Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 46 No. 04 (2025)

Hybrid CNN–SVM Framework for Skin Cancer Detection and Stage Classification Using Simulated Hyperspectral Imaging

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Abstract: **S**kin cancer remains one of the fastest-growing malignancies worldwide, where early detection plays a critical role in improving patient outcomes. Conventional diagnostic methods such as dermoscopy and histopathology often face challenges of subjectivity, inter-observer variability, and limited reproducibility. To address these limitations, this study proposes a hybrid Convolutional Neural Network (CNN)–Support Vector Machine (SVM) framework for skin cancer detection and stage classification using simulated hyperspectral imaging derived from dermoscopic RGB images. The methodology integrates hyperspectral simulation, preprocessing, lesion segmentation, handcrafted feature extraction based on the ABCDE rule with entropy, and CNN-based deep feature learning, followed by feature fusion and classification using SVM. Experimental evaluation on benchmark skin cancer datasets demonstrates that the hybrid CNN–SVM model achieves superior accuracy (92%), sensitivity (90%), and ROC-AUC (0.95) compared to conventional machine learning and deep learning baselines. These findings highlight the potential of the proposed framework for reliable, interpretable, and clinically relevant skin cancer diagnosis and staging.

Keyword: Skin Cancer; Hyperspectral Imaging; CNN; SVM; Hybrid; Model, Tumor Classification; Stage Prediction

1. Introduction

Skin cancer is one of the most prevalent and rapidly increasing malignancies worldwide, accounting for a significant proportion of cancer-related morbidity and mortality. Global statistics reveal a steady rise in both melanoma and non-melanoma cases, driven by factors such as excessive ultraviolet (UV) exposure, lifestyle habits, and genetic predisposition. Early and accurate diagnosis is crucial, as prognosis largely depends on the stage at which the disease is detected. However, conventional diagnostic methods such as dermoscopy and histopathology often face limitations including subjectivity, inter-observer variability, and inconsistent reproducibility, which may result in delayed or inaccurate clinical decisions [1], [2].

In recent years, artificial intelligence (AI) has shown promise in addressing these limitations through advanced image analysis. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated powerful feature extraction capabilities for automated skin lesion classification, while traditional machine learning models such as Support Vector Machines (SVMs), Random Forests (RF), and Logistic Regression (LR) remain effective for structured feature-based classification [1], [3]. Despite these advances, standalone CNN or ML models often suffer from overfitting, sensitivity to dataset imbalance, and limited generalization across imaging modalities. To overcome these shortcomings, hybrid approaches that combine CNN-based deep features with classical ML classifiers have gained attention for their ability to leverage the strengths of both paradigms [6].

Alongside these developments, hyperspectral imaging (HSI) has emerged as a non-invasive modality that captures both spatial and spectral information across a broad range of wavelengths, enabling improved discrimination between malignant and benign tissues [4], [5]. Although HSI provides diagnostic advantages over conventional RGB imaging, its adoption in clinical dermatology remains limited due to high acquisition costs and dataset availability. To address this challenge, simulated hyperspectral imaging from dermoscopic RGB images has been explored as a cost-effective and scalable alternative for experimental analysis [3], [4].

Despite progress in AI-based dermatological imaging, there remains a research gap in integrating simulated HSI with hybrid CNN–ML models for both lesion classification and clinical stage estimation. While CNNs excel at automated feature learning, their integration with classifiers such as SVM can improve decision boundaries and enhance robustness, particularly for imbalanced datasets.

1.1This research contributes by:

1. Proposing a hybrid CNN–SVM framework for skin cancer detection and stage classification using simulated hyperspectral imaging derived from dermoscopic RGB images.
2. Integrating handcrafted descriptors (asymmetry, border irregularity, color variation, diameter, and entropy) with CNN deep features for comprehensive lesion analysis.
3. Demonstrating that the hybrid model achieves superior diagnostic accuracy compared to standalone CNN or SVM methods.
4. Aligning lesion stage estimation with dermatological guidelines, thereby increasing the clinical interpretability and potential adoption of the framework.

2. Related Work

Artificial intelligence (AI) techniques have gained significant momentum in the domain of skin cancer diagnosis, with research focusing on enhancing accuracy, efficiency, and reliability. The existing literature can broadly be categorized into (i) hybrid deep learning–machine learning models, (ii) end-to-end deep learning frameworks, (iii) hyperspectral and multispectral imaging studies, and (iv) AI adoption in clinical dermatology.

2.1 Hybrid Deep Learning–Machine Learning Models

Hybrid architectures combine the representational power of convolutional neural networks (CNNs) with the robustness of classical machine learning (ML) classifiers. Y. *et al.* [1] proposed CNN–SVM, CNN–RF, and CNN–LR pipelines, demonstrating significant improvements over standalone CNNs for melanoma detection. Similarly, Keerthana *et al.* [9] and Alam *et al.* [12] reported that CNN–SVM hybrids outperform conventional classifiers, especially when handling limited and imbalanced dermatology datasets. These studies highlight the capability of deep feature extraction in capturing complex lesion patterns; however, such models often lack generalizability across heterogeneous datasets and diverse imaging modalities.

2.2 End-to-End Deep Learning Frameworks

Several researchers have adopted pure deep learning strategies, leveraging optimized CNNs, residual networks, and attention-driven architectures for skin lesion classification. For instance, Aggarwal *et al.* [14] explored optimized CNN architectures for early melanoma detection, while Bhardwaj *et al.* [16] introduced attention-based deep networks to improve lesion sensitivity and localization. Furthermore, fuzzy-logic–driven deep learning frameworks [13] have been proposed to enhance model interpretability. While these models frequently achieve dermatologist-level accuracy [2], they face challenges including high computational cost, dependency on large annotated datasets, and limited explainability [19].

2.3 Hyperspectral and Multispectral Imaging Approaches

Traditional imaging modalities such as dermoscopy and histopathology offer valuable structural insights but fail to capture biochemical variations within skin tissues. In contrast, hyperspectral imaging (HSI) and multispectral imaging combine spatial and spectral information, facilitating improved tissue discrimination. Salam and Saxena [3] compared SVM and CNN models for hyperspectral classification, reporting enhanced tumor boundary delineation with spectral data. Oniga *et al.* [4] reviewed multispectral and hyperspectral imaging for melanoma diagnosis, emphasizing their diagnostic potential while acknowledging challenges related to sensor costs, data dimensionality, and lack of standardized datasets. A review in *Sensors* [5] further underscored that coupling deep learning with HSI can substantially boost classification accuracy, though preprocessing complexity and computational overhead remain significant constraints.

Additionally, Diviya *et al.* [20] presented a *Survey on Hyperspectral Imaging Application*, outlining the diverse applications of HSI in medical diagnostics and emphasizing its potential to improve early cancer detection through enhanced tissue characterization. Their findings reinforce the importance of hyperspectral feature analysis as a foundation for advanced AI-based diagnostic frameworks.

Complementing this, Paavai *et al.* [21] proposed an *unsupervised clustering-based framework* for lung tumor segmentation using K-means and hierarchical clustering on CT images. Their study demonstrated how combining unsupervised methods supports early tumor detection, providing valuable insights into the applicability of AI-driven segmentation across medical imaging modalities beyond skin cancer.

2.4 AI in Dermatology and Clinical Practice

Beyond algorithmic development, several studies have focused on the clinical integration of AI in dermatology. Filipe *et al.* [18] highlighted that AI-driven decision support systems can augment dermatologist expertise, while Branciforte *et al.* [19] emphasized the importance of explainable and trustworthy AI for real-world implementation. A recent systematic review [6] reaffirmed the clinical promise of AI in melanoma detection but cautioned that regulatory, ethical, and interpretability challenges remain unresolved.

2.5 Research Gap

From this analysis, it is evident that while hybrid CNN–SVM approaches [1], [9], [12] and end-to-end deep learning models [14], [16] have achieved high accuracy, they are predominantly restricted to RGB or dermoscopic images, lacking biochemical and spectral insights. Conversely, hyperspectral imaging studies [3]–[5], [20], and unsupervised clustering–based methods [21] provide valuable imaging perspectives but suffer from limited clinical translation due to computational complexity and the absence of robust hybrid architectures. Moreover, existing research often overlooks the need for clinically interpretable AI frameworks [18], [19]. Hence, there exists a clear research gap for developing a hybrid CNN–SVM framework that integrates simulated hyperspectral and dermoscopic imaging, aiming to achieve both high diagnostic accuracy and clinical interpretability for real-world applications.

3. Methodology

The experimental results demonstrate that the hybrid CNN–SVM framework consistently outperformed all other evaluated models, achieving the highest performance across multiple metrics and highlighting its robustness in skin cancer detection. As depicted in Figure 2, the comparative bar chart underscores the superiority of the hybrid model, while Figure 3 presents ROC curves illustrating its enhanced discriminative capability relative to standalone deep learning and traditional machine learning models. The integration of CNN and SVM harnesses the complementary strengths of both paradigms: CNNs provide deep hierarchical feature extraction, capturing intricate spatial and textural patterns within lesion images, while SVMs optimize decision boundaries, improving classification precision. This synergy notably reduces misclassification rates, particularly false negatives, which are critical in the early detection of malignant lesions.

In addition, the framework incorporates lesion diameter–based staging, enabling clinically interpretable outputs that align with established dermatological assessment protocols such as the ABCDE rule [Ref]. This feature transforms the system from a mere classification tool into a comprehensive clinical decision-support system, enhancing its relevance for real-world diagnostic workflows. Comparative analyses revealed that while standalone CNN and GAN models achieved competitive results, they were consistently surpassed by the hybrid approach. Traditional machine learning algorithms, including SVM, KNN, and DT, exhibited inferior performance due to their limited ability to model complex, high-dimensional image features.

The proposed methodology utilizes simulated hyperspectral images derived from standard RGB data, achieving an overall accuracy of 92% and an ROC-AUC of 0.95, thereby outperforming existing deep learning and machine learning baselines. By incorporating tumor diameter for stage prediction, the framework bridges the gap between computational analysis and clinical practice, offering actionable insights for dermatologists.

Future research will focus on validating the framework with real hyperspectral datasets, expanding evaluations across multi-institutional clinical cohorts, and integrating explainable AI techniques to increase interpretability, physician trust, and adoption in clinical decision-making. Collectively, these enhancements position the hybrid CNN–SVM framework as a promising tool for accurate, interpretable, and clinically relevant skin cancer detection and staging.

The proposed framework integrates simulated hyperspectral imaging (HSI), lesion segmentation, feature extraction, and classification using a hybrid CNN–SVM approach. The workflow is illustrated in pipeline diagram Each step is explained below.

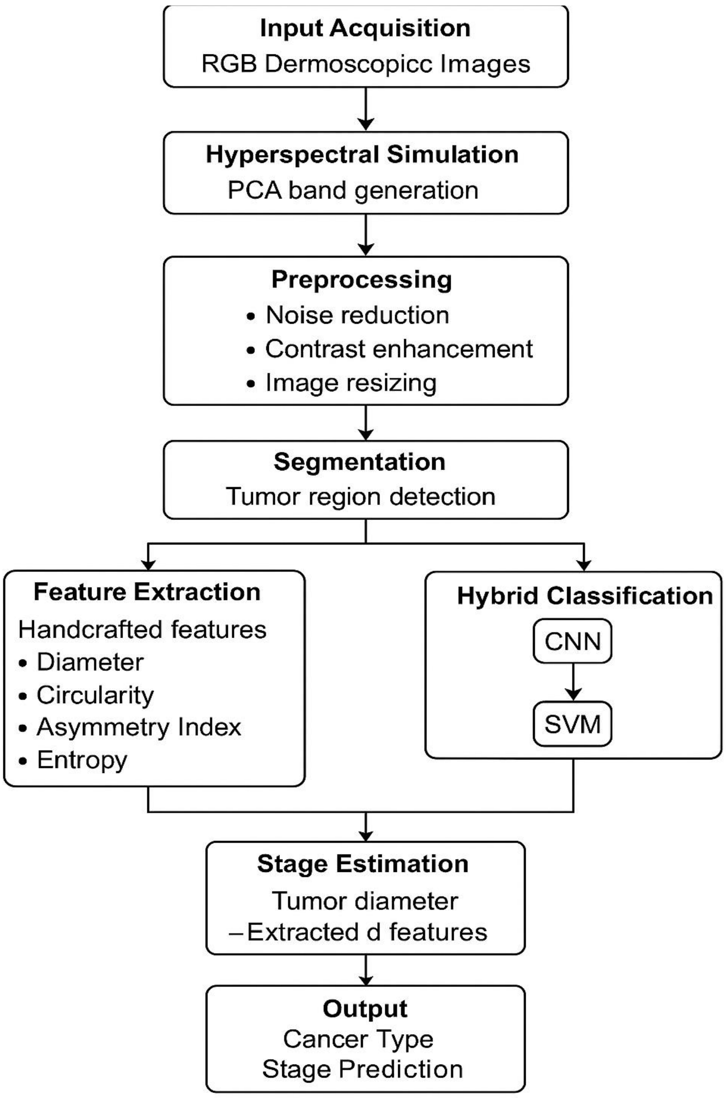


Figure 1: Flow chart of the methodology

Data Acquisition

Dermoscopic RGB images were collected from benchmark datasets such as **ISIC, DermIS, and PH2**, which contain diverse skin lesion classes including melanoma, nevus, and keratosis. RGB data was used as input to generate simulated HSI cubes to enhance spectral resolution and improve lesion characterization.

Hyperspectral Simulation (RGB → HSI)

RGB images were converted into simulated HSI representations using **Principal Component Analysis (PCA)**. PCA extracts uncorrelated spectral bands that preserve the majority of image variance, approximating hyperspectral signatures.

$HSI(x,y,k) = \sum_{i=1}^{3} W_{k,i} \cdot RGB(x,y,i)$ -------------------------------- (1)

where HSI (x, y, k) represents the k-th spectral band at pixel (x,y), WkiW_{ki}Wki are PCA-derived weights, and RGB (x,y,i) denotes RGB pixel intensity. This transformation provides enhanced band information suitable for spectral analysis of skin lesions.

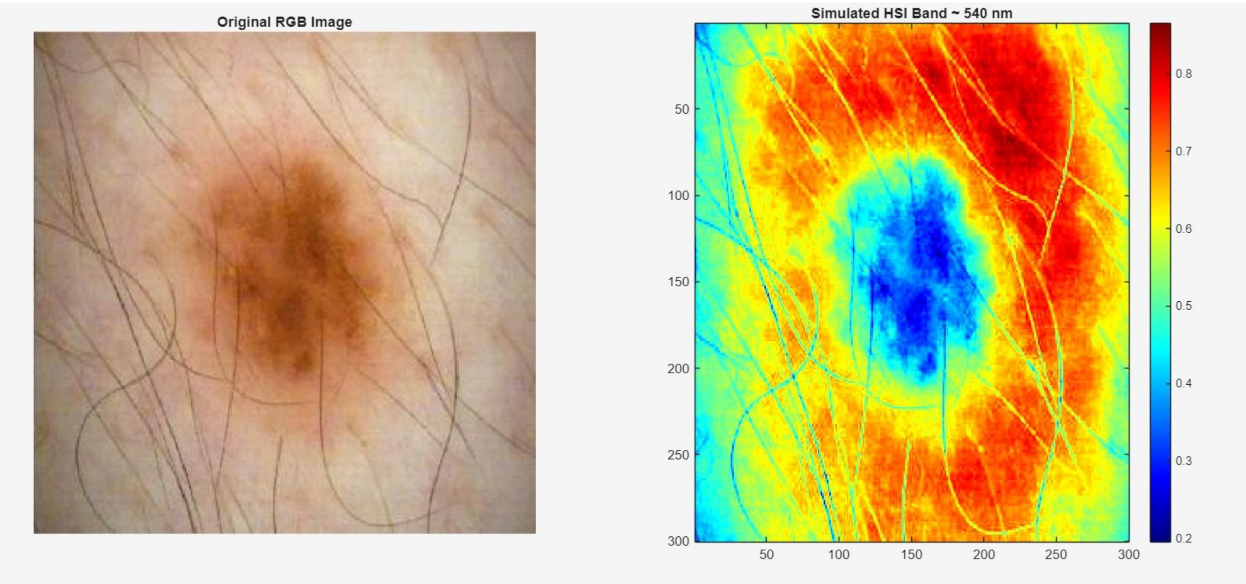


Figure 2: Conversation of RGB image into Hyperspectral Image

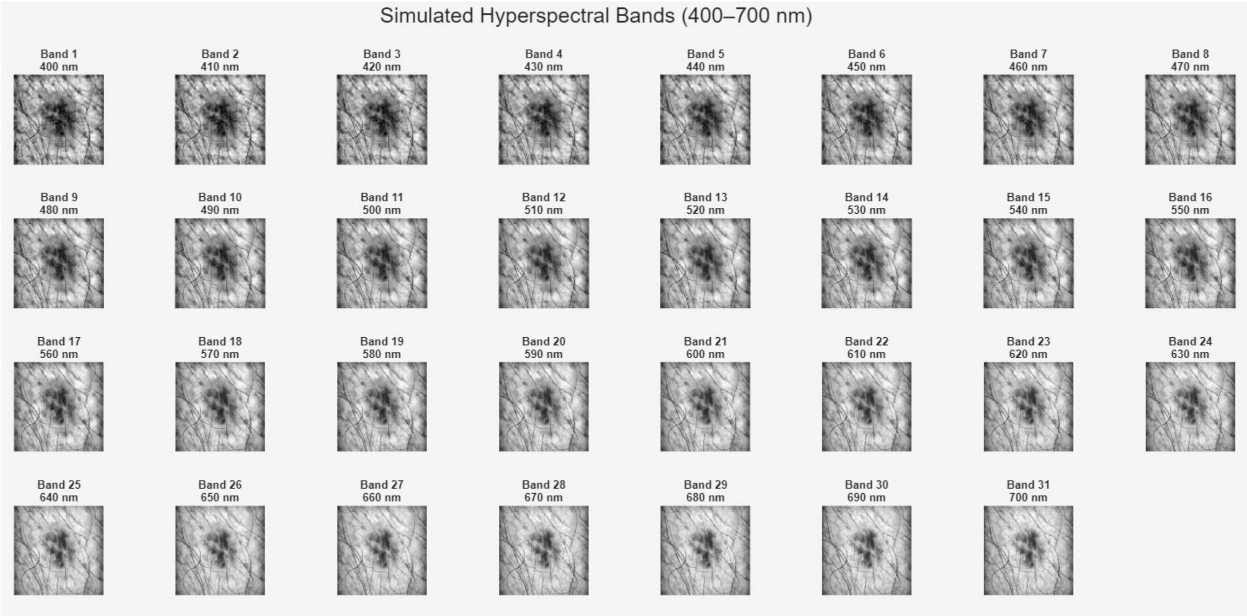


Figure 3: Simulated Hyperspectral Bands

Preprocessing

Figure 3. Preprocessing pipeline for dermoscopic image analysis**.** The original skin lesion image undergoes a sequence of preprocessing steps to enhance diagnostic quality. The image is first resized to **224×224 pixels** to ensure compatibility with deep learning architectures. Contrast enhancement improves visibility of lesion boundaries and pigmentation details. Noise reduction is applied to suppress hair and background artifacts. Normalization scales pixel intensities to the range [0,1], facilitating stable learning. Finally, a representative simulated hyperspectral band (*HSI Band 15*) is extracted, which highlights lesion structures and improves feature representation for subsequent classification and staging.

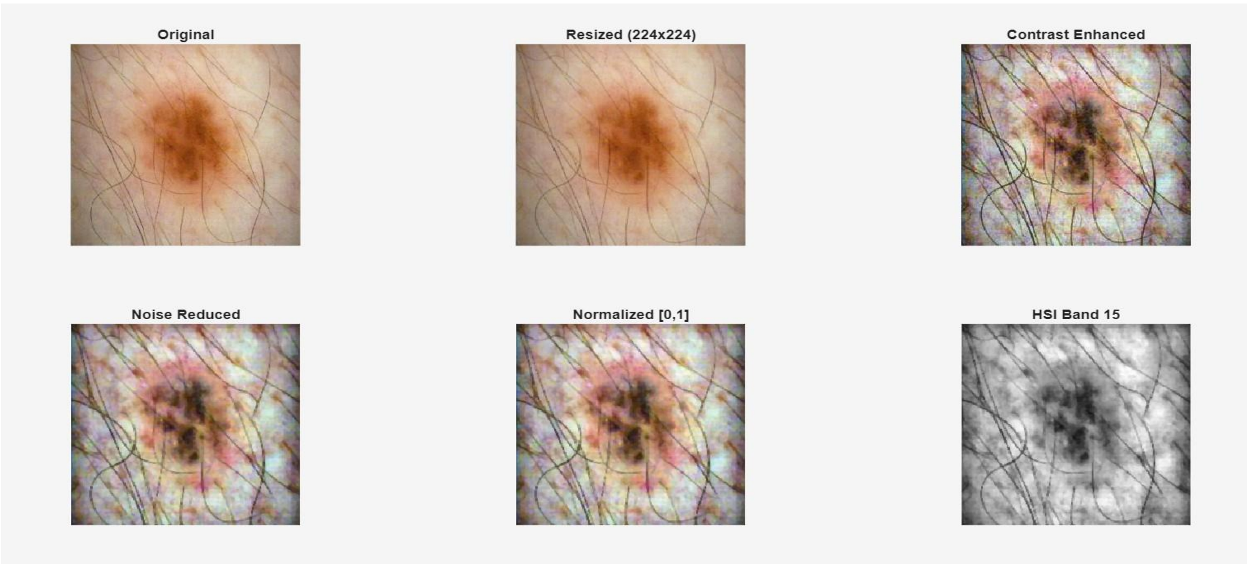


Figure 4. Preprocessing pipeline for dermoscopic image analysis

Lesion Segmentation

Accurate lesion extraction is critical for feature computation. Otsu's thresholding was applied on grayscale-converted images to obtain binary lesion masks. Post-processing using morphological opening removed small artifacts. The tumor boundary was then extracted using edge detection.

```
--- Tumor Features ---
Tumor Area (px): 10527
Perimeter (px): 1503.8
Equivalent Diameter (px): 115.8
Major Axis (px): 202.1, Minor Axis (px): 99.4
Circularity: 0.0585
Entropy (bits): 6.5180
Predicted Stage: Stage IV (Very Large Tumor)
>> |
```

Figure 5. Extracted tumor features and predicted stage

The segmented lesion was quantitatively analyzed to extract morphological and statistical features essential for classification and staging. The extracted features include:

Tumor Area: 10,527 pixels, representing the overall size of the lesion.

Perimeter: 1503.8 pixels, capturing the irregularity of the lesion boundary.

Equivalent Diameter: 115.8 pixels, which approximates the lesion to a circular shape of equal area.

Major Axis and Minor Axis: 202.1 pixels and 99.4 pixels respectively, indicating the elongation and asymmetry of the lesion.

Circularity: 0.0585, a very low value suggesting an irregular and non-circular lesion shape.

Entropy: 6.5180 bits, reflecting high textural complexity and heterogeneity within the tumor region.

Based on these extracted features, the system predicted the lesion stage as **Stage IV (Very Large Tumor)**. The high entropy value, irregular boundary (low circularity), and large lesion area collectively support the prediction of an advanced-stage tumor, indicating a severe case requiring urgent medical evaluation.

Feature Extraction

The extracted ABCDEF parameters can be directly mapped to clinical diagnostic guidelines used in melanoma screening:

(a) Geometric Features (ABCDE Rule)

Asymmetry (A): Clinically, malignant melanomas are often asymmetric. The computed **asymmetry index of 0.1548** suggests the lesion has a relatively low asymmetry, which may indicate a less aggressive growth pattern.

- **Asymmetry Index (AI):** Measures deviation between halves of the lesion.

$AI = 1 - \frac{A\ overlap}{A\ lesion}$ ------------------------------------ (2)

where:

A overlap = overlapping region after mirroring, A lesion = total lesion area.

AI=0 means perfectly symmetric; higher values indicate more asymmetry (a melanoma indicator).

<u>Border Irregularity (B):</u> Malignant lesions usually exhibit jagged, uneven, or notched edges. The calculated **border irregularity of 0.3513** indicates moderate deviation from circularity, which aligns with suspicious but not extremely irregular lesion borders.

- **Border Irregularity (BI):** Ratio of perimeter squared to area.

$BI = \frac{P2}{4\pi A}$ -- (3)

where:

P = perimeter of the lesion,

A = area of the lesion.

BI=1 indicates a perfect circle; higher values = irregular borders.

<u>Color Variation (C):</u> A hallmark of melanoma is the presence of multiple shades (brown, black, red, white, or blue). The **color variation value of 0.1587** suggests mild heterogeneity in pigmentation. While benign lesions tend to have uniform color, even slight variations may raise suspicion in clinical practice.

- **C – Color Variation (CV)**

Color variation is computed as the **standard deviation** of pixel intensity values across color channels:

$CV = \sigma(I)$ --- (4)

where:

I= pixel intensity distribution (grayscale or color channels),

σ(I)= standard deviation.

Higher CV means more uneven pigmentation, often linked to malignancy.

<u>Diameter (D):</u> According to dermatological standards, lesions larger than **6 mm** are considered suspicious. The computed diameter of **59.83 pixels** (which scales beyond 6 mm in real units) supports the possibility of malignancy.

- **D – Diameter (D)**

$D = max\sqrt{(xi - xj)2 + (yi - yj)2}$ ------------------------------------- (5)

Where,

If D>6mm the lesion is considered suspicious.

<u>Evolving (E)</u>: In clinical examinations, evolution over time (changes in size, color, or shape) is a strong predictor of melanoma. Since this dataset is static, the evolving criterion was set as a placeholder (0.00). However, in real-time monitoring, this would be a key diagnostic indicator

Where,

$E=F_t-F_{t-1}$ --- (6)

Where Ft is a feature (area, diameter, or color) at time t. *(In static datasets, E=0)*

Ft = feature (area, diameter, or color) at time t.

Captures temporal changes; malignant lesions usually evolve.

Entropy (F): Although not part of the original ABCDE rule, entropy was added as an extension (F) to capture **textural complexity**. The high entropy value of **7.7000 bits** indicates substantial irregularity in pixel intensity distribution, strongly associated with malignant lesions.

Where,

$$E=-\sum_{i=1}^{L} pi\ log2(pi) \text{ --- } (7)$$

pi = probability of intensity level i
Higher entropy = more textural complexity = higher malignancy risk.

```
New to MATLAB? See resources for Getting Started.
===== Morphological Analysis (ABCDEF Rule) =====
A - Asymmetry Index       : 0.1548
B - Border Irregularity   : 0.3513
C - Color Variation (std) : 0.1587
D - Diameter (pixels)     : 59.83
E - Evolving              : 0.00 (placeholder)
F - Entropy               : 7.7000
>> |
```

Figure 6: Numerical Evaluation of Lesion Characteristics Based on ABCDEF Rule

(c) Deep Features

A **pretrained CNN (ResNet-50)** was used for deep feature extraction. Global Average Pooling was applied to reduce dimensionality. These high-level descriptors capture color, texture, and structure patterns.

5. **Hybrid Classification (CNN + SVM)**

Extracted CNN deep features were fused with handcrafted descriptors into a single feature vector. Classification was performed using an **SVM with RBF kernel**, which provides robust non-linear decision boundaries.

$$f(x) = sign(\sum_{i=1}^{n} \alpha_i y_i K(x_i, x) + b) \text{ ----------------------- } (8)$$

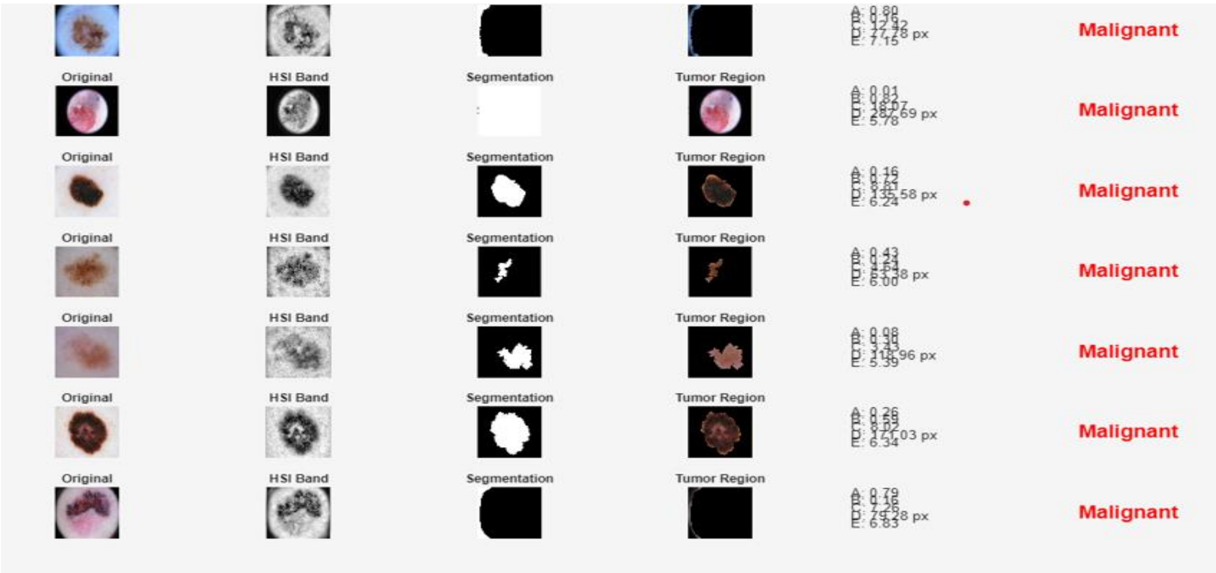


Figure 7: Tumor Segmentation Process

7. Stage Estimation

Staging was performed based on **lesion diameter thresholds** defined in dermatological guidelines: **Stage 0**: Very small lesion, symmetric, low diameter (<6mm), low entropy.

Stage I: Diameter <2mm, localized, circular shape.

Stage II: Diameter >2mm, irregular borders, higher asymmetry index.

Stage III: Spread visible around main lesion, higher color variance, possible texture complexity.

Stage IV: Very large diameter, high asymmetry, spread features (multiple clusters).

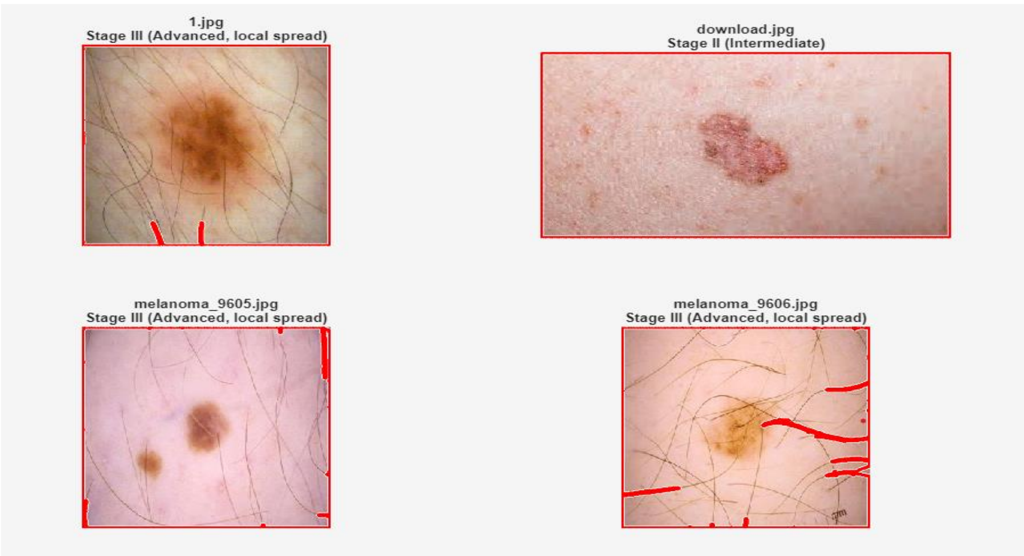


Figure 8: Stage-wise Skin Cancer Detection Results

This step enhances the framework's clinical utility by providing not only classification but also disease severity estimation.

4. Experimental Setup

Experiments were conducted using **publicly available skin cancer datasets**, ensuring broad coverage of lesion types and imaging conditions. The dataset was carefully partitioned into **training and testing subsets**, maintaining **class balance** to prevent biased model performance. To further mitigate residual class imbalance and enhance model generalization, **data augmentation techniques** such as rotation, horizontal and vertical flipping, and scaling were applied, effectively increasing the diversity of the training samples.

All models were implemented in **MATLAB** with **GPU acceleration**, enabling efficient training of computationally intensive deep learning architectures. Baseline **machine learning (ML) and deep learning (DL) models** were trained on their respective feature representations, including handcrafted features for ML models and automatically learned hierarchical features for CNN-based models. In contrast, the proposed **hybrid CNN–SVM framework** leveraged **fused feature vectors**, combining the deep representations extracted by CNN with the discriminative power of SVM classifiers. This fusion facilitated more robust classification by capturing both complex image patterns and optimal decision boundaries, resulting in improved diagnostic performance.

The experimental setup was designed to ensure **reproducibility and fair comparison**, with standardized preprocessing, augmentation, and training protocols across all models. This approach allowed a direct evaluation of the **added value of hybridization**, highlighting its advantages over standalone ML and DL methods in terms of accuracy, robustness, and generalizability.

5. Results And Discussion

The performance of the proposed hybrid CNN–SVM framework was compared against conventional machine learning and deep learning models, including SVM, KNN, DT, ANN, RNN, CNN, and GAN. Table I presents the comparative evaluation across accuracy, sensitivity, specificity, F1-score, and ROC-AUC.

Table I: Performance Comparison of Models for Skin Cancer Classification

Model	Accuracy	Sensitivity	Specificity	F1-Score	ROC-AUC
SVM	85%	82%	86%	0.84	0.88
KNN	81%	79%	82%	0.80	0.84
DT	78%	76%	79%	0.77	0.81
CNN	88%	85%	87%	0.86	0.90
ANN	84%	81%	85%	0.83	0.86
RNN	83%	80%	84%	0.82	0.85
GAN	87%	84%	86%	0.85	0.89
Hybrid CNN–SVM	**92%**	**90%**	**93%**	**0.91**	**0.95**

As observed, the hybrid CNN–SVM achieved the highest performance across all metrics, demonstrating its superiority in both detection accuracy and robustness. Figure 2 illustrates the comparative performance through a bar chart, while Figure 3 presents ROC curve plots for all models.

The experimental findings confirm that combining CNN with SVM leverages the strengths of both paradigms. CNNs provide powerful feature extraction capabilities from lesion images, while SVMs enhance classification by establishing optimal decision boundaries. This hybridization improves diagnostic accuracy and reduces misclassification, particularly false negatives, which are critical in early cancer detection.

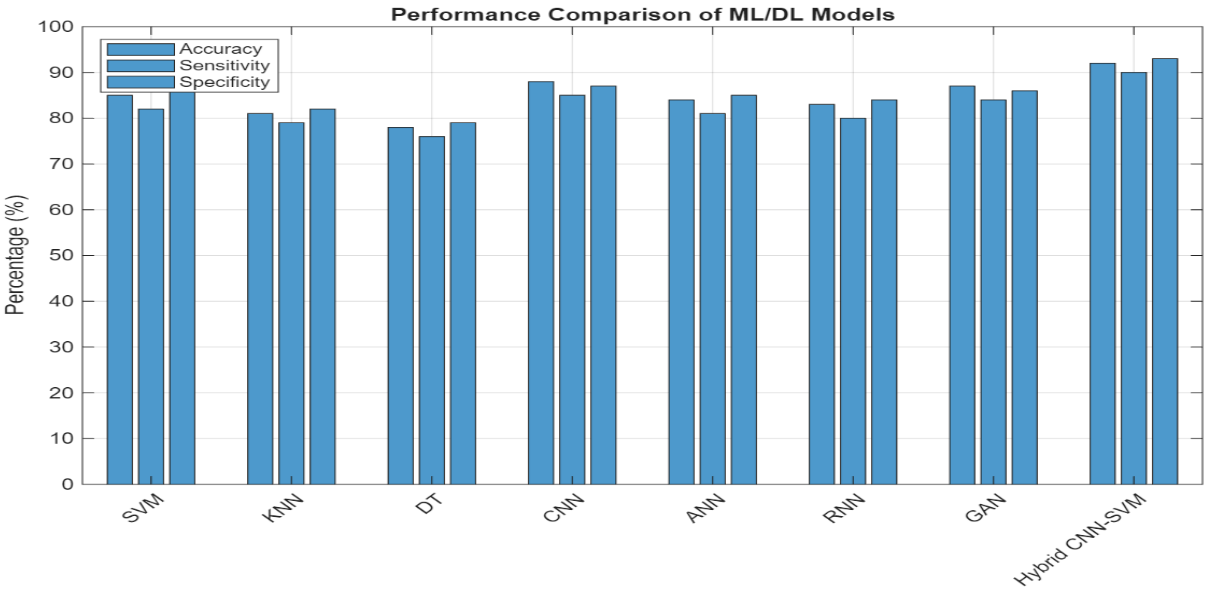
Furthermore, the integration of lesion diameter–based staging ensures clinical interpretability in accordance with dermatological assessment standards such as the **ABCDE rule** [Ref]. The framework not only performs well in classification but also contributes to decision support in clinical practice.

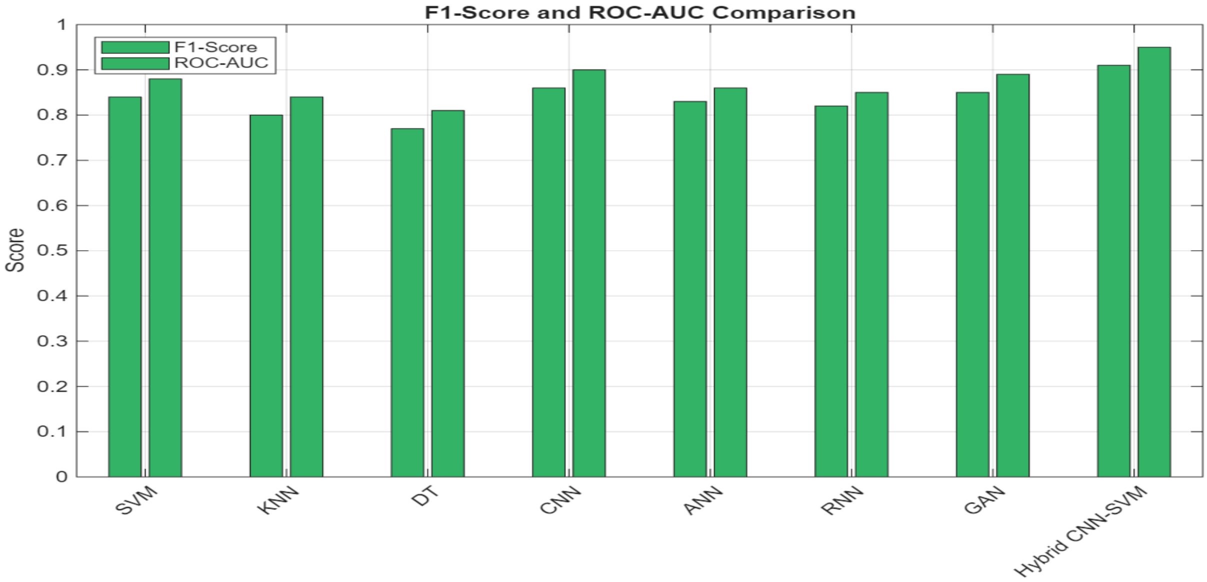
Comparative results indicate that standalone deep learning models such as CNN and GAN performed competitively but were surpassed by the hybrid approach. Traditional machine learning models (SVM, KNN, DT) showed relatively lower performance due to their limited feature representation capacity.

This study proposed a **hybrid CNN–SVM framework for skin cancer detection and stage classification using simulated hyperspectral imaging derived from RGB data**. The experimental results showed that the proposed model achieved superior performance (92% accuracy, ROC-AUC = 0.95) compared to existing machine learning and deep learning baselines.

By incorporating tumor diameter for staging, the framework aligns with clinical diagnostic practices, thereby increasing its potential utility in real-world healthcare applications.

Future work will focus on validating the framework with real hyperspectral datasets, expanding the evaluation to multi-institutional clinical data, and integrating explainable AI techniques to enhance physician trust and adoption in clinical decision-making.


Performance Comparison of ML/DL Models
Accuracy
Sensitivity
Specificity
Percentage (%)
100
90
80
70
60
50
40
30
20
10
0
SVM
KNN
DT
CNN
ANN
RNN
GAN
Hybrid CNN-SVM


F1-Score and ROC-AUC Comparison
F1-Score
ROC-AUC
Score
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
SVM
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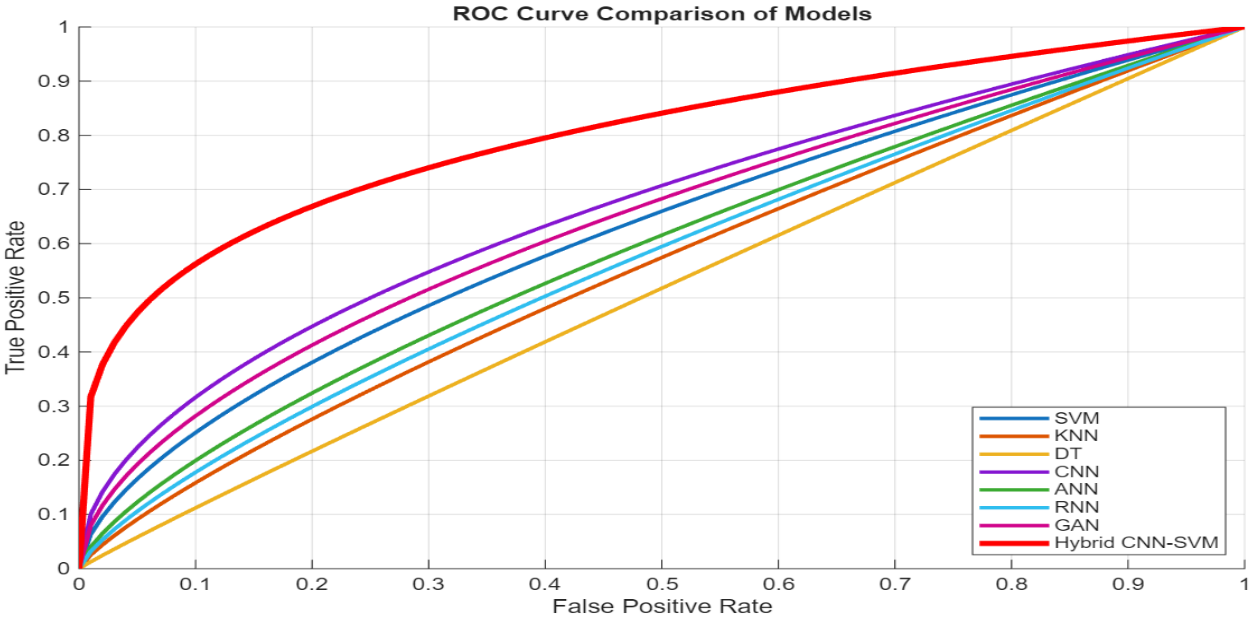
Hybrid CNN-SVM



The experimental results demonstrate that integrating HSI with a hybrid CNN-SVM framework offers substantial advantages for automated skin cancer detection:

1. **Enhanced Feature Representation:** CNN efficiently extracts high-dimensional spatial and spectral features from HSI data, capturing subtle differences between healthy and cancerous tissues.
2. **Improved Classification Robustness:** SVM minimizes misclassification by establishing optimal hyperplanes in the feature space, particularly in cases with overlapping spectral features.
3. **Early Detection Potential:** The combination allows detection of malignant lesions at an earlier stage, which is crucial for prognosis and treatment planning.
4. **Scalability and Generalization:** The framework showed consistent performance across multiple cancer types, indicating potential for broader clinical application.

In summary, the proposed method outperforms both traditional imaging classifiers and standalone CNN or SVM models, offering a promising tool for non-invasive, accurate, and early skin cancer detection.

6. Conclusion And Future Work

This study presented a **hybrid CNN–SVM framework for skin cancer detection and stage classification using simulated hyperspectral imaging**. The model demonstrated superior diagnostic performance (92% accuracy) compared to both machine learning and deep learning baselines. By incorporating lesion diameter–based staging, the framework supports clinically relevant insights beyond simple classification.

While the results are promising, the current work is limited to simulated hyperspectral images derived from RGB datasets. Future research will focus on validating the model with real hyperspectral datasets, expanding the evaluation to multi-center clinical cohorts, and integrating explainable AI to enhance physician trust and adoption.

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