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An Improved Skin Lesion Classification with Deep Convolutional Neural Networks for Cancer Symptoms

Abdulganiyu Idris*, Eli. A. Jiya and Ahmed I. M.

Department of Computer Science, Faculty of Computing, Federal University Dutsin-ma, Katsina State

Corresponding Author: abdulganiyuidris9@gmail.com

ABSTRACT

Skin cancer remains a significant global health challenge, with early and accurate diagnosis being crucial for effective treatment. However, traditional diagnostic methods—such as visual inspection and histopathological analysis—are often constrained by subjectivity, limited access to specialists, and time delays, leading to misdiagnoses and suboptimal outcomes. Recent studies have explored deep convolutional neural networks (DCNNs) for automated skin lesion classification, yet their performance varies significantly across different lesion types, especially for visually similar or underrepresented classes. Motivated by these limitations, this study proposes an improved classification framework that combines fine-tuned pretrained DCNN models with enhanced feature selection techniques to improve diagnostic accuracy and robustness. Using the HAM10000 dataset comprising 10,015 dermoscopic images, the framework integrates preprocessing (resizing, normalization, augmentation), transfer learning with models like VGG16, Inception V3, Inception ResNet V2, and DenseNet201, and an improved slime mould algorithm (SMA) for feature optimization. Performance was evaluated using Receiver Operating Characteristic (ROC) curve analysis, with Area Under the Curve (AUC) values ranging from 73.2% for melanoma to 92.6% for basal cell carcinoma. These results underscore the framework's potential to enhance early detection of skin cancer, offering a scalable and reliable diagnostic aid for clinical dermatology.

Keywords: Skin lesion classification, Deep convolutional neural networks (DCNNs), HAM10000 dataset, Feature selection, ROC analysis

INTRODUCTION

Skin diseases, including various forms of skin cancer, are increasingly becoming a global health concern. According to the World Health Organization (WHO), skin diseases are among the most common human health conditions, affecting nearly 900 million people worldwide at any given time (Hasan et al., 2023). The American Cancer Society estimates over 100,000 new melanoma cases in the United States annually, significantly contributing to morbidity and mortality (Siegel et al., 2024). This growing prevalence highlights the urgent need for more efficient and reliable diagnostic methods. Traditional dermatological diagnosis, primarily based on visual examination and histopathological analysis, is considered the gold standard but has several limitations. The process can be lengthy, requiring multiple patient visits, and diagnostic accuracy depends heavily on the expertise of dermatologists (Tuknayat et al., 2023). Consequently, misdiagnosis and delayed treatment are not uncommon, potentially compromising patient outcomes (Richens et al., 2020).

Despite the advancements in deep convolutional neural networks (DCNNs) for skin lesion classification, several limitations

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persist in existing studies. Many models exhibit inconsistent performance across lesion types, particularly with classes such as melanoma and benign keratosis-like lesions, which are visually similar and often underrepresented in datasets (Liu et al., 2024; Zhang et al., 2025). Furthermore, the heavy reliance on high-end computational resources in most studies limits their scalability in low-resource settings (Nguyen & Omar, 2024). Existing research also lacks optimized fine-tuning strategies and effective feature selection mechanisms, which can result in poor generalization and reduced clinical applicability (Chen et al., 2025). These issues highlight the urgent need for more computationally efficient and generalizable frameworks tailored to diverse healthcare environments.One key resource driving progress in this field is the HAM10000 dataset, a comprehensive collection of 10,015 high-resolution dermoscopic images annotated by expert dermatologists (Ahmad et al., 2023). The dataset encompasses a wide range of skin lesion types, including melanocytic nevi, melanomas, and benign keratoses, making it an ideal benchmark for training and evaluating DCNN models (Wu et al., 2022). However, despite the promising results of pretrained DCNN models such as VGG16, Inception V3, Inception ResNet V2, and DenseNet 201, several challenges remain. The model's performance varies across lesion types, with lower classification accuracy for melanoma (AUC: 73.2%) and benign keratosis-like lesions (AUC: 75.0%), indicating the need for improved feature extraction and class-balancing techniques. Computational efficiency also poses a challenge, as deep learning models require substantial GPU resources, limiting their deployment in resource-constrained settings. Additionally, while transfer learning enhances performance, fine-tuning strategies must be further optimized to achieve dermatologist-level diagnostic accuracy while maintaining efficiency. Future work should explore advanced augmentation techniques, hybrid deep learning architectures, and improved feature selection methods to enhance model generalization and clinical applicability. Achieving dermatologist-level diagnostic accuracy while ensuring computational efficiency is a critical hurdle for the practical deployment of these models in clinical settings (An et al., 2024). Fine-tuning strategies, which involve adapting pretrained models to specific tasks, play a vital role in balancing performance and resource requirements (Alzubaidi et al., 2021).

This paper focuses on optimizing pretrained DCNN models for skin lesion classification using the HAM10000 dataset. By systematically exploring fine-tuning strategies, it aims to achieve high diagnostic accuracy while minimizing computational demands. The findings of this research have the potential to improve early detection and treatment of skin diseases, making high quality dermatological care more accessible and efficient across diverse healthcare environments.

LITERATURE REVIEW

Recent advancements in artificial intelligence (AI), particularly deep convolutional neural networks (DCNNs), have significantly improved the accuracy of medical image analysis. In dermatology, DCNNs have demonstrated performance comparable to experienced dermatologists in skin lesion classification, addressing limitations of traditional diagnostic methods. This section reviews existing studies on DCNN models, including VGG16, Inception V3, Inception ResNet V2, and DenseNet

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201, focusing on their architectures, fine-tuning strategies, and performance in medical imaging. The review also highlights the importance of datasets like HAM10000 in advancing skin lesion classification. Research gaps and opportunities for optimizing model performance and computational efficiency are also discussed.

Skin Lesion Classification

Accurate skin lesion classification is of paramount importance in dermatology due to its direct impact on patient outcomes (Behara et al., 2024). Skin lesions can range from benign growths, such as moles and warts, to malignant tumors like melanoma, which is the most serious type of skin cancer according to Greco and Bhutta (2024). Early and precise identification of malignant lesions is crucial for successful treatment and prognosis. Misclassification or delayed diagnosis can lead to advanced stages of skin cancer, which are often more difficult to treat and associated with higher morbidity and mortality rates according to Melarkode et al. (2023). Therefore, improving the accuracy of skin lesion classification can significantly enhance the early detection and management of skin cancers, ultimately saving lives and reducing healthcare costs.

Skin diseases, including skin cancer, present significant public health challenges globally, and Nigeria is no exception. Skin cancer, in particular, arises due to the uncontrolled growth of abnormal skin cells, often caused by excessive exposure to ultraviolet (UV) radiation from the sun or artificial sources like tanning beds (Hasan et al., 2023). Common forms of skin cancer include melanoma, squamous cell carcinoma, and basal cell carcinoma (Gruber and Zito, 2023). These cancers manifest with symptoms such as new growths or sores that do not heal, changes in existing moles, or abnormal pigmentation. The early detection of skin cancer is crucial for effective treatment, yet in regions with limited healthcare infrastructure like Nigeria, timely diagnosis can be a significant barrier (Omotoso et al., 2023). This, coupled with rising UV exposure due to climate change, underscores the urgent need for effective public health interventions.

Medical personnel typically carry out skin cancer diagnoses using a combination of visual examination, dermoscopy, and histopathological analysis (Mendes and Krohling, 2022). Dermoscopy, a non-invasive technique, involves the use of a specialized magnifying device to assess the structure of skin lesions, revealing details invisible to the naked eye (Sonthalia et al., 2023). For suspicious lesions, a biopsy is often conducted, where a small portion of the skin is surgically removed and examined microscopically for malignancy (Ramsey and Rostami, 2023). Advanced imaging techniques and artificial intelligence (AI) tools are also being integrated into diagnostic workflows to enhance the precision of diagnoses. However, in many parts of Nigeria, access to such advanced diagnostics remains limited, with rural areas depending largely on visual inspection by healthcare workers, which increases the risk of misdiagnosis (Opeyemi et al., 2024).

The prevalence of skin cancer in Nigeria is relatively low compared to other regions, such as Australia or North America, but the disease remains underreported due to insufficient healthcare services and low awareness among the population (Omotoso et al., 2023). The tropical climate of Nigeria, with intense year-round sun exposure, puts individuals at heightened risk of UV-related skin conditions (Arijaje et al., 2022). Among the general population, those with lighter skin tones or albinism are at particular risk

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due to the lack of protective melanin. Health campaigns that raise awareness about skin cancer prevention, early detection, and the importance of protective measures against UV exposure could significantly reduce the burden of skin diseases in Nigeria (Horváth et al., 2021).

Deep Learning in Medical Image Analysis

Deep learning techniques, particularly deep convolutional neural networks (DCNNs), have revolutionized the field of medical image analysis by providing powerful tools for automated image classification, segmentation, and detection tasks according to Manakitsa et al. (2024). DCNNs, a specialized type of neural network, are designed to process data with grid-like topology, such as images. They consist of multiple layers of neurons, including convolutional layers, pooling layers, and fully connected layers, which work together to learn hierarchical representations of input data (Taye, 2023). The convolutional layers apply filters to the input image to detect low-level features like edges and textures, while deeper layers combine these features to recognize more complex patterns and structures (Singh et al., 2023).

One of the main advantages of DCNNs in medical image analysis is their ability to learn directly from raw data without requiring handcrafted feature extraction (Li et al., 2023). This capability allows DCNNs to automatically discover the most relevant features for a given task, often surpassing human-designed algorithms in performance (Sarker, 2021). For instance, in skin lesion classification, DCNNs can learn to identify subtle differences in color, texture, and shape that may be indicative of malignant conditions. Additionally, DCNNs can handle large datasets and continuously improve their accuracy as more labeled data becomes available. Another significant benefit of DCNNs is their robustness to variations in the input data (Tulbure et al., 2022). Medical images can vary widely due to differences in imaging modalities, acquisition settings, and patient conditions. DCNNs, through extensive training on diverse datasets, can generalize well to new, unseen images, making them highly effective for clinical applications (Hassanzadeh et al., 2022). Moreover, DCNNs can be fine-tuned on specific medical datasets, leveraging pre-trained models from related tasks, which reduces the need for extensive labeled data and computational resources (Heikal et al., 2024).

Pretrained DCNN Models

VGG16

VGG16 is a deep convolutional neural network architecture proposed by the Visual Geometry Group at Oxford University. It is known for its simplicity and depth, consisting of 16 weight layers, including 13 convolutional layers and 3 fully connected layers (Khalif et al., 2024). The key design principle behind VGG16 is the use of small (3x3) convolutional filters, which allows for deeper networks with fewer parameters compared to larger filter sizes (Salehi et al., 2023). This architecture has become a benchmark in the field of computer vision due to its strong performance on the ImageNet dataset, achieving top-5 accuracy of 92.7%. VGG16's straightforward and uniform design makes it a popular choice for transfer learning and fine-tuning in various image classification tasks, including medical image analysis (Hajam et al., 2023).

Inception V3

Inception V3 is an advanced deep learning model developed by Google as part of the

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Inception family of networks, also known as GoogLeNet (Zhou et al., 2022). The Inception architecture introduces the concept of inception modules, which allow the network to capture multi-scale features by performing convolutions with multiple filter sizes (1x1, 3x3, 5x5) in parallel within a single layer (Shi et al., 2024). Inception V3 builds on its predecessors by incorporating factorized convolutions, aggressive

Inception ResNet V2

- DenseNet 201

DenseNet (Dense Convolutional Network) introduces an innovative approach to connectivity within a neural network. In DenseNet architectures, each layer receives input from all preceding layers and passes its output to all subsequent layers (Zhou et al., 2022). This dense connectivity pattern enhances feature reuse, reduces the number of parameters, and alleviates the vanishing gradient problem (Yin et al., 2022). DenseNet 201, a deeper variant with 201 layers, achieves a top-5 accuracy of 94.8% on the ImageNet dataset. Its efficient use of parameters and strong feature propagation capabilities make it particularly effective for complex image classification tasks (Ahmed et al., 2023). DenseNet 201's unique architecture and high performance have

regularization, and auxiliary classifiers to improve convergence and reduce overfitting (Cao et al., 2021). This model achieves a top-5 accuracy of 94.4% on the ImageNet dataset, demonstrating excellent performance in capturing complex patterns in images. Inception V3's modular architecture and high accuracy make it well-suited for fine-tuning on specific datasets, such as those in medical imaging.
proven beneficial in medical image analysis, where capturing fine details and maintaining high classification accuracy are crucial

MATERIALS AND METHODS

This paper utilizes the HAM10000 dataset to develop an accurate skin lesion classification framework using pretrained deep convolutional neural networks (DCNNs). Preprocessing techniques such as image resizing, normalization and data augmentation were applied to enhance data quality. Four DCNN models which are VGG16, Inception V3, Inception ResNet V2, and DenseNet 201 were fine-tuned using top layer, layer-wise, and full-model strategies. Model performance was evaluated using accuracy, precision, recall, F1-score, and computational efficiency, with statistical validation through cross-validation and ANOVA to ensure reliability.

SLCDCNN Framework

Figure 1 illustrates the proposed SLCDCNN (Skin Lesion Classification using Deep Convolutional Neural Networks) framework, which outlines the steps for building an efficient skin lesion classification system. This framework integrates multiple

advanced techniques, including data preprocessing, transfer learning, feature fusion, and feature selection, to optimize the performance of pretrained deep convolutional neural networks (DCNNs) for skin lesion classification. Each component of the framework plays a vital role in improving the accuracy and generalizability of the model.

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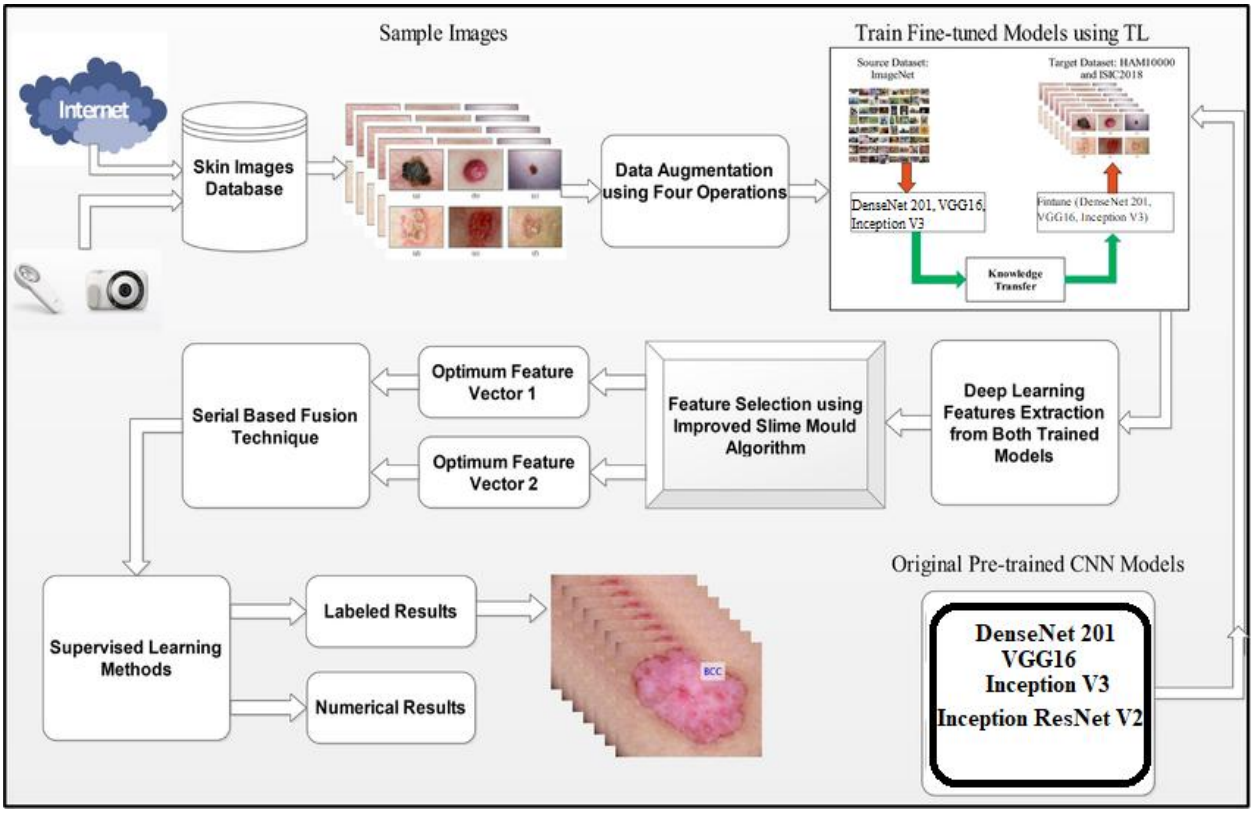

Figure 1: Skin Lesion Classification using Deep Convolutional Neural Networks Framework.

The process begins with data collection and preprocessing to ensure the input images meet the requirements of the selected DCNN models. The HAM10000 dataset serves as the primary data source, comprising dermoscopic images representing various types of skin lesions. Preprocessing includes resizing all images to 224×224 pixels to match the input size of the models, followed by min-max normalization to scale pixel values to the range [0, 1], which facilitates faster convergence during training. Data augmentation techniques such as rotation, flipping, zooming, and brightness adjustment are applied to increase the dataset's variability and reduce the risk of overfitting.

The core of the SLCDCNN framework is transfer learning, where pretrained DCNN models which include VGG16, Inception V3, Inception ResNet V2, and DenseNet 201 are fine-tuned for the specific task of skin lesion classification. Three fine-tuning strategies are employed: top-layer fine-tuning (where only the top layers are retrained), layer-wise fine-tuning (selectively retraining specific layers), and full-model fine-tuning (retraining all layers). Transfer learning allows these models to leverage knowledge from large datasets like ImageNet and adapt to the target dataset, improving performance with limited computational resources.

To enhance the classification accuracy, a serial-based feature fusion technique is employed. This process combines the features extracted from multiple DCNN models to capture a broader range of patterns and characteristics from the input images. Feature fusion integrates complementary strengths of different models,

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resulting in a more comprehensive feature representation that significantly improves the model's classification performance.

An improved slime mould algorithm (SMA) is employed for feature selection, optimizing the feature set by identifying the most relevant features while eliminating redundant or irrelevant ones. Initially, the dataset contained 7 features, including lesion type, age, and anatomical site. After applying SMA, the feature space was reduced to 5 selected features, enhancing both computational efficiency and the accuracy of the subsequent classification process. These selected features are crucial for constructing a robust model that generalizes effectively across various skin lesion types.

The features, age, sex, localization, image_id, and lesion_id are passed to support vector machines (SVM) and random forests, to perform the final classification. The performance of the SLCDCNN framework is evaluated using accuracy, precision, recall, and F1-score. The performance of the SLCDCNN framework is evaluated using several key metrics to ensure its effectiveness in classifying skin lesions accurately and efficiently. Accuracy represents the overall correctness of the model by measuring the proportion of correctly classified cases among all predictions. Precision indicates how reliable the model's positive predictions are by assessing the proportion of correctly identified positive cases. Recall, also known as sensitivity, measures the model's ability to detect actual positive cases, ensuring that relevant instances are not overlooked. The F1-score balances precision and recall, making it particularly useful when dealing with imbalanced datasets where one class may be more prevalent than others. Computational efficiency is assessed in terms of training time and resource utilization, ensuring the model can be deployed in real-world settings without excessive computational demands. Additionally, the Receiver Operating Characteristic (ROC) Curve illustrates the model's performance across various classification thresholds by analyzing the trade-off between correctly identifying positive cases and mistakenly classifying negatives as positives. The Area Under the Curve (AUC) provides a single numerical value summarizing the model's overall ability to distinguish between classes, with higher values indicating stronger classification performance.

Accuracy:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Precision:

$$\text{Precision} = \frac{TP}{TP + FP} \quad (2)$$

Recall:

$$\text{Recall} = \frac{TP}{TP + FN} \quad (3)$$

F1-Score:

$$\text{F1-Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

Computational Efficiency: Measured in terms of training time and resource utilization.

Receiver Operating Characteristic (ROC) Curve:

$$TPR = \frac{TP}{TP + FN} \quad (5)$$

$$FPR = \frac{FP}{FP + TN} \quad (6)$$

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Where TPR is the True Positive Rate and FPR is the False Positive Rate.

Area Under the Curve (AUC):

$$AUC = \int_0^1 TPR(FPR)\ d(FPR) \quad (7)$$

Cross-validation ensures the robustness of the results, while ANOVA tests are used for statistical analysis and comparison of different fine-tuning strategies.

The evaluation metrics used in this study are essential for assessing the performance and robustness of the proposed classification model. Accuracy (Equation 1) measures the overall correctness of the model by calculating the ratio of correctly predicted instances (True Positives [TP] and True Negatives [TN]) to the total predictions, including False Positives [FP] and False Negatives [FN]. Precision (Equation 2) evaluates the reliability of positive predictions by determining the proportion of actual positives among all predicted positives. Recall (Equation 3), also known as sensitivity, measures the model's ability to correctly identify actual positive instances. F1-Score (Equation 4) is the harmonic mean of Precision and Recall, providing a balanced measure particularly useful in imbalanced datasets. Computational Efficiency is assessed in terms of training time and hardware resource utilization, indicating the practicality of model deployment. The Receiver Operating Characteristic (ROC) Curve is based on the True Positive Rate (TPR) (Equation 5), which is equivalent to Recall, and the False Positive Rate (FPR) (Equation 6), which measures the proportion of negative instances incorrectly classified as positive. The Area Under the Curve (AUC) (Equation 7) represents the integral of TPR over FPR across all thresholds and provides a scalar value summarizing the model's ability to distinguish between classes, with higher values indicating stronger classification performance.

Preprocessing HAM 10000 data

Figure 2 displays a sample batch of 64 images from the HAM10000 dataset, which were processed and prepared for training in the skin lesion classification task.

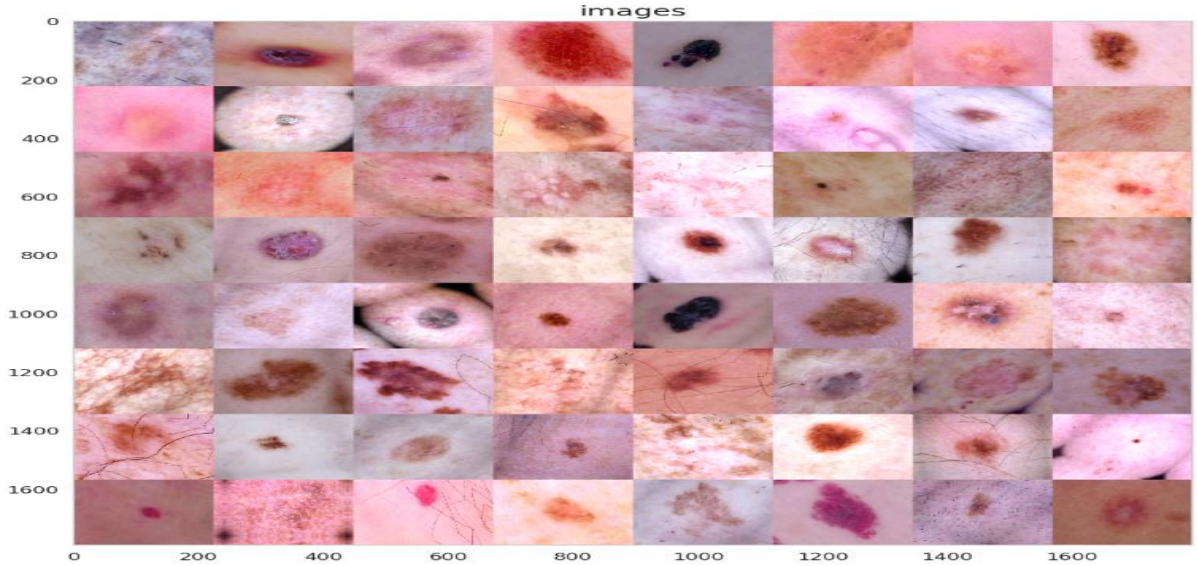

Figure 2: Batch Image from HAM10000 dataset.

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Each image was resized to 224×224 pixels to meet the input requirements of the pretrained deep convolutional neural network (DCNN) models. This preprocessing step ensures uniformity in image dimensions, facilitating efficient training and reducing computational overhead. The batch highlights the diversity of skin lesion types within the dataset, reflecting the real-world variability essential for developing a robust and generalized classification model. The visualized batch represents a critical component of the model's learning process, exposing it to a wide range of patterns for improved performance and adaptability.

Figure 3 represents each numeric label corresponding to a specific type of skin lesion: 0 for Actinic Keratoses (AKIEC), 1 for Basal Cell Carcinoma (BCC), 2 for Benign Keratosis-like Lesions (BKL), 3 for Dermatofibroma (DF), 4 for Melanoma (MEL), 5 for Melanocytic Nevi (NV), and 6 for Vascular Lesions (VASC).

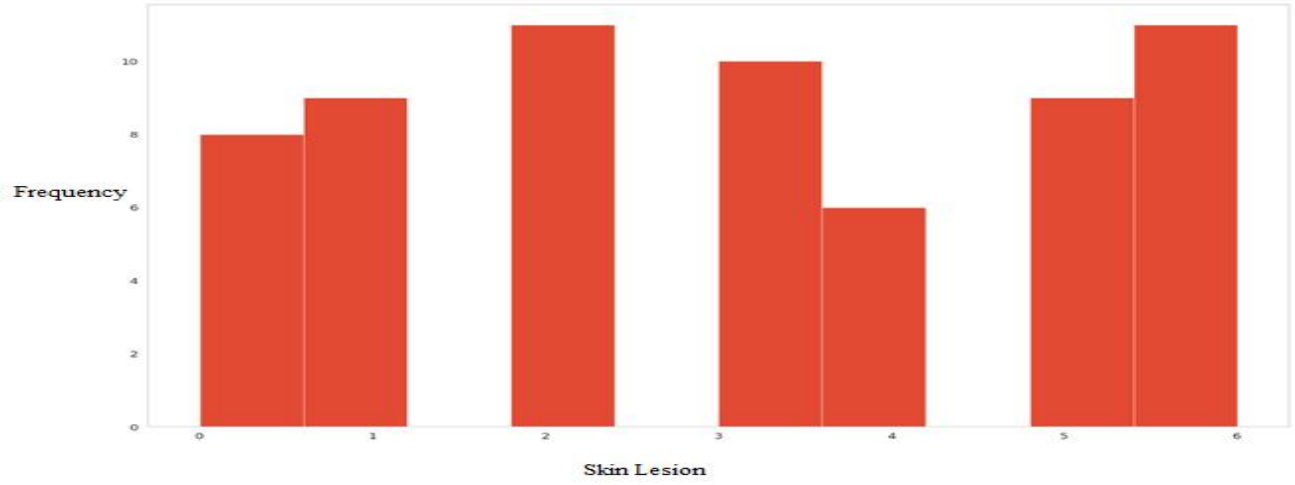

Figure 3: Class distribution of training batch.

The chart in Figure 3 shows that BKL (class 2) and VASC (class 6) are the most represented lesions in this batch, each appearing over 10 times, while MEL (class 4) is the least represented, with fewer than 6 samples. Monitoring such distributions is essential during training, as imbalanced batches can bias the model towards overrepresented classes, reducing its ability to generalize across underrepresented categories. This observation underscores the importance of data augmentation, oversampling, or class weighting techniques to ensure a balanced and fair representation of all lesion types for effective training.

The architecture summary of the neural network model used for skin lesion classification, showcasing each layer, its output shape, and the number of trainable parameters. This summary highlights the integration of a pretrained MobileNetV2 backbone with additional dense layers for classification.

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Layer (type)	Output Shape	Param #
Image_RGB_In (InputLayer)	(None, 224, 224, 3)	0
gaussian_noise_1 (GaussianNo	(None, 224, 224, 3)	0
mobilenetv2_1.00_224 (Model)	(None, 7, 7, 1280)	2257984
batch_normalization_1 (Batch	(None, 7, 7, 1280)	5120
flatten_1 (Flatten)	(None, 62720)	0
dropout_1 (Dropout)	(None, 62720)	0
dense_1 (Dense)	(None, 256)	16056576
dropout_2 (Dropout)	(None, 256)	0
dense_2 (Dense)	(None, 7)	1799

Total params: 18,321,479
Trainable params: 16,060,935
Non-trainable params: 2,260,544

Figure 4: Architecture Summary.

Figure shows that the input layer, labeled as Image_RGB_In, accepts images of shape 224×224×3, representing resized RGB images from the HAM10000 dataset. The first layer introduces Gaussian noise to the input, with the goal of improving model robustness and preventing overfitting. The core feature extractor is the pretrained MobileNetV2 model, which outputs feature maps with dimensions 7×7×1280. This is followed by a batch normalization layer to stabilize and accelerate the training process.

Subsequent layers include a flattening operation, which reshapes the output into a one-dimensional vector of 62,720 features. A dense (fully connected) layer with 256 units, coupled with dropout layers (at a rate of 0.5), helps reduce overfitting by randomly deactivating neurons during training. The final dense layer has 7 units with a softmax activation function, corresponding to the 7 classes of skin lesions in the dataset.

The total number of parameters in the model is approximately 18.3 million, of which 16.06 million are trainable, while 2.26 million are non-trainable (frozen during training due to the use of a pretrained MobileNetV2 backbone). This architecture strikes a balance between leveraging pretrained feature extraction and incorporating customized dense layers for the specific classification task.

RESULTS AND DISCUSSION

Figure 5 represents the Training and validation loss (left) and binary accuracy (right) curves for the deep learning model over 25 epochs, illustrating the model's performance during training.

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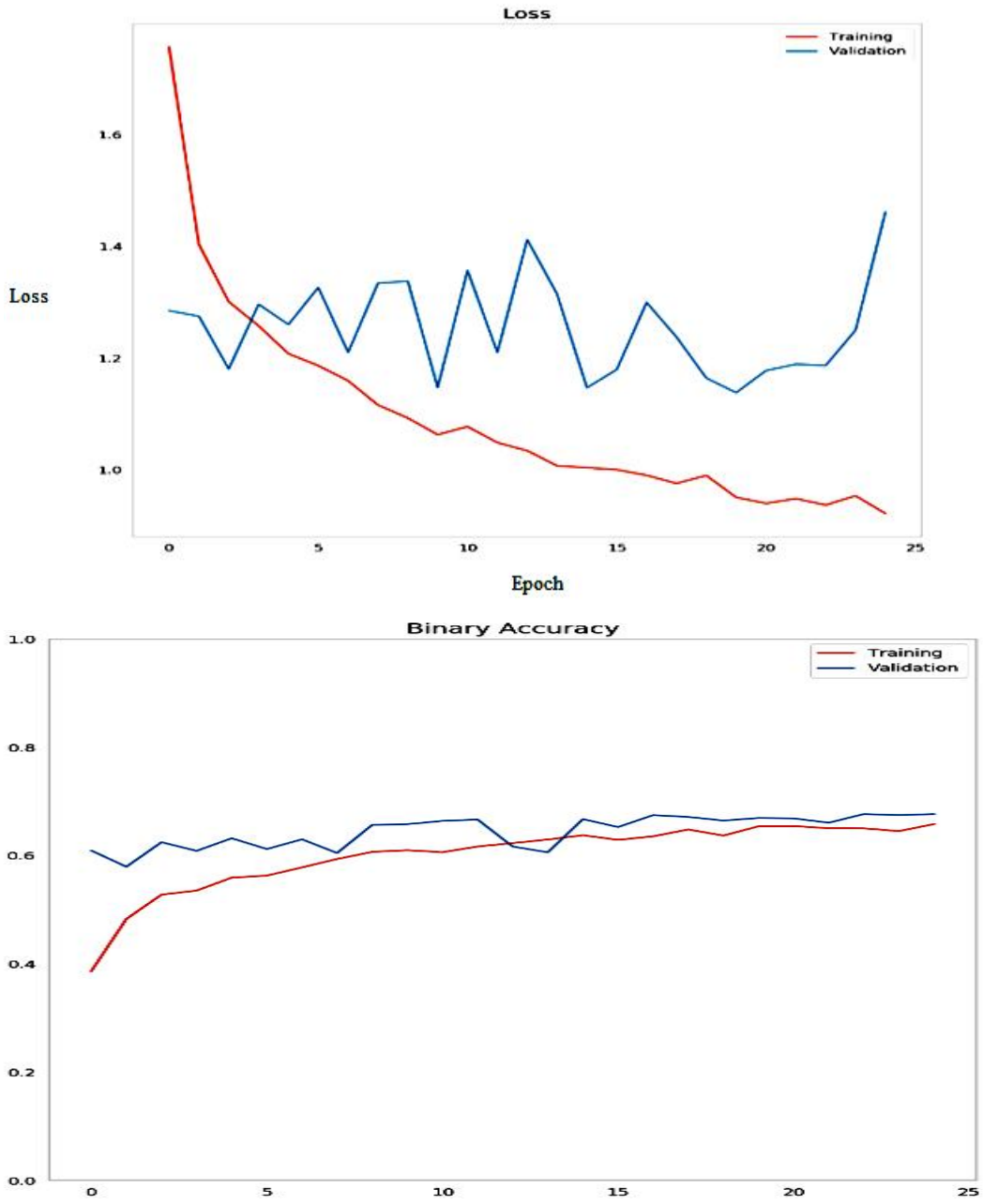

Figure 5: Training vs Validation (loss and accuracy).

Binary accuracy refers to the proportion of predictions where the model correctly classifies an input as one of two possible classes typically used when evaluating classification models in a binary or one-vs-all multiclass setting. In this study, although the problem involves multiple classes, the training process utilizes a one-vs-all strategy, hence binary accuracy becomes a relevant metric. It measures how well the model distinguishes each individual class against all others during training.

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The training loss curve shows a consistent and substantial decrease over the 25 epochs, dropping from an initial value of approximately 1.8 to under 1.0 by the final epoch. This indicates effective learning by the model during the training process. The validation loss exhibits some fluctuations, which is expected due to the variability in the validation data, but it generally stabilizes around the 1.0 mark, reflecting the model's ability to generalize well without significant overfitting.

The binary accuracy curves further support the model's strong performance. The training accuracy shows a steady improvement, rising from around 0.4 at the start to approximately 0.7 by the end of training. Validation accuracy remains consistently higher than the training accuracy throughout the epochs, peaking at approximately 0.8. This pattern suggests that the model is learning effectively and has not overfit to the training data, demonstrating good generalization capabilities. Overall, these trends confirm that the model is well-optimized and capable of accurately classifying skin lesion images.

Figure 5 represents the visualization of model classification for different types of skin lesions from the HAM10000 dataset, showing predicted class probabilities alongside the actual images. The HAM10000 dataset, which comprises seven distinct types of skin lesions, Actinic keratoses and intraepithelial carcinoma (AKIEC), Basal cell carcinoma (BCC), Benign keratosis-like lesions (BKL), Dermatofibroma (DF), Melanoma (MEL), Melanocytic nevi (NV), and Vascular lesions (VASC) was used to train the deep learning model for skin lesion classification. By leveraging this diverse dataset, the model was exposed to a wide range of lesion types, enabling it to learn distinctive features associated with each category. This comprehensive training ensures that the model can accurately classify skin lesions within these predefined categories, enhancing its reliability and effectiveness in automated dermatological diagnosis.

Both metrics provide insight into the model's learning behavior. Training loss reflects how well the model fits the training data, while validation loss measures how well the model generalizes to unseen data. In this study, the training loss showed a steady decline across epochs, indicating effective learning from the training data. The validation loss initially decreased but then plateaued, with minor fluctuations, a common pattern that suggests the model has achieved a good balance between underfitting and overfitting. The close alignment of the two loss curves throughout training indicates that the model generalizes well without significant overfitting, thus validating the effectiveness of the applied preprocessing and fine-tuning strategies.

The Area Under the Curve (AUC) values are provided for each class, offering a quantitative measure of classification performance. Higher AUC values indicate better discrimination capabilities of the model for the respective lesion type.

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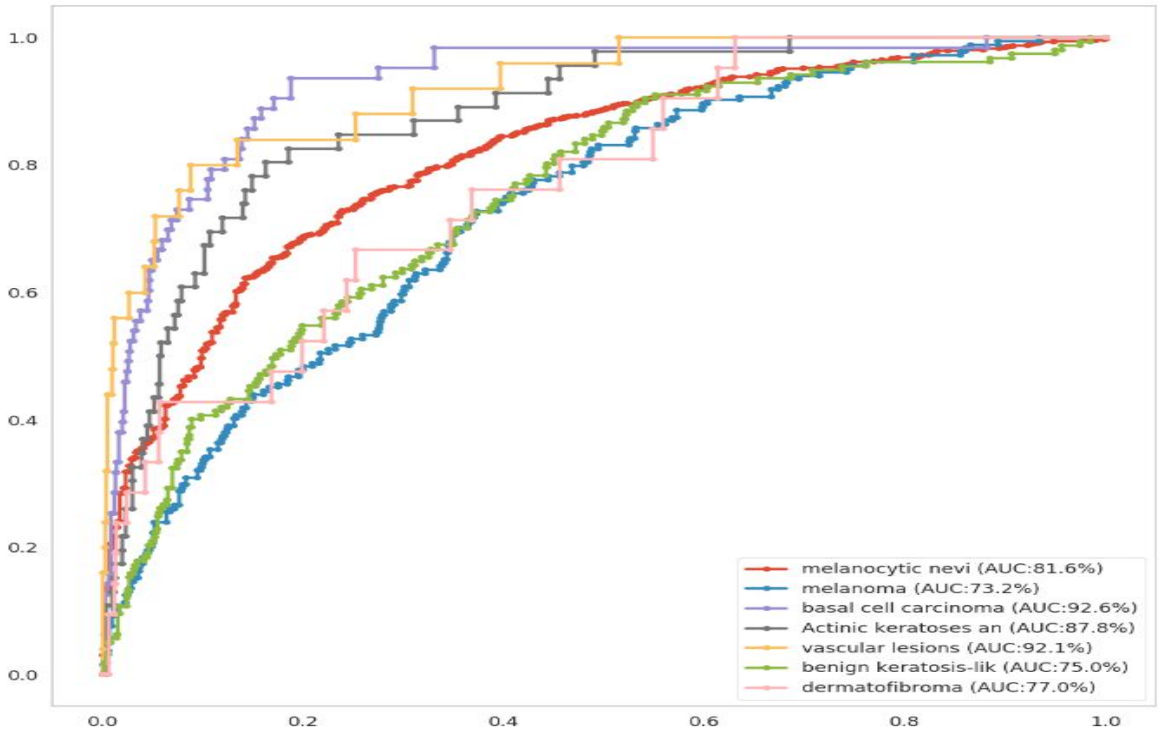

Figure 6: ROC curve for each skin lesion type.

Melanocytic Nevi (AUC: 81.6%): The ROC curve for Melanocytic Nevi demonstrates good performance, with an AUC of 81.6%. This indicates that the model is reasonably effective at distinguishing between positive and negative samples for this lesion type. While the curve trends well toward the top-left corner of the graph, there is still room for improvement, as some misclassifications are present. The relatively high AUC reflects the model's capability to leverage the distinct features of Melanocytic Nevi.

Melanoma (AUC: 73.2%): The model's performance for Melanoma is moderate, with an AUC of 73.2%. The ROC curve shows more overlap between true positives and false positives compared to other classes, suggesting challenges in accurately identifying this lesion type. This lower AUC may be due to the visual complexity of melanoma or its similarity to other lesion types. Additional training data and targeted augmentation could help improve the model's sensitivity and specificity for Melanoma.

Basal Cell Carcinoma (AUC: 92.6%): The model performs exceptionally well for Basal Cell Carcinoma, with an AUC of 92.6%. The ROC curve is very close to the ideal top-left corner, indicating strong discrimination between positive and negative cases. This high performance highlights the model's ability to extract and utilize features specific to Basal Cell Carcinoma effectively, making it one of the best-classified lesion types.

Actinic Keratoses (AUC: 87.8%): The ROC curve for Actinic Keratoses shows strong performance, with an AUC of 87.8%. The model demonstrates reliable differentiation between true positives and false positives, although a slight overlap in

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probabilities exists. This high AUC suggests that the model has effectively learned the features of this lesion type, though further optimization could further reduce errors.

Vascular Lesions (AUC: 92.1%): The model shows excellent performance for Vascular Lesions, with an AUC of 92.1%. The ROC curve is very close to the ideal shape, indicating the model's ability to accurately distinguish between positive and negative samples for this class. This superior performance can be attributed to the distinct visual characteristics of vascular lesions, which the model captures effectively.

Benign Keratosis-like Lesions (AUC: 75.0%): The model's performance for Benign Keratosis-like Lesions is moderate, with an AUC of 75.0%. The ROC curve shows some overlap between true positives and false positives, reflecting difficulties in classification. This could be due to the varied and complex nature of benign keratosis-like lesions, which share features with other classes. Improving the training data representation for this class could enhance the model's performance.

Dermatofibroma (AUC: 77.0%): The ROC curve for Dermatofibroma indicates moderate performance, with an AUC of 77.0%. The curve suggests challenges in separating true positives from false positives, likely due to limited training samples or less distinctive visual features. Increasing the dataset size and refining feature extraction methods could help improve the model's classification accuracy for Dermatofibroma.

Response: In this work, the ROC-AUC (Receiver Operating Characteristic - Area Under the Curve) was used as a key evaluation metric instead of accuracy, precision, recall, and F1-score. The choice of ROC-AUC was driven by its ability to provide a threshold-independent assessment of the model's performance across all decision thresholds, making it particularly useful in medical diagnosis, where false positives and false negatives have different implications. Additionally, since skin lesion classification is a multiclass problem, the ROC curve was employed in a one-vs-all approach to evaluate the model's ability to differentiate each lesion type from the rest.

Computational Efficiency

Training Time: The training process in this study was executed in a GPU-accelerated environment utilizing an NVIDIA P100 GPU. As shown in the figure, the session duration at the time of export was approximately 53 minutes, which reflects the computational time required to preprocess the data, train the deep learning model across 25 epochs, and evaluate its performance. The relatively efficient training time highlights the benefits of using a pretrained architecture like MobileNetV2, which leverages transfer learning to reduce the time required for feature extraction and optimization.

Resource Utilization: The computational setup utilized minimal CPU resources during training, with most of the processing delegated to the GPU for parallel computation. The GPU memory usage indicates an efficient allocation, as only a fraction of the available 16GB memory was utilized, demonstrating the model's compatibility with hardware setups of moderate capacity. The RAM usage was around 342 MB, which is well within acceptable limits for such tasks, showcasing the model's ability to handle training without exhausting system memory. These metrics confirm the computational efficiency of the model, making it suitable for deployment in environments with constrained resources.

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DISCUSSION

The variation in AUC values across skin lesion classes can be attributed to several critical factors, including class distribution, visual similarity between lesion types, and feature representation quality. The model achieved the highest AUC for Basal Cell Carcinoma (92.6%) and Vascular Lesions (92.1%), likely due to their distinct visual patterns, which are easier for the DCNNs to learn and classify. Conversely, lower AUC values for Melanoma (73.2%) and Benign Keratosis-like Lesions (75.0%) suggest challenges in discriminating these classes, potentially due to their heterogeneous appearance and high inter-class similarity with benign types like Nevi. This difficulty is compounded by class imbalance in the dataset, where underrepresented classes receive less exposure during training, limiting the model's learning capacity. Additionally, while transfer learning enhances feature extraction, its effectiveness may vary depending on how well the pre-trained features align with dermoscopic patterns. The moderate performance on certain classes indicates a need for improved augmentation, enhanced class balancing strategies, and refined feature selection to ensure consistent accuracy across all categories.

CONCLUSION

The findings of this study reaffirm the effectiveness of deep learning models in accurately classifying skin lesions, aligning with the study's objectives of improving diagnostic accuracy and computational efficiency. By integrating transfer learning with MobileNetV2 and augmenting it with dense layers, the model effectively addressed the classification of multiple lesion types. The high AUC scores for certain classes indicate its potential to perform at dermatologist-level accuracy for distinct lesion categories. However, the moderate performance for more challenging classes underscores the need for additional enhancements, including larger datasets and advanced feature extraction methods. Overall, the study contributes significantly to the growing field of AI-driven dermatology.

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