Mobile decision support system for melanoma detection based on deep learning techniques

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***Abstract*— Melanoma is one of the deadliest forms of skin cancer and a global health problem. Early and confident detection of melanoma increases chances of survival. Currently, there are various methods applied in medical practice for computer-assisted diagnosis of melanoma. This paper considers the need for mobile-based decision support system for melanoma detection. It includes the description of a prototype based on state-of-the-art machine learning methods and it proves there is a possibility of developing a system that serves as an early detection tool. The prime goal of the system is to classify skin lesions as benign or malignant, helping practitioners increase confidence of early examinations. The system consists of an Android application for clients, the database, skin lesion classifier and data exchange service on the server side. Three public available melanoma image databases have been used to develop this classifier, which is now able to achieve accuracy of more than 91%. The system was tested in practice and its accuracy confirmed comparing with the experts on another dataset and in a prospective study at the clinic. To the best of the author's knowledge, this is the first mobile automated supporting system for melanoma detection based on deep neural networks.**

I. INTRODUCTION

Melanoma has been classified as a general populace issue [[1]]. Due to that fact, many countries and research institutes have invested time and resources in this field. Scientists and medical professionals are exploring new methods in order to diagnose and prevent cutaneous melanoma (CM).

Primary prevention of melanoma consists of avoiding excessive exposure to ultraviolet rays. Secondary prevention is the early diagnosis of melanoma. This can be obtained by means of two main methods: patient's self-examination and medical examination [2].

The problem of efficient and early detection of melanoma is closely related to the outcome of the proposed therapy. If the cancer is detected and removed before it has metastasized, the chances of survival dramatically improve.

Numerous methods of melanoma detection are currently used in medical practice [3]. There are visual diagnostics, which include using standard photographic methods and state-of-the-art algorithm-driven imaging technologies. Moreover, devices for magnification and enhancement of malignant features serve in purpose of melanoma detection.

Recent advances in computer vision and proliferation of smart mobile devices present an opportunity to expand and enhance the practice of wide and early detection of visually detectable diseases. These advances in visual object recognition and classification have made it possible to design disease-recognition tools suitable for non-expert on-site use.

Based on these insights, the idea was creating an application for smart mobile devices that recognizes moles status including melanoma occurrence. Such an application will serve as an aid to practitioners, enabling fast and efficient recognition of melanoma and empowering the decision-making process when it comes to diagnostic processes.

Using the camera on a mobile device, one can take a picture of a skin region. Based on the photos taken, the mobile device processes the image and sends data to the remote server, where melanoma detection takes place. Information on the character of skin lesion is then delivered to the user in a matter of seconds.

This paper presents continuation of the authors' work in the same field, where they already analysed and developed melanoma risk prediction models using data mining techniques in [4]. The current research is extended on visually based prediction models, where authors contributed with the development of a new decision support system (DSS) for medical diagnostics.

Developed mobile-based DSS described in this paper also aims at creating the new database of skin lesion images that could be a valuable future contribution to many other researchers. Images sent by the users through their mobile application, if recognized as mole's images by the deep learning classifier, are stored in a database, and finally verified by a human expert. These steps are then followed by a method of biopsy for suspected melanomas for those patients, if possible. Along with it, as an optional feature, rough geolocation of taken images is stored in the database. Exact geolocation is not used in order to preserve user's privacy, but rough coordinates' resolution is still good enough to distinguish whether and to what extent disease is present in different areas. Therefore, this database could be used in future not just for developing new models for melanoma lesion extraction but also for spatial analysis, identifying the areas with increased number of possible melanoma diagnoses.

Decision support system for melanoma detection described in this paper consists of two main functional parts: backend and frontend. Backend contains the database, classifier and services to access them. Frontend is developed as an Android mobile application.

The rest of the paper is organized as follows: Section II presents related work, while Section III presents the methodology. Section IV presents the achieved results and related discussion. Section V presents our conclusions.

II. RELATED WORK

Due to the rapid growth of software technologies, information systems began to play an important role in every field of work. Computerized information systems can be applied in different forms to fit the purpose, manage and perform tasks, and to provide support for decision-making activities.

Decision support systems based applications in medical field have found its purpose to help medical practitioners and reduce human error factor. In a paper [5] authors conducted the studies on clinical DSS effect on practitioner's performance and patient's outcomes by comparing care with and without clinical DSS. The results of these studies showed that DSS improved practitioner's performance in 64% of the total number of studies. The diversity of medical DSS is rapidly increasing the desire to provide better healthcare and reduce the cost of clinical information management [6].

Currently, numerous computerized DSS are in use in different medical subfields. Yan et al. [7] presented the medical DSS for diagnosing heart diseases using multilayer perceptron (MLP), achieving accuracy of over 90%. The model's high precision proved its usefulness in the process of diagnosing heart diseases.

In melanoma diagnosis based on visual techniques using images, DSS could be applied as a tool for diagnostic conformation and as an early detection mechanism used by non-experts as well. The authors of the article [8] proposed a model based on Probabilistic Neural Network Classifier for melanoma detection. The model was trained to distinguish benign and malignant lesions, gaining the final accuracy of 88.6%. Gupta et al. [9] developed a system for early melanoma detection and categorized them into three classes: Malignant, Atypical and Common Nevus.

Masood et al. [10] proposed a method of developing automated DSS for early detection of skin cancer. Their system uses several steps in diagnostic process, such as segmentation, feature extraction, pattern recognition and classification, exploiting the Support Vector Machine (SVM). The proposed system obtained accuracy of 90.5%.

Sirakov and Mete [11] developed two automatic classification systems for skin lesions. The proposed systems use feature extraction (texture, shape and colour) and SVM classifier to find lesion features (LF), which are subsets that improve melanoma diagnosis. Their analysis showed that the second classifier achieved not only higher accuracy than the first one, but also higher sensitivity and accuracy than the major automated clinical DSS currently available, as authors claimed.

Due to exponential improvement in deep learning techniques, they are widely applied in different areas of image classification problem. Codella et al. [12] explored an automated method of melanoma detection using convolutional neural networks (CNNs) trained on images grouped in three classes: melanoma, atypical nevi and benign lesions. Two tasks were performed, the first one was easier: distinguishing melanoma from atypical and benign lesions, while the other was more difficult: distinguishing melanoma from only atypical lesions. The presented method in their paper used CNNs and gave better results in comparison with prior state-of-the-art ensemble modelling approaches. The achieved accuracy of the model was 93.1% for the first task and 73.9% for the second task. Taking that into account, we decided to use neural network approach in our research, the same as the authors of the above-mentioned study.

Aforementioned papers present detection model development techniques, but without intention to integrate them into a mobile DSS. Thus, developing mobile applications with all necessary features that could serve the purpose is an approach used in order to make DSS available for wider usage.

Fosu and Jouny [13] presented a mobile melanoma detection application using SVM to classify benign and malignant melanoma. An image of interest is sent to a server side with a deployed classifier, and the result is sent back to the user. Same as suggested in their work, we developed a system with the same functionality, supported by the latest artificial intelligence technologies and with additional features, such as geo-referencing of acquired images with possibility of later spatial analysis.

Driven by exceptional accuracy of deep CNNs in melanoma detection, the deep learning method is chosen as the prime technique for the skin lesion images classifier development.

Motivated by incredible benefits of having the mobile application for melanoma early detection as an assisting tool, the development process of proposed mobile-based decision support system is described in details further in this paper.

III. METHODOLOGY

The entire process of the mobile decision support system development includes several steps, which comprise of two main parts.

The first part of the process implies the development of classification model. This part involves selecting the appropriate database of melanoma images, pre-processing the images, determining the proper deep CNN architecture, and finally, accurate training and testing.

The second part of the system development process includes design and development of the software for the mobile-based DSS. This means development of the service side, which consumes melanoma classifier and serves the client with the predicted result based on the sent image. The mobile application that represents the client side of the system is used for capturing and sending the images and displaying the results afterwards. The complete process of the system development is presented in detail in further subsections.

A. Dataset

Gathering the images for training and validation dataset is essential step of the entire process of deep learning. Due to the fact that deep CNN predictions are based on input images, it is of great importance to obtain a large number of appropriate images suitable for targeted classification tasks.

Dermoscopy images are widely available and provide the best option for exploiting the state-of-the-art image processing and machine learning algorithms [14]. There is a couple of publicly available datasets of dermoscopy images commonly used by researchers, PH^2 [15] and EDRA [16].

Dataset used in this paper for training and validation purposes consists of images taken from several sources.

TABLE I.
DATASETS FOR TRAINING AND VALIDATION

	Class	Number of original images	Number of validation images	Sum - original	Total number of images: original and augmented
1.	Malignant	700	75	775	5600
2.	Benign	260	31	291	2080
		960	**106**	**1066**	**7680**

International Skin Imaging Collaboration (ISIC) has created the ISIC Archive for the Melanoma project [17]. This is a large public database of dermoscopy images that consists of 727 images of benign and 173 images of malignant lesions. In this paper, this database was used as a major part of melanoma dataset. The other sources of dataset in this paper are the images from public databases DermIS [18] and DermQuest [19], which include 48 images of benign and 118 images of malignant lesions. After the merging process, the resulting dataset finally counted 1066 images, 775 of benign, and 291 of malignant lesions. The dataset is divided into two sets, one for training and the other for validation. The training set was constructed using 700 original images of malignant lesions and 260 of benign lesions. Images from the training set were augmented and pre-processed using methods described in Section 3.2. After augmentation, the training set consisted of 7680 (5600 benign and 2080 malignant) images. Validation set had 106 original images, 75 benign and 31 malignant, which is shown in Table 1. Images from the validation dataset were not augmented, only pre-processed by the methods described further in Section 3.2.

B. *Pre-processing and augmentation process*

One of the common tasks in applying deep learning techniques for image classification problems is preparing the dataset for deep neural network training and testing, in order to reduce the time and achieve higher accuracy.

The pre-processing included downsizing the images to certain dimensions, beneficial to reduce the time acquired for training the CNN. A common approach to reduce over-fitting on the image data for training the deep CNN is to use augmentation methods. Data augmentation encompasses a suite of techniques that enhance the size and quality of training datasets such that better deep learning models can be built using them [20]. The augmentation process can be used during the training or during the testing phase. Data augmentation techniques seek to expand the amount of training data automatically by applying automatic transformations to images. Traditional augmentation techniques include horizontal image flips, cropping, translations, and rotation [21].

In this study, apart from flipping images, two more augmentation methods were used as well: affine and perspective transformations. The main goal of applying these transformations was to simulate the camera position and point of view.

Perspective transformation is typically used to modify the camera orientation, position and field of view [22]. In order to straighten out the geometric distortions or deformations that might appear with non-ideal camera, affine transformation is the commonly used technique.

Figure 1. illustrates the augmentation methods used on images in the melanoma training dataset.

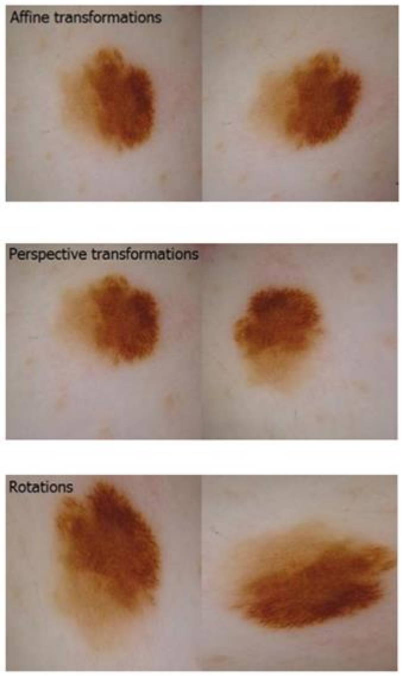

Figure 1. Example of augmentation

Deep neural networks (DNNs) have been proposed as a way of producing more predictive models [23]. Due to the rapid progress in deep learning, numerous institutes and researchers have devoted their time in designing new network architectures and developing fresh approaches, which can then be applied in many fields.

In order to develop a reliable DSS for melanoma detection, it is essential to choose the appropriate network architecture and to optimize parameters that will best serve for the certain task. Convolutional Neural Network (CNN or ConvNet) is a especial type of multi-layer neural network inspired by the mechanism of the optical system of living creatures [24]. CNNs combine three architectural approaches to establish a degree of shift and distortion invariance: shared weights, local receptive fields and spatial or temporal sub-sampling. They are hierarchical neural networks whose convolutional layers alternate with sub-sampling layers and vary depending on the way these layers are realized. Typical CNN architecture uses three main layer types: Convolutional layer, Pooling layer and Fully-connected layer [25].

In this paper, melanoma classifier model was trained and deployed using Caffe, deep learning framework developed by the Berkeley Vision and Learning Center (BVLC). It is a BSD-licensed C++ library with MATLAB and Python interfaces [26]. CaffeNet CNN model was used as the main architecture skeleton for melanoma classifier. CaffeNet model is a replication of AlexNet [27] model that differs in its hyperparameters. It contains 8 layers, 5 of them are convolutional layers and 3 are fully-connected layers. In addition, CaffeNet uses dropout layers to reduce the over-fitting [28]. CaffeNet architecture is modified and adjusted to support two categories (classes), one that represents malignant and the other benign lesions. Last layer of the model was altered and the output of the softmax layer was parameterized for the requirements of this study.

The input to a convolutional layer is an image with the size of nxnxr, where n is the square image dimension (height and width) and r is the number of channels. For instance, for an RGB image, the r would be 3. The convolutional layer will have k kernels or filters, with the size of mxmxq, where m is a smaller dimension than the image and q can be the same or smaller than the r. These filters are computed through all input channels and they are translation-invariant, so they provide a high response wherever a feature is detected [29].

A common practice to get intuition about network's learning is visualization of features. This was made in a fully trained melanoma classification model using techniques proposed by Zeiler et al. in [30]. Each layer's features are shown in a different block, where visualization displays the strongest activation for the provided feature map, beginning from the first convolutional layer, where features go from individual pixels to simple primitives like horizontal, vertical lines etc. to the fifth convolutional layer, where learned features like shapes and certain parts of lesions are displayed, Figure 2.

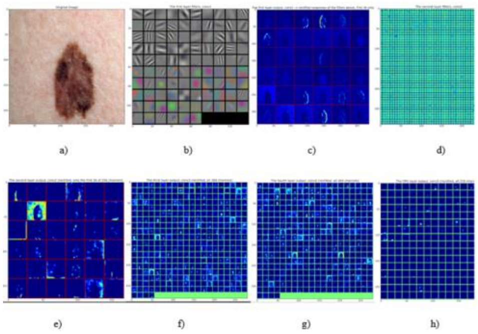

Figure 3. Visualization of features in trained melanoma classification model: a) Original image; b) The first layer filters, conv1; c) The first layer output, conv1 -> rectified responses of the filters, first 36 only; d) The second layer filters, conv2; e) The second layer output, conv2 (rectified, only the first 36 of 256 channels); f) The third layer output, conv3 (rectified, all 384 channels); g) The fourth layer output, conv4 (rectified, all 384 channels); h) The fifth layer output, conv5 (rectified, all 256 channels)

C. Data exchanging services

The backend of the system consists of a trained classifier, database and the service. The service provides access to the classifier, while the database and responses provide access to the client side of the system (frontend). Service is developed in Python using web.py framework. Python framework for developing the web service is a chosen technology because the classification model, which was trained using Caffe, can be easily deployed from the Python interface, too.

The Android application consumes the classification model by sending captured photos of skin lesions and its geolocation to the developed Python service, through HTTP requests. Service obtains the photo and forwards it to the trained model. When model classifies the photo, it stores it in the database with the predicted label and geolocation. The results are passed back to the service, which handles the response back to the client's application. Figure 3 illustrates the communications between the main parts of the system.

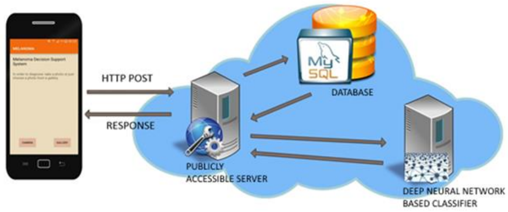

Figure 2. Block diagram of the melanoma DSS

D. Mobile application

In this section, the usage of the Android application developed for the purpose of mobile-based DSS will be explained. User interface is very simple and provides the possibility of determining whether the skin lesion is malignant or benign by capturing the photo of the skin at the scene or choosing it from the gallery. When the photo is chosen, it is sent together with the rough geolocation to the server side with one click of the recognize button, when the progress bar is shown. During that time, melanoma classification model is classifying the photo, labelling it, storing it to the image database and sending back the results. When the application gets the response, it is displayed to the user, as illustrated in Figure 4.

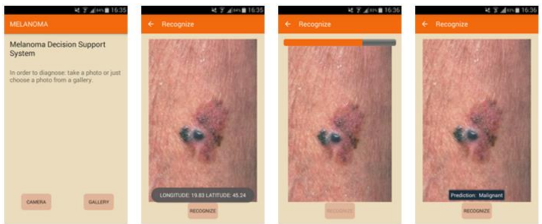

Figure 4. User interface of Android application

E. Experiment

Accuracy validation of the developed system and its classifier was confirmed in the following ways:

1. On the image dataset collected during the prospective study in the clinical centre;
2. By comparing the developed system predictions with expert predictions on another publicly available labelled dataset.

The prospective study was conducted in the Clinical Centre of Vojvodina, Novi Sad, Serbia. In this study, patients were hospitalized from January to March 2016 and confirmation of the clinical diagnosis was done via skin biopsy. Images gathered in this study (14 malignant and 36 non-malignant) built a prospective validation set for the developed deep neural network testing. Application detection results were compared to the ground-truth data obtained from the biopsies.

Comparison of the expert and mobile based DSS described in this paper was made on the dataset of images gathered from publicly available labelled dataset Dermnet

[31]. The dataset was constructed of 100 images of non-malignant and 50 images of malignant melanoma. The predictions of the trained model were made directly from the developed DSS application while the experts were manually assessing the images from the dataset.

IV. Results and Discussion

The DSS for melanoma detection described in this paper uses the deep CNN trained and validated on the database described in Section 3.1. First training of the network consisted of only original images. The achieved accuracy was only 65% in overall, due to the small amount of the original images gathered in the database for training. After the augmentation of the images from the training set, as described in the Section 3.2, achieved accuracy of the neural network was 91.68% overall. Accuracy and loss graph are illustrated in Figure 5.

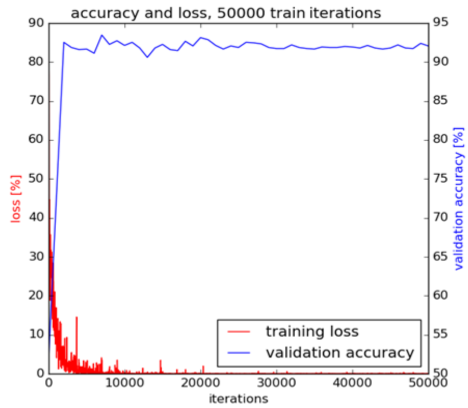

Figure 5. Accuracy and loss of the trained network

After 35000 train iterations, stable accuracy was gained (blue line) and loss was rapidly reduced after 15000 iterations (red line).

Accuracy of the model on validation set is displayed separately in classes of benign and malignant lesions images in Figure 6.

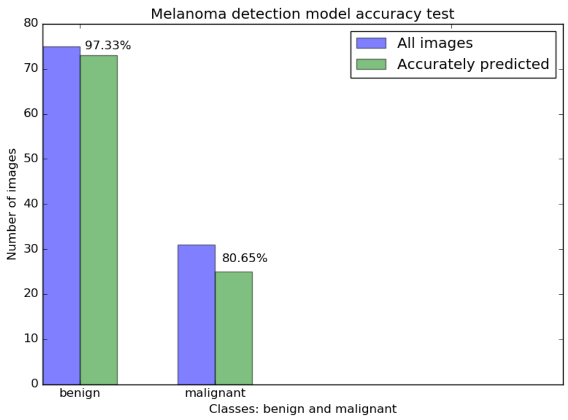

Figure 6. Accuracy of the trained model on separate classes: benign and malignant

From Figure 6, it is notable that the accuracy of the model was better on benign class, 97.33%, while the malignant class showed slightly less accuracy performance, 80.65%. These results can be explained with smaller amount of original images of malignant lesions involved in training the deep neural network.

Further fine-tuning of the deep neural network's parameters and hyper-parameters was not applied, as the aim of this paper was not only to present training the deep CNN for melanoma detection, but also to present the possibility of using the deep learning techniques in developing the entire system for melanoma detection.

The system developed in this paper sends images to the server side, storing them in the database. Furthermore, the incoming images, if labelled by biopsy, could be used for enriching the current database and with further fine-tuning of the CNN, the better result in accuracy could be achieved.

In order to better assess our results, we have tried to find an appropriate study and compare the research results with those from contemporary literature. As already specified, a study similar to ours was carried out by Fosu and Jouny [32]. They developed a mobile-based DSS for melanoma detection by using SVM as a classifier, contrary to ours. They used only 20 images for feature extraction without Internet source referenced and the results of the model lack a comment. Unfortunately, due to the lack of information in their paper, our two approaches of developing the melanoma detection DSS could not be directly compared.

Therefore, trained model was tested on the dataset that contains images from the prospective study described in the Section 3.6. Overall accuracy of the trained model on this dataset was 90%. Slightly better result was achieved for detecting the non-malignant moles 91.67%, while the model achieved 85.71% when recognizing the melanoma lesions.

In addition, model's accuracy was tested directly from the developed mobile DSS on the labelled images from the dataset downloaded from the Dermnet and compared with the expert's predictions as described in Section 3.6. Experts' predictions achieved the accuracy of 90.5% and model's accuracy was 91.5% in total. Experts' predictions were subjective in situations where the classification was not clear. In these situations they labelled them always as malignant in practice, in order to be sure after further detailed analysis. Regardless of the situation, trained network is not subjective and all the predictions are based on the recognized features from the image.

V. Conclusion

This paper describes development process of a new mobile-based system which serves as a decision support mechanism in early melanoma detection. The system consists of several pervasive components, where mobile application serves as a client side, designed to take images and display the results given by detection process, performed on the server side. The server side of the system includes deep learning based melanoma detection model, database and data exchange service. The system is able to recognize character of the skin lesion with accuracy of 91.68%, which is confirmed by detailed comparison with the experts and in the prospective study.

Being aware of the needs of the healthcare system, the authors intend to upgrade the system in order to increase the overall accuracy. A new model is intended to use data contained in images and extra metadata, like diameters of lesion, lesion site, patient's age, gender, etc. Most probably, the classifier will be constructed by combining deep learning techniques for image classification with other machine learning algorithms for metadata. In addition, selective search option is planned to be added to the classifier model enabling search for melanoma suspected lesions in the whole body images.

The proposed application can contribute to a practitioner in making early diagnosis and increase the number of survivals, which is the primary goal of our research.

VI. LIMITATIONS OF THE STUDY

Our goal was to make a proof of concept and to develop a DSS for melanoma detection for practitioners using state-of-the-art artificial intelligence methods.

Another limitation is the overall accuracy of the system (91.68%), which will be increased in the future by using more images for training, additional metadata and finally, by fine-tuning process of the deep neural network model.

ACKNOWLEDGMENT

Research presented in this paper was partly sponsored by the PanonIT company.

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