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Deep Learning Approaches for Early Detection of Skin Cancer Disease Detection Using Segmentation and Classification with Severity Analysis

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Abstract: The utmost prevalent type of the disease, skin cancer claims millions of lives every year, poses a serious public health threat particularly melanoma, which is often fatal if not detected early. Early diagnosis is crucial, yet traditional methods frequently fall short due to image quality limitations and the complexity of visual differentiation. With an emphasis on severity analysis, this study presents a sophisticated deep learning methods for skin cancer segmentation and classification. In order to improve quality and enable more accurate analysis, sophisticated picture pre-processing techniques are used to reduce noise while maintaining important characteristics. The refined images are then analyzed using a two-phase Self-Attention-based Hierarchical Capsule Network, which effectively extracts intricate patterns. Feature selection is optimized using the Tent Chaotic-based Walrus Optimization Algorithm (TCWOA), minimizing computational complexity. For segmentation, the Progressive Attention-based Multi-scale Hierarchical Residual Swin Transformer (PA-HRST) model is utilized. Classification is performed using the Global Attention-based Multilevel Semantic Knowledge Alignment Distillation Network (GA-MSKAD), accurately identifying seven skin cancer types. Finally, severity is predicted using the Residual Lasso Logistic Regression (RLLR) model. Using the HAM10000 dataset, which consists of 10,015 dermoscopy images from seven classes, the method shows its efficacy in detecting and forecasting skin conditions with a high testing accuracy of 99.18%. This comprehensive approach from image enhancement to severity assessment offers a significant improvement over conventional diagnostic tools. For future work, incorporating model interpretability, diverse datasets, and clinical metadata will be essential to further optimize results and support real-world medical applications.

Keywords: Classification, Segmentation, Melanoma, Capsule Network, Skin Cancer Disease, Pre-Processing, Feature Extraction

Introduction

The skin is the largest and most vital organ in the body, protecting the inside organs. It has multiple layers, such as the dermis, epidermis, muscles, blood vessels, lymphatic vessels, nerves, and subcutaneous tissues (Aldhyani *et al.*, 2022). Melanocytes, basal cells, and squamous cells make up the outermost layer, the epidermis. The surface layer is made up of squamous cells, basal cells are located at the base of the epidermis, and melanocytes produce melanin, a protective brown pigment that shields the deeper layers of skin from sunlight damage (Mishra *et al.*, 2021). This combination of factors can lead to the development of malignant neoplastic cells, resulting in skin cancer. The primary cause of skin cancer is prolonged exposure to ultraviolet (UV) radiation from the sun, which stimulates the production of melanin in the epidermis. Those who fail to protect their skin from UV rays risk damaging the DNA of skin cells. This damage can disrupt the normal mechanisms regulating cell growth and may ultimately lead to cancer. Among the various types of skin cancer, malignant melanoma is the most dangerous, associated with a high mortality rate among affected individuals (Islam *et al.*, 2021). Melanoma is the most frequent cancer in both men and women, with an estimated 300,000 new cases recorded worldwide in 2018. About 1.2 million cases of non-melanoma skin cancer and

324,635 cases of melanoma skin cancer collectively make up 33% of all cancer diagnoses (Tiwari *et al.*, 2023).

The World Health Organization (WHO) reports that more than one-third of all cancer diagnoses worldwide are skin cancers. It is a serious condition associated with high death rates, but early detection can significantly lower mortality rates (Akter *et al.*, 2022). Traditional biopsy methods can be painful and costly (Tahir *et al.*, 2023). Moreover, accurately identifying skin lesions through photographs can be challenging (Purni & Vedhapriyavadhana, 2024). Cancer can be categorized into six main classes (Iqbal *et al.*, 2021; Bala *et al.*, 2022).

1. Carcinoma, which starts in the skin, breasts, lungs, pancreas, and other organs
2. Sarcoma, which develops in connective tissues like bone and muscle
3. Leukemia, which begins in the bone marrow and produces abnormal blood cells
4. Lymphoma, which arises in immune system cells
5. Cancer of the brain and spinal cord which impacts the central nervous system
6. Melanoma, a skin cancer that starts in cells that produce pigment and can spread to other organs.

With advancements in technology, computer vision has become an increasingly practical tool (Allugunti, 2022). Recent developments in neural networks have shown great promise in classifying medical images, although a limited investigation of deep learning models often hampers their full potential (Das *et al.*, 2021). Studies indicate that deep learning models are particularly effective in the binary classification of skin lesions (Aljohani *et al.*, 2022).

To create an application for diagnosing skin cancer, key steps include thorough image segmentation and deep learning-based tracking, starting with processing images to a resolution of 120×120 pixels (Dorj *et al.*, 2018). Various deep learning approaches for image classification continue to improve (Garg *et al.*, 2021). However, convolutional neural networks (CNNs) face challenges, such as sensitivity to slight image alterations and vulnerability to adversarial attacks. Skin lesions can be classified as malignant (cancerous) or benign (non-cancerous). Malignant skin lesions can be lethal if left untreated, but benign skin lesions are usually harmless but can occasionally be unsettling (Alshahrani *et al.*, 2024). This specialized CNN technique aims to accurately classify different categories of dermoscopic images, though there is still a need for more effective models in skin cancer classification. Detecting cancer in different body regions is an ongoing challenge. Timely and accurate diagnoses can significantly reduce overall cancer-related mortality rates, underscoring the need for reliable models in skin cancer classification despite technological advancements. Effective detection methods are crucial not only for improving patient outcomes but also for lowering mortality rates. Among the several methods, efficient models for classifying skin cancer are still needed.

Several significant challenges arise in cutaneous lesion analysis due to inherent limitations in current methodologies. Insufficient contrast in lesion imagery often compromises boundary detection, with existing technologies frequently failing to produce precise segmentation between different tissue regions. This limitation is further exacerbated when preprocessing techniques are neglected, ultimately contributing to inaccurate diagnostic outcomes (Naqvi *et al.*, 2023).

The inherent variability in lesion morphology and texture presents another substantial obstacle, frequently leading to erroneous region segmentation (Hartanto & Wibowo, 2020). Additionally, current feature extraction methods often fail to adequately integrate critical relationships between erroneous regions, healthy tissue characteristics, and other clinically relevant features necessary for accurate classification (Adla *et al.*, 2022).

Practical implementation barriers include the time-intensive nature of many classification approaches, which often require extensive datasets that are both financially burdensome and particularly challenging to acquire for rare dermatological conditions (Behara *et al.*, 2022). Furthermore, the interpretability of results remains problematic, as understanding the rationale behind algorithmic decisions becomes increasingly complex when dealing with high-dimensional feature spaces, making clinical validation difficult.

Problem Formulation

A DNA abnormality causes skin cells to proliferate uncontrollably and generate a lot of cancer cells. This is how skin cancer starts. Early diagnosis increases the likelihood that a patient will seek treatment and recover completely. However, collecting various kinds of data, such as position and skin lines, presents several difficulties. Many studies have been conducted to provide an accurate diagnosis approach because it is non-invasive. Although disease domain knowledge is essential, segmentation is a frequently utilized strategy. Recently, researchers more interested in artificial intelligence (AI)-based deep learning techniques and machine learning (ML), especially in the medical field. Past studies in the field indicates the current efforts are effective, there is still a problem with the precision of skin cancer prediction. ML-based methods struggle to perform effectively on larger datasets. Severe time complexity can also result from delayed training and severe over fitting issues. As a result, a complex technique is needed to recognize skin problems in pictures. Validating skin disease prediction is also necessary for researching the efficacy of skin cancer classification and prediction. Early diagnosis increases a patient's chances of recovery and allows them to seek medical care.

Study Motivation and Objectives

Current methodologies for skin disorder analysis face significant limitations in identifying critical diagnostic elements such as skin lines and lesion positioning. While numerous studies have pursued non-invasive diagnostic approaches, conventional techniques often yield reduced classification accuracy and require substantial computational resources. These challenges necessitate the development of sophisticated systems capable of early and accurate skin cancer detection.

This study introduces a novel optimal visual transformer architecture designed to enhance physician decision support by addressing key limitations in existing approaches. While deep learning methods have shown promise in disease classification, previous implementations have struggled with artifacts including hair, moles, and air bubbles that complicate data interpretation. To overcome these obstacles, we propose a hybrid deep learning system that provides enhanced diagnostic assistance through improved feature representation and learning efficacy.

The primary contributions of this research include several innovative technical approaches. An Enhanced Low Pass Wiener Filter (ELPWF) performs preprocessing to enhance luminance in affected regions, while a Swin Transformer enables precise segmentation of diseased areas. For feature extraction, Two-phase Self-attention based Hierarchical Capsule Networks (TS-HCaps) capture spatial and hierarchical properties from ABCDE dermatological data.

The framework further incorporates the Tent Chaotic Walrus Optimization Algorithm (TCWOA) for optimal feature selection to maximize classification accuracy. Finally, a Global Attention-based Multilevel Semantic Knowledge Alignment Distillation Network (GA-MSKAD) classifies skin cancer types using the HAM10000 dataset, with multiple hybrid models engineered to enhance feature representation and learning performance.

Literature Review

This section provides a comprehensive examination and critical analysis of the diverse methodologies employed in dermatological condition detection and classification. The review systematically evaluates both traditional and contemporary approaches, highlighting their respective strengths, limitations, and applicability within clinical contexts.

Behara *et al.* (2024) integrated active contour segmentation with ResNet50 and Capsule Networks to enhance feature discrimination capabilities in skin lesion analysis. Adla *et al.* (2023) developed a novel computer-aided diagnosis system utilizing a hyper-parameterized FrCN model for epidermal lesion detection in dermoscopy images. In agricultural applications, Patil and Patil (2025) proposed a hybrid deep learning framework incorporating meta-heuristic optimization for early crop disease prediction and management. Meanwhile, Tembhurne *et al.* (2023) introduced an ensemble methodology combining deep learning with traditional machine learning techniques to improve skin cancer detection accuracy, thereby facilitating early diagnosis and enhanced healthcare outcomes.

Salih and Duffy (2023) developed an algorithm that automatically fine-tunes hyperparameters within a CNN framework to improve epidermal abrasion identification. Patil & Tandon (2025a) developed a successful deep learning model for skin cancer segmentation, classification, and severity analysis using HAM10000 in order to increase diagnosis accuracy through multi-phase processing. By maintaining spatial hierarchies and outperforming conventional CNN models Patil & Tandon (2025b) presented a deep learning technique based on capsule networks for precise cutaneous carcinoma segmentation and classification.

Khan & Inam Ullah (2023) used conventional techniques, wherein medical practitioners used swabs of fluid from skin rashes to diagnose the illness. Nevertheless, this approach has a number of drawbacks, such as its dependence on medical knowledge, exorbitant expenses, sluggish processing times, and frequently disappointing outcomes. An AI-based diagnostic system that can quickly identify the monkey pox virus was provided in this research. In order to detect and diagnose skin problems Singh *et al.* (2024) set out to create a system that combined multiple AI-based classifiers with metaheuristic optimizers. An image processing method for dermatological screening was introduced by Sany & Shill (2024). This method entails taking digital pictures of the afflicted skin areas and using image processing techniques to identify the disease.

A Derm-CDSM was introduced by Mittal *et al.* (2024) to identify skin disorders. This model combined a hybrid deep learning technique with an emphasis on improving segmentation capabilities. In order to achieve more precise illness detection, they also refined the segmentation process by applying an ICSO-optimized chameleon swarm optimization method. Using machine learning classification Inthiyaz *et al.* (2023) presented a computerized approach for identifying and classifying skin conditions. Convolutional methods are used to analyze, interpret, and classify image data that has a variety of attributes. In order to categorize particular skin problems Vayadande *et al.* (2024) introduced a comprehensive multiclass DL technique focused on comparing healthy skin with diseased epidermal areas impacted by diseases.

Hamida *et al.* (2024) concentrated on presenting a novel approach that combined the advantages of both DNN and RF methods. In order to greatly improve model performance and generalizability, this model included data enlargement and equilibrium procedures. An artificial intelligence (AI)-powered smartphone application for the detection of different skin conditions was conceptualized and developed by Maduranga & Nandasena (2022). CNN was the most effective technique among the others for detecting these disorders. Patients and dermatologists can use the mobile application, which is designed for quick and accurate action, to examine photos of afflicted areas and determine the exact type of disease. Anand *et al.* (2022) introduced a transfer learning-based approach that used a pre-trained Xception model by including extra layers. A new FC layer was created in place of the previous one, which was customized for seven different types of skin diseases.

An inventive transformer method that uses multimodal techniques to fuse images and information for the categorization of skin diseases was presented by Cai *et al.* (2023). This model extracts deep characteristics from images using an appropriate vision transformer (ViT). Yanagisawa *et al.* (2023) presented a CNN model for the segmentation of skin images, resulting in a dataset that is accurate for CAD. With a criterion specified for an image that has more than 80% skin area and more than 10% lesion area, CNN, which is based on DeepLabv3+, is the subject of this research. Wei *et al.* (2023) used fusion techniques to provide a CNN method for identifying skin disorders. Utilizing superficial and deep fusion approaches to fuse the features, as well as aggregating the module that integrates other techniques, further improves the feature extraction process.

Ayas (2023) implemented a Swin Transformer model for multiclass skin lesion classification, establishing an effective end-to-end framework that operates without requiring prior domain knowledge. To mitigate class imbalance challenges, the approach incorporated a weighted cross-entropy loss function. Meanwhile, Hameed *et al.* (2023) concentrated on binary classification tasks, while Narayan *et al.* (2023) developed a comprehensive deep learning pipeline for assessing Lumpy Skin Disease severity in cattle, encompassing data collection, preprocessing, segmentation, and feature extraction stages.

Mukadam and Patil (2023) developed a framework integrating an Enhanced Super Resolution GAN with a custom CNN architecture to improve image clarity, classification accuracy, and early diagnosis effectiveness. Similarly, Afrifa *et al.* (2025) created specialized deep neural network models for melanoma classification, achieving enhanced diagnostic precision and generating valuable insights for automated skin cancer detection systems. Complementing these efforts, Rao *et al.* (2023) introduced a hybrid methodology that combines comprehensive research approaches with deep learning techniques to establish robust frameworks capable of categorizing diverse skin disorders with improved reliability.

Tandon *et al.* (2024) conducted a comprehensive comparison study revealing that numerous researchers have achieved remarkable accuracy using convolutional neural network models and pre-trained architectures for automated cancer detection, while also identifying limitations in existing deep learning approaches. In agricultural applications, Patil and Patil (2021) developed a deep CNN model for cotton plant disease identification, implementing a complete pipeline encompassing image acquisition, preprocessing, augmentation, and fine-tuning throughout training and validation phases. Building on this work, Patil and Patil (2024c) introduced a modified level set algorithm for segmentation and proposed weight optimization in RNNs to enhance precision. To address this optimization challenge, their study implements a novel Modified Grasshopper Optimization Algorithm (GOA) for parameter tuning.

Patil and Patil (2024b) developed a stacking ensemble model for improved cotton disease prediction, while their subsequent work Patil and Patil (2024a) achieved exceptional performance with 99.6% accuracy using a similar ensemble technique for cotton disease identification. In parallel developments, Tandon *et al.* (2022) introduced VCNet, a hybrid architecture that integrates VGG-16's object recognition capabilities with CapsNet's robustness to spatial variations, addressing limitations of conventional CNNs in handling unusual image orientations. Similarly, Rathore and Prasad (2022) proposed a VGG-16 and capsule network fusion for detecting subtle diseases in wheat leaves, demonstrating the effectiveness of hybrid approaches for challenging agricultural classification tasks.

Research Gaps

The analysis of current literature reveals several significant limitations in existing approaches to dermatological image analysis.

Limited Generalization Across Diverse Datasets

While Behara *et al.* (2024) demonstrated promising results with their ResNet50 and Capsule Network integration, the model lacks validation across varied lesion types and demographic datasets, restricting its broader clinical applicability.

Insufficient Real-World Testing and Interpretability

Tembhurne *et al.* (2023) achieved improved detection rates through ensemble methods but neglected crucial aspects of model explainability and practical clinical deployment, limiting translational potential.

Inadequate Handling of Class Imbalance

Ayas (2023) addressed dataset imbalance through loss function modifications but overlooked more comprehensive solutions such as advanced data augmentation or sophisticated resampling techniques that could further enhance model robustness.

Computational Constraints in Practical Deployment

The integrated CNN and Enhanced SRGAN framework proposed by Mukadam & Patil (2023) demonstrates improved image clarity but raises concerns about computational demands and feasibility for resource-constrained clinical environments.

Limited Multimodal Data Integration

Afrifa *et al.* (2025) focused exclusively on image-based classification using melanoma datasets, omitting potentially valuable clinical metadata and patient history that could significantly improve diagnostic accuracy and clinical relevance.

Rationale

Deep learning methodologies have demonstrated exceptional capability in processing complex medical datasets and extracting clinically relevant insights from medical imagery. These computational approaches are particularly valuable in dermatological applications, where visual analysis forms the cornerstone of diagnostic procedures.

The present research addresses the critical need for advanced analytical systems in cutaneous oncology by developing a comprehensive deep learning framework for precise cancer classification, segmentation, and severity assessment. By integrating convolutional neural networks with complementary computational techniques, this study aims to enhance diagnostic precision and efficiency, thereby facilitating earlier detection and intervention.

This methodological approach seeks to overcome existing limitations in automated dermatological analysis while providing clinicians with reliable decision support tools. The anticipated outcome is a robust system capable of improving diagnostic workflows, reducing interpretation variability, and ultimately contributing to enhanced patient prognosis through timely and accurate skin cancer identification.

Material and Methods

The suggested model aims to complement the current diagnostic techniques used for dermatological illness evaluation, which are often applied for the detection of problems such skin lesions. The suggested framework is logically divided into several distinct stages.

Dataset

The Human Against Machine with 10000 training images (HAM10000) (Tschandl *et al.*, 2018) dataset, which contains annotated photos of 10,015 different skin lesions divided into seven primary categories, is used to generate dermoscopic images: Actinic Keratoses (AKIEC), Basal Cell Carcinoma (BCC), Benign Keratosis-like Lesions (BKL), Dermatofibroma (DF), Melanoma (MEL), Melanocytic Nevi (NV), and Vascular Lesions (VASC).

The dataset aims to support the development of machine learning and deep learning models for automated skin cancer detection. Its diversity and size make it a benchmark resource for evaluating classification, segmentation, and diagnostic algorithms in dermatology, contributing significantly to research in computer-aided diagnosis and early detection of skin cancer. Table 1 provides a detailed description of the dataset's composition and the number of photos that belong to each kind. The sample photos from our dataset are shown in Figure 1.

Table 1: Analysis of our dataset

Classes	No. of Image Samples
AKIEC	327
BKL	1099
BCC	514
VASC	142
MEL	1113
NV	6705
DF	115

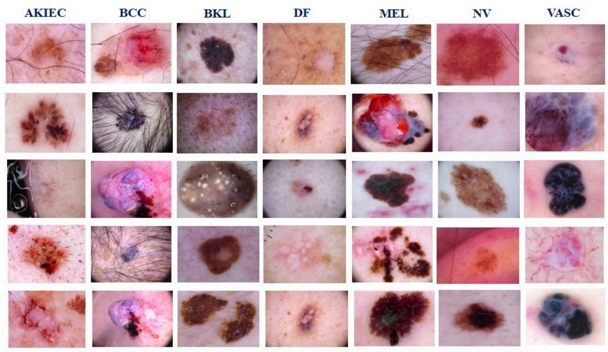

Fig. 1: Sample images of our dataset

The dataset was systematically partitioned to ensure robust model evaluation, following established machine learning protocols. The training subset comprised 80% of the total data (8,012 instances), the remaining 20% (2,003 instances) was reserved as an independent test set to provide unbiased performance assessment and validate the model's generalization capabilities on unseen data.

Pre-Processing

Effective pre-processing is essential for accurate skin tumor classification, as it addresses critical challenges including color normalization, hair removal, and noise reduction in dermatological images. While various pre-processing techniques have been developed for skin tumor analysis, existing methods often fail to preserve critical boundary information and contour details, ultimately compromising classification accuracy by obscuring diagnostically relevant tumor regions.

To overcome these limitations, this study introduces an Enhanced Low Pass Wiener Filter (ELPWF) that systematically addresses image quality degradation while preserving diagnostically critical features. Filter-based approaches are commonly employed to enhance image quality through high-frequency noise removal, de-interlacing, and deblurring operations. The ELPWF specifically optimizes noise reduction while maintaining essential lesion characteristics including boundary definition, color variation, and textural patterns, all crucial for accurate classification.

The proposed hybrid ELPWF model implements a dual-stage processing approach. Initially, a low-pass filter smooths continuous conditioning variables and mitigates the impact of outlier values. Subsequently, the Wiener filter component minimizes the mean square error between estimated and original true signals, ensuring optimal balance between noise suppression and feature preservation. This integrated approach enables robust pre-processing that enhances subsequent segmentation and classification performance while maintaining diagnostic integrity of lesion characteristics.

$$H\,(u,v) = \frac{Sxx(u,v)}{Sxx(u,v)+Snn(u.v)} \tag{1}$$

Where,

$H\,(u,v)$ = filter transfer function

Sxx (u,v) = power spectral density of the signal

Snn (u,v) = power spectral density of the noise

Feature Extraction

Following skin lesion image segmentation, robust feature extraction becomes essential for enhancing classification accuracy. This process involves isolating and quantifying distinctive lesion characteristics, including color patterns, textural variations, and morphological structures, to enable precise categorization. Traditional feature extraction approaches often encounter limitations in handling temporal complexity and spectral correlations, which can compromise accuracy and lead to the loss of diagnostically critical information.

To address these limitations, we propose a Two-phase Self-attention based Hierarchical Capsule Network (TS-HCaps), a specialized deep learning architecture designed for multi-class skin lesion classification. This framework processes dermatoscopic images from the HAM10000 dataset, focusing on learning robust, discriminative features with enhanced spatial awareness through the integration of self-attention mechanisms and capsule networks.

The TS-HCaps framework implements a sophisticated four-phase processing pipeline designed to extract comprehensive polarimetric and hierarchical features from dermatoscopic images. The complete architectural framework of the TS-HCaps feature extraction model is illustrated in Figure 2.

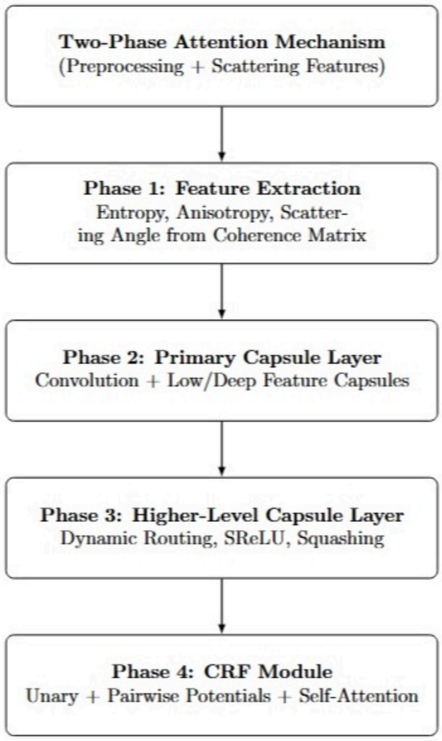

Fig. 2: Architectural view of Feature extraction utilizing TS-HCaps model

Phase 1: Polarimetric Feature Extraction

Initial processing calculates scattering and backscattering matrices through coherence matrix analysis, deriving essential polarimetric properties including Entropy, Anisotropy, and Scattering Angle. The framework further quantifies distributed scattering energy through subdivision and cross-division ratio computations. Statistical smoothing techniques are subsequently applied to enhance feature robustness and stability.

Phase 2: Capsule Network Initialization

Convolutional layers construct a primary capsule layer that integrates both low-level and deep-level features into neuron capsules. This architecture facilitates enhanced object representation while maintaining efficient backpropagation for optimized learning.

Phase 3: Hierarchical Feature Routing

A dynamic routing mechanism transforms lower-level capsules into higher-level representations using the Squashing ReLU activation function. This phase minimizes parameter requirements while effectively capturing complex object relationships through hierarchical feature organization.

Phase 4: Spatial Context Refinement

The final phase employs a Conditional Random Field to refine potentially misclassified features by computing unary and pairwise potentials. This integrates crucial spatial context and enhances boundary precision in feature classification.

Throughout this pipeline, integrated self-attention mechanisms strengthen internal feature dependencies, enabling the extraction of rich hierarchical information while simultaneously reducing dimensionality and improving overall classification accuracy.

Table 2 provides a comprehensive overview of the feature extraction capabilities of the TS-HCaps component, detailing the specific features extracted and their clinical relevance for skin cancer diagnosis.

Table 2: Feature extraction using TS-HCaps Component

Feature Type	Extracted Features	TS-HCaps Component
Color Features	RGB variance, lesion pigmentation, color irregularities	Initial convolutional layers
Texture Features	Fine granularity, streaks, globules, dots, surface smoothness	Convolution + capsule layers
Edge/Shape Features	Lesion boundaries, irregular shapes, asymmetry	Capsule networks
Spatial Relationship	Part-whole configurations, spatial layout of lesion sub-regions	Hierarchical capsule routing
Global Context Features	Attention to lesion vs non-lesion regions, suppress background noise	Phase 1 self-attention layer
Fine-grained Attention	Micro-patterns within lesions, internal region comparisons, inter-class differences	Phase 2 self-attention layer
Pose & Orientation	Direction, position, rotation of lesion parts	Dynamic routing in capsules
Class-specific Features	Encodings sensitive to melanoma, BCC, AKIEC, etc. based on learned class prototypes	Final classification capsule layer

Feature Selection

Feature selection plays a critical role in skin disease detection by enhancing classification accuracy while simultaneously reducing computational complexity. This process identifies the most discriminative characteristics while eliminating redundant or irrelevant data, thereby optimizing model performance and interpretability.

This study implements the Tent Chaotic Walrus Optimization Algorithm (TCWOA), an advanced metaheuristic approach that efficiently identifies optimal feature subsets for skin cancer diagnosis. The algorithm integrates two complementary biological inspirations: the intelligent foraging behavior of walruses and the unpredictable patterns of chaotic systems through Tent Chaotic Maps.

TCWOA enhances feature space exploration by leveraging chaotic dynamics to escape local optima while maintaining comprehensive search coverage. The walrus-inspired component provides intelligent exploitation of promising feature regions, creating a balanced optimization strategy that effectively navigates high-dimensional feature spaces. This hybrid approach significantly reduces dimensionality and training time by prioritizing clinically relevant skin lesion patterns while discarding non-informative data.

The integration of TCWOA within deep learning frameworks enhances model efficiency by focusing computational resources on the most diagnostically significant features, ultimately improving classification performance and clinical applicability. The complete pseudocode detailing the TCWOA implementation for feature selection is shown in Algorithm 1.

The equation of generalized fitness update is given below:

$$X_{new} = X_{best} + T.\sin(\lambda.\pi.r) \tag{2}$$

Where:

X_{new} = new candidate solution
T = tent chaotic map value
λ = control parameter
r = random number $\in [0, 1]$

Algorithm 1: TCWOA_FeatureSelection

Input: FeatureSet F, PopulationSize N, MaxIterations T
Output: OptimalFeatureSubset

1. Initialize walrus population W_i (i = 1 to N) with random binary strings (feature subsets)
2. Evaluate fitness of each W_i using classification accuracy or another objective function
3. Identify best solution W_{best} among population based on fitness
4. For t = 1 to T do
    a. For each walrus W_i in population:
        i. Generate chaotic parameter T_c using Tent map:
            if r < 0.7:
                $T_c = r / 0.7$
            else:
                $T_c = (1 - r) / 0.3$
            (where r is a random number in [0,1])
        ii. Update position using chaotic-sine strategy:
            $W_{i\_new} = W_{best} + T_c \times \sin(\pi \times \lambda \times \text{rand}())$
        iii. Convert W_{i_new} to binary (e.g., using thresholding or sigmoid)
        iv. Evaluate fitness of W_{i_new}
        v. If fitness(W_{i_new}) ≥ fitness(W_i):
            $W_i \leftarrow W_{i\_new}$
    b. Update W_{best} if a better solution is found in current iteration
5. Return W_{best} as OptimalFeatureSubset

Classification

This study performs a comprehensive comparative analysis between our proposed model and established hybrid architectures including ResNet-RNN, ResNet-VGG, EfficientNet-BiLSTM, CNN-Transformer, and Swin Transformer-CNN. For the skin cancer classification task, we implement the Global Attention-based Multilevel Semantic Knowledge Alignment Distillation (GA-MSKAD) network, an advanced deep learning framework designed to optimize feature representation and learning efficacy through integrated attention mechanisms and knowledge distillation.

The GA-MSKAD framework enhances classification performance through multilevel semantic knowledge alignment combined with global attention techniques, enabling improved representation of semantic relationships between network layers and fine-grained lesion details. The architecture employs a knowledge distillation approach that facilitates effective information transfer between teacher and student networks, ensuring robust generalization and accurate classification across diverse skin cancer types in the HAM10000 dataset.

The classification process begins with feature transformation through the Convolutional Block Attention Module (CBAM), which simultaneously leverages channel and spatial information to refine feature representations. Formally, given an input feature map $E_1 \in \mathbb{R}^{D \times G \times X}$, the framework processes it through transitional phase E_2 to generate the final output representation E_3, which is written as:

$$E_2 = N_D\left(E_1\right) \bigotimes E_1 \tag{3}$$

$$E_3 = N_T\left(E_2\right) \bigotimes E_2 \tag{4}$$

where, $N_D$and N_T represent channel and spatial attention maps and $\otimes$ expresses element-wise multiplication. This global attention mechanism enhances the quality of feature representations, which are then passed to the MSKAD model for accurate skin cancer classification. Figure 3 illustrates the architecture of the GA-MSKAD model.

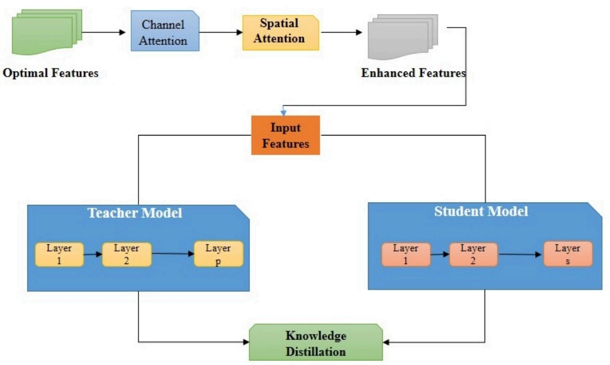

Fig. 3: Architecture for proposed GA-MSKAD model

Knowledge Distillation Framework

The distillation loss function facilitates effective knowledge transfer from the teacher to student model, enhancing generalization capabilities through a balanced optimization objective. The composite loss function is defined as:

$$L = \propto .L_{CE}\left(y.\hat{y}\right) + \left(1- \propto\right).T^2.KL\left(\sigma\left(\frac{z_s}{T}\right), \sigma\left(\frac{z_t}{T}\right)\right) \tag{5}$$

Where:

L_{CE} = cross-entropy loss

KL = Kullback-Leibler divergence

z_s, z_t = logits from student and teacher

T = temperature

$\propto$ = balancing parameter

The teacher module employs a high-capacity transformer model trained on extensive dermoscopic data, processing enhanced features to capture intricate semantic relationships between lesion components. The self-attention mechanism generates relational encodings E_ρ^r from initial embeddings E^r, producing attention outcomes defined as:

$$T_\rho^r = soft\max\left(\frac{P_\rho L_\rho{}^S}{\sqrt{c}}\right) U_\rho \tag{6}$$

The student module implements a Bidirectional Gated Recurrent Unit with Soft-Attention (BiGRU-SA) to process global semantic features encoded from initial embeddings E_{global}. An attention mechanism selectively emphasizes prominent global semantics while suppressing insignificant features through reweighting:

$$\hat{E_{global}} = \beta E_{global} \tag{7}$$

Segmentation

The initial pre-processing phase performs critical lesion isolation from medical imagery, establishing the foundation for subsequent analytical stages. During segmentation, advanced algorithms precisely delineate tumor lesions from surrounding healthy tissue, enabling accurate diagnostic assessment and treatment planning by isolating clinically relevant regions of interest.

This methodology partitions images into homogeneous segments, enhancing differentiation between pathological lesions and adjacent tissues. The Progressive Attention-based Multi-scale Hierarchical Residual Swin Transformer (PA-HRST) architecture significantly improves segmentation efficacy through integrated hierarchical residual learning and multi-scale attention mechanisms.

The PA-HRST framework processes enhanced input data through parallel convolutional and transformer pathways, integrating their feature representations. Channel attention mechanisms refine these combined

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features, which then undergo global average pooling and sigmoid activation. Residual connections maintain feature integrity throughout this process, while the Progressive Attention Module (PAM) performs final convolution operations to generate optimized segmentation outputs.

Severity Analysis

Severity analysis in skin cancer detection involves evaluating the progression stage of skin lesions by distinguishing between benign and malignant conditions. This critical assessment supports clinical decision-making by identifying lesions requiring immediate intervention or biopsy. Following segmentation and classification, deep learning models perform this analysis by extracting and evaluating key visual characteristics including asymmetry, border irregularity, color variation, and dimensional parameters.

The severity analysis employs a Regularized Logistic Regression model with Lasso (L1) regularization, which combines binary classification capability with sparse feature selection. The L1 regularization promotes model interpretability by selecting only the most clinically relevant lesion characteristics, such as color asymmetry, border irregularity, and textural patterns, while eliminating redundant or irrelevant features from high-dimensional dermoscopic data.

Following initial classification, residual analysis examines discrepancies between predicted and actual labels to iteratively refine the model, reducing noise and enhancing generalization performance. This approach ensures robust severity assessment by focusing computational attention on the lesion characteristics most indicative of malignancy risk, thereby improving diagnostic precision and clinical relevance.

Consider M skin cancer samples, each characterized by d-dimensional feature vectors. The input features form a matrix of dimensions M×d, with binary outcomes where 1 indicates malignancy and 0 indicates benign conditions. The log-odds of a sample representing the target skin cancer class is given by:

$$\log P\left(y_i = 1 \mid x_i\right) = \beta^T x_i \tag{8}$$

Here, x_i denotes the feature vector of the i^{th} sample, β represents the regression coefficients of the Log-Likelihood Regression Model (LLRM), and $P\left(y_i = 1 \mid x_i\right)$ is the probability that the i^{th} model corresponds to the target skin cancer, given the estimated regression coefficients.

Segmentation Performance Evaluation

Accurate evaluation of lesion detection models is essential for reliable skin cancer diagnosis and segmentation quality assessment. Multiple complementary metrics provide comprehensive performance analysis across different aspects of segmentation quality.

The Dice Coefficient (DC) and Jaccard Index quantify spatial overlap between predicted and ground truth lesion masks, with DC demonstrating enhanced sensitivity for smaller lesions while Jaccard provides more conservative boundary comparison. These metrics collectively assess the volumetric agreement between algorithmic outputs and expert annotations.

Sensitivity measures the model's capability to correctly identify true lesion pixels, while specificity evaluates its performance in recognizing non-lesion regions. Precision indicates the proportion of accurately predicted lesion pixels among all positive classifications. Although accuracy calculates overall pixel classification correctness, its utility is limited in imbalanced datasets where lesion regions represent a small fraction of total pixels.

The Hausdorff Distance provides critical boundary evaluation by measuring the maximum separation between predicted and actual lesion contours, offering insights into edge detection precision and morphological preservation.

Collectively, these metrics establish a multidimensional evaluation framework that comprehensively assesses segmentation performance across volumetric, boundary, and classification dimensions. Figure 4 illustrates the complete architectural design of the proposed segmentation framework, demonstrating the integration of these evaluation components within the overall system.

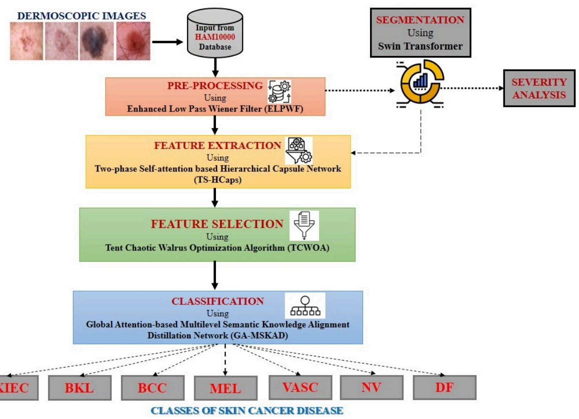
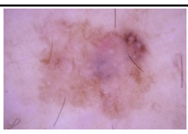
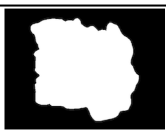
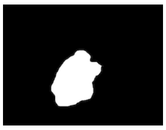
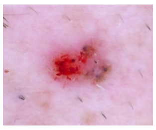
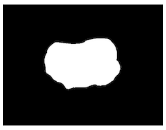
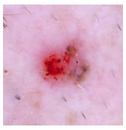
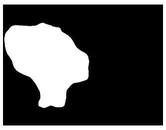
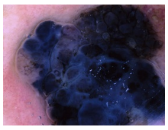
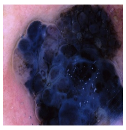
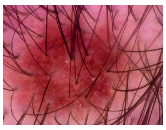
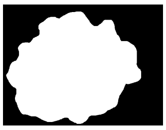
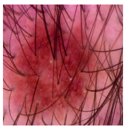


Fig. 4: Architectural design of the Suggested work

Results and Discussion

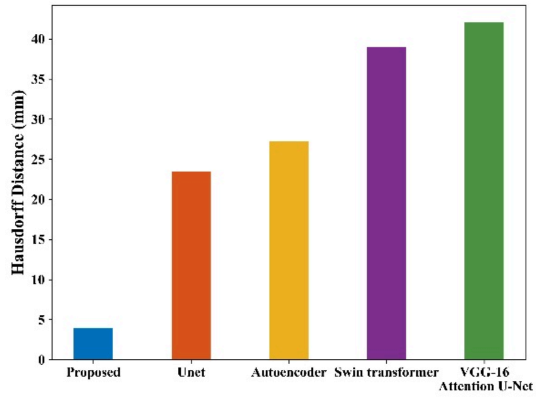
Using skin disease dataset HAM10000, this study tested the suggested strategy against existing hybrid classifier models to determine how much it improved performance. The presented work proposed technique that greatly improved the classification stage performance. Three essential steps in the skin lesion analysis pipeline are depicted in the illustration as depicted in Table 3 with seven disease classes: BKL, AKIEC, BCC, DF, MEL, NV, and VASC. The input image, which shows lesions of various sizes, colors, and textures, is the original dermoscopic image taken from the HAM10000 dataset. The segmented image shows the result of a lesion segmentation algorithm (such as attention-based Capsule Networks or U-Net), which precisely separates the lesion area from the background to allow for targeted study of the ROI. Lastly, by using methods like noise reduction, contrast improvement, hair removal, and normalization, the pre-processed image is an improved version of the original. Lesion clarity is increased, artifacts are decreased, and standardized input is guaranteed for feature extraction and classification tasks that follow.

Table 3: Performances of suggested method

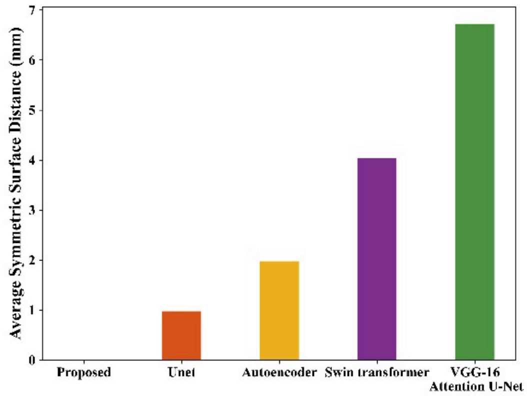
Class Name	Input Image	Segmented Image	Pre-processed Image
BKL			
AKIEC			
BCC			
DF			
MEL			
NV			
VASC			

Segmentation Analysis

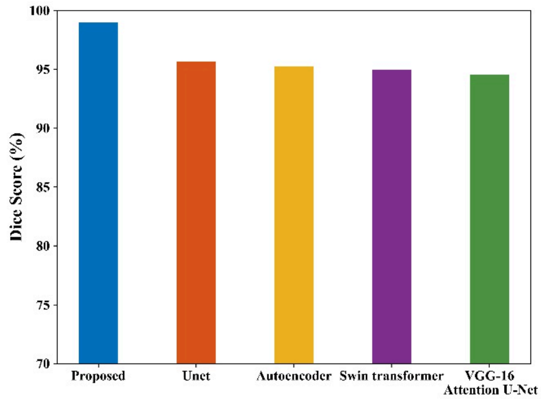
The segmentation model feeds pre-processed data into a progressive attention mechanism, which adds more relevant features and improves the segmentation model's performance. The suggested PA-HRST model compared with Swin Transformer (Pacal *et al.*, 2024), U-Net (Hu *et al.*, 2024), Autoencoder (Reddy *et al.*, 2023), and VGG-16 Attention U-Net (Jimi *et al.*, 2024) has a dice score of 9896%, an ASSD analysis of 0008 and HD analysis of 4%, which is compared with existing models to show their effective performance as shown in Figure 5.



(a)



(b)

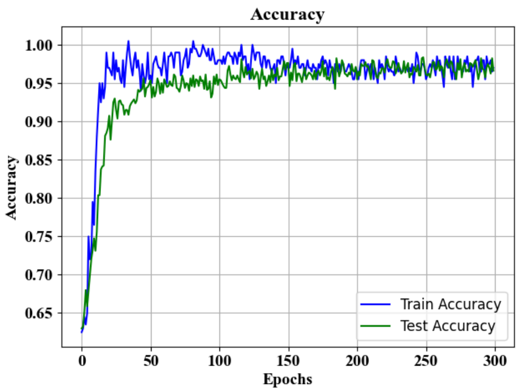


(c)

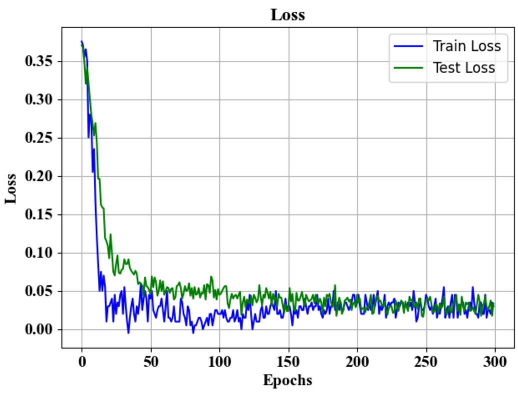
Fig. 5: Segmentation analysis of (a) HD, (b) ASSD, and (c) Dice Score

Model Performance

All experimental procedures executed within the parameters of this research were carried out utilizing Google Colaboratory, a platform that delivers integrated GPU support conferred by Google. The proposed model demonstrates exceptional performance with an accuracy of 99.18%, as evidenced in Figure 6, significantly surpassing existing hybrid approaches in classification efficacy.



(a)



(b)

Fig. 6: Model performance analysis showing (a) accuracy curve and (b) loss curve

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 (Zareen *et al.*, 2024) comes in second with 95.76%. The structured deep layers of VGG help the ResNet-VGG (Tabrizchi *et al.*, 2023) model achieve 94.73%.

By combining the sequential knowledge of BiLSTM with the lightweight efficiency of EfficientNet, the EfficientNet-BiLSTM (Venugopal *et al.*, 2023) achieves 9306% By combining Transformer's attention mechanism with CNN's spatial feature extraction, the CNN-Transformer (Pacal *et al.*, 2025) achieves a score of 9147%. At 9004%, the Swin Transformer-CNN (Pacal *et al.*, 2024) 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. Table 4 provides the performance metrics associated with each existing model and performance model.

Table 4: Performance comparison of classification methods with the Proposed Model

Methods	Performance Metrics (%)				
	Accuracy	Specificity	Recall	Precision	F1-score
ResNet-RNN	95.76	95.01	95.13	94.79	94.96
ResNet-VGG	94.73	94.47	94.65	94.39	94.52
EfficientNet-BiLSTM	93.06	92.53	92.7	92.47	92.59
CNN-Transformer	91.47	91.16	91.17	90.93	91.05
Swin Transformer-CNN	90.04	89.92	90.13	89.83	89.98
Proposed Model	99.18	99.03	99.13	99.09	99.11

Training and Testing Metrics for Proposed Methodology

The efficiency of the model is demonstrated in Figure 7 showing testing accuracy across 300 epochs for several deep learning models employed in skin cancer categorization. The suggested model continuously outperforms designs such as ResNet-RNN, ResNet-VGG, EfficientNet-BiLSTM, CNN-Transformer, and Swin Transformer-CNN, with a peak accuracy of almost 99.18%. This demonstrates differentiation between various skin lesions, which is essential and precise in identification, particularly the most deadly kind, melanoma. The suggested method's increased stability and accuracy point to its resilience in managing the visual unpredictability and complexity of dermoscopic images. Diagnostic reliability may be impacted by other models' lesser accuracy and greater variability, despite their respectable performance. This performance gap underscores the value of advanced hybrid architectures in enhancing skin cancer detection, supporting faster, more accurate clinical decisions that can ultimately save lives.

Figure 8 highlights the improved performance of the suggested model by showing the training accuracy across 300 epochs for several deep learning models used to classify skin cancer. Out of all the architectures, including CNN-Transformer, Swin Transformer-CNN, ResNet-RNN, ResNet-VGG, and EfficientNet-BiLSTM, the suggested model continuously achieves the greatest accuracy, exceeding 99%. This implies that it has a high capacity to recognize intricate patterns in dermoscopic images, which is crucial for detecting distinct categories, such as basal cell carcinoma and melanoma. Other models demonstrate consistently lower training accuracy, indicating less effective learning of complex skin lesion features. The suggested model's quick convergence and stability show effective feature extraction and generalization throughout training. In medical diagnostics, where early and accurate skin cancer categorization can greatly enhance patient outcomes, such performance is essential. These outcomes validate the efficacy of the suggested approach in training situations and its potential for clinical implementation in the real world.

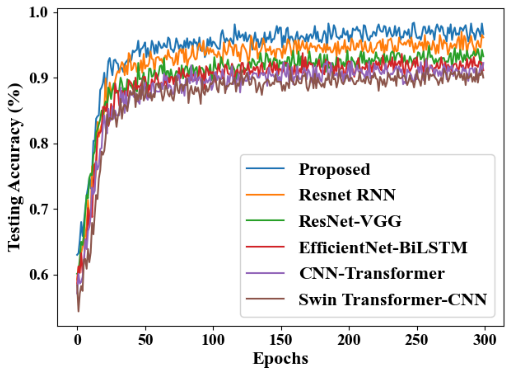


Fig. 7: Analysis of Testing Accuracy curve

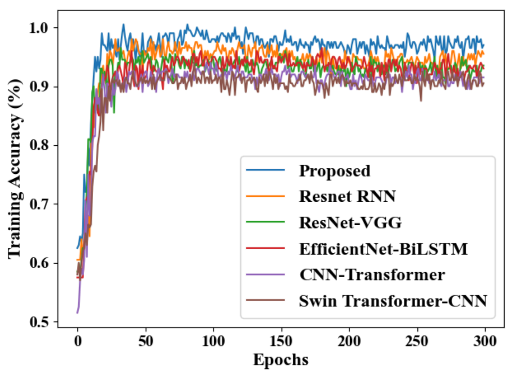


Fig. 8: Analysis of Training Accuracy curve

Figure 9 shows the testing loss across 300 epochs for several deep learning models used to classify skin cancer. Better generalization and prediction accuracy are indicated by a smaller testing loss, which is important in medical diagnosis. The model continuously outperforms models such as ResNet-RNN, ResNet-VGG, EfficientNet-BiLSTM, CNN-Transformer, and Swin Transformer-CNN, exhibiting the lowest and most steady loss throughout training. This implies that the model is quite successful in reducing mistakes while accurately identifying various forms. Other models, on the other hand, show more variable and larger loss values, which suggests less consistent performance and possible overfitting or underfitting. The model's quick convergence and high learning efficiency are demonstrated by the dramatic decrease in loss within the first 50 epochs, which is followed by stabilizing. The suggested model presents a viable method for improving diagnostic precision and lowering clinical risk in the setting of skin cancer, where early and precise categorization can save lives.

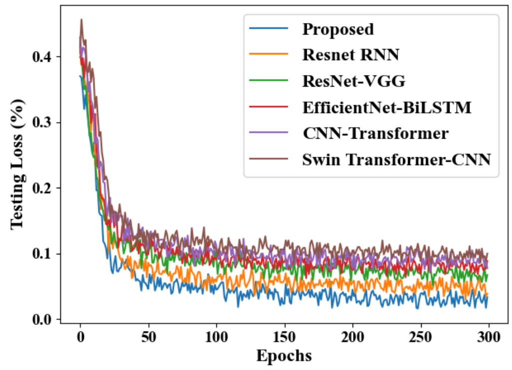


Fig. 9: Analysis of Testing Loss curve

Figure 10 shows the training loss for different deep learning models used to classify skin cancer across 300 epochs. Effective learning and few prediction mistakes during model training are demonstrated by the suggested model's achievement of the lowest and most consistent training loss. Conversely, models like Swin Transformer-CNN and CNN-Transformer exhibit more variable and higher loss, indicating less successful convergence. A sharp decline in loss throughout the early epochs demonstrates how well the suggested model can pick up intricate patterns. Accurately determining the forms depends on this efficiency, which helps with quicker and more accurate early diagnosis.

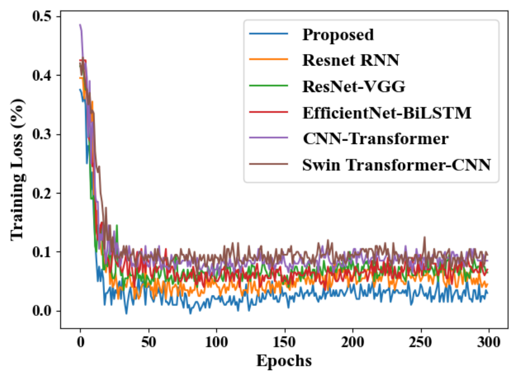


Fig. 10: Analysis of Training Loss curve

Confusion Matrix

The suggested model's confusion matrix shows excellent accuracy in identifying several types of skin cancer, such as actinic keratoses (AKIEC), basal cell carcinoma (BCC), and melanoma (MEL). Strong diagonal dominance is seen in the majority of classes, suggesting accurate predictions. Robust model performance is indicated by the low number of misclassifications, such as MEL being mistakenly classified as NV or VASC. Accurately identifying the types is essential for early detection and treatment of skin cancer. The model's potential for practical clinical use is supported by its dependability across various lesion types, providing a trustworthy instrument for automated skin disease classification and enhancing patient outcomes. Figure 11 highlights the strengths and weaknesses of proposed model in distinguishing benign from malignant lesions.

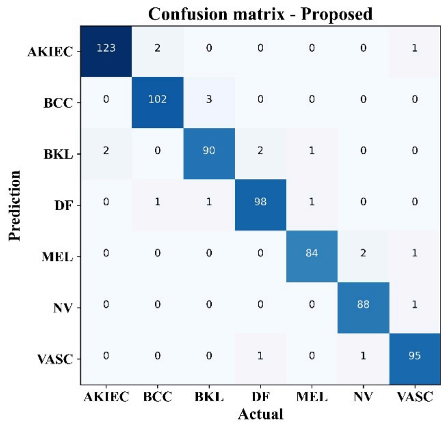


Fig. 11: Confusion Matrix for proposed model

Severity Analysis

This proposed model uses residual lasso with logistic regression to standardize 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. This suggested model attains an MAE of 0.08, MSE of 0.08, and RMSE of 0.282, respectively. Figure 12 depicts the proposed model severity analysis.

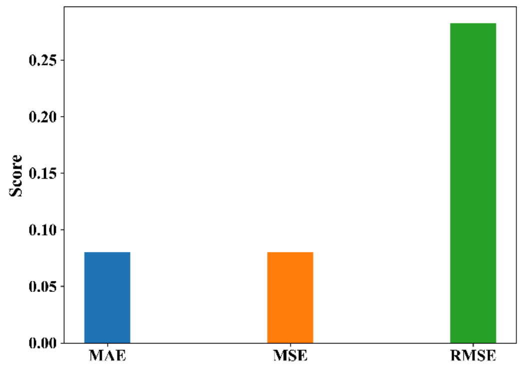


Fig. 12: Proposed model severity analysis

Conclusion

Deep learning is very effective in the analysis and information extraction of large medical data. Using severity analysis, this proposed model demonstrates an effective DL-based hybrid model for segmentation and classification. The HAM10000 database, which is publicly available on Kaggle to diagnose skin cancer early, is ideally suited for multi-class classification and segmentation. First, the hybrid ELPWF model's pre-processing phase lowers noise and enhances the quality of the input images. Complex temporal and hidden features are extracted using a hybrid DL-based features extraction model called TS-HCaps after input photos have been enhanced. The goal of this procedure is to lessen feature dimensionality problems. The hybrid TCWOA model then uses the extracted features as input to choose the best features in order to minimize computational complexity problems. The hybrid PA-HRST model uses the pre-processed data to segment the pertinent skin cancer region; the segmentation method is effective, as seen by the 4% HD analysis and 0.008078 ASSD achieve 99.18% accuracy, 99.09% precision, 99.13% recall, and a 99.11 F1-score in the classification model. The suggested framework performs better than current approaches and accurately classifies dermatological malignancies associated with skin cancer.

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Author’s Contributions

Punam R. Patil: Writing – original draft, Formal analysis, Conceptualization, Methodology, Validation, Software, resources, data curation.

Ritu Tandon: Writing – review and editing, supervision, Formal analysis, Conceptualization.

All authors contributed to the article and approved the submitted version.

Ethics

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

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