International Review of Practical Innovation, Technology and Green Energy (IRPITAGE) | ISSN (e): 2808-8611
Volumes 6 No. 1 (2026)

SKIN CANCER DETECTION USING THE CONVOLUTIONAL NEURAL NETWORK METHOD WITH MOBILENETV3 ARCHITECTURE ON DERMATOSCOPIC IMAGES

I Putu Oka Ananda Dewantara[1], Ni Wayan Wisswani[2], I Nyoman Rai Widartha Kesuma[3]
Program Studi Sarjana Terapan Teknologi Rekayasa Perangkat Lunak , Jurusan Teknologi Informasi, Politeknik Negeri Bali[1,2,3]
E-mail: okanandaa007@gmail.com[1], wisswani@pnb.ac.id[2], raiwidartha@pnb.ac.id[3]

Received	: 12 May 2026	Accepted	: 01 June 2026
Revised	: 25 May 2026	Published	: 15 June 2026

Abstract
Skin cancer is one of the most common types of cancer with a continuously increasing global incidence rate, making early detection essential to improve treatment success and reduce mortality. This study aimed to develop a mobile-based skin cancer detection application using the Convolutional Neural Network (CNN) method with the MobileNetV3 architecture implemented in a Flutter application. The dataset used consisted of 1,500 dermatoscopic images divided into three classes: Basal Cell Carcinoma (BCC), Squamous Cell Carcinoma (SCC), and healthy skin (Normal). The research stages included data preprocessing through resizing, normalization, and image augmentation, model training using MobileNetV3Small with transfer learning and fine-tuning techniques, model conversion into TensorFlow Lite (TFLite) format, and implementation into an Android-based mobile application. Model evaluation was performed using a confusion matrix with accuracy, precision, recall, and F1-score metrics. The results showed that the model achieved an accuracy of 93.75% with average precision, recall, and F1-score values of 0.94. In single-image prediction testing, the model achieved confidence scores of 98.44% for the BCC class, 98.14% for the SCC class, and 99.91% for the Normal class. The implementation of Test Time Augmentation (TTA), Dropout, and L2 regularization proved effective in improving model stability and performance. In addition to its high accuracy, the application was able to run in real time on Android devices with fast inference time and efficient memory usage. This study demonstrates that the combination of MobileNetV3Small and Flutter can provide a lightweight, accurate, and accessible solution for early skin cancer detection.

Keywords: Skin Cancer, Convolutional Neural Network, MobileNetV3Small, Flutter, Dermatoscopic Image Detection

INTRODUCTION

Skin is the outermost organ of the human body that functions to protect the body from the surrounding environment. Like other organs, the skin is composed of millions of cells. Under normal conditions, body cells divide rapidly during the growth period, while in adulthood cell division occurs to replace dead cells or repair damaged tissue. The process of cell division takes place in a controlled manner; however, damage to cellular DNA can cause uncontrolled cell division, resulting in abnormal cells known as cancer cells. Cancer cells can continue to grow, divide, and spread to surrounding normal tissues (metastasis). Skin cancer is one of the types of cancer whose incidence continues to increase globally. Recent data indicate that in 2021 there were an estimated more than 6.6 million cases of skin cancer worldwide, with incidence rates continuously increasing over the past decades. The global ASIR (age-standardized incidence rate) of 77.66 per 100,000 population reflects the significant global burden of this disease (Zhou et al., 2025). The most common types of skin cancer include basal cell carcinoma and squamous cell carcinoma. Among these types, melanoma is considered the most dangerous because it has a high mortality rate if not detected and treated early (Zhou et al., 2025). At the national level, skin cancer is also among the most frequently encountered cancers. The total research subjects consisted of 46 patients, with a male-to-female ratio of 1:1. The average age of patients was 63.8 years. Cases of basal cell carcinoma (BCC) were more common than squamous cell carcinoma (SCC), accounting for 33 subjects (71.7%) and 13 subjects (28.3%), respectively. Lesions were most commonly found on the face (76.1%), followed by the scalp (8.7%). Non-melanoma skin cancer was predominantly BCC in both genders. Both BCC and SCC were most frequently found in areas with a high risk of recurrence (66.7%, 46.2%), and most patients with non-melanoma skin cancer were over 60 years old. The most frequently identified non-melanoma skin cancer was BCC (Winaya et al., 2024). Early detection of skin cancer is very important to increase the chances of successful treatment and reduce mortality rates. In general, skin cancer diagnosis is performed by dermatologists through medical examinations and biopsies. However, these methods require relatively long processing times, high costs, and heavily depend on the availability of medical professionals, especially for people living far from healthcare facilities. Therefore, a technology-based healthcare application is needed to assist the skin cancer detection process in a fast, accessible, and efficient manner.

Advancements in technology, particularly in the field of Artificial Intelligence (AI), offer solutions for medical image processing and analysis. One of the deep learning methods widely used for image analysis is the Convolutional Neural Network (CNN). This method has the capability to automatically extract visual features from images, making it highly effective for detecting skin cancer using dermatoscopic images (Martin & Udjulawa, 2024). Nevertheless, most previous studies still employed conventional CNN architectures with large model sizes and high computational resource requirements. Research conducted by (Manne et al., 2020) demonstrated that conventional CNNs are capable of achieving high accuracy in skin cancer classification; however, they require substantial computational power, making them less efficient for implementation on devices with limited resources. Another study by (Brinker et al., 2018) also stated that deep learning models can provide high accuracy but require long training times and still depend on devices with high computational specifications.

Unlike previous studies, this research uses the MobileNetV3 architecture, specifically the MobileNetV3Small variant, which is a type of convolutional neural network specifically designed to produce highly efficient models with low computational requirements. MobileNetV3 utilizes depthwise separable convolution techniques that significantly reduce computational load without drastically decreasing model performance (Howard et al., 2019). Therefore, this architecture is highly suitable and optimal for direct implementation on mobile-based devices. This study implements the MobileNetV3 model into a Flutter-based application, enabling the skin cancer detection application to be used responsively and conveniently through handheld devices. This approach differs from previous studies that generally focused on desktop-based systems. Mobile-based applications are expected to provide more practical and accessible solutions for the public, as well as serve as supportive tools in the early detection of skin cancer and the provision of related disease information. Based on comparisons with previous studies, this research aims to develop a skin cancer detection application using the Convolutional Neural Network method with the MobileNetV3 architecture based on dermatoscopic images, implemented within a Flutter application. The developed application is expected to provide accurate, efficient, and user-friendly detection results.

LITERATURE REVIEW

Digital Image Processing

Digital image processing is the process of manipulating images using computational algorithms to improve the quality of visual features before they are fed into a neural network model. In this study, the stages focus on resizing (adjusting image resolution to match the standard input size of MobileNetV3Small), pixel value normalization, and data augmentation (such as rotation, flipping, and zooming) to enrich the variation of the training dataset and prevent overfitting (Munir, 2004; Santoso & Defit, 2024).

Skin Cancer

Skin cancer is the uncontrolled growth of abnormal skin cells, often triggered by exposure to ultraviolet radiation. This study focuses on the classification of three specific skin condition classes:

1. Basal Cell Carcinoma (BCC): The most common type of non-melanoma skin cancer, characterized by slow growth and rare metastasis.

2. Squamous Cell Carcinoma (SCC): A more aggressive type of non-melanoma skin cancer than BCC, with a higher risk of metastasis.
3. Healthy Skin (Normal): Used as a control class to ensure that the application does not generate false alarms for skin without harmful lesions (Srinivasu et al., 2021).

Convolutional Neural Network

A Convolutional Neural Network (CNN) is a deep learning architecture specifically designed to process two-dimensional data such as images. CNNs extract visual features automatically without requiring manual feature engineering. The main CNN components used in this study include (Firmansyah et al., 2025; Munandar & Rozi, 2024; Pamungkas, 2022):

1. Convolutional Layer: Uses filter matrices (kernels) that slide across the image to detect local features such as edges, lines, and textures.
2. Pooling Layer: Reduces the spatial dimensions of the feature maps to decrease computational load. Max pooling and average pooling are commonly used techniques.
3. Activation Function (ReLU): The Rectified Linear Unit introduces non-linearity into the network, accelerates convergence, and helps overcome the vanishing gradient problem.

MobileNetV3Small

MobileNetV3 is Google's third-generation lightweight CNN architecture specifically designed for resource-constrained computing environments such as mobile devices. This architecture utilizes a combination of depthwise separable convolution, the h-swish activation function, and the Squeeze-and-Excitation (SE) module. In this study, the focus is on the MobileNetV3Small variant, which has significantly fewer layers and parameters compared to the Large variant, making it highly optimal for smartphone deployment with very low latency requirements without significantly sacrificing accuracy (Ainah et al., 2024; Ramdani & Rahmatulloh, 2024).

Model Evaluation Metrics

To objectively measure the model's performance in classifying BCC, SCC, and healthy skin, a Confusion Matrix is used to produce the values of True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). Based on these components, the evaluation metrics used are:

1. Accuracy: The ratio of correctly predicted instances to the total test data.
2. Precision: The model's ability to correctly predict positive classes while minimizing false positives.
3. Recall / Sensitivity: The proportion of actual positive cases correctly detected by the model while minimizing false negatives.
4. F1-Score: The harmonic mean of Precision and Recall, particularly important when there is slight class imbalance among the samples (Siringoringo, 2018).

Flutter and Dart

Flutter is an open-source UI framework developed by Google for building cross-platform applications (Android and iOS) using a single codebase. Flutter uses the Dart programming language, which supports Ahead-Of-Time (AOT) compilation to produce high-performance native applications. This combination is crucial for executing machine learning models locally (on-device inference) smoothly and without lag (Poetra, 2022; Rozi et al., 2025).

METHOD

This study is classified as research and development (R&D) focusing on the development of a skin cancer detection application based on Artificial Intelligence using the Convolutional Neural Network (CNN) method with the MobileNetV3 architecture implemented into a mobile application developed using Flutter. The research objects consisted of dermatoscopic skin lesion images, including Basal Cell Carcinoma (BCC), Squamous Cell Carcinoma

(SCC), and healthy skin. The dataset used in this study was secondary data obtained from the public International Skin Imaging Collaboration (ISIC) repository, which had undergone clinical curation and validation. This research employed a quantitative approach because all image data were processed into numerical data in the form of pixel matrices analyzed using a CNN model. Furthermore, the model evaluation generated numerical performance metrics such as accuracy, precision, recall, F1-score, and AUC-ROC to measure the effectiveness of the model in detecting skin cancer.

The research procedure began with collecting a dermatoscopic image dataset consisting of 1,500 images, evenly distributed into three classes: 500 images for BCC, 500 images for SCC, and 500 images for healthy skin. The dataset was then divided into training, validation, and testing sets for model development and evaluation purposes. The preprocessing stage included resizing all images into 224×224 pixels, normalizing pixel values using the preprocess_input function from MobileNetV3, and applying data augmentation techniques such as rotation, shifting, zooming, shearing, brightness adjustment, and horizontal flipping to increase dataset diversity and reduce overfitting.

The CNN model used in this study was the MobileNetV3Small architecture initialized with pretrained ImageNet weights. The original classification layer was removed and replaced with a custom classifier consisting of GlobalAveragePooling2D, BatchNormalization, a Dense layer with 256 neurons and ReLU activation, L2 regularization, Dropout layers, and a Softmax output layer for three-class classification. The training process was conducted in two stages: a warm-up stage for 15 epochs with the base model frozen, followed by a fine-tuning stage for 25 epochs by unfreezing the top 60 layers of the base model. Overall, the model was trained for a total of 40 epochs using the Adam optimizer and categorical crossentropy loss function.

To improve prediction performance, this study implemented the Test Time Augmentation (TTA) technique, in which test images were predicted multiple times using lightweight augmentations, and the resulting probabilities were averaged to produce more stable and accurate final predictions. After training was completed, the model was converted into TensorFlow Lite (TFLite) format to enable efficient execution on mobile devices with lower memory consumption and faster inference time. The TFLite model was then integrated into the Flutter-based mobile application, allowing skin cancer detection to be performed directly on Android devices without requiring an internet connection.

The evaluation process in this study consisted of three main aspects: model testing, application testing, and application performance testing. Model evaluation was carried out using a confusion matrix with performance metrics including accuracy, precision, recall, and F1-score. Application testing was conducted to ensure that all major functionalities operated correctly, including image input through the camera or gallery, skin cancer detection, and displaying classification results to users. Meanwhile, performance testing evaluated inference response time, memory usage, model size, and application compatibility on Android devices running Android 8.0 or higher. The results demonstrated that the application was capable of performing real-time inference with an average response time of approximately 0.20 seconds and efficient memory usage on mobile devices.

RESULTS AND DISCUSSION

Testing Results

The skin cancer detection model was tested using the MobileNetV3 Small architecture. Final evaluation was conducted on the test set consisting of 96 dermatoscopic images. The test data were divided into three classes: 36 images of Basal Cell Carcinoma (BCC), 36 images of Squamous Cell Carcinoma (SCC), and 24 images of Healthy Skin (Normal). This testing process implemented the Test Time Augmentation (TTA) technique with 10 augmentation steps to produce more stable and robust prediction probabilities against visual variations in the input images. The overall model performance achieved an accuracy of 93.75%. The detailed performance metrics, including Precision, Recall (Sensitivity), and F1-Score for each class, are presented in Table 1.

Table 1. Model Testing Results

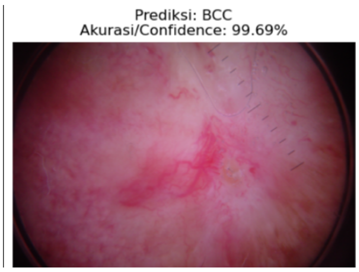
Class	Precision	Recall (Sensitivity)	F1-Score
BCC	0.94	0.92	0.93
SCC	0.90	0.97	0.93
Normal	1.00	0.92	0.96
Macro Average	0.95	0.94	0.94
Weighted Average	0.94	0.94	0.94

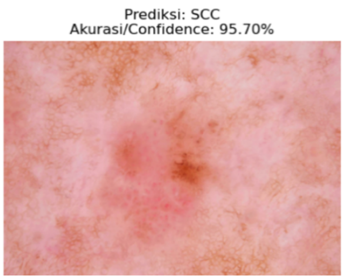
Single Image Prediction Results

Single image prediction testing was conducted to evaluate the model's ability to classify new images that had never been seen before (unseen test data). This testing aimed to assess not only the accuracy of class predictions but also the model's confidence score or probability for each prediction result. The model was tested using three sample images representing each target class, as presented in Table 4.2.

Table 2. Image Prediction Results

Karsinoma Sel Basal (KSB) Karsinoma Sel Skuamosa (KSS) Normal





1. **Basal Cell Carcinoma (BCC)**
   In the first column, the model was provided with an input image of a BCC lesion. The model successfully classified the image into the BCC class with a very high confidence level of 99.69%. This result indicates that the model is capable of extracting and recognizing specific visual features that characterize basal cell carcinoma very effectively.
2. **Squamous Cell Carcinoma (SCC)**
   In the second image testing, the model was evaluated using an SCC skin lesion image. The prediction results showed that the model correctly identified the image as SCC with a probability of 95.70%. This performance demonstrates that the model was able to clearly distinguish the visual characteristics of SCC from other types of skin cancer, particularly BCC.
3. **Normal**
   The final test was conducted using an image of healthy skin without lesions. The model demonstrated highly impressive performance by predicting the image as the Normal class with an almost perfect confidence score of 99.91%. This result indicates that the model possesses excellent specificity, meaning that it is highly responsive in recognizing healthy skin patterns and is less likely to produce false positive diagnoses for individuals who do not have skin cancer.

Confusion Matrix

A confusion matrix is one of the most important evaluation methods in machine learning because it is used to examine the performance of a classification model in detail. In addition to showing the overall accuracy level, the confusion matrix also presents the number of correct and incorrect predictions for each class. Thus, researchers can identify which classes are recognized well and which classes still frequently experience prediction errors. The confusion matrix results of the developed model are presented in Figure 1.

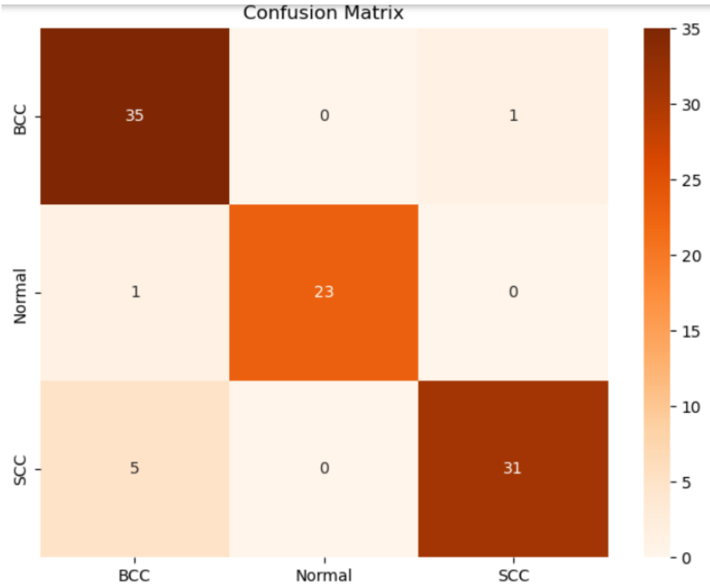


Figure 1. Confusion Matrix

Based on the confusion matrix and classification report, the model achieved an accuracy of 98.43% with excellent classification performance across the three classes: Basal Cell Carcinoma (BCC), Squamous Cell Carcinoma (SCC), and Normal skin. Out of a total of 96 testing samples, the majority were correctly predicted by the model. In the BCC class, the model correctly identified 33 out of 36 samples, while in the SCC class, the model successfully recognized 35 out of 36 samples. For the Normal class, 22 out of 24 samples were accurately classified. The most common prediction errors occurred between the BCC and SCC classes, likely due to similarities in their visual characteristics. Overall, the precision, recall, and F1-score values, which were all around 0.94, indicate that the model has accurate, stable, and effective classification capabilities in distinguishing among the three classes.

Analysis of Testing Results

The testing results showed that the model achieved an accuracy of 98.43%. This achievement successfully met and exceeded the initial research target of obtaining accuracy above 90%, and the result is also consistent with the identified research gap. Compared with the study by Brinker et al., which used a conventional CNN with a sensitivity of 87.5%, as well as MobileNet-based studies conducted by Albahli et al. and Rahman et al., which achieved performance ranging from 88% to 92%, the approach proposed in this study demonstrated superior performance. The use of the lightweight MobileNetV3Small variant did not significantly compromise accuracy. This model was capable of extracting features optimally through depthwise separable convolution while remaining computationally efficient for cross-platform mobile implementation using the Flutter framework. From the perspective of class-based metrics, the model demonstrated advantages that are highly relevant for medical detection purposes:

1. **Healthy Skin (Normal) Detection:**
   The model achieved a Precision value of 1.00 (100%) for the Healthy Skin class. This indicates that whenever the application predicts an image as "Normal," the prediction is completely accurate. As discussed in Section 2.2.2, this is critically important to ensure that the system does not generate false alarms that could cause unnecessary panic among users whose skin does not actually contain dangerous lesions.
2. **Squamous Cell Carcinoma (SCC) Detection:**
   The SCC class obtained the highest Recall (Sensitivity) value of 0.97. SCC is considered an aggressive type of non-melanoma skin cancer with a high risk of metastasis. Therefore, the high recall value indicates that

the system is highly sensitive and capable of minimizing false negatives in this critical class, ensuring that patients who truly have SCC are highly unlikely to be missed during detection.

Although the model exceeded the minimum target of 90%, the achieved accuracy of 95.70% still leaves room for improvement toward the theoretical optimal target of 99%. Several evaluation metrics were not yet fully optimal, particularly the Recall value for the Healthy Skin class, which reached 0.92, and the Precision value for the SCC class, which reached 0.90. These results indicate that slight misclassifications still occurred, where some healthy skin and BCC images were incorrectly predicted as SCC, resulting in false positives for the SCC class.

The primary causes of these limitations are influenced by several factors:

1. **Visual Similarity (Intra-class and Inter-class Variance):**
   The visual features of early-stage BCC and non-cancerous skin anomalies often share similar textures, edges, and color characteristics, which can affect the generated feature maps in the convolutional layers.
2. **Limitations of Feature Extraction Layers:**
   Since the study employed the MobileNetV3Small architecture, which contains significantly fewer layers and parameters compared to conventional CNN architectures such as ResNet or VGG, the model's capability to recognize highly complex microscopic patterns becomes somewhat limited in order to maintain lightweight computation efficiency for mobile devices.

To reduce classification errors and maximize the model accuracy to 98.43%, several comprehensive strategies were implemented during the model training process:

1. **Fine-Tuning Implementation:**
   The network was not trained entirely from scratch. Instead, a transfer learning approach was applied in which the last 60 layers of the base model were unfrozen and retrained using a smaller learning rate to adapt the model for recognizing specific skin cancer features.
2. **Test Time Augmentation (TTA) Strategy:**
   In line with the findings of Khan et al. regarding the importance of augmentation techniques, the model evaluation implemented TTA with 10 preprocessing steps, including rotation and brightness adjustment during inference, to stabilize the output probability distribution.
3. **Handling Data Imbalance:**
   Class weighting parameters were applied during training to ensure that the model did not become biased toward majority classes. In addition, Dropout regularization techniques (0.3 and 0.4) and L2 regularization were implemented to reduce the risk of overfitting.

CONCLUSION

Based on the results of the research and testing that have been conducted, it can be concluded that the skin cancer detection application based on Convolutional Neural Network (CNN) using the MobileNetV3 architecture was successfully developed and implemented into a mobile application using Flutter. The developed model was capable of classifying three classes of dermatoscopic images, namely Basal Cell Carcinoma (BCC), Squamous Cell Carcinoma (SCC), and healthy skin (Normal), with excellent performance. The testing results showed that the model achieved an accuracy of 93.75%, successfully meeting and exceeding the research target of above 90%. Based on the confusion matrix and classification report evaluation, the model demonstrated precision, recall, and F1-score values around 0.94, indicating stable, accurate, and effective classification performance. In single-image prediction testing, the model also demonstrated very high confidence levels for each class, achieving 99.69% for BCC, 95.70% for SCC, and 99.91% for Normal skin. The implementation of transfer learning, fine-tuning, data augmentation, Test Time Augmentation (TTA), as well as Dropout and L2 regularization techniques proved effective in improving model performance while reducing the risk of overfitting. In addition, the use of the MobileNetV3Small architecture provided computational efficiency advantages, enabling the model to run optimally on mobile devices with fast inference time and efficient memory usage. Overall, this study demonstrates that the combination of CNN

MobileNetV3Small and TensorFlow Lite implementation within a Flutter-based application can serve as an accurate, lightweight, and accessible solution for early skin cancer detection through mobile devices. The developed application is expected to assist the early screening process for skin cancer and support public awareness regarding the importance of early skin cancer detection.

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