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Research Article

ADVANCED SKIN CANCER DETECTION USING CONVOLUTIONAL NEURAL NETWORKS AND TRANSFER LEARNING

Emrah ASLAN *[*1], ***Yıldırım ÖZÜPAK*** [2]

[1]Silvan Vocational School, Dicle University, Diyarbakır, Turkey
[2]Silvan Vocational School, Dicle University, Diyarbakır, Turkey
[*]Corresponding author: emrah.aslan@dicle.edu.tr

Abstract: *This study investigates the effectiveness of MobileNetV2 transfer learning method and a deep learning based Convolutional Neural Network (CNN) model in the categorization of malignant and benign skin lesions in skin cancer diagnosis. Since skin cancer is a disease that can be cured with early detection but can be fatal if delayed, accurate diagnosis is of great importance. The model was trained with MobileNetV2 architecture and performed the classification task with high accuracy on images of skin lesions. Metrics such as accuracy, recall, precision and F1 score obtained during the training and validation processes support the high performance of the model. The accuracy of the model was 92.97%, Recall 92.71%, Precision 94.70% and F1 score 93.47%. The results show that the CNN-based MobileNetV2 model is a reliable and effective tool for skin cancer diagnosis, but small fluctuations in the validation phase require further data and hyperparameter optimization to further improve the generalization ability of the model. This study demonstrates that CNN-based models enhanced with MobileNetV2 transfer learning offer a powerful solution to medical image classification problems and have the potential to contribute to the development of early detection systems in the healthcare field.*

Keywords*: Skin cancer, CNN, Transfer learning, Classification, MobileNetV2*

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1. Introduction

Skin cancer continues to be an important health problem in terms of both incidence and mortality rates worldwide. This disease, which develops under the influence of various environmental and genetic factors, can lead to fatal consequences if not diagnosed early. According to World Health Organization (WHO) statistics, millions of new cases of skin cancer are recorded each year. Skin cancer is mainly divided into two groups: benign lesions and malignant lesions. While benign lesions are usually not life-threatening, malignant lesions, especially aggressive types such as melanoma, can metastasize rapidly and can be fatal. However, the vast majority of skin cancer cases can be effectively treated and life expectancy significantly prolonged when detected early [1].

Traditional methods of skin cancer diagnosis are based on physical examinations by dermatologists and biopsy of suspicious lesions. Although biopsy is an accurate method, it is invasive and often time-consuming. Furthermore, its widespread use is impractical, especially in developing countries and areas with limited health resources. Furthermore, differences in assessment between dermatologists and the risk of human error can create significant variability in the diagnostic process. This clearly highlights the need for faster, cheaper and more objective technologies for skin cancer diagnosis [2].

The use of artificial intelligence and deep learning approaches in medical imaging has expedited efforts to build automated skin cancer diagnosis systems in recent years. Deep learning algorithms have attracted attention with their superior performance, especially in image processing and classification [3]. CNN stand out among deep learning methods and are used as a powerful tool for extracting complex features from medical images. Thanks to its layered structure, CNN can analyze data in detail, starting from low-level features to high-level abstractions. Thanks to these features, it is considered as a promising technology for solving medical problems such as skin cancer [4].

In this study, a CNN-based model is developed to classify benign and malignant skin lesions. The proposed model aims to distinguish between malignant and benign lesions with high accuracy by extracting detailed features from dermatologic images. An open access dermoscopic image dataset is used for training and evaluation of the model. In addition, data augmentation techniques were used to increase the generalization capacity of the model. The main goal of the study is to make skin cancer diagnosis faster and more reliable, as well as to strengthen the decision support processes of expert dermatologists by promoting the use of artificial intelligence in healthcare.

The use of automated systems in skin cancer diagnosis has the potential to increase access to healthcare, especially in low-resource areas. In this context, the proposed model aims to make a significant contribution to the existing literature in the field of dermatology. By evaluating the feasibility and effectiveness of AI-based methods in skin cancer diagnosis, the study provides results that can guide future research. The integration of technology in healthcare is critical for both improving patient outcomes and developing cost-effective solutions. Accordingly, the proposed work represents an innovative approach to skin cancer diagnosis.

2. Literature Review

Murugan et al. developed a computer vision-based system for skin cancer diagnosis. First, skin images were processed with median filter and segmented with Mean Shift segmentation. Features were extracted with GLCM, Moment Invariants and GLRLM methods, and then these features were classified with SVM, Probabilistic Neural Networks and Random Forest classifiers. The best results were obtained with SVM+RF, which is a combination of SVM and Random Forest [5]. Luu et al. proposed a hybrid framework consisting of Stokes-decomposition method and artificial intelligence models. Optical parameters were extracted from skin cancer samples and classification was performed with nine different artificial intelligence models. All models showed high accuracy. This framework provides an efficient and accurate approach for skin cancer classification [6]. Tembhurne et al. proposed a method that combines machine learning and deep learning techniques for skin cancer detection. The deep learning model uses neural networks to extract features from images, while the machine learning model processes these features. The proposed model achieved high accuracy for benign and malignant cancer types [7].

Monika et al. performed classification for early detection of skin cancer using machine learning and image processing methods. Dull razor, Gaussian and Median filters were applied on dermoscopic images and k-means clustering was performed for color analysis. ABCD and GLCM were used for feature extraction and high accuracy was achieved with multi-class SVM [8]. Osvin Nancy et al. evaluated machine learning and deep learning algorithms for early detection by studying the effect of UV rays on skin cancer. Random Forest achieved 58.57% accuracy and 87.32% accuracy with boosting. MobileNetv2 and combination models achieved 88.81% accuracy. The results show that these techniques are promising for clinical applications [9]. Mazhar et al. examined the role of machine learning in improving the diagnostic processes of dermatologists. The paper discusses the basics, limitations and concerns of ML-based applications for skin cancer detection. Deep learning applications are used for disease classification and measurement of skin diseases. In addition, the key elements

required for skin cancer detection and issues such as lesion tracking are emphasized [10]. Gomathi et al. proposed a double optimization based deep learning network (DODL net) for early detection of skin cancer. Dermoscopic images were collected from the MNIST HAM10000 dataset and noise was reduced with an adaptive median filter. After segmentation with U-Net, features were extracted with BFO and PSO and seven skin cancer classes were classified with CNN [11].

Ghosh et al. developed a hybrid model for early detection of skin cancer using deep learning methods with 3,000 images. Class weights were added and VGG16 and ResNet50 were combined to solve the overrepresentation problem. The results show that this model improves the classification performance [12]. Priyadharshini et al. propose a hybrid Extreme Learning Machine (ELM) and Teaching-Learning-Based Optimization (TLBO) algorithm for early detection of melanoma. ELM provides fast and accurate classification, while TLBO optimizes the network parameters. This method aims to improve melanoma detection accuracy by classifying skin lesions as benign or malignant [13]. Balaha and Hassan developed five U-Net models optimized by Sparow Search Algorithm (SpaSA) for early detection of skin cancer. The proposed method is compared with 13 related works [14]. Shah et al. developed automated techniques for early detection of skin cancer using Artificial Neural Networks (ANN) and CNN. The research demonstrates the success of these methods in efficiently detecting skin cancer, highlighting the potential for more effective diagnostic systems. These studies could have a significant impact on improving patient outcomes [15]. In their study, Pacal et al. aim to achieve more efficient and accurate results in skin cancer diagnosis by improving the Swin Transformer architecture. The new model provides faster training times, higher accuracy and better parameter efficiency compared to traditional methods, while outperforming previous deep learning models on the ISIC 2019 dataset [16].

3. Material and Method

CNNs are deep learning models known for their outstanding success in image recognition and classification. CNNs are particularly notable for their ability to extract and classify features from dermoscopic images, especially in the diagnosis and classification of dermatological diseases. CNNs learn low-level features (e.g., edge and texture patterns) from input images and transform these features into more complex and meaningful representations. In skin cancer diagnosis, CNN models can accurately distinguish between different skin conditions such as melanoma, basal cell carcinoma, and benign lesions, with performance comparable to expert dermatologists. This study aims to train CNN on a large dermoscopic dataset using transfer learning methods and to evaluate the performance of the model in terms of accuracy, sensitivity and specificity. In this context, the proposed approach aims to contribute to the development of a reliable and fast tool for automatic skin cancer diagnosis.

In this study, the dataset used for skin cancer diagnosis was obtained from Kaggle (https://www.kaggle.com/datasets/fanconic/skin-cancer-malignant-vs-benign/data), an open access resource. The dataset includes benign and malignant skin cancer types and healthy skin images. This diversity is intended to make the model perform more generally in real-world applications.

3.1. Dataset

The dataset used in this study (https://www.kaggle.com/datasets/fanconic/skin-cancer-malignant-vs-benign/data) contains a balanced set of images to classify benign and malignant skin lesions [17]. The dataset is organized into two separate folders, each containing 1800 images. The images are 224x224 pixels in size and high resolution and provide detailed visual information about benign and malignant skin lesions. The balanced structure of the dataset aims to ensure that the model is equally sensitive to both classes. This structure aims to increase the generalization capacity of the developed model by avoiding biases that may arise from class imbalances. This dataset provides a suitable basis

for the training and testing processes of artificial intelligence and deep learning-based algorithms used in skin cancer diagnosis. Some sample images in the dataset are given in Figure 1.

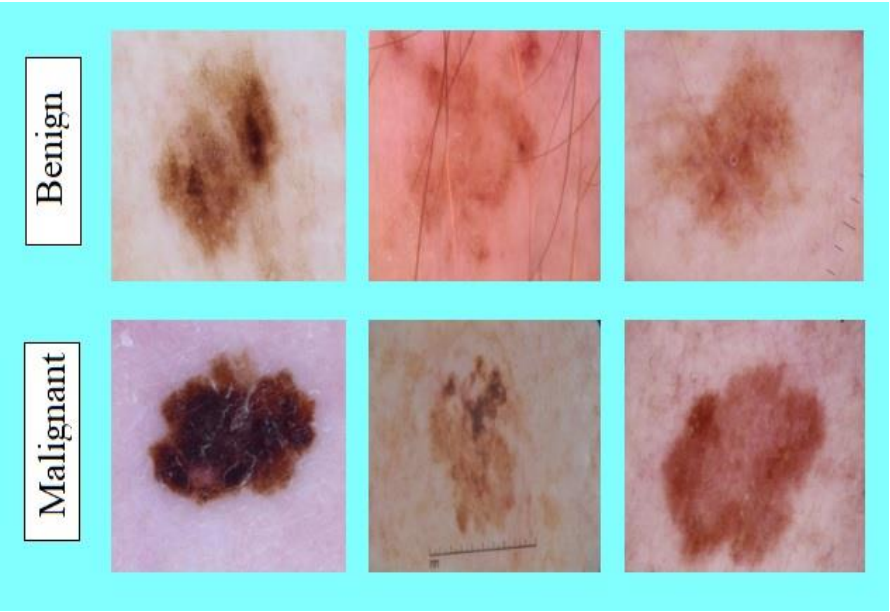

Figure 1. Some sample images from the dataset [17].

3.2. CNN Architecture

The architecture of the model is based on a CNN design optimized for skin cancer diagnosis. The model accepts RGB images of 224x224 pixels in the input layer and then passes through convolutional layers for feature extraction. In the first convolutional layer, 32 filters are used, and 64 and 128 filters are used in the subsequent layers, respectively [18, 19]. All convolutional layers include the ReLU activation function, while Max-Pooling of size 2x2 is applied after each layer to reduce the size of the feature maps. In order to prevent overlearning, the dropout technique was used and 25% of neurons were disabled in certain layers. After convolution, the feature maps were flattened and then transferred to a fully connected layer with 128 neurons. The final classification was carried out on an output layer using the Softmax activation function. For multi-class classification, the model was built employing a cross-entropy loss function and the Adam optimization algorithm, with accuracy serving as the evaluation metric [20, 21]. This architecture is designed to achieve high performance in the classification of skin cancer types by effectively extracting information from low-level features to abstract levels. The CNN structure used is presented in Figure 2.

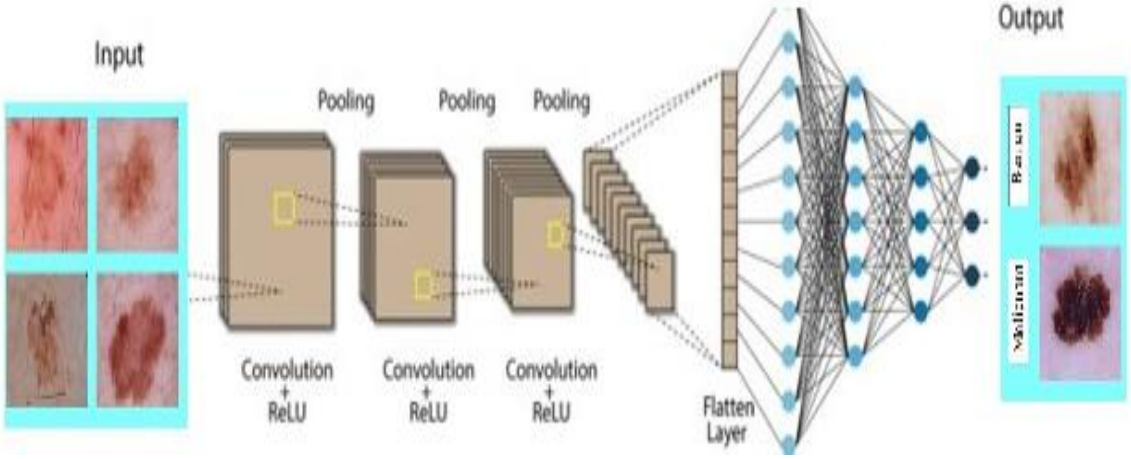

Figure 2. CNN architecture

3.3. Proposed Model

The model proposed in this paper for skin cancer classification is a MobileNetV2-based transfer learning approach that offers a lightweight and computationally efficient architecture. The MobileNetV2 model is a pre-trained deep learning model that can efficiently extract general features on limited datasets and is adapted to the classification task in this study. The input dimensions of the model are set to 160x160 to reduce the computational cost and to preserve the lightweight nature of the model.

In the proposed model, the generalization capability of the model is increased by using data augmentation methods. In the data augmentation phase, zoom, rotation, vertical shift, horizontal shift, and horizontal flip operations were applied on the images. These operations allowed to obtain more variation from a limited number of data sets and reduced the risk of overfitting the model. In the transfer learning process, the lower layers of the MobileNetV2 model (base model) were frozen and only the classifier part in the upper layers was retrained. In this part, a Global Average Pooling layer was added to the feature extractor part of the model, followed by a fully connected (dense) layer with 128 neurons and 40% Dropout to prevent overlearning. In the output layer, a single neuron with a sigmoid activation function was used for binary classification. During the training of the model, the learning rate was set as the learning rate and Binary Crossentropy was used as the loss function. Adam was chosen as the optimization algorithm due to its computational efficiency and fast convergence. Accuracy and validation accuracy metrics were used to measure the training and validation performance. In addition, the performance of the model was also evaluated with Training and Validation Loss (loss and val_loss).

In order to visualize and evaluate the model results, a graphical analysis of the accuracy and loss values was performed and the prediction performance of the model was detailed with a Confusion Matrix. These approaches provided an important tool to highlight the model's strengths and identify its shortcomings in the classification task. Despite its computationally lightweight nature, the proposed model was able to achieve high accuracy values and its performance on the dataset was found to be satisfactory. A visualization of the proposed model is given in Figure 3.

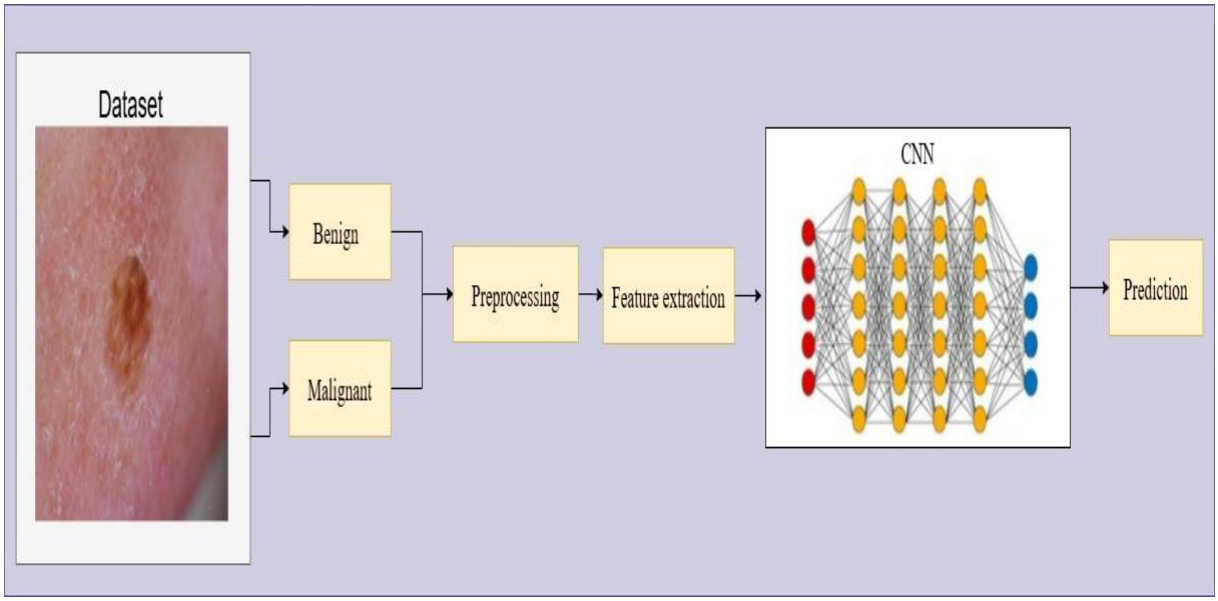

Figure 3. Architecture of the proposed model

3.4. Evaluation Metrics

In this study, the following metrics were used to evaluate the performance of the developed model:

Accuracy: It is a metric that assesses the model's overall success rate and is calculated as the ratio of correctly classified samples to total samples.

Precision: Measures the rate at which the model correctly predicts the positive class. It is particularly important for assessing the impact of false positives.

Recall or Detection Rate: Shows how much of the data belonging to the positive class can be correctly detected. It is a critical metric when false negatives are important. It is the harmonic mean showing the balance between precision and sensitivity. It is used to make a balanced assessment.

Confusion Matrix: Tabulates the model's true and false predictions for each class. This matrix provides a more detailed understanding of metrics such as accuracy, precision and sensitivity.

These metrics allow for a comprehensive analysis of both the model's classification success and its errors due to incorrect predictions. The results of the study are compared over different metrics to evaluate the generalization and classification success of the model [23]. The calculation equations for the metrics are given in (1) - (4). In the equation, TP stands for true positive, TN for true negative, FP for false positive and FN for false negative.

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

$$\text{Re}call = \frac{TN}{TP + FN} \quad (2)$$

$$\text{Pr}ecision = \frac{TP}{TP + FP} \quad (3)$$

$$\text{F1} = 2x\frac{\text{Pr}ecision\ x\ \text{Re}call}{\text{Pr}ecision + \text{Re}call} \quad (4)$$

4. Experimental Results

In this study, a deep learning-based CNN model was employed to conduct a thorough examination of skin cancer diagnosis. The model was highly accurate in classifying benign and malignant skin lesions and had a significant generalization capacity. In addition to analyzing the accuracy and loss values obtained in the training and validation phases, the classification performance of the model was measured using various evaluation metrics. In this context, metrics such as Accuracy, Recall, Precision and F1 score were calculated to evaluate the overall success and classification ability of the model. The results presented below clearly demonstrate the effectiveness of the model in skin cancer diagnosis.

Table 1. Performance metrics of the proposed model

Accuracy	Recall	Precision	F1 Score
0.9297	0.9271	0.9470	0.9347

Table 1 summarizes the accuracy, recall, precision and F1 score values of the proposed CNN model. The overall accuracy of the model was 92.97%, indicating that the model was able to correctly classify the majority of the data. Recall was 92.71%, reflecting the model's ability to correctly recognize malignant samples, while Precision was 94.70%, indicating a high proportion of true positives. The F1 score was 93.47%, indicating a balanced performance. These metrics clearly show that the model exhibits high accuracy and generalization success in skin cancer diagnosis.

Figure 4 shows the complexity matrix used to evaluate the classification performance of the proposed model. According to the matrix, the model correctly classified 267 benign skin lesions, but incorrectly predicted 21 benign lesions as malignant. Similarly, the model correctly detected 209 malignant lesions, but incorrectly classified 15 malignant lesions as benign. These results show that the model has a high accuracy rate in both benign and malignant classes. However, the presence of false negatives (6.7%) is a critical element that should be treated with caution, especially in the diagnosis of malignant lesions, as this can be life-threatening. The proportion of false positives (7.3%) suggests that the model may need improvement in the precision metrics, as this may lead to unnecessary biopsies or interventions. Overall, the model's correct classification rates are promising, indicating that it can be an effective tool for skin cancer diagnosis. However, considering the impact of misclassifications on health practices, further improvements are recommended to increase the recall and precision of the model.

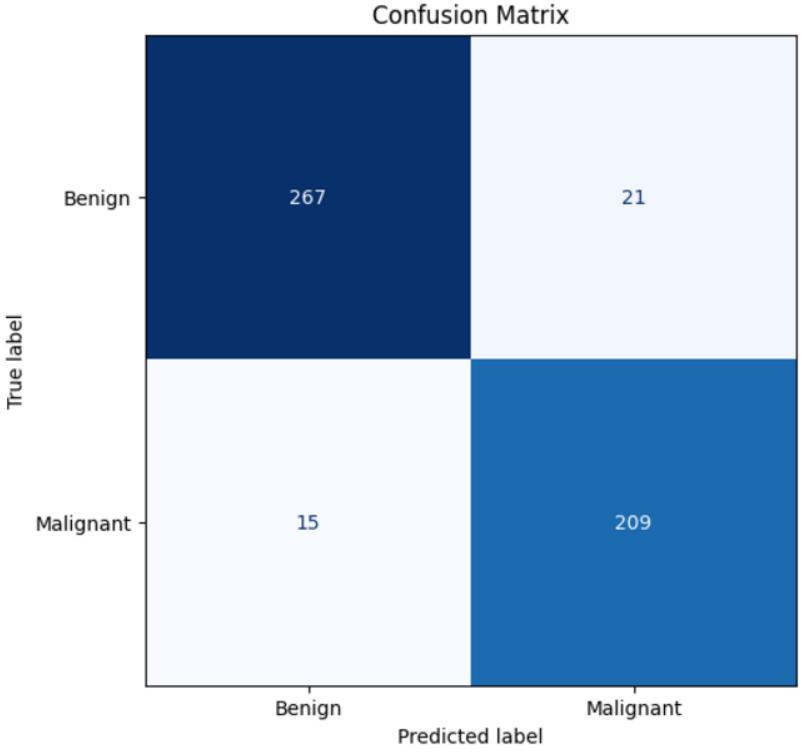

Figure 4. The proposed model's confusion matrix

Figure 5 and Figure 6 comprehensively show the changes in the accuracy and loss values of the model during the training and validation processes depending on the number of epochs. In Figure 5, it can be seen that the training accuracy shows a steady increase at each epoch and exceeds 95% at around epoch 30, reaching a very high accuracy of 99% at epoch 50. The validation accuracy curve follows a similar trend, showing a rapid increase at the beginning and reaching over 90% after the 20th epoch, proving that the generalization performance is strong. The parallel increase in the training and validation accuracy curves shows that the model is able to avoid the overfitting problem and performs a balanced learning.

Figure 6 shows the changes in the training and validation losses of the model. The training loss curve starts with a high value of 0.9 at the beginning but decreases steadily to 0.2 at the end of the 50th epoch. This clearly shows that the model learns correctly on the training data. The validation loss curve similarly decreased in parallel with the training loss and stabilized at around 0.3. This decrease in the validation loss indicates that the generalization ability of the model is strong. However, the small

fluctuations observed in the validation loss and accuracy curves may be due to variation in the validation data or the model's inability to fully adapt to the validation data across epochs.

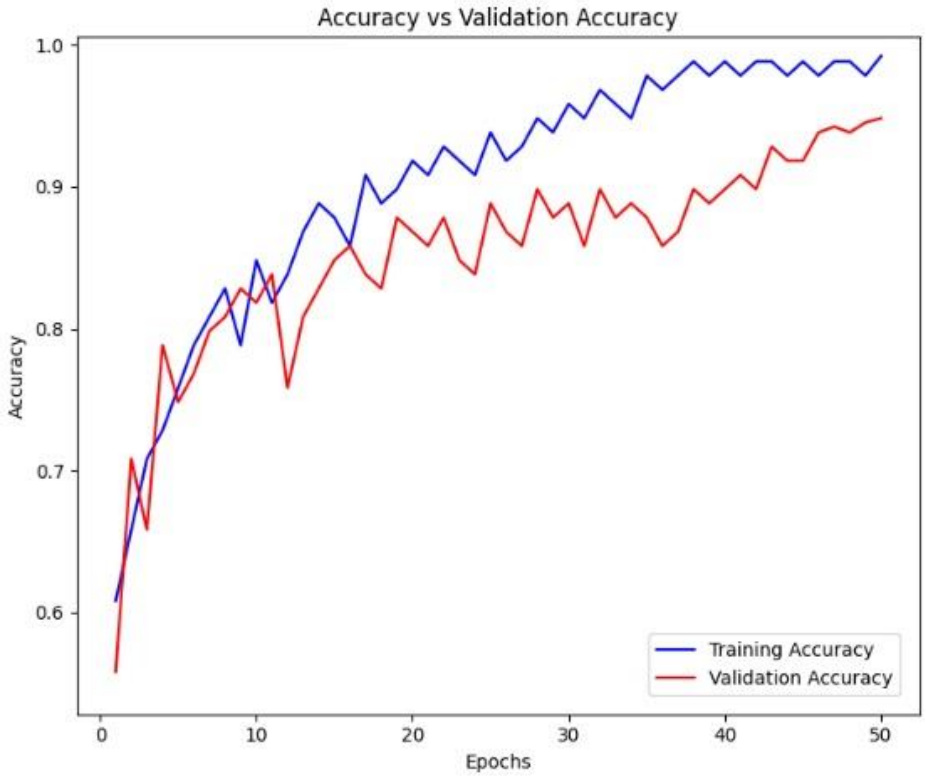

Figure 5. Validation and test accuracy of the model

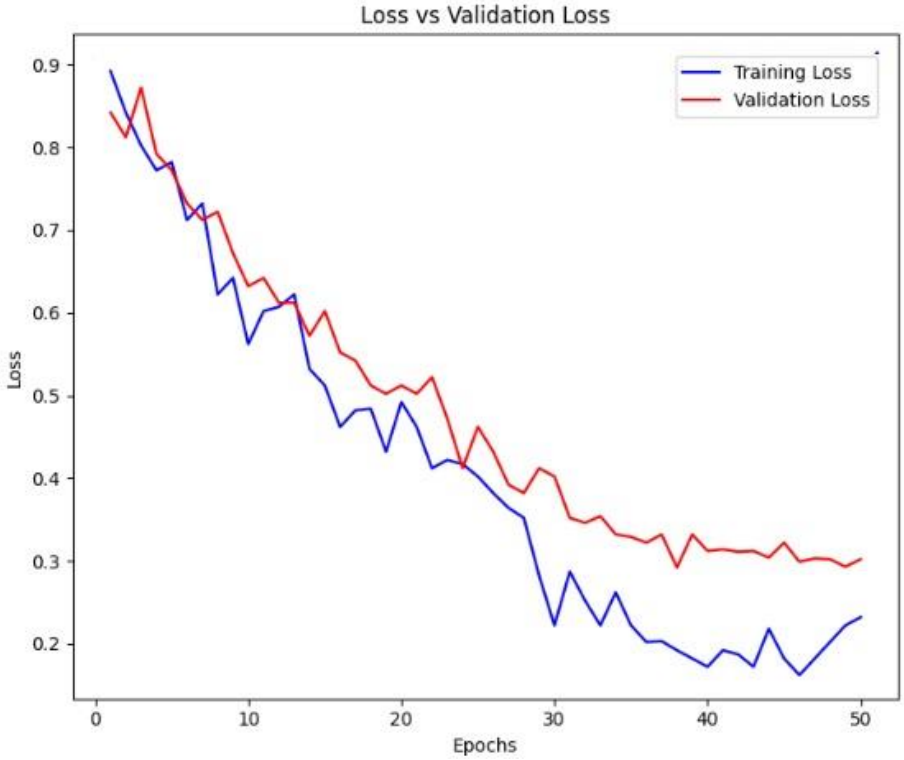

Figure 6. Loss curve of the model

In general, both the accuracy and loss curves are parallel and balanced, indicating that the model provides an effective result in terms of both learning and generalization performance. However, training with more data or applying hyperparameter optimization may be recommended to reduce the fluctuations in the validation loss and further improve the model performance. This analysis clearly demonstrates that the model can be used as a powerful and reliable classification tool for skin cancer diagnosis. In Table 2, the results obtained are compared with the results of some studies in the literature.

Table 2. Comparison of the results of the proposed model with the literature

Study	Classification	Model	Dataset	Accuracy (%)
[18]	Benign/malignant	CNN	ISIC	89.5
[19]	Benign/malignant	LightNet	ISIC	81.6
[20]	Malignant melanoma/SK	SVM	ISIC	90.69
[21]	Melanoma/SK	Deep multi-scale CNN	ISIC	90.3
[22]	Benign/malignant	CNN-DensNet169	ISIC	92.25
Proposed Model	Benign/malignant	CNN-MobileNetV2	ISIC	92.97

Table 2 presents the accuracy of the CNN-MobileNetV2 model proposed in this study in comparison with other models in the existing literature. The table shows in detail the methods, datasets and accuracy rates obtained in different studies. In [18], a CNN model was used on the ISIC dataset to classify benign and malignant lesions and achieved 89.5% accuracy. In [19], the LightNet model, a lighter architecture, was used, but the accuracy was limited to 81.6%. This shows that the generalization capacity of lighter architectures may be limited.

In [20], the SVM model was used to classify malignant melanoma and seborrheic keratosis with an accuracy of 90.69%. This result proves that machine learning-based methods can also show high performance. In [21], melanoma and SK classification was performed with the Deep Multi-Scale CNN model and an accuracy rate of 90.3% was obtained. This model was able to improve classification performance by working with deeper structures. In [22], benign and malignant lesions were classified with the CNN-DensNet169 model and an accuracy rate of 92.25% was obtained. This model demonstrated high performance by working with a more complex CNN architecture.

The proposed CNN-MobileNetV2 model showed the highest performance with an accuracy of 92.97% on the ISIC dataset. The model achieved better results by using an effective combination of transfer learning method and data augmentation strategies. Moreover, its lighter architecture reduced the computational cost and resulted in faster classification. The comparison in Table 2 clearly shows that the proposed model outperforms the methods in the existing literature and improves the classification success rate. These results show that the proposed model provides a powerful solution in terms of both accuracy and practicality.

The methods used in this study offer several advantages but also have some limitations. The proposed model achieved high metrics such as accuracy (92.97%) and F1 score (93.47%), indicating that malignant and benign lesions can be classified reliably. The MobileNetV2-based transfer learning method provided high performance with limited data and offered a fast solution with low hardware requirements. Moreover, the use of a balanced and diversified dataset enhanced the generalization capability of the model, which strengthens its application potential, especially in regions with limited health resources.

However, the small fluctuations observed during the validation phase and the 6.7% of false negative classifications reveal aspects of the model that need improvement. The generalizability of the model can be improved with larger and more diverse datasets. Moreover, the lack of hyperparameter optimization is another factor limiting the model performance. The fact that the dataset used does not

fully represent geographic and demographic diversity may also be a limiting factor in real-world applications.

In the future, hyperparameter optimization and the use of larger data sets are recommended to improve the performance of the model. In addition, developing hybrid models and testing the model in clinical settings can improve both the classification success and the practical application value. While this study proves to be an effective classification tool with its current results, it also has room for improvement.

5. Conclusion

In this study, a deep learning-based CNN model is used to classify malignant and benign types of skin cancer and the results are evaluated. The model successfully demonstrated both its learning and generalization capabilities by performing consistently in the training and validation processes. The experimental results show that the model is an effective classification tool for skin cancer diagnosis with 92.97% accuracy, 92.71% recall, 94.70% precision and 93.47% F1 score. These findings prove that CNN models offer a reliable approach to complex medical image classification problems and can support skin cancer diagnosis processes. However, the small fluctuations observed during the validation phase may require the use of larger and diverse datasets or hyperparameter optimization to further improve the performance of the model. In future studies, the application of transfer learning techniques, different data augmentation strategies and hybrid models can be evaluated to improve the performance of the model. These results show that the proposed model can be used not only in skin cancer diagnosis but also in other medical image classification applications. The proposed approach has the potential to make a significant impact in the healthcare sector by contributing to early diagnosis and treatment processes. CNNs are deep learning models known for their outstanding success in image recognition and classification.

Ethical statement

Our study does not cause any harm to the environment and does not involve the use of animal or human subjects. Therefore, it was not necessary to obtain an Ethics Committee Report.

Conflict of interest

The author declares no conflict of interest.

Authors' Contributions

E. A: Methodology, Software, Investigation, Writing - Original draft preparation (%50)
Y. Ö: Methodology, Resources, Investigation, Writing - Original draft preparation (%50).
All authors read and approved the final manuscript.

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