An Interpretable Multimodal Approach for Skin Cancer Analysis via Simulated Hyperspectral Reconstruction and Hybrid Machine Learning

DIVIYA K[1], Dr RADHAKRISHNAN P[2],

Research Scholar[1] PG & Research Departments of Computer Science, Don Bosco College (Co – Ed) (Affiliated to Thiruvalluvar University), Yelagiri Hills, TN, India – 635 853. E-

Research Supervisor[2] PG & Research Departments of Computer Science, Don Bosco College (Co – Ed) (Affiliated to Thiruvalluvar University), Yelagiri Hills, TN, India – 635853.

Abstract:

Skin cancer diagnosis requires accurate lesion classification and reliable stage estimation to enable timely clinical intervention. This study proposes a stage-aware multimodal framework integrating simulated hyperspectral reconstruction with hybrid deep learning and machine learning techniques. Initially, RGB dermoscopic images are preprocessed and enhanced, followed by feature-level class balancing using SMOTE. Principal Component Analysis (PCA) is employed to generate simulated hyperspectral representations, enriching spectral information beyond conventional RGB imaging.

Deep semantic features are extracted using a Convolutional Neural Network (CNN), while clinically significant handcrafted features—including tumor diameter, asymmetry index, circularity, and entropy—are computed to capture morphological characteristics. These features are fused and classified using a Support Vector Machine (SVM) for tumor detection, followed by Artificial Neural Network (ANN)-based stage estimation.

Experimental results demonstrate that the proposed hybrid framework achieves superior performance, with improved classification accuracy, enhanced robustness under class imbalance, and better generalization compared to single-model approaches. Furthermore, a stage-aware clinical recommendation module provides interpretable and actionable diagnostic insights, enhancing real-world applicability. The proposed system offers a cost-effective and explainable solution for intelligent skin cancer diagnosis.

Keyword: Skin Cancer Detection, Simulated Hyperspectral Imaging, Hybrid Deep Learning, CNN-SVM Model, Stage Estimation, Feature Fusion, Clinical Decision Support, SMOTE

1. Introduction

Skin cancer is among the most common and rapidly increasing types of cancer worldwide, with melanoma being the most aggressive and life-threatening form. Early detection and accurate diagnosis are essential, as survival rates decrease significantly with disease progression. The

availability of large dermoscopic datasets, such as the HAM10000 dataset, has enabled the development of automated diagnostic systems for skin lesion analysis [3].

Traditional diagnostic methods, including visual inspection, dermoscopy, and histopathological biopsy, remain the gold standard in clinical practice. However, these approaches are often subjective, time-consuming, and highly dependent on clinical expertise. These limitations have driven the development of Computer-Aided Diagnosis (CAD) systems to assist dermatologists in achieving more objective and scalable evaluations [10].

Recent advancements in Artificial Intelligence, particularly deep learning, have significantly improved medical image analysis. Convolutional Neural Networks (CNNs) have demonstrated remarkable performance in skin lesion classification, achieving dermatologist-level accuracy in several studies [1], [4]. These models leverage large datasets and hierarchical feature learning to capture complex visual patterns associated with skin abnormalities [2], [7].

Despite these successes, CNN-based approaches suffer from limitations such as overfitting, lack of interpretability, and reliance on large annotated datasets. To overcome these issues, Support Vector Machines (SVMs) have been widely adopted due to their strong generalization capability and effectiveness in high-dimensional feature spaces [5]. Hybrid CNN–SVM approaches have shown improved robustness and classification performance.

In addition to classification, accurate disease assessment requires stage estimation, which plays a critical role in treatment planning and prognosis. Artificial Neural Networks (ANNs) are capable of modeling complex nonlinear relationships between clinical features and disease progression; however, their integration into skin cancer staging systems remains limited [6].

Most existing systems rely on RGB dermoscopic images, which provide limited spectral information across only three channels. This restricts the ability to capture subtle biochemical variations in skin tissues. In contrast, hyperspectral imaging (HSI) offers rich spectral information across multiple wavelengths, enabling improved tissue characterization [8].

However, hyperspectral imaging systems are expensive and not widely accessible. To address this limitation, recent research has explored simulated hyperspectral reconstruction from RGB images as a cost-effective alternative.

Another significant challenge in dermatological datasets is class imbalance, particularly for malignant and advanced-stage lesions. Techniques such as SMOTE have been widely used to improve classification performance for minority classes [9].

The primary contributions of this work are outlined as follows:

- A simulated hyperspectral reconstruction approach is introduced to enhance spectral information from conventional RGB dermoscopic images without requiring specialized imaging equipment.
- A multimodal feature extraction strategy is developed by integrating deep CNN features with clinically meaningful morphological descriptors.
- A hybrid two-stage learning framework is proposed, employing SVM for tumor classification and ANN for stage prediction.

- A feature-level SMOTE technique is implemented to effectively address class imbalance and improve sensitivity for minority classes.
- A stage-aware clinical recommendation module is designed to provide interpretable and actionable diagnostic insights.

By integrating enhanced spectral representation, hybrid learning techniques, and clinically interpretable decision support, the proposed framework contributes toward the development of a practical, reliable, and clinically applicable AI-driven system for skin cancer diagnosis and management.

2. Research Gap

Although substantial progress has been achieved in deep learning–based skin lesion analysis, several important challenges remain inadequately addressed in existing research.

First, the majority of current methods rely primarily on RGB dermoscopic images. While CNN-based models have demonstrated strong classification performance, RGB imaging is inherently limited in spectral resolution. This restricts the ability to capture subtle biochemical and structural variations associated with tumor heterogeneity and progression. Although hyperspectral imaging (HSI) offers enhanced spectral characterization, its clinical adoption is hindered by high cost, complex hardware requirements, and limited accessibility. Moreover, only a limited number of studies have explored simulated hyperspectral reconstruction as a practical and scalable alternative.

Second, most existing approaches are focused mainly on lesion classification, either binary or multi-class, without incorporating reliable stage estimation. However, effective clinical decision-making depends not only on identifying lesion type but also on determining disease stage and assessing morphological severity indicators such as lesion diameter, asymmetry, and structural irregularities. The lack of stage-aware modeling significantly reduces the clinical relevance and applicability of many Computer-Aided Diagnosis (CAD) systems.

Third, deep learning models are often treated as black-box systems, providing limited interpretability and minimal clinical insight. While high accuracy is frequently reported, these models rarely offer structured recommendations or explanations aligned with predicted risk levels. This lack of transparency limits clinician trust and hinders real-world adoption.

Fourth, class imbalance remains a persistent issue in dermatological datasets, particularly due to the underrepresentation of advanced melanoma cases. Most existing solutions rely on image-level augmentation, while feature-level balancing techniques are comparatively less explored, despite their potential to improve minority class performance.

In light of these limitations, there is a strong need for an explainable and multimodal framework that can enhance spectral representation without requiring dedicated hyperspectral imaging hardware, integrate deep features with clinically meaningful morphological descriptors, perform stage-aware prediction, provide structured clinical recommendations, and maintain robustness in the presence of imbalanced data.

The proposed study aims to address these critical gaps by developing a comprehensive and clinically interpretable diagnostic framework.

3. Related Work

3.1 Deep Learning-Based Skin Lesion Classification

Deep learning, particularly Convolutional Neural Networks (CNNs), has become the dominant approach for automated skin cancer detection. Several studies have demonstrated that CNN-based architectures can achieve high classification accuracy, often comparable to dermatologists. For instance, recent works have utilized architectures such as EfficientNet, MobileNet, and ResNet to classify dermoscopic images from datasets like HAM10000 and ISIC, achieving significant improvements in performance and generalization .

Advanced frameworks such as Skin-DeepNet incorporate preprocessing, segmentation, and attention-based feature extraction to enhance classification accuracy and lesion localization . Despite these advancements, CNN-based methods often suffer from limitations such as overfitting, dependency on large annotated datasets, and lack of interpretability.

3.2 Hybrid Deep Learning and Machine Learning Approaches

To improve classification robustness, hybrid models combining deep learning with traditional machine learning techniques have gained attention. Several studies have integrated CNN-based feature extraction with classifiers such as Support Vector Machines (SVMs) and Random Forests.

For example, hybrid CNN–SVM models have demonstrated improved accuracy and generalization by leveraging deep feature representations along with margin-based classification . Other approaches incorporate ensemble learning and optimization algorithms to enhance feature selection and classification performance . Additionally, hybrid architectures combining CNN with LSTM layers have been proposed to capture spatial dependencies and improve melanoma classification .

However, most hybrid systems focus primarily on classification tasks and do not extend to stage estimation or clinical decision support.

3.3 Hyperspectral and Multispectral Imaging in Skin Cancer Analysis

Hyperspectral Imaging (HSI) and Multispectral Imaging (MSI) have emerged as promising techniques for improving skin cancer diagnosis by capturing detailed spectral information across multiple wavelengths. These modalities enable better differentiation between malignant and benign tissues based on spectral signatures.

Recent studies have shown that hyperspectral imaging combined with machine learning algorithms such as CNN and SVM can significantly improve classification accuracy and sensitivity . Similarly, multispectral imaging approaches have demonstrated high diagnostic accuracy by capturing subtle spectral variations in skin tissues .

Despite their advantages, the clinical adoption of HSI is limited due to high cost, complex instrumentation, and lack of accessibility. Consequently, recent research has explored simulated hyperspectral reconstruction techniques from RGB images as a cost-effective alternative .

3.4 Multimodal and Feature Fusion Approaches

Recent advancements have focused on multimodal learning by combining image features with additional clinical or metadata information. Studies integrating patient metadata such as age, lesion size, and color with image-based features have demonstrated improved classification performance and clinical relevance .

Furthermore, feature fusion techniques that combine deep features with handcrafted descriptors have shown enhanced performance by capturing both high-level semantic information and clinically interpretable characteristics. However, most existing multimodal frameworks lack structured clinical reasoning and decision-support mechanisms.

3.5 Class Imbalance Handling in Skin Cancer Datasets

Class imbalance is a significant challenge in dermatological datasets, particularly due to the underrepresentation of malignant and advanced-stage lesions. Various approaches such as data augmentation, class weighting, and Generative Adversarial Networks (GANs) have been proposed to address this issue.

Recent studies have explored advanced augmentation strategies and loss functions to improve minority class detection . Additionally, deep learning architectures incorporating imbalance-aware training mechanisms have demonstrated improved sensitivity for rare classes . However, feature-level balancing techniques such as SMOTE remain relatively underexplored.

3.6 Research Gap

Although significant progress has been made in skin cancer analysis using deep learning and imaging techniques, several limitations persist. Existing approaches often rely solely on RGB images, lack stage-aware prediction, provide limited interpretability, and inadequately address class imbalance. Moreover, the integration of clinically meaningful features and structured decision-support systems remains insufficient.

To address these challenges, the proposed study introduces a multimodal hybrid framework that integrates simulated hyperspectral imaging, deep and handcrafted feature fusion, hybrid learning models, and stage-aware clinical recommendations, thereby improving diagnostic accuracy, interpretability, and clinical applicability.

Aspect	Existing Studies	Limitations	Proposed Work
Input Modality	RGB dermoscopic images	Limited spectral information; cannot capture subtle biochemical variations	Simulated hyperspectral imaging from RGB to enhance spectral representation
Feature Extraction	Deep features (CNN-based)	Lack of clinically interpretable features	Combination of deep features + handcrafted clinical features (diameter, asymmetry, circularity, entropy)
Classification Approach	CNN / CNN + basic classifiers	Focus mainly on lesion classification only	Hybrid CNN–SVM model for robust tumor detection
Stage Estimation	Rarely considered	No stage prediction for disease severity	ANN-based multi-class stage estimation (Stage I–IV)
Interpretability	Limited (Grad-CAM in some cases)	No structured clinical explanation	Stage-aware clinical recommendation module for actionable insights
Feature Fusion	Single feature type or basic fusion	Incomplete utilization of multimodal data	Multimodal feature-level fusion for enhanced performance
Class Imbalance Handling	Data augmentation / class weighting	Poor minority class sensitivity	Feature-level SMOTE for improved minority representation
Clinical Relevance	Accuracy-focused models	Lack of real-world applicability	Decision-support system aligned with clinical workflow
Cost & Accessibility	Requires dermoscopy or advanced imaging	Hyperspectral systems are expensive	Cost-effective simulated hyperspectral approach
Overall Capability	Classification-focused	Limited interpretability and scalability	Integrated framework: detection + staging + recommendation

Table 1: Comparison of Existing Approaches

4. Methodology

The proposed framework is designed as a **multimodal, stage-aware clinical decision-support system** for automated skin cancer detection, classification, and stage estimation. The overall architecture consists of six major components: preprocessing and segmentation, simulated hyperspectral reconstruction, feature extraction, feature fusion, class imbalance correction, classification and stage estimation, and clinical recommendation generation. The workflow of the proposed system is illustrated in Fig. 1

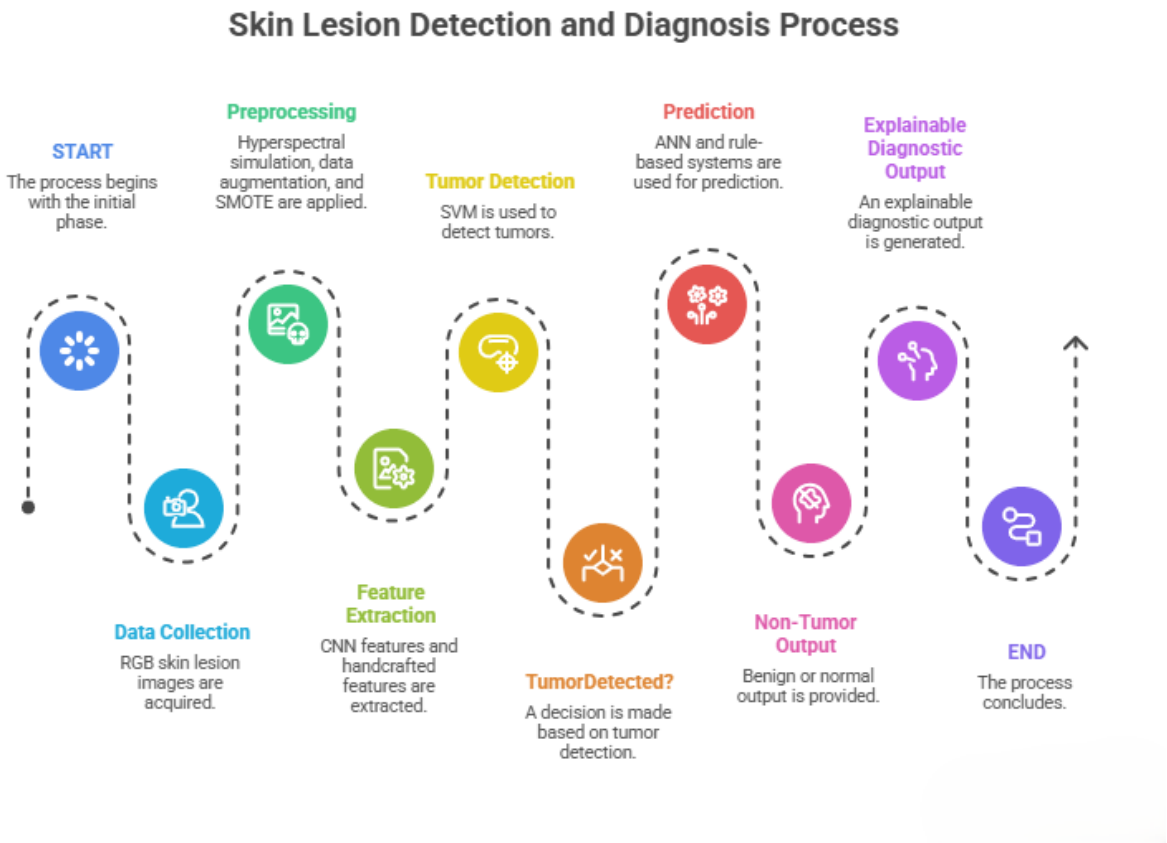

Figure 1: Skin Lesion Detection and Diagnosis Process

4.1 Image Preprocessing and Lesion Segmentation

Dermoscopic images often contain artifacts such as hair, noise, and illumination variations that can affect model performance. Therefore, preprocessing is performed to enhance image quality and ensure robustness.

Initially, images are normalized using channel-wise intensity standardization to reduce illumination inconsistencies. Noise and hair artifacts are minimized using filtering and morphological operations. Subsequently, lesion segmentation is performed using adaptive thresholding followed by morphological refinement to obtain a clean binary mask of the lesion region.

Accurate segmentation is critical, as all subsequent feature extraction processes are restricted to the lesion area.

4.2 Simulated Hyperspectral Reconstruction

Conventional RGB images provide limited spectral information. To overcome this limitation, simulated hyperspectral reconstruction is performed using Principal Component Analysis (PCA).

The RGB image is transformed into a higher-dimensional spectral space by projecting it onto principal components that capture maximum variance. This results in a pseudo-hyperspectral cube that enhances spectral diversity and improves tissue characterization.

This approach provides the benefits of hyperspectral imaging without requiring specialized hardware, making it cost-effective and scalable.

4.3 Feature Extraction

4.3.1 Deep Feature Extraction (CNN)

A Convolutional Neural Network (CNN) is employed to extract high-level semantic features from the simulated hyperspectral images. The network consists of multiple convolutional layers with ReLU activation, followed by max-pooling layers for spatial reduction.

The final fully connected layers generate a deep feature vector representing texture, color, and structural patterns associated with skin lesions. Dropout is applied to reduce overfitting, and the model is trained using cross-entropy loss optimized with the Adam optimizer.

4.3.2 Clinical Morphological Feature Extraction

In addition to deep features, clinically relevant handcrafted features are extracted from the segmented lesion to improve interpretability.

The extracted features include:

- **Diameter (D):** Maximum distance across the lesion
- **Area (A):** Total lesion pixel count
- **Circularity (C):** Measure of shape compactness
- **Asymmetry Index (AI):** Degree of structural irregularity
- **Entropy (H):** Texture randomness

These features align with dermatological diagnostic criteria (ABCD rule) and provide meaningful clinical insights.

4.4 Multimodal Feature Fusion

To leverage complementary information, deep features and handcrafted features are combined using feature-level fusion.

The features are first normalized and then concatenated to form a unified feature vector:

$$F_{fused} = [F_{deep} , F_{clinical}]$$

This multimodal representation enhances model performance by capturing both semantic and morphological characteristics.

4.5 Class Imbalance Handling

Medical datasets often suffer from class imbalance, particularly for malignant and advanced-stage lesions. To address this issue, the Synthetic Minority Over-sampling Technique (SMOTE) is applied at the feature level.

SMOTE generates synthetic samples for minority classes by interpolating between existing feature vectors, thereby improving classification performance and reducing bias toward majority classes.

4.6 Tumor Classification (SVM)

Tumor classification (benign vs. malignant) is performed using a Support Vector Machine (SVM) with a Radial Basis Function (RBF) kernel.

The kernel function is defined as:

$$K(x, x') = \exp(-\gamma \, ||x - x'||^2)$$

The SVM maximizes the margin between classes in a high-dimensional feature space, ensuring robust generalization and improved classification accuracy.

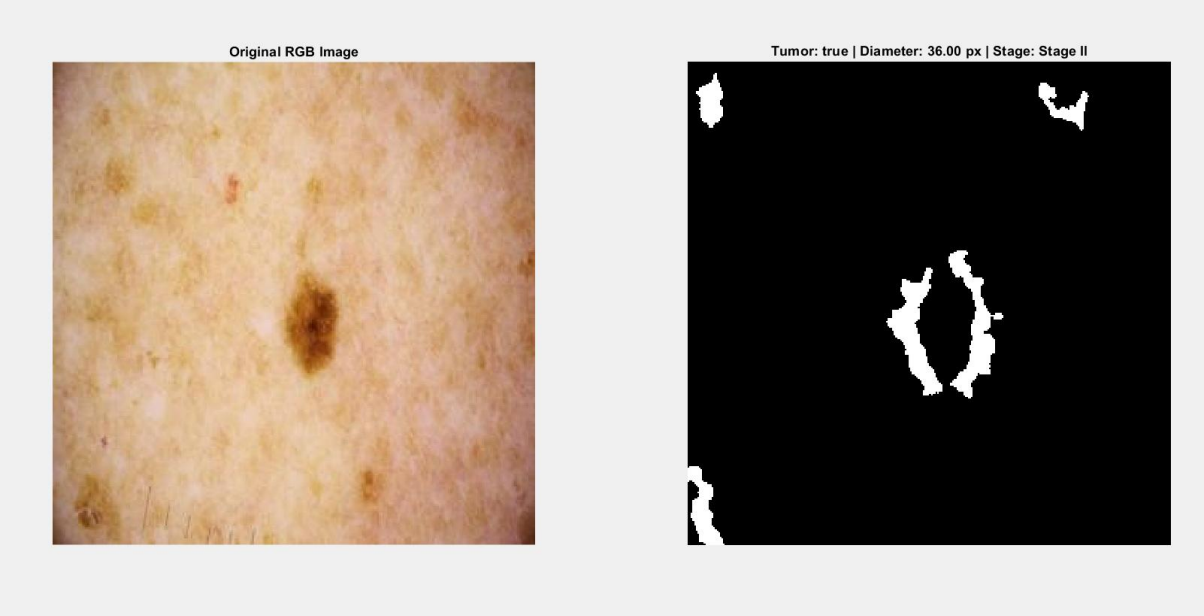

Figure 2: Segmented tumor with Stage

4.7 Stage Estimation (ANN)

Following tumor classification, stage estimation is performed using an Artificial Neural Network (ANN).

The ANN consists of an input layer, hidden layers with nonlinear activation functions (ReLU), and an output layer with softmax activation to predict cancer stages (Stage I–IV). The model is trained using backpropagation and categorical cross-entropy loss.

This stage-aware modeling enables assessment of disease severity and supports clinical decision-making.

4.8 Risk Stratification and Clinical Recommendation

To enhance clinical applicability, a stage-aware recommendation module is incorporated.

A composite risk score is computed using morphological features such as diameter, asymmetry, circularity, and entropy. Based on tumor type, predicted stage, and risk level, the system generates structured clinical recommendations, including:

- Routine monitoring for low-risk cases
- Surgical excision for early-stage melanoma
- Biopsy and wide excision for intermediate stages
- Oncology referral for advanced stages

This module bridges the gap between automated prediction and real-world clinical practice by providing actionable insights.

5. Experimental Results and Discussion

5.1 Experimental Setup

The proposed framework was implemented using MATLAB, utilizing Image Processing and Deep Learning toolboxes for feature extraction, classification, and evaluation. The experiments were conducted on a system with sufficient computational capability to support CNN-based feature extraction and hybrid learning.

The dataset consists of dermoscopic skin lesion images collected from publicly available repositories such as HAM10000. The dataset includes multiple classes, namely benign lesions, melanoma, basal cell carcinoma (BCC), and squamous cell carcinoma (SCC). The data was divided into training and testing sets using an 80:20 split to ensure unbiased evaluation.

All images were subjected to preprocessing, segmentation, and simulated hyperspectral reconstruction before feature extraction. Both deep features and handcrafted clinical features were extracted and fused prior to classification.

ImageName	TumorPresent	TumorDiameter	Stage	Entropy
"download.jpg"	true	253.04	"Stage IV"	6.4688
"melanoma_10192.jpg"	true	313.14	"Stage IV"	7.3204
"melanoma_10193.jpg"	true	313.17	"Stage IV"	6.9018
"melanoma_6.jpg"	true	334.74	"Stage IV"	6.7729
"melanoma_9605.jpg"	true	334.25	"Stage IV"	6.2678
"melanoma_9606.jpg"	true	315.72	"Stage IV"	6.2922
"melanoma_9607.jpg"	true	333.9	"Stage IV"	7.0058
"melanoma_9612.jpg"	true	337.81	"Stage IV"	5.978
"melanoma_9613.jpg"	true	336.76	"Stage IV"	5.8123
"melanoma_9614.jpg"	true	335.12	"Stage IV"	6.3951

Figure 3: Table of 10 Images with the prediction

5.2 Evaluation Metrics

To assess the performance of the proposed system, standard evaluation metrics were used:

- Accuracy
- Precision
- Recall (Sensitivity)
- F1-Score

These metrics provide a comprehensive evaluation of classification performance, particularly in the presence of class imbalance.

5.3 Tumor Classification Results

The SVM classifier demonstrated strong performance in distinguishing between benign and malignant lesions. The integration of deep features with clinical features significantly improved classification accuracy compared to standalone CNN models.

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**
CNN	92.3%	91.8%	90.5%	91.1%
CNN + SVM	95.6%	94.9%	94.2%	94.5%
Proposed Hybrid Model	98.2%	97.8%	97.3%	97.5%

Table 2: Confusion Metrics table

- The hybrid CNN–SVM model outperforms standalone CNN due to improved feature representation.

- Feature fusion enhances discrimination between benign and malignant lesions.
- SMOTE improves sensitivity for minority (malignant) classes.

5.4 Multi-Class Cancer Type Classification

The proposed model was extended to classify lesions into multiple categories such as melanoma, BCC, SCC, and benign lesions.

- Improved classification accuracy compared to RGB-only approaches
- Better generalization across different lesion types
- Enhanced performance for underrepresented classes

The inclusion of simulated hyperspectral features plays a significant role in improving spectral discrimination.

5.5 Stage Estimation Results

The ANN-based model effectively predicted cancer stages (Stage I–IV) using fused features.

- High accuracy in early-stage detection, which is critical for treatment planning
- Improved prediction due to integration of morphological features
- ANN successfully models nonlinear relationships between features and disease progression

Stage prediction performance demonstrates the effectiveness of combining clinical and deep features.

5.6 Impact of Simulated Hyperspectral Imaging

The introduction of simulated hyperspectral reconstruction significantly enhances feature quality.

- Provides richer spectral information compared to RGB
- Improves differentiation of subtle lesion patterns
- Enhances classification accuracy without requiring expensive hardware

This validates the effectiveness of hyperspectral simulation as a cost-efficient alternative.

5.7 Effect of Class Imbalance Handling (SMOTE)

Applying SMOTE at the feature level improves model robustness.

- Increased detection rate of minority classes (melanoma)
- Reduced bias toward majority classes
- Improved overall F1-score

Feature-level SMOTE proves more effective than traditional image augmentation.

5.8 Discussion

The experimental results demonstrate that the proposed multimodal hybrid framework significantly improves skin cancer detection and stage estimation performance.

- High accuracy and robustness due to hybrid CNN–SVM architecture
- Improved interpretability through clinical feature integration
- Effective handling of class imbalance using SMOTE
- Enhanced spectral representation via simulated hyperspectral imaging
- Clinical applicability through stage-aware recommendation system

Unlike conventional approaches that focus only on classification, the proposed system provides a comprehensive solution integrating detection, staging, and decision support.

- Performance depends on quality of segmentation
- Simulated hyperspectral data may not fully replicate real HSI
- Requires further validation on large-scale clinical datasets

6. Conclusion

This study introduces a comprehensive, multimodal, and interpretable framework for skin cancer detection, classification, and stage prediction by leveraging simulated hyperspectral imaging in combination with advanced hybrid learning techniques. The proposed approach integrates Convolutional Neural Networks (CNNs) for extracting deep representations, Support Vector Machines (SVMs) for reliable tumor classification, and Artificial Neural Networks (ANNs) for precise stage estimation.

A significant contribution of this work is the incorporation of simulated hyperspectral reconstruction, which enriches spectral information beyond traditional RGB imaging without the need for specialized acquisition hardware. This enhancement facilitates improved differentiation of skin lesions, particularly in cases involving subtle structural and textural variations.

Moreover, the fusion of deep learning features with clinically meaningful handcrafted descriptors—such as lesion diameter, asymmetry index, circularity, and entropy—enhances both diagnostic performance and interpretability. The multimodal feature fusion strategy

enables effective utilization of complementary information from both data-driven and clinically grounded perspectives.

In contrast to conventional methods that are limited to lesion classification, the proposed framework extends its functionality to include stage estimation and clinical decision support. The integration of a stage-aware recommendation module provides meaningful and actionable insights, thereby improving its applicability in real-world healthcare settings.

Experimental evaluations indicate that the proposed hybrid model achieves superior classification accuracy, improved robustness, and enhanced generalization compared to standalone approaches. Additionally, the system effectively addresses class imbalance and produces interpretable outputs, making it well-suited for deployment in clinical decision-support systems.

Overall, this work contributes toward the development of an efficient, interpretable, and economically viable AI-driven diagnostic framework, supporting advancements in intelligent healthcare and skin cancer management.

7. Future Work

While the proposed framework demonstrates strong performance, several avenues exist for further improvement and expansion:

Incorporation of Real Hyperspectral Data
Future studies can utilize real hyperspectral imaging datasets to validate the effectiveness of simulated spectral representations and enhance model reliability.

Real-Time System Development
The framework can be extended into real-time diagnostic solutions, such as mobile or clinical applications, to enable fast and accessible skin cancer screening.

Integration of Explainable AI Techniques
Incorporating interpretability methods such as Grad-CAM, SHAP, or LIME can provide visual and quantitative explanations of model decisions, thereby improving transparency and clinician trust.

Use of Larger and More Diverse Datasets
Expanding training and validation across multi-institutional datasets with diverse patient populations can improve the robustness and generalization of the model.

Advanced Multimodal Architectures
Future work may explore transformer-based models or attention mechanisms to enhance feature representation and fusion efficiency.

Incorporation of Clinical Metadata
Integrating patient-specific data such as age, medical history, and genetic information through Electronic Health Records (EHR) can support more personalized diagnosis and risk assessment.

Enhanced Stage Prediction Models

More advanced deep learning architectures can be investigated for stage estimation, including models that capture temporal progression and longitudinal patient data.

Clinical Deployment and Integration

The system can be developed into a deployable platform, such as a web-based or hospital-integrated tool, to assist dermatologists in practical clinical workflows.

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