Journal of Neonatal Surgery
ISSN(Online): 2226-0439
Vol. 14, Issue 15s (2025)
https://www.jneonatalsurg.com

OPEN ACCESS

An Efficient Skin Cancer Segmentation and Classification with Severity Analysis Using HAM10000

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Cite this paper as: Punam R. Patil, Dr. Ritu Tandon, (2025) An Efficient Skin Cancer Segmentation and Classification with Severity Analysis Using HAM10000. *Journal of Neonatal Surgery,* 14 (15s), 1866-1877.

ABSTRACT

The skin is the largest organ in the human body**.** The most common form of cancer that poses a significant threat to public health is skin cancer with melanoma being particularly deadly. The successful treatment depends on early advancement, yet traditional diagnostic methods often fail due to limitations in image quality and the complexity of visual differentiation. This study explores and propose an efficient deep learning approach for optimal segmentation and classification of skin cancer, with a focus on severity analysis. The proposed approach employs sophisticated image pre-processing techniques to remove noise while preserving essential features. These techniques ensure that the images used for analysis are of high quality, which is crucial for accurate diagnosis. The study focuses on extracting relevant features from these pre-processed images, leveraging innovative methods to capture complex patterns and dependencies within the data. For classification, the hybrid approaches integrates various advanced strategies to ensure robust and accurate identification of skin cancer types. These methods are designed to be efficient and effective, even in resource-constrained environments, addressing the computational challenges often associated with deep learning models. Furthermore, the study includes a comprehensive analysis of the severity of the identified cancers. The integration of these advanced techniques offers a holistic approach to skin cancer diagnosis, from initial detection to detailed severity analysis. The dataset is separated into training and testing. The experimental results performed on the HAM10000 dataset demonstrate that the proposed model can identify and predict skin diseases with 99.18% testing accuracy. Overall, the potential of advanced deep learning techniques to transform skin cancer diagnostics, offering a robust solution that enhances early detection, classification accuracy, and severity assessment, ultimately improving patient care and outcomes. To optimize model results, future investigations must take interpretability, dataset diversity, and the inclusion of medical metadata toward attention.

Keywords: *Deep Learning (DL), Skin cancer disease, classification, pre-processing, feature extraction, Hybrid approach.*

1. INTRODUCTION

The unquantifiable growth of abnormal cells within a biological system is an identifier of cancer. These cells possess the ability to replicate, divide, and spread via the lymphatic system and bloodstream, eventually disrupting and damaging healthy bodily tissues [1]. The epidermis, which is the skin's outer layer, comprises squamous cells, basal cells, and melanocytes. Squamous cell form the surface layer, basal cells reside at the bottom of the epidermis, and melanocytes generate melanin, a protective brown pigment shielding the deeper skin layers from sunlight harm [2]. Exposure to UV light can induce changes in DNA, prompting the proliferation of skin cells that can result in skin cancer. The primary forms of skin cancer are Melanoma, Squamous Cell Carcinoma, and Basal Cell Carcinoma, each associated with melanocytes, squamous cells, and basal cells, respectively [3]. Following cardiovascular disease, skin cancer has the world's second-highest mortality rate.

Skin cancer constitutes 33% of all cancer diagnoses, making it the most prevalently diagnosed variant of neoplastic disease. Non-melanoma skin cancer comprises 1.2 million cases, whereas melanoma represents 324,635 cases [4]. Exposure to environmental elements like air pollution, genetic predisposition, and unhealthy behaviors such as alcohol consumption and smoking can result in DNA damage, increasing the risk of developing cancer [5]. According to world health organization (WHO), melanoma alone accounts for 75% of all deaths related to skin cancer. The standard diagnostic approach for detecting skin cancer typically involves the biopsy method [6]. Identifying photographs accurately might pose challenges due to skin lesions [7].

Recent advancements in imaging processing techniques and artificial intelligence (AI) frameworks relevant to the diagnosis of diseases and prognosis have markedly enhanced the survival rates for different types of cancer [8]. Skin lesions can be classified into several categories, including melanoma (MEL), melanocytic nevus (NV), vascular lesion (VASC), and various others. MEL will grow and spread faster than the other types [9]. Computer-aided diagnosis (CAD) systems play a pivotal role in delivering preliminary assessments of diverse lesions. In alignment with the traditional medical imaging evaluation protocols, CAD systems generally utilize machine learning strategies to scrutinize images of dermatological lesions.

In modern times, technology has advanced to the extent that it holds a substantial influence within the medical field [10]. Recent advancements in technology have introduced the notion of neural networks, which exhibit impressive capabilities in classifying medical images. However, their potential is often restricted due to a narrow exploration of deep learning models [11]. Recent research indicates notable efficacy in binary classification of skin lesions using deep learning models [12]. The fundamental criteria necessary for the formulation of a skin cancer diagnostic application, which underscores extensive image segmentation and deep learning-oriented tracking of skin lesions, necessitate the initial manipulation of the data by resizing it to a resolution of 120×120 [13].

Finally the images are fed into the neural network models and the process further moved for the purpose of detection. The fundamental components to various DL-based image classification have been continuously improved [14]. Furthermore CNN related image classification have border problems including the ability to learn erroneous sensitivity to slight picture alteration and adversarial weakness. In order to accurately classify dermoscopic skin lesions images into different classes, this specialized CNN technique is designed [15]. Among the various models, still there is a need for effective model in skin cancer classification.

1.1 Problem formulation:

Skin cancer- the most widely recognized forms of cancer, posing a significant threat to individuals worldwide. Among its various forms, deadly lymphoma, a type of skin tumor, results in numerous fatalities each year. Early detection of skin cancer, including melanoma, is critical for effective treatment through straightforward extraction procedures. However, late-stage diagnosis is associated with a significantly higher risk of mortality, with survival rates dropping to less than 20% after the disease reaches an advanced stage. Dermatologists utilize various non-intrusive tools for diagnosis, such as visible images captured by cameras or smartphones. Unfortunately, these images often suffer from inadequate quality. Dermatoscopic devices, on the other hand, provide superior visual representation and serve as valuable non-invasive tools for detecting deadly pigmented skin lesions.

Dermoscopy enhances the differentiation between various types of sores based on appearance and morphological characteristics. Melanoma, a highly malignant disease, poses significant challenges when it comes to identification using traditional methods like ordinary cameras. This disease affects DNA, leading to overexposure of skin cells to harmful ultraviolet (UV) rays and subsequent skin pigmentation. If melanoma is not detected early, it can infiltrate deeper into the body, causing damage to lymph nodes and blood vessels. Traditional methods of skin cancer identification, including the use of ordinary cameras, often fall short in accurately diagnosing melanoma due to the limitations in image quality and the complexity of visual differentiation. This underscores the necessity for advanced diagnostic tools. CNN and other DL methods have shown immense potential in facilitating accurate diagnosis and treatment.

1.2 Motivation

The primary aim of this study is to create an efficient deep learning approach for the optimal segmentation and classification of skin cancer, with a focus on severity analysis. Deep learning is particularly well-suited for analyzing large amounts of medical data and extracting valuable information from it. By leveraging the capabilities of CNN and other DL techniques, the goal is to enhance the accuracy and effectiveness of skin cancer diagnosis, thereby enabling early detection and improving patient outcomes. This approach promises to address the challenges posed by traditional diagnostic methods, providing a robust solution for identifying and categorizing skin cancer, particularly melanoma, at various stages of severity.

1.3 Significance of the study

1. Diagnosing of various medical conditions in the arena of Dermoscopy, classification of skin lesions plays an invital role.
2. To profound issue of melanoma detection there is widely used of multispectral imaging and confocal microscopy.
3. Early detection of skin cancer requires accurate detection as well as high classification rates for melanoma.
4. Now a days, one of the deadliest skin cancer type is Melanoma whose early diagnosis increases survival chances of patient.

1.4 Objectives of the study

1. To study and explore the increasing role of Deep learning methods in skin cancer disease.
2. To design and implement hybrid deep learning model for skin cancer disease detection.

3. To optimize the model for Skin Cancer Classification and severity prediction.
4. To measure the performance of proposed model in terms of accuracy, precision and recall with the existing models with severity analysis for skin cancer detection.

1.5 Organization of the work

The subsequent sections of this manuscript are organized as follows: Section 1 provides a comprehensive overview of deep learning methodologies pertinent to the diagnosis of skin cancer with its problem formulation, motivation, significance and objectives of the study while Section 2 presents an exhaustive review of relevant techniques associated with the identification of skin diseases. Section 3 articulates a succinct overview, supplemented with illustrative imagery, of the entire methodology employed for the hybrid skin cancer detection model proposed in this study. In Section 4, a meticulous assessment of the performance metrics achieved by the proposed model is undertaken, in comparison to existing methodologies, enhanced by graphical representations. Lastly, Section 5 elucidates the overarching conclusions derived from the proposed model, along with prospective future directions.

2. RELATED WORK:

The following is an overview that some of the strategies used in skin disease detection. The overview of diverse methodologies for the detection of skin diseases is as,

Behara et al. [16] focused on introducing specific methodologies for sky-scraping the feature discrimination and its performance by combining the snake models which belonged to active contour segmentation (AC) along with ResNet50 and Capsule Network. Adla et al. [17] introduced a new CAD system which was based on the detection of epidermis lesions and then created a hyper-parameter FrCN model which was optimized for identifying various kinds of skin cancer through utilizing dermoscopy images. Dubey et al. [18] aimed to address the need for skin cancer detection with more accuracy and efficiency. The author presented a novel based approach with Golden Hawk optimization technique which is hybridized with a distributive capsule neural network (GHO-DCaNN). Santoso et al. [19] focused on analyzing and calculating the Tiny Pyramid ViG technique which is integrated with a Capsule Network. The authors aggregated Graph Neural Networks (GNN) with Capsule Networks for the purpose of enhancing the classification accuracy. Salih et al. [20] focused on the CNN technique along with the hyper parameter tuning for the detection of epidermis abrasion, integrating an algorithm for fine-tune hyper parameters automatically.

Sivasangeetha et al. [21] introduced an Enhanced Coot Optimization technique for diagnosing skin cancer accurately. This authors implemented novel measures to sky-scrap the training of a refined Coot search optimization-based melanoma image segmentation system. Ali et al. [22] suggested a partitioning technique which was said to be an adaptive and effective technique namely, GLCM- fuzzy Gray-Level Co-occurrence Matrix. This method tackled the challenge of accurately segmenting images, particularly those with dim colour changes and disturbances at the border margins. Pal et al. [23] focused on the identification of Munro’s Micro abscess (MM) in psoriasis diagnosis which was relied on detecting neutrophils within the SC- Stratum Corneum layer of the skin epidermis. The authors presented a computational framework aimed at aiding human experts and minimizing potential diagnostic errors. UNet and CapsNet architectures are integrated for classification and segmentation process.

Lan et al. [24] presented a FixCaps which is an improved CapsNet for dermoscopic image classification. This method boasted larger receptive field compared to CapsNets, achieved through a sizable kernel size of 31 × 31 at the bottom convolution layer. Aggrey et al. [25] tackled the complexities of skin cancer classification by presenting a novel approach of integrating convolutional blocks and Capsule Neural Network inside the CapsNet framework. Tiwari et al. [26] compared the effectiveness of multi-layer perceptron, CNN, along with the capsule network for the purpose of distinguishing the analysis between the malignant and benign nevus. Khan et al. [27] relied on traditional methods which involved the identification of the disease through swabs of fluid from skin rashes by medical professionals. However, this method has several limitations, including its reliance on medical expertise, high costs, slow processing times, and often unsatisfactory results. This paper presented an AI-based diagnostic system which is capable of immediately detecting the monkey pox virus.

Singh et al. [28] aimed to develop a system which integrated metaheuristic optimizers along with several AI-based classifiers for the purpose of detection and diagnosing skin diseases. Sany et al. [29] presented an image processing approach for dermatological screening, involving capturing digital photographs of affected skin patches and applying image processing techniques for disease detection. Mittal et al. [30] presented a Derm-CDSM for the purpose of detecting skin disorder. This model focused on the enhancing segmentation capabilities and also integrated a hybrid deep learning technique. Moreover they enhanced the segmentation process by utilizing an ICSO- improved chameleon swarm optimization method, aimed for more accurate disease identification. A computerized method for diagnosing and categorizing skin issues using ML classification was introduced by Inthiyaz et al. [31]. Convolutional approaches are utilized for analysing, processing, and categorizing image data, involving diverse properties within the images.

Vayadande et al. [32] presented an extensive multiclass DL techniques concentrated at comparing healthy skin and unhealthy epidermis area affected by diseases, with the goal of classifying specific skin conditions. Hamida et al. [33] focused on introducing an innovative methodology which merged the merits of both RF and DNN algorithms. This model incorporated data enlargement and an equilibrium techniques for significantly boost model performance and generalizability. Maduranga et al. [34] introduced the conceptualization and creation of an AI-powered mobile application intended for detecting various skin diseases. Among various techniques, CNN emerged as the most efficient method for identifying these conditions. The mobile application, engineered for swift and precise action, empowers patients and dermatologists to analyze images of affected areas to identify the specific disease type.

Anand et al. [35] introduced a transfer learning-based approach utilizing a pre-trained Xception model, which was customized by inserting extra layers. The original FC layer, tailored for seven skin disease classes, was replaced with a new FC layer. Shanthi et al. [36] introduced a methodology for identifying four types of skin diseases through computer vision techniques, with a particular emphasis on CNN and the architecture comprised approximately 11 layers by utilizing the CNN techniques. An inventive transformer strategy that uses multimodal techniques to fuse images and information for the categorization of skin diseases was presented by Cai et al. [37]. This model extracts deep characteristics from images using an appropriate vision transformer (ViT).

A Convolutional Neural Network (CNN) model was published by Yanagisawa et al. [38] for the segmentation of skin pictures, producing a dataset that is correct for CAD. This paper focused on CNN, based on DeepLabv3+, automatically identifies skin and lesion areas, with criteria set of the image for skin area at more than 80% and for lesion area with more than 10%. Wei et al. [39] presented a CNN method for skin disorder identification by utilizing fusion techniques. By utilizing cavernous and superficial fusion techniques for the purpose of fusing the features, and the aggregation of the module which incorporates other techniques, further leads to the enhancement of the feature extraction process. Ayas et al. [40] introduced multiclass skin lesion classification by the utilization of a Swin Transformer model which combines the strengths of both transformers and CNNs. This model operated on an end-to-end mapping basis, eliminating the need for prior knowledge. Moreover, a weighted cross-entropy loss function is utilized for tackling the issues of the class imbalance.

Hameed et al. [41] presented various methodologies and particularly focused on differentiating malignant lesions from benign lesions. Narayan et al. [42] addressed the seriousness of Lumpy Skin Disease (LSD) in cattles and presented a DL methodology. This method processed through data capturing and followed by pre-processing and further through segmentation and feature extraction. Muhaba et al. [43] presented the computerized structure for diagnosing epidermis disorder utilizing medical photos along with the patient data, utilizing the DL pre-trained MobileNet-v2 model. Gautam et al. [44] presented a superior performance technique by utilizing CNN for the classification and observation of epidermis diseases in a prior state. This method involved pre-processing skin disease images using various techniques, extracting important features from the images, and analyzing them at various phase by utilizing Deep Convolutional Neural Network (DCNN).

Rao et al. [45] presented a hybrid method by integrating comprehensive research techniques and DL methodologies for developing strong frameworks to classify different skin conditions. This method utilized Binary Butterfly Optimization Algorithm (BBOA) and Deep CNN (DCNN) to automate skin disease classification, aimed to enhance prognosis accuracy while efficiently gathering stateful knowledge for precise predictions. Tandon et al. [46] gives a thorough comparative analysis has revealed that a significant proportion of researchers attained notable accuracy through the deployment of convolutional neural network models, concurrently leveraging pre-trained models for the automated diagnosis of cancer patients. Additionally, various limitations associated with the current deep learning-based automated cancer diagnostic models have been delineated. Patil et al. [47] explained deep convolutional neural network (CNN) model to facilitate the detection of diseases in cotton plants by utilizing images of both infected and healthy cotton leaves, with the image acquisition process encompassing all stages involved in training and validation.

Patil et al. [48], elucidates the introduction of a novel modified level set algorithm intended for the segmentation procedure. From the resultant segmented image, features such as texture characteristics, which encompass "Local Binary Pattern (LBP) and Grey-level Co-occurrence Matrix (GLCM)," alongside statistical features and higher-order statistical features, are extracted. In order to enhance the precision and accuracy of the classification, it is proposed to optimally adjust the weights of the RNN. To accomplish this objective, a new Modified Grasshopper Optimization Algorithm (GOA) will be presented in this study. Patil et al. [49] explained a stacking ensemble model for more accurate disease prediction, used for classification after the dataset was trained with Custom CNN to achieve excellent accuracy for cotton disease prediction. Patil et al. [50] employs a stacking ensemble technique for the identification of cotton diseases, achieving an accuracy rate of 99.6%. Tandon et al. [51] explained a hybrid architecture VCNet is introduced, merging the attributes of capsule network and VGG-16. The VGG-16 framework is employed for the purposes of object recognition and classification tasks. Conversely, CapsNet is utilized to mitigate the limitations inherent in convolutional neural networks concerning image rotation, tiling, and other atypical image orientations. A hybrid architecture that integrates the VGG-16 framework with a capsule network is proposed by Rathore et al. [52] for the purpose of identifying ambiguous diseases in wheat foliage.

2.1 Research Gaps:

1. Class Imbalance in Datasets: Many studies, such as those by Anand et al. [35] and Shanthi et al. [36], face challenges related to class imbalance in datasets, which can skew the model performance and reduce its generalizability. Addressing these imbalances through more advanced data augmentation techniques or synthetic data generation could enhance model robustness.
2. Computational Resource Requirements: Models like those suggested by Behara et al. [16] and Adla et al. [17] achieve high accuracy but require significant computational resources, which may not be feasible in resource-constrained environments. Developing more lightweight and efficient models without compromising accuracy remains a critical area for future research.
3. Image Quality and Pre-Processing Dependency: Approaches by Yanagisawa et al. [38] and Wei et al. [39] highlight the importance of accurate segmentation and feature extraction. However, the reliance on high-quality images and extensive pre-processing can limit the applicability of these models in real-world scenarios where image quality may vary. Research focused on enhancing model performance with low-quality or non-standardized images could make these tools more universally applicable.
4. Model Interpretability and Transparency: Despite achieving high performance, models like the one proposed by Dubey et al. [18] often function as "black boxes," making it challenging for clinicians to trust and adopt these technologies. Enhancing the interpretability of these models could bridge the gap between AI researchers and medical practitioners.
5. Integration of Multimodal Data: There is a need for more comprehensive studies that integrate multimodal data, including clinical metadata and patient history, as seen in the work of Muhaba et al. [43]. Such integrative approaches could improve diagnostic accuracy and provide a more holistic view of patient health, but they are currently underexplored.

2.2 Rationale

1. Deep learning methodologies are exceptionally advantageous for the examination of extensive medical datasets and the extraction of significant insights therefrom.
2. With a focus on severity analysis, the current study aims to create a strong deep learning framework for the best possible segmentation and classification of cutaneous cancers.
3. By harnessing the potential of CNN alongside other deep learning strategies, the objective is to augment the precision and efficacy of skin cancer diagnostics, thereby facilitating early identification and enhancing patient prognoses.

The noteworthy contributions of this proposed article are as follows:

1. Skin diseases have been identified and predicted using this proposed model.
2. The proposed model classifies Actinic Keratosis, Benign keratosis, Melanoma, Melanocytic nevi, Basal cell carcinoma, Dermatofibroma as respective classes.
3. The performance metrics for the proposed model demonstrate encouraging outcomes, including accuracy, recall, precision, specificity, MCC, Cohen’s kappa, and F1 score.

3. MATERIALS AND METHODS:

The proposed model seeks to augment the existing methodologies employed for the diagnostic assessment of dermatological diseases, which are conventionally utilized for the identification of conditions such as skin lesions. The proposed framework is methodically structured into multiple discrete phases. The below figure 2 illustrates the architectural design of the recommended framework as follows:

3.1 Dataset: To standardize and improve the data quality, preprocessing is applied to datasets that start with photographs. In this work, we used the HAM10000 (Human Against Machine with 10000 training images) dataset for our experiments, which consists of 10,015 skin lesion imagery from various populations arranged into seven main types used for classification. The composition of the dataset is comprehensively described in Table 1, which also provides the quantity of images associated with each type. Figure 1 illustrates the sample photographs from our dataset.

Table 1: Analysis of our dataset

Classes	Acronym	No. of Image Samples
AKIEC	Actinic keratoses and intraepithelial carcinoma	327
BKL	Benign keratosis-like lesions	1099
MEL	Melanoma	1113
NV	Melanocytic nevi	6705
BCC	Basal cell carcinoma	514
DF	Dermatofibroma	115
VASC	Vascular lesions	142

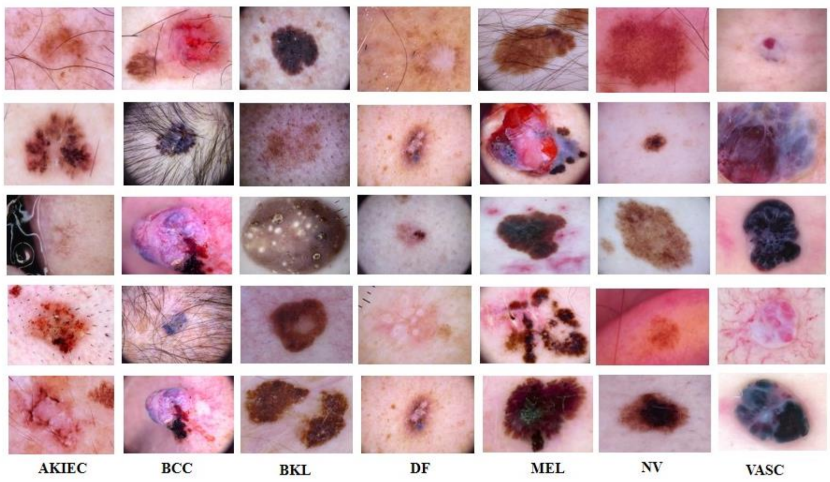

Figure 1: Sample images of our dataset

The proposed methodology divides the dataset strategically into two subsets: 80% of the data is used to train the model i.e. training Data Count: 8,012, with the remaining 20% kept for testing i.e. testing Data Count: 2,003.

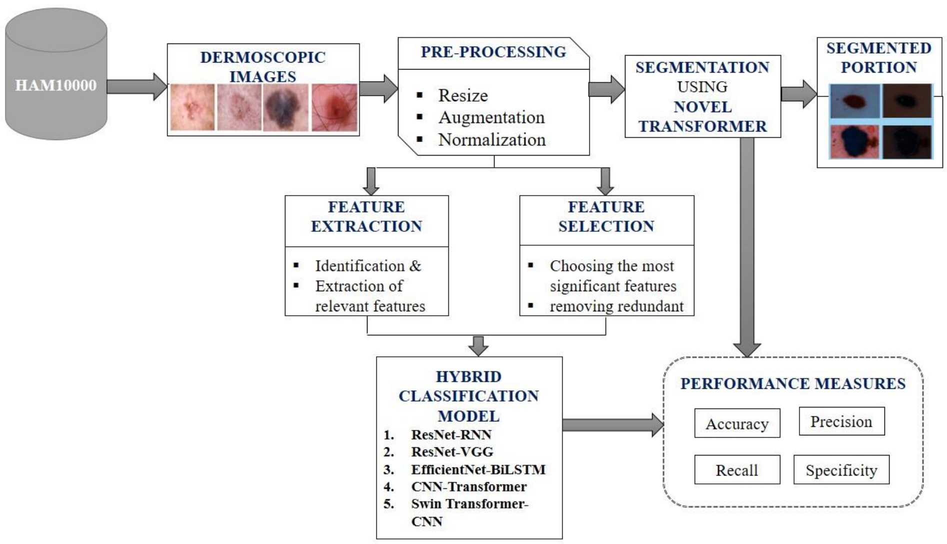

Fig. 2. Proposed Architecture of the work

3.2 Pre-processing: Preprocessing improves image quality in skin disease identification by lowering noise and maintaining crucial lesion features. By reducing high-frequency noise, a Gaussian Low-Pass Filter (GLPF) smoothes the image and aids in the removal of artifacts such as hair. It might, however, cause blurring. Using local statistical features, the Wiener Filter is used for adaptive noise reduction and de-blurring in order to combat this. By striking a balance between edge preservation and noise reduction, this combination enhances feature extraction for precise illness categorization. Deep learning-based diagnosis and segmentation are more suited for the final processed image. The below figure 3 shows an input image with its pre-processed image as,

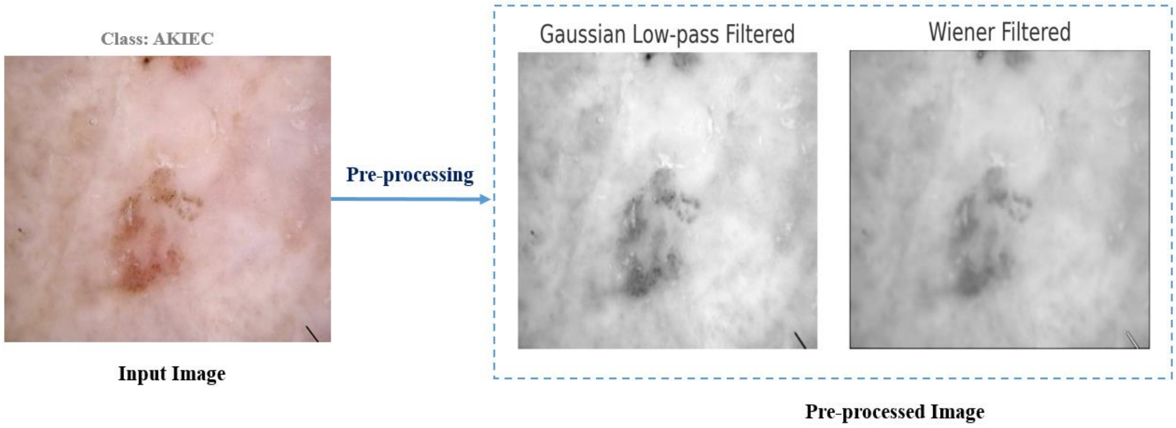

Fig.3 Input image with its pre-processed image using Gaussian Low-pass & Wiener Filter

3.3 Segmentation: The process of segmentation in skin disease detection is critical for the precise delineation of lesion boundaries. The Progressive Attention-based Multi-scale Hierarchical Residual Swin Transformer (PA-HRST) enhances segmentation efficacy by harnessing the powers of multi-scale attention and hierarchical residual learning techniques. The Swin Transformer adeptly captures both global and local contextual features, while progressive attention mechanisms refine the delineation of lesion boundaries across various scales. The use of residual connections facilitates the preservation of essential details, thereby mitigating the risks of over-segmentation and augmenting precision. PA-HRST proficiently differentiates skin lesions from adjacent tissues, thereby improving segmentation accuracy, which is vital for the early detection of skin cancer. This methodology guarantees robust and meticulous lesion mapping, thereby benefiting the field of deep learning-based medical image analysis.

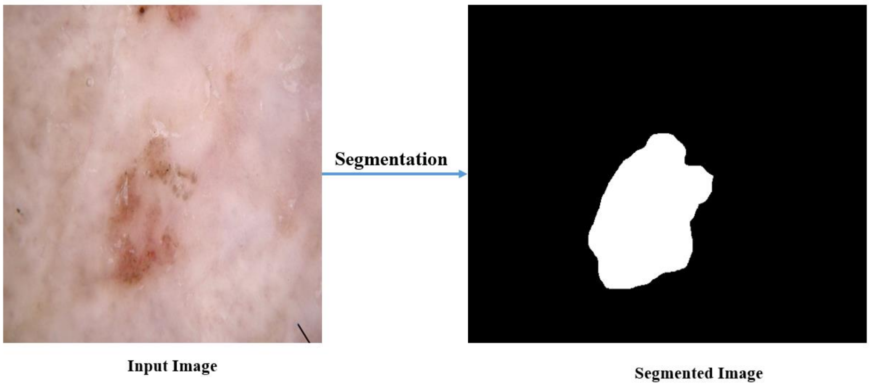

Fig.4 An Input image with its Segmented Image

3.4 Feature Extraction: The mechanism of feature extraction in the context of skin disease detection is vital for realizing correct classification outcomes. The Two-phase Self-attention based Hierarchical Capsule Network (TS-HCaps) augments feature extraction by utilizing the principles of self-attention alongside capsule networks. In the initial phase, self-attention mechanisms accentuate the significant regions of lesions while concurrently diminishing the influence of extraneous features. During the subsequent phase, hierarchical capsule layers effectively encapsulate spatial relationships and variations inherent in skin textures. In contrast to Convolutional Neural Networks (CNNs), TS-HCaps adeptly preserves spatial hierarchies and proficiently accommodates variations in rotation and scale. This enhancement bolsters the robustness of skin disease identification, rendering it particularly applicable for real-world dermatological practices. The synergistic integration of self-attention and capsule networks guarantees a superior representation of features, thus facilitating accurate classification.

3.5 Feature Selection: The process of feature selection in the context of skin disease detection significantly augments classification accuracy while concurrently minimizing computational complexity. The Tent Chaotic Walrus Optimization Algorithm (TCWOA) represents a sophisticated metaheuristic approach that proficiently identifies optimal features. Through the incorporation of Tent Chaotic Maps, TCWOA enhances its exploratory capabilities and mitigates the risks of converging to local optima, thereby ensuring a diverse selection of features. It prioritizes the most pertinent characteristics of skin lesions while discarding redundant data, leading to a reduction in dimensionality and training durations. This optimization methodology enhances the efficacy of deep learning frameworks by emphasizing essential patterns, thereby facilitating expedited and more accurate detection of skin diseases. TCWOA is particularly well-suited for applications within real-time and resource-constrained dermatological environments.

3.6 Hybrid Classification Model: The different hybrid models like ResNet-RNN, ResNet-VGG, EfficientNet-BiLSTM, CNN-Transformer, and Swin Transformer-CNN are compared with our proposed model in terms of performance metrics. The performance metrics indicates our proposed methodology provides outstanding performance as compared to existing methods.

4. RESULTS AND DISCUSSION

Using skin disease dataset HAM10000, this study tested the suggested strategy against existing hybrid classifier models to determine how much it improved performance. The subsequent segment compares the performance of the proposed model and the prevailing models. The presented work proposed technique that greatly improved the classification stage performance.

All experimental procedures executed within the parameters of this research were carried out utilizing Google Colaboratory, a sophisticated platform that delivers integrated GPU support conferred by Google. The below figure 5 (a) and 5 (b) demonstrate that the proposed model achieves metrics as accuracy is 0.9918, thereby indicating an enhanced performance in comparison to existing hybrid models.

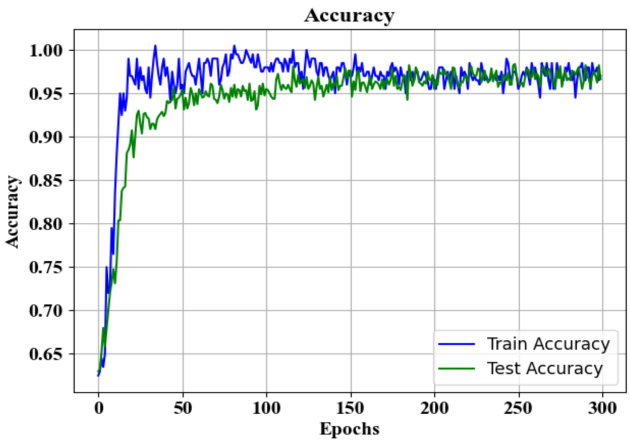

Figure 5 (a). Analysis of Accuracy for proposed methodology

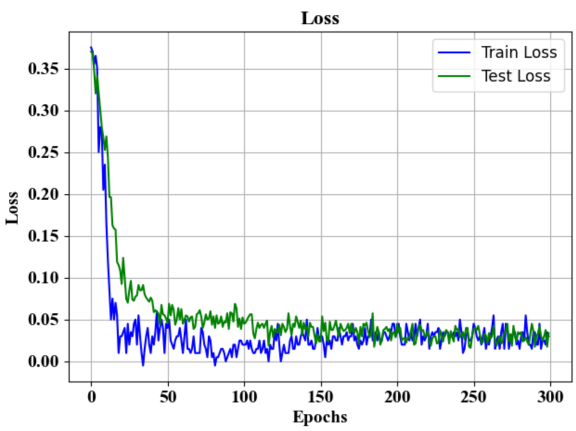

Figure 5 (b). Analysis of Loss for proposed methodology

The efficacy of merging deep learning architectures is demonstrated by the performance accuracy of several hybrid classification models. The Proposed Model outperforms other models by achieving the maximum accuracy of 99.18%. Using the sequential learning skills of RNN with the feature extraction capabilities of ResNet, the ResNet-RNN comes in second with 95.76%. The structured deep layers of VGG help the ResNet-VGG model achieve 94.73%. By combining the sequential knowledge of BiLSTM with the lightweight efficiency of EfficientNet, the EfficientNet-BiLSTM achieves 93.06%. By combining Transformer's attention mechanism with CNN's spatial feature extraction, the CNN-Transformer achieves a score of 91.47%. At 90.04%, the Swin Transformer-CNN combines CNN's local feature capture with hierarchical attention. The better performance of the suggested model points to an improved design that improves learning, generalization, and feature extraction. This demonstrates its potential for high-accuracy real-world applications like biometric recognition, autonomous systems, and medical imaging. Its wider applicability could be confirmed by additional research on computing robustness and efficiency.

5. CONCLUSION AND FUTURE WORK

Deep learning is particularly well-suited for analyzing large amounts of medical data and extracting valuable information from it. This study aims to review various research papers about different implemented methods based on skin lesion and much more attention on how automatic diagnosis of the skin cancer disease was performed earliest by various researchers. With an emphasis on severity analysis, we seek to create an effective deep learning method for the best skin cancer segmentation and classification in order to raise the survival rate. The HAM10000 database were used in this work to diagnose skin cancer early. The objective is to improve patient outcomes by enabling early identification of skin cancer and increasing the accuracy and efficacy of skin cancer diagnosis by utilizing CNN and other DL techniques. The performance analysis will be done by comparing the adopted method over other hybrid conventional models through the various measures like classification accuracy, sensitivity, precision, recall etc. In contrast to existing methodologies, the proposed framework demonstrates superior performance and an accurate classification of dermatological malignancies related to skin cancer. Future research initiatives will involve the analysis of supplementary datasets concerning skin diseases in order to further validate the efficacy of the proposed model. In future studies, we plan to investigate how to combine sophisticated attention mechanisms with optimization strategies to improve the resilience and efficacy of our method for patient early diagnosis and prevention.

Acknowledgement

The authors would like to acknowledge the department of Computer Science & Engineering at SAGE University, Indore, M.P., for providing research facilities and technical assistance.

Funding Sources

There are no sources of Funding.

Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.

Author contributions

All authors contributed to the study conception and design. Also skin disease dataset data collection and analysis were performed by Punam R. Patil[1] also manuscript was written by Punam R. Patil[1] and Dr. Ritu Tandon[2]. All authors read and approved the final manuscript.

Ethics Approval

There are no human subjects in this article and informed consent is not applicable.

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