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RESEARCH ARTICLE

Melanoma Skin Cancer Classification based on CNN Deep Learning Algorithms

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Abstract Melanoma, the deadliest form of skin cancer, is on the rise. The goal of this study is to present a deep learning system implementation for the detection of melanoma lesions on a server equipped with a graphics processing unit (GPU). When applied by a dermatologist, the recommended method might aid in the early detection of this kind of skin cancer. Evidence shows that deep learning may be used in a variety of settings to successfully extract patterns from data such as signals and images. This research presents a convolution neural network–based strategy for identifying early-stage melanoma skin cancer. Images are input into a deep learning model known as a convolutional neural network (CNN) that has already been pre-trained. The CNN classifier, which is trained with large amounts of data, can discriminate between malignant and nonmalignant melanoma. The method's success in the lab bodes well for its potential to aid dermatologists in the early detection of melanoma. However, the experimental results show that the proposed technique excels beyond the state-of-the-art methods in terms of diagnostic accuracy.

Keywords*:* Deep learning, CNN, melanoma, skin cancer, classification.

Introduction

Almost all instances of melanoma, the worst form of skin cancer, can only be treated by surgery. Nearly 20% of patients who have surgery for this lethal condition do not see a recovery. Melanoma accounts for 75% of all deaths from skin cancer. More than 50,000 cancer deaths occur annually as a direct result of this [1, 2]. The most common cause of melanoma is unprotected exposure to ultraviolet light. There is a much higher prevalence of melanoma in most of Europe, particularly in nations like Switzerland and Denmark. Although melanoma has a high mortality rate, it is often treatable if caught early [2]. Also, even for seasoned dermatologists, it may be difficult to tell the difference between a melanoma and a benign mole during the early stages of the development of either kind [3]. Algorithms are being programmed onto computers to do this. Low-complexity approaches are developed to aid laypeople and are optimized for use on mobile devices like tablets and smartphones [4, 5]. Expert judgment in this area, however, necessitates the use of complex computational methods and apparatus [6].

In addition to the gold standard of a skin biopsy, dermatologists may utilize a variety of quantitative marking approaches, such as the “ABCD” rule, 7-point checklist and 3-point checklist [3], to detect melanoma at an early stage. Recently, computer vision, ML, and DL have been used to melanoma

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detection with great success [7-11]. Using a suggested CNN architecture and benchmark datasets [12], this paper applies deep learning to the problem of detecting malignant melanoma.

Object tracking [13], object identification [14], and picture categorization [15] are just a few of the computer vision applications where deep learning techniques have lately showed promise. Without the need to extract handmade characteristics, deep learning methods may learn a collection of high-level features from low-level ones, resulting in excellent accuracy for classification applications. In the field of medical imaging, there has been a recent trend toward leveraging the greater potential of deep learning approaches [16-18]. To automatically extract the collection of complicated high-level characteristics, convolutional neural networks (CNNs) use trainable filters and pooling operations applied to the raw input pictures [19]. In this study, we want to use deep learning techniques to create a fully automated melanoma diagnostic system. Digital photographs that are often affected by noise and lighting effects are preprocessed for this purpose. By reprocessing the pictures in this way, CNN is better able to extract useful discriminative features. After that, a CNN architecture is used to determine whether or not the pictures represent melanoma. Some methods are discussed that enhance the number of samples in order to overcome the limits of the training dataset and the relatively small number of photos, such as rotating, cropping, and resizing the dataset images. In comparison to state-of-the-art approaches, the suggested system performs better in experiments [20].

Here is how the document is structured [21]. The methodology, i.e., melanoma detection using deep neural network autoencoders, is detailed in the works cited section. In the next paragraphs, a brief overview of deep learning is presented. Following that is a summary of the work that is being presented, including a discussion of the dataset and the suggested CNN malignant lesion detection architecture. In the last section, we explore the work's significance and its potential future applications [22].

Related Works

Numerous scientists have recently focused on identifying cancerous lesions applying deep learning architecture. The study, [23] made use of the 170 color photos included in the MEDNODE collection. They've added to the original photos, for a grand total of 6120. Using several picture augmentation methods, including cropping (at 5 and 10%) and rotation (0, 90, 180, and 270 degrees), 35 modified versions of the original image were created. After that, we resize all the pictures to 188 by 188. The photos were classified by the authors into two groups, malignant and benign, using deep CNN. For their study, they used a dual-convolutional architecture with a 20-feature map, 5-by-5-kernel first layer and a 50-feature map, 5-by-5-kernel second layer. There is a pooling layer in between every convolution layers. At last, a fully linked two-class layer is provided for the classification job. The system uses a 32GB Intel i7 CPU, and GPU from the Titan and GeForce series, and 32GB of RAM. The dataset still separated into training at 80% and testing at 20%. They were able to attain an 81% rate of correct categorization. In their research, Ayan and Unver [24-26] shown how data augmentation may boost the accuracy of deep learning-based melanoma categorization. They took 1000 original photos of varying sizes from the famous ISIC dataset, splitting them in half to create sets of 500 images representing malignant and benign tumors. Before being fed into the CNN, every picture is scaled down to a uniform 224 by 224 pixels. Their CNN design consists of 11 layers in total, including 4 convolution layers, 2 max-pool layers, 3 dropout levels, and 2 fully linked dense layers. In the absence of data augmentation, they were able to reach an accuracy of 78%; with data augmentation, however, the 2-class classification accuracy climbed to 81% using an NVIDIA K4200 as a GPU card and 64 GB size of the RAM. This was accomplished by increasing the number of photos by a factor of five. All of the code for their proposed system was written in Python. Three widely used CNN designs, VGG19, ResNet50, and VGG19-SVM, were evaluated for their efficacy in classifying melanomas by Kwasigroch *et al*. [27]. They have used several picture enhancement methods, such as transformation, to the ISIC dataset (i.e., rotation, flip, shift, etc.). So, they employed an asymmetrical dataset with 9300 healthy pictures and 670 cancerous ones. They were able to improve classification accuracy by 81.2 percentage points, 75.5 percentage points, and 80.7 percentage points, respectively, experimented by VGG19, VGG19-SVM and ResNet50, respectively. In their research, they have employed the GeForce GPU beside 6 GB of RAM and a Python-based software. Classification accuracy of 81.33 percent was achieved [28] using the same ISBI of 2016 challenge dataset, which included 900 training pictures and 379 test images, respectively. Their deep convolutional neural network is based on the VGG16 architecture. Using the ISBI of 2016 challenge dataset included 173 malignant and 727 benign pictures [29-31] updated the LightNet architecture to consist of seventeen layers, including five blocks, and achieved 81.6% 2-class classification accuracy. Convolution, ReLU, pooling, and a dropout layer are present in each and every block. This deep CNN's last block is completely linked and uses a soft-max classification layer.

Dataset

Melanoma Skin Cancer Dataset of 10000 Images: This dataset contains two classes of melanoma cancer, malignant and benign. The dataset consists of 9600 images for training the model and 1000 images for evaluation of the model. Sample of dataset shown in Figure 1.

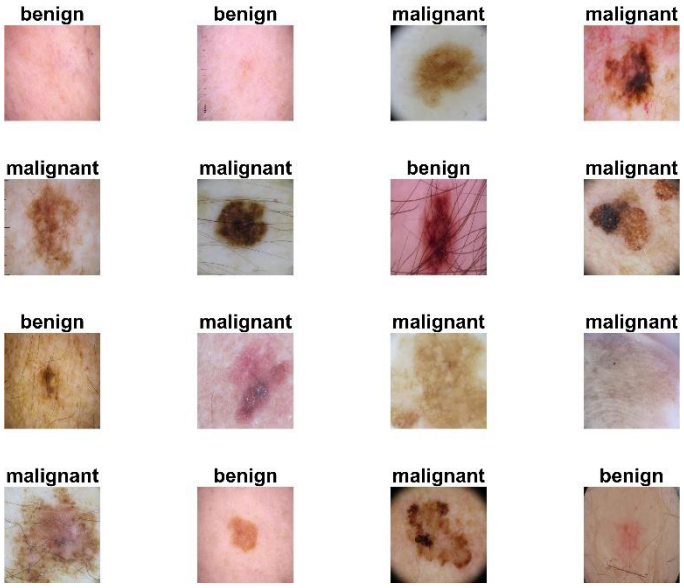

Figure 1. Sample melanoma skin cancer dataset

CNN Architecture

Specifics of the planned CNN are addressed below. It's not easy to extract a collection of features that can accurately distinguish across distinct classes. On the one hand, we run the risk of feeding the network illogical characteristics if we use a very broad feature set. However, there is always the risk of inadequate description when using a limited range of traits. This means that a discriminative feature set may be obtained from a labeled training set using automated feature extraction methods, rather than requiring the manual specification of feature extraction processes.

The purpose of this article is to automatically diagnose melanoma using CNN, a deep learning system. Convolutional neural networks use a collection of sophisticated convolve-filters. A variety of picture structures may be analyzed. Therefore, the picture itself is used as input when using CNN, and relevant features are extracted automatically by the network. Typical CNNs include many convolve and pooling layers, with a fully linked layer serving as the final layer. The input picture is filtered by a convolution kernel placed in a convolution layer. Typically, a pooling layer comes after every convolve layer. The pooling layer compresses the feature map by picking the maximum or mean values within each set frame. This is done so that broad recurring patterns in the photos may be identified. In a shrunk picture, these broad trends become more apparent. In this research, five convolving layers make up the CNNs employed. Each convolution layer is followed by a single pooling layer. The four layers above it provide their data into a fully linked layer two stage with 120 and 2 neurons. Using a linear transfer function, the final diagnosis is formed by this 2-layer network. You can see the suggested setup in Figure 2.

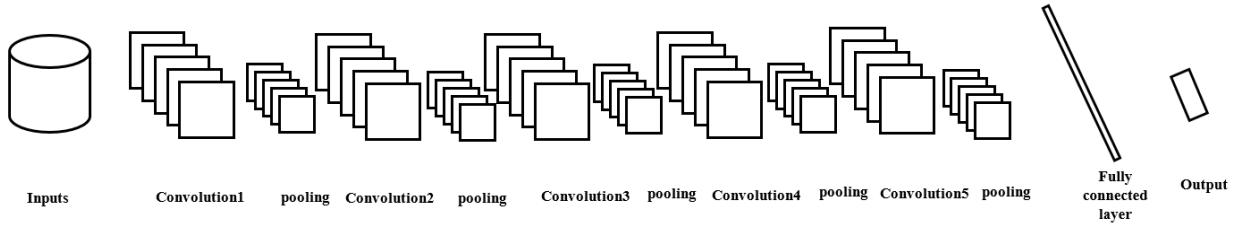

Figure 2. The block diagram of the proposed CNN Architecture

In general, a lot of data is needed to train a CNN correctly. However, available datasets for melanoma identification using non-dermoscopic pictures often contain a small number of images owing to problems in the collecting and labeling of images. We must thus make do with the little data set used for training. A total of 10,000 training photos and 1,000 test images were employed. Images were 300 pixels on the longest side. Figure 3 displays the architecture in all its glory.

Code	Code details	Captions
'imageinput'	300×300×3 images and 'zerocenter' normalization	Image Input
'conv_1'	8 2×2×3 convolutions and stride [1 1] and padding [1 1 1 1]	Convolution
'batchnorm_1'	Batch normalization and 8 channels	Batch Normalization
'relu_1'	ReLU	ReLU
'maxpool_1'	2×2 max pooling and stride [2 2] and padding [0 0 0 0]	Max Pooling
'conv_2'	16 3×3×8 convolutions and stride [1 1] and padding [1 1 1 1]	Convolution
'batchnorm_2'	Batch normalization and 16 channels	Batch Normalization
'relu_2'	ReLU	ReLU
'maxpool_2'	2×2 max pooling and stride [2 2] and padding [0 0 0 0]	Max Pooling
'conv_3'	32 2×2×16 convolutions and stride [1 1] and padding [1 1 1 1]	Convolution
'batchnorm_3'	Batch normalization and 32 channels	Batch Normalization
'relu_3'	ReLU	ReLU
'maxpool_3'	2×2 max pooling and stride [2 2] and padding [0 0 0 0]	Max Pooling
'conv_4'	64 3×3×32 convolutions and stride [1 1] and padding [1 1 1 1]	Convolution
'batchnorm_4'	Batch normalization and 64 channels	Batch Normalization
'relu_4'	ReLU	ReLU
'maxpool_4'	2×2 max pooling and stride [2 2] and padding [0 0 0 0]	Max Pooling
'conv_5'	128 2×2×64 convolutions and stride [1 1] and padding [1 1 1 1]	Convolution
'batchnorm_5'	Batch normalization and 128 channels	Batch Normalization
'relu_5'	ReLU	ReLU
'maxpool_5'	2×2 max pooling and stride [2 2] and padding [0 0 0 0]	Max Pooling
'batchnorm_6'	Batch normalization and 32 channels	Batch Normalization
'relu_6'	ReLU	ReLU
'fc'	2 fully connected layer	Fully Connected
'softmax'	softmax	Softmax
'classoutput'	crossentropyex with classes 'Benign' and 'Malignant'	Classification Output

Figure 3. The detail proposed CNN Architecture

Result and Discussion

We used 10,000 dermoscopy pictures from the Melanoma Skin dataset to evaluate our suggested method. Some of the photos in the dataset have subpar quality, which naturally reduces the classifier's efficacy. We were able to get an F1 of 90.87%, a sensitivity of 92.46%, a specificity of 92.23%, a precision of 92.46%, and an error rate of 9%. Without dermoscopic imaging, dermatologists typically have a 60% success rate in diagnosing melanoma in a skin lesion, confusion matrix shown in Figure 4. Our approach

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may be of considerable use to dermatologists in the early diagnosis of melanoma skin cancer. Table 1 compares outcomes from this study with those from others that have focused on classifying malignant melanomas.

Figure 4. Shows the result of confusion matrix.

Table 1. Comparison the results with other works

Authors	Accuracy
Nasr-Esfahani *et al*. [21]	81%
Ayan and Unver [22]	78%
Kwasigroch *et al*. [23]	80.7%
Lopez *et al*. [24]	81.33%
Ali and Al-Marzouqi [25]	81.6%
Proposed method	91%

Conclusion

In this research, we present the implementation of a computationally intensive approach based on deep learning that makes use of photographs. The technique distinguished melanoma cases from noncancerous ones successfully. To improve the performance of the system, we utilized an existing melanoma skin dataset to train a convolutional neural network (CNN) for melanoma classification. While conventional learning methods attempt to extract features from data, our suggested technique leaves that task to CNN. The experimental results demonstrated the superior accuracy of our algorithm compared to the competition. However, if additional augmented data is incorporated into the network and CNNs are used, the classification accuracy may improve. As a result, it is still worthwhile to read up on the methodology.

Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

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