Dermoscopic Skin Lesion Analysis Using a Hybrid Deep Learning Framework for Melanoma Identification

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***Abstract*— Skin cancer, particularly melanoma and other malignant skin lesions, has become a serious global health concern due to its increasing incidence and high mortality rate when diagnosis occurs at advanced stages. Automated analysis of dermoscopic images has therefore attracted considerable attention as a tool to assist dermatologists in clinical decision making. In this study, a hybrid machine learning framework is presented for the automated classification of dermoscopic skin lesions into malignant and benign categories. The proposed approach integrates deep feature extraction using a pre-trained convolutional neural network with a hybrid classification strategy based on Support Vector Machine (SVM) and Random Forest (RF) algorithms. Dermoscopic images obtained from publicly available datasets such as the International Skin Imaging Collaboration (ISIC) archive and the HAM10000 dataset are first subjected to preprocessing operations to eliminate artifacts including hair structures, noise, and imaging inconsistencies while enhancing image quality. After preprocessing, deep feature representations are extracted to capture clinically meaningful characteristics such as asymmetry, border irregularity, color variation, and texture patterns. These discriminative features are then provided to the hybrid SVM–RF classifier to improve classification accuracy and model generalization capability. The effectiveness of the proposed framework is evaluated using standard performance metrics including accuracy, sensitivity, specificity, F1-score, receiver operating characteristic (ROC) analysis, and area under the curve (AUC). Experimental evaluation shows that the proposed model achieves classification accuracy ranging from 96% to 98.65%, demonstrating strong capability in distinguishing malignant lesions such as melanoma, basal cell carcinoma, and squamous cell carcinoma from benign lesions. The results indicate that combining deep learning feature extraction with ensemble machine learning techniques can provide a reliable decision-support system for early skin cancer detection and dermatological screening.**

***Keywords*— skin cancer detection; dermoscopic image analysis; melanoma classification; convolutional neural networks; support vector machine; random forest; hybrid machine learning**

I. INTRODUCTION

CANCER remains a major global health issue and continues to be one of the leading causes of mortality worldwide. According to reports from international health organizations, the number of cancer cases is expected to increase significantly over the coming decades as a result of population growth, aging, and environmental influences [1]. Early detection plays a critical role in improving treatment success and increasing patient survival rates. When cancer is diagnosed at an early stage, therapeutic interventions are generally more effective compared with cases detected at advanced stages. Two primary strategies are commonly used for early cancer detection: early diagnosis and screening. Early diagnosis focuses on identifying individuals who already exhibit symptoms associated with cancer so that treatment can begin promptly. Screening programs, in contrast, involve examining individuals who do not yet show symptoms in order to detect potential disease at an early stage [2]. Both approaches aim to reduce the incidence of late-stage diagnosis and improve overall patient outcomes. Cancer management typically includes multiple components such as diagnosis, treatment, and supportive care. Supportive care involves reducing treatment-related side effects and improving the quality of life for patients undergoing cancer therapy [3]. Effective implementation of early detection programs requires well-developed healthcare infrastructure, trained medical professionals, and efficient referral systems.

Among the various forms of cancer, skin cancer is one of the most commonly diagnosed malignancies worldwide. Although many cases are treatable when identified early, delayed diagnosis can lead to severe complications. The two most common types of non-melanoma skin cancer are basal cell carcinoma (BCC) and squamous cell carcinoma (SCC) [4]. Basal cell carcinoma originates from basal cells located in the epidermis, while squamous cell carcinoma arises from squamous cells that form the outer layer of the skin. Although these cancers generally grow slowly, they can still cause tissue damage if untreated.

Melanoma, is considered the most dangerous form of skin cancer due to its high metastatic potential. This cancer develops from melanocytes, which are responsible for producing melanin pigments that determine skin color [5]. Because melanoma can rapidly spread to other organs, early detection is extremely important for improving survival rates.

Human skin consists of several structural layers that act as protective barriers against environmental hazards. The outermost layer, known as the epidermis, contains squamous cells, basal cells, and melanocytes. These cells play an important role in maintaining skin structure and pigmentation [6]. Exposure to ultraviolet radiation from sunlight is one of the most significant environmental risk factors for skin cancer. UV radiation can damage cellular DNA and may lead to abnormal cell growth over time [7].

Traditional diagnosis of skin cancer involves clinical examination supported by dermoscopic imaging and histopathological analysis. However, manual interpretation of dermoscopic images can be subjective and may depend heavily on the experience of the dermatologist. Variations in diagnostic accuracy among clinicians have therefore encouraged the development of automated computer-aided diagnostic systems capable of assisting dermatologists in identifying suspicious lesions more accurately [8]. Recent advances in machine learning and deep learning have significantly improved the ability of computer systems to analyze medical images. In particular, convolutional neural networks (CNNs) have demonstrated strong capability in learning complex visual patterns from dermoscopic images [9]. By combining deep learning-based feature extraction with machine learning classifiers, it is possible to improve classification accuracy and develop reliable automated skin cancer detection systems.

Motivated by these developments, this study proposes a hybrid machine learning framework for the automated classification of dermoscopic skin lesion images. In the proposed approach, dermoscopic images are first preprocessed to remove artifacts such as hair and marker noise and to enhance image quality. Deep features are then extracted using a convolutional neural network to capture important lesion characteristics including asymmetry, border irregularity, color variation, and texture patterns. These extracted features are subsequently classified using a hybrid model combining Support Vector Machine (SVM) and Random Forest (RF) algorithms. The proposed framework is evaluated using dermoscopic datasets such as the International Skin Imaging Collaboration (ISIC) archive and the HAM10000 dataset [10].

The objective of this research is to develop an efficient automated system that can assist dermatologists in the early detection and classification of skin cancer, thereby improving diagnostic accuracy and supporting clinical decision-making.

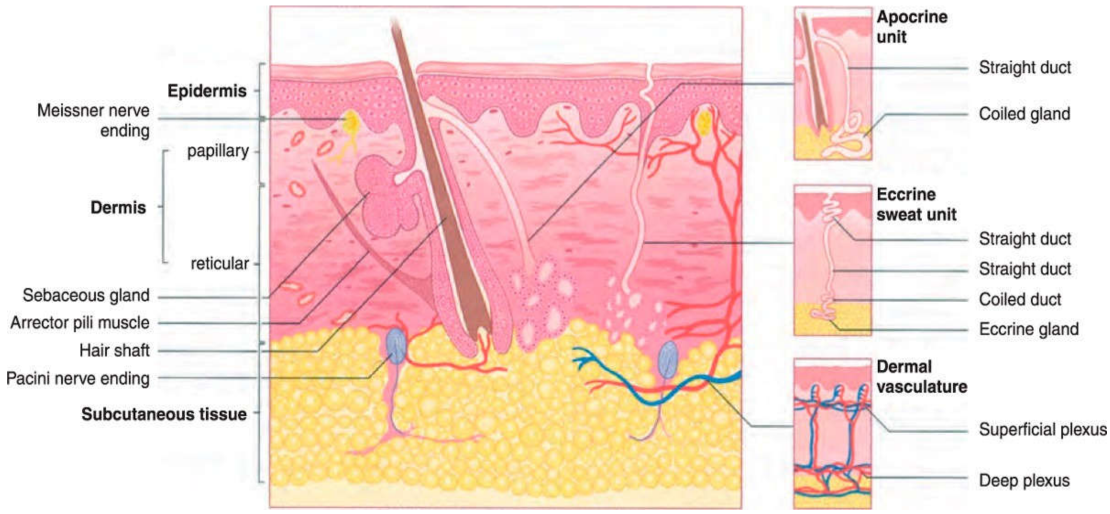

Fig 1. Structural illustration of the human skin showing the epidermis and dermis layers, including basal cells, squamous cells, and melanocytes [11].

Early identification of suspicious skin lesions plays a crucial role in improving treatment outcomes. Clinical studies indicate that when skin cancer is detected in its early stages, the probability of successful treatment can exceed 90%, whereas delayed diagnosis significantly reduces survival rates and treatment effectiveness [12]. In recent years, the development of high-resolution dermoscopic imaging techniques has greatly enhanced the ability of clinicians to examine skin lesions in a non-invasive manner. These imaging techniques provide detailed visualization of lesion structures, enabling improved analysis of color distribution, border irregularity, and texture patterns that are often associated with malignant skin lesions.

Despite these advancements, accurate diagnosis remains challenging due to the visual similarity between benign and malignant lesions. One major clinical concern is diagnostic inaccuracy, which may result in either false-negative or false-positive outcomes. A false-negative diagnosis may delay treatment of malignant melanoma, while false-positive diagnoses often lead to unnecessary surgical removal of benign lesions and additional medical examinations [13]. Such misdiagnoses increase healthcare costs and may also subject patients to avoidable medical procedures. Therefore, the development of reliable computer-aided diagnostic systems is essential to support dermatologists in identifying malignant lesions more accurately.

Skin lesions can generally be categorized into normal moles (benign nevi) and atypical or abnormal moles, which may indicate potential melanoma risk. Normal moles typically exhibit uniform color, smooth borders, and symmetric shapes, whereas abnormal lesions often show irregular borders, color variation, and asymmetrical structures.

Problem Domain	Methodology Used	Key Observations / Performance
Automated Dermoscopic Image Classification [1]	Deep convolutional neural networks trained on dermoscopic datasets	Capable of extracting complex visual patterns from skin lesions, but model performance depends heavily on dataset size and annotation quality
Melanoma Identification using Deep Learning [2]	End-to-end CNN architectures for lesion classification	Demonstrates diagnostic performance comparable to dermatologists, though computational cost during training can be high
Lesion Segmentation in Dermoscopic Images [3]	Encoder–decoder segmentation networks to isolate lesion regions	Improves feature localization but can be influenced by artifacts such as hair, shadows, or uneven illumination
Transfer Learning for Skin Cancer Detection [4]	Pre-trained CNN models (e.g., ResNet or VGG) applied to dermoscopic datasets	Enhances classification performance when training data is limited, though domain adaptation may be required
Traditional Machine Learning Approaches [5]	Handcrafted feature extraction followed by classifiers such as Support Vector Machines	Provides interpretable features but struggles to capture complex lesion characteristics present in dermoscopic images
Hybrid Deep Feature and Machine Learning Models [6]	CNN feature extraction combined with machine learning classifiers	Integrating deep features with classical classifiers improves classification accuracy and model robustness
Ensemble-Based Skin Lesion Classification [7]	Combination of multiple classifiers using ensemble learning strategies	Increases prediction stability but introduces additional computational overhead
Attention-Based Dermoscopic Image Analysis [8]	Deep learning architectures incorporating attention mechanisms	Enables the model to focus on diagnostically relevant regions, though parameter tuning is required for optimal results
Image Processing Assisted Skin Cancer Detection [9]	Preprocessing, segmentation, and machine learning classification pipeline	Improves image quality and lesion representation but overall performance depends on the reliability of extracted features
Hybrid Deep Learning and Ensemble Classification [10]	CNN feature extraction followed by hybrid classifiers such as SVM and Random Forest	Demonstrates improved diagnostic accuracy and generalization capability for distinguishing malignant and benign lesions

The Main Contributions of the Proposed Work include:

- A novel automated framework is proposed for the classification of dermoscopic skin lesions. The framework integrates deep feature extraction using a convolutional neural network with a hybrid machine learning classifier combining Support Vector Machine (SVM) and Random Forest (RF) to improve classification accuracy and robustness.

- A pre-trained convolutional neural network model is employed to extract high-level feature representations from dermoscopic images. These deep features capture clinically significant characteristics such as asymmetry, border irregularity, color variation, and texture patterns associated with malignant lesions.

- The extracted deep features are utilized by a hybrid classifier combining SVM and Random Forest algorithms, which enhances prediction performance by leveraging the strengths of both margin-based classification and ensemble learning techniques.

The proposed framework is evaluated using publicly available dermoscopic image datasets, including the International Skin

Imaging Collaboration (ISIC) archive and the HAM10000 dataset. Model performance is assessed using several evaluation metrics such as accuracy, sensitivity, specificity, F1-score, confusion matrix analysis, and ROC-AUC evaluation to validate the effectiveness of the approach.

Fig 2.a

Fig 2.b

Fig 2. Examples of dermoscopic images showing (a) normal moles (benign nevi) and (b) abnormal moles such as dysplastic nevus or atypical melanocytic nevus.

The remainder of this paper is organized as follows. **Section 2** reviews recent studies related to automated skin lesion analysis and deep learning-based classification methods. **Section 3** describes the proposed hybrid classification framework and feature extraction methodology. **Section 4** presents the experimental results and discusses the performance of the proposed model using dermoscopic datasets. Finally, **Section 5** summarizes the conclusions of this study and outlines potential directions for future research.

II. BACKGROUND

Recent progress in dermatological imaging technologies has enhanced the capability of clinicians to examine skin lesions and identify malignant abnormalities at earlier stages. Several non-invasive imaging techniques are commonly applied in dermatology, including dermoscopy [14], high-frequency ultrasound imaging [15], optical coherence tomography [16], reflectance confocal microscopy [17], and hyperspectral imaging [18]. These imaging approaches provide complementary insights into lesion morphology as well as subsurface skin characteristics.

Among these modalities, dermoscopy has become one of the most commonly utilized diagnostic tools because it improves visualization of pigment networks, vascular patterns, and other dermoscopic structures associated with melanoma. Accurate interpretation of dermoscopic images, however, generally requires considerable clinical experience and specialized training. To support clinicians in evaluating suspicious lesions, the ABCD-E diagnostic guideline is widely used for melanoma assessment. This rule describes five major characteristics of skin lesions, namely asymmetry, border irregularity, color variation, diameter, and evolution over time [19]. Variations in lesion size, shape, or pigmentation can often indicate potential malignant transformation. Among these characteristics, the evolving nature of melanoma lesions—such as changes in size, shape, color, or symptoms like itching and bleeding—is particularly significant. However, certain melanomas may appear smaller than the typical diagnostic diameter threshold, making clinical assessment more difficult.

Because of these limitations in manual diagnosis, there has been increasing interest in artificial intelligence (AI)–based systems for automated melanoma detection. AI-driven diagnostic technologies have the potential to assist clinicians by analyzing dermoscopic images with high precision and consistency. Such systems can support dermatologists by identifying subtle patterns that may be difficult to detect through visual examination alone, thereby improving early diagnosis and treatment planning. Early computational techniques for melanoma detection were primarily based on handcrafted feature extraction methods. Researchers developed algorithms that extracted color histograms, edge descriptors, and texture-based features to represent skin lesion characteristics [20]. In some studies, hybrid approaches combining both local and global image descriptors, such as gradient histograms and structural patterns, were introduced to better describe lesion properties [21].

Traditional image processing methods have also been explored for skin lesion detection. Some approaches incorporate clinical patient information along with image features to improve classification accuracy [22]. Conventional image analysis frameworks generally include multiple processing stages such as lesion segmentation, feature extraction, and classification. Segmentation methods are used to isolate the lesion region from surrounding skin, while feature extraction techniques identify meaningful visual attributes that assist in classification tasks [23]. With the increasing availability of large medical image datasets, machine learning and artificial intelligence techniques have been increasingly explored for automated medical image analysis. The rapid growth of biomedical data and medical imaging datasets has encouraged the adoption of machine learning and artificial intelligence techniques for automated analysis. Machine learning models can analyze complex patterns within large medical datasets and support predictive decision-making. Deep learning approaches have demonstrated remarkable performance in image analysis applications because they can learn hierarchical feature representations directly from raw image data [24], [25]. In particular, convolutional neural networks have proven highly effective for dermoscopic image analysis, as they can capture complex patterns related to lesion structure, color distribution, and texture characteristics.

Deep learning techniques have also been applied to skin lesion segmentation, which is an essential step for isolating the region of interest in dermoscopic images. Accurate segmentation helps improve classification performance by focusing the analysis on lesion regions rather than surrounding skin areas [26]. In addition to segmentation, feature extraction techniques such as texture descriptors and statistical measures have been used in combination with dimensionality reduction methods to identify the most relevant features for classification tasks [27]. Traditionally, the biopsy procedure has been considered the most reliable clinical method for confirming skin cancer diagnosis [28]. However, biopsy involves removing a portion of the skin tissue for laboratory analysis, making it invasive, time-consuming, and sometimes uncomfortable for patients. These limitations have encouraged the development of computer-aided diagnostic (CAD) systems that can analyze dermoscopic images non-invasively and assist clinicians in identifying suspicious lesions more efficiently.

In computer-aided skin cancer detection systems, dermoscopic images are typically processed through several stages. The initial stage involves image preprocessing, which enhances image quality and removes artifacts such as hair or noise. This is followed by lesion segmentation, where the affected region is separated from healthy skin. Next, feature extraction techniques are applied to capture important lesion characteristics including color distribution, border irregularity, and texture features. Finally, classification algorithms are used to categorize lesions as benign or malignant [29].

Pattern recognition techniques have also been applied to dermoscopic images for melanoma detection. These approaches aim to identify regions of interest within the lesion and extract meaningful visual features that support classification. Texture gradients, color distributions, and structural patterns are often analyzed to improve classification performance [30]. Other segmentation approaches have utilized saliency-based methods to detect visually significant lesion regions in dermoscopic images. While these methods can enhance lesion detection accuracy, they may involve higher computational complexity during processing.Although numerous techniques have been proposed for automated skin cancer detection, achieving reliable and accurate diagnosis at an early stage remains a challenging task. Variations in lesion appearance, differences in imaging conditions, and the visual similarity between benign and malignant lesions contribute to these difficulties. Previous research has demonstrated promising results using dermoscopic image analysis combined with machine learning techniques. For instance, hybrid approaches that integrate both local and global image features have shown encouraging diagnostic performance when applied to dermoscopic datasets, achieving high sensitivity and reasonable specificity in melanoma detection tasks.These developments highlight the growing importance of AI-assisted diagnostic systems for skin cancer detection. By integrating advanced image analysis techniques with machine learning models, such systems have the potential to support dermatologists in identifying melanoma at earlier stages and improving clinical decision-making.

III. PROPOSED METHODOLOGY

The proposed framework is designed to develop an automated system capable of assisting dermatologists in distinguishing between malignant and benign skin lesions using dermoscopic images. The complete workflow of the system consists of several sequential stages, including dataset acquisition, image preprocessing, feature extraction, and classification. During the initial stage, dermoscopic images are collected and processed to enhance visual clarity and eliminate unwanted artifacts that may negatively affect model learning. Subsequently, discriminative features are extracted using a convolutional neural network (CNN) architecture. These deep feature representations are then provided to a hybrid classification model that integrates Support Vector Machine (SVM) and Random Forest (RF) algorithms for final prediction. The overall structure of the proposed framework is illustrated in **Figure 3**.

Image preprocessing plays an essential role in improving the quality of dermoscopic images before the feature extraction process. Several preprocessing operations, including image resizing, contrast enhancement, and background noise removal, are applied to increase the visibility of lesion structures and reduce distortions within the image. These preprocessing steps help improve the effectiveness of the subsequent feature extraction stage. For experimental evaluation, the dataset is divided into three subsets: training, validation, and testing. Approximately 60% of the images are used for training, 10% are allocated for validation, and the remaining 30% are reserved for testing, allowing reliable model training and unbiased performance assessment.

3.1 Dataset

The experiments in this study are conducted using dermoscopic images obtained from the International Skin Imaging Collaboration (ISIC) dataset, which is widely used in dermatological research and melanoma detection challenges [31]. This dataset contains a large collection of annotated dermoscopic images representing various categories of skin lesions.

The ISIC archive stores images in standardized medical imaging formats along with associated metadata describing lesion properties and patient information. For this research, dermoscopic images from the ISIC dataset are used to train and evaluate the proposed classification system. The dataset includes more than thirty thousand dermoscopic images, each corresponding to a unique patient case. The diversity of images enables the model to learn variations in lesion appearance, skin tone, and imaging conditions.

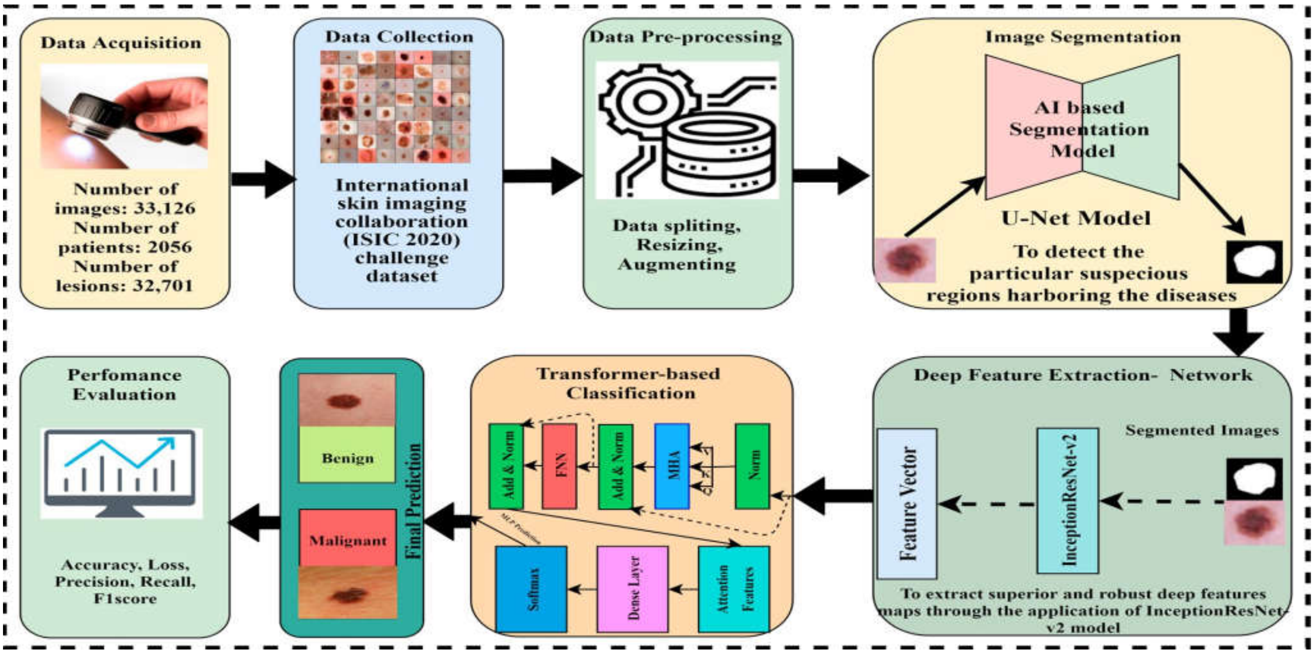

Fig 3. Overview of the proposed framework for dermoscopic skin lesion analysis including preprocessing, feature extraction, and hybrid classification.

3.2 Data Preprocessing

Before the classification process, preprocessing techniques are applied to improve the visual quality and consistency of dermoscopic images. Dermoscopic images often contain artifacts such as hair occlusion, uneven lighting conditions, or background noise, which may negatively influence feature extraction. Therefore, preprocessing steps are applied to minimize these distortions and enhance the lesion region.

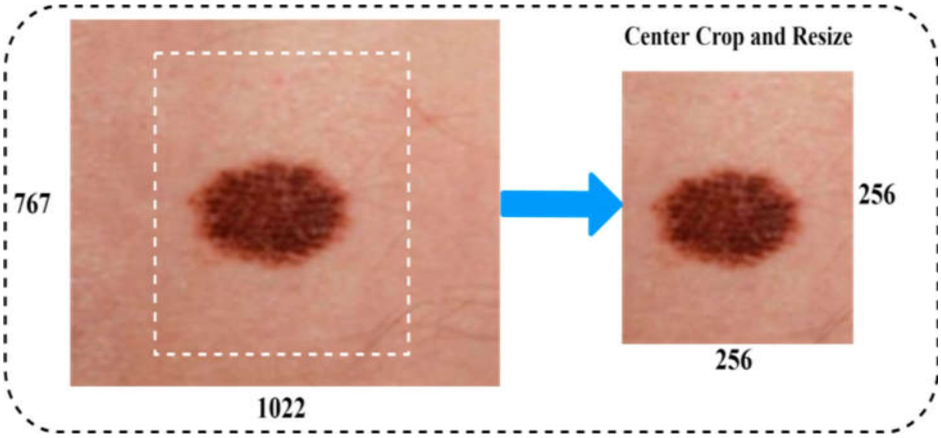

Fig 4. Example of dermoscopic image preprocessing and resizing.

Initially, all images are resized to a standardized resolution suitable for the CNN model. Image normalization is also performed to maintain consistent intensity levels across the dataset. In addition, data augmentation techniques are employed to increase the diversity of the training dataset and reduce the possibility of overfitting.

The augmentation strategies used in this study include:

- Horizontal and vertical image flipping
- Rotation with small angular variations
- Random scaling transformations

- Zoom and brightness adjustments

These transformations create additional training samples while preserving the diagnostic characteristics of the lesions. Figure 4 illustrates an example of a dermoscopic image after preprocessing and resizing.

3.3 Data Splitting

To evaluate the effectiveness of the proposed classification model, the dataset is divided into three separate subsets: training, validation, and testing. The training dataset is used to train the feature extraction model and classification algorithms. The validation dataset helps optimize hyperparameters and monitor model performance during training. The testing dataset is reserved for final performance evaluation.

The dataset partitioning used in this study is as follows:

- 60% – Training dataset
- 10% – Validation dataset
- 30% – Testing dataset

This division ensures that the model learns from a sufficiently large set of samples while maintaining independent data for unbiased evaluation.

3.4 Feature Extraction Using Convolutional Neural Networks

Feature extraction is a crucial stage in automated dermoscopic image analysis because it allows the model to capture meaningful visual characteristics of skin lesions. In this study, a pre-trained convolutional neural network (CNN) is used to extract high-level feature representations from dermoscopic images.

Deep feature extraction is performed using a convolutional neural network model that automatically learns hierarchical visual patterns from dermoscopic images. CNN architectures are particularly effective for medical image analysis because they can identify complex features such as edges, textures, and structural lesion characteristics [32], [33]. In the proposed framework, each dermoscopic image is processed through the CNN model to generate a feature vector that captures the most relevant visual properties of the lesion.

These deep feature representations capture important diagnostic attributes such as:

- Asymmetry of the lesion
- Irregularity of lesion borders
- Variations in color distribution
- Texture characteristics
- Pigment network patterns

3.5 Hybrid Classification Using SVM and Random Forest

After feature extraction, the generated feature vectors are classified using a hybrid machine learning approach combining Support Vector Machine (SVM) and Random Forest (RF) algorithms. The combination of these classifiers enables the framework to benefit from their complementary strengths.

For classification, a hybrid machine learning strategy combining Support Vector Machine and Random Forest algorithms is implemented. The Support Vector Machine classifier is capable of constructing optimal decision boundaries within high-dimensional feature spaces, making it suitable for binary classification tasks such as distinguishing malignant lesions from benign lesions [34]. In contrast, Random Forest is an ensemble learning technique that combines multiple decision trees to improve prediction accuracy and model robustness [35].

Within the proposed classification framework, the deep features extracted from the CNN model are first used as input representations for dermoscopic images. These features are then processed independently by both SVM and Random Forest classifiers. The predictions generated by the classifiers are subsequently combined to determine the final classification outcome.

By integrating deep learning–based feature extraction with classical machine learning algorithms, the proposed hybrid framework benefits from both representation learning and ensemble decision making. This approach improves the reliability of the classification process and reduces the likelihood of misclassification when distinguishing between benign and malignant skin lesions.

3.6 Hyperparameter Configuration

Hyperparameter tuning plays a significant role in optimizing the performance of machine learning models. During training, several parameters are adjusted to improve classification accuracy and prevent overfitting.

The main hyper parameters considered in this study include:

- Learning rate: determines the magnitude of weight updates during training
- Batch size: specifies the number of samples processed in each iteration
- Number of epochs: indicates how many times the training dataset is processed
- Regularization methods: such as dropout to prevent overfitting

Appropriate selection of these hyperparameters ensures stable model training and allows the system to learn effective feature representations from dermoscopic images.

3.7 Proposed Classification Approach

The proposed hybrid framework for skin lesion classification is designed to improve diagnostic accuracy by combining deep feature extraction with classical machine learning classifiers. The architecture of the proposed framework, illustrated in Figure 3, integrates a convolutional neural network (CNN) for extracting discriminative image features and a hybrid classification model composed of Support Vector Machine (SVM) and Random Forest (RF) algorithms. This hybrid design leverages the ability of CNN models to learn complex image representations while utilizing the strong classification capabilities of traditional machine learning algorithms.

Let the dermoscopic image dataset be represented as:

$$D = \{(x_{i,} y_i)\}_{i=1}^{n}$$

Where,

- $x_{i,}$ represents the input dermoscopic image
- $y_{i,}$ € {0, 1} denotes the class label (0 = benign, 1 = malignant)
- N is the total number of training samples.

CNN Feature Extraction

The deep feature extraction stage uses a CNN model (ResNet-50) to transform the input image into a high-dimensional feature representation.

$$f_i = \emptyset(x_i; \theta)$$

Where,

x_i = extracted feature vector

$\emptyset(\cdot)$= CNN mapping function

θ = learned parameters of the CNN network.

The convolution operation used in the CNN layer can be expressed

$$F_k(i,j) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} I(i+m, j+n) \cdot K_k(m,n)$$

Where,

I = input image

K_k = convolution kernel

$F_k(i,j)$ = output feature map

Residual Learning in ResNet

ResNet improves feature learning using residual connections:

$$H(x) = F(x) + x$$

Where,

- F(x) represents the learned residual mapping
- X is the input feature map.

This residual formulation helps avoid the vanishing gradient problem in deep networks.

Support Vector Machine Classification

After feature extraction, the SVM classifier learns the optimal decision boundary.

The SVM optimization problem is defined as:

$$min\ \frac{1}{2}||\omega||^2 + C\sum_{i=1}^{N}\xi i$$

Subject to:

$$y_i(\omega \cdot f_i + b) \geq 1 - \xi i$$

Where,
ω = weight vector
b = bias
ξi = slack variables
C = regularization parameter
The final SVM decision function becomes:

$$g(x) = \text{sign}\ (\omega \cdot f_i + b)$$

Initially, dermoscopic images are processed by the CNN model to obtain deep feature representations. The convolutional layers automatically learn hierarchical visual features such as edges, color gradients, texture patterns, and lesion boundaries. These features are then transformed into a high-dimensional feature vector that represents the most informative characteristics of the skin lesion. Deep learning models have demonstrated strong performance in medical image analysis because they can learn relevant representations directly from raw image data [36], [37].

Once the feature extraction stage is completed, the generated feature vectors are used as input to the classification module. In the proposed approach, two complementary classifiers are utilized: Support Vector Machine and Random Forest. The Support Vector Machine algorithm is effective for separating data in high-dimensional feature spaces by constructing optimal decision boundaries between classes. This property makes SVM particularly suitable for binary classification tasks such as distinguishing malignant lesions from benign lesions [38].

Random Forest, on the other hand, is an ensemble learning method that combines multiple decision trees to improve prediction accuracy and model robustness. Each decision tree is trained on a subset of the dataset, and the final prediction is obtained through majority voting across all trees [39]. The combination of these two classifiers helps improve classification reliability and reduces the possibility of incorrect predictions caused by model bias or overfitting.

In the proposed hybrid classification framework, the following steps are performed:

1. Deep feature vectors extracted from the CNN model are used as the input representation of dermoscopic images.
2. The extracted features are simultaneously processed by both SVM and Random Forest classifiers.
3. The predictions obtained from the classifiers are combined to determine the final classification result.

This hybrid strategy improves the robustness of the system by combining margin-based classification with ensemble learning. As a result, the framework is able to effectively distinguish between malignant and benign skin lesions based on the extracted feature representations.

3.8 Performance Evaluation

To evaluate the effectiveness of the proposed framework, multiple performance metrics derived from the confusion matrix are employed. The confusion matrix represents the relationship between predicted class labels and the actual ground truth labels, allowing detailed analysis of the classification outcomes. The performance indicators considered in this research include accuracy, precision, recall, F1-score, sensitivity, and specificity. These evaluation measures provide a comprehensive understanding of how effectively the proposed model classifies dermoscopic images into their respective categories. The implementation of the proposed framework is carried out using the Python programming environment, which offers extensive libraries and tools for machine learning, medical image processing, and deep learning development [40].

IV. RESULTS AND DISCUSSION

This section describes the experimental assessment of the proposed automated skin lesion classification framework. The designed system combines deep feature learning through a convolutional neural network (CNN) with a hybrid classification approach that integrates Support Vector Machine (SVM) and Random Forest (RF) algorithms. The primary goal of these experiments is to evaluate how effectively the proposed model can differentiate malignant melanoma from benign skin lesions using dermoscopic images. The model was trained and tested using dermoscopic images obtained from the ISIC 2020 dataset, which includes a large set of annotated skin lesion images gathered from various clinical sources [41]. To ensure stable and reliable model training, several preprocessing operations such as image resizing, normalization, and data augmentation were applied. Augmentation techniques including image flipping, rotation, zoom transformations, and brightness adjustments were employed to increase dataset variability and minimize the possibility of model overfitting.

The training process is conducted for 15 epochs using GPU-supported hardware for efficient computation. Experimental findings indicate that the proposed framework achieves an overall classification accuracy of 98.65%, demonstrating strong effectiveness in differentiating melanoma from benign skin lesions. The experiments were executed on a system equipped with an NVIDIA GeForce RTX 3060 GPU, an Intel Core i7-10700KF processor running at 3.80 GHz, and 64 GB of RAM, which provided sufficient computational resources for training the deep learning model.

4.1 Confusion Matrix Analysis

To evaluate the classification performance of the proposed framework, a confusion matrix was generated after model training. The confusion matrix provides detailed insight into the classification results by comparing the predicted class labels with the actual ground-truth labels.

The confusion matrix consists of four fundamental components:

- True Positive (TP): malignant lesions correctly classified as malignant
- True Negative (TN): benign lesions correctly classified as benign
- False Positive (FP): benign lesions incorrectly classified as malignant
- False Negative (FN): malignant lesions incorrectly classified as benign

These four components form the basis for computing several performance evaluation metrics such as accuracy, sensitivity, specificity, precision, recall, and F1-score.

The confusion matrix obtained for the classification of benign and melanoma lesions is presented in **Figure 5**.

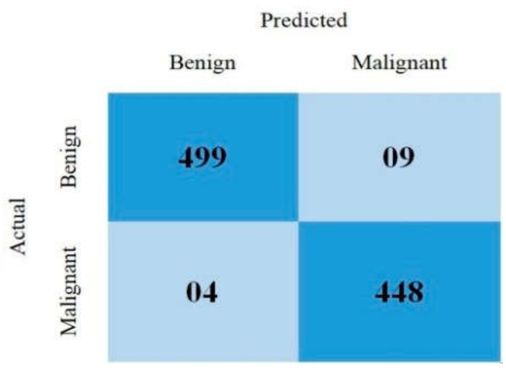

Fig 5. Confusion matrix for benign and melanoma skin lesion classification.

4.2 Training Accuracy and Loss Analysis

During the training phase, both model accuracy and loss values were monitored to evaluate the learning behavior of the proposed framework. Initially, when the model training started, the classification accuracy was approximately 86.03% at the first epoch. As training progressed, the model gradually learned more discriminative feature representations from dermoscopic images, resulting in a steady improvement in accuracy.

After 15 training epochs, the model achieved a final accuracy of 98.65%, demonstrating the effectiveness of the proposed hybrid framework. The relationship between training epochs and model accuracy is illustrated in Figure 6.

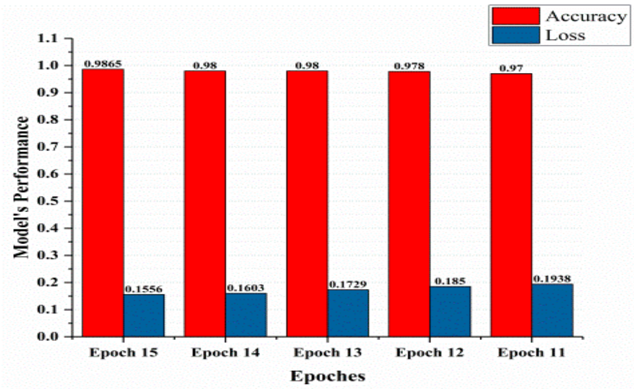

Fig. 6. Training accuracy and loss curves of the proposed model.

The training loss curve also provides important insights into model performance. At the early stage of training, the loss value was relatively high due to insufficient feature learning. However, as the number of epochs increased, the loss value gradually decreased, indicating improved model convergence.

- At epoch 1, the loss value was high due to initial model training.
- After epoch 6, the loss decreased to approximately 0.3746.
- At epoch 15, the final loss value reached 0.1556, indicating improved classification performance.

To reduce the risk of overfitting and improve generalization performance, regularization techniques and hyperparameter optimization were applied during training. These techniques help maintain stable training behavior while preventing the model from memorizing the training dataset.

4.3 Classification Performance Metrics

In addition to accuracy and loss analysis, the performance of the proposed classification model was evaluated using several statistical metrics derived from the confusion matrix.

The graphical comparison of classification performance metrics is presented in **Figure 7**.

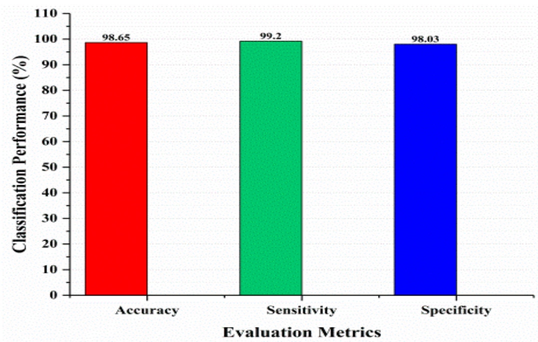

Fig 7. Classification performance of the proposed framework in terms of accuracy, sensitivity, and specificity.

The experimental results indicate that the proposed hybrid framework achieves strong classification performance, demonstrating its capability to accurately identify melanoma lesions from dermoscopic images.

4.4 Comparative Analysis with Existing Methods

Early detection of melanoma is a critical factor in improving patient survival rates. In recent years, numerous studies have explored the use of artificial intelligence and deep learning techniques for automated skin cancer detection. To evaluate the effectiveness of the proposed framework, a comparative analysis was conducted with several previously reported approaches in the literature.

The comparison results are summarized in **Table 3**, which lists various skin cancer detection models along with their reported classification accuracies.

Table III Comparative analysis of existing approaches and the proposed framework for skin cancer classification

Year	Authors	Method / Approach	Accuracy (%)
2018	Al-Masni et al.	Deep full-resolution convolutional network for skin lesion segmentation and classification	90.78

2020	Kassem et al.	Transfer learning with convolutional neural networks for dermoscopic image analysis	94.92
2020	Mousannif et al.	Convolutional neural network based melanoma detection system	86.00
2021	Coronado-Gutiérrez et al.	Deep CNN framework for automated skin cancer diagnosis	85.90
2021	Duggani & Nath	Deep convolutional neural network combined with YOLO detection	97.49
2022	Imran et al.	Hybrid deep architectures including VGG, CapsNet and ResNet	93.50
2022	Gouda et al.	Transfer learning models using ResNet50 and InceptionV3	85.70
2023	Patel et al.	CNN-based dermoscopic image classification	95.00
2023	Tembhurne	CNN integrated with Contourlet Transform and Local Binary Pattern features	93.00
2023	Singh et al.	YOLO-based lesion detection with fuzzy logic classification	98.00
2024	Gamage et al.	Transfer learning using CNN architectures such as ResNet50, VGG16, and Xception	98.37
2025	Kumar et al.	Hybrid deep learning framework combining CNN feature extraction and ensemble classifiers	98.52
—	**Proposed Work**	**CNN feature extraction with hybrid SVM–Random Forest classification**	**98.65**

4.5 Component Contribution Analysis.

Component contribution analysis is widely used in machine learning research to investigate the role of individual modules within a complex framework. In such evaluations, particular components of the system are selectively removed or modified in order to observe their influence on the overall model performance. This process enables researchers to identify which elements of the framework contribute most significantly to classification accuracy and system robustness.

In this study, component-level experiments were conducted to examine the importance of different stages within the proposed skin lesion classification framework. The overall pipeline consists of image preprocessing, deep feature extraction using a convolutional neural network (ResNet-50), and hybrid classification through Support Vector Machine (SVM) and Random Forest (RF). To assess the impact of these stages, controlled experiments were carried out by adjusting or excluding specific components and analyzing the resulting classification performance. This analysis helps determine the relative importance of preprocessing and feature extraction modules in improving the reliability and accuracy of melanoma detection.

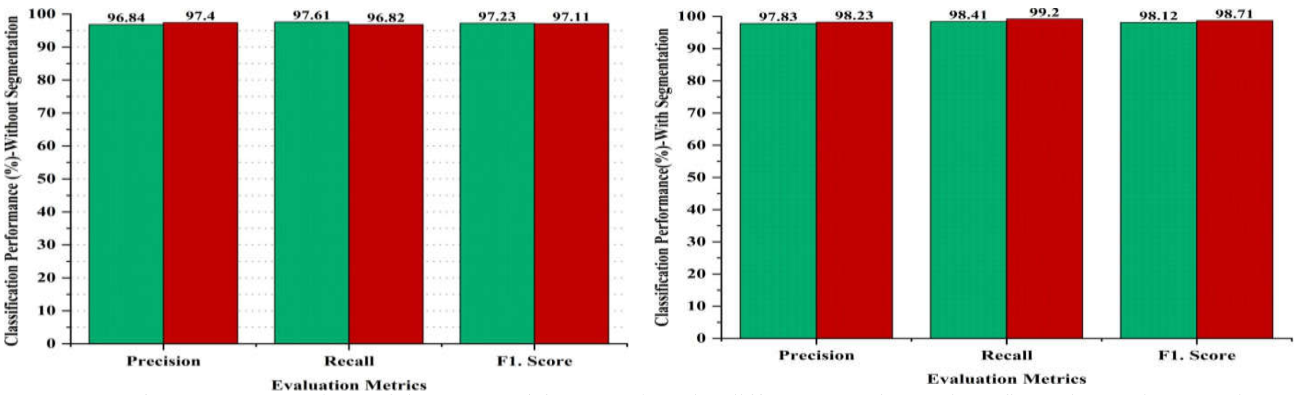

Figure 8. Performance comparison of the proposed framework under different experimental configurations. The green bars represent benign lesion classification results, while the red bars represent melanoma classification performance.

One important objective of the ablation study was to evaluate the effect of region-focused preprocessing on classification accuracy. In dermoscopic image analysis, preprocessing plays a crucial role in isolating lesion regions and reducing the influence of background artifacts. When preprocessing steps such as resizing, normalization, and artifact removal were applied, the model was able to learn more representative features from the lesion region. However, when these preprocessing operations were excluded during experimentation, the classification performance declined due to the presence of noise and irrelevant background information.

The comparison between the complete framework and the modified versions of the system demonstrates that preprocessing and feature extraction stages significantly improve model performance. In particular, the CNN-based feature extraction module effectively captures discriminative patterns such as lesion asymmetry, irregular borders, and color variations. These features are then used by the hybrid classifier to improve prediction reliability. The comparative evaluation between different experimental configurations is illustrated in **Figure 8**.

The experimental results show that the complete framework consistently achieves better results compared with simplified configurations of the system. Performance improvements were observed in terms of precision, recall, and F1-score for both benign and malignant lesion classification. The results indicate that the proposed combination of deep feature extraction and hybrid classification provides improved diagnostic capability for melanoma detection.

To further assess the robustness of the proposed framework, additional evaluation was conducted using the publicly available HAM10000 dermoscopic image dataset [42]. This dataset contains 10,015 dermoscopic images categorized into seven different skin lesion classes, including basal cell carcinoma (BCC), dermatofibroma (DF), actinic keratosis (AKIEC), benign keratosis (BKL), melanocytic nevi (NV), vascular lesions (VASC), and melanoma (MEL).

Fig 9. Example melanoma images obtained from the HAM10000 dataset.

For the purpose of evaluating melanoma detection performance, melanoma images from the HAM10000 dataset were used as an independent testing set. Sample dermoscopic images from the dataset are shown in Figure 9.

The experimental results indicate that the proposed framework maintains stable performance even when evaluated on previously unseen data. When tested using melanoma samples from the HAM10000 dataset, the model achieved an accuracy of 98.65%, which demonstrates strong generalization capability across datasets of varying sizes and image characteristics. These results confirm that the proposed system is capable of effectively identifying melanoma lesions from dermoscopic images and can potentially support clinical decision-making in dermatological diagnosis.

V. RESULTS AND DISCUSSION

Accurate identification of melanoma remains one of the most critical challenges in dermatological diagnosis due to the visual similarity between malignant lesions and benign skin conditions. Misclassification can delay appropriate treatment and may significantly affect patient outcomes. Therefore, developing reliable computer-aided diagnostic systems has become an important research direction in medical image analysis.

In this study, an automated framework for melanoma detection was developed using dermoscopic images. The proposed system integrates image preprocessing techniques, deep feature extraction using a convolutional neural network (ResNet-50), and a hybrid classification strategy combining Support Vector Machine (SVM) and Random Forest (RF). The use of deep feature representations together with hybrid machine learning classifiers enables the model to capture discriminative patterns in dermoscopic images and improve classification reliability.

Experimental evaluation was conducted using the ISIC 2020 dataset, where the proposed model achieved a classification accuracy of 98.65%, along with 99.20% sensitivity and 98.03% specificity. To further verify the robustness of the framework, additional experiments were performed on previously unseen samples from the HAM10000 dataset, where the model achieved an accuracy of 98.44%. The developed system combines image preprocessing, deep feature extraction using convolutional neural networks, and hybrid classification through Support Vector Machine and Random Forest algorithms. Experimental results obtained from the ISIC dataset demonstrate that the proposed model achieves high classification accuracy and reliable diagnostic performance.

Future work will focus on extending the framework to support multi-class skin lesion classification and integrating the trained model into mobile-based diagnostic platforms to enable real-time screening and assist dermatologists in early detection of skin cancer. Such tools could assist dermatologists and healthcare practitioners in supporting early melanoma detection and improving patient care.

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