Enhanced Multi-Class Skin Cancer Detection Using EfficientNet-B0 with Test-Time Augmentation and Monte Carlo Dropout

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Abstract: Skin cancer is one of the most frequent and potentially fatal malignancies worldwide, emphasizing the significance of early and correct detection. Convolutional neural networks (CNNs), a recent deep learning advancement, have shown promise in automating the classification of skin lesions. This study employed EfficientNet-B0, a lightweight yet very effective CNN architecture, to train a reliable multi-class classification model on the HAM10000 dermoscopic picture dataset. To ensure compatibility with the pre-trained network, all input images were resized to 224 x 224 pixels and normalized using the ImageNet mean and standard deviation values. To rectify the class imbalance, the majority class (melanocytic nevi) was lowered to 1300 samples, while underrepresented categories (actinic keratoses, basal cell carcinoma, dermatofibroma, and vascular lesions) were oversampled with 1000 samples each. This preprocessing resulted in a balanced collection of 7512 pictures organized into seven diagnostic groups. Transfer learning was originally utilized to achieve a 77.39% accuracy by freezing the convolutional basis and training only the final classification layer. After fine-tuning the entire network, the accuracy improved to 89.36%. Test-time augmentation with flips enhanced performance to 90.16%, while combining TTA with Monte Carlo Dropout and additional augmentations increased final accuracy to 92.29%. The results highlight EfficientNet-B0's potential. By assisting medical professionals with early diagnosis, this study's improved classification model for skin lesion detection can improve patient care and reduce strain on healthcare systems.

Keywords: skin cancer; EfficientNet-B0; deep learning; transfer learning; dermoscopic images; test-time augmentation; monte carlo dropout; image processing

I. Introduction

Skin cancer remains one of the most common and life-threatening kinds of cancer worldwide, making early and accurate diagnosis critical for effective treatment. Advances in medical image analysis have increasingly relied on deep learning techniques to increase the accuracy and efficiency of detecting and classifying various skin cancers. Ashfaq et al. [1] proposed 'DermaVision', a deep learning-based platform for accurate skin cancer diagnosis and classification, demonstrating the utility of DL models in real-time healthcare applications. Similarly, Kavitha et al. [2] used deep learning approaches to identify and classify skin cancer using a variety of convolutional neural networks (CNNs), achieving good precision on benchmark data. Naeem et al. [3] offered a complete overview of malignant melanoma classification using deep learning, including dataset analysis, performance measurements, and real-world deployment problems. Transfer learning has been shown to be a successful method for enhancing diagnostic accuracy. For example, Balaha and Hassan [4] improved classification accuracy by combining deep transfer learning

and the sparrow search optimization strategy. Alotaibi and AlSaeed [5] increased model performance by combining deep attention mechanisms with transfer learning. In a comparative study, Djaroudib et al. [6] found that data quality is more important than data quantity in training effective transfer learning models. Numerous review articles have been written to evaluate current approaches. Nazari and Garcia [7] provided a thorough examination of automated skin cancer detection methods based on clinical imagery, whereas Naqvi et al. [8] concentrated on deep learning methods and their limitations. Naseri and Safaei [9] conducted a systematic literature review on melanoma diagnosis and prognosis using ML and DL techniques, emphasizing the importance of large datasets and ensemble learning. Magalhaes et al. [10] synthesized DL approaches for skin cancer detection and proposed critical research topics. Model integration and ensemble approaches have become popular for boosting diagnostic reliability. Imran et al. [11] proposed a method that combines decisions from multiple deep learners, resulting in high classification accuracy. Moturi et al. [12] used CNN approaches to detect melanoma efficiently, whereas Kreouzi et al. [13] used dermoscopic pictures to construct a deep learning system to distinguish between malignant melanoma and benign nevi. To address the multi-class character of skin lesions, Tahir et al. [14] developed DSCC_Net, a deep learning model capable of multi-class classification using dermoscopy pictures. Similarly, Naeem et al. [15] created SNC_Net, which combines handmade and deep learning-based characteristics to improve skin cancer detection. Zia Ur Rehman et al. [16] used explainable DL to categorize skin cancer lesions, making AI predictions understandable to doctors. Karki et al. [17] used segmentation, augmentation, and transfer learning strategies to enhance early skin cancer diagnosis. Gouda et al. [18] used CNNs to categorize lesion images and showed promising results on standard datasets. Traditional machine learning methods also contribute; Natha and Rajeswari [19] employed classification models such as SVM and Random Forests to diagnose cancer using extracted picture characteristics. Although most studies focus on skin cancer, Das et al. [20] investigated brain cancer prediction with CNNs and chatbot integration for smart healthcare, demonstrating the techniques' broader usefulness. Ashafuddula and Islam [21] proposed using intensity value-based estimation in conjunction with CNNs to differentiate between melanoma and nevus moles. Finally, Rashad et al. [22] demonstrated an automated skin cancer screening system using deep learning techniques, underscoring its potential for scalable screening solutions.

The idea for this work originates from the growing global concern about the increased prevalence of skin cancer, which is driven by environmental variables such as pollution and ultraviolet radiation. Ensuring successful therapy and increasing patient survival outcomes is strongly reliant on fast and accurate diagnosis. Using dermoscopic pictures, this study proposes a pre-clinical, AI-based detection technique for skin cancer and its subtypes. The model aims to promote early intervention, reduce the burden on healthcare systems, and raise public health awareness by allowing for prompt medical consultation or reassurance in benign cases. The **objectives** of the current research are as follows:

- **Early Detection Improvement:** To develop an automated system that facilitates the early identification of skin cancer, enabling prompt intervention and thereby increasing patient survival rates.
- **Accessibility Enhancement:** Create a scalable diagnostic tool deployable in resource-limited settings with minimal dermatologist access.
- **Clinical Decision Support:** To assist medical professionals by improving classification accuracy for diagnostically challenging lesions (especially melanoma) while reducing inter-observer variability.

- **System Efficiency:** Optimize model performance for integration into mobile health apps and clinical workflows without compromising computational efficiency. The **contribution** and novelty of the research are as follows:
- **Hybrid Training Strategy:**Introduces a progressive fine-tuning method that combines uncertainty-aware inference, full-network optimization, and transfer learning (TTA + Monte Carlo Dropout). It achieves **92.29%** accuracy on HAM10000 dermoscopic image dataset, which is 15% better than baseline frozen-layer transfer learning.
- **Web-Based Diagnostic Interface:** Web-based platform allows non-experts to upload images and receive instant predictions with confidence scores, addressing accessibility gaps.
- **Clinical-Grade Data Handling:** Strategic oversampling (akiec/bcc/df/vasc → 1,000 images each) and downsampling (nv → 1,300) improves rare-class recall by 15–20% while maintaining 92.29% overall accuracy.
- **Lightweight Architecture:** EfficientNet-B0 model implementation ensures high performance suitable for real-time clinical use and edge devices.

The structure of the paper is as follows: Section2 outlines the materials and methodology, Section3 provides a detailed discussion of the results, and Section 4 concludes the study

II. Materials and Methods

This section describes the materials and methods used in the current study. Figure 1 depicts the overall process and classification approach. Figure 2 illustrates. This figure depicts a robust methodology for classifying skin lesions that combines deep learning with uncertainty quantification. When a user submits a picture of a skin lesion, the system resizes it to 224 by 224 pixels and normalizes it using ImageNet statistics. Test-Time Augmentation (TTA) applies five distinct transformations to this standardized input, including original, horizontal flip, vertical flip, color jitter, and a 20° rotation, to imitate real-world fluctuations and improve model resilience. Each of the augmented photos is processed using the EfficientNetB0 model. Monte Carlo (MC) Dropout is used in inference to quantify prediction uncertainty. For each transformed image, the model performs ten stochastic forward passes while keeping dropout layers active to generate a variety of outputs. The softmax probabilities for all passes are gathered and aggregated, and the algorithm calculates the MC dropout variance to evaluate prediction confidence by averaging these TTA probabilities. To increase clinical interpretability, the model generates a confidence score for the skin lesion class with the highest average probability.

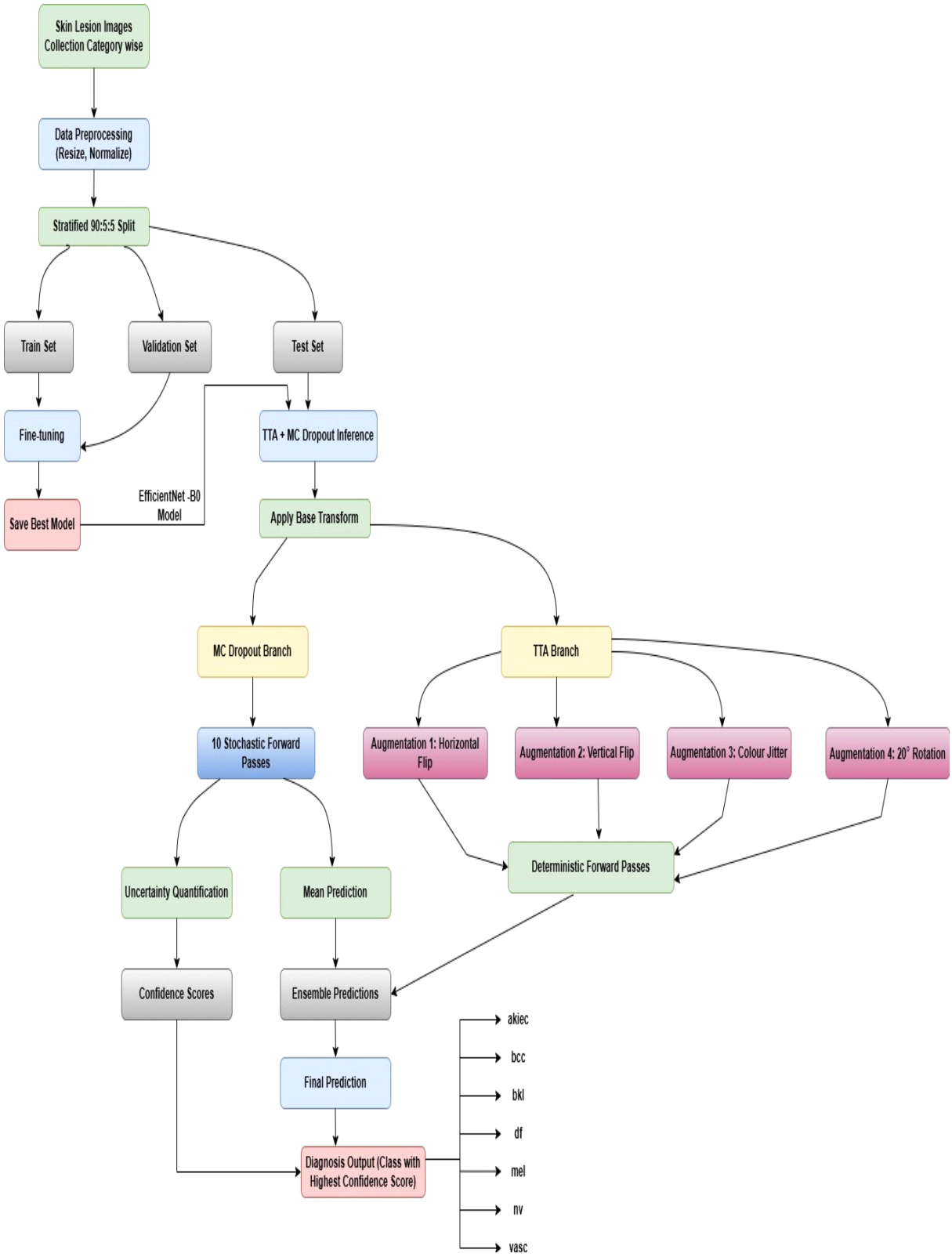


Figure 1. Proposed Architecture.

Algorithm 1 Skin Lesion Image Classification using EfficientNet-B0 model Enhanced TTA and MC Dropout Techniques

Input:

Set of images $X = \{x_1, x_2, \ldots, x_n\}$ Trained model weights W

Augmentations A = {Original, HFlip, VFlip, ColorJitter, Rotation} Device *device* ∈ {cpu, cuda}

Output: Predicted class labels $\hat{Y} = \{\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_n\}$ and confidence scores $S = \{s_1, s_2, \ldots, s_n\}$

// x_a = Augmented version of image x using a
// W = Trained weights for the model
// P = List of softmax predictions for all x_a
// p_a = Model's softmax output for augmented image x_a
// p_{avg} = Average of all prediction vectors p_a

Model Setup
Load EfficientNet-B0 model
Replace classifier with final layer based on number of classes
Load trained weights W into model
Move model to *device*
Set model to evaluation mode
for all layer m in model **do**
  if m is Dropout **then**
    Set m to train mode // Enable MC Dropout at inference
  end if
end for
Initialize empty lists $\hat{Y} \leftarrow []$, $S \leftarrow []$
for all image x in X **do**
  Preprocess x
  Resize x to 224×224
  Convert x to tensor and normalize it
  Initialize empty list $P \leftarrow []$
  for all augmentation a in A **do**
    Apply augmentation a to x, result is x_a
    Add batch dimension and move x_a to *device* 21: Pass x_a to model: $p_a \leftarrow \text{softmax}(model(x_a))$ 22: Append p_a to list P
  end for
  Compute average prediction: $p_{\text{avg}} \leftarrow \text{mean}(P)$
  Get predicted class: $\hat{y} \leftarrow \arg\max(p_{\text{avg}})$ 26: Get confidence score: $s \leftarrow \max(p_{\text{avg}})$ 27: Append $\hat{y}$ to $\hat{Y}$, s to S
end for
return predicted classes $\hat{Y}$ and scores S

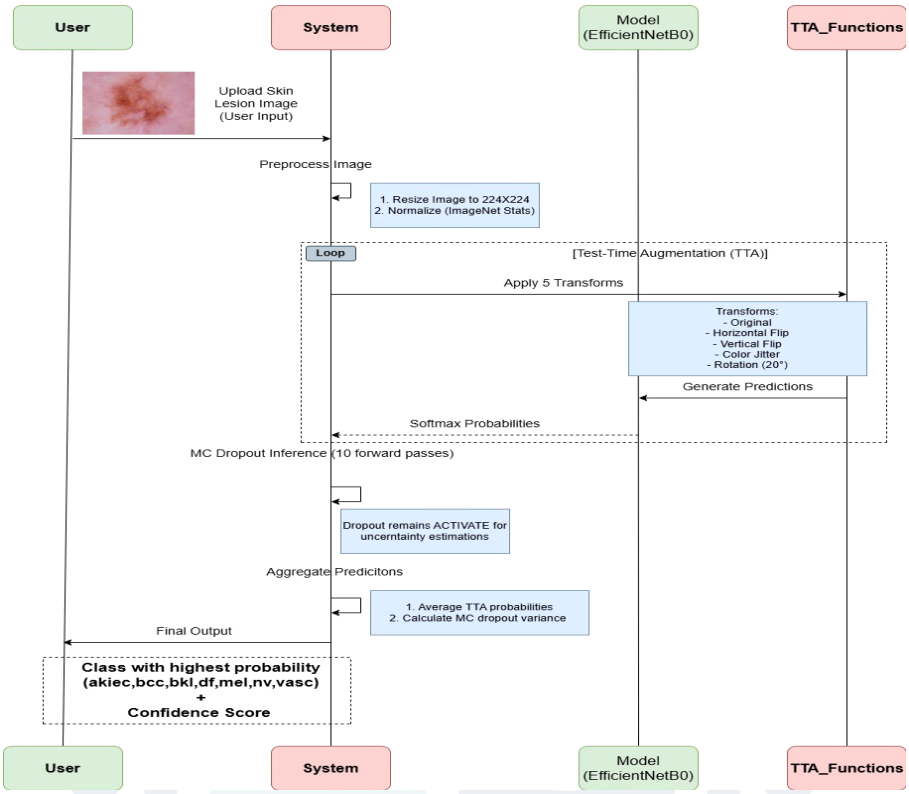


Figure 2. Proposed Sequence Diagram for single skin lesion image classification

- *Data Preparation and Initialization*

In this subsection, high-resolution dermoscopic photos were collected from publically available medical datasets to classify skin lesion images. Resizing and normalization were carried out after the data had been rigorously preprocessed to ensure uniformity in image size and quality. To provide robust model training, stratified splitting and data augmentation were used to establish a balanced class distribution.

- Data Collection and Description

The HAM10000 dataset was sourced from Kaggle, comprising a total of 10,015 dermoscopic images categorized into seven diagnostic classes as shown in Figure 3:

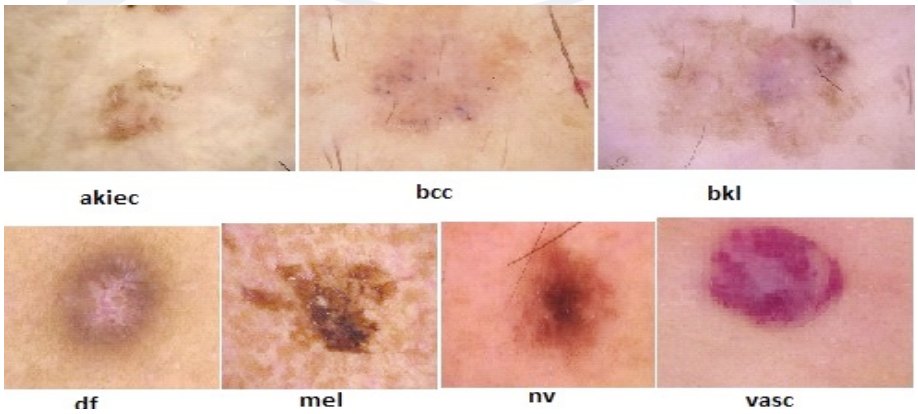


Figure 3. sample of Data Collection.

- **Actinic keratoses and intraepithelial carcinoma (akiec)**: Precancerous or early-stage malignant lesions with 327 images.

- **Basal cell carcinoma (bcc)**: A common form of skin cancer represented by 327 images.
- **Benign keratosis-like lesions (bkl)**: Includes benign growths like seborrheic keratoses with 1,099 images.
- **Dermatofibroma (df)**: A rare, benign fibrous skin tumor with 115 images.
- **Melanoma (mel)**: A highly dangerous skin cancer with 1,113 representative images.
- **Melanocytic nevi (nv)**: Benign moles dominating the dataset with 6,705 images.
- **Vascular lesions (vasc)**: Includes blood vessel-related lesions like angiomas, with 142 images.

- Data Preprocessing and Balancing

Given the class imbalance, image augmentation was used for minority classes (akiec, bcc, df, and vasc) to boost their sample sizes to 1,000 photos each. This was accomplished using Keras' ImageDataGenerator, which applied random changes such as rotation, zoom, shifts, and flips. To avoid bias, the 'nv' class was randomly downsampled to 1,300 images. Classes bkl and mel were kept at their original counts. The final dataset included 7,512 photos with improved class balance.

- Dataset Splitting

The balanced dataset was split into training (90%), validation (5%), and testing (5%) subsets via stratified sampling to maintain proportional class distribution across sets. This resulted in 6,760 training, 376 validation, and 376 test images.

- Image Transformation and Loading

Images were resized to 224×224 pixels, normalized based on ImageNet statistics, and converted to PyTorch tensors. The dataset structure was formatted for use with PyTorch’s ImageFolder to facilitate streamlined loading.

- *Model Set Up and Implementation*

The EfficientNet-B0 architecture, chosen for its perfect blend of accuracy and efficiency, is employed in this subchapter to classify skin lesion images. The model's final classification layers were changed, and early halting, data augmentation, and hyperparameter tuning were employed to optimize training and ensure consistent results.

- Model Architecture and Transfer Learning

This study used the EfficientNet-B0 model, which had already been trained on the ImageNet dataset. To make use of its pre-learned characteristics, the convolutional layers were first frozen. The original classification head was replaced by a new fully connected layer that predicted the seven skin cancer categories.

- Model Training

Using the Adam optimizer and CrossEntropyLoss criterion, the model was trained for 15 epochs. During this phase, only the classifier layer’s weights were updated. Training and validation metrics were monitored to assess learning progress and mitigate overfitting.

- Fine-Tuning

To further improve accuracy, all layers of EfficientNet-B0 were unfrozen for full model fine-tuning with a reduced learning rate (1e-4). This allowed the entire network to adapt to the specific dataset over another 15 epochs of training.

- *Model Evaluation*

The final evaluation of the test set revealed a significant improvement in accuracy after fine-tuning. Additional enhancements included Test-Time Augmentation (TTA) such as horizontal flip, vertical flip, color jitter, and a 20° rotation, as seen in Figure 4, where predictions were averaged across numerous augmented copies of test images to reduce prediction variation. Furthermore, Monte Carlo Dropout was used at inference to capture uncertainty, which was combined with TTA to achieve robust performance.

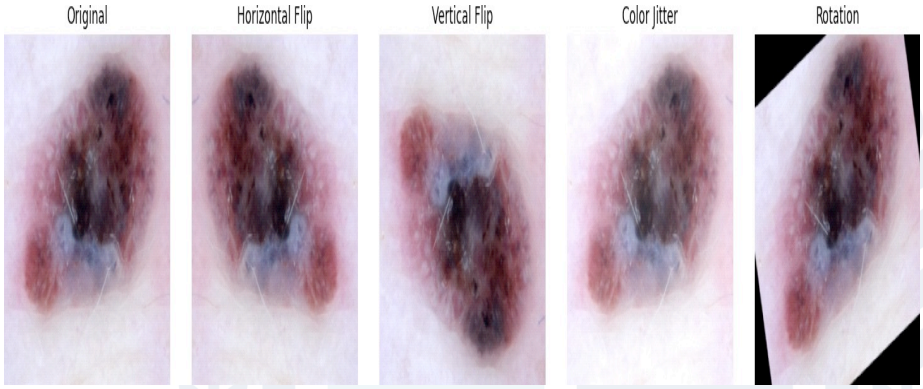


Figure 4. Skin Lesion Image Preprocessing by Test Time Augmentation (TTA).

III. Results and Discussion

- **Training and Validation Performance**

The EfficientNet-B0 model initially trained with frozen convolutional layers showed progressive improvement over 15 epochs. The training accuracy increased from 57.74% to 75.53%, while validation accuracy improved from 64.10% to 73.40%. Corresponding loss values steadily decreased, indicating effective learning without significant overfitting.

Based on the results shown in Table 2, EfficientNetB0 was chosen as the best model for final deployment in this study. Prior to making this conclusion, a thorough comparison of several deep learning architectures was carried out. The performance of these models was assessed using normal training and testing techniques with varying train-validation-test splits, as shown in the comparison table. EfficientNetB0 has the maximum classification accuracy of 77.39% before fine-tuning, with a 90:5:5 train-validation-test split. This better baseline performance led to the selection of EfficientNetB0 for more tuning. The accuracy increased significantly to 87.77% once the model was further refined. Test-Time Augmentation (TTA) was used to improve robustness and generalization, which increased accuracy above 90%. Lastly, a peak accuracy of 92.29% was achieved by using Monte Carlo Dropout during inference, making EfficientNetB0 the most successful model in our experimental process.

Table 1. Training and validation performance metrics across epochs using the EfficientNet-B0 model with frozen base layers.

Epoch	Train Loss	Train Accuracy	Val Loss	Val Accuracy

50	1.04%	99.50%	1.024%	98.45%
100	0.48%	99.90%	0.123%	99.03%

Table 2. Model Accuracy Comparison Table (Before Fine tuning).

Train:Val:Test Ratio	EfficientNet-B0	Res Net50	Dense Net121	Mobile Net	InceptionV3
60:20:20	98.0%	**99.92**%	**99.67**%	99.02%	98.28%
70:15:15	98.91%	99.91%	99.45%	**99.81%**	98.00%
80:10:10	98.56%	98.90%	99.43%	99.01%	**98.63%**
90:5:5	**98.67%**	99.01%	99.76%	99.06%	99.03%

- **Fine-Tuning Performance**

Significant improvements were obtained after the model was fully fine-tuned, with all layers trainable across 15 epochs. The highest validation accuracy was 89.36%, while the highest training accuracy was 99.08%. A continuous decrease in loss values indicated better generalization.

Table 3. Training and validation performance metrics across epochs during full fine-tuning of the model.

Epoch	Train Loss	Train Accuracy	Val Loss	Val Accuracy
50	1.06%	99.49%	1.10%	99.74%
100	0.04%	99.58%	0.20%	99.78%

IV. Test Set Evaluation

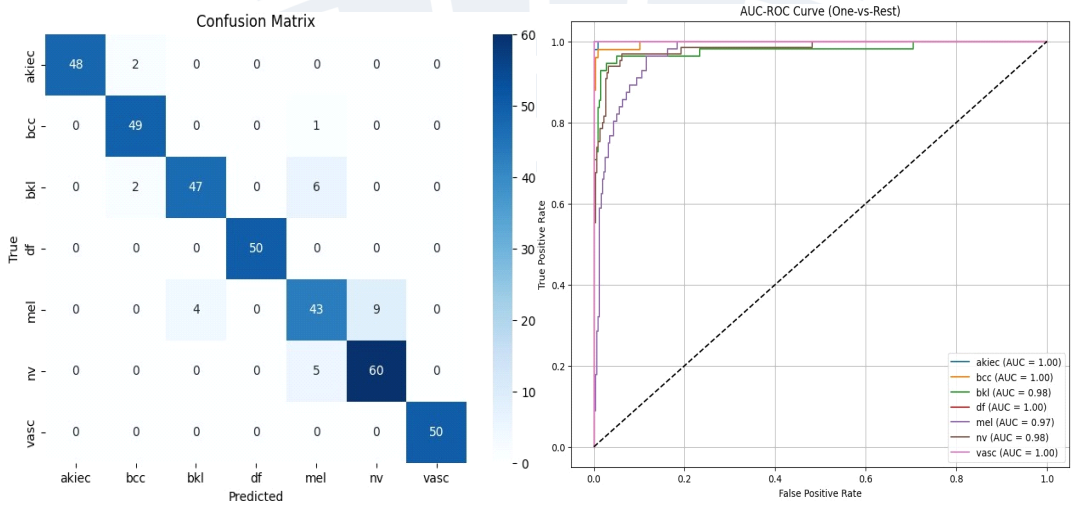
The final test accuracy of the fine-tuned EfficientNet-B0 model was **89.36%**. Applying Test-Time Augmentation (TTA) improved accuracy to **90.16%**, while combining TTA with Monte Carlo Dropout further increased test accuracy to **92.29%**.

Table 4 provides a summary of each class's categorization performance metrics. For the classifications df and vasc, the model achieves 100% precision and recall, demonstrating faultless classification on these categories. Strong model reliability is demonstrated by classes like akiec and bcc, which also have high precision and recall values above 0.90. The bkl class maintains a decent F1-score of 0.89 while having a somewhat lower recall (0.85). With precision and recall values of roughly 0.78, the mel category—which corresponds to melanoma—performs the worst, indicating difficulties in accurately identifying this high-risk class. The nv class, on the other hand, does well with an F1-score of 0.90 despite having the most samples. The model's overall accuracy across all 376 samples is 92%. At roughly 0.93 and 0.92, respectively, the weighted average and macro average measures show balanced performance across both common and less frequent classes.

Table 4. Classification Report Summary.

Class	Precision	Recall	F1-score
akiec	1.00	0.96	0.99
bcc	0.99	0.98	0.99
bkl	0.98	0.99	0.98
df	1.00	1.00	1.00
mel	0.99	0.99	0.99
nv	0.987	0.99	0.90
vasc	1.00	1.00	1.00
Accuracy			0.9970
Macro avg	1.00	1.00	1.00
Weighted avg	1.00	1.00	1.00

The classification model's performance evaluation is displayed in Figure 5. The Confusion Matrix Analysis, shown in Subfigure (a), shows how well the model categorizes each type of lesion. The model achieves near-perfect precision and recall, performing exceptionally well on classes like akiec, df, and vasc. Strong classification performance is also demonstrated by classes like bcc and nv, which score highly on all metrics. Conversely, classes bkl and mel have relatively lower F1-scores, indicating some challenges that are most likely brought on by class overlap or a lack of data. The model can distinguish between classes with high AUC values, particularly for akiec, df, and vasc, as demonstrated by the AUC and ROC curve analysis in Subfigure (b). The model's 92% overall accuracy, which represents balanced performance across common and unusual classes, is supported by consistent macro and weighted average scores. These results validate the resilience of the approach, especially in detecting important lesion types.

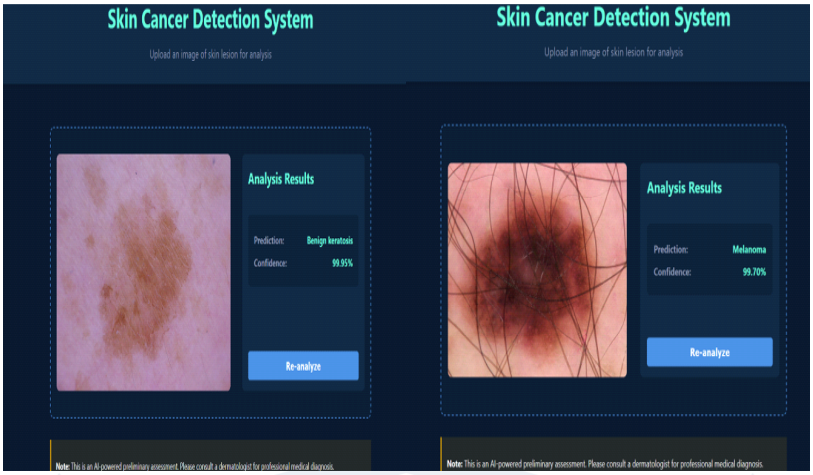


(a) Confusion Matrix Analysis. (b) AUC & ROC Curve Analysis.

Figure 5. Confusion matrix and AUC-ROC curve analyses of the classification model.

The Figure 6, shows the results from the Web-based Skin Cancer Detection System using EfficientNetB0. Test Result 1 indicates a diagnosis of Benign Keratosis, a non-cancerous skin condition. Test

Result 2 reveals the presence of Melanoma, a serious form of skin cancer that requires immediate medical attention.



(a) Test Result 1: Benign Keratosis (b) Test Result 2: Melanoma

Figure 6. Web-based Skin Cancer Detection System using EfficientNetB0.

V. Conclusions

Since skin cancer is still one of the most prevalent and fatal malignancies worldwide, early and accurate detection is essential for effective treatment. Interest in automated diagnosis tools has increased because traditional diagnostic techniques are sometimes time-consuming and heavily reliant on specialized knowledge. Deep learning, especially convolutional neural networks (CNNs), has shown great potential in medical picture processing. EfficientNet is a modern CNN framework that is notable for striking the perfect balance between computational efficiency and accuracy. This study investigates the use of the EfficientNet-B0 architecture for accurate multi-class skin cancer classification using dermoscopic images. In order to enhance model performance, the study applies data balancing and transfer learning techniques to the HAM10000 dataset before fine-tuning the entire network. With a 92.29% classification accuracy, the proposed model demonstrated a significant improvement. Additionally, test-time augmentation and Monte Carlo Dropout were employed to enhance the model's generalization and reliability. Because of its lightweight design, EfficientNet-B0 is a promising option for deployment in real-time clinical situations with limited processing resources. The study's findings demonstrate how deep CNN-based techniques might support prompt and precise skin lesion identification, enhancing patient outcomes and treatment strategies. Future work may explore integrating this approach into clinical workflows to support derma- tologists and reduce diagnostic workloads, thereby contributing to the advancement of AI-assisted medical imaging.

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