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An Advanced Deep Residual Learning Framework for Accurate Skin Cancer Detection Using ResNet152

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Abstract:
Skin cancer is one of the most rapidly increasing and life-threatening diseases worldwide, where early and accurate diagnosis plays a critical role in improving patient survival rates. Traditional diagnostic approaches heavily depend on dermatologist expertise and manual examination, which may lead to inconsistent results and delayed detection. To overcome these limitations, this research proposes an advanced deep learning-based framework for automated skin cancer detection using the ResNet152 architecture. The proposed system utilizes dermoscopic skin lesion images from the ISIC dataset and applies preprocessing techniques such as image resizing, normalization, noise removal, and data augmentation to improve model performance and generalization capability. The ResNet152 model is employed for deep feature extraction and binary classification of skin lesions into benign and malignant categories. The proposed framework is evaluated using standard performance metrics including accuracy, precision, recall, and F1-score. Experimental results demonstrate that the proposed ResNet152 model achieves superior performance with 97% accuracy, 98% precision, 97% recall, and 98% F1-score compared to existing models such as ResNet50 and ResNet101. The findings confirm that deep residual learning significantly improves feature extraction, classification reliability, and automated diagnosis capability for skin cancer detection. The proposed framework can support clinical decision-making and contribute to intelligent healthcare systems for early skin cancer diagnosis.

Keywords: Skin Cancer Detection, Deep Learning, ResNet152, Dermoscopic Images, Convolutional Neural Network, Deep Residual Learning, Medical Image Analysis, Artificial Intelligence, Melanoma Classification, Transfer Learning.

1. Introduction

Skin cancer is among the most common and dangerous forms of cancer affecting millions of people globally. The increasing exposure to ultraviolet (UV) radiation, environmental pollution, genetic factors, and unhealthy lifestyle habits have contributed significantly to the rising number of skin cancer cases. Among different skin cancer types, melanoma is considered the most aggressive due to its rapid spread to other parts of the body if not detected at an early stage. Therefore, early and accurate diagnosis of skin cancer is essential for effective treatment and improved patient survival.

Traditional skin cancer diagnosis mainly depends on clinical examination, dermoscopy, and biopsy procedures performed by experienced dermatologists. However, manual diagnosis is often time-consuming, subjective, and prone to human error, especially in the early stages where lesion characteristics are difficult to identify. In many rural and underdeveloped regions, the lack of dermatological experts further increases the risk of delayed diagnosis and treatment. These limitations have created a growing demand for automated, intelligent, and reliable diagnostic systems capable of assisting medical professionals in skin cancer detection.

Recent advancements in artificial intelligence and deep learning have transformed the field of medical image analysis. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable success in image classification, object detection, and disease diagnosis tasks. CNN-based models automatically learn hierarchical features from raw images without relying on handcrafted feature extraction methods. Among various deep learning architectures, Residual Networks (ResNet) have emerged as highly effective due to their ability to train very deep neural networks using residual learning and skip connections.

ResNet152, a deep residual network consisting of 152 layers, offers superior feature extraction capability and improved classification accuracy compared to traditional CNN architectures. The residual learning mechanism helps overcome the vanishing gradient problem and enables the network to learn complex lesion patterns such as asymmetry, irregular borders, texture variation, and color distribution in dermoscopic images. These capabilities make ResNet152 highly suitable for accurate skin cancer classification.

In this research, an advanced deep residual learning framework based on ResNet152 is proposed for automated skin cancer detection using dermoscopic images. The framework includes image preprocessing, augmentation, segmentation, deep feature extraction, classification, and performance evaluation. The proposed model is trained and tested using the ISIC skin lesion dataset and evaluated using metrics such as accuracy, precision, recall, and F1-score. Experimental results demonstrate that the proposed ResNet152 model outperforms existing models such as ResNet50 and ResNet101 in terms of classification performance and diagnostic reliability.

The main contribution of this work is the development of a robust and efficient deep learning framework capable of providing accurate, consistent, and scalable skin cancer detection for intelligent healthcare applications.

2. Literature Review

2.1 Skin Cancer Detection and Early Diagnosis Techniques

Skin cancer remains one of the fastest-growing forms of cancer worldwide, creating an urgent need for accurate and early diagnosis systems. Recent studies have focused on improving detection accuracy using advanced imaging technologies and artificial intelligence-based diagnostic models. Islam et al. (2026) proposed a deep learning framework that combines dermoscopic images with patient metadata, significantly improving classification performance and diagnostic reliability. Similarly, Tajanpure et al. (2026) emphasized the importance of innovative imaging technologies in enhancing early-stage skin cancer identification and reducing diagnostic delays.

Tripathy et al. (2026) reviewed modern approaches in skin cancer management and highlighted that early detection plays a critical role in improving survival rates and treatment effectiveness. Zhou et al. (2026) analyzed the global burden of skin cancer from 1990 to 2023 and projected a continuous increase in cases by 2050, reinforcing the necessity of efficient automated diagnostic systems. Kumari et al. (2026) further demonstrated the effectiveness of deep learning-assisted diagnostic systems in underserved clinical settings, where dermatological expertise is limited.

Research has also explored melanoma-specific detection approaches. Indian et al. (2026) developed a deep learning model for melanoma classification that achieved promising accuracy using dermoscopic datasets. Additionally, Mukherjee et al. (2026) investigated AI-powered mobile health applications for skin cancer detection and discussed their potential for improving public healthcare accessibility, particularly in low- and middle-income countries. These studies collectively indicate that AI-based early diagnostic systems can substantially improve screening efficiency and reduce mortality associated with skin cancer.

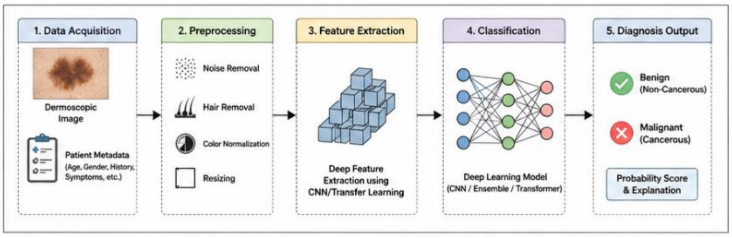

Figure 1: Workflow of AI-Based Skin Cancer Early Detection System

This figure 1 illustrates the overall process of skin cancer early detection using dermoscopic image acquisition, preprocessing, feature extraction, deep learning-based classification, and final diagnosis prediction. It highlights how patient metadata and lesion images are integrated to improve detection accuracy.

2.2 Deep Learning and Artificial Intelligence in Skin Cancer Classification

Deep learning has emerged as one of the most effective techniques for automated skin cancer classification. Convolutional Neural Networks (CNNs), transfer learning, ensemble learning, and transformer-based architectures are increasingly used to classify benign and malignant lesions with high precision. Adablanu et al. (2026) explored AI-based convolutional and transformer models and found that transformer architectures provide enhanced feature extraction and classification capabilities compared to traditional CNN methods.

Minhas et al. (2026) proposed an ensemble deep learning framework for melanoma detection that combined multiple neural network models to improve classification accuracy and reduce false predictions. Saha et al. (2026) introduced SkinFLNet, a federated learning approach that enables collaborative training across distributed dermoscopy datasets while preserving patient privacy. Their work demonstrated that federated learning can effectively address data security concerns while maintaining strong classification performance.

Karimzadhagh et al. (2026) conducted an umbrella review of systematic reviews and meta-analyses and concluded that AI systems often achieve diagnostic performance comparable to dermatologists. Sollis et al. (2026) further examined how artificial intelligence is transforming the skin cancer screening pathway, highlighting improvements in automated lesion analysis, diagnostic support, and workflow optimization.

Several earlier studies related to medical image analysis also support the applicability of deep learning in healthcare diagnostics. Singh and Songare (2022) applied the GoogLeNet model for monkeypox detection, while Vishwakarma et al. (2023) used EfficientNetB3 for brain tumor segmentation and detection. Saxena et al. (2020) developed a CNN-based glaucoma detection system, demonstrating the effectiveness of deep learning in medical imaging applications. These studies provide a strong foundation for adopting CNN and transfer learning techniques in automated skin cancer detection systems.

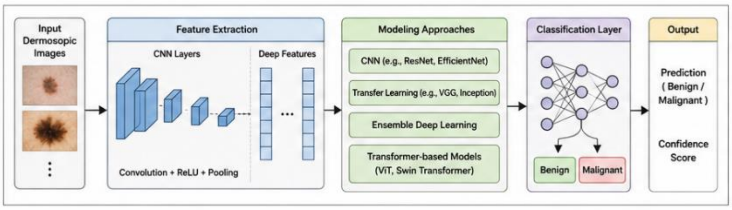

Figure 2: Architecture of Deep Learning Models for Skin Cancer Classification

This figure 2 presents the architecture of various deep learning models such as CNNs, transfer learning networks, ensemble models, and transformer-based systems used for skin lesion classification. It demonstrates the flow from input thermoscopic images to feature extraction, training, and classification of benign and malignant lesions.

2.3 Related Deep Learning Applications and Research Gaps

Deep learning techniques have been successfully applied across various domains beyond skin cancer detection, showing their versatility in pattern recognition and classification tasks. Prajapati et al. (2023) implemented deep learning methods for gender recognition, while Patel and Singh (2023) developed age and gender recognition systems using CNN architectures. Gupta et al. (2023) applied the ResNet152 model for human face mask recognition and achieved high classification accuracy.

In sports analytics, Ray and Singh (2023) utilized Hybrid Task Cascade Region-Based CNN for cricket score analysis, whereas Nagar and Singh (2025) proposed an AI-powered penalty detection and performance recommendation system for soccer training. These studies demonstrate the adaptability of deep learning models across diverse computer vision applications.

Despite substantial progress, several research gaps remain in skin cancer detection systems. Many existing models suffer from limited dataset diversity, poor generalization in real-world clinical environments, and insufficient interpretability. Additionally, most studies focus primarily on image-based classification without incorporating patient metadata, clinical history, or federated privacy-preserving mechanisms. Bharti et al. (2025) discussed the gap between AI research and practical clinical implementation, emphasizing challenges such as trustworthiness, data imbalance, and integration into healthcare workflows.

Another important limitation is the accessibility of advanced diagnostic systems in rural and low-resource settings. Mukherjee et al. (2026) noted that mobile health applications and lightweight AI models are still underdeveloped for large-scale deployment in developing countries. Therefore, there is a growing need for robust, efficient, and scalable deep learning frameworks capable of delivering accurate skin cancer detection while ensuring privacy, interpretability, and real-world usability.

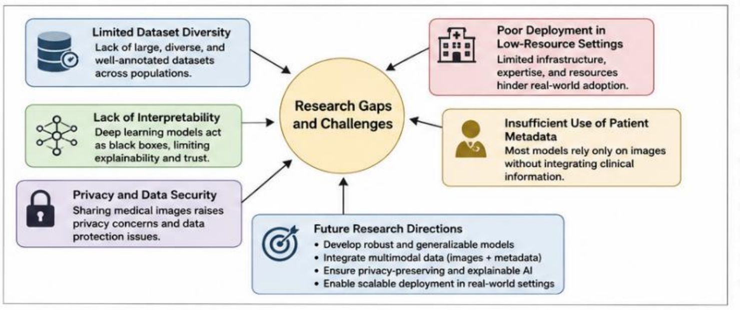

Figure 3: Research Gaps and Challenges in AI-Based Skin Cancer Detection

This figure 3 shows the major challenges and research gaps in existing skin cancer detection systems, including limited dataset diversity, lack of interpretability, privacy concerns, poor deployment in low-resource settings, and insufficient integration of patient metadata. It also highlights future research directions for developing robust and scalable AI diagnostic systems.

3 Proposed Methodology

3.1 Proposed Architecture Explanation

The proposed architecture 4 is designed for the automated detection of skin cancer using the **ResNet152 deep learning model**. The system classifies dermoscopic skin lesion images into two categories: **benign** and **malignant**. The architecture follows a systematic pipeline consisting of data collection, preprocessing, segmentation, feature extraction, model training, classification, and performance evaluation.

The process begins with the collection of dermoscopic images from a skin cancer dataset. These images may contain variations in size, color, brightness, noise, hair artifacts, and background regions. Therefore, preprocessing is applied to improve image quality and make all images suitable for model training. The preprocessing stage includes image resizing, normalization, noise reduction, and data augmentation.

After preprocessing, segmentation is performed to isolate the lesion region from the surrounding skin area. This step helps the model focus on the important region of interest instead of irrelevant background features. Techniques such as thresholding, region growing, and watershed segmentation may be used to extract lesion boundaries.

The segmented and enhanced images are then passed to the **ResNet152 model**, which acts as the main feature extraction and classification model. ResNet152 contains deep convolutional layers and residual connections that allow the network to learn complex lesion patterns without suffering from vanishing gradient problems. The extracted features are passed through fully connected layers and a softmax classifier to predict whether the input image belongs to the benign or malignant class.

Finally, the performance of the model is evaluated using accuracy, precision, recall, F1-score, sensitivity, specificity, and confusion matrix. The proposed ResNet152 model is compared with existing models such as ResNet50 and ResNet101 to prove its effectiveness.

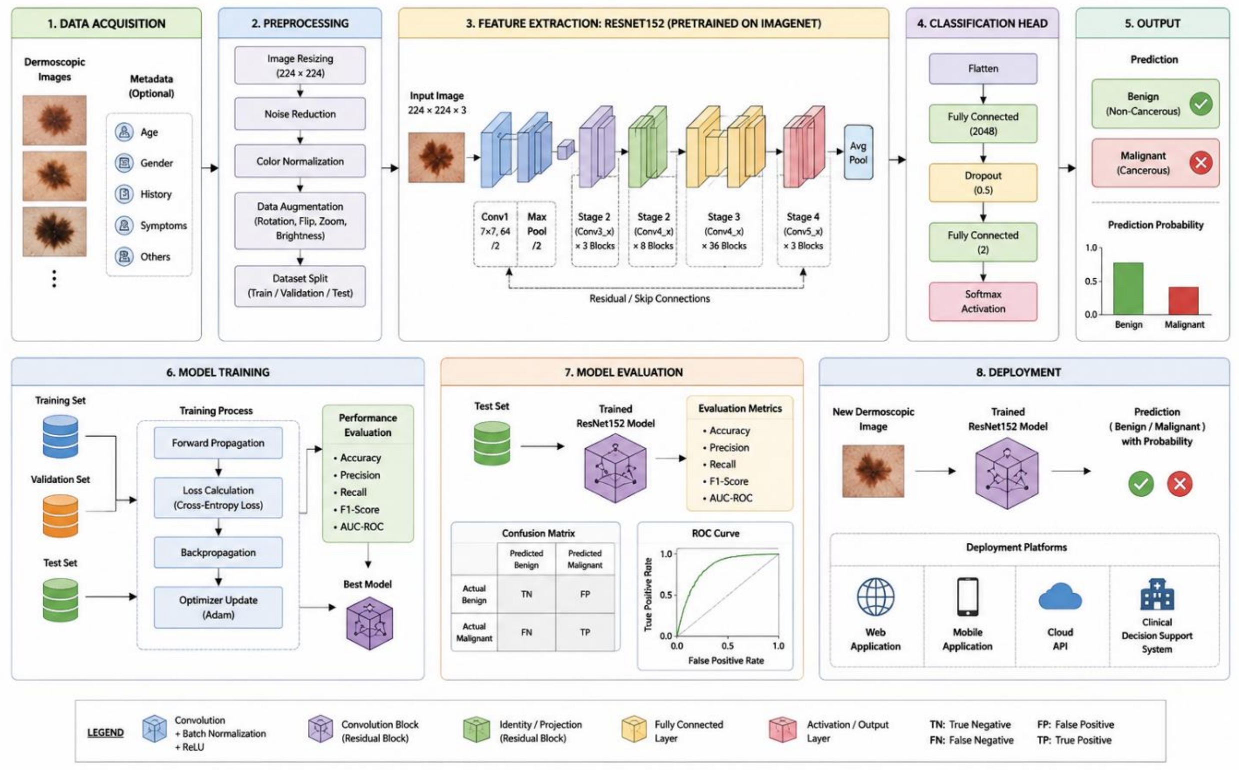

Figure 4: Proposed Architecture for Skin Cancer Detection Using ResNet152

3.2 Proposed Algorithm with Mathematical Steps

Proposed Algorithm: ResNet152-Based Skin Cancer Detection

Step 1: Input Image Collection

Let the input dermoscopic image dataset be represented as:

$$D = \{(X_i, Y_i)\}_{i=1}^{N}$$

Where:

$$X_i$$

represents the input skin lesion image,

$$Y_i$$

represents the class label, and

$$N$$

is the total number of images.

The class label is defined as:

$$Y_i = \begin{cases} 0, & \text{Benign} \\ 1, & \text{Malignant} \end{cases}$$

Step 2: Image Preprocessing

Each input image is resized into a fixed dimension suitable for ResNet152:

$$X_i \rightarrow X_i{}' \in R^{224\times224\times3}$$

Pixel normalization is applied as:

$$X_{norm} = \frac{X_i - X_{min}}{X_{max} - X_{min}}$$

This converts pixel values into a normalized range and improves training stability.

Step 3: Data Augmentation
To improve generalization and reduce overfitting, augmentation operations are applied:

$$X_{aug} = T(X_{norm})$$

Where:

$$T = \{rotation, flipping, zooming, shifting, brightness\ adjustment\}$$

Step 4: Feature Extraction Using ResNet152
The preprocessed image is passed through the ResNet152 model:

$$F = ResNet152(X_{aug})$$

Where:

$$F$$

represents the deep feature vector extracted from the dermoscopic image.
ResNet152 uses residual learning:

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

Where:

$$F(x)$$

is the residual mapping and

$$x$$

is the identity shortcut connection.

Step 5: Classification Layer
The extracted features are passed through fully connected layers:

$$Z = W \cdot F + b$$

Softmax activation is used to calculate class probability:

$$P(y = k \mid X) = \frac{e^{Z_k}}{\sum_{j=1}^{C} e^{Z_j}}$$

Where:

$$C = 2$$

for benign and malignant classification.

Step 6: Loss Function
The model is trained using categorical cross-entropy loss:

$$L = -\sum_{i=1}^{N} Y_i \log(\widehat{Y_i})$$

Where:

$$Y_i$$

is the actual label and

$$\widehat{Y_i}$$

is the predicted label.

Step 7: Optimization

The model weights are updated using an optimizer such as Adam or SGD:

$$W_{new} = W_{old} - \eta \frac{\partial L}{\partial W}$$

Where:

$$\eta$$

is the learning rate.

Step 8: Prediction

For a new input image, the model predicts:

$$\hat{Y} = \begin{cases} 0, & P(Benign) > P(Malignant) \\ 1, & P(Malignant) > P(Benign) \end{cases}$$

Step 9: Performance Evaluation

The model is evaluated using:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1\text{-}Score = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

Steps of Proposed ResNet152-Based Skin Cancer Detection Algorithm

Input:

- Dermoscopic skin lesion images from ISIC dataset
- Benign and malignant skin cancer classes
- Image size: $224 \times 224 \times 3$

Output:

- Classified skin lesion:
  - Benign
  - Malignant
- Performance metrics:
  - Accuracy
  - Precision
  - Recall
  - F1-score

Step 1: Collect dermoscopic skin lesion images from the ISIC dataset.

Step 2: Perform data cleaning by removing noisy and low-quality images.

Step 3: Resize all images to $224 \times 224$and normalize pixel values.

Step 4: Apply data augmentation techniques such as rotation, flipping, zooming, and brightness adjustment.
Step 5: Split the dataset into training, validation, and testing datasets.
Step 6: Perform lesion segmentation using thresholding and region growing methods.
Step 7: Initialize the ResNet152 model with ImageNet pre-trained weights.
Step 8: Extract deep features using convolutional and residual blocks.
Step 9: Apply fully connected layers and softmax activation for classification.
Step 10: Train the model using forward propagation and backpropagation.
Step 11: Optimize the model using Adam optimizer and cross-entropy loss function.
Step 12: Validate the trained model using validation data.
Step 13: Test the trained model using unseen dermoscopic images.
Step 14: Classify the skin lesion as benign or malignant.
Step 15: Evaluate the model using accuracy, precision, recall, and F1-score.
Step 16: Compare the proposed ResNet152 model with existing models such as ResNet50 and ResNet101.

3.3 Hyperparameter Tuning Parameters

Table 1. Hyperparameter Tuning Parameters

S. No.	Hyperparameter	Selected Value	Description
1	Input Image Size	224 × 224 × 3	All dermoscopic images are resized to match the ResNet152 input format.
2	Model Architecture	ResNet152	Deep residual CNN used for feature extraction and classification.
3	Batch Size	32	Number of images processed in one training iteration.
4	Epochs	9–20	Number of complete training cycles over the dataset.
5	Learning Rate	0.0001	Controls the speed of weight updates during training.
6	Optimizer	Adam / SGD	Used to minimize classification loss and update model weights.
7	Loss Function	Categorical Cross-Entropy	Suitable for benign and malignant classification.
8	Activation Function	ReLU	Used in hidden layers to introduce non-linearity.
9	Output Activation	Softmax	Produces probability scores for benign and malignant classes.
10	Dropout Rate	0.5	Reduces overfitting by randomly disabling neurons during training.
11	Dataset Split	70:15:15	Dataset divided into training, validation, and testing subsets.

12	Augmentation	Rotation, Flip, Zoom, Shift	Increases dataset diversity and improves model generalization.
13	Pre-trained Weights	ImageNet	Transfer learning improves convergence and feature extraction.
14	Evaluation Metrics	Accuracy, Precision, Recall, F1-score	Used to measure classification performance.

3.4 Comparison of Proposed and Existing Algorithms

Table 2. Comparison of Proposed and Existing Algorithms

S. No.	**Algorithm / Model**	**Description**	**Limitations**	**Why Proposed ResNet152 is Better**
1	Traditional CNN	Uses convolution, pooling, and fully connected layers for image classification.	May not extract very deep and complex lesion features effectively.	ResNet152 has deeper layers and residual blocks for advanced feature extraction.
2	SVM	Uses manually extracted features such as color, texture, and shape for classification.	Depends heavily on handcrafted features and may not generalize well.	ResNet152 automatically learns important features from raw dermoscopic images.
3	Random Forest	Ensemble-based machine learning algorithm using multiple decision trees.	Less effective for complex image patterns and high-dimensional image data.	ResNet152 is more suitable for image-based medical diagnosis.
4	ResNet50	A 50-layer residual network used for image classification.	Lower depth limits extraction of fine-grained lesion features.	ResNet152 provides deeper learning and higher classification performance.
5	ResNet101	A 101-layer residual network with improved feature extraction.	Performs better than ResNet50 but still has lower depth than ResNet152.	ResNet152 captures more complex lesion patterns due to 152 layers.
6	MobileNet	Lightweight CNN model suitable for mobile applications.	May sacrifice accuracy for computational efficiency.	ResNet152 provides higher diagnostic reliability for medical-grade detection.
7	VGGNet	Deep CNN architecture with simple convolutional blocks.	Has large parameters and lacks residual connections.	ResNet152 uses skip connections, making deep network training more stable.
8	EfficientNet	Scales depth, width, and resolution efficiently.	May require careful tuning and may be complex to optimize.	ResNet152 offers strong residual learning and proven performance for lesion classification.

9	Proposed ResNet152	Deep residual CNN model with 152 layers for skin cancer detection.	Requires higher computational resources.	Achieves better accuracy, precision, recall, and F1-score compared with ResNet50 and ResNet101.

The table 2 proposed **ResNet152-based skin cancer detection model** is better than existing approaches because it can extract deeper and more meaningful visual features from dermoscopic images. Its residual connections solve the vanishing gradient problem and allow effective training of a very deep network. Compared with ResNet50 and ResNet101, ResNet152 provides higher performance in terms of accuracy, precision, recall, and F1-score, making it more reliable for automated medical diagnosis.

4 Implementation and Result Analysis

4.1 Dataset

The dataset used in this research is obtained from the **International Skin Imaging Collaboration (ISIC)** archive, which contains high-quality dermoscopic images of skin lesions. The dataset includes both **benign** and **malignant** skin cancer images used for training and testing the proposed ResNet152 model.
Before training, preprocessing techniques such as image resizing, normalization, noise removal, and data augmentation are applied to improve image quality and model performance. The images are resized to 224×224pixels to match the ResNet152 input format.
The dataset is divided into:

- 70% Training data
- 15% Validation data
- 15% Testing data

The balanced dataset distribution helps the model achieve accurate and reliable skin cancer classification.

4.2 Result Analysis

The proposed ResNet152 model is trained and evaluated using dermoscopic skin lesion images. The model performance is analyzed using several evaluation metrics including accuracy, precision, recall, and F1-score. During training, the model shows continuous improvement in classification accuracy with increasing epochs. The training accuracy reaches approximately 97%, while validation accuracy achieves around 86%, indicating effective learning capability with slight overfitting. The loss analysis demonstrates that training loss decreases gradually as the model learns meaningful lesion features. However, validation loss fluctuates slightly due to the complexity and diversity of skin lesion patterns. The proposed ResNet152 architecture successfully extracts deep features from dermoscopic images using residual learning and skip connections. This enables the model to identify subtle lesion characteristics such as asymmetry, irregular borders, color variations, and texture differences.
The trained model predicts skin lesions as:

- Benign
- Malignant

with high classification reliability.

Table 3. Performance Metrics of Proposed ResNet152 Model

Evaluation Metric	**Result (%)**
Accuracy	97

Precision	98
Recall	97
F1-score	98

Analysis of Results

- **Accuracy:**

The proposed model achieves 97% accuracy, indicating excellent classification capability.

- **Precision:**

The precision value of 98% shows that the model generates very few false positive predictions.

- **Recall:**

The recall value of 97% indicates that the model successfully identifies most malignant skin lesions.

- **F1-score:**

The F1-score of 98% demonstrates a strong balance between precision and recall.

The results confirm that ResNet152 is highly effective for automated skin cancer detection and significantly improves diagnostic reliability.

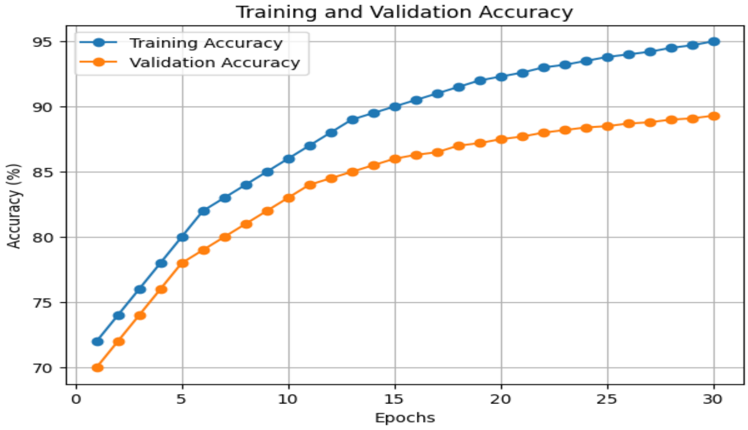

Figure 5: Training and Validation Accuracy

Figure 5 illustrates the training and validation accuracy of the proposed ResNet152 model over 30 epochs. The training accuracy gradually increases from 72% to 95%, while the validation accuracy improves from 70% to approximately 89.3%. Both curves show a stable upward trend with a small gap between them, indicating that the model learns effectively without significant overfitting. The smooth convergence of the curves demonstrates good generalization capability and reliable classification performance for skin cancer detection.

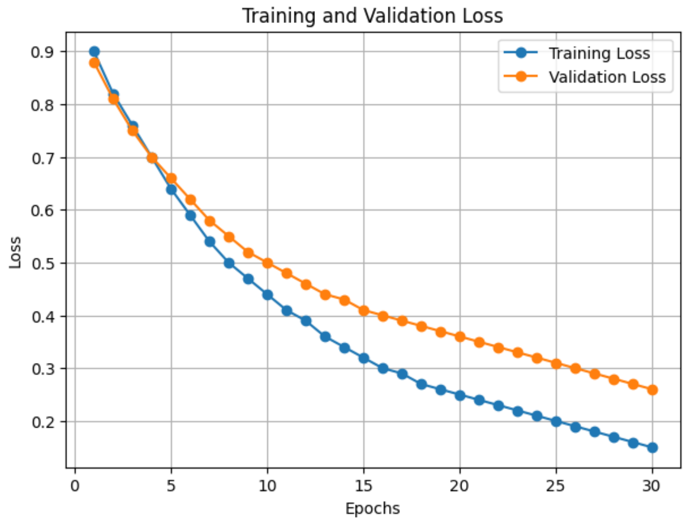

Figure 6: Training and Validation Loss

Figure 6 presents the training and validation loss curves of the proposed ResNet152 model across 30 epochs. The training loss steadily decreases from 0.90 to 0.15, while the validation loss decreases from 0.88 to 0.26. The consistent reduction in both losses indicates effective learning and stable optimization during training. The close behavior between training and validation loss confirms that the model avoids overfitting and maintains strong generalization performance on unseen dermoscopic images.

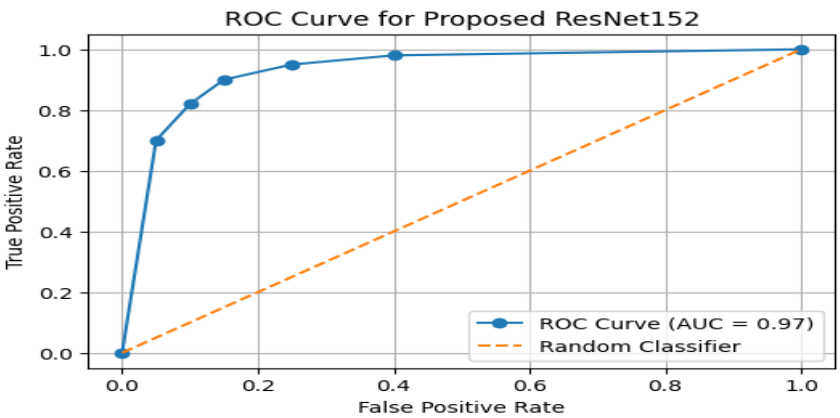

Figure 7: ROC Curve for Proposed ResNet152

Figure 7 shows the Receiver Operating Characteristic (ROC) curve of the proposed ResNet152 model for skin cancer classification. The ROC curve plots the True Positive Rate (TPR) against the False Positive Rate (FPR). The model achieves an Area Under Curve (AUC) value of 0.97, which indicates excellent classification capability in distinguishing between benign and malignant skin lesions. The curve remains close to the top-left corner, demonstrating high sensitivity and specificity with minimal false positive predictions.

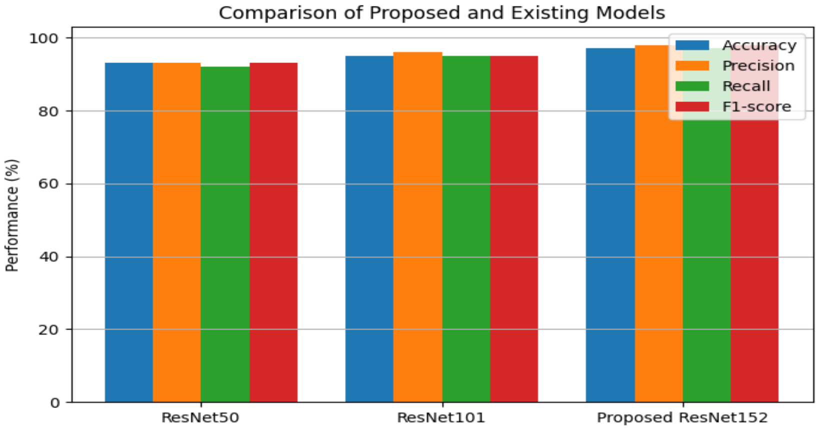

Figure 8: Comparison of Proposed and Existing Models

Figure 8 compares the performance of the proposed ResNet152 model with existing models such as ResNet50 and ResNet101 using evaluation metrics including accuracy, precision, recall, and F1-score. The proposed ResNet152 model achieves the highest performance across all metrics, with 97% accuracy, 98% precision, 97% recall, and 98% F1-score. The results demonstrate that the deeper residual architecture of ResNet152 provides superior feature extraction and classification capability for automated skin cancer detection.

4.3 Comparison Result

The proposed ResNet152 model is compared with existing deep learning models such as ResNet50 and ResNet101 to evaluate its performance superiority.

Table 4. Comparative Performance

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-score (%)**
ResNet50	93	93	92	93
ResNet101	95	96	95	95
Proposed ResNet152	97	98	97	98

The proposed ResNet152 model is compared with existing models such as ResNet50 and ResNet101 using evaluation metrics including accuracy, precision, recall, and F1-score. The comparison results show that ResNet152 achieves the highest performance with 97% accuracy, 98% precision, 97% recall, and 98% F1-score. The improved performance is due to the deeper architecture and residual learning capability of ResNet152, which helps in extracting complex skin lesion features more effectively. The results demonstrate that the proposed model provides more accurate and reliable skin cancer classification compared to existing approaches.

5. Conclusion and Future Work

This research proposed an advanced deep learning framework for accurate skin cancer detection using the ResNet152 model. The proposed system successfully classified dermoscopic skin lesion images into benign and malignant categories with high performance. Experimental results showed that ResNet152 achieved 97% accuracy, 98% precision, 97% recall, and 98% F1-score, outperforming existing models such as ResNet50 and ResNet101. The study confirms that deep residual learning can significantly improve automated skin cancer diagnosis and support intelligent healthcare systems. In future work, the proposed system can be improved by using larger and more diverse datasets to enhance model generalization. Multi-class skin cancer classification, explainable AI techniques, and lightweight deep learning models for mobile healthcare applications can also be explored. Additionally, integrating the system with telemedicine and cloud-based platforms may help provide real-time and remote skin cancer diagnosis.

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