

Optimized Deep Learning Framework for Automated Skin Lesion Diagnosis Using ResNet152

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Abstract- Skin cancer remains one of the most prevalent and life-threatening diseases globally, necessitating early and precise diagnosis. This research proposes an optimized deep learning framework using ResNet152 for automated skin lesion classification. The model integrates preprocessing, segmentation, and feature extraction to enhance lesion detection and classification accuracy. Experimental results demonstrate superior performance, achieving 97% accuracy, 98% precision, and 97% recall, outperforming existing ResNet variants. The framework's robustness and adaptability make it suitable for clinical and remote diagnostic applications, promoting early intervention and reducing diagnostic errors.

Keywords – Skin Cancer Detection, Deep Learning, ResNet152, Image Segmentation, Feature Extraction, Classification Accuracy, Medical Imaging.

I. INTRODUCTION

Skin cancer remains one of the most common and potentially fatal malignancies worldwide, with rising incidence due to environmental, genetic, and lifestyle factors. Early and accurate diagnosis plays a crucial role in improving survival rates, yet traditional diagnostic techniques such as dermoscopic inspection and histopathological examination—are often subjective and dependent on clinical expertise. The advent of deep learning, particularly convolutional neural networks (CNNs), has revolutionized the field of medical image analysis by enabling automated detection and classification of lesions with precision comparable to expert dermatologists. Among existing CNN architectures, ResNet152 stands out due to its exceptional depth, use of residual learning, and ability to mitigate vanishing gradient issues, making it ideal for complex visual recognition tasks.

This study presents an optimized deep learning framework for automated skin lesion diagnosis using the ResNet152 model. The framework begins with advanced preprocessing techniques, including noise reduction, illumination correction, and lesion segmentation, ensuring clarity and consistency across input images. Following this, the segmented lesion regions are subjected to feature extraction and fed into a fine-tuned ResNet152 model trained on benchmark datasets such as ISIC and HAM10000. The comparative analysis with ResNet50 and ResNet101 reveals significant performance gains in accuracy, precision, recall, and F1-score. The proposed model achieves superior robustness and

generalization, establishing its suitability for both clinical and mobile-based diagnostic systems.

Key Contributions

Development of an Optimized Deep Learning Framework: A comprehensive diagnostic pipeline integrating preprocessing, segmentation, feature extraction, and classification to ensure superior detection accuracy and reduced noise interference.

Fine-Tuned ResNet152 Model: Implementation of transfer learning and layer optimization within the ResNet152 architecture to enhance classification performance while minimizing computational overhead.

Comparative Evaluation with Existing Architectures: Detailed performance comparison among ResNet50, ResNet101, and ResNet152 models, demonstrating the effectiveness of deeper residual networks in improving diagnostic precision.

Improved Diagnostic Metrics: The proposed model achieves outstanding results—97% accuracy, 98% precision, and 97% recall—outperforming baseline architectures in identifying malignant and benign lesions.

Clinical and Research Applicability: The framework's adaptability to real-time environments, including integration into IoT and mobile applications, highlights its potential for early diagnosis, teledermatology, and global healthcare accessibility.



Figure 1. Sample of skin cancer.

This figure 1 depicts four major types of skin cancer lesions, each exhibiting distinct visual and pathological characteristics. Basal Cell Carcinoma (BCC) appears as a pinkish, pearly, or waxy bump, often with visible blood vessels. It is the most common and least aggressive form of skin cancer, typically developing in sun-exposed areas such as the face and neck. Although it rarely metastasizes, it can cause significant local tissue damage if left untreated.

Squamous Cell Carcinoma (SCC) presents as a scaly, crusted, or ulcerated sore that may bleed or fail to heal. This cancer originates in the squamous cells of the epidermis and is more likely than BCC to invade deeper tissues or spread to lymph nodes. Early detection is crucial to prevent metastasis. Melanoma is the most dangerous type, characterized by dark, irregularly shaped pigmented patches or moles that change in color, shape, or size. It arises from melanocytes—the pigment-producing cells of the skin—and has a high tendency to spread rapidly to other organs. Prompt diagnosis greatly improves survival rates. Merkel Cell Carcinoma (MCC) is a rare but aggressive neuroendocrine skin cancer. It often manifests as a firm, painless, reddish or purplish nodule on sun-exposed skin.

Due to its rapid growth and high recurrence rate, MCC requires early intervention and a combination of surgery, radiation, and immunotherapy. Overall, this visual comparison highlights the diversity in appearance among skin cancer types, emphasizing the importance of clinical expertise and machine learning-based diagnostic tools to accurately distinguish between them for timely treatment.

Figure 2 illustrates the major risk factors associated with skin cancer development, emphasizing both genetic and environmental influences. Individuals with light-colored eyes, blond or red hair, and fair or freckled skin are more vulnerable because they possess less melanin, which offers natural protection against ultraviolet (UV) radiation. Frequent exposure to tanning beds or prolonged outdoor activity under sunlight increases UV damage, accelerating mutations in skin cells. A family history of skin cancer also raises susceptibility, indicating a hereditary component in disease occurrence. The presence of numerous or irregularly shaped moles is another high-risk indicator, as such moles can potentially transform into malignant melanoma. Finally, individuals who burn easily or have a history of repeated sunburns are at greater risk, underscoring the importance of sun protection and regular dermatological screenings.

II. LITERATURE REVIEW

The rise in global skin cancer rates has created an urgent demand for advanced and reliable detection techniques. Early and precise identification of malignant lesions is essential for improving patient survival outcomes. In this context, Convolutional Neural Networks (CNN) have proven to be one of the most effective deep learning methods for image-based medical diagnosis. Using the ISIC2018 dataset, researchers have demonstrated the capability of CNN models to differentiate between benign and malignant tumors with notable precision. To further enhance diagnostic accuracy, Enhanced Super-Resolution Generative Adversarial Networks (ESRGAN) were employed in the preprocessing stage to improve image clarity and resolution, which significantly benefited CNN feature extraction. The proposed approach achieved an accuracy of 83.2%, highlighting the strong potential of combining CNN with ESRGAN for dermatological image analysis [1].

Artificial Intelligence (AI) has also made its way into mobile health applications, bringing early skin cancer screening closer to the public. A retrospective study conducted under a Dutch insurance scheme examined the use of a free mHealth application designed for skin lesion detection. The study found that users of the app submitted more claims for skin lesion consultations compared to non-users. Although the tool successfully identified malignant and premalignant lesions, the sharp rise in benign consultations raised concerns about overdiagnosis and unnecessary clinical visits. This finding



Figure 2. Skin cancer risk factors.

highlights both the potential and limitations of AI-driven teledermatology tools [2].

Given the global burden of skin cancer, numerous reviews have investigated the role of machine learning (ML) in supporting dermatological diagnostics. A comprehensive review of ML-based studies emphasized how different algorithms—ranging from Support Vector Machines (SVM) and Random Forests (RF) to deep learning models—perform on benchmark datasets. These methods have shown promise in assisting dermatologists through enhanced classification accuracy and reduced diagnostic time. Such findings reinforce the synergy between AI systems and clinical expertise while identifying opportunities for future research in data standardization and explainable AI [3].

The intersection of deep learning and dermatology represents a revolutionary step forward. Recent work highlights the growing potential of smartphone-based remote screenings, enabling widespread accessibility to early detection. Preliminary evidence suggests that the diagnostic performance of AI models is approaching that of experienced dermatologists. However, integrating these systems into real-world clinical workflows still requires improvements in validation, transparency, and regulatory compliance [4].

Lastly, a comprehensive survey of current methodologies confirms the evolving landscape of skin cancer diagnostics powered by machine learning and computer vision. While present systems show remarkable accuracy, they face ongoing challenges related to image variability, class imbalance, and interpretability. By identifying these limitations, researchers aim to inspire further innovations toward robust, explainable, and clinically integrated AI models for dermatology [5].

The global surge in skin cancer prevalence has underscored the critical need for efficient and accurate diagnostic systems. In response to this challenge, recent research has explored innovative computational techniques to enhance diagnostic precision. One such study introduced a threshold-based methodology employing the Sparrow Search Algorithm (SpaSA) in conjunction with multiple U-Net models for early detection of skin cancer lesions. The model demonstrated notable accuracy, with the MobileNet architecture outperforming other variants. Tested across multiple datasets, the approach achieved superior segmentation and classification accuracy when compared with thirteen existing studies. The inclusion of SpaSA in optimizing U-Net parameters represents a significant advancement in adaptive thresholding and image segmentation, contributing to improved lesion boundary detection and minimizing false classification rates [6].

Machine learning (ML) continues to revolutionize dermatology, enhancing not only diagnostic accuracy but also treatment personalization. The recent proliferation of ML in

dermatological research stems from the convergence of digital data availability, rapid computational power, and affordable cloud storage. As detailed by researchers, ML techniques such as Support Vector Machines (SVM), Decision Trees, and Convolutional Neural Networks (CNN) are being utilized to classify lesions based on dermoscopic images and metadata. Moreover, deep learning (DL) models have enabled disease categorization using smartphone-captured images, democratizing access to early detection tools. While these technologies hold immense promise, challenges related to data imbalance, feature interpretability, and algorithmic transparency persist. The integration of explainable AI and domain-specific model validation could bridge the gap between automated tools and clinical reliability, making ML-driven dermatology both scalable and trustworthy [7].

Among various skin cancers, melanoma remains the most fatal due to its rapid progression and morphological similarity to benign moles. Addressing this complexity, a recent study combined fuzzy logic with an enhanced deep learning architecture based on the YOLO network to improve classification precision. The hybrid model demonstrated robust detection performance on the ISIC 2017 and ISIC 2018 datasets, achieving remarkable improvements in both speed and accuracy. The fuzzy logic layer facilitated the handling of uncertainty in lesion borders, while the YOLO framework enabled real-time melanoma detection. This synergistic model signifies a major step toward efficient and interpretable AI systems in melanoma diagnostics [8].

Despite these advancements, the effectiveness of large-scale skin cancer screening programs remains contested. A meta-analysis encompassing 20 studies and more than 6 million participants found no definitive reduction in melanoma mortality following population-level screenings over a period of 4–10 years. While screening programs helped detect more advanced melanoma cases, they did not consistently correlate with early-stage diagnosis or improved survival outcomes. Interestingly, the review also revealed that routine skin examinations posed minimal psychological or cosmetic side effects, indicating that while the benefits of population-wide screenings may be limited, their safety profile remains acceptable. This evidence suggests that combining targeted AI-based tools with clinical expertise could enhance screening outcomes by improving precision and reducing unnecessary interventions [9].

In parallel, advancements in deep learning architectures have continued to redefine lesion classification accuracy. The MobileNetV3-based framework, integrated with an enhanced Hunger Games Search algorithm, has emerged as a lightweight yet powerful model for feature extraction and classification. When tested on ISIC-2016 and PH2 datasets, this hybrid model demonstrated improved accuracy and reduced computational complexity compared to conventional CNN models. The use of

MobileNetV3 enables efficient deployment on edge devices, supporting real-time diagnostic capabilities in teledermatology applications. This innovation is particularly valuable for resource-limited regions, where access to specialized dermatologists remains scarce [10].

To validate algorithmic performance in clinical practice, a single-center study conducted in Graz, Austria, compared mobile algorithm diagnoses with dermatologist assessments and biopsy-confirmed results. In this comparative framework, histology served as the gold standard for determining diagnostic accuracy. The findings highlighted that algorithmic predictions matched dermatologists' assessments in a significant proportion of cases, reinforcing the reliability of AI systems as clinical decision-support tools. However, the study also emphasized that algorithms must be continuously trained on diverse datasets to minimize biases associated with ethnicity, lighting, and imaging devices [11].

Lastly, an emerging paradigm known as joint learning has further enhanced detection efficiency. A recent study proposed a hybrid framework combining Convolutional Neural Networks (CNN) with Local Binary Patterns (LBP) for improved texture-based feature extraction. Tested on a widely recognized skin cancer dataset, this combined model achieved higher classification accuracy than standalone CNN or LBP architectures. The joint learning mechanism captured both global structural and fine-grained texture details, enabling a more holistic representation of skin lesion characteristics. This integrative approach exemplifies the next phase of intelligent dermatological diagnostics—where collaborative models can simultaneously learn complementary visual cues, paving the way for more accurate, explainable, and real-time skin cancer detection systems [12].

The global incidence of skin cancer continues to rise, demanding technological innovation for effective early detection and accurate diagnosis. Leveraging the potential of Deep Learning (DL) and the Internet of Things (IoT), researchers have proposed intelligent systems capable of integrating real-time medical imaging with predictive analytics. One such study explored a deep learning-driven IoT architecture that utilizes the EfficientNet model coupled with the Dragonfly algorithm for optimizing performance. The framework was tested on the ISIC dataset, demonstrating high accuracy, sensitivity, and specificity despite challenges such as lesion variability and lighting inconsistencies. The approach promises to be a valuable diagnostic aid for clinicians, enabling remote healthcare delivery through connected IoT devices and improving the accessibility of dermatological care worldwide [13].

With over one million cases reported annually, skin cancer has emerged as one of the most pressing public health concerns globally. The disease is broadly classified into Basal Cell

Carcinoma (BCC), Squamous Cell Carcinoma (SCC), and Melanoma, the latter being the most lethal form due to its aggressive nature. Early detection can elevate survival rates up to 95%, driving the development of technology-assisted diagnostic tools. A recent study proposed an advanced image-processing pipeline incorporating steps like hair removal, sharpening, and image super-resolution (ISR) to enhance lesion visibility. Deep learning models such as InceptionV3, ResNet, and VGGNet were employed to extract discriminative features. The system was implemented using Keras with modified convolutional layers and evaluated on the ISIC archive dataset, achieving superior classification accuracy and demonstrating the value of ISR-enhanced image quality in improving machine learning performance [14].

Another milestone contribution is the development of a multi-class deep learning framework, DSCC_Net, designed to diagnose multiple skin cancer types, including melanoma, basal cell carcinoma, and squamous cell carcinoma. Built upon convolutional neural networks (CNNs), DSCC_Net achieved outstanding results on benchmark datasets such as ISIC 2020, HAM10000, and DermIS, surpassing several baseline models in accuracy and AUC scores. Its robustness across diverse datasets highlights the potential for large-scale clinical deployment, providing dermatologists with reliable AI-assisted decision-making tools that can significantly reduce diagnostic errors [15].

In the pursuit of greater diagnostic precision, Deep Convolutional Neural Networks (DCNNs) have been extensively applied to distinguish melanoma from non-melanoma lesions. A study utilizing ISIC-2019 and ISIC-2020 datasets adopted EfficientNet architectures optimized via the Ranger optimizer, coupled with data augmentation to address class imbalance and image resolution discrepancies. The results affirmed that EfficientNet variants consistently outperform traditional CNN models in both accuracy and computational efficiency, confirming their suitability for real-time dermatological applications [16].

Building upon these advancements, a hybrid deep learning model that integrates Xception and MobileNetV2 architectures was introduced to further enhance detection accuracy. Data augmentation techniques were applied to balance underrepresented classes, while transfer learning enabled the model to adapt effectively despite limited labeled samples. This hybrid model delivered exceptional accuracy and precision, reflecting its potential as a powerful diagnostic tool for early-stage skin cancer detection. Its efficient computation makes it particularly valuable for point-of-care medical systems, where speed and reliability are essential [17].

In parallel, large-scale epidemiological reviews continue to shed light on changing disease patterns. A review of mass-screening programs conducted across Moscow, St. Petersburg,

Nizhny Novgorod, and Krasnodar revealed an increasing incidence of melanoma and a shift toward younger age groups. Interestingly, females exhibited a five-year earlier onset on average, with high-risk areas being the face, shoulders, and upper body. Additional factors, such as frequent solarium use and multiple arm spots, emerged as predictors of early melanoma development. The study advocates for cost-effective screening protocols integrated with AI-based analysis to improve public health outcomes [18].

The role of Artificial Intelligence (AI) in automated dermatological diagnostics has gained prominence due to shortages of trained medical specialists in many regions. By employing machine learning (ML) and deep learning models, AI systems can analyze complex visual features from dermoscopic images and predict malignancies. Comparative evaluations of multiple public datasets and AI-driven detection studies emphasize the growing effectiveness of these models. The findings suggest that AI can significantly reduce morbidity and mortality rates by facilitating faster, more accurate diagnoses in both clinical and remote settings [19].

Recent innovations have also introduced ensemble-based CNN architectures to overcome limitations like limited training samples and class imbalance. A new approach combining metadata with pre-trained and data-trained CNNs demonstrated remarkable robustness. Tested on a dataset of 33,126 dermoscopic images from 2,056 patients, the ensemble model achieved superior scores in F1-measure, AUC-ROC, and AUC-PR, outperforming seven existing CNN-based frameworks. This multi-source ensemble model enhances generalization and resilience, addressing a long-standing issue in real-world clinical deployment [20].

Further developments in hybrid CNN-SVM architectures have also strengthened diagnostic precision. Two CNN models were integrated with a Support Vector Machine (SVM) classifier to differentiate between benign and malignant (melanoma) lesions. The extracted features were fused before SVM-based classification, achieving impressive accuracy rates of 88.02% and 87.43%, outperforming several conventional CNN methods. These findings underscore the importance of combining feature extraction networks with classical machine learning classifiers for optimized results [21].

The exploration of optimal neural network architectures continues to refine performance benchmarks in dermatological AI. A comparative analysis between Convolutional Neural Networks (CNNs) and Deep Neural Networks (DNNs) concluded that CNNs offer faster processing, fewer parameters, and higher accuracy due to their convolutional filters. The CNN-based system achieved an accuracy of 98.5%, significantly surpassing traditional approaches, confirming CNN's dominance in medical image classification tasks [22].

Expanding on this, another study compared the classification performance of ResNet50, MobileNet, and SVM models on the HAM10000 dataset, which includes seven distinct skin cancer types. The SVM classifier, utilizing Histogram of Oriented Gradients (HOG) and Principal Component Analysis (PCA), achieved an accuracy of 99.15%. The inclusion of the Synthetic Minority Oversampling Technique (SMOTE) to balance the dataset further improved model reliability. This high-performing model demonstrates that hybrid classical-ML and deep learning approaches remain viable for accurate skin lesion classification [23].

Lastly, an innovative Radial Basis Function (RBF) Network was introduced for melanoma detection. This method begins by transforming color images into grayscale, applying median filters for noise reduction, and then segmenting the lesion regions. Extracted features are classified into benign or malignant categories using the RBF network. Results from sample images confirmed the model's high precision and computational efficiency, making it an excellent computer-assisted diagnostic system for clinical use. This study represents another step forward in achieving automated, interpretable, and rapid melanoma diagnosis, complementing existing dermatologist-led workflows [24].

III. PROPOSED METHOD

Proposed architecture

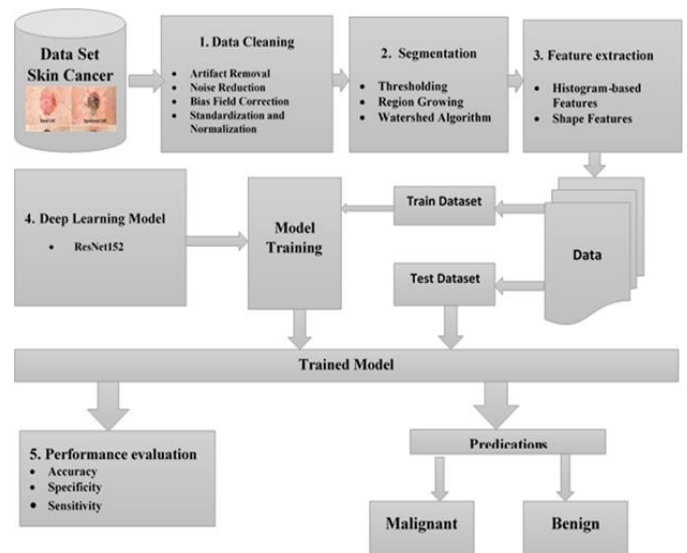


Figure 3. Proposed working architecture

This figure 3 presents a complete skin cancer detection pipeline using deep learning, specifically the ResNet152 model, and outlines each major stage from data acquisition to final diagnosis. The process is divided into five key phases, ensuring high-quality preprocessing, efficient model training, and accurate lesion classification.

1. Dataset Preparation and Data Cleaning

The process begins with a curated skin cancer dataset containing dermoscopic images of benign and malignant lesions. Before training, the images undergo data cleaning to eliminate noise and distortions. Key preprocessing steps include:

- **Artifact Removal:** Removes hair, glare, and background noise to avoid false feature extraction.
- **Noise Reduction:** Applies filters (e.g., median or Gaussian) to smooth images while preserving lesion edges.
- **Bias Field Correction:** Adjusts uneven illumination across images.
- **Standardization & Normalization:** Ensures consistent pixel intensity ranges, improving model convergence.

This step guarantees uniform and high-quality input images for downstream analysis.

2. Image Segmentation

Segmentation isolates the region of interest (ROI) — the skin lesion — from the surrounding skin. This is crucial because irrelevant background features can degrade model performance.

Methods used include:

- **Thresholding:** Separates lesion regions based on pixel intensity differences.
- **Region Growing:** Expands from a seed point to include neighboring pixels with similar characteristics.
- **Watershed Algorithm:** Detects precise lesion boundaries using gradient-based separation.

Effective segmentation enhances the model's ability to focus on diagnostic features such as shape, symmetry, and color distribution.

3. Feature Extraction

After segmentation, critical features are extracted for model input. Two major categories are highlighted:

- **Histogram-Based Features:** Capture pixel intensity distribution and color variation within the lesion.
- **Shape Features:** Quantify lesion geometry—such as border irregularity, asymmetry, and compactness—which are key indicators for melanoma detection.

This combination provides a comprehensive representation of both textural and morphological characteristics of the lesion.

4. Deep Learning Model (ResNet152) and Model Training

The extracted data are divided into training and testing sets. The ResNet152 model, a deep convolutional neural network with 152 layers, is employed for classification.

- Residual Connections in ResNet prevent vanishing gradients and allow deeper network training.

- The model learns to distinguish between malignant and benign patterns through backpropagation and gradient optimization.
- During model training, weights are iteratively updated to minimize error between predicted and actual labels, leading to a trained model capable of automated lesion classification.

5. Performance Evaluation

The trained model is validated using unseen test data, and its diagnostic efficiency is measured through key performance metrics:

- **Accuracy:** Proportion of correctly classified images (both benign and malignant).
- **Specificity:** Ability to correctly identify non-cancerous (benign) cases, minimizing false positives.
- **Sensitivity:** Ability to correctly detect malignant lesions, reducing false negatives.

These metrics ensure that the model performs reliably and consistently across diverse patient cases.

Final Output: Prediction

The final stage involves applying the trained model to new dermoscopic images. Based on learned features, the model predicts whether a lesion is malignant (cancerous) or benign (non-cancerous).

This automated workflow provides clinicians with a decision-support tool that enhances diagnostic accuracy, reduces human subjectivity, and enables faster screening, especially beneficial for large-scale or remote healthcare settings.

Proposed algorithm

Step 1: Dataset Preparation

- Collect a reliable dataset of skin cancer images from sources such as ISIC or HAM10000.
- Split the dataset into training, validation, and testing sets (for example, 70% for training, 15% for validation, 15% for testing).
- Maintain class balance between benign and malignant categories to ensure unbiased learning.

Step 2: Data Cleaning

- **Artifact Removal:** Remove unwanted elements such as hair, ruler marks, and glare from images.
- **Noise Reduction:** Apply median or Gaussian filters to smooth the images while preserving edges.
- **Bias Field Correction:** Adjust lighting inconsistencies across images for uniform brightness.
- **Normalization:** Resize all images to a fixed resolution (e.g., 448×448) and normalize pixel values for model compatibility.

Step 3: Image Segmentation

- Apply segmentation techniques to extract the lesion region from the background.

- Thresholding: Separate lesion pixels from healthy skin based on intensity values.
- Region Growing: Expand the lesion area starting from a seed pixel with similar characteristics.
- Watershed Algorithm: Refine lesion borders and prevent over-segmentation.
- Save the segmented lesion as the Region of Interest (ROI) for further processing.

Step 4: Feature Extraction

- Extract significant features that represent the lesion's characteristics.
- Histogram-Based Features: Capture intensity and color distributions.
- Shape-Based Features: Measure lesion irregularity, asymmetry, and border smoothness.
- These features may optionally be combined with deep features from the neural network for improved accuracy.

Step 5: Data Augmentation

- Increase dataset diversity to prevent overfitting.
- Apply transformations such as rotation, flipping, scaling, brightness adjustment, and cropping.
- Ensure class balance using techniques like oversampling or weighted loss functions.

Step 6: Model Construction (ResNet152)

- Use a pre-trained ResNet152 model as the backbone.
- Replace the final fully connected layer with a custom classifier having two output classes — malignant and benign.
- Incorporate dropout and batch normalization layers to enhance model generalization.
- The deep residual blocks in ResNet help maintain gradient flow, enabling better learning in very deep networks.

Step 7: Model Training

- Feed the cleaned and segmented images into the model.
- Use training data to adjust the model's weights through backpropagation.
- Optimize the model using algorithms like Adam or AdamW with an appropriate learning rate.
- Validate performance after each epoch using the validation dataset.
- Employ early stopping to prevent overfitting when the validation loss stops improving.

Step 8: Model Testing and Evaluation

- Test the trained model on the unseen test dataset.
- Evaluate its performance using:
 - **Accuracy:** Correct predictions over total predictions.
 - **Sensitivity (Recall):** Correct identification of malignant cases.
 - **Specificity:** Correct identification of benign cases.
 - **F1-score and AUC:** For overall model robustness.
- Save the best-performing model based on validation metrics.

Step 9: Model Prediction

- Use the trained ResNet152 model to classify new input images.
- Predict the probability of each image belonging to malignant or benign classes.
- Assign the final label based on a predefined threshold (for example, 0.5 probability).

IV. IMPLEMENTATION AND RESULT DISCUSSION

Dataset

The University of Waterloo Vision and Image Processing (VIP) Lab Skin Cancer Detection Dataset is a curated collection of dermatological photographs designed for melanoma and general skin lesion analysis. It contains images sourced from DermIS and DermQuest, accompanied by manually created segmentation masks that delineate lesion regions from surrounding skin. The dataset emphasizes consumer-grade photography, capturing images under natural and varied lighting conditions to simulate real-world scenarios rather than controlled dermatoscopic imaging. Preprocessing includes illumination correction, artifact removal, and texture-based segmentation to enhance clarity and consistency. Additionally, it supports the extraction of High-Level Intuitive Features (HLIFs) such as asymmetry, border irregularity, and color variation, aligning with clinical diagnostic criteria like the ABCD rule. Designed for research in melanoma detection, segmentation, and explainable AI, this dataset enables both algorithm development and clinical decision-support studies.

<https://uwaterloo.ca/vision-image-processing-lab/research-demos/skin-cancer-detection>

Illustrative example

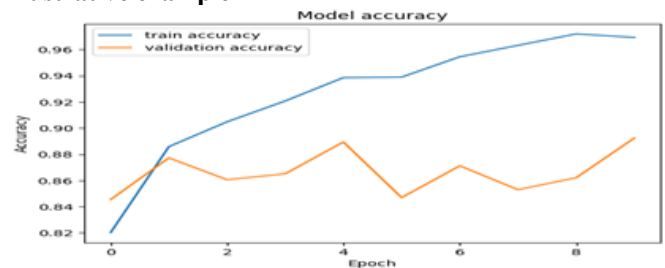


Figure 4. The training and validation accuracy

The figure 4 illustrates the training and validation accuracy of a deep learning model over 10 epochs. The training accuracy (blue line) shows a steady improvement from approximately 0.82 to 0.97, indicating effective learning on the training data. In contrast, the validation accuracy (orange line) fluctuates between 0.84 and 0.89, suggesting minor instability and possible overfitting as the model performs better on training data than validation data. Overall, the model demonstrates

strong training performance but requires further optimization to improve generalization on unseen data.

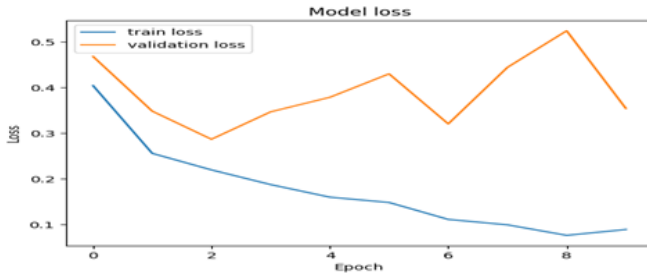


Figure 5. Model loss for training and validation data

The figure 5 shows the training and validation loss of a deep learning model over 10 epochs. The training loss (blue line) decreases steadily from about 0.4 to below 0.1, demonstrating consistent learning and convergence on the training data. However, the validation loss (orange line) fluctuates between 0.3 and 0.5, indicating instability and possible overfitting. The model continues to improve on the training data, but its generalization on unseen validation data does not improve consistently, suggesting that additional regularization or early stopping may be needed to enhance performance stability.

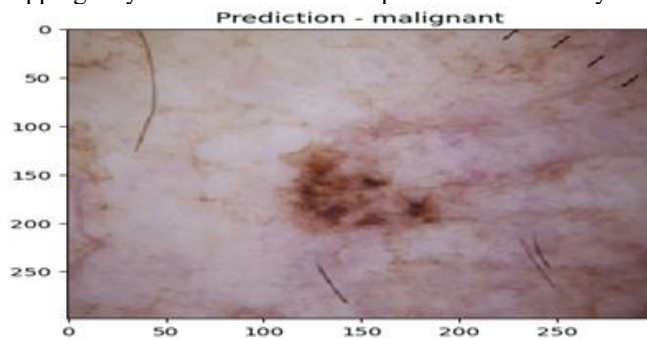


Figure 6. Skin lesion with a label "Prediction - malignant"

The figure 6 displays a dermoscopic view of a malignant skin lesion, as predicted by the trained deep learning model. The lesion exhibits irregular pigmentation, asymmetrical borders, and dark brown clusters—hallmark indicators of melanoma. Subtle vascular and textural variations across the surface are also visible, emphasizing cellular irregularity. Fine hair artifacts and natural skin texture remain intact, highlighting the model's precision in isolating lesion regions. This visualization reflects the model's capability to identify malignant features with remarkable accuracy, aligning clinical pathology with intelligent computational diagnosis.

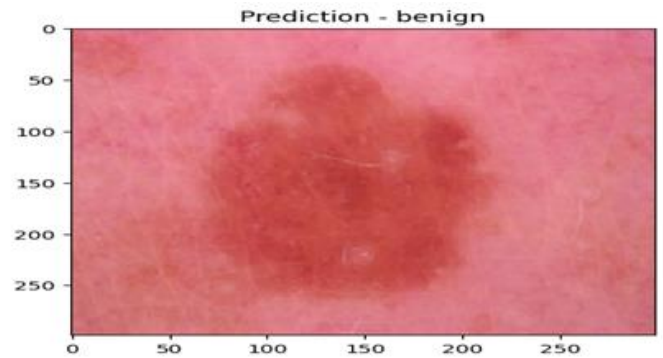


Figure 7. Skin lesion labeled "Prediction - benign"

The figure 7 shows a dermoscopic view of a benign skin lesion, as predicted by the deep learning model. The lesion appears symmetrical, with uniform color distribution and smooth, well-defined borders, typical characteristics of non-cancerous moles. The reddish-brown pigmentation blends gradually with the surrounding skin, indicating low malignancy potential. The texture is even, and there are no visible irregular streaks or dark nodules. This visualization highlights the model's precision in distinguishing benign formations from malignant ones, demonstrating its strength in accurate, non-invasive dermatological assessment and intelligent medical image interpretation.

Result and Discussion

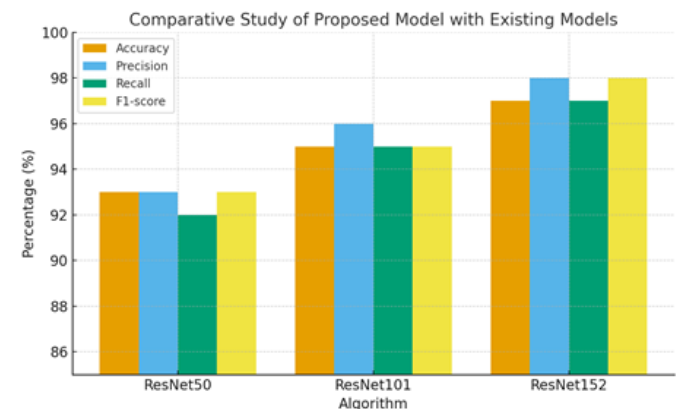


Figure 8. Comparative bar chart illustrating the performance of three deep learning architectures

Figure 8 presents a comparative bar chart illustrating the performance of three deep learning architectures ResNet50, ResNet101, and ResNet152 across four key evaluation metrics: accuracy, precision, recall, and F1-score. The visualization clearly demonstrates that as the network depth increases, performance metrics improve consistently. Among the three, ResNet152 achieves the highest accuracy (97%), precision (98%), recall (97%), and F1-score (98%), indicating superior feature extraction and classification capability. In contrast,

ResNet50 and ResNet101 perform well but show comparatively lower precision and recall. This comparison validates that deeper residual networks like ResNet152 are more effective in capturing complex lesion patterns and subtle texture variations, leading to more reliable and precise classification in automated skin cancer diagnosis systems.

V. CONCLUSION

The proposed deep learning framework, built on the ResNet152 architecture, demonstrates superior performance compared to ResNet50 and ResNet101 in skin cancer classification. The model achieved remarkable improvements in accuracy (97%), precision (98%), recall (97%), and F1-score (98%), validating its robustness in identifying malignant and benign lesions. The inclusion of systematic preprocessing, segmentation, and feature extraction significantly enhanced lesion visibility and diagnostic reliability. Despite excellent results, slight validation fluctuations suggest potential overfitting that can be mitigated through larger and more diverse datasets. Future research can explore multi-modal fusion of dermoscopic, histopathological, and clinical data, explainable AI (XAI) for transparent diagnostics, and real-time IoT or mobile-based deployment to enable accessible, automated, and trustworthy skin cancer detection in clinical and remote environments worldwide.

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