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A New Convolutional Neural Network Model for Skin Cancer Detection in Dermatoscopic Images

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Abstract – Skin cancer is the abnormal growth of skin cells and one of the most common cancers of all. There are several types of skin cancer. Melanoma, a form of skin cancer, has increased 237% in Turkey in the last 30 years. While the U.S. adds about one million new cases of melanoma each year, this rate in Turkey is 1.9 per 100 thousand men and 1.3 per 100 thousand women. The death rate from skin cancer is 1 in 100 patients worldwide. As with all cancers, early diagnosis of this cancer is crucial, and artificial intelligence (AI) appears to be a promising technology for detecting early-stage skin cancer from dermoscopic images in recent years. AI-based studies for skin cancer classification are usually performed using three different types of images: dermoscopic images, clinical images, and histopathological images. In this study, a new deep learning model called CNN-BM (Convolutional Neural Network-Based Model) is proposed for skin cancer diagnosis using dermoscopic images. In this context, HAM10000, a commonly employed public dataset consisting of 10015 dermoscopic images, is utilized. The proposed model not only increases the success rate in the training process, but also reduces the execution time. CNN-BM consists of convolution, max pooling, dropout, flatten, and activation layers. Relu and sigmoid functions are chosen as activation functions. CNNs are sensitive to the batch size values, which significantly affects the quality of the model. Unlike other deep learning models used in the literature for skin cancer diagnosis, the proposed model uses a small batch size to prevent overfitting and increase the regularization effect. Similarly, by incorporating a dropout layer and dense-sparse-dense training techniques into the model, overfitting is avoided and the success rate of the network is increased. To determine the most efficient values for the hyperparameters, a trial-and-error method is employed. Research findings indicate that the success of the model is superior to other studies in the literature with 86.48% accuracy and 85.13% precision rates.

Keywords – skin cancer, cancer detection, CNN, CNN-BM, deep learning

I. Introduction

Skin cancer is the abnormal growth of skin cells and one of the most common cancers of all [1]. As with all cancers, early detection of skin cancer is critical. The heavy workload in the medical field necessitates a practical method for early detection of skin cancer. Given the current state of artificial intelligence (AI) technology, it is foreseeable that this need can be met by an intelligent (expert) system that employs an AI-based technique.

Review of the literature reveals that the AI-based studies for skin cancer classification are usually performed based on three different types of images [2].

- Dermoscopic images
- Clinical images
- Histopathology images

Examples of these images are shown in Fig. 1.

Dermoscopic, also known as, dermatoscopic, images are taken with a high-resolution digital single-lens reflex (DSLR) camera or smartphone. Clinical images are taken with the camera without touching the lesion. Histopathology is the study of changes in organs, tissues, and cells under the microscope using various methods.

a. b. c.

Fig. 1. Examples of the types of images where AI-based studies are carried out for the diagnosis of skin cancer: a. dermoscopic image, b. clinical image c. histopathology image [2].

There are different types of skin cancer, and it is one of the most common cancers of all. Melanoma, a form of skin cancer, has increased 237% in Turkey in the last 30 years. Although melanoma is the least common form of skin cancer (less than 2%), it is the highest risk form. Basal cell carcinoma, along with melanoma, is the most common form of basal and areal cancer in the group of skin cancers. While the United States adds about one million new cases of melanoma each year, the rate in Turkey is 1.9 per 100,000 men and 1.3 per 100,000 women. The death rate from skin cancer is 1 in 100 patients worldwide [2].

According to the latest statistics, 91,270 and 192,310 new cases of melanoma were diagnosed in the United States in 2018 and 2019, respectively [3].

The rate of melanoma and the number of deaths from this disease are expected to increase in the coming decades [4]. A recent report shows a 53% increase in the diagnosis of new melanoma cases per year from 2008 to 2018 [5].

In a study conducted by Haenssle et al., the deep learning method InceptionV4 was trained on a large dermoscopic image dataset containing more than 100,000 benign lesions and melanoma images, and its performance was compared with 58 dermatologist diagnoses [6]. The results show that in the test dataset with 75 benign lesions and 25 melanoma images, dermatologists had a sensitivity of 86.6% and a specificity of 71.3%, while the deep-learning method achieved a sensitivity of 95% and a specificity of 63.8%.

In a study by Tschandl et al., popular deep-learning architectures known as InceptionV3 and ResNet50 were applied to a combined dataset of 7895 dermoscopic and 5829 close-up lesion images for the diagnosis of non-pigmented skin cancers [7]. Performance was compared with 95 dermatologists who were divided into three groups based on their experience. In the study, deep learning algorithms were found to achieve the same accuracy as human experts and were found to outperform the accuracy rate of the dermatologist groups for early stage and intermediate cancer cases.

Codella et al. developed a method consisting of deep-learning algorithms in the ISIC-2016 dataset and compared the performance of this method with 8 dermatologists to classify 100 skin lesions as benign or malignant. It was highlighted that the corresponding method with 76% accuracy and 62% specificity outperformed the success of dermatologists who had 70.5% accuracy and 59% specificity [8].

The rest of this paper is organized as follows. Section 2 provides information about the dataset used in the study and explains the proposed methodology. The experimental results are analyzed in Section 3. Finally, Section 4 concludes the paper and highlights some possibilities for future work.

II. MATERIAL AND METHOD

A. Dataset

The HAM10000, a commonly used public dataset consisting of 10015 dermoscopic images, was utilized in this work since it is reported in the literature as a reference database for academic machine-learning studies [9].

HAM10000 was created by Stanford University by collecting data obtained from various patients at the Research Hospital [10].

The disease types and sample numbers in the dataset are as follows:

- Mel - 1113 patterns (Melanoma),
- NV - 6705 patterns (Melanocytic nevi),
- BCC - 514 patterns (Basal cell carcinoma),
- AKIEC - 327 patterns (Intraepithelial carcinoma & Actinic keratoses),
- BKL - 1099 patterns (Benign keratosis),
- DF - 115 patterns (Dermatofibroma),
- VASC - 142 patterns (Vascular lesions).

The cancer risk of the diseases included in the dataset is given in Fig. 2. In addition, sample images of disease types are presented in Fig. 3.

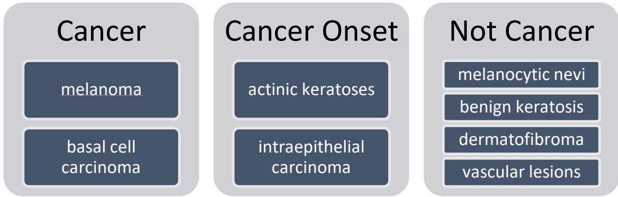

Fig. 2. Classification of disease types in the HAM10000 dataset

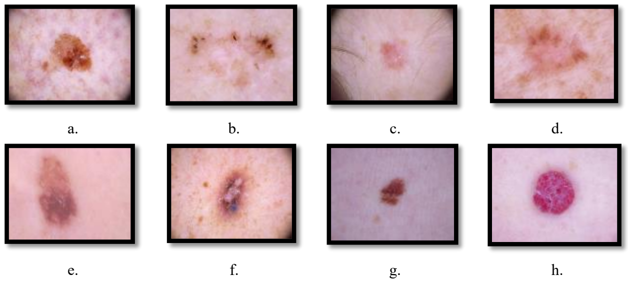

Fig. 3. Images of disease types in the HAM10000 dataset. a. Melanoma cancer, b. Basal cell carcinoma, c. Actinic Keratoses (Solar Keratoses) d. Intraepithelial Carcinoma (Bowen's disease) e. Benign keratosis, f. Dermatofibroma, g. Melanocytic nevi, h. Vascular lesions

In this dataset, which consists of 10015 dermoscopic images with a size of 450×600 and includes 7 diagnostic categories, information on patient age, sex, and diagnostic region can also be found.

B. Proposed Deep-Learning Architecture

Deep learning is a subfield of machine-learning that is essentially a neural network with three or more layers. These neural networks attempt to simulate the behavior of the human brain and perform the learning process from a large amount of data. While a single-layer neural network can still make approximate predictions, additional hidden layers can help optimize and improve accuracy. Deep learning is the foundation for many AI applications and services that improve automation by performing analytical and physical tasks without human intervention. A key concept that has gained attention in recent years is the dense-sparse-dense paradigm, which has further improved the capabilities and efficiency of deep neural networks.

Deep learning focuses on artificial neural networks inspired by the interconnected structure of neurons in the human brain. Traditionally, neural networks were designed with densely connected layers, where each neuron in one layer is connected to each neuron in the subsequent layer. While this approach offered good modeling capabilities, it also presented problems in terms of computational resources and overfitting.

The dense-sparse-dense paradigm attempts to address these issues by introducing sparsity into neural network architectures. Sparsity means that only a subset of the connections is active, while the rest are set to zero. This sparsity can be achieved by various techniques, such as pruning, which removes connections with small weights, or structured sparsity, which imposes patterns on the connectivity of the network.

The introduction of sparsity reduces the overall size of the network, resulting in significant computational savings in training and inference. In addition, sparsity promotes a more efficient representation of data by forcing the network to focus on relevant features and discard redundant or less informative connections. This not only improves generalization, but also reduces overfitting, leading to better performance on unseen data.

However, sparse networks alone may have limited informative power due to the smaller number of connections. To overcome this limitation, the dense-sparse-dense paradigm combines the advantages of both dense and sparse connectivity. The first dense layers capture complex patterns and enable rich representations, while subsequent thin layers selectively highlight important connections and promote efficiency.

The key to effectively implementing the dense-sparse-dense paradigm lies in learning algorithms and optimization techniques. Iterative methods such as the Alternating Direction Method of Multipliers (ADMM) are widely used to train sparse networks by iteratively enforcing sparsity constraints and updating network parameters. These methods strike a balance between accuracy and efficiency and enable the successful integration of sparse layers into deep neural networks.

The introduction of the dense-sparse-dense paradigm has led to significant benefits in several application areas. In computer vision, sparse convolutional neural networks have shown excellent performance in tasks such as image classification, object recognition, and semantic segmentation. In natural language processing, the incorporation of sparsity into recurrent neural networks has improved language modeling and machine translation tasks.

In summary, the dense-sparse-dense paradigm represents a significant advance in the field of deep learning and addresses the challenges of computational complexity and overfitting. By introducing sparsity into neural network architectures, it enables more efficient and effective representation of data. The combination of dense and sparse layers enables a balance between expressiveness and computational efficiency. As deep learning continues to evolve, the dense-sparse-dense paradigm holds promise for further enhancing the capabilities of neural networks and driving advancements in AI applications across diverse fields. In this study, a new CNN-based deep-learning model (CNN-BM) was developed for diagnosing skin cancer on dermoscopic images. Fig. 4 shows the architecture of the proposed deep-learning model.

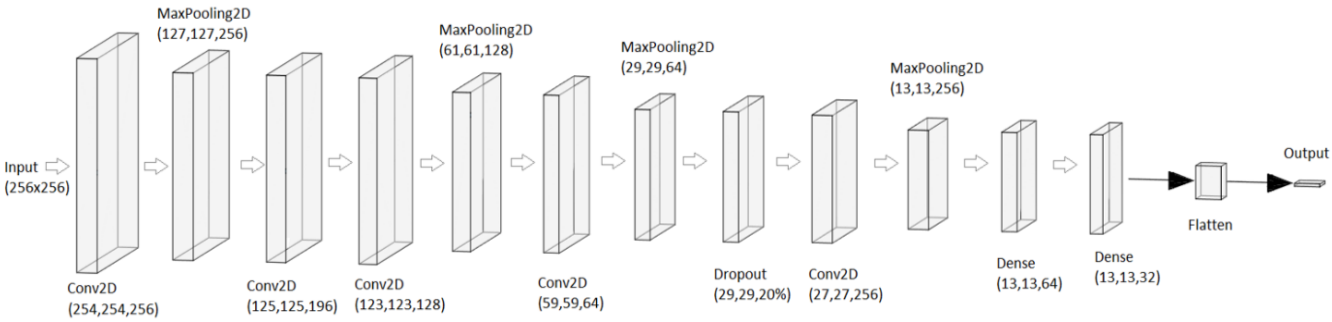

Fig. 4. Architecture of CNN-BM

The CNN-BM consists of 15 layers in total, including input and output layers. The model was implemented using the *Python* language and the *Keras* library. *Relu* functions in Convolution layers and *Sigmoid* functions in *Dense* layers were used as activation functions. Images were given as input to the network with the size of 256x256 and a *batch size* of 8 was utilized. *binary_crossentropy* was selected as the Loss function while *adam* was used as the Optimizer function.

Each filter takes a subset of the input data at a time and are applied to the entire input. There is a total of 5 convolution layers in CNN-BM. A pooling layer effectively downsamples the output of the previous layer, thus the number of operations required for subsequent layers are reduced. There are 4 *MaxPooling* layers in CNN-BM. *Dropout* layer was used to forget some neurons to avoid overfitting during training. The operations were divided into *dense-sparse-dense* layers to prevent overfitting. In the output layer, there are 2 classes, namely skin cancer and not skin cancer.

III. EXPERIMENTAL RESULTS

The experiments performed resulted in an accuracy of 86.48% and a precision of 85.13%, as shown in Table 1. The experimental success rates were obtained by averaging the results from five runs of the developed model.

Table 1. Success rates of the algorithms

Reference Study	Classifier	Accuracy (%)	Precision (%)
[12]	DenseNet 201	81.27	-
	ResNet 50	79.95	-
	Inception v3	77.04	-
	InceptionResNet v2	81.79	-
[13]	Dermatologist 1	65,6	-
	Dermatologist 2	66,0	-
	CNN	69,4	-
	CNN-PA	72,1	-
[11]	CNN		**85.73**
	MobileNetV2		84.98
	CNN-BM (Proposed Method)	**86.48**	**85.13**

Examining the studies performed with deep-learning models on dermoscopic images, it can be seen that the proposed CNN-BM achieves the highest accuracy value of 86.48%, as listed in Table 1. In terms of precision values, it can be seen that the CNN model in the study by Kousis et al.

[11] has a rate of 85.73% and the CNN-BM has a rate of 85.13%.

In order to achieve higher success rates, previously applied performance enhancement techniques in the field of deep learning were utilized in this study. Some of these methods are discussed in this paragraph. By using the dropout layer, an attempt is made to break the bonds in the fully-connected layers. In this way, the nodes have less information about each other, and consequently, the nodes are less affected by weight changes of the other nodes. We believe that more consistent models can be created using the dropout method. In 2016, the dense-sparse-dense method was first presented in the article *DSD: Regularizing Deep Neural Networks with Dense-Sparse-Dense Training Flow* [14]. In this method, the operations performed in a single fully-connected layer are divided into three layers in the form of dense-sparse-dense. In this way, the effect of the weights on each other is first reduced, and then new information is learned by reconnecting them. In this case, the problem of overfitting caused by detailed learning is avoided. As a result of the reduced overfitting, the success on the test data is increased.

IV. CONCLUSION

The integration of deep learning and the dense-sparse-dense paradigm has shown promise for skin cancer diagnosis. Skin cancer is a common and potentially life-threatening disease, and accurate and timely diagnosis is critical for effective treatment.

Deep learning techniques, with their ability to learn complex patterns and representations from large data sets, have shown remarkable potential for automated skin cancer diagnosis. Using deep neural networks, these techniques can analyze skin images and detect subtle signs of malignancy with high accuracy.

The dense-sparse-dense paradigm complements deep learning by optimizing the efficiency and interpretability of skin cancer diagnostic models. By incorporating sparsity into neural network architectures, the paradigm reduces computational complexity and improves generalization performance. It allows the network to focus on relevant features while discarding redundant or less informative links, resulting in more efficient and accurate skin cancer diagnosis.

Implementing the dense-sparse-dense paradigm in skin cancer diagnosis requires sophisticated learning algorithms and optimization techniques. By iteratively enforcing sparsity constraints and updating network parameters, these techniques strike a balance between accuracy and efficiency. This integration provides clinicians with powerful diagnostic tools that can aid in early detection, provide second opinions, and improve overall patient care.

In addition, advances in deep learning and the dense-sparse-dense paradigm have the potential to address challenges in skin cancer diagnosis, such as limited access to dermatologists, variability in human expertise, and increasing caseloads. By using automated systems, healthcare providers can improve their diagnostic capabilities, reach underserved populations, and reduce the burden on healthcare systems.

In summary, the integration of deep learning and the dense-sparse-dense paradigm holds great potential for improving skin cancer diagnosis. By harnessing the power of neural networks and optimizing their efficiency, these approaches offer the opportunity to improve accuracy, efficiency, and accessibility in skin cancer detection. Continued research, development, and collaboration between medical professionals and AI experts are essential to unlock the full potential of this technology and ultimately improve patient outcomes in skin cancer diagnosis and treatment.

In this study, a deep-learning model for skin cancer detection is developed to take advantage of artificial intelligence technology. The proposed model not only increases the success rate in the training process, but also reduces the execution time since the execution time varies in direct proportion to the number of layers [15] and the proposed model contains fewer layers than other architectures. If the batch size is chosen to be small, overfitting that may occur on the entire data is prevented because the data is processed in small chunks [16]. By choosing a small batch size in the model, overfitting was avoided and the regularization effect was increased. In addition, the inclusion of a dropout layer and dense-sparse-dense training techniques in the model avoids overfitting and increases the success rate of the network. The experimental results of the study show that the success rates of 86.48% accuracy and 85.13% precision were achieved thanks to the proposed method.

Increasing the number of samples in the dataset and analyzing the impact of this on the success rates of the developed model could be a research topic for the future studies.

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