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Research Article

New Deep Learning Approaches for Binary Skin Cancer Classification

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Abstract:

Skin cancer remains one of the most prevalent malignancies worldwide, with melanoma accounting for the most lethal form due to its high metastatic potential. Early and accurate diagnosis is essential to improve patient survival, yet access to specialized dermatological expertise is limited in many regions. Recent advances in deep learning, particularly Convolutional Neural Networks (CNNs), have significantly enhanced the capabilities of computer-aided diagnosis (CAD) systems. This study introduces and evaluates three lightweight and optimized CNN-based architectures for binary skin cancer classification: (1) a Modified MobileNet with Residual Blocks, (2) an AlexNet enhanced with Squeeze-and-Excitation (SE) Attention, and (3) a custom-designed CNN with integrated Residual Connections. Using a benchmark dermoscopic dataset from the ISIC Archive, we apply standardized preprocessing and data augmentation techniques, followed by rigorous model training and evaluation. Results show that the Modified CNN achieves the highest accuracy (84.70%), precision (84.56%), recall (84.78%), and F1-score (84.63%), outperforming or matching state-of-the-art models such as ResNet-101, while maintaining computational efficiency. These findings support the feasibility of deploying such models in mobile health applications, offering a scalable solution for early melanoma screening in resource-constrained environments.

1. Introduction

Skin cancer has become one of the most common types of cancer worldwide, and its incidence has increased significantly in recent years. Between 2009 and 2019, diagnoses of skin cancer rose by 54% globally [1]. Melanoma, in particular, is the most aggressive and deadliest subtype, responsible for over 9,000 annual deaths in the United States [2], more than 1,200 in Australia, and over 20,000 deaths each year across Europe [3]. Although early-stage melanoma has a 5-year survival rate of 99%, this rate drops drastically to around 20% when the cancer metastasizes [4]. Early detection is thus critical to improving prognosis and reducing mortality.

However, accurate diagnosis at early stages requires highly trained dermatologists, and many regions particularly remote or underserved areas suffer from a shortage of such specialists. This gap has stimulated growing research in computer-aided diagnosis (CAD) systems to provide accessible, cost-effective, and accurate classification of skin lesions [5]. While most CAD systems rely on dermoscopic images captured with specialized equipment in clinical settings, few studies have investigated lightweight deep learning models deployable on mobile devices using smartphone-captured images. Such mobile solutions could serve as effective screening tools, especially for workers exposed to radiation or ultraviolet sources major risk factors for skin cancer [2][7].

In recent years, deep learning particularly Convolutional Neural Networks (CNNs), has revolutionized medical image analysis. CNNs automatically learn rich hierarchical features from raw data without requiring handcrafted descriptors [6]. Yu et al. [8] introduced a deep residual network model for region-of-interest-based melanoma classification and achieved an accuracy of 85.5% on the ISIC 2016 dataset. Similarly, Pham et al. [9] used image enhancement techniques and SVM to reach 87.2% accuracy. Zhang et al. [10] proposed the transformer-based SkinFormer architecture, which achieved 91.3% accuracy on the HAM10000 dataset, addressing CNN limitations through global contextual modeling. Li et al. [11] developed a hybrid CNN-ViT ensemble, reaching a F1 score of 89.7% on ISIC 2020 database. Other notable contributions include Han et al. [12], who enhanced ResNet with attention mechanisms, achieving sensitivity and specificity rates of 90.5% and 91.8% respectively, and Ahmed et al. [13], who applied contrastive learning to tackle dataset imbalance. Lightweight models have also shown promise: Wang et al. [14] introduced EfficientNet-Lite, achieving 88.6% accuracy with reduced computational demands. In addition, Singh et al. [15] applied GANs for synthetic data augmentation, improving detection in underrepresented melanoma classes. Efforts have also been made to improve interpretability and accessibility. Alonso et al. [16] presented an explainable AI framework using Grad-CAM visualizations, achieving 88.1% sensitivity, while Siddiqui et al. [17] proposed a federated learning framework that preserved patient data privacy and delivered a mean F1 score of 90.2% across multiple datasets. Oliveira et al. [18] combined dermoscopic images and clinical metadata in a multimodal deep learning model, achieving 93.1% accuracy. Capsule networks, as explored by Gomez et al. [19], offered compact architectures with fewer parameters and competitive performance (87.5% accuracy on PH2).

Data augmentation and preprocessing have also played key roles in enhancing model performance. Ayan and Ünver [20] reported improved results using CNNs trained with augmented data on ISBI 2016, while Srividhya et al. [21] incorporated edge detection and handcrafted features before CNN classification, reaching 95% accuracy. Moldovanu et al. [22] used a hybrid dataset and achieved 96% accuracy with a feedforward backpropagation network, although individual dataset performance was not isolated. Several models have combined classical machine learning techniques with CNNs. Albert et al. [23] proposed the PECK method, combining SVMs with CNNs for melanoma detection, achieving 91% accuracy. Winkler et al. [24] and Waheed et al. [25] further demonstrated the potential of CNNs and SVMs in clinical datasets, achieving up to 96% accuracy. Ashraf et al. [26] used k-means clustering for ROI extraction followed by CNN and transfer learning, obtaining 97% accuracy.

Computer vision techniques have been widely adopted in the medical domain to facilitate rapid, non-invasive, and cost-effective disease detection. These techniques replicate human vision capabilities, enabling machines to interpret and classify images or videos. In the context of melanoma detection, various approaches have emerged, ranging from classical machine learning with manual feature extraction to modern deep learning architectures. Early methods employed image segmentation and handcrafted features to train classifiers like Support Vector Machines (SVM). For example, Sonia et al. [27] utilized Non-Subsampled Contourlet Transform (NSCT) to extract energy features, achieving an accuracy of 96.7%, a sensitivity of 97.5%, and a specificity of 96.3% when classifying 120 dermoscopic images into benign or malignant categories. Similarly, Pérez-Ortiz et al. [28] extracted 86 features capturing lesion shape, color, pigment networks, and texture to classify melanoma lesions into five categories. Using a cascade SVM and oversampling for class balancing, they attained a classification accuracy of 58.36% on a dataset of 556 images. Indraswari et al. [29] combined lesion size, shape, and color features to classify 60 dermoscopy images via SVM, achieving 83.3% accuracy, 80% sensitivity, and 86.7% specificity.

Recent advancements in deep learning have enabled superior classification performance without the need for manual segmentation or feature engineering. Brinker et al. [30] reported that Convolutional Neural Networks (CNNs) outperformed 136 out of 157 dermatologists in melanoma classification tasks. Lopez et al. [31] adapted the VGG16 network for binary classification using transfer learning on the ISBI 2016 dataset, reaching 68.67% accuracy. Kassani and Kassani. [32] evaluated multiple deep learning architectures on the ISIC 2018 dataset, with ResNet50 achieving 93.73% precision, 92.53% recall, and 92.08% overall accuracy. Rokhana et al. [33] designed a lightweight CNN consisting of six convolutional and three max-pooling layers, yielding 84.67% accuracy, 91.97% sensitivity, and 78.71% specificity on the ISIC archive. In addition, recent studies have further explored innovative deep learning strategies for skin lesion classification. Dorj et al. [34] utilized a pre-trained AlexNet model for feature extraction, combined with SVM for classification, resulting in robust performance. Filho et al. [35] proposed a texture-based method using Structural Co-occurrence Matrices (SCM) and tested it on ISIC 2016 and 2017 datasets. Among various classifiers, SVM delivered the highest specificity at 90%. Li et al. [36] introduced the Lesion Indexing Network

(LIN), a deep architecture capable of extracting more nuanced features than conventional models. The LIN achieved 91.2% accuracy, although its segmentation component required refinement.

Saba et al. [37] applied a contrast stretching technique for image enhancement, followed by a CNN and XOR operation to delineate lesion boundaries. Features were extracted via InceptionV3 using transfer learning, and tests were conducted on PH2 and ISIC 2017. Esteva et al. [38] also leveraged InceptionV3 for skin cancer classification based on clinical imagery, with evaluation validated by a certified dermatological board. Le et al. [39] built a ResNet50-based model using transfer learning with hyperparameter tuning and global average pooling to combat overfitting, tested on the HAM10000 dataset. Iqbal et al. [40] proposed a 68-layer CNN for multiscale feature extraction and evaluated it on ISIC 2017–2019 datasets. Srinivasa et al. [41] combined MobileNetV2 and LSTM networks to preserve temporal dependencies, achieving 85.34% accuracy on the HAM10000 dataset. Shahin et al. [42] developed a binary classification approach incorporating preprocessing (noise removal, normalization, augmentation) with multiple CNN architectures, reaching 91.93% accuracy on HAM10000. Farhat et al. [43] extracted features using deep models and selected them via a metaheuristic algorithm, classifying with Extreme Machine Learning (EML), achieving 93.40% and 94.36% accuracy on HAM10000 and ISIC 2018 respectively. Lastly, Chaturvedi et al. [44] presented a multi-class classification method with fine-tuned and ensemble deep learning models, attaining 93.20% accuracy on HAM10000.

Among the recent innovations, MobileNetV2 stands out due to its computational efficiency and suitability for deployment on resource-constrained devices. Featuring inverted residual blocks and linear bottlenecks, MobileNetV2 significantly reduces memory usage while maintaining strong classification performance. Its lightweight nature enables integration into mobile-based diagnostic tools, enhancing early detection accessibility in remote or underserved areas.

In light of these developments, our study proposes and evaluates three optimized architectures for binary skin cancer classification: an Adaptive Residual Convolutional Model, AlexNet with Squeeze-and-Excitation Attention, and MobileNet with Residual Connections. These models aim to deliver high performance with computational efficiency, supporting real-time applications and deployment in low-resource environments, such as mobile diagnostic platforms.

2. Materials

The proposed method follows a structured and modular pipeline for skin lesion classification, as illustrated in Figure 1. It combines preprocessing techniques, deep learning architectures, and classification evaluation in a unified workflow designed to efficiently differentiate between benign and malignant lesions. Initially, raw dermoscopic images undergo essential data preparation steps including resizing, normalization, and data augmentation. These preprocessing operations aim to standardize the input format and improve generalization performance during training. The preprocessed images are then passed through various pre-trained convolutional neural networks, serving as the base models. In this study, we investigate three architectures: MobileNet, AlexNet, and a custom Convolutional Neural Network (CNN). Each of these networks is further enhanced through architectural modifications to boost their learning capability. These include Residual Blocks, Squeeze-and-Excitation modules, and Residual Connections, depending on the base model. Once the architecture is defined, the models are fine-tuned using a consistent training configuration, which includes binary classification settings, a learning rate of 0.001, a batch size of 32, and training for 50 epochs using the Adam optimizer. To evaluate the model performance, several standard metrics are computed, including accuracy, precision, recall, and F1-score. The final classification outputs are divided into two categories: benign and malignant lesions.

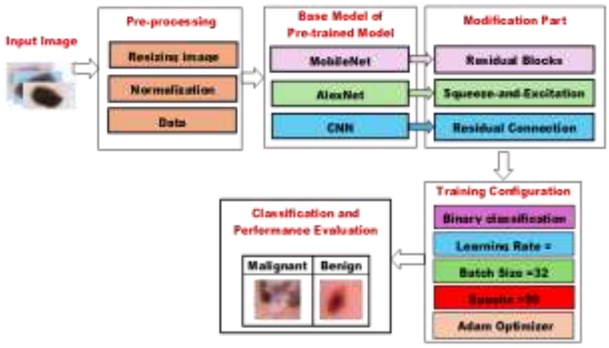

Figure. 1. *Overview of the proposed method for binary skin lesion classification using modified CNN architectures.*

2.1. Dataset

This study employs a publicly available skin lesion dataset retrieved from Kaggle [45], which is part of the ISIC (International Skin Imaging

Collaboration) Archive [46]. The dataset includes high-resolution dermoscopic images and is labeled into two distinct categories: benign and malignant. These two classes are clinically significant <for the early detection and differentiation of skin cancer. To provide a representative overview, Figure 2 illustrates a selection of sample images from both benign and malignant categories, reflecting the morphological diversity found within the dataset.

Figure 2. *Sample of benign and malignant dermoscopic images from the dataset.*

The entire dataset was divided into training and testing subsets. The training set comprises 1,440 benign and 1,197 malignant images, while the testing set includes 300 benign and 360 malignant cases. In total, the dataset contains 3,297 annotated images, with a slight imbalance between the two classes. This distribution is visually presented in Figure 3, which shows the proportions of each class across training, testing, and total sets. Such visualization helps to better understand the dataset composition and guides the evaluation of class imbalance effects during model training.

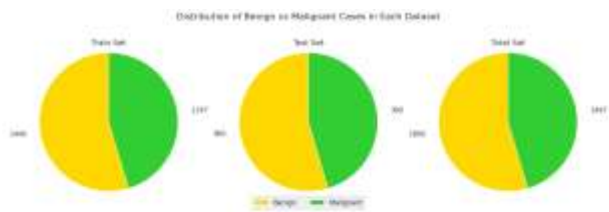

Figure 3. *Class distribution in the train, test, and total datasets*

2.2. Data Preparation

Effective data preparation is essential for enhancing the performance and generalization capability of deep learning models in image classification tasks. In this study, several preprocessing steps were implemented to ensure input consistency and enrich the dataset.

All dermoscopic images were resized to a standardized resolution of 224×224 pixels, ensuring compatibility with the input dimensions required by the pre-trained CNN models used in this work. Following resizing, pixel normalization was applied to scale intensity values within a common range, which aids in stabilizing training and accelerates model convergence [47].

To mitigate overfitting and increase the diversity of the training dataset, a comprehensive data augmentation strategy was employed. This included horizontal and vertical flips, random rotations ($90°$ increments), and adjustments to brightness and contrast. These transformations preserved the semantic integrity of the images while synthetically expanding the dataset, thereby enhancing the model's ability to generalize across various lesion appearances [48, 49].

The combined preprocessing pipeline ensured that the dataset was both normalized and diversified, facilitating more robust and stable training of the skin lesion classification models.

3. Methods

This study explores three distinct pre-trained deep learning architectures for binary skin lesion classification: MobileNet, AlexNet, and a custom-designed CNN. These models were selected based on their established performance in image classification and their adaptability to medical imaging tasks. Each base model is further modified through the integration of architectural enhancements aimed at improving feature representation and overall classification accuracy.

3.1. MobileNet with Residual Blocks

MobileNet is a lightweight deep learning architecture designed for efficient computation and deployment on mobile and embedded devices. It utilizes depthwise separable convolutions, which drastically reduce computational complexity while maintaining high accuracy.

To enhance its feature learning capabilities, we integrated residual blocks into the MobileNet architecture, drawing inspiration from ResNet. These residual connections help alleviate the vanishing gradient problem by allowing identity mappings, wherein the input of a block is added directly to its output. This mechanism improves

gradient flow and preserves critical spatial features within the image.
As illustrated in Figure 4, the enhanced MobileNet architecture comprises:

- Depthwise separable convolutional layers for efficient feature extraction.
- Residual connections to facilitate gradient propagation and feature reuse.
- Fully connected layers customized for binary classification tasks.

This configuration enables the architecture to maintain computational efficiency while enhancing learning depth and accuracy in skin lesion classification.

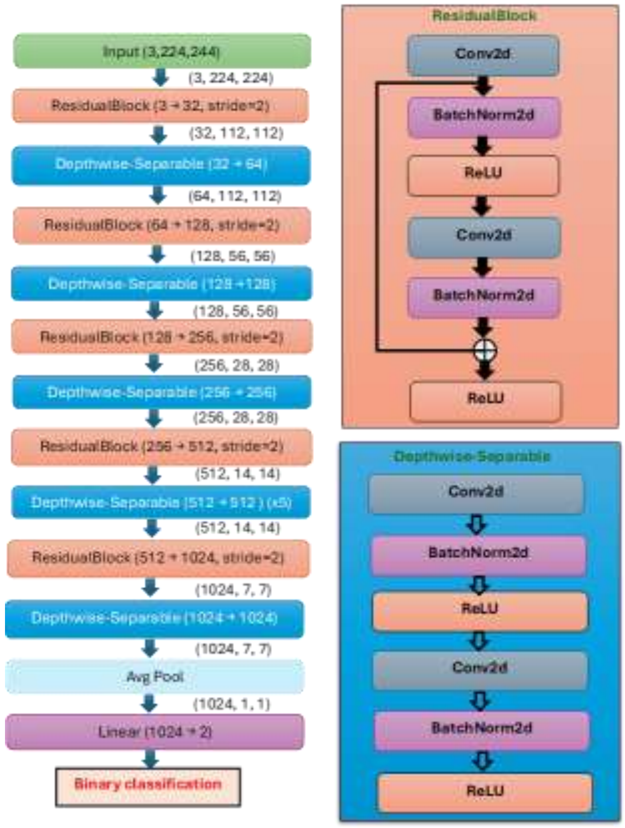

Figure 4. Modified MobileNet with integrated Residual Blocks.

3.2. AlexNet with Squeeze-and-Excitation

AlexNet is a pioneering deep learning architecture initially developed for large-scale image classification. In our study, we enhanced the original framework by incorporating a channel-wise attention mechanism using Squeeze-and-Excitation (SE) blocks to improve feature selection and model focus.
As illustrated in figure 5, the SE block applies attention in two stages:

- Squeeze: Global average pooling is used to capture channel-wise statistics, reducing each feature map to a single descriptor.
- Excitation: Adaptive reweighting of channels is performed using fully connected layers and a sigmoid activation function to highlight informative features.

These SE blocks are inserted after each convolutional layer in the AlexNet architecture, as illustrated in Figure 5, enabling the model to prioritize significant diagnostic cues. This is especially useful for capturing subtle patterns that differentiate benign from malignant skin lesions. The revised AlexNet framework includes:

- Convolutional layers with integrated SE attention blocks.
- Max-pooling layers for downsampling.
- Fully connected layers for classification.
- A final sigmoid activation function for binary output.

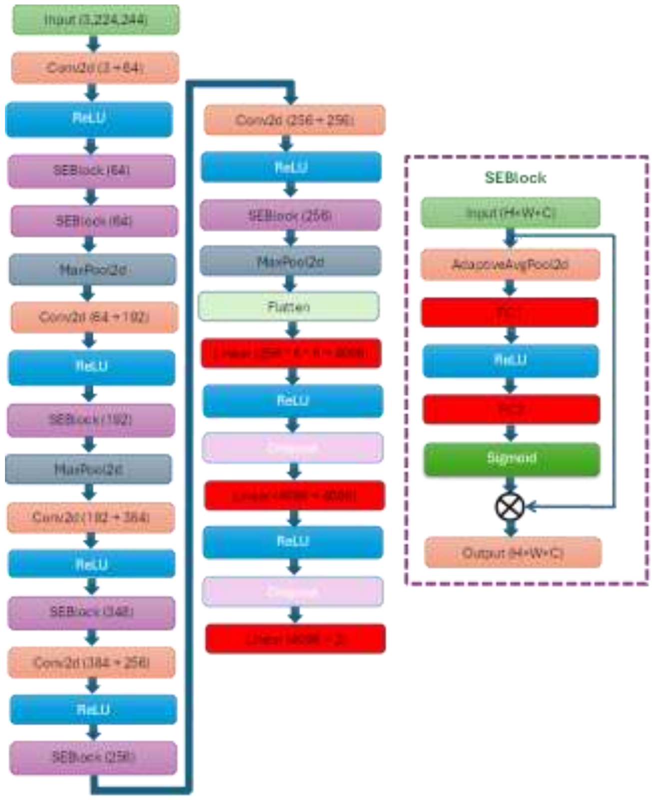

Figure 5. Modified AlexNet with integrated Squeeze-and-Excitation blocks.

3.3. Modified CNN

The final architecture explored in this study is a custom-designed Convolutional Neural Network (CNN) that incorporates residual connections to improve training efficiency and feature retention. Unlike classical CNN models, this approach integrates a skip connection that bridges the second and third convolutional blocks, enabling better gradient flow and enhanced feature reuse, as illustrated in figure 6.

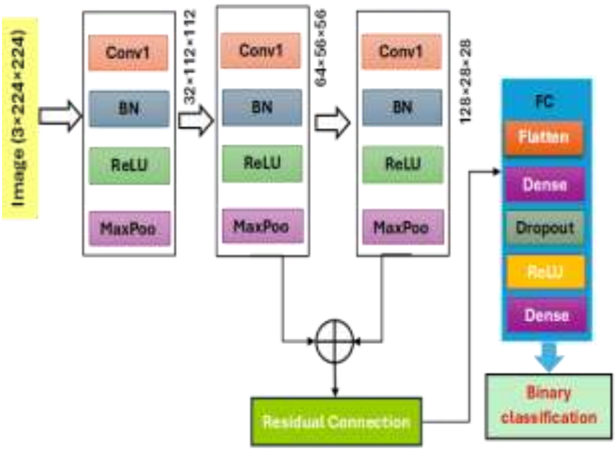

Figure 6. *Flowchart of CNN with Residual Connections for binary classification.*

The model is composed of three convolutional blocks:

- Conv1: Converts the input (*3×224×224*) into 32 feature maps of size *112×112*.
- Conv2: Expands to 64 filters and reduces dimensions to *56×56*.
- Conv3: Uses 128 filters with an output of *28×28*. A *1×1* convolution is applied to align dimensions and facilitate the residual connection from the second block.

After the convolutional layers, the resulting feature maps are flattened into a vector of 100352 elements. This vector is passed through a fully connected layer of 256 neurons, followed by a dropout layer (50%) to mitigate overfitting. The final output layer contains 2 neurons activated via a sigmoid function to perform binary classification.

3.4. Training configuration

To validate the effectiveness of our proposed architectures, we implemented three customized deep learning models: MobileNet with Residual Blocks, AlexNet with Squeeze-and-Excitation, and CNN with Residual Connections. Each model was configured specifically for binary skin lesion classification, focusing on accurately distinguishing between benign and malignant dermoscopic images.

The models were trained using a consistent setup across all architectures. We employed the Adam optimizer with a learning rate of 0.001, a batch size of 32, and trained each model for 50 epochs. This configuration ensures sufficient iterations to update the model weights and allows the networks to generalize better while avoiding overfitting. Throughout the training process, model convergence and loss reduction were closely monitored to maintain performance stability.

4. Results and Discussions

4.1. Evaluation metrics

To assess the classification performance of the implemented models, we employed four standard evaluation metrics: Accuracy, Precision, Recall, and F1 score. These metrics provide a comprehensive understanding of each model's ability to correctly identify skin cancer cases. Metrics are computed using the following equations [50]:

$$accuracy = \frac{\mathrm{TP+TN}}{\mathrm{TP+TN+FP+FN}} \quad (1)$$

$$precision = \frac{\mathrm{TP}}{\mathrm{TP+FP}} \quad (2)$$

$$recall = \frac{\mathrm{TP}}{\mathrm{FN+TP}} \quad (3)$$

$$F1\ score = 2 \times \frac{\mathrm{precision} \times \mathrm{recall}}{\mathrm{precision} + \mathrm{recall}} \quad (4)$$

where *TN* true negatives, *TP* true positives, *FP* false positives, and *FN* false negatives.

4.2. Experimental results

Table 1 presents a performance evaluation of the proposed models, including Modified MobileNet, Modified AlexNet, and Modified CNN with Residual Connections, in terms of accuracy, precision, recall, and F1 score metrics. Results indicate that the Modified CNN achieves the highest performance across all the metrics, with an accuracy of 0.8470, precision of 0.8456, recall of 0.8478, and an F1 score of 0.8463. This suggests that the residual connection in the custom CNN architecture effectively enhances feature learning and gradient flow, contributing to superior classification performance.

Table 1. *Performance comparison of the proposed models.*

Metrics	Modified MobileNet	Modified AlexNet	Modified CNN
Accuracy	0.8348	0.8409	0.8470
Precision	0.8336	0.8395	0.8456
Recall	0.8358	0.8417	0.8478
F1 score	0.8341	0.8402	0.8463

Modified AlexNet follows closely with slightly lower performance, achieving an accuracy of 0.8409, making it a competitive architecture due to its attention mechanism. In contrast, Modified MobileNet yields slightly lower scores but remains highly efficient and lightweight, with an accuracy of 0.8348, making it suitable for resource-constrained environments.

Figure 7 illustrates the confusion matrices for the three proposed models in classifying benign and malignant cases. These matrices provide detailed insights into true positives, true negatives, false positives, and false negatives. The Modified CNN demonstrates the most balanced performance, correctly identifying 305 benign and 250 malignant cases, with 55 benign misclassified as malignant and 50 malignant misclassified as benign.

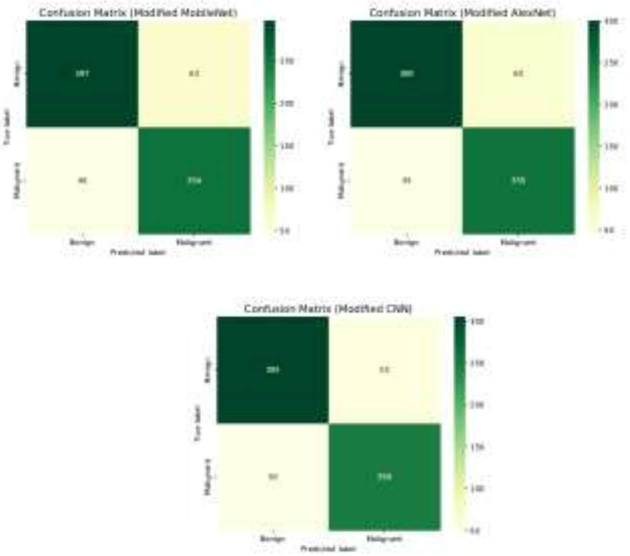

Figure 7. *Confusion matrices of the proposed models.*

Modified AlexNet also performs well, correctly classifying 300 benign and 255 malignant samples, with 60 false positives and 45 false negatives. Meanwhile, Modified MobileNet correctly predicts 297 benign and 254 malignant cases, with 63 benign misclassified as malignant and 46 malignant misclassified as benign. These findings confirm the effectiveness of the Modified CNN model in balancing sensitivity and specificity.

Figure 8 displays the ROC (Receiver Operating Characteristic) curves of the proposed models.

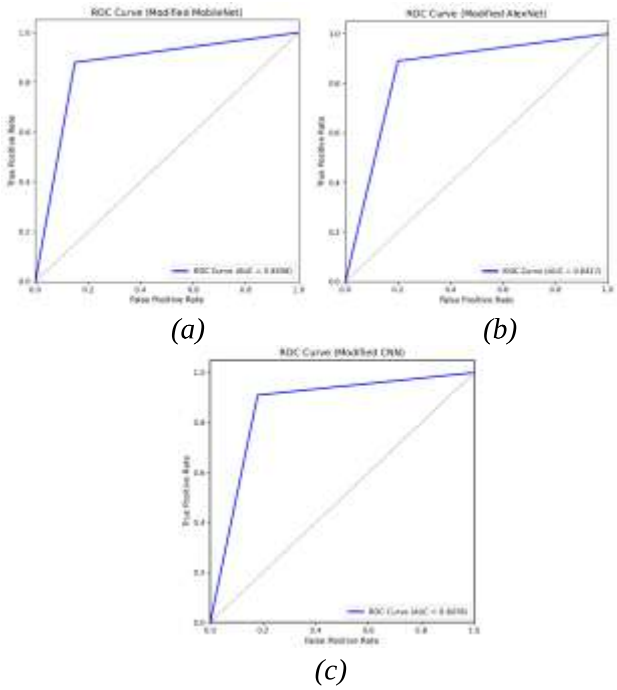

Figure 8. *ROC curves of the proposed architectures*

(a) modified Mobilenet (b)modified AlexNet (c) modified CNN.

The Area Under the Curve (AUC) values further validate model performance. The Modified CNN achieves the highest AUC score of 0.8478, followed by Modified AlexNet with 0.8417, and Modified MobileNet with 0.8358. All models maintain curves close to the top-left corner, indicating strong classification capability, with Modified CNN achieving the best trade-off between the true positive and false positive rates.

Table 2 presents a comparative analysis of selected prior studies that used the same dataset for skin lesion classification. It highlights the diversity of model architectures employed and their respective accuracy scores, providing context for evaluating our proposed models.

Table 2. *Comparative analysis of selected studies on skin lesion classification.*

Study and (Year)	Model and (Accuracy)
Hiswati [51] *(2021)*	CNN (54%)
Demir et al. [52] *(2019)*	ResNet-101 (84.09%)
Aydin [53] *(2023)*	CNN (80%), Xception (80%)
Dagnaw et al. [54] *(2024)*	ResNet18 (82.4%)
This Study *(2025)*	Modified MobileNet (83.48%) Modified AlexNet (84.09%) **Modified CNN (84.70%)**

The comparative results indicate a clear evolution in classification performance over time, moving from early CNN architectures with modest accuracy (e.g., Hiswati [51] reporting only 54%) to more sophisticated convolutional and hybrid models.

Our Modified CNN, achieving 84.70% accuracy, outperforms several prior works, including the standard CNN by Aydin [53] (80%) and ResNet18 used by Dagnaw et al. [54] (82.4%). It also performs on par with ResNet-101 (84.09%) reported by Demir et al. [52], despite being a lighter and more computationally efficient architecture.

Similarly, the Modified AlexNet (84.09%) matches the performance of Demir's ResNet-101, demonstrating the effectiveness of enhancing legacy architectures through structural modifications and advanced training strategies. Modified MobileNet also reaches a notable 83.48%, offering a compelling solution for real-time or embedded medical applications where inference time and computational cost are critical.

5. Conclusion

This study demonstrates the effectiveness of three optimized CNN-based architectures for binary classification of skin lesions, with a focus on lightweight design and high accuracy. Among the proposed models, the Modified CNN with Residual Connections exhibited the best overall performance across key metrics, proving its capacity to extract meaningful features and maintain robust generalization. The Modified AlexNet and MobileNet models also achieved competitive results, confirming the value of integrating attention mechanisms and residual structures into existing frameworks.

When compared to existing literature, our models surpass several prior CNN approaches in accuracy while requiring fewer computational resources. This balance between performance and efficiency is critical for practical deployment, especially on mobile devices or in remote medical settings where access to specialists and high-end hardware is limited.

Future work will focus on extending this research to multi-class classification, integrating clinical metadata, and improving model interpretability through explainable AI techniques. Ultimately, this work contributes to the growing field of accessible and intelligent diagnostic tools, reinforcing the potential of deep learning to support dermatologists and improve outcomes in the fight against skin cancer.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.

- **Author contributions:** The authors declare that they have equal right on this paper.

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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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