



[Science Archives \(ISSN:2582-6697\)](http://www.sciencearchives.org)

Journal homepage: www.sciencearchives.org



<http://dx.doi.org/10.47587/SA.2021.2410>



Research Article

Detection of skin melanoma using deep learning approach

Husam Khalaf Salih Juboori*

Department of Computer Engineering Techniques, Al-Rasheed University College, Baghdad, Iraq

*Husam.k.k.salih@alrasheedcol.edu.iq

Received: Nov 24, 2021 / Revised: Dec 04, 2021/ Accepted: Dec 25, 2021

Abstract

Skin cancer is now well recognized as a leading cause of death in humans. Skin cancer is defined as the abnormal proliferation of skin cells on the human body that has been exposed to sunlight for an extended period. Skin cancer can develop in any place on the female organism. Most malignancies are treatable if caught in their early stages. As a result, it is critical to discover skin cancer at an early stage to save the patient's life. With modern technology, it is feasible to detect skin cancer at an early stage and treat it effectively. In this paper, we present a system for the identification of microscopic images that are based on a deep learning technique and an entity encoding scheme, both of which are implemented in Python. Note that the deep interpretation of a rescaled dermoscopic image is first retrieved by an extraordinarily deep residual human brain, which already has previously been trained on a large natural ImageNet dataset before being applied to the dermoscopic image. Local deep descriptors are then gathered by ordered less visual statistic characteristics, which are then used to construct a global picture representation based on a fisher vector encoding scheme. Finally, we used the fisher vector coded interpretations to arrange melanoma photos using a convolution neural network, which was trained on the data (CNN). This system can provide more discriminatory information despite its limited training examples because of its limited ability to distinguish between significant changes inside the same class of skin cancer and tiny changes between skin cancer and other types of skin cancer.

Keywords: Dermoscopic, Image Recognition, CNN Algorithm, Melanoma Detection, Segmentation

Introduction

Even for expert dermatologists, predicting skin lesions can be a challenging task because of the small variation among surrounding skin and injuries, the apparent similarity between skin sores, the bewildered lesion outskirts, and other factors. Clinicians can benefit from the use of a technological and mechanical detection system that uses pre-determined photographs to diagnose malignant skin lesions at the earliest possible stage. When compared to regular CNN, the development in deep learning consists of dilated convolution, which is known to have improved accuracy while requiring a similar level of processing complexities as the traditional CNN (Ali et al., 2017)

To give proper treatment recognition of skin lesions is important. Hence, the survival rate is increased due to early recognition of melanoma in dermoscopic images.

The accurate detection of melanoma skin lesions is possible to highly trained dermatologists. Therefore, due to the lack of differentiation among lesions and skin, the visual similarity between melanoma and non-melanoma lesions, and other reasons, it might be difficult to diagnose melanomas in the early stages. A reliable automatic detection method for skin tumors, such as a system that can automatically evaluate skin lesions, will be extremely beneficial in enhancing the performance and reliability of pathologists, especially at a time when expertise is in short supply (Patil et al., 2020).

To address these limitations, we have developed a framework for identifying the difficulties associated with automatic and reliable melanoma diagnosis in dermoscopy images. It is important to note that this work makes two distinct contributions. A framework based on deep CNN and an equivalent approach has been offered as a cost-effective solution. To improve the accuracy of melanoma recognition, it

is beneficial to develop representative features from limited training data.

The proposed framework utilizes segmentation for extracting the feature and CNN for analyzing melanoma and non-melanoma images. Then lots of experiments were carried on to compare the proposed approach with existing CNN-based methods utilizing the public ISBI 2016 skin lesion data.

Literature survey

In this study (Kamboj, 2018), the authors used the MED-NODE dataset. From the segmented part, color features are extracted and for performance checking of the system, the author used three classifiers: Naïve Bayes, Decision Tree, and KNN. The proposed methodology consists of the following steps:

Preprocessing: The digital images contain artifacts. A thresholding algorithm is used for removing artifacts.

Segmentation: To find the region of interest segmentation is used.

Feature Extraction: Colour features are extracted from segmented part

Classification: To classify the image whether it is melanoma or benign author used three classifiers.

82.35% accuracy is obtained by decision tree which is greater among these three classifiers.

Andre Esteva et al. presented a fully automatic solution for skin lesion segmentation using a learned 19-layer deep convolutional neural networks (CNNs) with no prior knowledge of the data in this research (Esteva et al., 2017). They employ a series of tactics to guarantee adequate learning despite the fact that they have minimal training data. During using managed to cross entropy as the weight vector for picture segmentation, the amount with input image pixels is significantly imbalanced. In order to reduce the need for sample re-weighting, an original regression model based on Jaccard distance is created in addition to the conventional technique. To measure the effectiveness, efficiency, and system more effective of the proposed framework, the author used two publicly available databases: ISBI 2016 and the PH2. On these two datasets, the proposed method outperforms other state-of-the-art methods, according to the author's experiments.

In this research paper (Ali et al., 2017), The authors suggested a Convolutional Neural Network model for melanoma identification and compared it to existing models' performance. According to the author, the architecture they devised is basic and only requires a few parameters. We show in this paper that utilising a typical convolutional neural network with only a few parameters, the suggested system may obtain equivalent results in terms of accuracy and specificity. For classifying the ISBI 2016 challenge dataset, Lequan Yu et al. created a model with and without a segmentation module. A convolutional neural network is utilized to offer precise segmentation. Softmax classifier and support vector machine classifier are the two classifiers

utilised here for categorization. This classifier produces the average results. Data augmentation is done to the input image in the form of rotation and shifts. The results of classification with and without segmentation are similar, according to the paper. Classification accuracy is reported to be 85.5 percent with segmentation and 82.8 percent without segmentation.

The author of this study (Yu et al., 2017) suggested a new approach for melanoma detection using deep convolutional neural networks (CNNs) and compared it to existing methods. To the author's knowledge, the substantially deeper networks in their system are capable of achieving more rewarding and discriminative features, resulting in much more specific and accurate detection. To take advantage of complex systems, the author presented several strategies for ensuring effective preparation and learning in the face of limited training data. The following advancements are used in the technique:

Incorporate the residual knowledge of how to adjust to corruption and overfitting difficulties when a network grows and sophistication. It will ensure that the presentation improvements achieved through network depth expansion are maintained.

To achieve exact skin lesion identification, a deep convolution residual network (FCRN) is constructed. The network's capacity is increased even further by incorporating several co context integrated data methodology further into network infrastructure.

The final step is to combine the Measures intended (for segmentation) and recurrent neural network (for classification) in order to develop a two-stage classification framework.

Due to the use of segmented outcomes rather than the whole dermoscopy images, this technique allows the classification network to extract more meaningful and explicit features that are less reliant on the training data shortage. As a result, the author used the ISBI 2016 Skin Lesion Analysis towards Melanoma Detection Challenge dataset to conduct his evaluation.

The deep learning system is implemented on a computer with GPU (Patil et al., 2021) The clinical images are used instead of dermoscopic images. The input clinical images contain noise effects and illumination, these effects are pre-processed to enhance the images using preprocessing. These images are fed to CNN classifier (Convolutional Neural Network) for the classification purpose. Proposed System is consisted following methodology:

Preprocessing: The clinical images taken by digital cameras contains noise and illumination. In this technique these effects are reduced to enhance the image (Leelarani et al., 2020)

CNN Proposed: The clinical images of training dataset after removal of noise are fed to the proposed CNN. The CNN method is used to detect the melanoma from clinical (non-dermoscopic images).

Result shows that the proposed method is superior in terms of diagnostic accuracy in comparison to other methods.

In this study (Gaikwad et al., 2020), the author proposed a deep Siamese CNN (SCNN) architectural, which can learn classification model with less guidance than some other CNN designs currently available since it is taught with just binary image pair information and can be trained with only binary image pair information (Gaikwad et al., 2020). The primary goal of most studies is to confine their technique to a single supervised convolutional neural network as a starting point (CNN). To test the trained picture representation, the author uses a publicly accessible multi - class classification personalized medicine sample of tissue dataset to perform material medical image processing techniques on a task of medical image retrieval. Using this experiment, it was discovered that the deep SCNN proposed by the author is comparable to the present single supervised CNN, and that it requires significantly less supervision throughout the training process.

In this paper (Patil, 2020) for classification, the support vector machine was employed by the author. The automatic image analysis tool makes use of techniques such as non-invasive medical image processing or medical image processing in order to give an accurate and rapid evaluation of the lesion. The proposed system consists of the following steps:

The picture dataset should be collected. Using dermoscopy, these images have been acquired.

Preprocessing

Thresholding is used to segment the data set.

Gray level co-occurrence matrices (GLCM) and ABCD (Asymmetry, border, colour, and diameter) rules, among other techniques, are used to extract statistical features from images.

Principal component analysis is used to select the feature (PCA).

Total dermoscopy score to be calculated

After that, categorization is carried out with the help of support vector machines (SVM). The SVM is used to categorise the photos.

Using this classification system, an accuracy of 92.1 percent can be reached.

In this paper (<https://www.isicarchive.com>), the author provides the results of a feasibility study on the possibility of developing a global skin disease diagnosis system based on Deep Convolutional Neural Networks (CNN). The system first trained the CNN architecture using the 23,000 skin illness photos from the Dermnet dataset, and then tested its performance using images from the Dermnet and OLE datasets, both of which contain skin disease images, respectively. Testing on the Dermnet dataset has demonstrated that the proposed method can obtain top-1 accuracy of 73.1 percent and top-5 accuracy of 91.0 percent when employing the proposed mechanism, according to the

experimental results. Based on the results of a test on the OLE dataset, it was determined that the top-1 as well as top-5 accuracies were 31.1 percentage and 69.5 percent during this period. The author also suggests that by using more training photos, the accuracy of the system can be further improved.

The spread of melanoma occurred via metastasis hence it is proven to be very fatal. As per statistical proof or evidences the most of deaths that occurred due to skin cancer are as a result of melanoma.

It is necessary to use the DBSCAN clustering method in order to locate clusters in big spatial databases that contain noise. A modified version of the widely used density-based clustering technique, DBSCAN, was used in conjunction with a pre-processing step in this investigation (Shen et al., 2016). A fast density-based lesion detection (FDBLD) approach was used in this study, which reduced the number of duplicate calculations in DBSCAN by selectively selecting querying points and core points. It is the goal of this research to improve the performance of the proposed algorithm for detecting lesion borders in dermoscopy pictures by incorporating FDBLD into the process. The pre-processing stage has a significant impact on FDBLD. The primary goal of this work is twofold: first, to eliminate the reliance on FDBLD in the pre-processing step, allowing colour information to be utilised; and second, to improve the accuracy of the results by utilising more colour information. In order to do this, a new distance metric has been included into FDBLD.

Natural hair algorithm has been developed that is capable of keeping skin lesion characteristics such as colour and texture while also being able to distinguish between light hairs as well as dark hairs. Essentially, the proposed method is built around three fundamental steps:

Thresholding and matched filter with first derivative of Gaussian (MF-FDOG) were used to segment rough hairs, which produced positive reactions for light as well as dark hairs.

Hairs were processed using morphological edge-based approaches, which were then restored using a quick marching in painting technique.

A dermatologist-drawn manual hair mask was used as a ground truth to determine the system's diagnostic accuracy (DA) and texture-quality measure (TQM) metrics, which were used to calculate the system's performance (Abbas et al., 2013)

The results obtained by the experiments conducted by the researcher's show that the approach presented in the literature have high precision values. They are also capable of restoring the hair pixels, also it does not affect the texture of the lesions. The presented approach is fully automated and it is also easy to integrate it with the CAD systems. Independent CAD systems are not required for the implementation of the presented system.

System architecture

The proposed framework design is depicted in the following figure 1. The system consists of several modules, including an input dataset, pre-processing, picture segmentation, feature extraction, training and testing using the CNN algorithm, and others. In our research, we employed the CNN algorithm to distinguish between photos of melanoma and images of non-melanoma.

The following are the stages that must be completed for our suggested system to be implemented. The system will accept an image dataset as input.

Pre-processing is carried out in order to improve the image quality and remove hairs from the image. Several features are retrieved from the input image dataset, and a learning file is generated as a result. The CNN classification method is applied to the freshly created training file dataset as well as the new test input photos. The output of the Machine learning algorithms is melanoma detection, which is determined by whether or not the input test reveals melanoma. At the conclusion, a graphical evaluation is carried out in order to assess the performance of the proposed system.

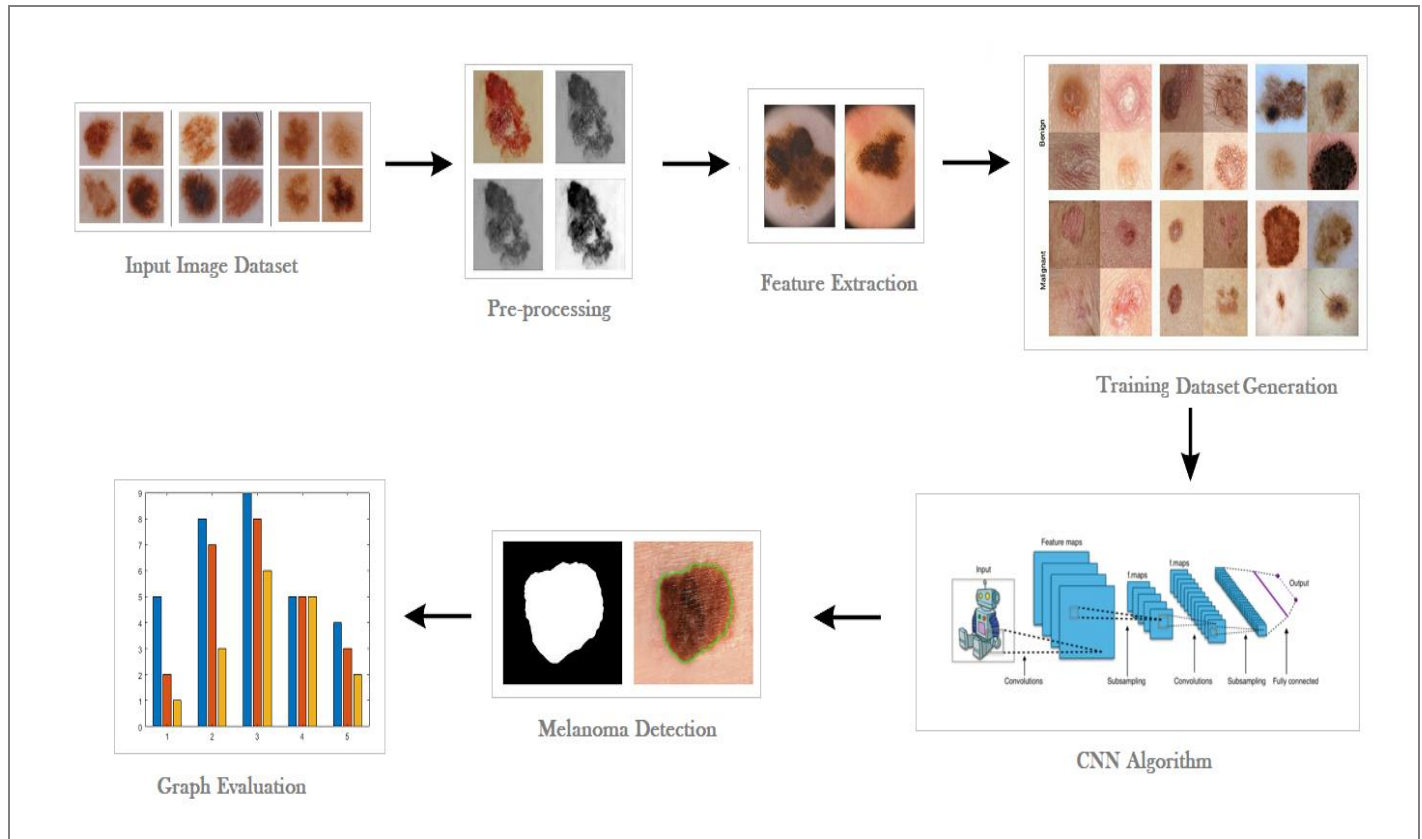


Fig 1. System Architecture

Result and discussion

Dataset and Database used

ISIC dataset was used for training, validation, and testing purposes (Bissoto et al., 2018). The ISIC dataset includes a number of 10015 dermoscopic images of seven skin lesion classes with significant class imbalances.

Experimental Setup

All of the experiments are implemented in Python in conjunction with Anaconda (Jupyter) tools, algorithms, and strategies, as well as the able to compete classification approach with feature extraction stage, and run in an

environment consisting of an Intel Core i5-6200U processor running at 2.30 GHz on a Windows 10 (64 bit) machine with 8GB of RAM. All of the results are presented in Table 1.

Result

The performance analysis is depicted in Fig. 2. Graph. In terms of spam sensitivity and specificity, we present a summary of the results of the three machine learning approaches. The reading from which the graph in Fig.2 is derived is shown in Table 1. When looking at the accuracy graph, we can see that the SVM method is the most accurate, while the k nearest neighbour method gives us a lower

percentage of accuracy. When looking at the spam precision graph, we can see that the proposed CNN method has better accuracy when compared to that of the SVM and CNN with softmax algorithms. The x-axis in the following graphs represents different categorization algorithms, and the y-axis represents percentages.

Table 1. Performance parameters reading

Algorithms	AC	SE	SP
CNN (SoftMax)	0.850	0.500	0.934
SVM	0.844	0.520	0.824
CNN (Proposed)	0.939	0.507	0.854

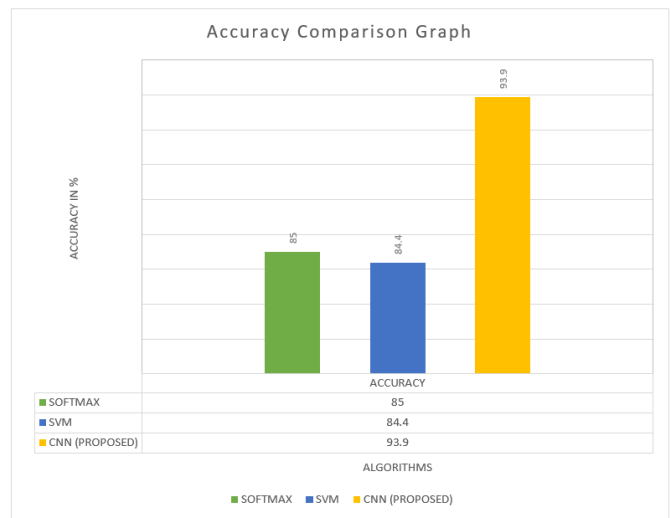


Fig. 3 Accuracy comparison graph

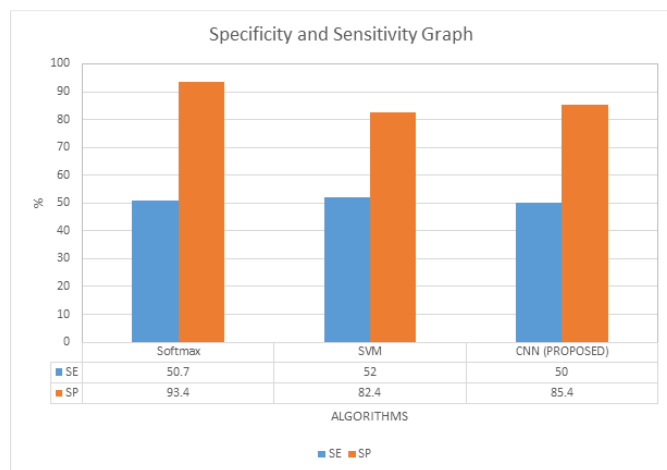


Fig 2. Specificity and sensitivity graph

Conclusion

Skin cancer is one of the worst types of cancer in the world, according to medical experts. As a result, we develop a computer-assisted skin lesion classification system that incorporates various deep neural network topologies as well as transfer learning techniques and segmentation. The CNN classifier was also used for melanoma and non-melanoma image detection, and alternative pre-processing and augmentation methods were implemented to decrease the influence of the ISIC's class imbalance, which was distinctive of the study.

References

Ali, A. A., & Al-Marzouqi, H. (2017, November). Melanoma detection using regular convolutional neural networks. In *2017 International Conference on Electrical and Computing Technologies and Applications (ICECTA)* (pp. 1-5). IEEE.

Abbas, Q., Garcia, I. F., Emre Celebi, M., & Ahmad, W. (2013). A feature-preserving hair removal algorithm for dermoscopy images. *Skin Research and Technology*, *19*(1), e27-e36.

Bissoto, A., Perez, F., Ribeiro, V., Fornaciali, M., Avila, S., & Valle, E. (2018). Deep-learning ensembles for skin-lesion segmentation, analysis, classification: RECOD titans at ISIC challenge 2018. *arXiv preprint arXiv:1808.08480*.

Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. *nature*, *542*(7639), 115-118.

Gaikwad, M., Gaikwad, P., Jagtap, P., Kadam, S., & Patil, R. R. (2020). Melanoma Cancer Detection using Deep Learning. <https://www.isicarchive.com/#!/topWithHeader/onlyHeaderTop/gallery>

Kamboj, A. (2018, December). A color-based approach for melanoma skin cancer detection. In *2018 First International Conference on Secure Cyber Computing and Communication (ICSCCC)* (pp. 508-513). IEEE.

Leelarani, K., Sangeetha, K., Nilofer, B., & Sangeetha, M. (2020). Bone Fracture Detection System using Image processing.

Patil, R., & Bellary, S. (2020). Machine learning approach in melanoma cancer stage detection. *Journal of King Saud University-Computer and Information Sciences*.

Patil, R., & Bellary, S. (2021). Transfer Learning Based System for Melanoma Type Detection. *Revue d'Intelligence Artificielle*, *35*(2), 123-130.

Shen, J., Hao, X., Liang, Z., Liu, Y., Wang, W., & Shao, L. (2016). Real-time superpixel segmentation by DBSCAN clustering algorithm. *IEEE transactions on image processing*, *25*(12), 5933-5942.

Yu, L., Chen, H., Dou, Q., Qin, J., & Heng, P. A. (2016). Automated melanoma recognition in dermoscopy images via very deep residual networks. *IEEE transactions on medical imaging*, *36*(4), 994-1004.

How to cite this article

Juboori, H.K.S. (2021). Detection of skin melanoma using deep learning approach. *Science Archives*, Vol. 2 (4) 330-334. <http://dx.doi.org/10.47587/SA.2021.2410>

This work is licensed under a [Creative Commons Attribution 4.0 International License](https://creativecommons.org/licenses/by/4.0/)



Publisher's Note: MD International Publishing stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.