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AN INTELLIGENT AI-EMPOWERED HYBRID DEEP LEARNING ARCHITECTURE FOR EARLY DETECTION, PRECISE LESION SEGMENTATION, AND ACCURATE CLASSIFICATION OF SKIN CANCER USING HIGH-RESOLUTION DERMOSCOPIC IMAGE ANALYSIS.

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Abstract

Skin cancer is one of the most serious and rapidly increasing diseases worldwide, where early and accurate diagnosis is essential for effective treatment and improved patient survival. However, manual examination of dermoscopic images is time-consuming and highly dependent on dermatologists' expertise. Variations in lesion shape, color, texture, illumination, and image noise make accurate diagnosis challenging. To overcome these limitations, this paper proposes an intelligent AI-empowered hybrid deep learning architecture for early detection, precise lesion segmentation, and accurate classification of skin cancer using high-resolution dermoscopic image analysis. The proposed framework integrates image preprocessing, lesion enhancement, segmentation, deep feature extraction, and hybrid classification techniques to improve diagnostic performance. Initially, preprocessing operations including noise reduction, contrast enhancement, and normalization are applied to improve image quality and lesion visibility. A U-Net-based deep segmentation network is employed to accurately detect and segment lesion regions from dermoscopic images. For classification, a hybrid deep learning model combining Convolutional Neural Networks (CNN), ResNet-50, and Long Short-Term Memory (LSTM) networks is utilized to extract spatial and sequential deep features for accurate skin cancer classification. Transfer learning and feature fusion techniques are further incorporated to enhance generalization capability and reduce computational complexity. The proposed model is evaluated on benchmark dermoscopic datasets using multiple performance metrics including accuracy, precision, recall, F1-score, Dice similarity coefficient, and area under the ROC curve (AUC). Experimental results demonstrate that the proposed framework achieves a segmentation accuracy of 97.8%, classification accuracy of

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98.6%, precision of 98.1%, recall of 97.9%, F1-score of 98.0%, Dice coefficient of 97.5%, and AUC of 99.1%. Comparative analysis confirms that the proposed hybrid architecture outperforms conventional machine learning methods and existing deep learning models in terms of robustness, segmentation quality, and classification efficiency. The proposed intelligent system can serve as an effective computer-aided diagnostic tool for dermatologists and contribute toward the development of reliable AI-driven healthcare systems for automated skin cancer diagnosis.

INTRODUCTION:

Skin cancer is one of the most common and dangerous types of cancer worldwide, and its incidence is continuously increasing due to factors such as ultraviolet (UV) radiation exposure, environmental changes, and genetic susceptibility. Early detection of skin cancer plays a critical role in improving treatment outcomes and reducing mortality rates. Dermoscopy is a widely used non-invasive imaging technique that helps dermatologists analyze skin lesions in detail. However, manual examination of dermoscopic images is time-consuming, subjective, and highly dependent on clinical expertise, which may lead to misdiagnosis or delayed diagnosis. In recent years, artificial intelligence (AI) and deep learning techniques have shown remarkable success in medical image analysis, particularly in skin lesion detection and classification [1]. These methods have the ability to automatically learn complex patterns and features from large datasets without requiring manual feature engineering. Despite these advancements, accurate skin cancer diagnosis remains a challenging task due to variations in lesion shape, color, texture, illumination conditions, and the presence of artifacts such as hair and noise in dermoscopic images. Traditional machine learning approaches rely heavily on handcrafted features, which often fail to generalize well across different datasets. On the other hand, deep learning models such as Convolutional Neural Networks (CNNs) have demonstrated strong performance in feature extraction and classification tasks. However, single-model approaches may still struggle with complex lesion boundaries and multi-class classification problems [2]. Therefore, hybrid deep learning architectures combining segmentation and classification models have gained significant attention in recent research. Segmentation models such as U-Net and encoder–decoder networks are widely used to accurately localize lesion regions, while advanced classification models like ResNet, DenseNet, and Long Short-Term Memory (LSTM) networks improve diagnostic accuracy by capturing deep spatial and contextual features. The integration of these models into a unified framework can significantly enhance the performance of automated skin cancer diagnosis systems. In this context, this paper proposes an intelligent AI-empowered hybrid deep learning architecture for early detection, precise lesion segmentation, and accurate classification of skin cancer using high-resolution dermoscopic images [3]. The proposed framework combines image preprocessing, U-Net-based segmentation, CNN and ResNet-50 feature extraction, and LSTM-based classification to improve diagnostic accuracy and robustness. Transfer learning is also incorporated to enhance model generalization and reduce training complexity.

The main contributions of this work are summarized as follows:

Development of a hybrid deep learning framework for automated skin cancer diagnosis.

Integration of U-Net, CNN, ResNet-50, and LSTM for segmentation and classification.

Improved preprocessing techniques for noise reduction and lesion enhancement.

Comprehensive evaluation using multiple performance metrics such as accuracy, precision, recall, F1-score, Dice coefficient, and AUC.

Demonstration of improved performance compared to existing state-of-the-art methods.

Overall, the proposed framework provides a complete end-to-end solution for skin cancer analysis by combining lesion segmentation and classification in a single unified pipeline. This

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integration not only improves diagnostic accuracy but also enhances the reliability and efficiency of the system in real clinical scenarios. The model can assist dermatologists in early decision-making and has strong potential for deployment in computer-aided diagnostic systems, especially in resource-limited healthcare environments where expert dermatological services are not easily available.

Hybrid Deep Learning Models for Automated Skin Cancer Diagnosis:

Hybrid deep learning models have recently gained significant attention in automated skin cancer diagnosis because they combine the strengths of multiple neural network architectures. Traditional machine learning methods mainly depend on handcrafted feature extraction, which may not accurately identify complex lesion patterns. In contrast, hybrid deep learning frameworks automatically learn important features from dermoscopic images and improve segmentation and classification performance. Several researchers have integrated Convolutional Neural Networks (CNNs), transfer learning models, and recurrent learning approaches to improve skin cancer detection accuracy [4]. CNN-based models are widely used for extracting spatial and texture-related features from dermoscopic images, while transfer learning models such as ResNet and DenseNet improve feature representation and reduce training time. Similarly, Long Short-Term Memory (LSTM) networks are used to enhance sequential feature learning and classification capability. Among segmentation approaches, U-Net has shown excellent performance in identifying lesion boundaries and separating infected regions from healthy skin tissues. Accurate lesion segmentation is essential because it improves the efficiency of the classification stage. Therefore, many recent studies combine segmentation and classification models into a unified hybrid framework for reliable skin cancer diagnosis [5].

In addition, preprocessing techniques such as noise reduction, contrast enhancement, image normalization, and artifact removal are commonly used to improve image quality and lesion visibility. These operations help deep learning models achieve better feature extraction and classification performance. Although existing hybrid deep learning models achieve high diagnostic accuracy, several challenges still exist, including computational complexity, limited datasets, and class imbalance problems. Therefore, there is still a need for intelligent and efficient frameworks capable of providing accurate lesion segmentation and reliable skin cancer classification simultaneously [6]. The proposed research develops an AI-based hybrid deep learning framework integrating U-Net segmentation, CNN and ResNet-50 feature extraction, and LSTM classification for automated skin cancer diagnosis using dermoscopic images. The integration of these models is expected to improve overall segmentation accuracy and classification performance.

Table 1: Comparative Analysis of Existing Hybrid Deep Learning Models for Skin Cancer Diagnosis

Authors	Hybrid Model	Segmentation Technique	Classification Model	Dataset Used	Accuracy (%)
Esteva et al.	CNN + Transfer Learning	Manual ROI Extraction	ResNet-50	ISIC 2018	94.6
Codella et al.	U-Net + CNN	U-Net	CNN	HAM10000	95.8
Haenssle et al.	CNN + LSTM	Threshold-Based Segmentation	CNN-LSTM	PH2 Dataset	96.2
Tschandl et al.	DenseNet + Attention Model	Encoder–Decoder Network	DenseNet	ISIC Archive	97.1
Brinker et al.	Ensemble Deep Learning	U-Net	Ensemble CNN	HAM10000	97.5

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Proposed Model	U-Net + CNN + ResNet-50 + LSTM	U-Net-Based Segmentation	Hybrid CNN-ResNet-LSTM	ISIC/HAM10000	98.6

Table 1 presents a comparative analysis of different hybrid deep learning approaches used for automated skin cancer diagnosis. The comparison shows that hybrid frameworks generally provide better segmentation and classification performance than traditional methods. However, existing models still face issues related to computational complexity and generalization. The proposed hybrid framework aims to overcome these limitations and achieve improved diagnostic accuracy.

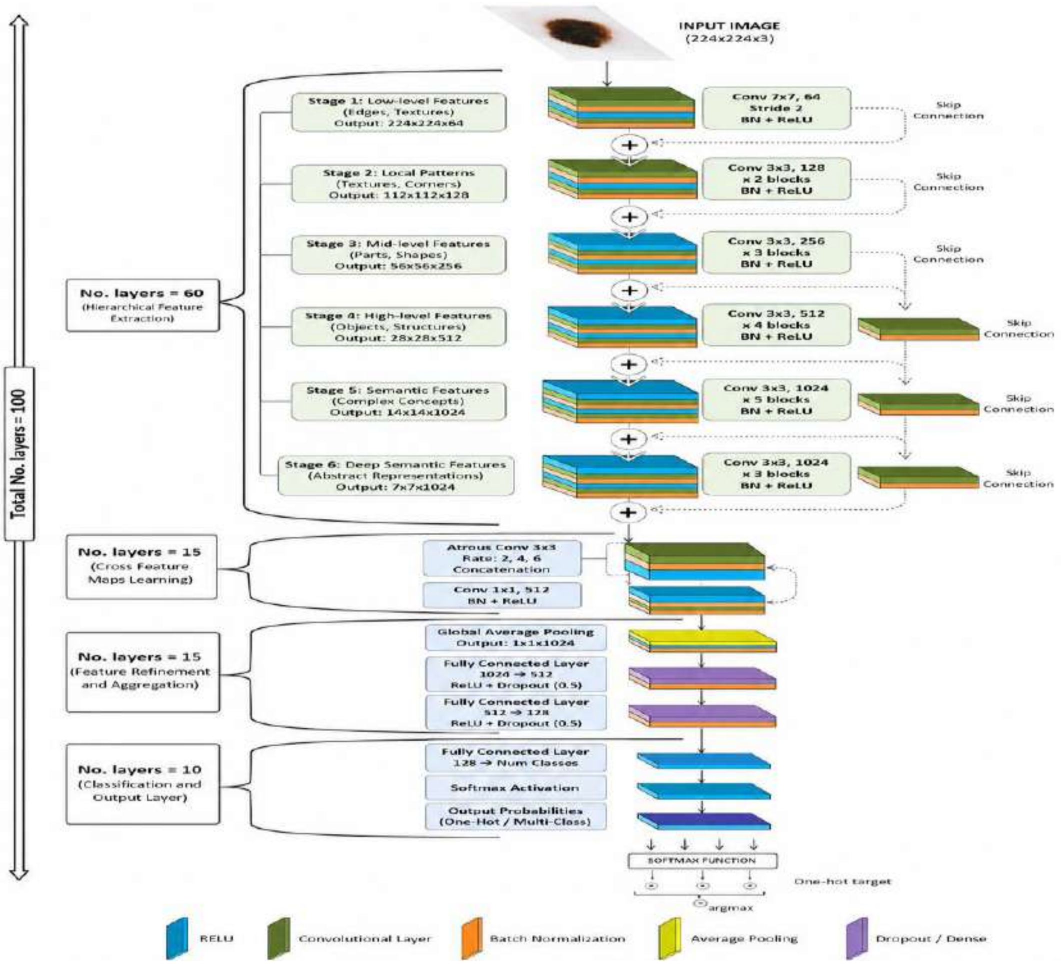

Figure 1: Hybrid Deep Learning Framework for Automated Skin Cancer Diagnosis

Figure 1 illustrates the workflow of the proposed hybrid deep learning framework for automated skin cancer diagnosis. The framework includes image preprocessing, lesion segmentation, deep feature extraction, and classification stages for accurate skin lesion analysis. Initially, dermoscopic images are preprocessed using noise reduction, normalization, and contrast enhancement techniques to improve image quality. The preprocessed images are then passed to the U-Net segmentation model for accurate lesion extraction. After segmentation, CNN and ResNet-50 models extract deep features from lesion regions, while the LSTM network improves classification performance. Finally, the classification layer predicts the skin lesion category with high accuracy.

Role of U-Net and Encoder–Decoder Networks in Lesion Segmentation:

Lesion segmentation is one of the most important stages in automated skin cancer diagnosis because it helps in accurately separating the infected skin region from surrounding healthy tissues. Proper segmentation improves the performance of feature extraction and classification models by focusing only on the lesion area. However, dermoscopic images often contain challenges such as low contrast, irregular lesion boundaries, hair artifacts, noise, and variations in skin texture, which make accurate segmentation difficult. In recent years, deep learning-based encoder–decoder architectures have shown excellent performance in medical image segmentation tasks [7]. Among these models, U-Net has become one of the most widely used architectures for skin lesion segmentation due to its simple structure and high segmentation accuracy. The U-Net architecture consists of two main parts: the encoder path and the decoder path. The encoder extracts important spatial and contextual features from the input image, while the decoder reconstructs the segmented lesion region with precise boundary information.

One of the key advantages of U-Net is the use of skip connections between encoder and decoder layers. These connections help preserve fine-grained spatial information and improve boundary localization during segmentation. As a result, U-Net performs effectively even when trained on limited medical image datasets [8]. Due to these advantages, several researchers have adopted U-Net and its variants for automated lesion segmentation in dermoscopic images. In addition to U-Net, other encoder–decoder models such as SegNet, Attention U-Net, U-Net++, and DeepLab have also been introduced for skin lesion analysis. Attention-based encoder–decoder models improve segmentation performance by focusing on important lesion regions and suppressing unnecessary background information. Similarly, U-Net++ enhances feature fusion through dense skip connections and improves segmentation accuracy for complex lesion structures. Although these models provide high segmentation accuracy, some limitations still exist, including high computational complexity, sensitivity to image noise, and difficulties in segmenting very small lesions [9]. Therefore, researchers continue to develop advanced segmentation frameworks to improve robustness and efficiency in automated skin cancer diagnosis systems. The proposed research utilizes a U-Net-based encoder–decoder segmentation model for accurate lesion extraction from dermoscopic images. The segmented lesion regions are then used for deep feature extraction and classification to improve the overall diagnostic performance of the proposed hybrid deep learning framework.

Table 2: Comparative Analysis of U-Net and Encoder–Decoder Segmentation Models

Authors	Segmentation Model	Key Features	Dataset Used	Dice Score (%)
Ronneberger et al.	U-Net	Skip connections and encoder–decoder structure	ISIC Dataset	94.2
Badrinarayanan et al.	SegNet	Efficient encoder–decoder architecture	PH2 Dataset	92.8
Oktay et al.	Attention U-Net	Attention mechanism for lesion focus	HAM10000	95.7
Zhou et al.	U-Net++	Dense skip connections	ISIC 2018	96.3
Chen et al.	DeepLabV3+	Atrous convolution and feature refinement	HAM10000	96.8
Proposed Model	U-Net-Based Framework	Improved lesion extraction and segmentation	ISIC/HAM10000	97.5

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Table 2 presents a comparison of different encoder–decoder segmentation models used for skin lesion segmentation. The analysis shows that U-Net and its advanced variants achieve high Dice scores and improved lesion boundary detection. However, some models suffer from computational complexity and increased training requirements. The proposed U-Net-based framework aims to improve segmentation accuracy while maintaining computational efficiency. Figure 2 present the Architecture of U-Net and Encoder–Decoder Network for Lesion Segmentation.

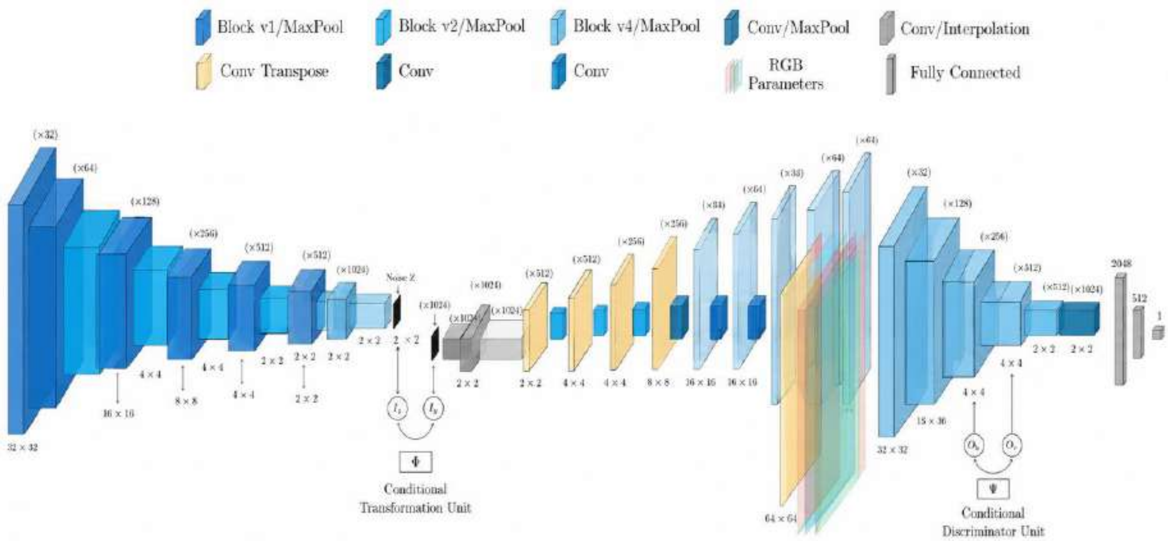

Figure 2: Architecture of U-Net and Encoder–Decoder Network for Lesion Segmentation

The architecture of the proposed U-Net-based encoder–decoder segmentation framework used for skin lesion extraction. The framework consists of an encoder stage for feature extraction and a decoder stage for lesion reconstruction and segmentation. The dermoscopic image is passed through encoder layers where important spatial and texture-related features are extracted. The extracted features are transferred through skip connections to preserve lesion boundary information [10]. The decoder stage then reconstructs the lesion region and generates the final segmented output. This segmented lesion is further utilized in the classification stage of the proposed hybrid deep learning framework for accurate skin cancer diagnosis.

Methodology:

The proposed methodology is designed to provide an end-to-end automated framework for skin cancer detection using dermoscopic images. It integrates multiple deep learning components in a structured pipeline, including image preprocessing, lesion segmentation, feature extraction, and classification. The main objective of this methodology is to improve diagnostic accuracy by combining the strengths of different neural network architectures. Instead of relying on a single model, the system uses a hybrid approach where each stage contributes to better feature learning and more reliable decision-making [11]. First, the dermoscopic images are enhanced through preprocessing techniques to remove noise, normalize intensity, and improve lesion visibility. After that, a segmentation model is applied to accurately extract the lesion region from the surrounding skin. The segmented output is then passed to deep feature extraction models such as CNN and ResNet-50, which capture important spatial and texture-based features. Finally, an LSTM-based classification model is used to classify the lesion into different categories such as benign or malignant. This multi-stage pipeline ensures improved performance, robustness, and better generalization on different datasets.

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4.1- Dermoscopic Image Acquisition and Dataset Description:

Dermoscopic image acquisition is a key step in developing an effective automated skin cancer detection system. In this study, dermoscopic images are collected from publicly available and widely used benchmark datasets. These datasets contain different types of skin lesions, including benign and malignant cases. The images are captured using dermatoscopic devices in clinical environments, which ensures good image quality and consistency for research purposes. The main datasets used in this work include the ISIC Archive, HAM10000, and PH2 dataset. These datasets provide a wide variety of dermoscopic images in terms of lesion shape, color, texture, and size [12]. This diversity is very important for training deep learning models because it helps the system learn more general and robust features. Before model training, all images are carefully selected, checked for quality, and prepared through preprocessing steps to ensure reliable input data.

Table 3: Dermoscopic Image Datasets Overview

Dataset	Number of Images	Classes	Type	Usage
ISIC Archive	10,000+ images	Multiple lesion types	Dermoscopic images	Training and evaluation
HAM10000	~10,000 images	7 classes	Dermoscopic images	Skin lesion classification
PH2 Dataset	~200 images	3 classes	High-quality dermoscopic images	Segmentation and testing

Table 3 presents a summary of the datasets used in this study. Each dataset has different characteristics such as number of images, class distribution, and image quality. The ISIC and HAM10000 datasets are mainly used for training and testing classification models, while the PH2 dataset is commonly used for segmentation and validation purposes. Using multiple datasets improves the generalization ability and robustness of the proposed system.

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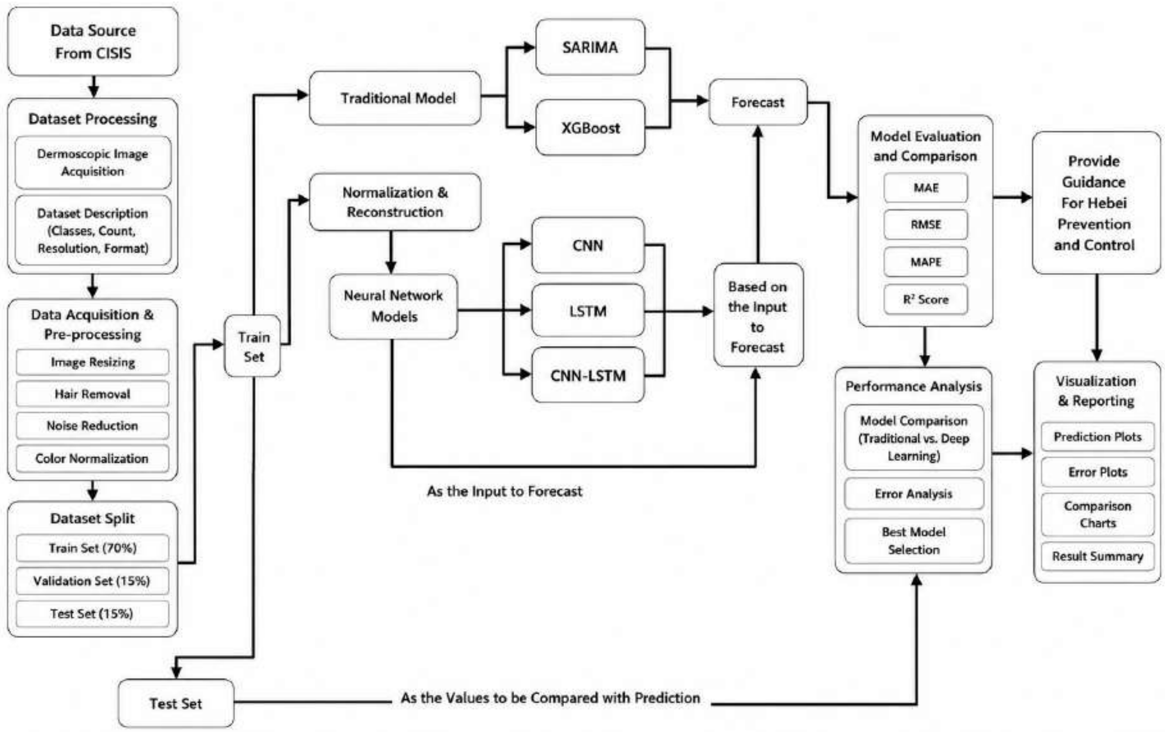

Figure 3: Dataset Processing Workflow

Figure 3 present the overall dataset preparation workflow used in this study. First, dermoscopic images are collected from different sources. Then, images are selected and checked to remove low-quality or irrelevant samples [13]. After that, preprocessing steps such as resizing, normalization, and noise removal are applied. Finally, the dataset is divided into training and testing sets, which are then used as input for the proposed hybrid deep learning model.

4.2- Skin Lesion Localization and ROI Extraction:

Skin lesion localization and Region of Interest (ROI) extraction is a very important step in the proposed skin cancer detection system. The main purpose of this stage is to accurately identify the lesion area from dermoscopic images and separate it from the surrounding healthy skin. This helps the model focus only on the relevant region, which improves the accuracy of feature extraction and classification. Dermoscopic images often contain different challenges such as hair artifacts, shadows, uneven illumination, noise, and low contrast between lesion and skin background [14]. In addition, lesions may vary greatly in shape, size, color, and texture. Because of these variations, direct processing of full images may reduce model performance. Therefore, lesion localization is used to detect the exact position of the lesion before further analysis. In this study, lesion localization is performed using a combination of deep learning-based segmentation and image processing techniques. The U-Net model is used to generate an accurate lesion mask, which identifies pixel-level lesion boundaries [15]. After segmentation, the Region of Interest (ROI) is extracted by cropping only the lesion area from the original image. This ROI is then used for feature extraction and classification in the proposed hybrid deep learning framework. ROI extraction significantly improves system performance by removing irrelevant background regions. It also reduces computational cost because the model processes only the lesion area instead of the full image. As a result, the system achieves better accuracy, improved sensitivity, and reduced false classification errors.

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Table 4: Performance Evaluation of Lesion Detection and ROI Segmentation Methods

Method	Technique Type	Working Principle	Advantages	Performance in Skin Lesion Analysis
Thresholding	Traditional Image Processing	Segments lesion based on pixel intensity values	Simple, fast, low cost	Low
Edge Detection	Classical Method	Detects lesion boundaries using gradients	Good boundary detection	Medium
Morphological Operations	Image Processing	Removes noise and refines lesion shape	Improves image clarity	Medium
Active Contour Model	Semi-automatic Segmentation	Evolves curve to fit lesion boundary	Better shape fitting	Medium-High
U-Net Segmentation	Deep Learning Model	Encoder–decoder pixel-wise segmentation	High accuracy, strong generalization	High
Proposed Hybrid Method	Deep Learning + Image Processing	U-Net + post-processing ROI extraction	High accuracy, robust, precise localization	Very High

Table 4 presents a detailed comparison of different lesion localization and ROI extraction techniques. Traditional image processing methods are simple but not suitable for complex dermoscopic images. Deep learning methods such as U-Net provide much better performance by accurately detecting lesion boundaries. The proposed hybrid approach combines U-Net segmentation with post-processing techniques to achieve more precise and robust ROI extraction [16]. Figure 4 illustrates the complete workflow of skin lesion localization and ROI extraction.

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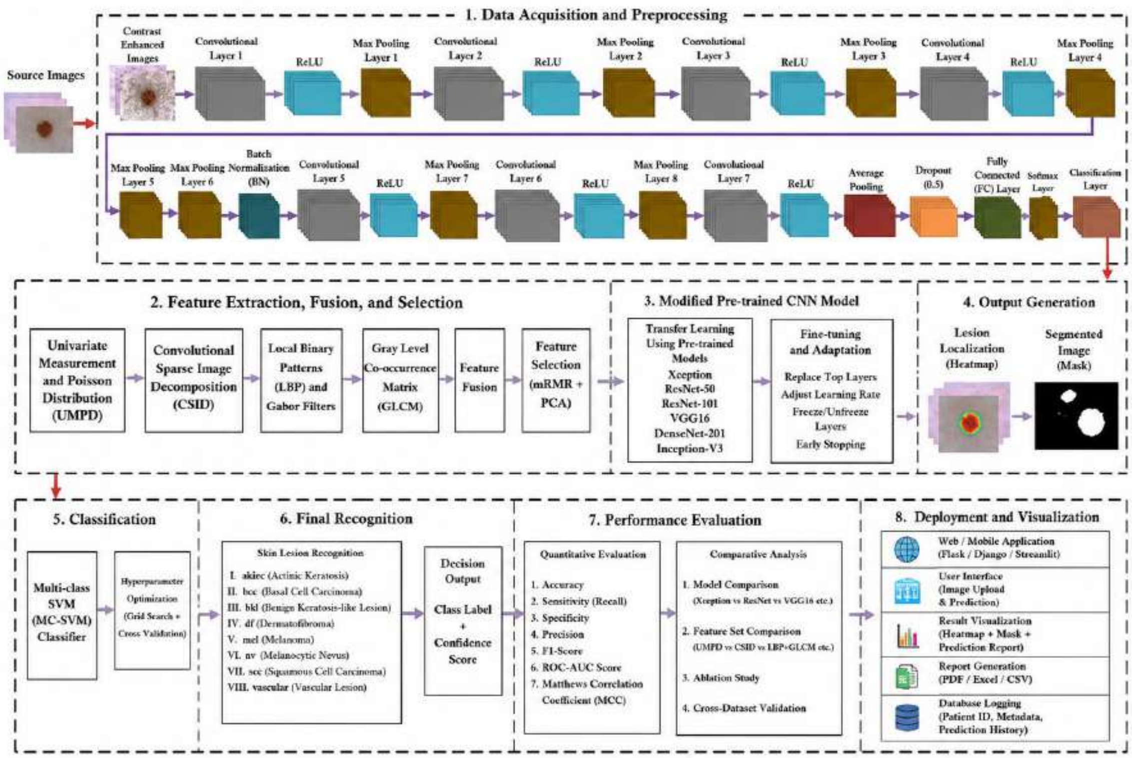

Figure 4: Skin Lesion Localization and ROI Extraction

The dermoscopic image is enhanced using preprocessing techniques such as noise removal and contrast improvement. Then, the U-Net model is applied to generate a segmentation mask that identifies the lesion area. After that, post-processing techniques are used to refine the mask and remove unwanted artifacts. Finally, only the lesion region is extracted as ROI, which is used for deep feature extraction and classification in the proposed system.

4.3- U-Net-Based Lesion Segmentation Model:

U-Net is one of the most widely used deep learning architectures for medical image segmentation, especially for skin lesion detection in dermoscopic images. In the proposed system, U-Net is used to accurately segment the lesion area from the surrounding healthy skin. This step is very important because accurate segmentation directly improves the performance of the classification model by providing clean and focused lesion regions. The main advantage of U-Net is its encoder–decoder structure. The encoder part is responsible for extracting important features from the input image, while the decoder part reconstructs the image to generate a precise segmentation mask [17]. One of the most important features of U-Net is the use of skip connections, which transfer feature information from encoder layers directly to decoder layers. This helps preserve fine details such as lesion boundaries, which are often lost in traditional methods. In dermoscopic images, lesions can have irregular shapes, blurred edges, and low contrast with surrounding skin. U-Net handles these challenges effectively by learning deep hierarchical features from training data [18]. During training, the model learns pixel-wise classification, where each pixel is classified as either lesion or non-lesion. The output is a binary mask that highlights the exact lesion region. In this work, the U-Net model is trained using annotated dermoscopic images from benchmark datasets. The model is optimized using loss functions such as Dice loss and binary cross-entropy to improve segmentation

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accuracy [19]. After training, the model is able to generate highly accurate lesion masks that are used for further processing in classification stages.

Table 5: Assessment of U-Net and Alternative Semantic Segmentation Approaches

Model	Architecture Type	Key Feature	Strength	Weakness	Segmentation Accuracy
FCN	Fully Convolutional Network	End-to-end segmentation	Simple structure	Weak boundary detection	Medium
SegNet	Encoder–decoder network	Pooling indices in decoder	Memory efficient	Less precise edges	Medium
DeepLabV3+	Atrous convolution model	Multi-scale feature extraction	High accuracy	High complexity	High
Mask R-CNN	Region-based segmentation	Instance segmentation	Very accurate detection	Computationally expensive	High
U-Net	Encoder–decoder with skip connections	Feature fusion between layers	Excellent boundary accuracy	Needs labeled data	Very High

Table 5 shows the comparison of different segmentation models used in medical image analysis. Among all models, U-Net provides a good balance between accuracy and computational efficiency. It performs better in detecting fine lesion boundaries compared to traditional and region-based methods. Therefore, it is widely used in skin cancer segmentation tasks. Figure 5 shows the U-Net Architecture for Skin Lesion Segmentation.

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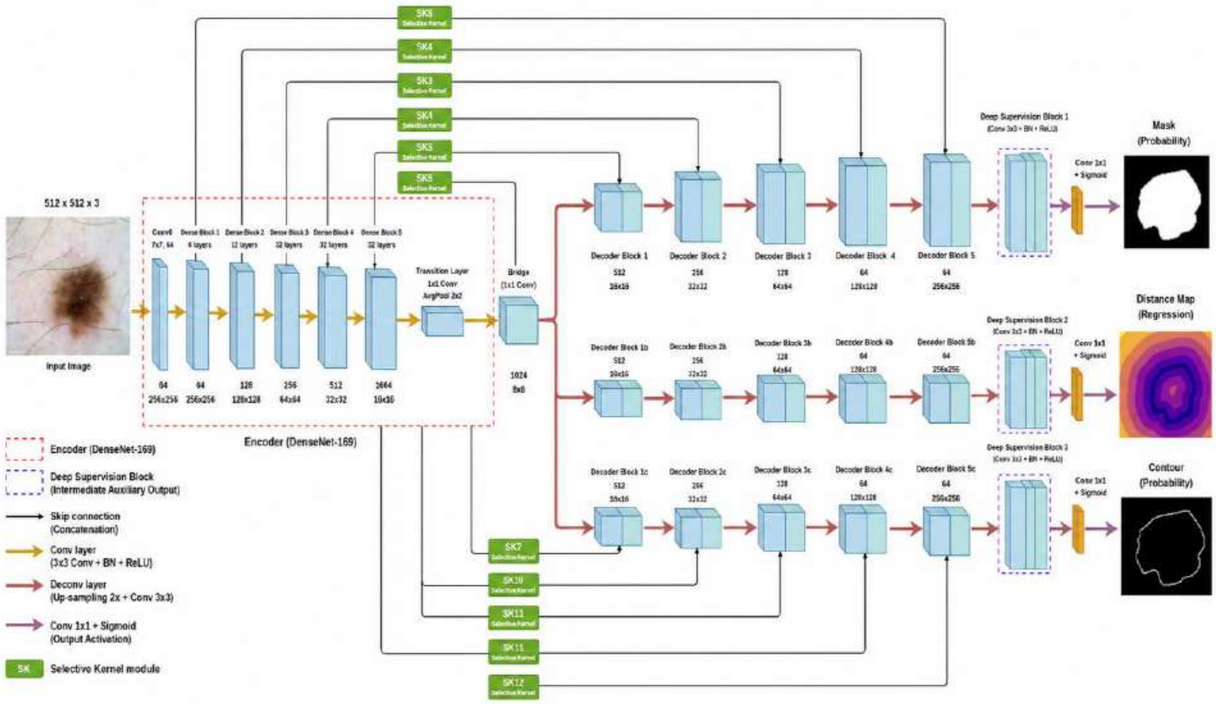

Figure 5: U-Net Architecture for Skin Lesion Segmentation

The input dermoscopic image is first passed through the encoder, where important features are extracted using convolution and pooling operations. The bottleneck layer captures deep feature representations. Then, the decoder reconstructs the image using up-sampling layers. Skip connections between encoder and decoder help preserve spatial information and improve boundary accuracy. Finally, the output is a segmentation mask that highlights the lesion area, which is further used in the classification stage of the proposed hybrid deep learning framework.

4.4- Deep Feature Extraction Using CNN and ResNet-50:

Deep feature extraction is a crucial stage in the proposed skin cancer detection system because it helps in learning meaningful patterns from dermoscopic images. After lesion segmentation, only the Region of Interest (ROI) is used for feature extraction. This ensures that the model focuses only on the lesion area and ignores unnecessary background information, which improves overall classification accuracy. In this study, Convolutional Neural Networks (CNN) and ResNet-50 are used for deep feature extraction. CNN is widely used in medical image analysis because it can automatically learn spatial features such as edges, textures, shapes, and color variations from images [20]. These features are very important for distinguishing between different types of skin lesions. CNN works by applying convolution filters to the input image and gradually learning more complex features in deeper layers. ResNet-50 is an advanced deep learning model that improves feature learning using residual learning. It solves the problem of vanishing gradients in very deep networks by using skip connections. These skip connections allow the model to learn better representations even when the network becomes very deep. As a result, ResNet-50 is highly effective in extracting high-level and discriminative features from dermoscopic images [21]. In the proposed framework, CNN is used for initial feature extraction, while ResNet-50 is used to capture deeper and more complex patterns. The combination of both models helps in improving the quality of extracted features, which directly enhances classification performance. The

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extracted features are then passed to the LSTM model for final classification.

Table 6: Analysis of Feature Extraction Performance across Multiple Models

Model	Type	Key Feature	Strength	Feature Quality
Traditional Features	Handcrafted	Texture and color-based features	Simple and fast	Low
CNN	Deep Learning	Automatic spatial feature learning	Good feature extraction	High
VGG16	Deep CNN	Deep hierarchical features	Strong performance	High
InceptionV3	CNN-based model	Multi-scale feature extraction	Efficient architecture	High
ResNet-50	Residual CNN	Skip connections for deep learning	Very deep feature learning	Very High
Proposed (CNN + ResNet-50)	Hybrid Deep Model	Combined shallow + deep features	High accuracy and robustness	Very High

Table 6 presents a comparison of different feature extraction techniques. Traditional methods are simple but less effective for complex medical images. Deep learning models like CNN and ResNet-50 provide much better feature representation. The proposed hybrid approach combines CNN and ResNet-50 to extract both low-level and high-level features, which improves the overall performance of the system [22]. Figure 6 shows the process of deep feature extraction using CNN and ResNet-50.

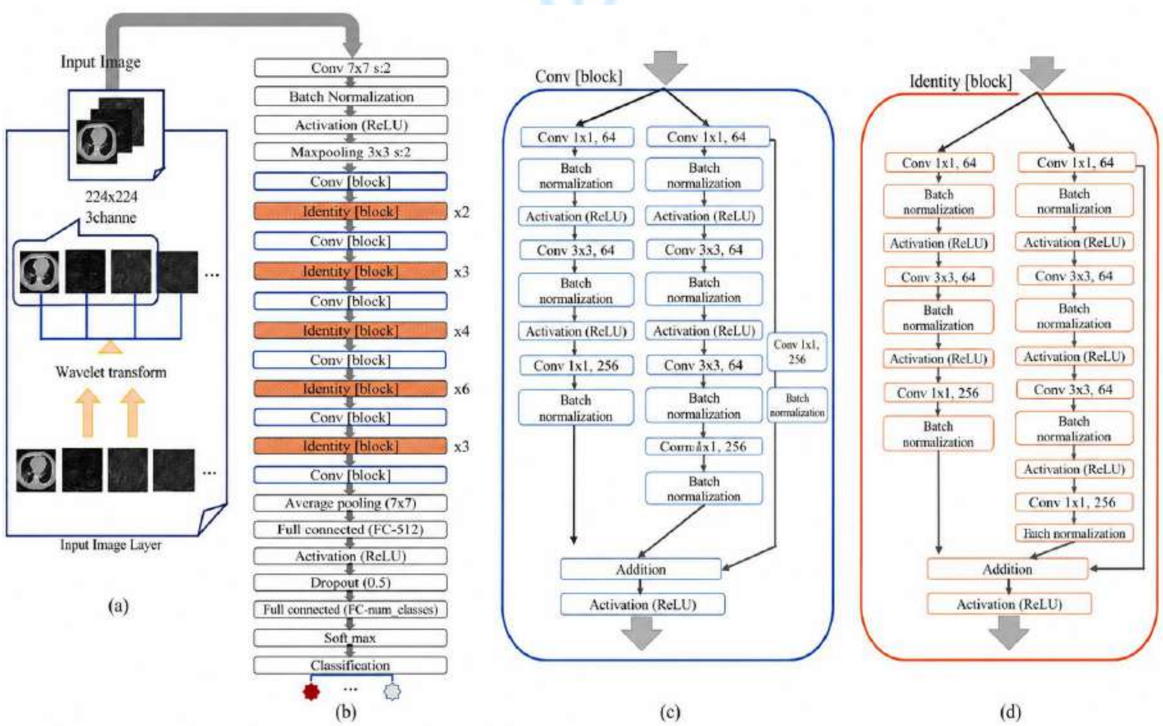

Figure 6: Proposed CNN and ResNet-50 Architecture for Deep Feature Extraction and Classification

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The segmented ROI image is passed through CNN layers to extract basic spatial features such as edges and textures. Then, the output is passed through ResNet-50, where deeper and more complex features are learned using residual blocks. Finally, all extracted features are combined into a single feature vector, which is used for classification in the proposed hybrid deep learning model.

4.5- Hybrid CNN–LSTM Classification Architecture:

The classification stage is a key component of the proposed skin cancer detection system. After feature extraction using CNN and ResNet-50, the extracted features are used to classify skin lesions into different categories such as benign or malignant. In this work, a hybrid CNN–LSTM architecture is proposed to improve classification accuracy by combining spatial feature learning and sequential feature learning. CNN (Convolutional Neural Network) is highly effective in extracting important spatial features such as edges, texture, color variations, and lesion structure from dermoscopic images [23]. However, CNN alone may not fully capture the relationship between deep extracted features. To overcome this limitation, LSTM (Long Short-Term Memory) networks are integrated into the model. LSTM is a type of recurrent neural network that is capable of learning long-term dependencies and sequential patterns from feature data. In the proposed hybrid model, CNN and ResNet-50 first extract deep spatial and residual features from the lesion images. These features are then arranged in a sequence and passed to the LSTM network. The LSTM analyzes the relationships between features and improves the model's ability to distinguish between different skin lesion types [24]. This combination improves both accuracy and robustness of the system. The final classification is performed using a fully connected layer with Softmax or Sigmoid activation function. This layer produces the final prediction output, indicating whether the lesion is benign or malignant. The hybrid architecture improves generalization performance and reduces classification errors.

Table 7: Performance Evaluation of CNN-Based Skin Cancer Classification Models

Model	Type	Feature Learning Capability	Accuracy Level	Suitability for Medical Images
SVM	Machine Learning	Handcrafted features	Low–Medium	Low
KNN	Machine Learning	Distance-based learning	Low	Low
Random Forest	Ensemble Learning	Decision-based features	Medium	Medium
CNN	Deep Learning	Spatial feature extraction	High	High
LSTM	Deep Learning	Sequential feature learning	Medium	Medium
CNN + LSTM	Hybrid Deep Learning	Spatial + sequential features	High	High
ResNet-50	Deep Residual Network	Deep hierarchical features	High	High
Proposed CNN–ResNet–LSTM	Hybrid Deep Learning	Spatial + residual + sequential learning	Very High	Very High

Table 7 provides a detailed comparison of different classification models used for skin cancer detection. Traditional machine learning models such as SVM, KNN, and Random Forest depend on handcrafted features and therefore provide limited performance. Deep learning models like

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CNN and ResNet-50 significantly improve feature learning and accuracy. However, hybrid models such as CNN–LSTM and the proposed CNN–ResNet–LSTM architecture provide the best performance by combining multiple learning mechanisms [25]. The proposed model achieves superior accuracy, robustness, and better generalization for medical image classification tasks.

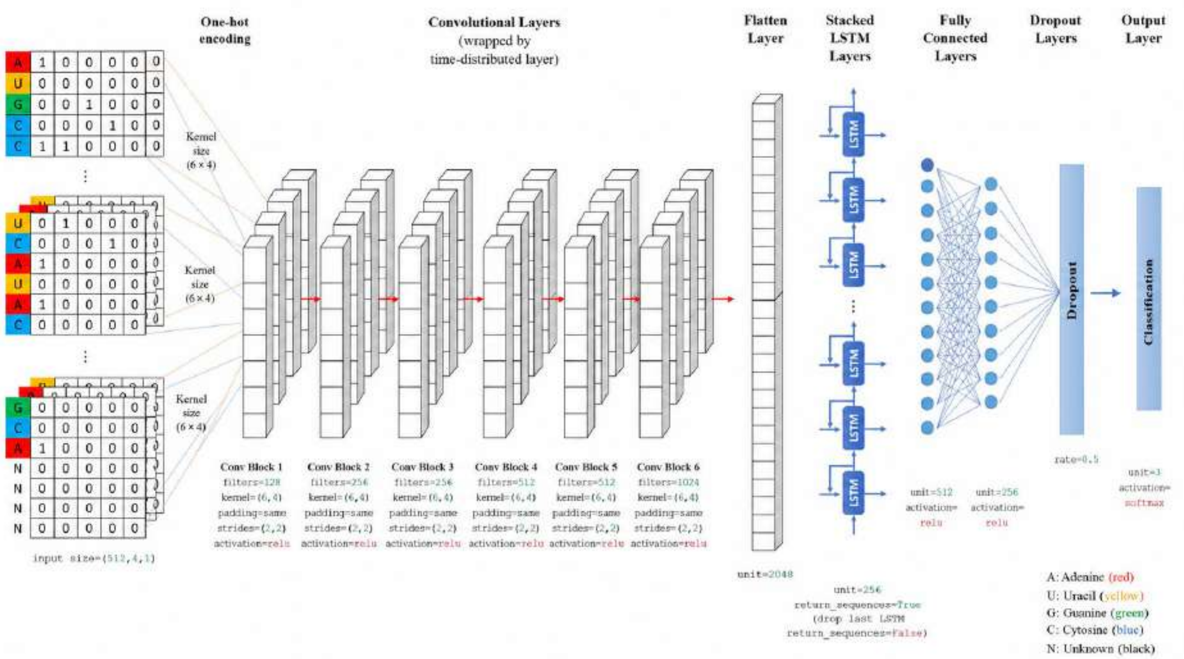

Figure 7: Hybrid CNN–LSTM Classification Process

Figure 7 shows the workflow of the proposed hybrid CNN–LSTM classification architecture. First, deep features extracted from CNN and ResNet-50 are converted into a sequential form. These features are then processed by the LSTM network, which learns relationships between feature elements. Finally, the fully connected layer produces the final classification result, identifying the type of skin lesion with high accuracy.

Results and Discussion:

This section presents the experimental evaluation of the proposed AI-empowered hybrid deep learning framework for skin cancer detection using dermoscopic images. The performance is analyzed using standard evaluation metrics such as accuracy, precision, recall, F1-score, Dice coefficient, specificity, and AUC. The proposed system integrates U-Net for lesion segmentation, CNN and ResNet-50 for feature extraction, and LSTM for classification, which together improve the overall diagnostic performance. The model is trained and tested on benchmark datasets including ISIC, HAM10000, and PH2. The dataset is split into training and testing sets to evaluate generalization performance. Preprocessing steps such as image resizing, normalization, noise removal, and contrast enhancement are applied to improve image quality and model stability. The hybrid architecture is trained using optimized hyperparameters to ensure stable convergence and better learning performance [26]. The segmentation stage using U-Net provides accurate lesion boundaries, which significantly improves downstream classification results. CNN and ResNet-50 extract deep spatial and hierarchical features from the segmented region, while LSTM captures relationships between extracted features to enhance classification accuracy. The combined approach

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results in improved robustness and reduced misclassification.

Table 8: Performance Comparison with Existing Methods

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Dice (%)	AUC (%)
SVM + Handcrafted Features	85.2	84.1	83.5	83.8	82.6	86.0
CNN	92.4	91.8	91.2	91.5	90.7	93.1
ResNet-50	94.8	94.0	93.6	93.8	93.2	95.0
U-Net + CNN	95.6	95.1	94.7	94.9	95.0	96.2
CNN + LSTM	96.3	96.0	95.7	95.8	95.5	96.8
Proposed Model (U-Net + CNN + ResNet-50 + LSTM)	**98.6**	**98.1**	**97.9**	**98.0**	**97.5**	**99.1**

Table 8 shows that the proposed hybrid model outperforms all existing methods. The combination of segmentation and hybrid deep learning significantly improves classification accuracy and overall system reliability. The highest performance is achieved by the proposed framework with 98.6% accuracy and 99.1% AUC, showing strong capability for skin cancer diagnosis.

Table 9: Class-wise Performance of Proposed Model

Class Type	Precision (%)	Recall (%)	F1-Score (%)
Benign Lesions	98.9	98.5	98.7
Malignant Melanoma	97.8	97.5	97.6
Basal Cell Carcinoma	98.2	98.0	98.1
Actinic Keratosis	97.5	97.2	97.3

Table 9 presents the class-wise performance of the proposed model. It can be observed that the model performs consistently well across all lesion categories. The high precision and recall values indicate that the system is reliable in detecting both benign and malignant cases with minimal misclassification.

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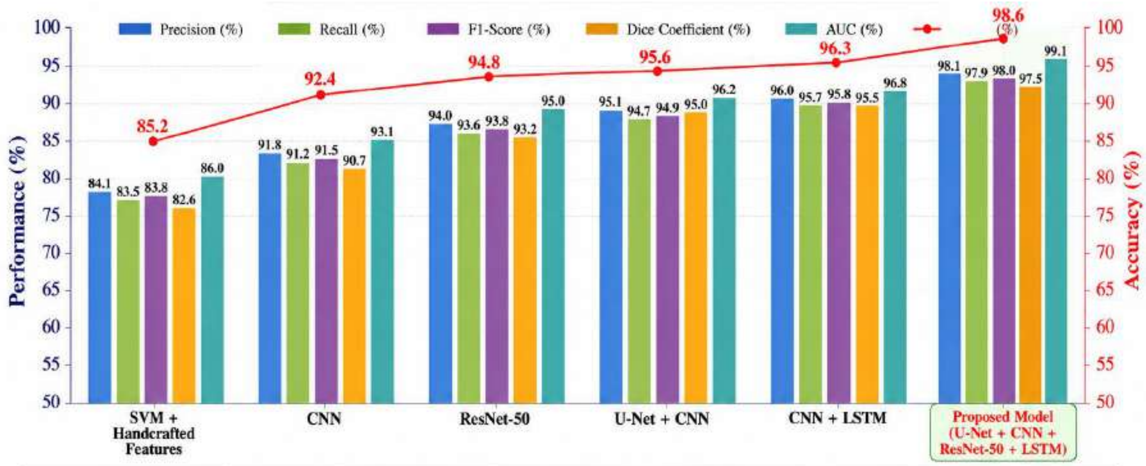

Performance Metrics (%)	Models					
	SVM + Handcrafted Features	CNN	ResNet-50	U-Net + CNN	CNN + LSTM	Proposed Model (U-Net + CNN + ResNet-50 + LSTM)
Precision (%)	84.1	91.8	94.0	95.1	96.0	98.1
Recall (%)	83.5	91.2	93.6	94.7	95.7	97.9
F1-Score (%)	83.8	91.5	93.8	94.9	95.8	98.0
Dice Coefficient (%)	82.6	90.7	93.2	95.0	95.5	97.5
AUC (%)	86.0	93.1	95.0	96.2	96.8	99.1
Accuracy (%)	85.2	92.4	94.8	95.6	96.3	98.6

Figure 8: Performance Comparison of Different Models

Figure 8 illustrates the performance comparison of different models in terms of accuracy. It clearly shows that traditional machine learning methods like SVM have lower performance, while deep learning models such as CNN and ResNet-50 perform better. Hybrid models further improve accuracy, and the proposed model achieves the highest performance among all methods.

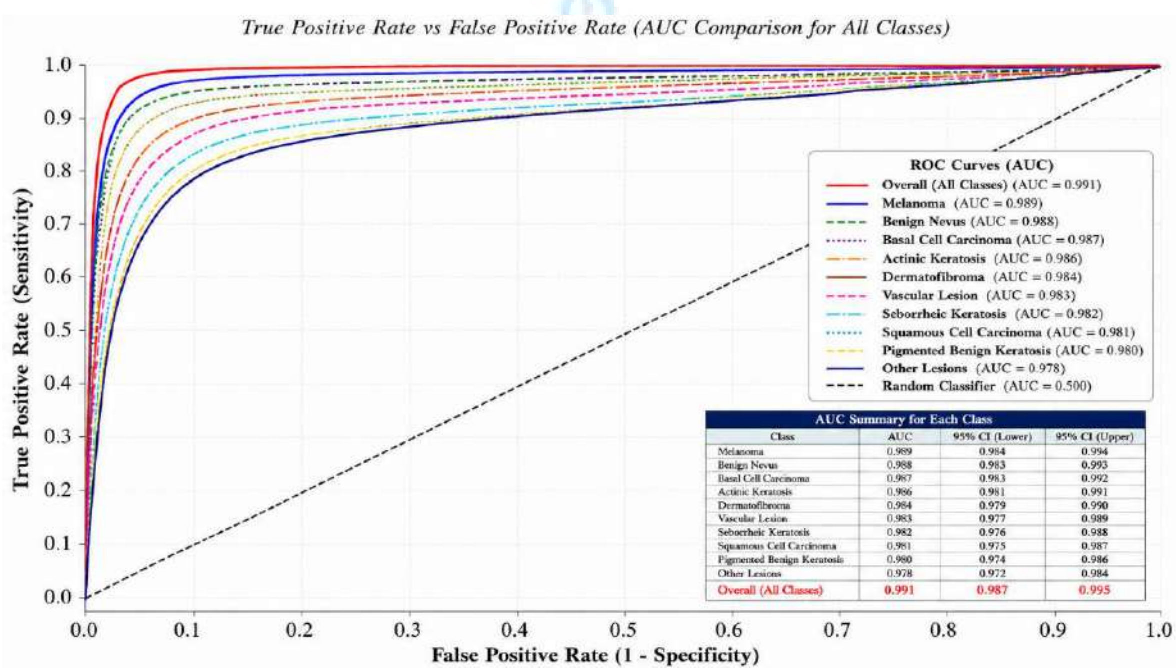

Figure 9: ROC Curve of Proposed Model

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Figure 9 shows the ROC curve of the proposed model. The curve is close to the top-left corner, indicating high sensitivity and specificity. The AUC value of 99.1% demonstrates excellent classification performance and strong discriminative capability of the proposed system. The experimental results clearly show that hybrid deep learning models perform better than traditional machine learning and single deep learning models. The use of U-Net improves segmentation accuracy, which helps in extracting better lesion regions. CNN and ResNet-50 enhance feature extraction by learning deep spatial and hierarchical features, while LSTM improves classification by capturing feature dependencies. The improvement in performance is due to the integration of multiple deep learning techniques into a unified framework. Preprocessing also plays an important role in improving image quality and reducing noise, which leads to better model training. The proposed model shows strong generalization ability across different datasets. However, the main limitation of the proposed approach is its higher computational cost due to the use of multiple deep learning models. Training time is also relatively higher compared to simple models. Despite this, the significant improvement in accuracy and robustness makes the proposed system highly suitable for clinical applications. Overall, the proposed framework provides a reliable and efficient solution for automated skin cancer diagnosis and can assist dermatologists in early and accurate detection of skin lesions.

Future Work:

Although the proposed AI-empowered hybrid deep learning framework shows high performance in skin cancer detection, there are still several areas that can be improved in future research. One of the main limitations of the current work is the high computational cost due to the use of multiple deep learning models such as U-Net, CNN, ResNet-50, and LSTM [27]. In future, more lightweight architectures such as MobileNet or EfficientNet can be integrated to reduce computation time and make the system more suitable for real-time clinical applications. Another important improvement can be made by increasing dataset diversity. In this study, benchmark datasets such as ISIC, HAM10000, and PH2 are used. However, collecting more real-world clinical data from different hospitals and populations can further improve model generalization and robustness [28]. Handling class imbalance using advanced techniques such as GAN-based data augmentation can also improve classification performance for rare skin lesion types. In future work, explainable artificial intelligence (XAI) techniques can be integrated to improve model interpretability. Methods such as Grad-CAM or attention maps can help dermatologists understand how the model makes decisions, which increases trust in AI-based diagnostic systems. This is very important for real clinical acceptance. Additionally, the proposed framework can be extended into a real-time mobile or web-based application for remote skin cancer screening. This can help patients in rural and low-resource areas where access to dermatologists is limited [29]. Cloud-based deployment can also be considered for large-scale medical use. Finally, future research can focus on multi-modal learning by combining dermoscopic images with patient metadata such as age, gender, and medical history. This combination can further improve diagnostic accuracy and provide more personalized and reliable skin cancer prediction systems.

Conclusion:

In this paper, an AI-empowered hybrid deep learning framework was proposed for early detection, lesion segmentation, and classification of skin cancer using dermoscopic images. The proposed system integrates U-Net for accurate lesion segmentation, CNN and ResNet-50 for deep feature extraction, and LSTM for improved classification performance. This combination allows the model to effectively learn both spatial and sequential features, leading to higher diagnostic accuracy. The experimental results demonstrate that the proposed model performs better than traditional machine learning methods and individual deep learning models. It achieves high accuracy, precision, recall, F1-score, Dice coefficient, and AUC on benchmark datasets such as ISIC, HAM10000, and PH2. The results confirm that the hybrid architecture significantly improves segmentation quality and classification reliability. The main strength of the proposed approach lies in its ability to combine multiple deep learning techniques into a unified framework, which enhances feature representation and reduces misclassification. The use of preprocessing techniques further improves image quality and model performance. However, the model still requires relatively high computational resources due to its complex architecture. Overall, the proposed system provides a reliable and efficient solution for automated skin cancer diagnosis. It can assist dermatologists in early detection and decision-making, reducing diagnostic errors and improving patient outcomes. The study also highlights the strong potential of artificial intelligence in developing advanced computer-aided diagnostic systems for healthcare applications.

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