Journal of Information Systems Engineering and Management
2025, 10(40s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Melanoma Skin Cancer Detection Application using Convolutional Neural Network (CNN)

Arvin Anthony S. Araneta
College of Engineering, Eastern Samar State University – Salcedo Campus, Philippines

ARTICLE INFO

Received: 30 Dec 2024

Revised: 12 Feb 2025

Accepted: 26 Feb 2025

ABSTRACT

Introduction: The skin, the body's largest organ, protects against external threats, notably harmful ultraviolet (UV) radiation, excessive exposure to which can cause melanoma, a potentially fatal skin cancer.

Objectives: This study developed a melanoma detection model by training a machine learning algorithm on a Kaggle image dataset, assessing its accuracy, and then integrating it into a mobile app for user-friendly skin image analysis.

Methods: This study developed a deep Convolutional Neural Network (CNN) to accurately detect melanoma in dermoscopic images with 5,000 classified as benign and 4,605 as malignant. The model's performance was evaluated on an independent test set of 1,000 images, equally distributed between benign and malignant classes.

Results: The result shows that training and validation accuracy improved over 20 epochs (starting at 0.6472 and 0.8409, respectively, and reaching over 0.90, converging to 0.9044 and 0.9096), while training and validation loss decreased (from 0.6548 and 0.4521 to 0.2235 and 0.2806), respectively.

Conclusions: A trained machine learning model was optimized for mobile deployment by converting it to TensorFlow Lite and then integrated into an Android application developed with Android Studio. This study demonstrates a reliable model for melanoma prediction, successfully implemented in a mobile application for improved early diagnosis. Future work should focus on enhancing the model's performance through expanded datasets and alternative algorithms.

Keywords: Melanoma, CNN, Image Recognition, Mobile Application.

INTRODUCTION

The skin, our body's largest organ, is a vital interface between ourselves and the environment, acting as a dynamic shield against external threats [1]. Beyond its role in temperature regulation and sensory perception [2], it provides a crucial defense against harmful ultraviolet (UV) radiation from the sun, particularly relevant for populations with prolonged sun exposure. Specialized cells, melanocytes, produce melanin, a pigment that absorbs UV radiation, offering a natural form of photoprotection [3]. While essential for vitamin D synthesis, excessive sun exposure can lead to significant health risks, including the development of melanoma, a potentially fatal form of skin cancer [4]. This risk is especially significant in people who have jobs with much outdoor activity, like fisherfolk, who are often exposed to intense sunlight.

Melanoma begins when melanocytes experience changes in their DNA. DNA directs healthy cells when to grow, divide, and die. In cancer cells, these changes indicate fast growth and endurance, enabling them to flourish as healthy cells perish. This results in extra cells, leading to melanoma. [5]. Studies conducted show that the primary factor for melanoma includes the exposure to ultraviolet radiation (UVR), either from sunlight or artificial tanning devices. This harmful impacts play a role in the development of melanoma [6]. Any pigmented spot that exhibits characteristics outlined in the “ABCDE” mnemonic should be regarded as questionable for melanoma. The ABCDE system encompasses Asymmetry, Border irregularity, Color variation, Diameter exceeding 6 mm, and Evolution or progression of the lesion's growth [7]. From a patient-centered perspective, the timely identification of these changes

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is paramount, as early diagnosis directly correlates with improved therapeutic efficacy and enhanced survival rates [8].

In the Philippines, merely 1275 board-certified dermatologists cater to a population of 109 million Filipinos. Over 50% of these dermatologists are located in the capital, while a region in the Southern Philippines has just 1 dermatologist for 4 million residents. Therefore, for numerous Filipinos, the initial point of contact is the community health center, where misdiagnosis frequently occurs due to the relative scarcity and limited experience in evaluating suspicious lesions. [9]. Each year, a considerable number are identified with skin cancer in the Philippines, a condition that can impact people from different ethnic backgrounds, such as Caucasians, Mestizas, Chinese-Filipinos, and Filipinos with darker skin. Individuals with fair skin are especially susceptible to skin cancer or melanoma in the Philippines because they have less defense against harmful UV radiation from the sun. Individuals who often participate in outdoor pursuits such as golfing, visiting beaches, playing sports, flying, working in fields, farming, and selling are at a higher risk for skin cancer [10].

Detecting melanoma at an early stage is incredibly important. Detecting it earlier results in less intrusive surgery, reduced adverse effects from treatments, and a significantly decreased likelihood of enduring health issues. Crucially, it significantly enhances the chances of survival [11]. Plus, treating melanoma in its early stages is much more cost-effective for healthcare systems, as simple procedures like removing the affected area are often all that's needed.

Diagnostic tools like total body photography and dermoscopy enhance a clinician's capability to identify melanoma beyond just visual assessment, and are now regarded as standard techniques for early detection. New technologies like in vivo reflectance confocal microscopy are being studied to assess their effectiveness for noninvasive melanoma diagnosis. [12].

Deep Learning algorithms are crafted to replicate the workings of the human cerebral cortex. These algorithms are forms of deep neural networks, meaning neural networks that have several hidden layers. Convolutional neural networks are deep learning models capable of training on extensive datasets containing millions of parameters, using 2D images as input and applying filters to generate the expected results [13]. Medical image classification is crucial for clinical treatment and educational purposes. Nonetheless, conventional methods have hit their peak in performance. Additionally, utilizing them requires significant time and effort for the extraction and selection of classification features. The deep neural network is a developing machine learning approach that has demonstrated its capability for various classification tasks. Significantly, the convolutional neural network excels by achieving the top outcomes on diverse image classification tasks [14].

From the foregoing, this study aims to create a melanoma detection application that will translate a diagnostic capability into a readily accessible mobile application. The developed application will serve a preliminary assessment by employing deep learning algorithms to analyze fisherfolks' skin images. A classification model will now distinguish between benign and malignant lesions. It also aims to facilitate timely medical consultation and improve health outcomes. This advancement in initial skin lesion evaluation offers substantial promise for closing healthcare disparities in remote locations such as Salcedo, Eastern Visayas, Philippines, where there's restricted access to dermatology experts. In these communities, where prompt identification is crucial for effective treatment and better survival rates, this accessible technology can enable healthcare professionals and individuals to make educated choices about timely medical care. By detecting potentially cancerous lesions at an early stage, we seek to greatly enhance melanoma results and foster better health equity among these at-risk groups.

METHODS

This study details the development and testing of an model tool for melanoma skin cancer detection. It covers the preparation of images from Kaggle, training the model for pattern recognition, accuracy measurement, and reliability assessments. Finally, it explains how this trained model was integrated into a user-friendly mobile application for real-world skin image analysis.

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2.1 Study Design

To build our melanoma skin cancer detector, Python was used to create a deep-learning system, a Convolutional Neural Network (CNN), which acts like a digital detective for skin images. The CNN first looks for simple patterns such as lines and edges, and then gradually learns to recognize more complex features that indicate melanoma. It produces a visual representation, layer by layer, until it can differentiate between healthy skin and potentially melanoma spots. Ultimately, the system makes a clear decision, classifying each image as either benign or malignant, enabling it to accurately separate healthy skin from melanoma lesions.

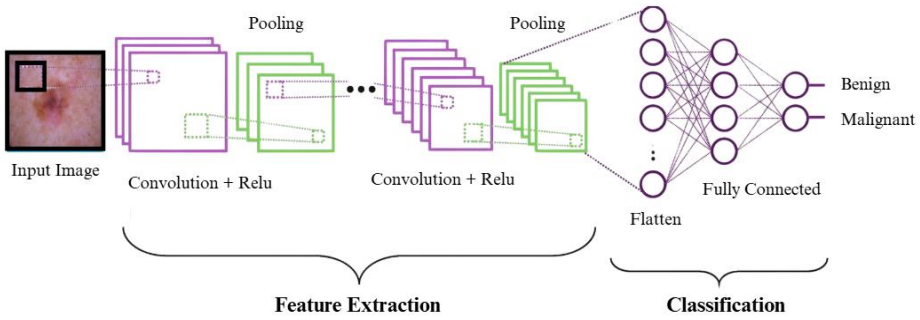

Figure 1. Convolutional Neural Network (CNN) Architecture

2.2 Data Collection

The dataset that was used to train and test the model for melanoma cancer detector is from Kaggle [15]. It contains 9,605 pictures as presented in Figure 2, and is labeled as either benign or malignant. To ensure that the model will accurately identify skin cancer, a separate group of 1,000 images is evenly grouped between benign and malignant examples. This setup was essential to rigorously test how well the model could generalize and perform in real-world scenarios.

Fig. 2. Distribution of Sample in the Training Data Set

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The categorization of training sample images shown in Figures 3 as benign and Figure 4 as malignant followed recognized dermatological diagnostic standards. In addition to the offline dataset evaluation, real-time testing of the developed application will utilize actual images sourced from fisherfolk, the focus group of the study, to evaluate its performance in a practical environment.

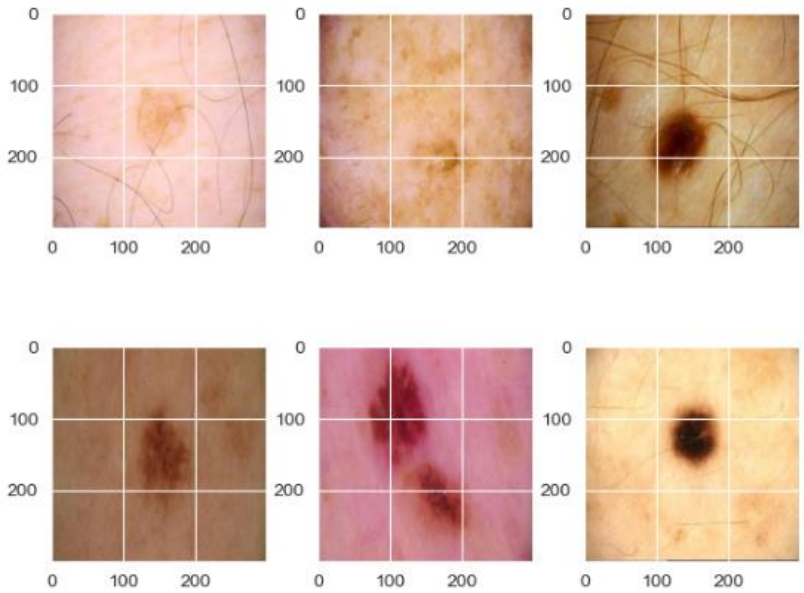

Fig. 3. Sample Image for Benign Classification

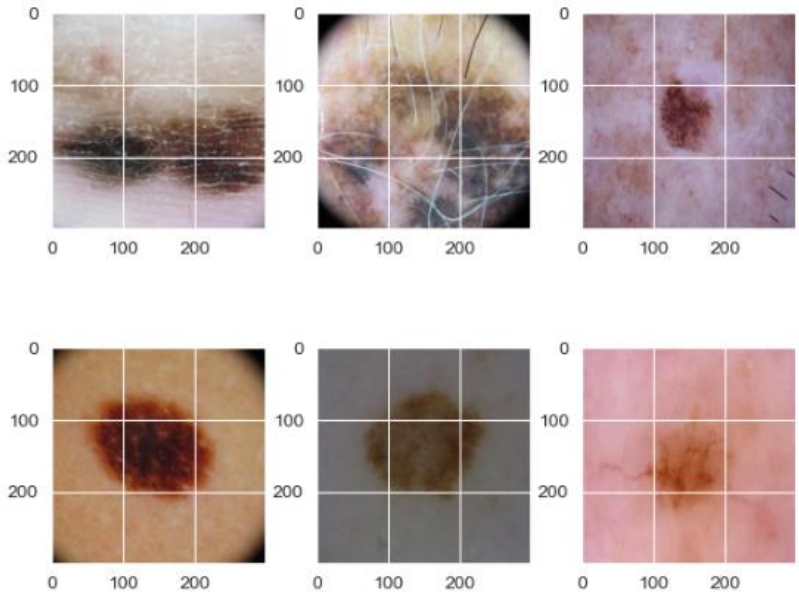

Figure 4. Sample Image for Malignant Classification

2.3 Conceptual Framework

The conceptual framework of the study presents a direct route from image acquisition to melanoma classification for fisherfolk. The process starts by capturing high-resolution skin images using the mobile camera feature of the created application. The captured image will act as the primary input. Following this, the inputs are analyzed by an advanced

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melanoma skin cancer classification model that utilizes the capabilities of convolutional neural networks (CNNs). The CNN examines the intricate visual information of the image, identifying possible melanoma signs. Ultimately, the application displays the classification findings in an easy-to-understand format, outlining the detected features and the probability of melanoma existence, as illustrated in Figure 5. This framework creates an efficient, mobile-oriented method for initial melanoma skin cancer evaluation.

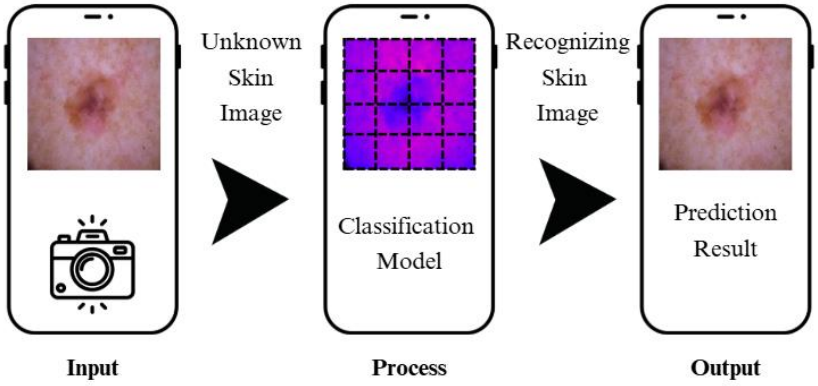

Figure 5. Conceptual Framework of the Melanoma Skin Cancer Classification Application

2.4 Model Training

The convolutional neural network (CNN) processes input images through a series of sequential layers, designed to extract hierarchical features. Initially, convolutional layers employ learnable filters (kernels) that slide across the input tensor, performing element-wise multiplications and summations to generate feature maps. These maps are subsequently passed through a rectified linear activation function (ReLU), which introduces non-linearity by setting negative values to zero, thereby accelerating learning and enhancing feature representation. Max pooling layers, specifically utilizing a 2x2 filter and stride of 2, then perform downsampling, reducing the spatial dimensions of the feature maps and decreasing computational complexity. This repetitive process of convolution, ReLU activation, and pooling continues, gradually extracting features from lower to higher-level representations. The generated layers are subsequently transformed into a one-dimensional vector and input into fully connected (dense) layers. In training the model to accurately identify skin cancer, a technique known as backpropagation was employed. Subsequently, to reach a definitive decision, the softmax function was applied. This function provides a probability score for every image, showing the likelihood of it being benign or malignant.

To evaluate the effectiveness of the model, it was assessed with a different collection of skin images it had not encountered previously. Standard metrics such as accuracy, precision, and recall were computed to assess the model's diagnostic effectiveness. From the accurately and inaccurately recognized images, these scores provided us with a comprehensive view of how dependable our AI was in differentiating between healthy skin and possible melanoma.

RESULTS

3.1 CNN Model for Melanoma Image Classification

Figure 6 shows the summary of model layers. It starts with taking a close-up picture of a mole and breaking it down into basic patterns like lines and edges using 'conv2d_8'. To prevent the model from memorizing details instead of truly understanding them, the use 'dropout_8' was initiated, randomly turning off parts of the model during training. This keeps it flexible and prevents it from relying on just a few specific features. Then, 'max_pooling2d_8' shrinks the image, focusing on the most important parts, like summarizing the key elements of a sketch.

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The model then deepens its understanding, adding more detail with 'conv2d_9', 'conv2d_10', and 'conv2d_11'. It adds layers of shading and texture, gradually recognizing more complex shapes and patterns that might indicate melanoma. Each layer builds upon the previous one, refining the image and extracting more abstract features, moving from simple edges to complex shapes and textures.

Throughout this process, 'dropout' was used to keep the model focused and 'max pooling' to simplify the image and keep the focus on the most important details. This step-by-step approach allows our model to learn the subtle differences between healthy skin and potentially cancerous spots, helping it to accurately identify melanoma.

Layer (type)	Output Shape	Param #
conv2d_8 (Conv2D)	(None, 222, 222, 32)	896
dropout_8 (Dropout)	(None, 222, 222, 32)	0
max_pooling2d_8 (MaxPooling2D)	(None, 111, 111, 32)	0
conv2d_9 (Conv2D)	(None, 109, 109, 64)	18,496
dropout_9 (Dropout)	(None, 109, 109, 64)	0
max_pooling2d_9 (MaxPooling2D)	(None, 54, 54, 64)	0
conv2d_10 (Conv2D)	(None, 52, 52, 128)	73,856
dropout_10 (Dropout)	(None, 52, 52, 128)	0
max_pooling2d_10 (MaxPooling2D)	(None, 26, 26, 128)	0
conv2d_11 (Conv2D)	(None, 24, 24, 256)	295,168
dropout_11 (Dropout)	(None, 24, 24, 256)	0
max_pooling2d_11 (MaxPooling2D)	(None, 12, 12, 256)	0
flatten_3 (Flatten)	(None, 36864)	0
dense_6 (Dense)	(None, 512)	18,874,880
dense_7 (Dense)	(None, 2)	1,026

Total params: 19,264,322 (73.49 MB)
Trainable params: 19,264,322 (73.49 MB)
Non-trainable params: 0 (0.00 B)

Figure 6. Summary of Model Layers

Once the model has carefully analyzed the skin image, breaking it down into its key features, we must prepare those features for the final decision-making step. Flattening using 'flatten_3' comes in where the different pieces of information the model has gathered are laid out in a single, organized line. This converts the complex, multi-layered information into a simple, straightforward list, making it easier for the model to make its final assessment. This flattening operation prepares the learned feature representations to be fed into the fully connected dense layers for the classification task. The dense_6 layer is a fully connected layer with a substantial number of parameters (18,874,880). This layer functions as a powerful classifier, capable of learning complex, non-linear relationships between the extracted features and the target classes. The sheer number of parameters in this layer signifies its ability to model intricate decision boundaries, but it also highlights the potential for overfitting. Therefore, effective regularization techniques, such as dropout, are essential during training.

The final layer, dense_7, is the output layer of the network. It consists of only two units, indicating that this CNN is designed for a binary classification problem – specifically, the classification of images into two categories: melanoma and non-melanoma. The output of this layer represents the model's predicted probabilities for each class. The class with the higher probability is the model's prediction. The total number of trainable parameters in this network, 19,264,322, underscores the model's complexity. Such a large model can potentially achieve high accuracy in melanoma detection, but it necessitates a large and diverse dataset for training to ensure good generalization and prevent overfitting. Careful selection of hyperparameters, effective regularization techniques, and rigorous validation are crucial for deploying this model effectively in a clinical setting.

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3.2 Model Accuracy

Figure 7 illustrates a model's performance in classifying melanoma skin cancer images across 20 epochs. The graph demonstrates a general upward trend in both training and validation accuracy. In the early epochs, training accuracy (green line) starts relatively low but exhibits rapid growth, suggesting efficient learning from the training data. Validation accuracy (blue line) also shows improvement, reflecting the model's capacity to generalize to unseen data and perform effectively on the validation set.

Accuracy is calculated as the proportion of correctly classified images within a set. Training and validation accuracy are computed by dividing the number of correctly classified images by the total number of images in the training and validation sets [16].

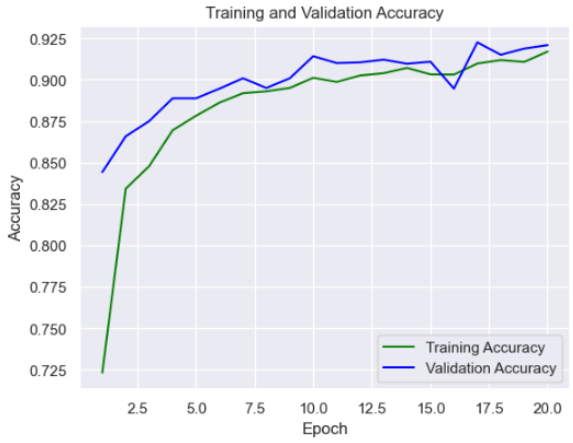

Figure 7. Training and Validation Accuracy Plot of CNN Model

The result of the training was further validated by its performance. In its first epoch, it started by correctly identifying about 65% of the training images, but surprisingly, it did much better on the test images, getting about 84% right. Over time, it kept improving, getting over 90% of the images right in both the training and test sets by the end. This shows it was learning the key patterns. However, it had a few stumbles along the way, with some minor dips in its test scores. By the final epoch, it performs very well, correctly classifying over 90% of both the training and test images. Its performance was similar on both sets, which means it didn't just memorize the training examples; it recognizes melanoma, proving it can generalize well to new, unseen images.

3.3 Model Loss

Figure 8 illustrates the model as it tackled the challenge of identifying melanoma in skin images. We tracked how 'wrong' the model was during training—its loss—over 20 learning cycles, or epochs. Both the training loss and the validation loss generally decreased, showing that the model was steadily improving. At the start, the model was quite uncertain, leading to a higher training loss. However, it quickly grasped the patterns in the training data, resulting in a rapid drop in training loss. This signifies that the model was effectively learning to distinguish between healthy skin and melanoma. The validation loss also decreases, though with some fluctuations, indicating the model's ability to generalize to unseen data.

Categorical cross-entropy loss was used to quantify the difference between the model's predicted and true probability distributions for image classes (benign or malignant). Training loss was calculated on the training dataset to update model weights, while validation loss was calculated on the validation dataset to evaluate performance and monitor overfitting [17].

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Examining the training results, we see that the training loss starts at 0.6548 in the first epoch and decreases to 0.2235 by the final epoch. This consistent decrease in training loss confirms the model's learning progress. The validation loss, which starts at 0.4521, also generally decreases, reaching 0.2806 at the end. However, there are notable fluctuations, such as a sharp increase in epoch 3 (0.4982) and epoch 16 (0.3889), which might indicate overfitting or instability during those epochs. The overall decreasing trend in both training and validation loss, along with the convergence of these values towards the end, suggests that the model has effectively learned the underlying patterns in the data and is generalizing well without significant overfitting, despite the observed fluctuations. The fluctuations in validation loss warrant further investigation to ensure model stability and robustness.

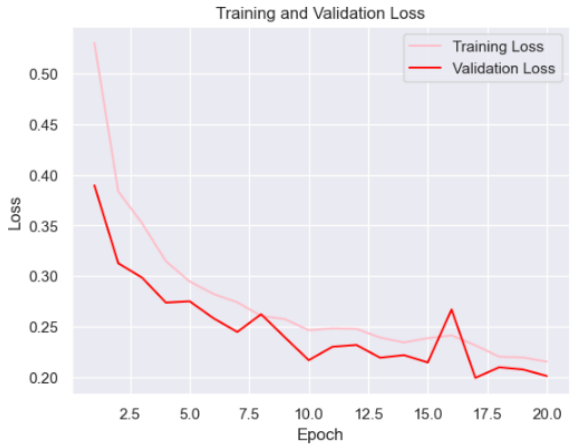

Figure 8. Training and Validation Loss Plot of CNN Model

3.4 Model Performance

Figure 8 presents the confusion matrix which demonstrates the model's performance in classifying "Benign" and "Malignant" cases. While the model shows strong accuracy, with 1167 True Negatives (93% of benign) and 1044 True Positives (91% of malignant), it also reveals notable error rates. Specifically, 83 False Positives (7% of benign) and 107 False Negatives (9% of malignant) suggest areas for improvement, particularly in minimizing missed malignant diagnoses.

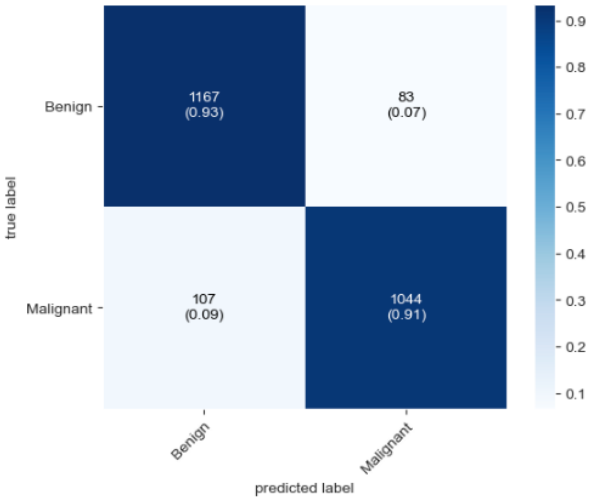

Figure 8. Confusion Matrix for Benign/Malignant Classification

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e-ISSN: 2468-4376
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The performance of the model was evaluated using a confusion matrix, yielding several key metrics. The accuracy, representing the overall correctness of the model, was calculated as (TP + TN) / Total, resulting in 92.08% based on the values of True Positives (TP), True Negatives (TN), and the total number of samples. Precision, which measures the proportion of correctly predicted positive cases out of all predicted positive cases, was determined to be 91.60% using the formula TP / (TP + FP), where FP represents False Positives. The recall, also known as sensitivity, indicating the proportion of correctly predicted positive cases out of all actual positive cases, was found to be 93.36%, calculated as TP / (TP + FN), where FN represents False Negatives. Finally, the F1-score, a harmonic mean of precision and recall, providing a balanced measure of the model's performance, was calculated as 92.47% using the formula 2 * (Precision * Recall) / (Precision + Recall).

3.5 Mobile Application Interface

The model for melanoma spectrum learning sessions commenced with training a sophisticated Convolutional Neural Network on a popular data set of skin lesion images by using heavy tools like Python and TensorFlow and separating malignant lesions from benign ones with high accuracy. Then, the trained model was converted into a smaller and more efficient one using TensorFlow Lite to make this technology available on mobile devices. The model was incorporated into an Android application created using Android Studio.

User interfaces for the application were designed to be simple and easy to follow, as depicted in Figure 9. Users should be able to easily upload or capture images of skin lesions, which the model will then process for an initial assessment of melanoma risk. The application states that predictions made by the model are merely for support, emphasizing that it is not intended to replace any professional medical opinion. In the development process, user experience, data privacy, and ethics were considered. This includes the application of secure data handling and explanations of the application's clear and easy-to-understand results. Rigorous application testing and iterative refinement are integral to ensuring its accuracy, reliability, and usability. Ultimately, the application aims to assist users in gaining a preliminary insight into their skin health while facilitating timely consultations with health professionals.

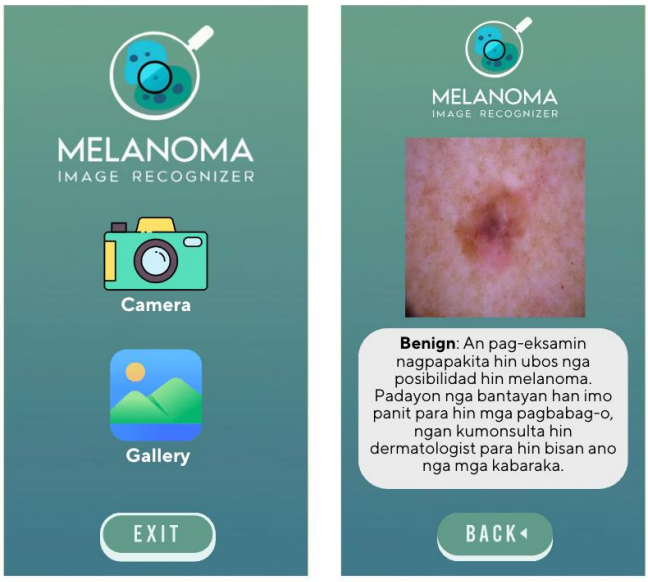

Figure 9. Graphical User Interface of the Developed Application

CONCLUSION AND RECOMMENDATION

This study successfully created a melanoma skin cancer detection model that was integrated into the developed mobile application. Through the use of CNN, the produced model achieved a training accuracy of 90.44%. Throughout the validation phase, the model reached an accuracy of 90.96% and had a loss value of 0.2806. The

findings suggest that the model exhibits strong reliability in predicting melanoma images. Additionally, the model's reliability was showcased through the utilization of the created application, which improves the early diagnosis and identification of melanoma skin cancer.

In the future, it is essential to enhance the model's performance by utilizing additional datasets of melanoma images and employing alternative algorithms for improved predictive outcomes.

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