OKU Fen Bilimleri Enstitüsü Dergisi
7(3): 1030-1045, 2024

OKU Journal of The Institute of Science and Technology, 7(3): 1030-1045, 2024

Osmaniye Korkut Ata Üniversitesi Fen Bilimleri Enstitüsü Dergisi

Osmaniye Korkut Ata University Journal of The Institute of Science and Technology

Skin Lesions Identification and Analysis with Deep Learning Model Using Transfer Learning

Halit ÇETİNER[1*]

[1]Isparta University of Applied Sciences, Vocational School of Technical School, Computer Technology, Isparta

[1]https://orcid.org/0000-0001-7794-2555
*Corresponding author: halitcetiner@isparta.edu.tr

Research Article

Article History:
Received: 21.06.2022
Accepted:30.10.2022
Published online: 25.06.2024

Keywords:
Skin cancer
Deep learning
CNN
DenseNet201

ABSTRACT

Sunlight has beneficial as well as harmful rays. Environmental pollution occurs as a result of the depletion of the ozone layer caused by the damage caused by humans to the environment. As a result of these pollutants, skin diseases can be seen in areas exposed to direct sunlight, such as the head and neck. Early detection of actinic keratosis (akiec), basal cell carcinoma (bcc), bening keratosis (bkl), dermafibroma (df), melanoma (mel), melanocytic nevi (nv), and vascular (vasc) skin cancer types, which is one of the most common skin diseases, is important for medical intervention. Otherwise, severe spread, called metastasis, may occur as a result of aggressive growths. For the stated reasons, a deep learning model based on transfer learning, which can classify skin cancer types, has been proposed to assist the medical personnel who serve in this field. With this proposed model, the aim is to classify at high accuracy rates without any pre-processing. As a result of the experimental studies carried out as a result of the stated goals, an accuracy rate of 99.51% was achieved with the proposed model.

Transfer Öğrenme Kullanan Derin Öğrenme Modeli ile Cilt Lezyonlarının Tanımlanması ve Analizi

Araştırma Makalesi

Makale Tarihçesi:
Geliş tarihi: 21.06.2022
Kabul tarihi: 30.10.2022
Online Yayınlama: 25.06.2024

Anahtar Kelimeler:
Deri kanseri
Derin öğrenme
CNN
DenseNet201

ÖZ

Güneş ışıklarından faydalı ışınları olduğu gibi zararlı ışınları da bulunmaktadır. İnsanların çevreye verdikleri zararlar ile oluşan ozon tabakası incelmeleri sonucunda çevresel kirlilik meydana gelmektedir. Bu kirlilikler neticesinde de baş ve boyun gibi doğrudan güneş ışığına maruz kalan bölgelerde cilt hastalıkları görülebilmektedir. En sık olarak görülen cilt hastalıklarından olan actinic keratosis (akiec), basal cell carcinoma (bcc), bening keratosis (bkl), dermafibroma (df), melanoma (mel), melanocytic nevi (nv), ve vascular (vasc) cilt kanseri türlerinin erken aşamada tespit edilmesi tıbbi müdahale açısından önemlidir. Aksi takdirde agresif büyümeler sonucunda metastaz adı verilen şiddetli yayılmalar meydana gelebilmektedir. Belirtilen sebeplerden dolayı bu alanda hizmet veren uzman sağlık personeline yardımcı cilt kanser türlerini sınıflandırabilen transfer öğrenme tabanlı derin öğrenme modeli önerilmiştir. Önerilen bu model ile herhangi bir ön işleme tabi tutmadan yüksek doğruluk oranlarında sınıflandırma yapmak hedeflenmiştir. Belirtilen hedefler sonucunda yapılan deneysel çalışmalar neticesinde önerilen model ile %99,51 oranında başarı oranına ulaşılmıştır.

To Cite: Çetiner H. Skin Lesions Identification and Analysis with Deep Learning Model Using Transfer Learning. Osmaniye Korkut Ata Üniversitesi Fen Bilimleri Enstitüsü Dergisi 2024; 7(3): 1030-1045.

1. Introduction

The world population is expected to reach ten billion people in approximately 30 years (Perroy, 2015). According to statements made by the World Health Organization (WHO) and similar organizations, human diseases have increased rapidly in recent years (Pimentel et al., 2007). With the increase in population, the damage of people to nature also increases. Human diseases occur due to the increase in water, air and soil pollution depending on the human population. According to reports shared by the National Cancer Institute, there is an increase in cancer cases due to environmental factors such as chemicals, radiations, and tobacco (Pimentel et al., 2007). There has been an increase in cancer cases recently due to many different reasons such as lifestyle, environmental change, the sun, radiation, and physical inactivity. Skin cancer is the most common type of cancer among cancer diseases (Dorj et al., 2018).

Sun rays in two different wavelengths come from the Sun. One of them is UV-B wavelength and the other is UV-A wavelength. UV-B represents sun rays with wavelengths of 280-320 nm, whereas UV-A represents sun rays with wavelengths of 320-400 nm (Moan et al., 2008). Most of the UV-A wavelength comes directly from UV-B and is not dispersed from the Sun. It is recommended to take these rays at appropriate times. If you are not exposed to the sun at the right time in line with wrong information or accidentally, different skin diseases can be experienced (Moan et al., 2008). In addition, the increase in skin cancer is reported to be associated with anthropogenic pollution due to increased UV-B radiation as the ozone layer becomes thinner (McMichael and McMichael, 1993; McKenzie et al., 2003; Martens and McMichael, 2009).

Swelling on the skin that is outside the normal appearance can be cancerous (Morid et al., 2021). There are seven types of skin cancer, in general. These are actinic keratosis (akiec), basal cell carcinoma (bcc), benign keratosis (bkl), dermafibroma (df), melanoma (mel), melanocytic nevi (nv), and vascular (vasc) types. As in many diseases, early diagnosis in skin cancer is a great opportunity to prevent the spread of cancer. There is a lot of research with machine learning and image processing techniques on the detection, segmentation, and classification of skin cancer. There are many different studies that classify melanoma, a dangerous type of skin cancer. A mobile application has been developed to classify the type of melanoma in one study (Ramlakhan and Shang, 2011). In another study, skin cancer is seen to be classified using deep neural networks (Esteva et al., 2017). The type of melanoma clustered with the K-means clustering technique is seen to be classified by SVM (Almansour and Jaffar, 2016; Anas et al., 2017). Decision support systems have been developed to diagnose melanoma using different input parameters such as damage degree, texture, color, distinctive characteristics and affected area (Ruiz et al., 2011; Giotis et al., 2015). In addition to these, automatic melanoma diagnosis systems have been established in studies such as (Blum et al., 2004; Isasi et al., 2011). Pomponi et al. (Pomponiu et al., 2016) achieved a 93.64% accuracy rate with the AlexNet pre-trained architecture, while Codella et al. (Codella et al., 2015) achieved a 93.1% accuracy rate with

AlexNet. In another study, the classification of skin lesions was performed with a model consisting of a combination of VGG19 and ResNet architectures (Kwasigroch et al., 2017).

Original studies can be carried out in the sub-field of deep learning, which is a special area of machine learning in many different fields such as computer vision, speaker recognition, frequency analysis, natural language processing, and artificial intelligence in health. Recently, it has also been used in drug therapy and computerized pathologies (Suganyadevi et al., 2022). Deep learning algorithms consist of methods that are extremely hardware dependent. The hardware costs that enable deep learning algorithms to work easily at the beginning are very high. In this case, it prevented the widespread use of deep learning algorithms. Today, the decrease in hardware costs and the increase in data sets that serve to solve problems in different fields have increased the interest in deep learning algorithms (Pacal et al., 2020).

Convolutional Neural Network (CNN), defined as a sub-field in deep neural networks, has achieved great success in many artificial intelligence applications such as computer vision and natural language processing. In 2010, ImageNet introduced a new method using deep CNN to classify 1,2 million images with high resolutions (Krizhevsky et al., 2012). The biggest advantage of the ImageNet dataset is pretrained network (Dorj et al., 2018). After the specified step, CNN is a popular deep learning architecture used in many different fields, including biomedical image analysis (Morid et al., 2021). CNN needs a large dataset with labels as well as a large memory for full training operations performed from scratch.

Creating a large dataset with labels is an intensive and tedious process that requires expertise. For this reason, transfer learning techniques have become widespread as an alternative to CNN education. CNN structures with variable parameters can be created using pre-trained neural networks called ImageNet.

In the literature, it has generally focused on the use of transfer learning-based machine learning (Cheplygina et al., 2019) and non-transfer learning-based deep learning methods (Litjens et al., 2017; Bakator and Radosav, 2018). However, in general, it is very rare to train deep learning models from pretrained networks that do not contain medical images (Morid et al., 2021). Morid et al. analyzed 8421 studies in order to explain this deficiency in the literature in their review articles. To address the shortcomings mentioned in the literature, a model based on the DenseNet201 architectural model pre-trained using ImageNet is proposed within the scope of the article. Hosny et al. (Hosny et al., 2018) proposed an AlexNet-based model to classify melanoma, the deadliest of skin cancers. They used a skin cancer dataset with little data diversity in their proposed model. When the proposed model is examined, it is seen that only the classification layer with the softmax activation function of the AlexNet-based model has changed. Jain et al. (Jain et al., 2021) have classified skin cancers using 6 different pre-trained deep learning architectures named VGG19, InceptionV3, Inception ResNetV2, ResNet50, Xception, and MobileNet. Xception states that the transfer learning model gives better results than the other 5 different transfer learning based models. They also report that this model has reached 90.48% accuracy of this model. At the same time, they report that they obtained the highest values as precision, recall and F1 score values from the Xception transfer learning based model. In the reported study, it is seen that the data set is divided into 80% and 20% as training and testing, respectively. This will result in a different result in each study. In this article, a different deep learning model is proposed and training and test data are separated according to the KFold technique. Rashid et al. (Rashid et al., 2022) proposed a MobileNetV2-based transfer learning model and a model that classifies skin cancer called melanoma. They are focused on classifying the types of skin cancer of benign and malignant melanoma. Similar to the (Jain et al., 2021) study in the literature, it separated training, testing, and validation data by 70%, 15%, and 15%, respectively.

According to the specified information, it was decided to develop a decision support system that assists experts. The main contributions of this study to the literature, which was conducted to classify the seven most common types of skin cancer, are presented below.

- The proposed DenseNet201 model reached an accuracy rate of 97,5% according to the KFold3 results.
- The proposed DenseNet201 model achieved 15% more accuracy than the basic DenseNet201 model.
- While the basic model has an average accuracy of 80.96%, the proposed model has an average accuracy rate of 98.73%.
- According to the F1 score, recall and precision performance measurement metrics, the basic model had an average rate of 82%, 79%, and 81%, respectively, while the proposed model achieved rates of 98%, 97%, and 98%, respectively.
- With the proposed deep learning model, a new transfer learning-based model has been designed that is capable of classifying skin cancer types.
- A satisfactory level of performance has been obtained from the designed model.

The remainder of the article consists of three sections. In the first section, the materials and methods used in the article are mentioned. In the second section, the performance results of the model used and proposed are presented by discussion. In the third section, the article is concluded.

2. Material and Methods

2.1. Material

Automatic training and classification of skin lesions may yield poor results when dataset size and diversity are small. In this sense, extensive data set research has been conducted covering different types of skin cancers. This study was trained and tested on the International Skin Imaging Collaboration (ISIC) 2018 dataset (International Skin Imaging Collaboration, 2018). ISIC dataset is a dataset with different skin lesions that is widely used in the literature.

In this article, the performance results of the model developed based on the proposed CNN and pretrained CNN models using the specified images are compared. The comparison process has been extended by including similar studies in the literature. Although the 4 most common types of skin cancer are reviewed in the literature (Dorj et al., 2018), in this article 7 different types of skin cancer are classified. It consists of seven different classes, akiec, bcc, bkl, df, mel, nv, and vasc. Nv, mel, bkl, bcc, akiec, vasc, and df consist of 6705, 1113, 1099, 514, 327, 142 and 115 images, respectively.

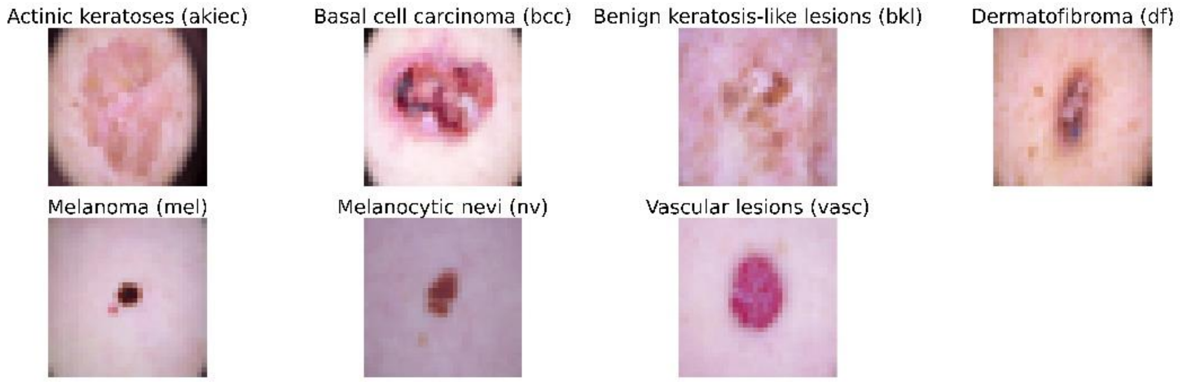

Figure 1. Skin lesion classes in the used dataset

Figure 1 shows the types of skin cancer in the dataset. The Bcc and akiec types are among the deadly types of skin cancer. It is also known that these species are difficult to detect. As a result of the early detection of bcc and akiec species, complete recovery can be achieved. As in different types of cancer, in these types of cancer, in case of late detection, the disease lesions metastasize. Seven different types of skin cancer, other than bcc and akiec, are less common (Shoieb et al., 2016). According to data shared by the World Health Organization, there has been an increase in bcc and akiec types of around 5% in America only in 2021 (Khan et al., 2021).

The ozone layer is thinning due to environmental pollution that occurs with population growth. As a result of the depletion of the ozone layer, there is an increase in anthropogenic pollution and skin diseases due to UV-B radiation (McMichael and McMichael, 1993; McKenzie et al., 2003; Martens and McMichael, 2009). The basis of this problem is the misinformation of the public (Moan et al., 2008). According to Moan's study, it is stated that the best time to be exposed to the sun is not in the afternoon (Moan et al., 2008). In general, there is an increase in diseases related to the harmful rays of the sun due to false information (Moan et al., 2008). For these reasons, it has become a necessity to assist specialists in the early and timely detection of growing diseases. For this reason, two different deep learning models have been defined to assist experts. One of these deep learning models represents the model developed within the scope of this article, while the other represents the basic DenseNet201 model used for comparison.

2.2. Performance evaluation metrics

False Negative (FN), True Negative (TN), False Positive (FP), True Positive (TP) markers were used to evaluate the performance of the proposed model. TP, FP represent correct and incorrectly predicted skin images, respectively. On the other hand, TN and FN represent normal and incorrectly estimated skin images, respectively. Performance comparisons of the proposed and basic model are made based on the specified specifiers such as TN, FN, FP, and TP. Based on these indicators, accuracy, precision, recall, and F1 score metrics are calculated. In this sense, the formulas commonly used in the literature to calculate the metrics specified are given below (Goutte and Gaussier, 2005):

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$F1 = 2x\frac{PrecisionxRecall}{Precision + Recall}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

The performances of the basic models proposed in this article were calculated according to the accuracy, recall, precision and F1 score formulas. In addition to the measurement results obtained from these formulas, accuracy and loss information is presented graphically. In this study, the accuracy, recall, precision and F1 score formulas used to evaluate the performance of deep learning models are presented above. Loss and accuracy results showing performance measurements calculated according to these formulas are given graphically.

2.3. DenseNet201

DenseNet architectures, one of the pre-trained deep learning architectures, was developed by (Huang et al., 2017). This is an architecture developed by optimizing the gradient flow problem in the ResNet architecture. Traditional convolution layer networks have more parameters than DenseNet. DenseNet has layers with few parameters to facilitate the flow of information between layers and optimize the network gradient. Furthermore, DenseNet consists of efficient models that provide the possibility of repetitive use of features obtained from convolution layers between layers (Pleiss et al., 2017). DenseNet201 uses direct connectivity between layers to provide a significant performance boost in datasets. Transfer learning is seen to be carried out with pretrained networks to facilitate cancer diagnosis with DenseNet models (Yu et al., 2019).

DenseNet architectural models have convolution, pooling, global pooling layers, fully connected, and classification layers. In addition to these, there are transition layers called transition layer 1 with dimensions of 28x28x128, transition layer 2 with dimension of 14x14x256, and transition layer 3 with dimensions of 7x7x896. There are Dense block 1 in 56x56x256, Dense block 2 in 28x28x512, Dense block 3 in 14x14x1792, and Dense block 3 in 7x7x1920. Dense blocks have different sizes of filtering cores. General mathematical formulas for DenseNet architectures are given in x_n equation. In x_n equation, DenseNet represents the reuse feature, which is one of the most important features of architectural model-specific structures.

$$x_n = H_n(x_{n-1})$$
$$x_n = H_n([x_0, \ldots, x_{n-1}])$$

In x_n equation, n. the feature map in the layer is represented by x_n. H_n consists of batch normalization, ReLU activation layer and convolution layer with a window size of 3x3.

2.4. The proposed DenseNet201

A new DenseNet201-based deep learning model has been designed to automatically classify the most common skin cancer types in the world to help experts. This model has been developed with fine tuning using transfer learning techniques.

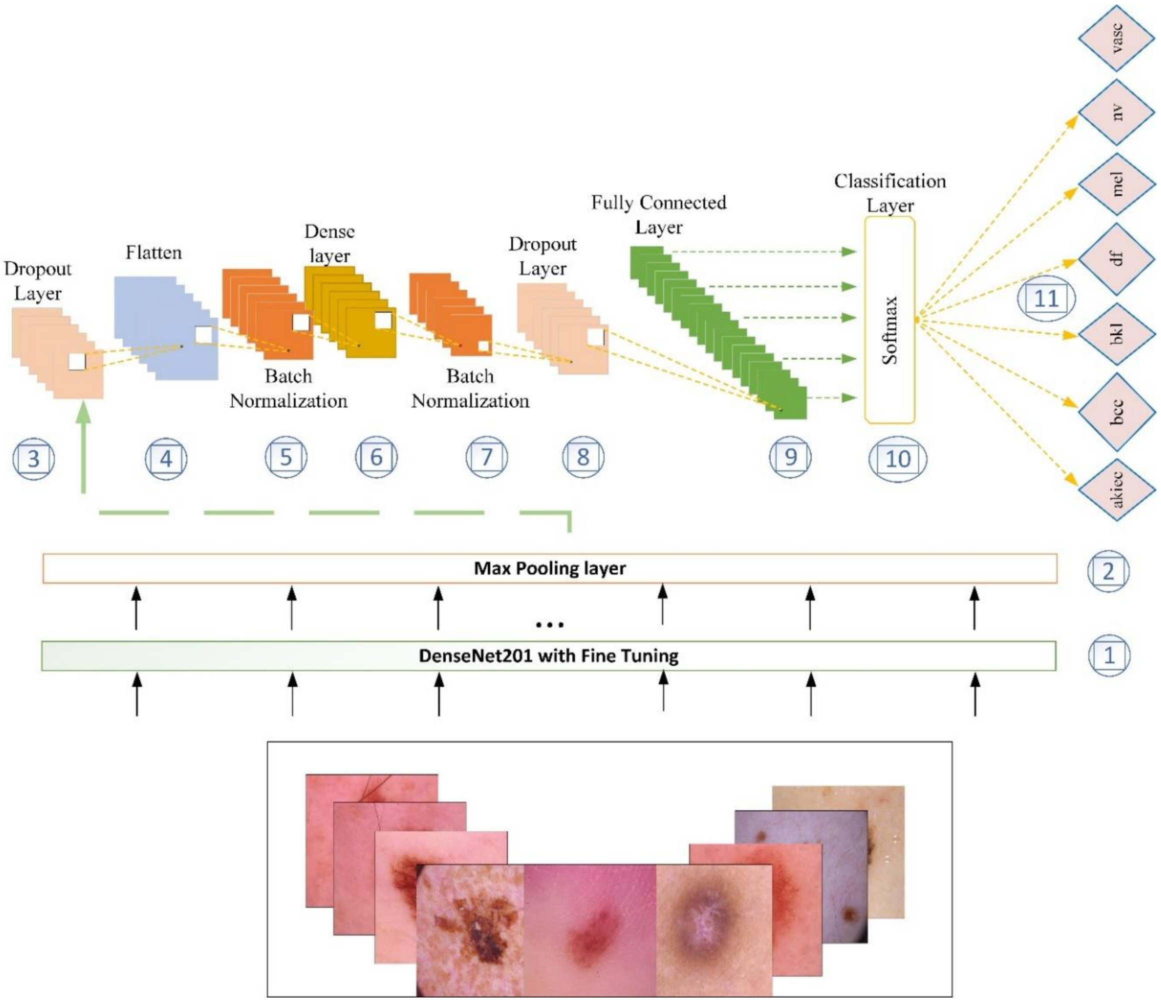

Figure 2. Flowchart of the proposed DenseNet201 model for skin type classification

No changes have been made to the basic transition and dense layers. However, fully connected and classification layers, which are the top layers, have been removed. Although the weight values of the layers with the moving mean and moving variance properties are used in the remainder, the weight values of the layers without these properties are not used. In essence, the block diagram of the proposed model is shown in Figure 2 in detail.

To correctly evaluate the success of this designed model, a model called the basic DenseNet201 model was created, which does not include any additional layers or features. The performance values of both models created were evaluated using certain criteria. In the proposed model, 32x32x3 size is used instead of the original size in order to increase the processing speed. The specified dimensions are, respectively, width, height, and volume images with three color channels, which are accepted as input. In the creation of the proposed DenseNet201 model, layers with moving mean and moving variance are set as trainable, others as non-trainable. In the second step shown in Figure 2, maximum pooling was achieved using 5x5 windows. In the third step, 0.5 neuron dropout was performed to prevent the network from memorizing. In the fourth step, the flatten layer was added. This layer is used to transform the features obtained from the convolution layer into a one-dimensional array (Çetiner, 2021).

3. Experimental Results and Discussion

As a result of experimental studies, a new method has been proposed to automatically classify the most common types of skin cancer. Accuracy values are given in order to test the performance of the proposed model. Training and test data splits were obtained using the KFold3 technique, in case the results could be different during each trial. The data obtained as a result of these divisions are presented separately for the normal model and the proposed model. Table 1 presents the KFold values of the basic model. According to these values, the basic model accuracy rates are between 77.95% and 83.79%. As a result of experimental studies, an average accuracy rate of 80,96 was achieved with the basic model. In addition to these, F1 score, recall and precision performance metrics are presented in Table 1. According to these metrics presented, the KFold3 option offers a higher F1 score value than other KFold options, while the KFold3 option gives the highest value in the recall and precision values.

Table 1. Performance results of the basic model according to KFold values

Optimization Method	KFold	Accuracy	Loss	F1 Score	Recall	Precision
Adam	1	77.95	0.67	79	76	78
Adam	2	81.15	0.57	83	80	82
Adam	3	83.79	0.50	85	82	84
Average		80.96	0.58	82	79	81

In Table 2, the accuracy and loss rates obtained from the proposed model are presented. According to these values presented, an accuracy varying between 96.93% and 99.73% has been achieved. As the average of these accuracies, an accuracy of 98.73% was achieved. As a result of the obtained rates, there is a 17.77% difference in success between the basic model and the proposed model. As a result, the proposed model has obtained a satisfactory result according to the performance results examined.

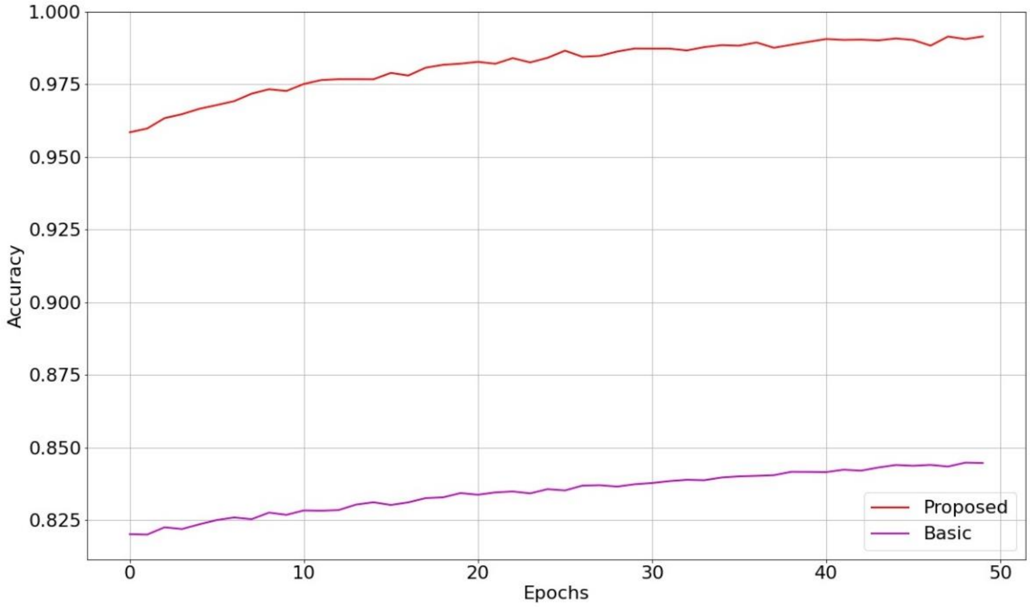

Figure 3. Training accuracy graph of the basic and proposed DenseNet201 model for skin type classification

Table 2. Performance results of the proposed model according to KFold values

Optimization Method	KFold	Accuracy	Loss	F1 Score	Recall	Precision
Adam	1	96.93	0.094	98	95	97
Adam	2	99.31	0.019	99	98	99
Adam	3	99.93	0.002	99	98	99
Average		98.73	0.38	98	97	98

In Figure 3, the training accuracy graphs of the basic and proposed DenseNet201 model are presented. According to these graphs presented, the highest training accuracy of the basic model in classifying skin cancer types approached 85%, while the proposed model exceeded 97.5%. KFold, which is close to the average of the results in Table 1 and Table 2, was preferred. Figures 3, 4, 5, and 6 are plotted according to the preferred KFold. According to the results in Table 1, KFold3 with the highest accuracy was preferred. According to the results in Table 2, KFold2, which is closest to the average result, was preferred. In addition to these, F1 score, recall and precision performance metrics are given in Table 2. According to these values, the metrics except the recall and precision values of the KFold1 option are the same or higher than the average measurements. According to the results of the measurements obtained, the performance metrics of the proposed model are at a satisfactory level.

According to the specified preferences, the training accuracy loss and test accuracy, loss graphs in Figure 3-6 were obtained. The loss graphs of the basic and proposed model are presented in Figure 4. According to these presented graphs, the loss graph of the basic model is around 0.5, while the loss graph of the proposed model is below 0.1. As the epoch approaches, it is seen that these results are taken in the 50th iteration. All result plots shown in Figures 3-6 were obtained as a result of training the models using Adam optimization method with 50 epoch steps and using 0.01 learning rate.

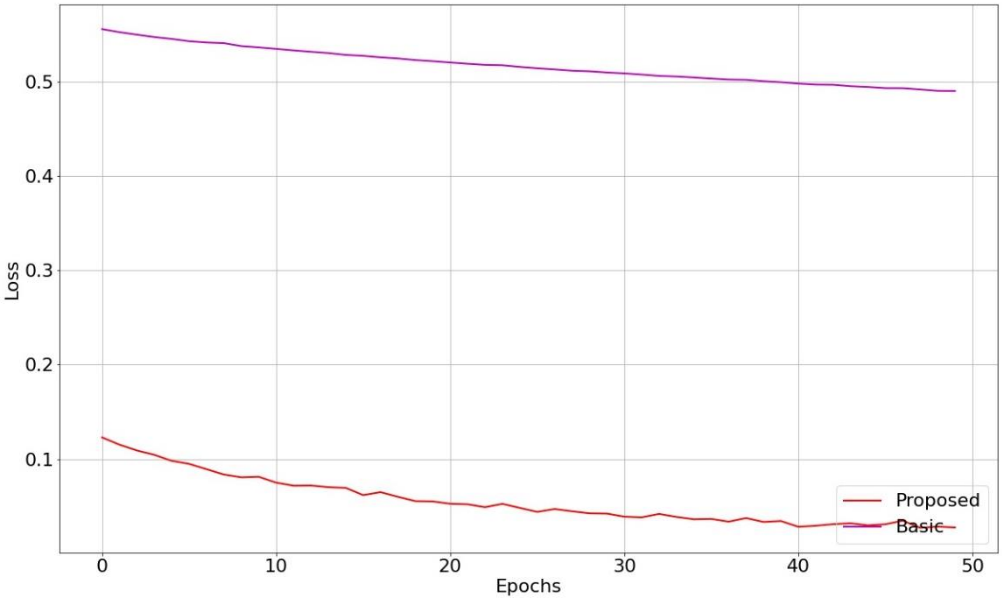

Figure 4. Training loss graph of the basic and proposed DenseNet201 model for skin type classification

Although these results are given, the main thing in academic studies is the results obtained from images that are not used in training. At this point, the test accuracy rates of the basic and proposed models are shown in Figure 5. According to the graphical results in Figure 5, the basic model reached an accuracy of 82.5%. According to the other result in the graph in Figure 5, the proposed model has reached a accuracy of 97.5%. Since both models basically have a certain weight value at the beginning, the accuracy graph values started from a non-zero point. These points indicate that the models are proposed on the basis of pre-trained transfer learning.

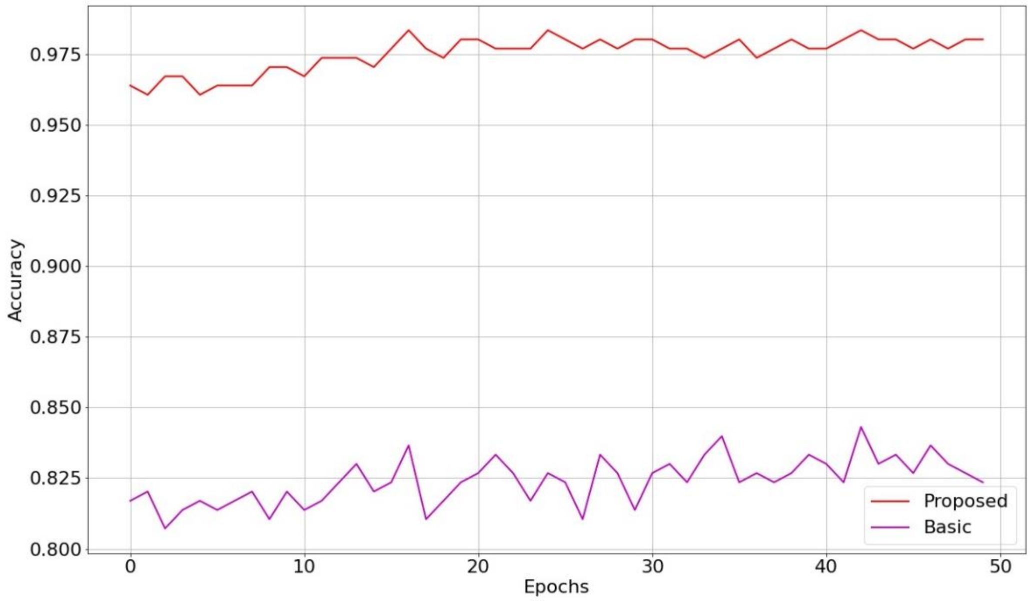

Figure 5. Test accuracy graph of the basic and proposed DenseNet201 model for skin type classification

According to the results in Figure 6, while the loss is above the value of 0.1 in the proposed model, the loss is above the value of 0.5 in the basic model. The results are obtained according to this training and test accuracy, and loss graphs are as presented.

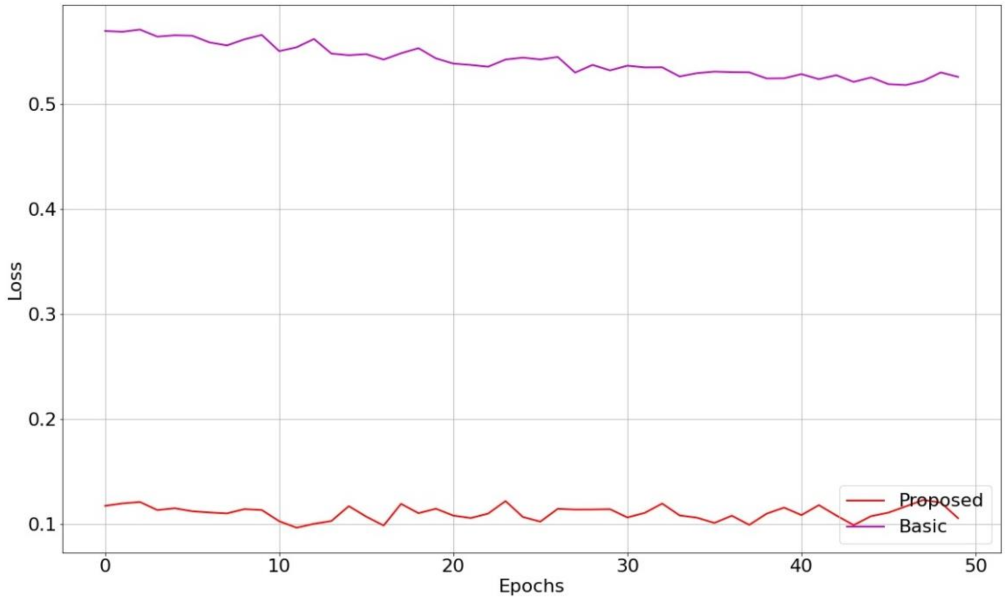

Figure 6. Test loss graph of the basic and proposed DenseNet201 model for skin type classification

The confusion matrix with the accuracies shown by class is shown in Figure 7. When the performance metrics obtained on the basis of nv, mel, bkl, bcc, akiec, vasc and df classes are examined, there are classes that are classified without any errors in the results obtained, as well as classes with incorrect classification. However, the mistakes made are too few to be underestimated on a class basis. Although the most errors were obtained in the nv class, the least errors were obtained in the vasc and df classes. Using the proposed model, the accuracy rates of seven different skin cancer classes on a class basis are shown in Figure 7. As can be seen in Figure 7, accuracies of 97.03%, 97.53%, 97.52%, 100%, 98.41%, 99.11% and 100% were achieved in akiec, bcc, bkl, df, mel, nv, and vasc classes, respectively. No pre-trained architectural structures were used in the study, in which skin cancer classification was performed with 30-layer CNN architecture on different datasets (Çetiner, 2023). This study contributes to the literature in terms of determining the effect of DenseNet blocks on the classification of skin cancer. Basic CNN methods are more suitable for real-time hardware systems, although they are lighter than structures consisting of millions of layers, although it has a negative effect on performance results.

According to the results given in Table 3, Kawahara and Hamarneh (Kawahara and Hamarneh, 2016)'s CNN model yielded a 75.1% accuracy in a ten-class skin cancer dataset. According to Estava et al. (Esteva et al., 2017)'s respectively CNN and CNN-PA model reported, respectively, 69.4% and 72.1% accuracy rates in a 3-class skin cancer dataset.

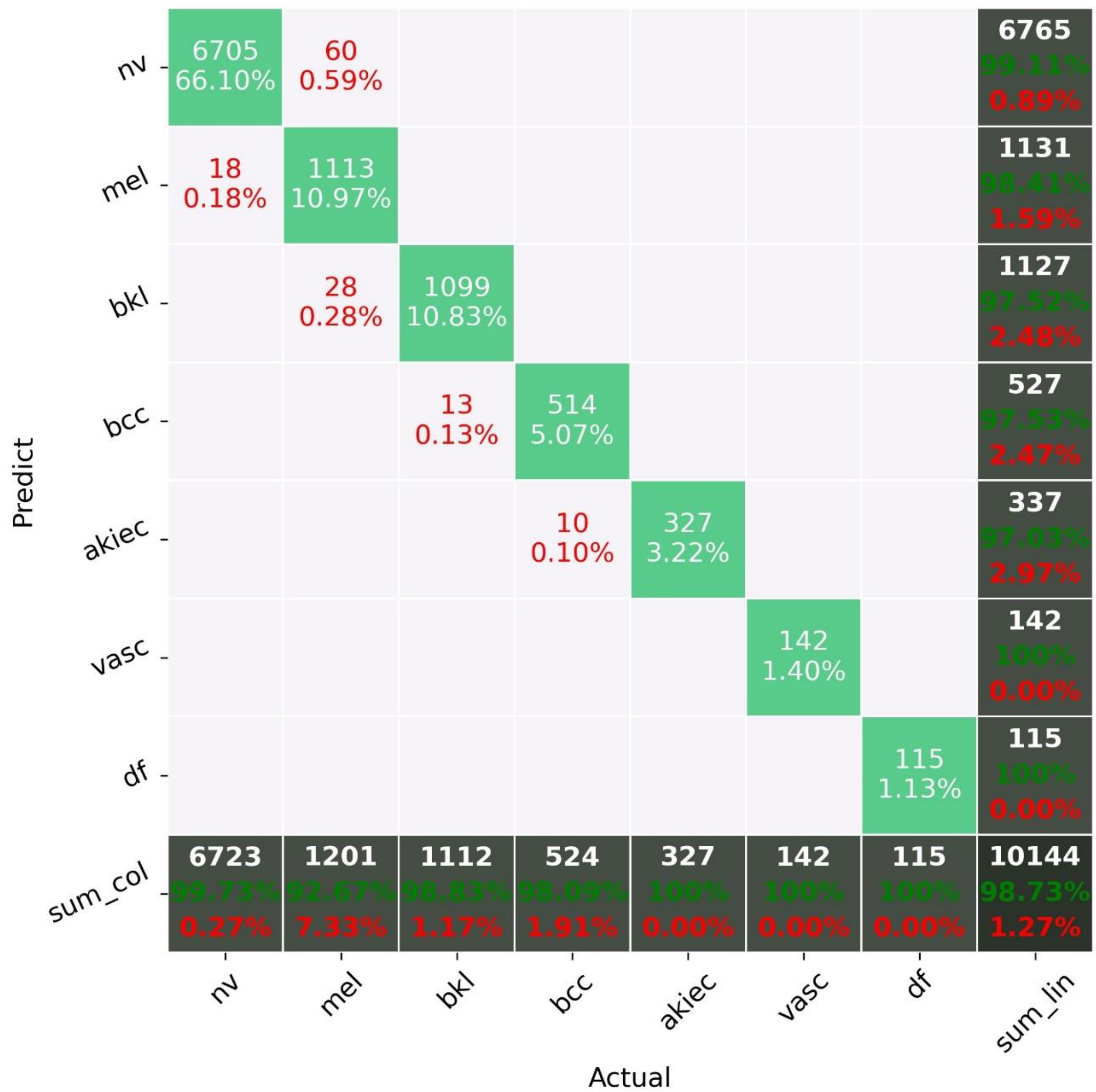

Figure 7. Confusion matrix of the proposed DenseNet201 model for skin type classification

According to Estava et al. (Esteva et al., 2017) CNN and CNN-PA models, respectively, are reported to reach 48,9% and 55,4% accuracies in a 9-class skin cancer data set.

Table 3. Comparison table with studies in the literature using the same and similar datasets

Model	Number of Classes	Accuracy (%)
(Kawahara and Hamarneh, 2016)’s CNN	Ten	75.1
(Esteva et al., 2017)’s CNN	Nine	48.9
(Esteva et al., 2017)’s CNN-PA	Nine	55.4
(Milton, 2019)’s InceptionResNetV2	Seven	70.0
(Milton, 2019)’s PNASNet-5 Large	Seven	76.0
(Milton, 2019)’s SENET 154	Seven	74.0
(Milton, 2019)’s Inception V4	Seven	67.0
(Chaturvedi et al., 2020)’s MobileNet	Seven	83.15
(Esteva et al., 2017)’s CNN	Three	69.4
(Esteva et al., 2017)’s CNN-PA	Three	72.1
Proposed Model	Seven	98.73

In another study, Milton (Milton, 2019)'s InceptionResNetV2, PNASNet-5 Large, SENET 154, Inception V4 deep learning models reported 70.0%, 76.0%, 74.0%, 67.0% accuracies, respectively.

Chaturvedi et al. (Chaturvedi et al., 2020)'s MobileNet model reached 83.15% accuracy. Chaturvedi et al. (Chaturvedi et al., 2020)'s MobileNet model is important in terms of getting these results in the same data set as the data set used in the article. For this reason, the results of Chaturvedi et al. (Chaturvedi et al., 2020)'s MobileNet model can be compared with the results of the proposed model. Chaturvedi et al. transfer learning was carried out in the model. It is stated that it is based on the MobileNet architecture due to its light weight. According to Table 3, it is seen that there are different data sets from three different skin cancer classes to 10 different skin cancer classes. Among the datasets with seven different skin cancer classes, the highest accuracy was achieved with the proposed model. It is difficult to make an exact comparison with classes with nine and ten different classes of skin cancer. The proposed model gave higher accuracies than the studies in the literature. In this sense, it is thought to have a significant contribution to the literature.

4. Conclusions

The types of skin cancer, which increase with age, are more common in young people under 55 years of age (Kumar et al., 2015). The risk of disproportionate growth of skin cancer in young people is much higher than in older patients. This article proposes a new deep learning-based method for the automatic classification of skin cancer cases that have increased rapidly in recent years. Experimental studies have been carried out to see whether this proposed model gives better results than the basic model in terms of performance. As a result of the experimental studies, advanced results were obtained. The results obtained were obtained according to the KFold3 technique. Cross-validation is an effective technique as it prevents the model from getting different results on each run.

To advance this article, a web-based tool can be developed with the help of Tensorflow.js library. With this developed tool, users who do not have any software knowledge can determine whether skin images are skin cancer or not. Due to this, the transformed model will provide the opportunity to access from a web-based browser or mobile browser. The study, which is carried out on the scale of the specified characteristics, is expected to contribute to the early detection of skin diseases by applying it to different biomedical lesions.

Conflict of Interest Statement

The article author declares that there is no conflict of interest.

Contribution Rate Statement Summary of Researchers

The author declares that he has contributed 100% to the article.

References

Almansour E., Jaffar MA. Classification of dermoscopic skin cancer images using color and hybrid texture features. IJCSNS Int J Comput Sci Netw Secur 2016; 16(4): 135–139.

Anas M., Gupta K., Ahmad S. Skin cancer classification using K-means clustering. International Journal of Technical Research and Applications 2017; 5(1): 62–65.

Attique Khan M., Sharif M., Akram T., Kadry S., Hsu C. A two-stream deep neural network-based intelligent system for complex skin cancer types classification. International Journal of Intelligent Systems 2021; Wiley Online Library.

Bakator M., Radosav D. Deep learning and medical diagnosis: A review of literature. Multimodal Technologies and Interaction 2018.

Blum A., Luedtke H., Ellwanger U., Schwabe R., Rassner G., Garbe C. Digital image analysis for diagnosis of cutaneous melanoma. Development of a highly effective computer algorithm based on analysis of 837 melanocytic lesions. British Journal of Dermatology 2004; Wiley Online Library 151(5): 1029–1038.

Çetiner H. Python Ortamında derin öğrenme uygulamaları. 2021; Anı yayıncılık: Ankara.

Çetiner H. Classification of cancer images with CNN-based deep learning approach. Journal 2023; 12(1): 30–38.

Chaturvedi SS., Gupta K., Prasad PS. Skin lesion analyser: an efficient seven-way multi-class skin cancer classification using MobileNet. International Conference on Advanced Machine Learning Technologies and Applications 2020; Springer, 165–176.

Cheplygina V., de Bruijne M., Pluim JPW. Not-so-supervised: a survey of semi-supervised, multi-instance, and transfer learning in medical image analysis. Medical image analysis 2019; Elsevier 54: 280–296.

Codella N., Cai J., Abedini M., Garnavi R., Halpern A., Smith JR. Deep learning, sparse coding, and svm for melanoma recognition in dermoscopy images. International Workshop on Machine Learning in Medical Imaging 2015; Springer, 118–126.

Dorj UO., Lee KK., Choi JY., Lee M. The skin cancer classification using deep convolutional neural network. Multimedia Tools and Applications 2018; 77(8): 9909–9924. https://doi.org/10.1007/s11042-018-5714-1.

Esteva A., Kuprel B., Novoa RA., Ko J., Swetter SM., Blau HM., Thrun S. Dermatologist-level classification of skin cancer with deep neural networks. Nature 2017; 542(7639): 115–118. https://doi.org/10.1038/nature21056.

Giotis I., Molders N., Land S., Biehl M., Jonkman MF., Petkov N. MED-NODE: A computer-assisted melanoma diagnosis system using non-dermoscopic images. Expert systems with applications 2015; Elsevier 42(19): 6578–6585.

Goutte C., Gaussier E. A probabilistic ınterpretation of precision, recall and f-score, with ımplication for evaluation. Lecture Notes in Computer Science 2005; 345–359.

Hosny KM., Kassem MA., Foaud MM. Skin cancer classification using deep learning and transfer learning. 2018 9th Cairo International Biomedical Engineering Conference (CIBEC) 2018; 90–93.

Huang G., Liu Z., Van Der Maaten L., Weinberger KQ. Densely connected convolutional networks. Proceedings of the IEEE conference on computer vision and pattern recognition 2017;, 4700–4708.

International Skin Imaging Collaboration. ISIC Archive. 2018;

Isasi AG., Zapirain BG., Zorrilla AM. Melanomas non-invasive diagnosis application based on the ABCD rule and pattern recognition image processing algorithms. Computers in Biology and Medicine 2011; Elsevier 41(9): 742–755.

Jain S., Singhania U., Tripathy B., Nasr EA., Aboudaif MK., Kamrani AK. Deep learning-based transfer learning for classification of skin cancer. Sensors (Basel, Switzerland) 2021; 21(23). https://doi.org/10.3390/s21238142.

Kawahara J., Hamarneh G. Multi-resolution-tract CNN with hybrid pretrained and skin-lesion trained layers. International workshop on machine learning in medical imaging 2016; Springer, 164–171.

Krizhevsky A., Sutskever I., Hinton GE. Imagenet classification with deep convolutional neural networks. Advances in neural İnformation Processing Systems 2012; 25.

Kumar A., Shrestha PR., Pun J., Thapa P., Manandhar M., Sathian B. Profile of skin biopsies and patterns of skin cancer in a tertiary care center of Western Nepal. Asian Pacific Journal of Cancer Prevention 2015; Asian Pacific Journal of Cancer Prevention 16(8): 3403–3406.

Kwasigroch A., Mikolajczyk A., Grochowski M. Deep neural networks approach to skin lesions classification — A comparative analysis. 2017 22nd International Conference on Methods and Models in Automation and Robotics (MMAR) 2017; IEEE, 1069–1074.

Litjens G., Kooi T., Bejnordi BE., Setio AAA., Ciompi F., Ghafoorian M., Van Der Laak JA., Van Ginneken B., Sánchez CI. A survey on deep learning in medical image analysis. Medical image analysis 2017; Elsevier 42: 60–88.

Martens P., McMichael AJ. Environmental change, climate and health: issues and research methods. 2009; Cambridge University Press.

McKenzie RL., Björn LO., Bais A., Ilyasd M. Changes in biologically active ultraviolet radiation reaching the Earth’s surface. Photochemical & Photobiological Sciences 2003; Royal Society of Chemistry 2(1): 5–15.

McMichael AJ., McMichael T. Planetary overload: global environmental change and the health of the human species. 1993; Cambridge University Press.

Milton MAA. Automated skin lesion classification using ensemble of deep neural networks in ISIC 2018: Skin lesion analysis towards melanoma detection challenge. arXiv preprint arXiv:1901.10802 2019;

Moan J., Dahlback A., Porojnicu AC. At what time should one go out in the sun? Advances In Experimental Medicine and Biology 2008; United States 624: 86–88. https://doi.org/10.1007/978-0-387-77574-6_7.

Morid MA., Borjali A., Del Fiol G. A scoping review of transfer learning research on medical image analysis using ImageNet. Computers in Biology and Medicine 2021; 128: 104115.

Pacal I., Karaboga D., Basturk A., Akay B., Nalbantoglu U. A comprehensive review of deep learning in colon cancer. Computers in Biology and Medicine 2020; 126: 104003. https://doi.org/https://doi.org/10.1016/j.compbiomed.2020.104003.

Perroy R. World population prospects. United Nations 2015; 1(6042): 587–592.

Pimentel D., Cooperstein S., Randell H., Filiberto D., Sorrentino S., Kaye B., Nicklin C., Yagi J., Brian J., O'Hern J., Habas A., Weinstein C. Ecology of ıncreasing diseases: Population growth and environmental degradation. Human ecology: An Interdisciplinary Journal 2007; Springer US 35(6): 653–668. https://doi.org/10.1007/s10745-007-9128-3.

Pleiss G., Chen D., Huang G., Li T., van der Maaten L., Weinberger KQ. Memory-efficient ımplementation of densenets. 2017.

Pomponiu V., Nejati H., Cheung NM. Deepmole: Deep neural networks for skin mole lesion classification. 2016 IEEE International Conference on Image Processing (ICIP) 2016; IEEE, 2623–2627.

Ramlakhan K., Shang Y. A mobile automated skin lesion classification system. 2011 IEEE 23rd International Conference on Tools with Artificial Intelligence 2011; 138–141.

Rashid J., Ishfaq M., Ghulam A., Saeed MR., Hussain M., Alkhalifah T, Alturise F., Samand N. Skin cancer disease detection using transfer learning technique. Applied Sciences 2022.

Ruiz D., Berenguer V., Soriano A., Sánchez B. A decision support system for the diagnosis of melanoma: A comparative approach. Expert Systems with Applications 2011; Elsevier 38(12): 15217–15223.

Shoieb DA., Youssef SM., Aly WM. Computer-aided model for skin diagnosis using deep learning. Journal of Image and Graphics 2016; 4(2): 122–129. https://doi.org/10.18178/joig.4.2.122-129.

Suganyadevi S., Seethalakshmi V., Balasamy K. A review on deep learning in medical image analysis. International Journal of Multimedia Information Retrieval 2022; 11(1): 19–38. https://doi.org/10.1007/s13735-021-00218-1.

Yu X., Zeng N., Liu S., Zhang YD. Utilization of DenseNet201 for diagnosis of breast abnormality. Machine Vision and Applications 2019; 30(7): 1135–1144.