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Classification of skin cancer using VGGNet model structures

VGGNet model yapıları kullanılarak cilt kanserinin sınıflandırılması

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Abstract

Skin cancer is one of the most common type of cancer in humans. This type of cancer is produced by skin cells called melanocytes and occurs as a result of division and multiplication of the mentioned cells. The most important symptom of skin cancer is the formation of spots on the skin or the observation of changes in the shape, color, or size of the existing spot. It is necessary to consult a specialist to distinguish the difference between a normal spot and skin cancer. Expert physicians examine and follow up the spots on the skin using skin surface microscopy, called dermatoscopy, or take a sample from the suspicious area and request it to be examined in laboratory environment. This situation increases the cost of the procedure for the diagnosis of skin cancer and also causes it to be treated at a later stage. Therefore, there is a need for a method that can detect skin cancer early. Thanks to machine learning, become popular in recent years, many diseases can be diagnosed with software that helps expert physicians. In this study, VGGNet model structures (VGG-11, VGG-13, VGG-16, VGG-19) that quickly classify skin cancer and become a traditional convolutional neural network architecture using deep learning method, a subfield of machine learning, were used. It has been observed that the VGG-11 architecture, which is one of the VGGNet model structures, detects skin cancer with superior success accuracy (83%) compared to other model structures.

Keywords: Deep learning, Machine learning, Skin cancer classification, VGGNet

Öz

Cilt kanseri insanlarda en sık rastlanan kanser türlerinden birisidir. Bu kanser türü melanosit denilen cilt hücreleri tarafından üretilmekte ve bu hücrelerin bölünüp çoğalması sonucunda meydana gelmektedir. Cilt kanserinin en önemli belirtisi deri üzerinde leke oluşması veya var olan lekenin şeklinde, renginde veya büyüklüğündeki değişiklerin gözlenmesidir. Normal bir leke ile cilt kanserinin farkını ayırt etmek için uzman bir hekime başvurmak gereklidir. Uzman hekimler dermatoskopi olarak adlandırılan deri yüzeyi mikroskopisi kullanarak deri üzerindeki lekeleri incelerler ve takip altına alırlar veya şüpheli gördüğü bölgeden parça örneği alarak laboratuvar ortamında incelenmesini isterler. Bu durum cilt kanseri teşhisinin yapılabilmesi için hem işlem maliyetini artırmakta hem de daha geç evrede tedavi edilmesine yol açmaktadır. Bundan dolayı cilt kanserini erken teşhis edebilen bir yazılıma ihtiyaç duyulmaktadır. Son yıllarda popüler olan makine öğrenmesi sayesinde uzman hekimlere yardımcı olan bir yazılım ile birçok hastalık tanısı konulabilmektedir. Bu çalışmada makine öğrenmesinin bir alt alanı olan derin öğrenme yöntemi kullanılarak cilt kanserini hızlı bir şekilde sınıflandıran ve geleneksel bir evrişimsel sinir ağı mimarisi haline gelen VGGNet model yapıları (VGG-11, VGG-13, VGG-16, VGG-19) kullanılmıştır. VGGNet model yapılarından biri olan VGG-11 mimarisi diğer model yapılarına göre cilt kanserini daha üstün başarı doğruluğunda (%83) tespit ettiği gözlemlenmiştir.

***Anahtar kelimeler**: Derin öğrenme, Makine öğrenmesi, Cilt kanseri sınıflandırma, VGGNet*

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1. Introduction

Cancer is a type of disease that develops when an organ or tissue cell divides and multiplies spontaneously and can spread beyond the region where it is located (Akyel & Arıcı, 2020). There are more than 100 types of cancer worldwide. Cancer types usually get their names from the tissue or organ where the cancers originate.

Skin cancer is one of the most common and deadly cancer types worldwide (Dildar et al., 2021; Hosny et al., 2018; Göreke, 2021). In this type of cancer, the color pigments called melanin, which gives the skin its color, are produced by skin cells called melanocytes. Skin cancer is defined as melanoma that occurs when these cells divide and multiply uncontrollably (Göreke, 2021). The most important symptom of melanoma is the formation of spots on the skin or the observation of changes in the shape, color, or size of the existing spot (Saba, 2021). Since skin cancer usually starts on the skin surface, it is a type of cancer that has a high chance of being diagnosed at an early stage (Ergün & Kılıç, 2021). Skin cancer can occur on the normal skin surface without warning, or it can develop on a pre-existing mole. For this, it is necessary to define the location and appearance of moles in the body well. Therefore, in order to identify skin cancer early, a person should regularly check his or her own skin at regular intervals (Kadampur & Al Riyaee, 2020). Not every mole formed in various parts of the body is harmful. However, over time, causes such as distorted asymmetrical appearance, growth, color change, inflammation, redness, or bleeding seen in moles can cause skin cancer. Therefore, melanoma moles should not be confused with other typical moles. Therefore, it is necessary to consult a specialist physician to distinguish the difference between a normal spot and skin cancer.

The specialist physician first visually examines the suspicious skin area (Nawaz et al., 2021). Since some types of skin tissue disorders are similar, it is very important to make an accurate diagnosis (Demir, 2021). Therefore, specialist physicians examine and follow up the spots on the skin using skin surface microscopy, called dermatoscopy, or take a sample from the suspicious area and ask them to be examined in the laboratory environment (Manasa & Murthy, 2021). This situation both increases the cost of the procedure for the diagnosis of skin cancer and causes it to be treated at a later stage. Therefore, disease recognition and detection from spots on the skin is generally an image classification process (Yıldız, 2019). In recent years, deep learning methods, a sub-field of machine learning, which has excelled in problems such as disease recognition and detection, have achieved successful results by using big data (Manne et al., 2020; Dildar et al., 2021; Thomas et al., 2021). Deep learning basically uses software that responds faster and more accurately than humans to classify more complex structures by analyzing the raw data given to it as input (Kaya et al., 2021a and b). Therefore, deep learning methods have gained importance in detecting the type of skin cancer (Dascalu & David, 2019).

The subject of this study is Few-Shot Learning for Dermatological Conditions and Examination of Skin Analysis from Multi-Modal Data Sources Algorithms to Mitigate Class Imbalance. Therefore, in this study, VGG-11, VGG-13, VGG-16, and VGG-19 model structures, which have become a traditional convolutional neural network architecture and are also known as VGGNet, were compared to determine the type of skin cancer. For the training of these models, a dataset containing 1000 benign and 1000 malignant skin cancer types was used, and it was seen that the VGG-11 model had superior performance compared to other model structures.

The remainder of the work is organized as follows. In section 2, recent studies on the detection of skin cancer types are presented. In section 3, information about the materials and methods related to the study is given. In section 4, the experimental results of the study are shown. Finally, in section 5, conclusions and future work are given.

2. Related works

In the literature, deep learning models have been frequently used in the classification of skin cancer images. In a study of skin cancer classification using deep learning and transfer learning, an automated skin lesion classification using a pre-trained deep learning network is proposed. In the proposed method, melanoma, common nevus and atypical nevus a typical skin cancer type were classified with 98.61% success accuracy, 98.33% sensitivity, 98.93% specificity and 97.73% precision (Hosny et al., 2018).
In the study of detection and classification of skin cancer using transfer learning, a new learning-oriented internet of health and things (IoHT) framework is proposed. With this proposed framework, features are

automatically extracted from images using pre-trained VGG-19, Inception-V3, ResNet-50, and SqueezeNet architectures. The proposed framework achieved higher success accuracy (99.60%) in skin lesion classification compared to pre-trained architectures (Inception V3 92.30%, VGG19 94.35%, SqueezeNet 95.70%, ResNet50 97.15%) (Khamparia et al., 2021).

In another study, ResNet-101 and Inception-V3 deep learning architectures were used to detect skin cancer with high accuracy. According to the classification results, an accuracy rate of 84.09% was obtained with the Resnet-101 architecture and 87.42% with the Inception-V3 architecture (Demir et al., 2019). In a region-of-interest-based study for skin cancer detection, a new system is proposed to identify and differentiate melanoma with nevus cancer using a transfer learning approach. Since only images containing melanoma cells were needed to train the proposed system, the K-means algorithm was used to extract ROIs from images. In addition, DermIS and DermQuest datasets were used in the proposed system training and success accuracy of 97.9% and 97.4% were obtained, respectively (Ashraf et al., 2020). In the skin cancer classification model based on VGG-19 and transfer learning, model training and test accuracy were obtained by using the Human Against Machine dataset at a rate of 98.50% and 97.50%, respectively. Also, the model training and test loss were obtained as 0.009 and 0.119, respectively (Abuared et al., 2020).

In an advanced skin cancer classification technique study using a deep convolutional neural network (DCNN) with transfer learning models, a new model is proposed to accurately classify benign and malignant skin lesions. AlexNet, ResNet, VGG-16, DenseNet, and MobileNet architectures were compared on the same dataset to evaluate the performance of the proposed model. As a result of the comparison, the proposed model achieved a more successful training accuracy rate (93.16%) and a test accuracy rate (91.93%) compared to other existing models (Ali et al., 2021). In another study, a classification model was developed for pigmented skin lesions using deep learning. For this model training, datasets belonging to six classes consisting of malignant tumors (malignant melanoma and basal cell carcinoma) and benign tumors (nevus, seborrhoeic keratosis, senile lentigo, and hematoma/hemangioma) were used. This dataset has been trained and tested with a faster region-based convolutional neural network (FRCNN). As a result of the test, skin lesions belonging to six classes were classified with an accuracy of 86.2% (Jinnai et al., 2020).

3. Material and method

3.1. System configuration

Many studies are required to achieve the best results from deep learning models. In the study, it is important to choose a suitable programming language to reach fast and accurate results from the model structures. In this study, Python programming language was used to apply VGGNet model structures and evaluate the results. In this study, a computer with Intel Core i7-9750H 2.60 GHz processor, 8 GB RAM, and Nvidia GeForce GTX 1650 graphics card with 896 CUDA cores was used to process and evaluate the data of VGGNet model structures and obtain the results.

3.2. Acquisition of image data

In this study, a dataset containing images of benign skin cancers and malignant skin cancers was used (Kaggle, 2021). In this dataset, 1800 benign skin cancer images with 224x224 pixel size and 1497 malignant skin cancer images are in RGB color format. A total of 3297 skin images are divided into training (80%), and test (20%) datasets. The images of both skin cancers in the dataset are given in Figure 1.

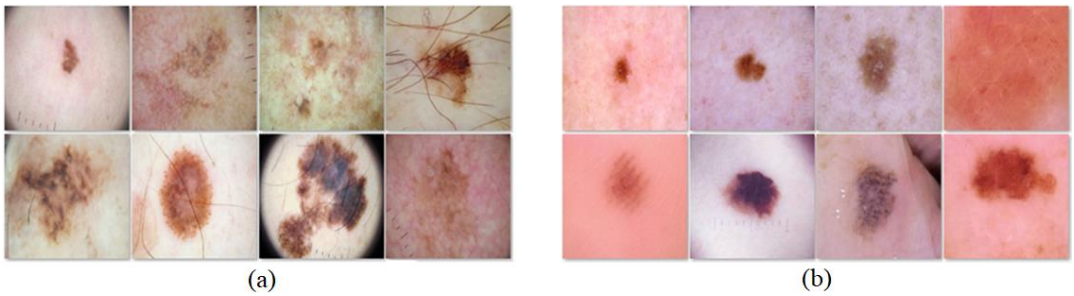

Figure 1. Skin cancer dataset images (a) malignant (b) benign

3.3. VGGNet model structures

Convolutional neural networks, one of the deep learning algorithms that are frequently used in recent years, have shown outstanding success in areas such as image classification and object recognition. Convolutional neural networks are a neural network structure that mimics the learning structure of the human brain. This neural network is a deep learning algorithm that can separate various objects in the image by taking any input image (Albawi et al., 2017). A convolutional neural network algorithm is often preferred to solve complex problems in different deep learning models and to reduce the number of parameters in neural networks. Convolutional neural networks basically consist of input, convolution, pooling, fully connected, and output layers. Thanks to these layers, the learning of the neural network takes place (Li et al., 2018; Pathak et al., 2018).

In this study, VGG-11, VGG-13, VGG-16, and VGG-19 models from VGGNet model structures, which have become a traditional convolutional neural network architecture, were used. VGGNet model diagram is given in Figure 2 and VGGNet model configuration is given in Table 1.

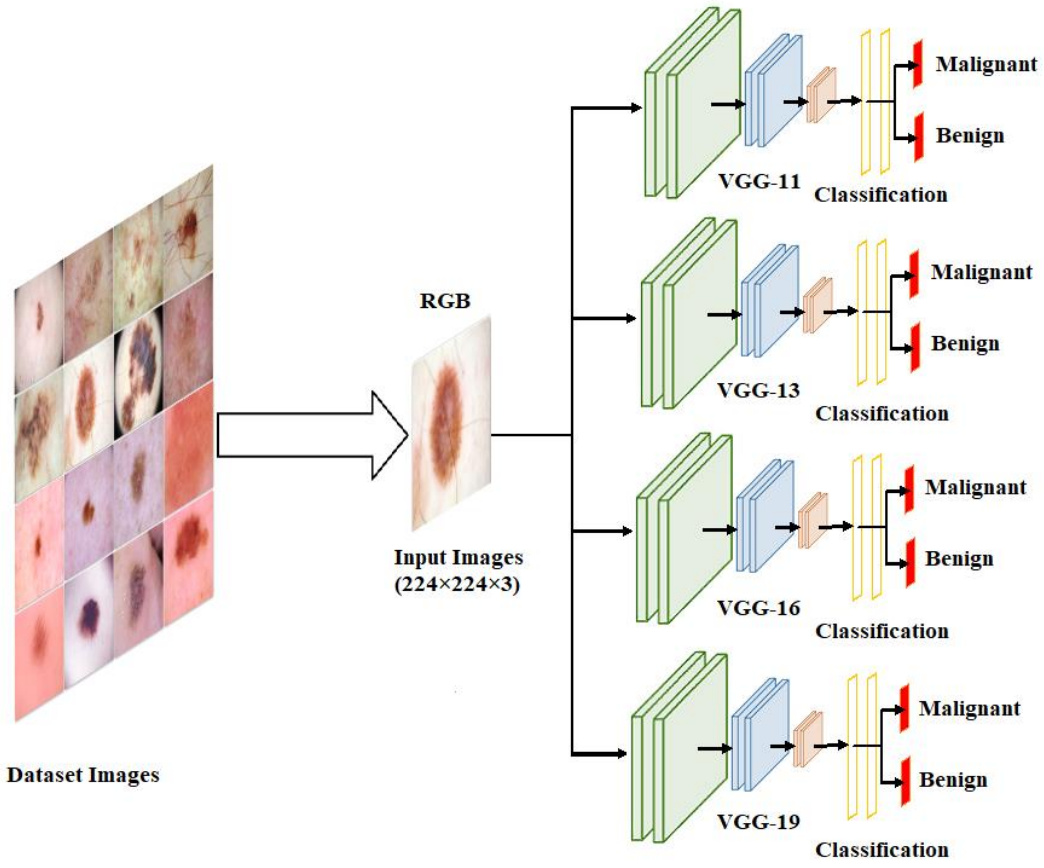

Figure 2. VGGNet model diagram

VGGNet is a standard convolutional neural network architecture with multi-layer GPU support (Kaya et al., 2020). VGGNet architecture forms the basis of object recognition models. The VGGNet architecture takes an input image in RGB color format with a size of 224×224 pixels during the training and a 3×3 filter is used in each convolution layer. Also, after each convolution block, the data size is reduced from input to output by using a 2-step pooling layer with a pixel size of 2×2 (Simonyan & Zisserman, 2014).

3.4. Training and testing

A 2-class dataset consisting of benign and malignant skin cancer types was used for training and testing the VGGNet model structures discussed in the study. Out of a total of 3297 skin cancer images in the data set, 2637 are used for model training and 660 are used for model tests. In addition, 20 epochs, 64 mini-batch sizes,

Adamax for optimization algorithm, and ReLU parameters as activation function were used for training the model structures used in the study.

Table 1. VGGNet configuration (Simonyan & Zisserman, 2014)

VGG-11	VGG-13	VGG-16	VGG-19
Input (224×224 RGB image)			
Conv3-64	Conv3-64 Conv3-64	Conv3-64 Conv3-64	Conv3-64 Conv3-64
maxpool			
Conv3-128	Conv3-128 Conv3-128	Conv3-128 Conv3-128	Conv3-128 Conv3-128
maxpool			
Conv3-256 Conv3-256	Conv3-256 Conv3-256	Conv3-256 Conv3-256 Conv3-256	Conv3-256 Conv3-256 Conv3-256 Conv3-256
maxpool			
Conv3-512 Conv3-512	Conv3-512 Conv3-512	Conv3-512 Conv3-512 Conv3-512	Conv3-512 Conv3-512 Conv3-512 Conv3-512
maxpool			
Conv3-512 Conv3-512	Conv3-512 Conv3-512	Conv3-512 Conv3-512 Conv3-512	Conv3-512 Conv3-512 Conv3-512 Conv3-512
maxpool FC-4096 FC-4096 FC-2 softmax			

4. Results and discussion

In the study, the classification of skin cancer types was made by running each of the VGGNet model structures separately 5 times. The low model loss value in the classification of skin cancer types means that the model network has learned well. Therefore, each VGGNet model structure was run 5 times and the obtained loss values are given in Table 2. In addition, the model structure with the lowest loss value as a result of the training conducted 5 times was discussed and the performance values of this model's test success accuracy are given in Table 3. In addition, the classification accuracy and loss graphs obtained as a result of the training test of each model with the lowest loss value are given in Figure 3.

Table 2. Loss values obtained by running VGGNet model structures 5 times

Models	Model Training 1	Model Training 2	Model Training 3	Model Training 4	Model Training 5
VGG-11	0.7283	0.6093	0.4885	0.4879	**0.4524**
VGG-13	0.5939	0.5309	0.6191	0.4894	**0.4293**
VGG-16	0.4048	0.3935	**0.3931**	0.4243	0.4068
VGG-19	**0.3670**	0.4059	0.4274	0.4102	0.3690

When the results given in Table 3 are examined, it is seen that the highest test success accuracy (83%) in skin cancer type classification is obtained with VGG-11. In addition, when the graphs given in Figure 3a are examined, it is seen that the test result of the VGG-11 model structure is better than the other models. However, it is seen that VGG-13 achieved 82%, VGG-16 81%, and VGG-19 81% success accuracy. According to the results obtained, it is seen that the models with less number of layers learn better. Therefore, the reason why the model with fewer layers learns better is that the skin cancer dataset used in the study is two-class and

accordingly the images are very different from each other. This suggests that a less layered model may be preferred depending on the number of classes in the dataset and the distinguishability of the images.

In addition, the performance of the model with the lowest loss value among the VGGNet model structures discussed in the study was tested and the confusion matrix given in Table 4 was obtained.

Table 3. Performance results of the model for the lowest loss value obtained as a result of the training made 5 times

Models	Class	Precision	Recall	F1-Score	Accuracy	Loss
VGG-11 (Model Training 5)	Benign	0.86	0.84	0.85	0.83	0.45
	Malignant	0.81	0.83	0.82		
VGG-13 (Model Training 5)	Benign	0.85	0.82	0.83	0.82	0.43
	Malignant	0.79	0.82	0.81		
VGG-16 (Model Training 3)	Benign	0.81	0.86	0.83	0.81	0.39
	Malignant	0.82	0.75	0.78		
VGG-19 (Model Training 1)	Benign	0.81	0.85	0.83	0.81	0.37
	Malignant	0.81	0.75	0.78		

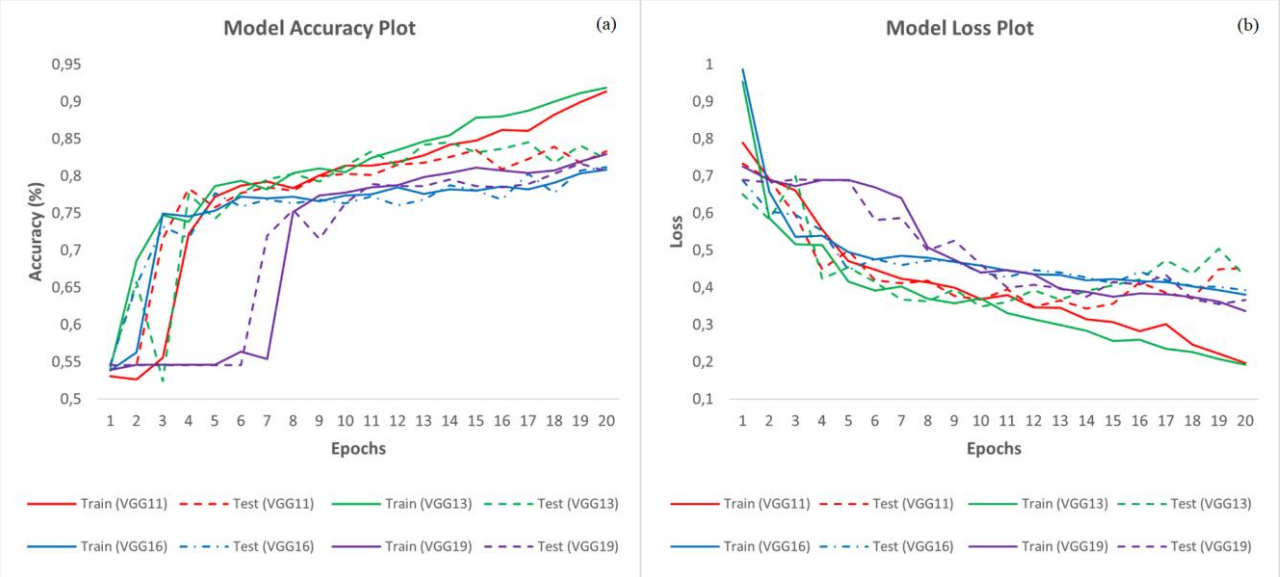

Figure 3. VGGNet model (a) training test accuracy and (b) loss graph

Table 4. Confusion matrix values of VGGNet model structures

Models	Benign		Malignant	
	True Positive	False Negative	True Negative	False Positive
VGG-11 (Model Training 5)	301	59	249	51
VGG-13 (Model Training 5)	296	64	247	53
VGG-16 (Model Training 3)	311	49	225	75
VGG-19 (Model Training 1)	306	54	226	74

When Table 4 is examined; it is seen that benign and malignant skin cancer types are classified with VGG-11 83.33%, VGG-13 82.27%, VGG-16 81.21%, and VGG-19 80.61% success accuracy. According to the results obtained from the VGGNet model structures; It is seen that the number of layers used in the VGG-11 model structure is more suitable for determining the type of skin cancer and has a higher classification performance than other models. However, it is seen that the VGG-19 model structure has the most unsuccessful classification performance in total, with 54 misclassifications in the benign class and 74 misclassifications in the malignant class. Example images of misclassifications obtained with the VGG-19 model are shown in Figure 4.

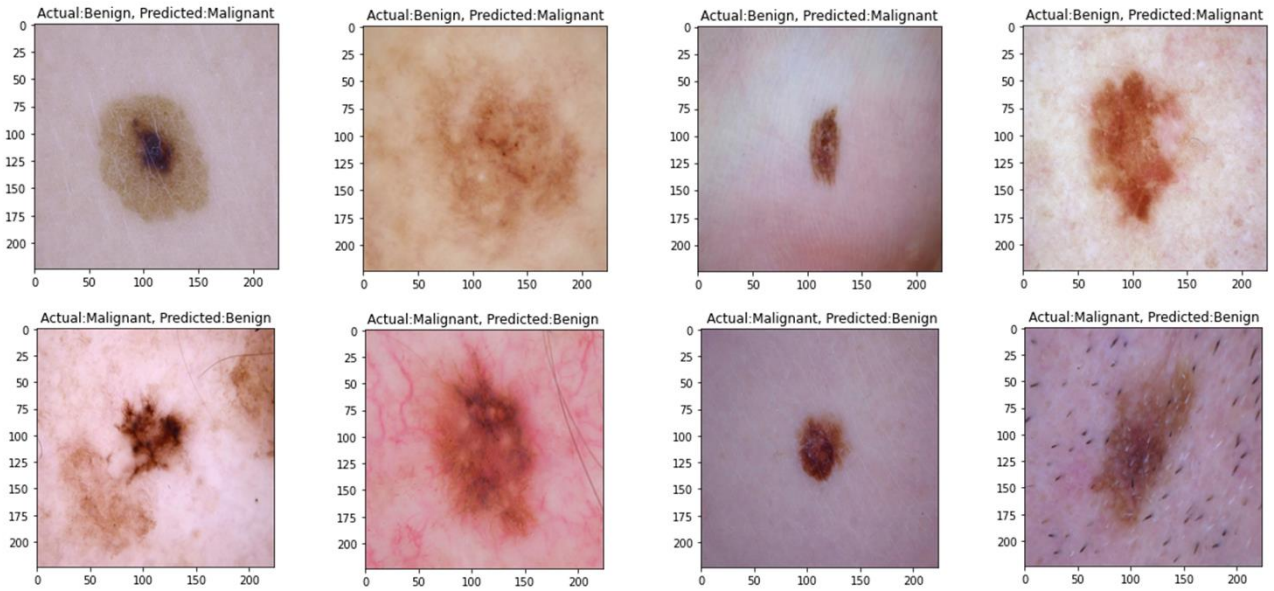

Figure 4. Example images of misclassifications obtained with the VGG-19 model

The skin cancer dataset (Kaggle, 2021) used in the study was used in different studies in the literature and the results of the success rates obtained are given in Table 5 comparatively.

Table 5. Comparison of studies using the same dataset as the proposed study

References	Model	Accuracy (%)
Agarwal & Singh (2022)	DenseNet201, ResNet50, XceptionNet, MobileNet	86.57
Hasan et al. (2021)	SVM, VGG16, ResNet50, Sequential	93.18
Tumpa & Kabir (2021)	ABCD + GLCM + LBP	97.70
Toğaçar et al. (2021)	MobileNetV2 & Autoencoder & SNN	95.27
Shorfuzzaman (2021).	Stacked model	95.76
Soylu & Rukiye (2021)	DarkNet-19, DarkNet-53, ShuffleNet, SqueezeNet	89.89
Proposed method	VGG-11, VGG-13, VGG-16, VGG-19	83.00

5. Conclusions

In this study, VGGNet model structures that classify skin cancer types and become a traditional architecture were used. These model constructs were trained and tested using a dataset of 3297 skin cancer images. According to the training and test results, the best classification success accuracy was obtained with the VGG-11 model structure, with 83% and 0.45 loss rates. The model structure with the lowest classification success accuracy was 81% with VGG-19 and the loss rate was 0.37.
As a result, the VGGNet model structures compared in the study showed good success in classifying the skin cancer type. The applicability of VGGNet model structures in classifying skin cancer types in the field of health increases the importance of the study and is expected to contribute to studies that classify and locate skin cancer types in real-time in future studies. In the future, classification studies can be performed with datasets containing multiple classifications (Actinic keratosis, basal cell carcinoma, dermatofibroma, melanoma, etc.) for skin cancer.

Author contribution

The authors' contribution rates in the study are equal.

Declaration of ethical code

The authors of this article declare that the materials and methods used in this study do not require ethical committee approval and/or legal-specific permission.

Conflicts of interest

The authors declare that there is no conflict of interest.

References

Abuared, N., Panthakkan, A., Al-Saad, M., Amin, S. A., & Mansoor, W. (2020). Skin cancer classification model based on VGG 19 and transfer learning. *In 2020 3rd International Conference on Signal Processing and Information Security (ICSPIS)* (pp. 1-4), Dubai. https://doi.org/10.1109/ICSPIS51252.2020.9340143

Agarwal, K., & Singh, T. (2022). Classification of skin cancer ımages using convolutional neural networks, *arXiv preprint*. https://doi.org/10.48550/arXiv.2202.00678

Akyel, C., & Arıcı, N. (2020). Cilt kanserinde kıl temizliği ve lezyon bölütlemesinde yeni bir yaklaşım. *Politeknik Dergisi*, *23*(3), 821-828. https://doi.org/10.2339/politeknik.645395

Albawi, S., Mohammed, T. A., & Al-Zawi, S. (2017). Understanding of a convolutional neural network, *2017 International Conference on Engineering and Technology (ICET)*, (pp. 1-6), Antalya. https://doi.org/10.1109/ICEngTechnol.2017.8308186

Ali, M. S., Miah, M. S., Haque, J., Rahman, M. M., & Islam, M. K. (2021). An enhanced technique of skin cancer classification using deep convolutional neural network with transfer learning models. *Machine Learning with Applications*, *5*, 100036. https://doi.org/10.1016/j.mlwa.2021.100036

Ashraf, R., Afzal, S., Rehman, A. U., Gul, S., Baber, J., Bakhtyar, M., Mehmood, I., Song, O. Y., & Maqsood, M. (2020). Region-of-Interest based transfer learning assisted framework for skin cancer detection. *IEEE Access*, *8*, 147858-147871. https://doi.org/10.1109/ACCESS.2020.3014701

Dascalu, A., & David, E. O. (2019). Skin cancer detection by deep learning and sound analysis algorithms: A prospective clinical study of an elementary dermoscope. *EBioMedicine*, *43*, 107-113. https://doi.org/10.1016/j.ebiom.2019.04.055

Demir, A., Yilmaz, F., & Kose, O. (2019). Early detection of skin cancer using deep learning architectures: resnet-101 and inception-v3. *In 2019 Medical Technologies Congress (TIPTEKNO)* (pp. 1-4), İzmir. https://doi.org/10.1109/TIPTEKNO47231.2019.8972045

Demir, F. (2021). Derin öğrenme tabanlı yaklaşımla kötü huylu deri kanserinin dermatoskopik görüntülerden saptanması. *Fırat Üniversitesi Mühendislik Bilimleri Dergisi*, *33*(2), 617-624. https://doi.org/10.35234/fumbd.900170

Dildar, M., Akram, S., Irfan, M., Khan, H. U., Ramzan, M., Mahmood, A. R., Alsaiari, S. A., Saeed, A. H. M., Alraddadi, M. O., & Mahnashi, M. H. (2021). Skin cancer detection: A review using deep learning techniques. *International journal of Environmental Research and Public Health*, *18*(10), 5479. https://doi.org/10.3390/ijerph18105479

Ergün, E., & Kılıç, K. (2021). Derin öğrenme ile artırılmış görüntü seti üzerinden cilt kanseri tespiti. *Black Sea Journal of Engineering and Science*, *4*(4), 192-200. https://doi.org/10.34248/bsengineering.938520

Göreke, V. (2021). Cilt lezyonlarının sınıflandırılmasında derin öğrenme tabanlı bir yöntem. *Türk Doğa ve Fen Dergisi*, *10*(1), 30-36. https://doi.org/10.46810/tdfd.797683

Hasan, M. R., Fatemi, M. I., Monirujjaman Khan, M., Kaur, M., & Zaguia, A. (2021). Comparative analysis of skin cancer (benign vs. malignant) detection using convolutional neural networks. *Journal of Healthcare Engineering*, *2021*, 1-17. https://doi.org/10.1155/2021/5895156

Hosny, K. M., Kassem, M. A., & Foaud, M. M. (2018). Skin cancer classification using deep learning and transfer learning. *In 2018 9th Cairo International Biomedical Engineering Conference (CIBEC)* (pp. 90-93), Cairo. https://doi.org/10.1109/CIBEC.2018.8641762

Jinnai, S., Yamazaki, N., Hirano, Y., Sugawara, Y., Ohe, Y., & Hamamoto, R. (2020). The development of a skin cancer classification system for pigmented skin lesions using deep learning. *Biomolecules*, *10*(8), 1123. https://doi.org/10.3390/biom10081123

Kadampur, M. A., & Al Riyaee, S. (2020). Skin cancer detection: Applying a deep learning based model driven architecture in the cloud for classifying dermal cell images. *Informatics in Medicine Unlocked*, *18*, 100282. https://doi.org/10.1016/j.imu.2019.100282

Kaggle-Your Home for Data Science. (2021, December 12). https://www.kaggle.com/fanconic/skin-cancer-malignant-vs-benign

Kaya, V., Baran, A., & Tuncer, S. (2021a). Dinamit destekli terör faaliyetlerinin önlenmesi için derin öğrenme temelli güvenlik destek sistemi. *Avrupa Bilim ve Teknoloji Dergisi*, 22, 81-85. https://doi.org/10.31590/ejosat.845467

Kaya, V., Tuncer, S., & Baran, A. (2021b). Detection and classification of different weapon types using deep learning. *Applied Sciences*, *11*(16), 7535. https://doi.org/10.3390/app11167535

Kaya, V., Tuncer. S., Baran, A. (2020). Derin öğrenme yöntemleri kullanılarak nesne tanıma. *International Science and Technology Conference (ISTEC)* (pp. 277-287), Lefkoşa.

Khamparia, A., Singh, P. K., Rani, P., Samanta, D., Khanna, A., & Bhushan, B. (2021). An internet of health things-driven deep learning framework for detection and classification of skin cancer using transfer learning. *Transactions on Emerging Telecommunications Technologies*, *32*(7), e3963. https://doi.org/10.1002/ett.3963

Li, P., Wang, D., Wang, L., Lu, H. (2018). Deep visual tracking: Review and experimental comparison. *Pattern Recognition*, *76*, 323-338. https://doi.org/10.1016/j.patcog.2017.11.007

Manasa, K., & Murthy, D. G. V. (2021). Skin cancer detection using VGG-16. *European Journal of Molecular & Clinical Medicine*, *8*(1), 1419-1426.

Manne, R., Kantheti, S., & Kantheti, S. (2020). Classification of skin cancer using deep learning, convolutional neural networks-opportunities and vulnerabilities-a systematic review. *International Journal for Modern Trends in Science and Technology*, *6*(11), 101-108. https://doi.org/10.46501/IJMTST061118

Nawaz, M., Mehmood, Z., Nazir, T., Naqvi, R. A., Rehman, A., Iqbal, M., & Saba, T. (2021). Skin cancer detection from dermoscopic images using deep learning and fuzzy k-means clustering. *Microscopy research and technique*, *85*(1), 339-351. https://doi.org/10.1002/jemt.23908

Pathak, A. R., Pandey, M., Rautaray, S. (2018). Application of deep learning for object detection. *Procedia Computer Science*, *132*, 1706-1717. https://doi.org/10.1016/j.procs.2018.05.144

Saba, T. (2021). Computer vision for microscopic skin cancer diagnosis using handcrafted and non-handcrafted features. *Microscopy Research and Technique*, *84*(6), 1272-1283. https://doi.org/10.1002/jemt.23686

Shorfuzzaman, M. (2021). An explainable stacked ensemble of deep learning models for improved melanoma skin cancer detection. *Multimedia Systems*, *28*(4), 1309-1323. https://doi.org/10.1007/s00530-021-00787-5

Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. *arXiv preprint*. https://doi.org/10.48550/arXiv.1409.1556

Soylu, E., & Demir, R. (2021). Development and comparison of skin cancer diagnosis models. *Avrupa Bilim ve Teknoloji Dergisi*, 28, 1217-1221. https://doi.org/10.31590/ejosat.1013910

Thomas, S. M., Lefevre, J. G., Baxter, G., & Hamilton, N. A. (2021). Interpretable deep learning systems for multi-class segmentation and classification of non-melanoma skin cancer. *Medical Image Analysis*, *68*, 101915. https://doi.org/10.1016/j.media.2020.101915

Toğaçar, M., Cömert, Z., & Ergen, B. (2021). Intelligent skin cancer detection applying autoencoder, MobileNetV2 and spiking neural networks. *Chaos, Solitons & Fractals*, *144*, 110714. https://doi.org/10.1016/j.chaos.2021.110714

Tumpa, P. P., & Kabir, M. A. (2021). An artificial neural network based detection and classification of melanoma skin cancer using hybrid texture features. *Sensors International*, *2*, 100128. https://doi.org/10.1016/j.sintl.2021.100128

Yıldız, O. (2019). Melanoma detection from dermoscopy images with deep learning methods: A comprehensive study. *Journal of the Faculty of Engineering and Architecture of Gazi University*, *34*(4), 2241-2260. https://doi.org/10.17341/gazimmfd.435217