfer learning-based research [37] utilised the Xception model with fully connected (FC) layers, achieving 96.40% accuracy, highlighting superior classification efficiency. Another CNN-based vision model [38] using the DermNet dataset achieved 98.6%–99.04% accuracy. In [39], a ViT-Vision Transformer model was employed for skin disease detection and classification, achieving 81.6% accuracy, showing potential for transformer-based analysis. A CNN model [40] incorporating Computer-Aided Diagnosis (CAD) techniques achieved approximately 90% accuracy, enabling improved lesion segmentation and classification. The CNN fusion model [41] used for classification, achieving 95.29% accuracy and an F1 score 89.99%, is effective in multi-model integration. A Swin Transformer and CNN-based hybrid approach [42] achieved 97.2% accuracy and 97.9% specificity, confirming its high reliability for skin lesion classification. Using the HAM10000 dataset, a binary-class CNN model [43] classified seven types of skin cancer, attaining 95.2% accuracy, emphasising strong dataset adaptability.

In [44], a six-step deep learning (DL) process was implemented for feature extraction and classification, though it resulted in low accuracy. The MobileNet-v2-based automated system [45] achieved 97.5% multiclass classification accuracy, proving its strength in diagnosing epidermal diseases. To analyse and extract features, a Deep Convolutional Neural Network (DCNN) [46] was created, achieving high accuracy in skin disease detection. Lastly, the study [47] integrating DCNN with the Biogeography-Based Optimisation Algorithm (BBOA) achieved up to 98% accuracy, exhibiting outstanding automation and optimisation in the classification of skin diseases.

Research Gaps

- Computer Resource Requirements: Although the frameworks put out by Behara et al. [18] and Adla et al. [19] achieve high levels of accuracy, they require a significant amount of computer power, which may not be feasible in settings with constrained resources.
- Model Interpretability and Transparency: Despite achieving high performance levels, models like the one shown by Dubey et al. [20] usually function as "black boxes," making it challenging for physicians to have faith in and use these technologies efficiently.

- Class Imbalance in Datasets: A number of studies, such as those by Anand et al. [37] and Shanthi et al. [38], run into issues with class imbalance in datasets, which can skew model performance and reduce its generalisation ability.
- Image Quality and Pre-Processing Dependency: Yanagisawa et al. [40] and Wei et al. [41] devised methodologies that highlight the vital need for accurate segmentation and efficient feature extraction.
- Integration of Multimodal Data: As demonstrated by the research of Muhaba et al. [45], there is an urgent need for more thorough studies that integrate multimodal data, including clinical metadata and patient history.

3. PROPOSED METHODOLOGY

The well-designed deep learning (DL) methods introduced in this research are specifically for successful skin cancer classification and segmentation. Figure 1 shows the architectural structure of the proposed framework. For improving feature precision, pre-processing was applied to the input dermoscopic images initially for noise elimination using an Enhanced Low Pass Wiener Filter (ELPWF), which effectively removes unwanted noise while maintaining vital image details. After denoising, the pre-processed data were examined, and discriminative features were extracted based on the Two-phase Self-Attention based Hierarchical Capsule Network (TSHCaps). It effectively preserves complex spatial relationships and hidden features while concentrating on the most important regions of the image with self-attention mechanisms.

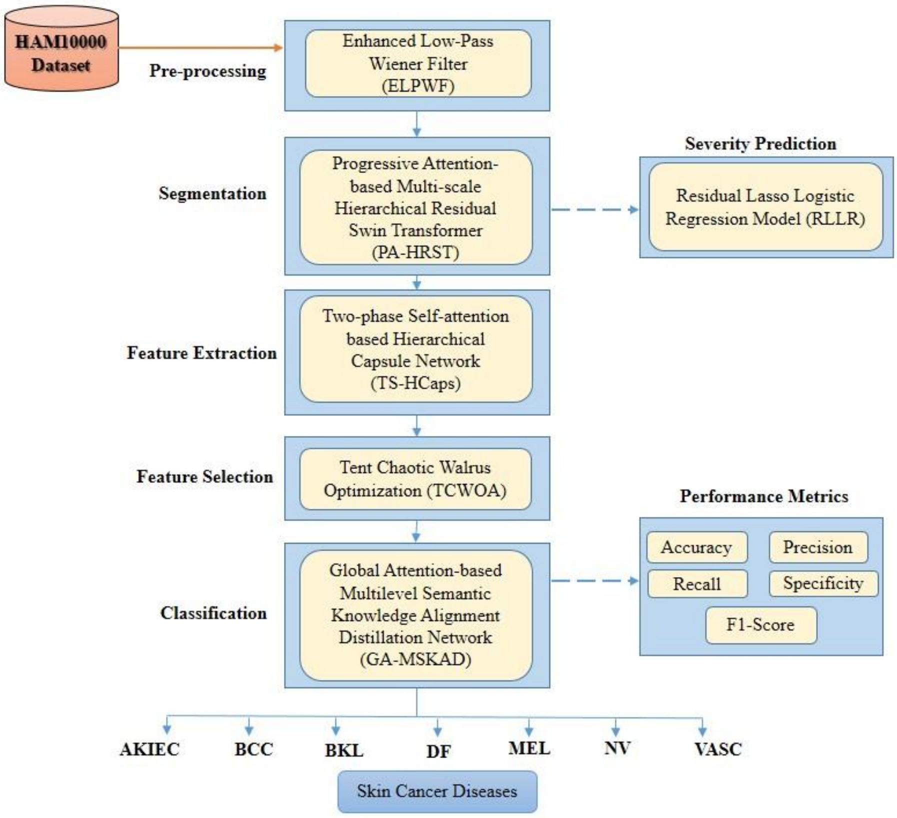

Figure 1. Architectural View of the Proposed Work

The Tent Chaotic Walrus Optimisation Algorithm (TCWOA) was then utilised for optimal feature selection so that efficient computation is achieved by removing unnecessary computations and keeping the most instructive attributes. The resulting features were then subjected to the Progressive Attention-based Hierarchical Residual Swin Transformer (PA-HRST), which processes local and global contextual information by utilising its hierarchical structure. So that the decision-making interpretability and transparency are enhanced. Finally, the Global Attention-based Multilevel Semantic Knowledge Alignment Distillation Network (GA-MSKAD) was used to enhance classification accuracy via multilevel semantic alignment and knowledge distillation. Subsequent to classification, the Residual Lasso Logistic Regression (RLLR) model was used to forecast the severity level of the identified cancer, utilising different clinical and image-related severity measures to supply a complete diagnostic assessment, as shown in Figure 1.

4. RESULTS & DISCUSSION

This study was tested on the skin disease dataset HAM10000 using the proposed strategy against existing hybrid classifier models such as ResNet-RNN [48], ResNet-VGG [49], EfficientNet-BiLSTM [50], CNN-Transformer [51], and Swin Transformer-CNN [52] to determine how much it improved performance.

4.1 Dataset Description:

The dataset comprises dermatoscopic images from diverse populations, gathered and stored using various modalities. The standard skin lesion dataset HAM10000 contains 10,015 skin lesion images from different populations organised into seven primary kinds [53].

4.2 Classification Analysis

The CNN model's performance on a dataset encompassing 300 epochs, along with the accuracy and loss analysis conducted for the proposed CNN model, yielded the findings depicted in Table 1 below.

TABLE 1**.** Results and Performance of Own CNN Model

Parameters	Proposed Own CNN model
Training Accuracy	99.55
Training Loss	0.015
Testing Accuracy	99.18
Testing Loss	0.1114
Training Time	1.1092
Testing Time	0.8144
Epoch	300

As shown in Table II below, the proposed hybrid model outperforms all comparative approaches across all performance metrics. While traditional combinations such as ResNet-RNN and ResNet-VGG achieve accuracies of 95.76% and 94.73%, respectively, the proposed model achieves 99.18% accuracy, 99.03% specificity, 99.13% recall, 99.09% precision, and an F1-score of 99.11%, demonstrating its superior capability in skin cancer classification. The results highlight the effectiveness of integrating hierarchical attention mechanisms, capsule-based feature extraction, and metaheuristic optimisation in enhancing overall model performance. As per Table 2

TABLE 2. Performance Comparison of Classification Methods with the Proposed Model

Models	Accuracy	Specificity	Recall	Precision	F1-score
ResNet-RNN	0.9576	0.9501	0.9513	0.9479	0.9496
ResNet-VGG	0.9473	0.9447	0.9465	0.9439	0.9452
EfficientNet-BiLSTM	0.9306	0.9253	0.927	0.9247	0.9259
CNN-Transformer	0.9147	0.9116	0.9117	0.9093	0.9105
Swin Transformer-CNN	0.9004	0.8992	0.9013	0.8983	0.8998
Proposed Model	**0.9918**	**0.9903**	**0.9913**	**0.9909**	**0.9911**

4.3. Severity analysis

Figure 3 depicts the severity analysis of the proposed RLLM model. The proposed model uses a Residual LASSO with logistic regression to standardise the regression process by finding slightly significant features. Here, the residual LASSO model identifies the most relevant features uniform in noisy information, and the LR model predicts the severity of cancer.

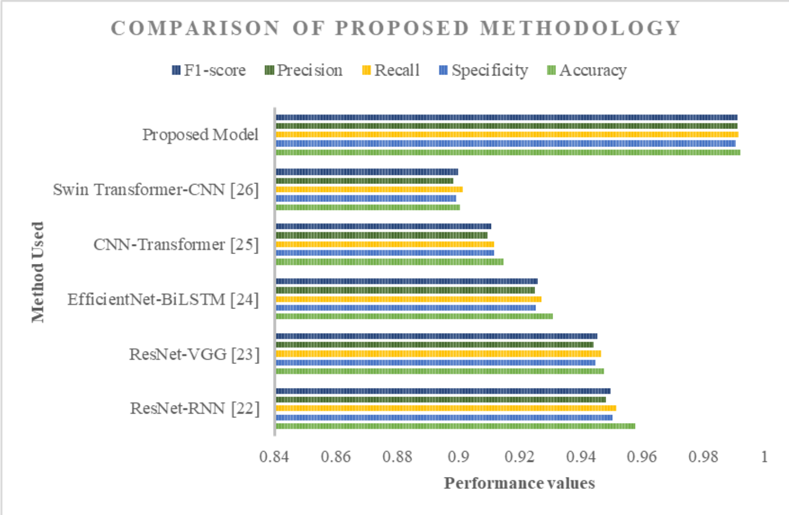

Figure 2. Performance Comparison of Proposed Model with Baseline Methods

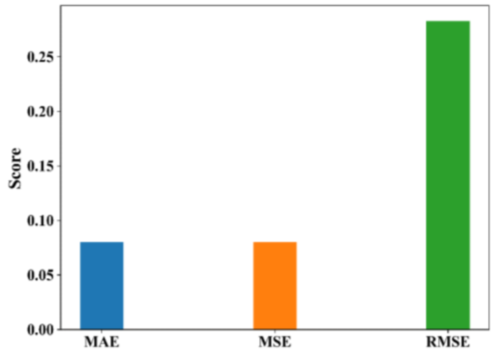

Figure 3. Severity analysis of the proposed model [53]

The proposed model achieved very low error values, an MAE of 0.08, an MSE of 0.08, and an RMSE of 0.282, indicating high accuracy and reliability in the severity analysis of skin diseases with minimal prediction deviations. Use "Tables caption" style for table caption and "Table body" style for text inside the table. Tables must be in an editable format. Avoid using pictures.

CONCLUSIONS

Large volumes of medical data can be analysed, and useful information can be extracted using deep learning. This study aims to analyse a number of research publications concerning various approaches that have been applied based on skin lesions, with a particular focus on how different researchers performed the first automatic diagnosis of skin cancer. In order to increase the survival rate, we want to develop an efficient deep learning technique for the best skin cancer segmentation and classification, with a focus on severity analysis. This study used the HAM10000 database to make an early diagnosis of skin cancer. By enabling early detection of skin cancer and boosting the precision and effectiveness of skin cancer diagnosis through the use of CNN and other DL techniques, the goal is to enhance patient outcomes. Through a variety of metrics, including classification accuracy, sensitivity, precision, recall, and so on, the selected technique will be compared to other hybrid conventional models in order to undertake a performance study. The suggested framework performs better than current approaches and accurately classifies dermatological malignancies associated with skin cancer.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTION

Punam R. Patil: Writing – original draft, Formal analysis, Conceptualisation, Methodology, Validation, Software, resources, data curation. **Ritu Tandon:** Writing – review and editing, supervision, Formal analysis, Conceptualisation. All authors contributed to the article and approved the submitted version.

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