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SkinCNN: Classification of Skin Cancer Lesions with A Novel CNN Model

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Abstract
Recently, there has been an increase in the number of cancer cases due to causes such as physical inactivity, sun exposure, environmental changes, harmful drinks and viruses. One of the most common types of cancer in the general population is skin cancer. There is an increase in exposure to the sun's harmful rays due to reasons such as environmental changes, especially ozone depletion. As exposure increases, skin changes occur in various parts of the body, especially the head and neck, in both young and old. In general, changes such as swelling in skin lesions are diagnosed as skin cancer. Skin cancers that are frequently seen in the society are known as actinic keratosis (akiec), basal cell carcinoma (bcc), bening keratosis (bkl), dermatofibroma (df), melanoma (mel), melanocytic nevi (nv), and vascular (vasc) types. It is not possible to consider all possible skin changes as skin cancer. In such a case, the development of a decision support system that can automatically classify the specified skin cancer images will help specialized healthcare professionals. For these purposes, a basic model based on MobileNet V3 was developed using the swish activation function instead of the ReLU activation function of the MobileNet architecture. In addition, a new CNN model with a different convolutional layer is proposed for skin cancer classification, which is different from the studies in the literature. The proposed CNN model (SkinCNN) achieved a 97% accuracy rate by performing the training process 30 times faster than the pre-trained MobileNet V3 model. In both models, training, validation and test data were modelled by partitioning according to the value of cross validation 5. MobileNet V3 model achieved F1 score, recall, precision, and accuracy metrics of 0.87, 0.88, 0.84, 0.83, 0.84, and 0.83, respectively, in skin cancer classification. The SkinCNN obtained F1 score, recall, precision, and accuracy metrics of 0.98, 0.97, 0.96, and 0.97, respectively. With the obtained performance metrics, the SkinCNN is competitive with the studies in the literature. In future studies, since the SkinCNN is fast and lightweight, it can be targeted to run on real-time systems.

1. Introduction

The world population is expected to increase substantially in the next quarter century [1]. It is noted that with the increase in the number of people, there has been a rapid increase in the number of human diseases [2]. As the world's population grows, so too does the damage done to the environment, especially to nature. The main reason for this is that people unconsciously cause water, air and soil pollution. The damage to the main material of nature returns as an increase in human diseases. It is observed that there is a great increase in cancer cases due to various environmental factors, especially chemicals, tobacco and radiation [2].

Five years ago today, in 2018, nearly ten million people are reported to have died from cancer [3]. There has been a serious increase in cancer cases

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in recent years due to various reasons such as constant work, constant exposure to blue rays, physical inactivity, harmful sun rays and radiation [4]. Although there are many different types of cancer, skin cancer is one of the most common and deadly cancers [5]. It is reported that the pollution caused by UV-B rays emitted by the sun is directly linked to the depletion of the ozone layer. As a result, a large increase in skin cancer cases has been observed [6]–[8]. Skin cancer of the melanoma type is affected by 86% of ultraviolet radiation, while other types of skin cancer are affected by 90% of ultraviolet radiation [9].

Dermatology is an important department in the medical field with cases of serious diseases. It is common in countries such as the United States, regardless of age, gender, or culture. So much so that at least 1 out of 3 patients has serious skin disease [10]. Due to the reasons and reasons stated, skin diseases are accepted as a global health problem [11].

Skin diseases should be comprehensively scanned with medical imaging devices and lesions should be defined. Variable-sized skin growths that occur on the skin should be examined under observation [12]. Analyzes are carried out with different techniques according to changes in skin structure, irregularities on the border, asymmetrical structure, and uniform color structure [13]. These techniques support the analysis of skin diseases via medical images. In this context, akiec, nv, df, bcc, mel, bkl, and vasc, which are the most common types of skin cancer in the world, are examined. Several factors, including sun exposure and population longevity, may be contributing to the increasing incidence of this cancer [14]. Mendes et al. report that although skin cancer is widespread, its treatment is successful thanks to early detection and treatment. However, if the disease is detected late, the chance of survival drops to around 15% [14].

As with other health problems, early diagnosis of skin cancer saves lives. With early detection, there is a good chance of preventing the disease from spreading to other organs. There are studies that classify melanoma, one of the deadliest skin cancers. According to Barata et al, two different systems are proposed to detect melanoma skin type in dermoscopy images. The first system uses local features and pockets to group skin lesions. This article reports that color images provide more detailed information than textural features in the detection of skin lesions [15]. In line with this finding, operations were performed to analyze data on color images. In another study, a decision support system is proposed using different inputs to obtain the characteristic features of melanoma [16], [17]. Pomponi et al. developed a CNN model with multiple convolution and fully connected layers [18]. In the first of the convolutional layers of their model, they apply 96 kernels of size 11x11x3 to a color skin image. The second convolutional layer applies filtering to the normalized and pooled image with 256 kernels of 5x5x48 dimensions. The other convolutional layers are linked together without any normalization or pooling. In the sixth and seventh rows, the fully connected layer is connected with 4096 neurons. It can be seen that the K-Nearest Neighbor (KNN) classifier is used to classify the obtained features. Younis et al. classify skin cancer using a MobileNet-based neural network [4].

Shoieb et al. proposed a CNN structure to extract superficial features of skin cancers [19]. It classifies the data obtained from the proposed structure using the Support Vector Machine (SVM) algorithm. When we look at the literature, in deep learning, which is a sub-field of machine learning, original studies can be carried out in very different categorical areas such as natural language processing, text analysis, emotion analysis, speaker recognition, computer vision applications and artificial learning in health [20], [21]. In previous years, the high hardware requirements of deep learning algorithms prevented progress from being made. In today's conditions, interest in deep learning algorithms has increased due to the widespread use of high-powered computers and the increase in current dataset environments. CNN-based algorithms are defined as a subfield of deep learning. Natural language processing has achieved significant success in areas such as text and sentiment analysis, which are sub-topics of natural language processing. These achievements were crowned with the classification of the ImageNet dataset, a large dataset of 1.2 million images. A new method using CNN is presented to classify this dataset [22]. Since then, CNN methods have been used in various fields, especially in biomedical image analysis [12]. There are pre-trained deep neural networks based on CNN methods and models that do not use pre-trained networks.

In general, it is possible to classify skin cancers using transfer learning-based or non-transfer learning-based methods. Non-transfer learning methods generally use fewer layers than transfer learning methods. It is lighter than other models because of the small number of layers. Due to its light weight, it can perform faster training and classification processes. For this reason, a new CNN model that automatically classifies skin cancer types is presented in this study. This CNN model was used to attempt to classify seven different types of skin cancer that are commonly encountered.

One of the objectives of this study is to measure the effect of CNN models without using any weight values on the classification of skin cancers compared to transfer learning-based models.

Convolution layers, which are used to extract discriminative features that can be used in CNN models, are used successively in the first layers to reduce the noise in the images. In addition, the discriminative power of the model was increased by obtaining detailed features.

The contributions of the study carried out in this context to the literature are presented in articles.

- The SkinCNN, on the other hand, has achieved a 97% success rate by performing the training process 30 times faster than the proposed MobileNet V3 model.
- The SkinCNN is faster than existing transfer learning-based work in the literature, since it is built with basic convolution layers without using any weights.
- The reliability of the model was ensured by obtaining similar results in experimental studies using data separated by cross validation 5 techniques. It is proved that similar results are obtained instead of obtaining different results in each run of the SkinCNN.
- The SkinCNN model has 5% difference from the articles compared to the literature.
- A new deep learning-based CNN model has been proposed to assist healthcare professionals.

The following sections of the paper consist of three parts. In the first section following this chapter, we describe the theoretical background of the dataset experimentally studied and the models developed in this paper. The second section compares the performance measures of the proposed models. The third section concludes the paper with future work.

2. Material and Method

2.1. Materials

As a result of the experimental studies, it can be stated that the size and diversity of the dataset is effective in training the deep learning model. For this reason, a dataset with high data diversity was used in this article. The dataset [23] used was prepared by skin specialists in the Dermatology department of Austria. This dataset consists of labeled images obtained by experts in 2 different dermatology departments. The number of labelled images is 10.015 [23].

Seven different classes were examined in the dataset used. These seven different classes consist of the class labelled akiec, nv, bcc, bkl, df, mel, and vasc. The numbers of data belonging to the classes akiec, bkl, nv, bcc, df, mel, vasc are 327, 1.099, 6.705, 514, 115, 1.113, 142, respectively. It is seen that there is data imbalance between cancer classes in the dataset. In order to improve the classification results, horizontal and vertical rotation of the images from data augmentation techniques were applied to the images on a class basis to eliminate the data imbalance. These operations were applied to other classes other than the nv class, and the number of images belonging to each class was equalized to the nv class.

In Figure 1, each of akiec, nv, bcc, mel, bkl, df, vasc skin cancer types are seen in two. If fatal skin cancers are not detected early, the chance of survival drops to 15% [14]. In this case, the disease metastasizes as a result of the spread of disease lesions to neighboring organs. Among the types of skin cancer akiec, nv, bkl, mel, df, bcc, and vasc shown in Figure 1, the types of bcc and akiec are known to be more lethal than other types. These more lethal types can be completely cured if treated early. Bcc and akiec are the most common of the seven types listed. [19]. It is reported that there is a 5 percent increase in these species in the Americas region in 2021 [24].

The ozone layer is thinning due to environmental pollution caused by various reasons such as not recycling waste materials, polluting the soil with plastic materials, increasing harmful vehicle emission rates, unfiltered factory operation or filter renewal. As a result of the thinning of the ozone layer, which creates UV-B radiation, the skin is more exposed to harmful rays.

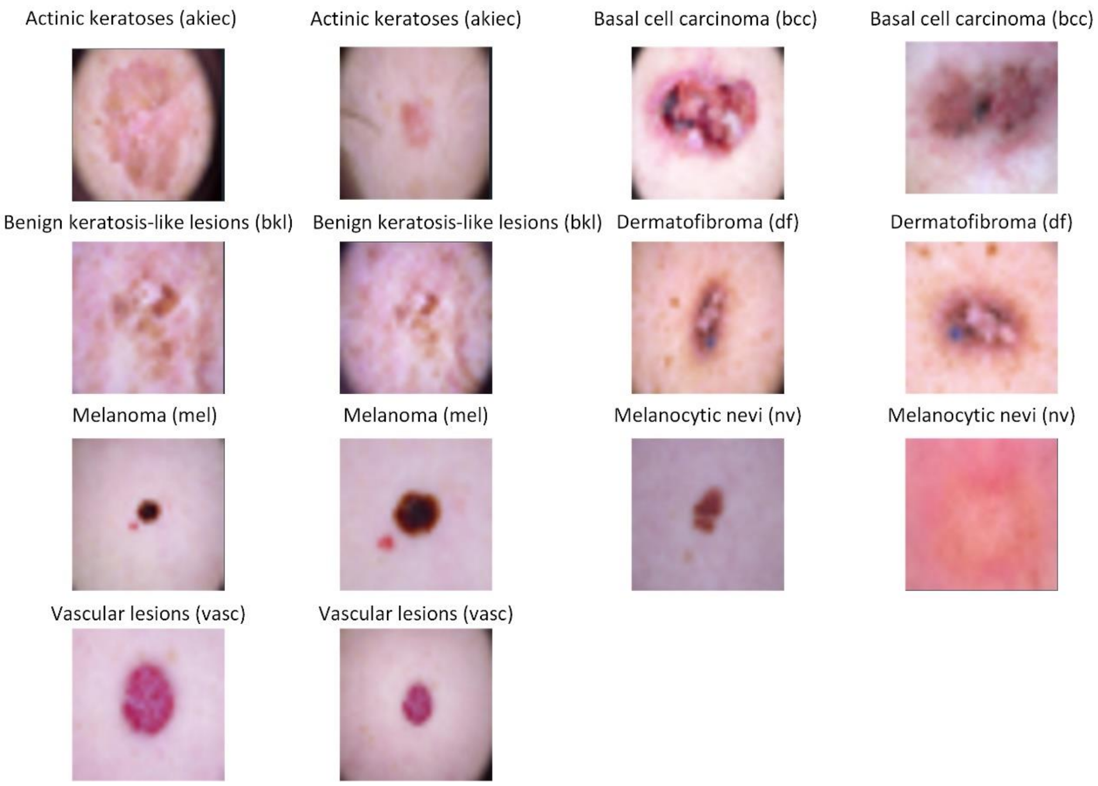

Figure 1. Skin lesion classes in the used dataset

In order to intervene in time on the increasing number of skin diseases due to the above-mentioned problems, it is imperative to develop decision support systems for medical professionals. For this purpose, two different deep learning models based on MobileNet V3 and CNN have been defined. While the MobileNet V3 model is based on pre-trained transfer learning, the CNN model is a model consisting of convolutional layers with different recommended filters. In this study, both models were compared according to the metrics F1 score, recall, precision, accuracy on the same dataset.

2.2. Materials

CNN networks for mobile devices have developed rapidly in recent years. There are three different versions of MobileNet networks [25]. One of them, the MobileNet V1 architecture, was developed on the basis of the VGG architecture [26]. Based on the MobileNet V1 architecture, a new architecture with a linear bottle beaker structure has been proposed [27]. The latest version of MobileNet networks is a model called MobileNet V3, which is created with the help of search optimization algorithms of the NAS and NetAdapt networks, leaving layers with high computational costs to increase efficiency and accuracy. In this model, the h-swish activation function is generally used instead of the ReLU activation function [28]. NetAdapt networks have the feature of working integrated with an algorithm that investigates the architectural structure of mobile phones. In order to achieve high accuracy, the swish function, which is used instead of the ReLU activation function, is also a kind of activation function. This activation function is defined in Equation 1.

$$swish(x) = x\emptyset\sigma(x) \tag{1}$$

Since the sigmoid function in Equation 1 causes the processing load on mobile devices, the hard swish function of the swish function has been created.

$$h - swish[x] = x\frac{ReLU6(x+3)}{6} \tag{2}$$

This function uses the ReLU6 function instead of the sigmoid function in the swish function. The use of the ReLU6 function instead of the sigmoid function is shown in Equation 2.

2.3. Proposed CNN Model (SkinCNN)

To classify common skin cancer types, two different models are proposed, based on the MobileNet V3 architecture, the third version of the MobileNet series, and the CNN architecture. With these deep learning architecture models, a new decision support system for skin specialists is presented. With the presented system, the infrastructure for accelerating and facilitating transactions is created. The proposed model has been named as SkinCNN. The SkinCNN system is shown in Figure 2 in detail. In addition to the 2D convolutional, max pooling layers, a dropout layer core structure is used that applies a 0.2% dropout. This structure is connected three times in a row. The convolutional layer in this core structure consists of the kernel with a 3x3 window and 16, 32 and 64 filters, respectively. In the second layer of the model, a convolution layer with a ReLU activation function with 16 filters is defined.

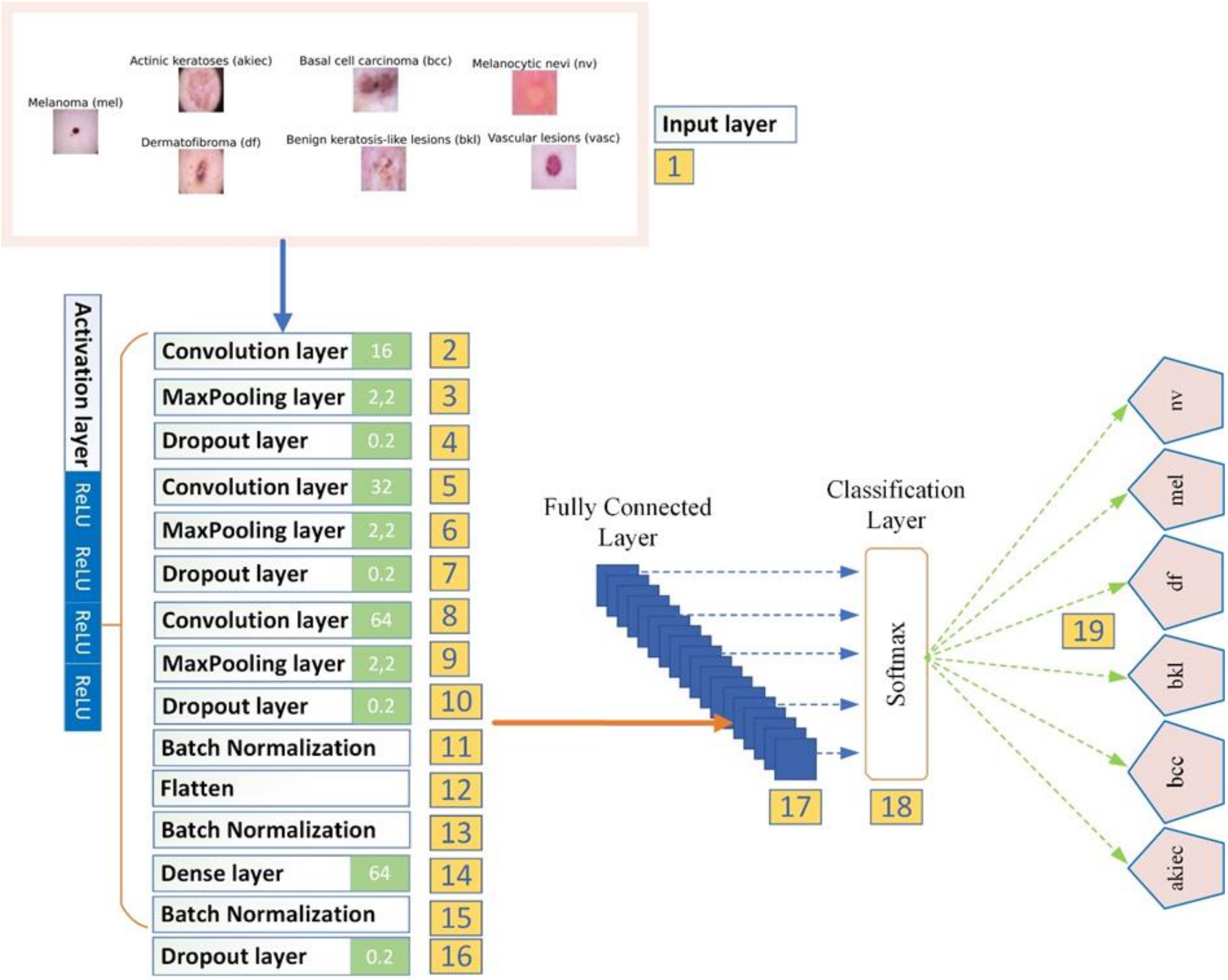

Figure 2. The SkinCNN for skin type classification

The third layer is a max pooling layer with 2x2 window sizes. The fourth layer is a dropout layer with a neuron dropout rate of 0.2%. The fifth layer is a convolution layer with a ReLU activation function with 32 filters. In the sixth layer, a max pooling layer was added, which performs feature selection in 2x2 window sizes. The seventh layer is a dropout layer with a neuron dropout rate of 0.2%.

The eighth layer is a convolution layer with a ReLU activation function with 64 filters. In the ninth layer, a new layer was added with maximum pooling in the third and sixth layers. The tenth layer is a dropout layer with a neuron dropout rate of 0.2%. In the eleventh step, shown in Figure 2, a batch normalization was performed to normalize the inputs between layers. In the on twelfth step, the flatten layer and the feature maps of the other layers were transformed into a one-dimensional array. In the thirteenth step, the batch normalized layer was added again. In the fourteenth step, a dense layer of 64 neurons was added. In the fifteenth step, a third batch normalization layer was added to normalize the inputs between layers. In the sixteenth step, a 0.3% dropout layer was added. The purpose of this layer is to prevent the model from having an overfitting problem. In the seventeenth step, there is a fully connected layer which combines the attributes between the layers and gives input to the output. In the eighteenth step, there is a classification layer with a softmax activation function. This layer estimates the label of the target class according to the output obtained from the layers. In the nineteenth step, the target labels are displayed. The labels in the dataset containing the most common types of skin cancer are visualized.

In Figure 2, the entire flow diagram from input to output is shown with symbolic figures. The performance results of the model obtained as a result of the use of layers in this demonstration and the basic MobileNet V3 model are presented in Section 3. The performance comparison was made on a computer with the same graphics card and processor, with all operations turned off except for the training model. As a result of the comparison processes, both models proposed are light and fast.

3. Results and Discussion

A new method is presented to compare the performance of MobileNet V3 and SkinCNN models. Table 1 and Table 2 are given in order to test this presented method successfully. Table 1 gives the performance results of the basic MobileNet V3 model based on the cross validation 5 values. Table 2 presents the performance results of the SkinCNN according to the cross validation 5 values. Cross validation 5 was used to separate the training and test data of the dataset. By using this structure, training of models with the Adam optimization method is provided. The Adam optimization method was established with a learning rate of 0.001, with a delay value of 0. While Beta 1 value is 0.9, Beta 2 value is determined as 0.999.

The performance chart of the basic MobileNet V3 model is shown. The results obtained according to 5 different cross validation values are given separately. According to these results, loss and accuracy results are given. In addition to these, F1 score, recall, and precision measurement values are presented.

In Table 2, the performance results of the SkinCNN obtained according to 5 different cross validation values are given. As in Table 1, the accuracy and loss results are shown. In addition to these, F1 score, recall, and precision values are also presented. As shown in Table 2, the average accuracy rate of 95.47% was achieved from the SkinCNN. The accuracy and loss graphs of the results obtained from both models are presented together for convenience during comparison.

In the structure shown in Figure 3, the SkinCNN accuracy exceeds 92.5%. The accuracy of the basic MobileNet V3 model is about 77.5%. On average, the difference between the two models in training modelling is 15%. As the epoch value, the training process was carried out on 50 epoch iteration in both models. The SkinCNN has achieved a satisfactory result. The proposed abbreviation shown in the legend of the graphs represents the SkinCNN model.

Table 1. Performance results of the MobileNet V3 model according to cross validation 5 values

Cross validation	F1 Score	Recall	Precision	Accuracy	Loss
1	0.77	0.78	0.78	77.12	0.67
2	0.82	0.82	0.81	81.16	0.57
3	0.87	0.88	0.84	83.40	0.50
4	0.79	0.81	0.79	80,42	0.54
5	0.79	0.80	0.79	80,70	0.55
Average				80.56	0.56

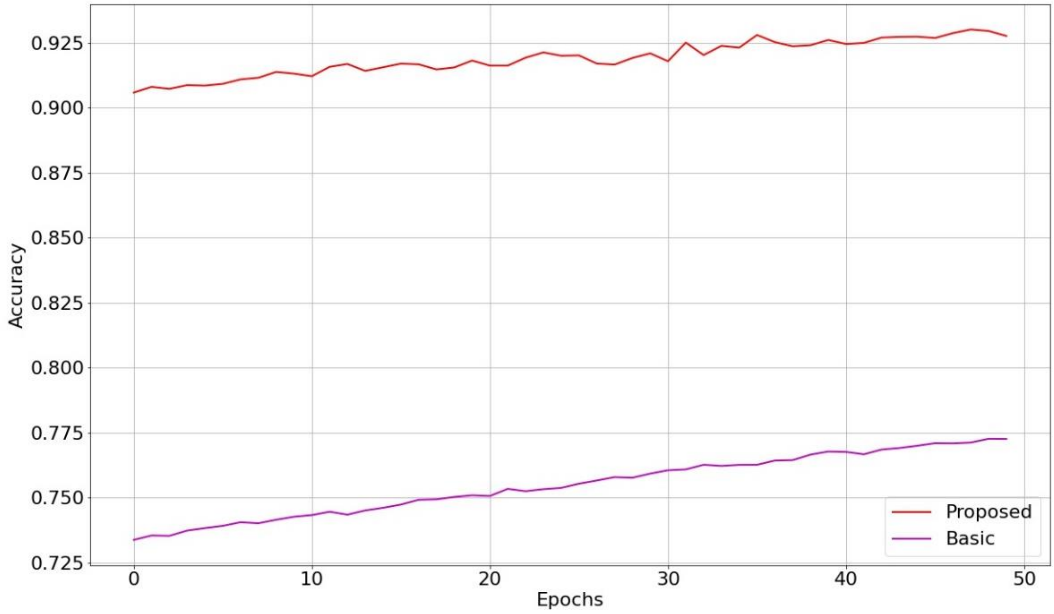

Figure 3. Training accuracy graph of MobileNet V3 and SkinCNN model

According to this result, the proposed system can be used on portable devices such as mobile devices. However, there will be a situation that we can say more clearly by looking at the test accuracy rates. Figure 4 shows the training loss graph for the basic MobileNet V3 and the SkinCNN. According to this average graph, the loss value of the SkinCNN is less than 0.2. The basic MobileNet V3 loss graph approaches 0.7. There is a loss value of 0.5 between the two models. The mean values of the SkinCNN are used in other given performance graphs, including the figures in Figure 3 and Figure 4. These mean values are shown in Table 2. However, in the compared MobileNet V3 model, the results of the highest cross validation value are reflected in the graph. However, the difference is quite large. When the structures of Figures 3 and 4 are examined, it can be said that both models can be used in the classification of skin cancer. However, to consolidate this decision, the test accuracy and loss graphs of both models should be presented. For this reason, the accuracy and loss graphs are presented in Figure 5 and Figure 6.

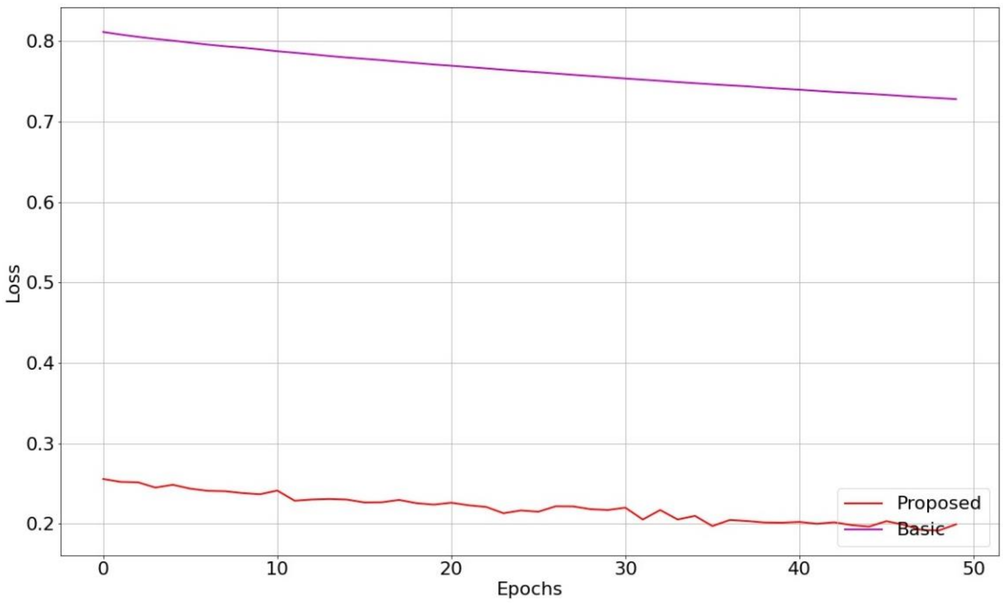

Figure 4. Training loss graph of MobileNet V3 and the SkinCNN model

After showing the loss values obtained as a result of the training modelling in Figure 4, the test accuracy and loss values can be checked. The average accuracy of the SkinCNN is over 0.95%. The accuracy of the basic MobileNet V3 model is close to 0.75%. There is a 20% difference between the accuracy rates of the two models.

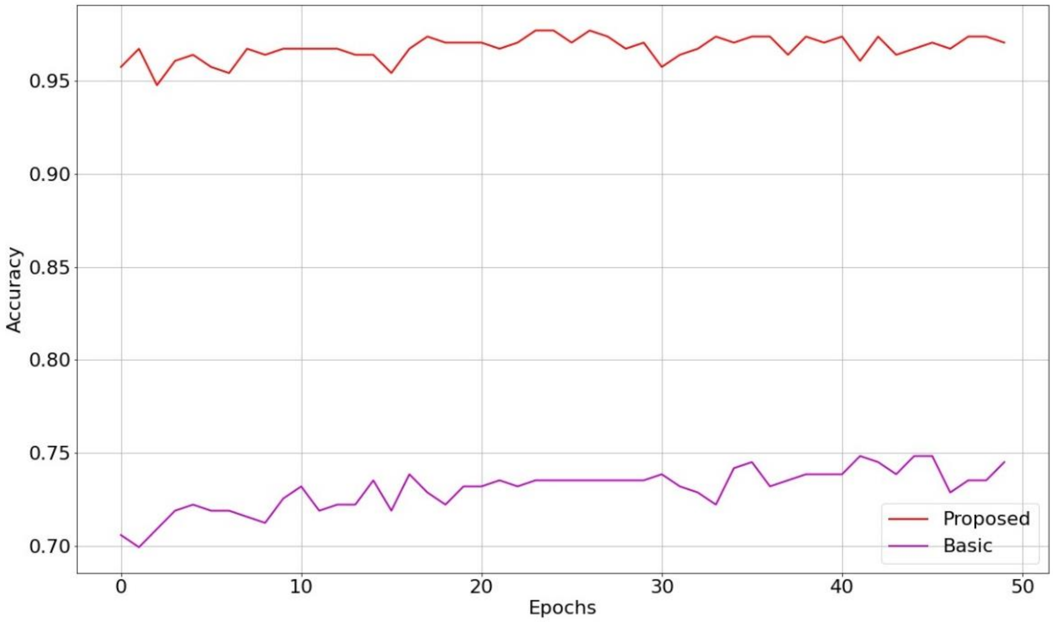

Figure 5. Test accuracy graph of MobileNet V3 and SkinCNN model

In Figure 6, the test loss graphs between the SkinCNN and the basic MobileNet V3 model are presented. Based on these values of the presented graph, the SkinCNN has a loss of less than 0.1%. The basic MobileNet V3 model has a loss of close to 0.8%.

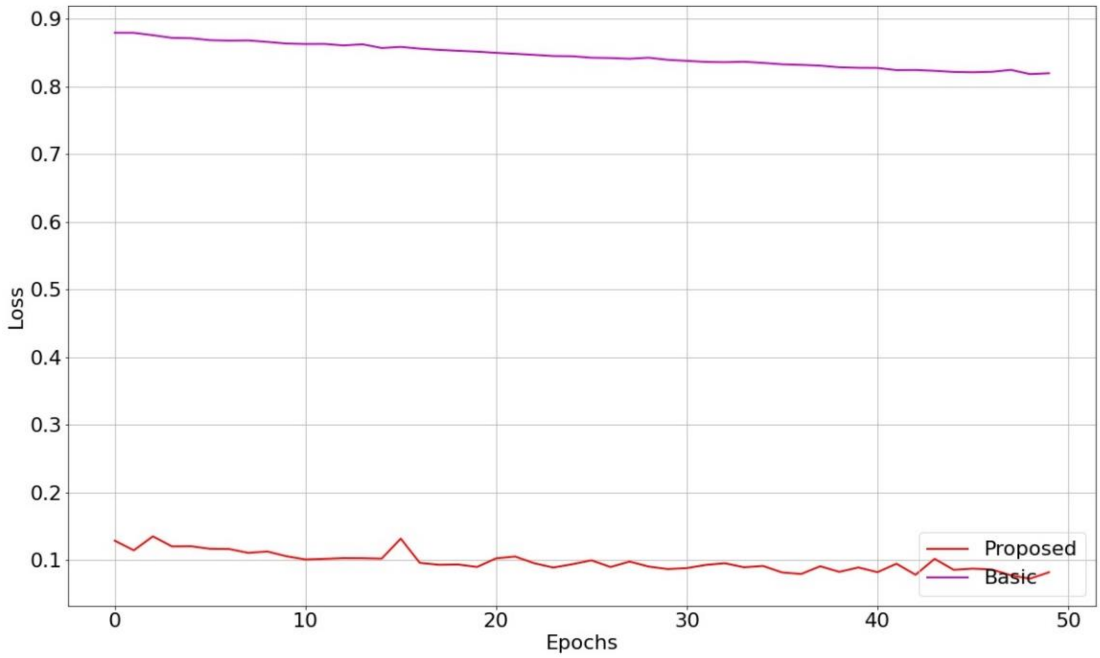

Figure 6. Test loss graph of MobileNet V3 and SkinCNN model

In Figure 7, the cross validation 5 accuracy result of the Fold option is shown, which has the highest accuracy value of the SkinCNN. According to the result shown, it goes above 97.5% towards the 50th epoch step.

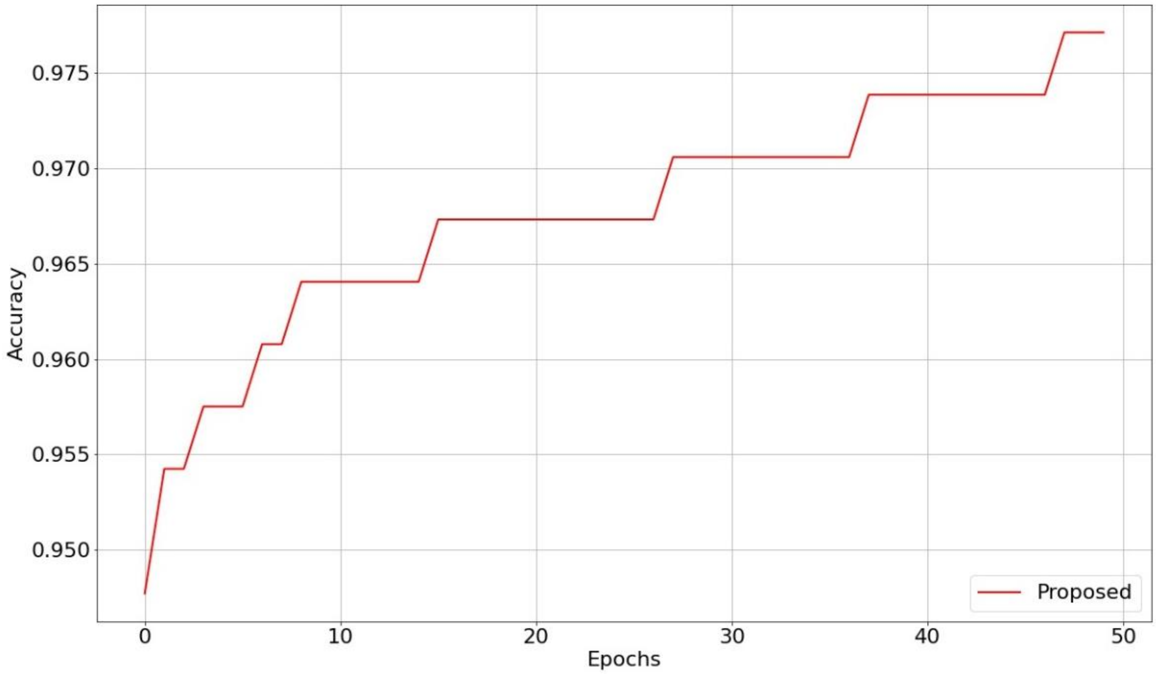

Figure 7. Test accuracy graph of the SkinCNN

Figure 8 shows the loss graph of the SkinCNN. According to this loss graph, it is seen that the loss value approaches 0.07% towards the 50th epoch step. As a result of the performance results obtained, it is possible to use the proposed structure actively in different biomedical problems. Due to its light weight, it can also be used on portable devices such as mobile devices.

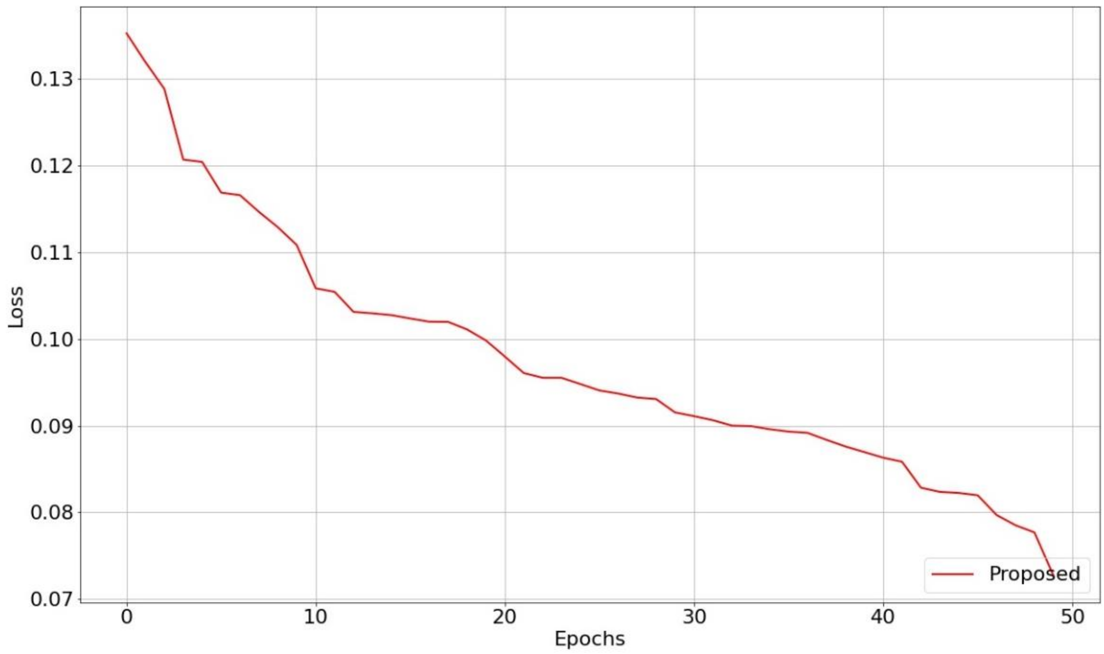

Figure 8. Test loss graph of the SkinCNN

In Table 3, the results obtained with the same or similar datasets are compared with the proposed study. Although the number of classes in the SkinCNN is 7, it can be seen that other studies compared use between 2 and 10 classes. There is only one exception. The exception is the study by Jianu et al. It was found that they classified melanoma, one of the types of skin cancer, as benign and malignant [29]. For this reason, the number of skin cancer types in this study was set to 1. The method, accuracy values and number of species for each of the other models compared are presented. The F1 score, recall and precision metrics were requested to be presented together to allow a detailed comparison with the proposed study in the specified table. However, as the metrics were not found in the compared articles, they are not included in Table 3.

Table 2. Comparison results on the same and similar skin datasets

References	Methods	Accuracy	Number of species
[29]	Feature and statistically based method	81%	1
[16]	Color and texture lesion descriptor method	81%	2
[30]	Regression based classifier, CNN deep learning	81.8%	10
[30]	Regression based classifier, CNN deep learning	85.5%	5
[30]	Regression based classifier, CNN deep learning	94.8%	2
[31]	Two deep learning	91.2%	3
[32]	Sparse coding, deep learning, SVM	93.1%	3
This study	SkinCNN	97.82%	7

According to Giotis et al. make the classification of melanoma and nevus types from skin cancer types by using color and texture features [16]. Kawahara et al. classified the features extracted by a pre-trained CNN method with the logistic regression classifier method [30]. There is a difference in the success rate depending on the number of classes. Li and Shen offered a deep learning framework that uses two fully connected layers [31]. Codella et al. used deep learning, sparse coding, and support vector machine methods to classify the types of species that emerged in the development of melanoma species [32].

4. Conclusion and Suggestions

Environmental pollution, which is increasing due to various reasons such as people's unconscious behavior, excessive consumption and non-compliance with regulations, is damaging the ozone layer. As a result of the damage to the ozone layer, the possibility of exposure to harmful solar radiation has also increased. For these reasons, a system that automatically classifies seven of the common types of skin cancer that can be seen in different age groups, young and old, has been proposed. The SkinCNN is compared in terms of performance with the MobileNet V3 model, a new architecture designed for use on mobile devices. From the results obtained, it is easy to say that the SkinCNN can be used in mobile devices together with the MobileNet V3 model.

The classification process using the SkinCNN and the MobileNet V3 model gave F1 score, recall, precision and accuracy values of 0.98, 0.97, 0.96, 0.97 and 0.87, 0.88, 0.84, 0.83 respectively. The performance results obtained show that the SkinCNN is as simple and stable as the MobileNet V3 model. To test the reliability of the results, cross-validation 5 data were disaggregated. If it is desired to develop models for which performance criteria are given by experimental studies, it would be appropriate to further develop the MobileNet V3 model. MobileNet is a model with three different structures with MobileNet V1, MobileNet V2 and MobileNet V3 models. It is possible to propose different models using this very successful model. It is possible to test these proposed structures on portable devices and equipment.

In further studies, this study can be developed into a system that can assist specialists in different locations, especially in areas where skin specialists or dermatologists are scarce. To achieve this, the system can be transferred to different platforms and transformed into an environment where different user groups can upload and test skin images. In this way, different users, especially newly qualified dermatologists, can benefit.

Conflict of Interest Statement

There is no conflict of interest regarding the study.

Statement of Research and Publication Ethics

The study is complied with research and publication ethics.

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