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Use of Neural Network-Based Deep Learning Techniques for the Diagnostics of Skin Diseases

D. A. Gavrilov*, A. V. Melerzanov, N. N. Shchelkunov, and E. I. Zakirov

Melanoma is one of the most dangerous types of cancer. The accuracy of visual diagnosis of melanoma directly depends on the experience and specialty of the physician. Current development of image processing and machine learning technologies allows systems based on artificial neural convolutional networks to be created, these being better than humans in object classification tasks, including the diagnostics of malignant skin neoplasms. Presented here is an algorithm for the early diagnostics of melanoma based on artificial deep convolutional neural networks. This algorithm can discriminate benign and malignant skin tumors with an accuracy of at least 91% by examination of dermatoscopy images.

Relevance of the Problem

Melanoma is currently one of the most dangerous types of cancer. Data from the World Health Organization (WHO) indicate that the incidence of this disease increases inexorably year on year [1, 2]. Although skin melanoma has an external location, the diagnosis is often made at the late stages of disease development due to late medical attendances. At the same time, despite the high death rate, early diagnosis of melanoma and timely treatment can produce virtually 100% survival [3].

Malignant neoplasms of the skin are visually apparent tumors and can generally be detected by doctors of all specialties during routine examination. The most widely used diagnostic method is dermatoscopy [2]. The diagnostics of melanoma and skin diseases is generally based on the use of dermatoscopes for examining the patient's skin with magnification. The accuracy of the visual diagnostics of melanoma depends directly on the experience and specialty of the physician, and also on the incidence of the disease and the physician's routine practice [4].

The primary diagnostics of skin neoplasms is performed by specialists using macroscopic and dermatoscopic photographs with powerful magnification and uniform illumination of the part of skin being imaged [5]. The most widely distributed symptom complex for the diagnosis of melanoma is the ABCDE test [6]. This test was proposed by Friedman et al. in 1985 for general practitioners [7], and it allows various parameters to be followed: A (asymmetry) – asymmetry of the pigmented spot; B (border irregularity) – unevenness of the margin; C (color) – irregular coloration; D (diameter) – having a diameter of >6 mm. The presence of three or more of these features is evidence pointing towards a malignant tumor. An additional criterion, E, is used for repeated dynamic observations of people in the at-risk group. Parameter E assesses the dynamics of changes in color, shape, and size of the pigmented skin area [8]. In addition, there is a series of other characteristics allowing malignant neoplasms to be discriminated from benign using nothing more than an image [8].

The concept of using computer vision to solve the task of identifying skin cancers arose relatively recently. Computer technology or machine vision consists of a set of methods providing for the identification and classification of different objects. Scientific studies aiming to improve the differential diagnostics of melanoma using computer techniques and expert systems were started in many large centers in Germany, Austria and other countries from 1987, following the suggestion of N. Cascinelli [4], the president of the WHO Melanoma Program, which has now developed into the World Melanoma

Moscow Institute of Physics and Technology, Dolgoprudny, Moscow Region; E-mail: gavrilou@gmail.com
* To whom correspondence should be addressed.

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Society. For a long time, results were not accurate enough for practical exploitation. Examples include systems for assessing the components of the ABCDE test [9] reaching 70% accuracy.

Clinics currently use special dermatology systems providing digital solutions allowing diagnostics using a dermatoscope, camera and special professional software [10]. In general, such programmable systems provide computer analysis of images of pigmented skin formations and provide the opportunity to store the images obtained and to create and archive patient records and perform accurate assessments of the course of disease [10].

Current development in image processing and machine learning techniques have produced systems based on artificial neural convolutional networks which are better than humans in object classification tasks – including the diagnostics of skin neoplasms [11]. The best known example of the use of artificial intelligence techniques based on deep learning methods in medicine is the IBM Watson system, which supports decision-making in the diagnostics and treatment of patients with oncological diseases at the New York Oncology Center [12]. The use of computer programs for the diagnostics of skin cancers can provide significant support for diagnoses made by dermatologists and general practitioners [13]. In addition, the introduction of such diagnostic systems provides for the potential application of expert decision-making systems and remote consultation facilities, i.e., telemedicine.

Presented here is the development of an algorithm for the early diagnosis of melanoma based on artificial deep convolutional neural networks. The algorithm discriminates between benign and malignant skin lesions with accuracy of at least 91% using automatic analysis of images of pigmented skin formations.

Methods

The main problem in constructing deep convolutional neural networks is that there are as yet insufficient public image collections to use for training the system and adjusting the model. One of the largest collections of images of skin formations is the International Skin Imaging Collaboration (ISIC) [14]. The sets of images in the archive were obtained in real clinical studies, so they may have some noise or various distortions. The main types of distortion are shown in Fig. 1.

An important – and the most difficult – task addressed here is that of creating algorithms resistant to these problems using a restricted dataset.

The approach known as Transfer Learning [16] was used by the authors to address this task. It should be

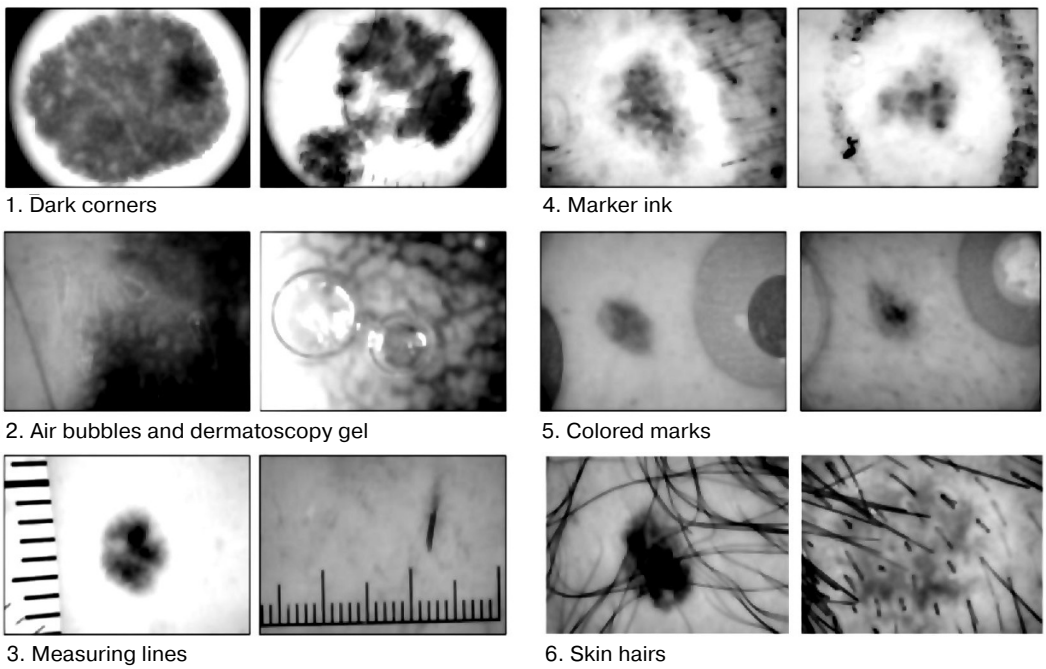

Fig. 1. Examples of interference on images [15].

noted that solution of the task of training the neural network to classify skin diseases from scratch was not addressed. The model was a neural network with Inception v.3 architecture [17, 18] (Fig. 2) giving high-quality classification of different images and is part of the ILSVRC (ImageNet Large Scale Visual Recognition Challenge). This pretrained neural network can be retrained for use as a component of a larger network. The Inception v.3 network was used to prepare the image classification model using the ImageNet Challenge dataset [19, 20]. The network pretrained on images from the ImageNet archive was adjusted for classification of skin diseases by removing the upper classification layers and adding new neurons for identification of skin diseases. The need to use the ImageNet network pretrained with images arose because of the small size of the training set, use of which for training from scratch would lead to the need for retraining and the inability to obtain good classification of new data.

The resulting model was then adjusted to the training set, which included 10,000 photographs of skin formations, giving the network the opportunity to discriminate types of skin formations. To expand the set, the number of initial images was increased to 1,000,000 using distortions. Distortions included: rotations, mirror reflections, removal of parts of images, stretching and compressing, and altering image lighting.

Training was monitored using an independent test set consisting of 1000 images. The test set images were not used in the training algorithm.

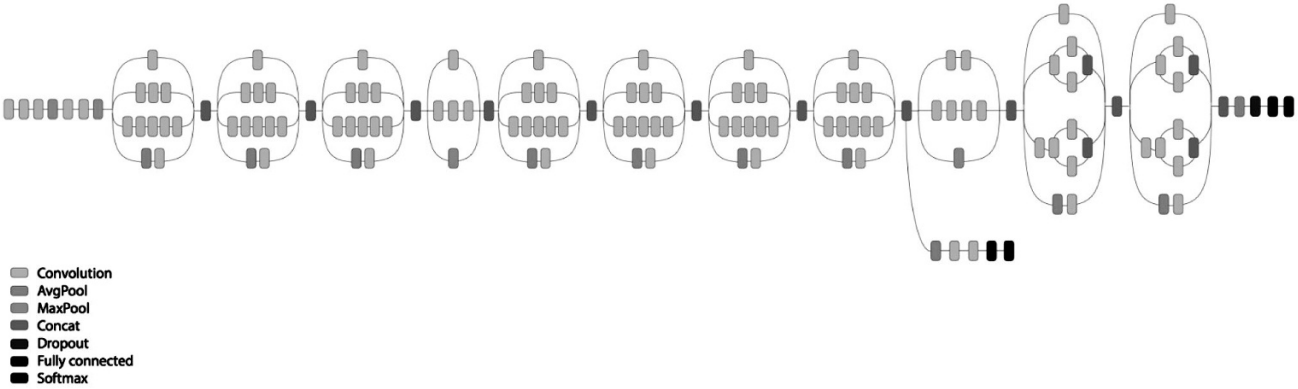

Fig. 2. Architecture of Inception v.3 neural network [17].

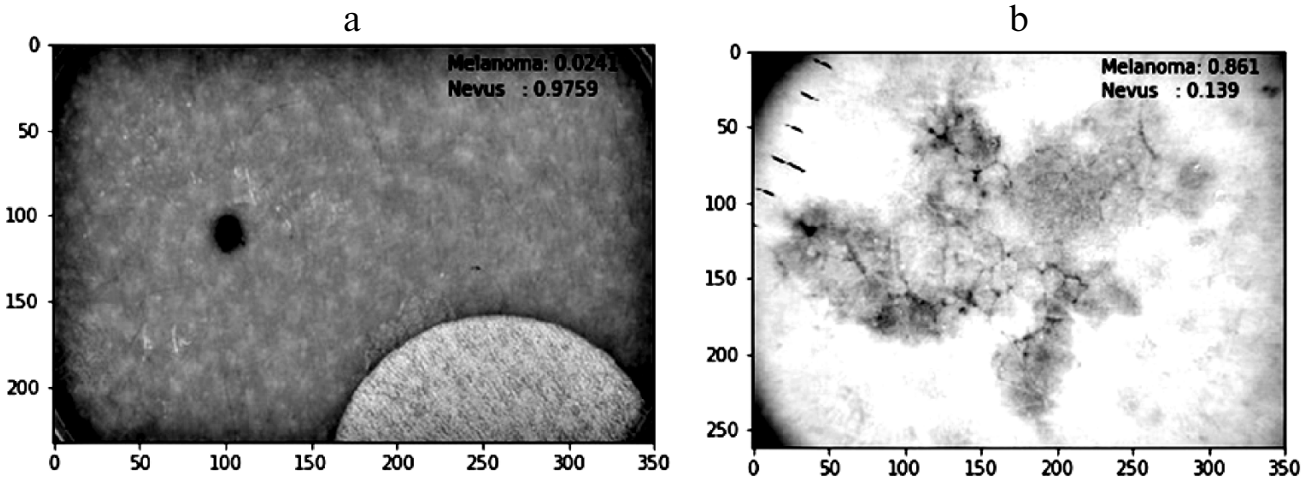

Fig. 3. Examples of correct classification of: a) nevus; b) melanoma.

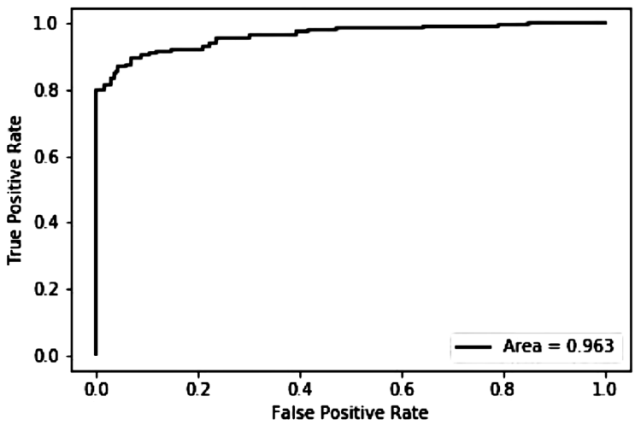

Fig. 4. AUC-ROC plot for melanoma/nevus recognition for ensemble of models.

Quality was increased by training five networks with identical architecture but with different weightings, which were combined to form an ensemble of models which made decisions on the majority voting principle. The sensitivity and specificity of the best of these models were 85% and 92% respectively, which is comparable with the diagnostic accuracy of clinical examination using dermatoscopy [21].

Results

The Inception v.3 starting model can only operate with images with 300 × 300 resolution, which is far below the usual size of dermatological images. As small details are extremely important for the correct diagnosis of diseases, the existing model was supplemented with convolutional layers to allow classification based on higher-resolution images.

The model developed here provides for studies of dermatoscopic images with resolution 700 × 700 pixels. Recognition accuracy for skin melanoma of over 91% was obtained with AUC-ROC 0.96 (ROC curves are plots for assessing the quality of binary classifications), which is comparable with diagnostic results from highly experienced physicians (Fig. 3).

The multifarious nature of neoplasms, the complexity of their structure, and the similarity of the clinical picture of different types of skin lesions introduce difficulties with visual examination and diagnosis even for specialists [22]. An additional task for the model was to distinguish benign formations such as seborrheic keratosis from dermatological photographs with accuracy 97% and AUC-ROC 0.99. The algorithm developed here discriminates melanoma from seborrheic keratosis and benign nevus (Fig. 4).

Conclusions

This study allowed a convolutional deep learning neural network for automatic diagnostics of skin neoplasms to be created.

This model provides for qualitative diagnosis of skin melanoma with an accuracy of at least 91%, which is comparable with the work of highly experienced dermatologists.

Further development of this model will include creation of web apps and apps for mobile devices to allow patients to carry out preliminary self-diagnosis using their own photographs. No less important is to enlist the support of large medical institutions for continual expansion and marking up of the training set.

An online version of the system has been created and can be accessed at http://nn.nerstech.com. Immediate plans are to improve functionality by allowing the user to highlight the skin lesion. This will increase classification accuracy when the photograph includes several skin lesions.

The development has great potential for use in telemedicine systems for the complex analysis of health in humans. Discussions with key manufacturers of systems of this type are currently ongoing.

The authors are interested in collaborating with researchers working on development of applied machine vision systems.

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