A New Approach using Deep Learning and Reinforcement Learning in HealthCare: Skin Cancer Classification

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Abstract *– Nowadays, skin cancer is one of the most important problems faced by the world, due especially to the rapid development of skin cells and excessive exposure to UV rays. Therefore, early detection at an early stage employing advanced automated systems based on AI algorithms plays a major job in order to effectively identifying and detecting the disease, reducing patient health and financial burdens, and stopping its spread in the skin. In this context, several early skin cancer detection approaches and models have been presented throughout the last few decades to improve the rate of skin cancer detection using dermoscopic images.*

This work proposed a model that can help dermatologists to know and detect skin cancer in just a few seconds. This model combined the merits of two major artificial intelligence algorithms: Deep Learning and Reinforcement Learning following the great success we achieved in the classification and recognition of images and especially in the medical sector. This research included four main steps. Firstly, the pre-processing techniques were applied to improve the accuracy, quality, and consistency of a dataset. The input dermoscopic images were obtained from the HAM10000 database. Then, the watershed algorithm was used for the segmentation process performed to extract the affected area. After that, the deep convolutional neural network (CNN) was utilized to classify the skin cancer into seven types: actinic keratosis, basal cell carcinoma, benign keratosis, dermatofibroma melanocytic nevi, melanoma vascular skin lesions. Finally, in regards to the reinforcement learning part, the Deep Q_Learning algorithm was utilized to train and retrain our model until we found the best result. The accuracy metric was utilized to evaluate the efficacy and performance of the proposed method, which achieved a high accuracy of 80%. Furthermore, the experimental results demonstrate how reinforcement learning can be effectively combined with deep learning for skin cancer classification tasks.

Keywords*: Skin Cancer, Deep Learning, Reinforcement Learning, Classification, CNN, Deep Q_Learning, Dermoscopy Image, Segmentation*

1. INTRODUCTION

Cancer is a disease caused by the transformation of cells that become abnormal and proliferate excessively, it is one of the main causes of death worldwide, with approximately 10 million deaths in 2020 [1]. The majority of human cancers are skin cancers, and their prevalence is increasing more quickly than all other cancers [2].

Skin cancer is one of the most serious forms of cancer [3] it arises when skin cells grow irregularly; factors contributing to its occurrence include UV radiation exposure, a family history of the disease, decreased immunity, etc. Morocco reported 114 fatalities and 248 new cases of melanoma in 2020 [4].

The three main types of skin cancer are: Basal cell carcinoma, Squamous cell carcinoma, and Melanoma, this last is regarded as the most hazardous form of all the other varieties. Early and accurate detection is considered the best method of surviving and avoiding the worst effects of cancer and cured. But that is a difficult task since malignant tumors and normal moles share visual characteristics, which makes it difficult, particularly for the detection of type melanoma [5].

Dermoscopic imaging methods are most frequently employed by dermatologists to examine skin lesions based on their collection of morphological characteristics. But only qualified medical professionals with the proper vision and experience can employ this approach to its full potential [6]. These difficulties have recently presented the research community with a major challenge to develop new and innovative systems based on artificial intelligence (AI) tools including those based on computer algorithms, deep learning, and deep reinforcement learning networks [7] for aided assist experts to early diagnosing of skin cancer and prevention.

Artificial intelligence (AI) is a branch of computing dedicated to the design of machines capable of imitating human intelligence that relies on the creation and application of algorithms executed in a dynamic computing environment. Its purpose is to allow computers to think and act like human beings. With advances the last few years have seen in computing and information science, artificial intelligence (AI) is rapidly becoming an integral part of modern healthcare. AI algorithms are used to help healthcare professionals in clinical settings, in ongoing research, and in diagnostic dermatology [8]. The most popular algorithms used are deep learning, machine learning, and reinforcement learning.

Deep learning is a branch of machine learning, which is based on a group of algorithms inspired by the human brain (ANN) that seek to shape high-level abstractions of data using multiple layers (input layer, hidden layer, output layer). It has been applied in several areas such as speech recognition [9], bioinformatics [10], and also detection/diagnosis in medical imaging [11]. Recently, the convolutional neural network (CNN) is considered the most successful algorithm applied for major medical image tasks, such as image classification, segmentation, localization, and detection.

Reinforcement Learning is the most popular method of machine learning that handles sequential decision problems [12], it involves letting computers learn from their experiences through a reward or penalty system. Reinforcement learning has achieved very success in recent years in the following artificial intelligence applications: robot control, computer vision, autonomous driving, and computer gaming. And also, has emerged as one of the crucial areas in the field of artificial intelligence impacting the field of health care including diagnosis, prognosis, and other medical treatments [13].

Deep Q_Networks (DQNs) [14] are neural networks that use deep Q_learning to provide models, it's been composed of convolutional neural networks and other structures that use specific methods to learn more about various processes with high accuracy. DQN can be effectively used to detect skin cancer [15].

In this work, we have proposed a new and intelligent model to increase the diagnostic accuracy of skin cancer. This model combines the merits of two major artificial intelligence algorithms: Deep Learning (CNN) and Reinforcement Learning (DQN). We have collected 10015 dermoscopy images from the ISIC site archive, which contains 7 types of skin cancers. firstly, the pre-processing techniques have been applied, such as reading, resizing images, cleaning images, and applying One Hot Encoding on the labels of the dataset and splitting into a training set and a test set. After that, the segmentation process was used to extract the affected area using the watershed algorithm. Then, extracting important features from images and classified the dermoscopy images using the deep convolutional neural network (CNN). And about the reinforcement learning part, we used the Deep Q_Learning algorithm to train and retrain our classification model until we found the best result.

The main contributions of the proposed work are:

- Use of reinforcement learning to classification tasks, and especially to classify dermoscopy images for the first time in the literature.
- This paper proposes a method for detecting skin cancer kinds in dermoscopy images utilizing the ISIC database.
- The proposed model performs significantly better in the classification task.
- Best performance metrics obtained using a deep algorithm contain many layers with different parameters.
- Combined reinforcement learning with deep learning to detect and classification of skin cancer.

The structure of this paper is as follows: Section 2 presents an overview of related literature. Section 3, called materials and methods, first provides a description of the dataset used. Next, presents the theory of deep learning (CNN) and reinforcement learning (DQL), and finally, explains in detail the method proposed. Section 4 contains the experiment results, including the experiment settings and evaluation of the proposed model. Finally, Section 5 concludes the current study, with a little discussion and suggests possible future work avenues.

2. LITERATURE REVIEW

Skin cancer is one of the greatest challenges in the medical domain. Recently, various types of diagnostic techniques based on artificial intelligence tools that can early detect and classify skin cancer have been proposed and developed.

In related works, many researchers have used IA algorithms to automatically diagnose skin diseases.

- **Machine Learning based Approaches:**

In [16] the authors proposed an approach to detect and classify eight types of skin cancer using dermoscopic images collected by the ISIC 2019 challenge dataset. Which has been used principally in the preprocessing phase with Gaussian and median filters for noise removal and image enhancement. Also, the Dull Razor method to remove any extra hair from the skin lesion. After that utilized the clustering algorithm: Color-based k- means clustering to segmentation. To facilitate the classification purposes two methods of extracting features have been applied: ABCD and GLCM. In the end, the authors decide to use part of the support vector machine (MSVM) due to the great success it has achieved to solve multi-class problems. This approach attained good accuracy.

In [17] the authors concentrate on the identification diagnosis of skin cancer melanoma with Supervised Machine Learning using Cubic Regression. This method required various steps like the image processing technique to select of suitable color model for the image being processed, segmentation by creating masking to segment the image, feature extraction, and machine learning with two modes: train and test, and graphical presentation of data have used cubic regression as a good solution for displaying the result. The main objective of this project is to train a machine to automatically display the stages of skin cancer.

In [18] the authors implemented a model based on the KNN algorithm to detect and classify skin lesions (normal or benign). The proposed model consists of four steps: preprocessing involved with two-phase: image enhancement and hair removal, segmentation using the thresholding method, feature extraction, and classification with KNN which is based on calculating the distance between a number of data points in an image. The proposed system showed satisfactory accuracy of classification. In this way, this model was able specifically to classify skin lesions.

- **Transfer Learning-based Approaches:**

In [19] the authors used a deep convolutional neural network (DCNN) to classify skin lesions between benign and malignant based on the HAM10000 dataset that incorporates the following steps: preprocessing with applied some filter to remove noise, data reduction, normalization of data, feature extraction and transformed data label to numeric, data augmentation techniques to the expansion of the data and increase the number of images. the goal of the authors is to compare the performance between DCNN and transfer learning models as VGG16 and other models. The proposed DCNN model achieved a robust result.

In [20] the authors presented a pre-trained Xception model with a method fine-tuned to classify skin cancer by adding a series of layers after the base layer of the Xception model and retraining the model weights. The input images are resized to 224 x 224 pixels. The used loss function is categorical cross entropy, while the optimizer is Adam with a learning rate of 0.0001. The results obtained indicate that the proposed model is both efficient.

In [21] the authors developed a model that combines pre-trained convolutional neural networks (DenseNet201) architectures as feature extractors and machine learning (Cubic SVM) as a classifier. The choice of these models depends on the results of several training steps on the PH2 dataset. The methodology used contains three principal stages: input images, the feature extraction with compared three pre-trained models: ResNet, DenseNet, and EfficientNet. Classification with compared four algorithms: Artificial Neural Network, Support Vector Machines, K-Nearest Neighbor, and Random Forest. The result obtained shows the great performance of the model to detect skin lesions.

- **Deep Learning based Approaches:**

In [22] the authors proposed a medical artificial solution called the LCNet model based on a deep convolutional neural network (DCNN) to classify binary skin cancer using dermoscopy images. This model contained many layers designed using 11 blocks, the block of the network is composed of convolutional, pooling, BN, and leakyReLU layers that make use of a different set of parameters, including the number of kernels, stride, and filter to extract features and classify skin lesions. The authors applied data augmentation to address the problem of lack of data. This method achieved good results in expediting the process of melanoma diagnosis automatically.

In [23] the authors designed an automatic technique based on a deep learning algorithm with Fuzzy K-Means Clustering to detect and identify the kinds of skin cancer. The method proposed in this paper contains three steps: firstly, preprocessing using the morphological closing process and other filters and then applying a faster RCNN to obtain fixed-length feature vectors through four stages: convolution layers, regional proposal networks, and classification. and finally, for segmentation FKM has been used due to it working well for overlapped data. This method has been evaluated by three datasets PH2, ISIC-2017, and ISBI-2016, and the experimental results exhibit the advantage and the performance of using this method in the detection and segmentation of skin lesions.

In [24] to automatically identify skin cancer the authors proposed a system using a convolutional neural network (CNN) containing 3 hidden layers: a convolution layer, a pooling layer, a fully connected layer with softmax activation, and uses multiple optimizers such as Adam, Nadam, SGD, and RMSprop with learning rates of 0.001. The authors found that adam optimizer provided the best performance in identifying skin lesions in 5 categories (i.e., dermatofibroma, nevus pigmentosus, squamous cell carcinoma, and melanoma) from the ISIC dataset after using augmentation techniques. The objective of the study is to obtain the best performance of the skin cancer classification methods existing.

- **Overview of our proposed approach:**

The idea behind our approach is to build an efficient and intelligent system to assist doctors in skin cancer detection, increase diagnostic accuracy, and make patients' lives easier. The system proposed combines two major artificial intelligence algorithms: Deep Learning (CNN) and Reinforcement Learning (DQN) due to the great advantages to learn high-level features from data, and innovation to do the task of classification and detection.

The novelty of this research manifests itself in the following:

- How to effectively combined reinforcement learning with deep learning. And how deep reinforcement learning can help in the medical context, especially in the diagnosis and detection of skin cancer.
- A novel approach to the classification and detection the skin cancer is proposed which is based on deep reinforcement learning. This is a first to the best of my knowledge.
- For the first time used reinforcement learning for the classification task and especially to classify the dermoscopic images.
- The architecture of the two algorithms is deep and contains many layers with different parameters.
- This paper addresses the issue of investigating the performance of the CNN-DQN model for the classification and detection of skin lesions.
- The results explain the success of our proposed approach, as we found satisfactory accuracy.

Our proposed approach contains four steps: (1) The input dermoscopy images passed in the preprocessing process to remove the noise, cleaning, normalization, and splitting data. (2) Extract the affected area with applied the watershed algorithm to the output of the preprocessing phase. (3) classification using the deep convolutional neural network (CNN) model containing a sequence of convolutional layers, pooling layers, several activation functions, Batch Normalization, Dropout, and fully connected layer ''Softmax function''. (4) Training phase using the reinforcement learning (Deep Q_Learning algorithm) until to obtain the best result.

3. MATERIALS AND METHODS

In this section, we present the dataset used first and then a description of two algorithms used: deep learning ''CNNs'' and reinforcement learning ''DQN', and finally we provide the detail about our proposed model.

3.1. DATA DESCRIPTION

To conduct this research and analyze the experimental findings of the suggested strategy. We have used the publicly available HAM10000 dataset. This dataset contains 10015 dermatoscopic images devised of seven different classes of skin lesions as shown in Table 1 [25]. These dermoscopic images were originally 600 x 450 pixels in RGB format, which We then resized all to 28 x 28 pixels to reduce network input and parameters.

We used the Train_Test_Split technique to randomly split the data: 80% for training and 20% for testing.

Table 1. Presents the seven classes and the type of cancer in each class

Class	Type	Number of images
Actinic keratosis	Benign or Malignant	327
basal cell carcinoma	Malignant	541
benign keratosis	Benign	1099
Dermatofibroma	Benign	155
Melanocytic nevi	Benign	6705
Melanoma	Malignant	1113
vascular skin lesions	Benign or Malignant	142

3.2. DEEP LEARNING

Deep learning is a type of artificial intelligence derived from machine learning where the machine is able to learn by itself. Deep Learning is based on a network of artificial neurons inspired by the human brain. Recently, deep learning has been shown to be a particularly effective technology due to its ability to manage massive volumes of data. which it's used for different work such as object detection, image classification, and speech recognition… The convolutional neural network algorithm is the most popular and used, particularly for classifying medical images.

3.3. CNN

CNN is a multi-layer neural network with a special architecture developed to extract increasingly complex data characteristics from each layer in order to determine the output as shown in Fig. 1. Used primarily when an unstructured data set exists [26, 27]. One of the most popular uses of this architecture is image processing, classification, and segmentation.

The layers of a CNN consist of an input layer, an output layer, and a hidden layer that consists of multiple convolutional layers, clustering layers, fully connected layers, and normalization layers.

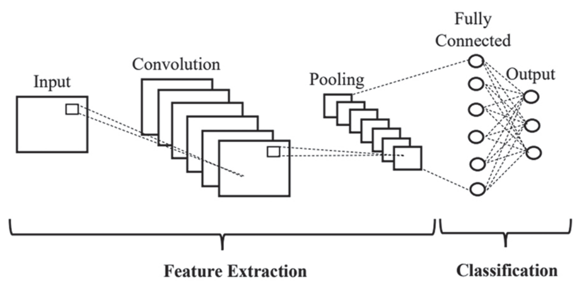

Fig. 1. The convolutional neural network architecture

This work has incorporated the CNN algorithm into diagnostic skin cancer with dermoscopic images, where we implemented a deep CNN architecture for the classification task.

3.3. REINFORCEMENT LEARNING

An agent and an environment are the two principal elements of the machine learning technique known as reinforcement learning (RL) [28]. This type of learning is based on interaction with the environment by trial and error using feedback from its own actions and experiences. The main objective of reinforcement learning is to find the most appropriate action model for maximizing the total cumulative rewards of RL agents.

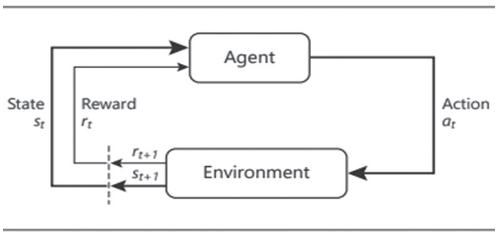

Fig. 2. Illustration of the agent-environment interface [28].

In recent years, reinforcement learning has emerged as one of the crucial areas in the field of artificial intelligence impacting the field of health care. Deep Reinforcement Learning (DRL) combines deep neural networks and reinforcement learning. The goal of this combination is to create self-learning software agents to establish winning strategies for maximizing long-term rewards. In DRL, values or policy functions are represented as deep neural networks, making it easy to apply related deep learning techniques. such as Deep Q_Network (DQN).

3.3.1 DEEP Q_NETWORK

DQN or Deep_Q Networks is one of the first successful algorithms that combine deep learning and reinforcement learning to learn approaches directly from high-dimensional raw data. DQN has accelerated the development of reinforcement learning and expanded its application scenarios by combining convolutional neural networks (CNNs) with Q_learning.

DQN was proposed by DeepMind in 2015 to integrate the benefits of deep learning into reinforcement learning [29]. Reinforcement learning focuses on training agents to take action at specific stages in the environment in order to maximize rewards.

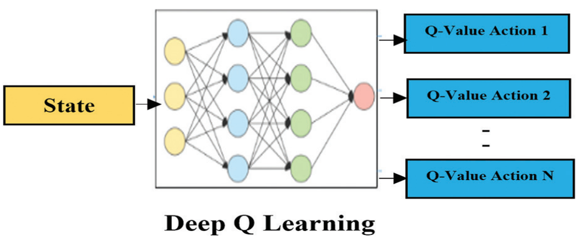

Fig. 3. The Deep Q-Network (DQN) algorithm

In this work, we have proposed a DQN network architecture to train and retrain our classification model.

3.4. PROPOSED METHODOLOGY

In this proposed study, a new and efficient skin cancer diagnosis model has been implemented for the precise classification and detection of malignant and benign skin cases.

Fig. 4 shows the complete workflow of our architecture consisting of two parts: Deep Learning and Reinforcement Learning.

The complete model consists of several steps starting from the input phase of applying the image preprocessing phase for analysis of the dermoscopic images before applying any feature extractor and classification methods [30]. Then, the first stage outputs are passed in the segmentation phase to determine the zone of cancerous skin and to effectively monitor the boundary areas of this zone. After that, the segmented image outputs are fed into Deep CNN Model to obtain the output probability.

In the final part, the result of the classification model is passed with a reinforcement learning environment with the DQN Algorithm to train and retrain our classification model up to find the best accuracy of classification task of skin cancer with the use of deep reinforcement learning.

The principal steps of our approach are:

1. Collecting the dermoscopic images for the dataset from skin cancer types images.
2. Applying image preprocessing techniques, such as reading, resizing images, cleaning images, and applying One Hot Encoding on the labels of the dataset.
3. Using Train_Test_Split to splitting the dataset into two sets: a training set and a test set.
4. Applying data segmentation using a watershed algorithm.
5. Extracting important features from images and classifying the dermoscopic images using the CNN network.
6. Reducing overfitting [31] and reducing error rates using dropout.
7. Training and retraining our classification model 'CNN' with reinforcement learning algorithm 'DQN'.
8. Choosing the optimal hyper-parameter.
9. Evaluating our model on the test dataset.

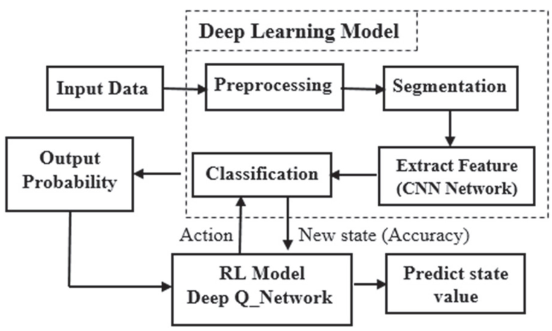

Fig. 4. The architecture of the proposed method.

Preprocessing: Image pre-processing is an important task that not only saves training time but also helps to significantly improve the next step by increasing the efficiency of the model. In this study, the preprocessing techniques used are:

- Collection of the dataset: we have collected 10015 dermatoscopic images of seven different classes of skin cancer types from the publicly available HAM10000 dataset.
- Import the necessary libraries.
- Reading and Resizing images: the images are resized to 28x28 to make the computation and training faster.
- Exploratory Dataset Analysis (EDA) to facilitate analysis of the data.
- Cleaning Dataset: remove duplicates, hair removal...
- Apply One-Hot Encoding for labels.
- Normalization: is a technique used to avoid the problems caused by the loss of contrast in the image.
- Splitting Dataset: The data were randomly split using the Train_Test_Split technique: 80% for training and 20% for testing.

Segmentation: After applying pre-processing techniques to the images to avoid all kinds of impurities, this image should be segmented, focusing on the area of interest to simplify the classification. Therefore, the next step is image segmentation. This is a technique used in image processing that divides an image into many parts, depending on the quality of the pixels in the image. Image segmentation involves recognizing and segmenting areas of interest based on how identical the colors and shapes are.

In our case, to extract the information about the skin cancer lesion with high confidence we have used the Watershed Algorithm is an efficient and successful segmentation technique in medical imaging. Because it's less sensitive to noise and is less computationally and calculation expensive. [32, 33]

Feature Extraction and Classification: CNN-based feature extraction and classification techniques are the most common method in image processing especially medical. here, next to image segmentation, the segmented image output passed to our CNN model.

We have proposed deep layers CNN, we increased the size and complexity of the model to give high accuracy and better efficiency. The structure of our CNN architecture proposed includes a sequence of convolutional layers, pooling layers, several activation functions, Batch Normalization, Dropout, and a Fully-Connected Layer "Softmax function" to obtain outputs of the probability of each class being present. The size of the convolution kernel was kept constant at all stages. In our case, to avoid the overfitting problem we used the average polling layer with a small window size of 2*2.

Training and Evaluation: Recently, RL algorithms have been effectively and successfully combined with a Deep-NN [34]. This combination has been used to approximate RL functions using the Deep-NN model or when using RL to train Deep-NN.

In our case, we have applied the DQN algorithm with some fully connected layers and activation functions for train and retraining our deep CNN network until we found the best result with the optimal hyper-parameters. We followed a special process to train our model: Firstly, we selected random images for fed into the classification model to obtain the output probability (state). Then, we passed the result of the classification model in the RL model to predict state value.

Finally, in our RL environment, we selected an image with a height prediction value (Action) to train our CNN classification model to obtain the new state (Accuracy).

4. RESULTS

Our proposed system for the detection and classification of skin cancer was evaluated with the HAM10000 dataset which is described in the datasets section of the paper. This system uses deep reinforcement learning which combines the CNN and DQN algorithms thanks to their good performance. The proposed methodology was discussed in Section 3. And the performance of this last to classify the dermoscopic images was evaluated using the following parameter: accuracy.

We trained our proposed model with 80% of the training set by testing different optimizers such as SGD, RMSprop, Adam optimizer with a learning rate of 0.0001, and other hyper-parameters. After multiple tunings, we achieved the best result with 100 epochs and obtained an accuracy value of 80%. In light of this, the combination of deep learning (CNN) and reinforcement learning (DQN) is considered a more powerful and robust tool for classifying skin cancer. The idea is to take a decision based on many results obtained by training and retraining the CNN model.

Table 2. summarizes the accuracy obtained for training our proposed model.

Algorithm	Accuracy [%]	Optimizer	Learning rate
	69.57	Adam	1e-3
CNN+DQN	50.02	RMSProp	1e-5
	80	**Adam**	**1e-4**

We compare the performance of our method (CNN-DQN) and other methods while classifying skin cancer, as shown in Table 3.

Table 3. Comparison with the existing work.

Reference	Method	Accuracy [%]
[35]	DNN	76
[36]	CNN	79.45
[37]	EfficientNetB3	78
Proposed Model		**80**

Our proposed model (CNN-DQN) performs better and outperforms other methods in terms of accuracy as seen in table 3, this explains the importance and the benefit of using the combination of deep learning and reinforcement learning for classification tasks.

5. DISCUSSION AND CONCLUSION

Skin cancer is a serious type of cancer, where increasing and affects many people every day. This cancer can be treated if it is detected in its early stages, but multiclass skin cancer diagnosis and classification is a tough undertaking. In addition, current clinical techniques used are few. For this reason, recently the IA algorithms were developed to support doctors to supplement clinical practices.

In this study, we proposed a new model as a solid and technical solution for the detection and classification of skin cancer combines with deep learning and reinforcement learning. This combination is important in making machines more intelligent in decision-making and obtaining high-performance accuracy in medical imaging and also it provides several advantages including optimal balancing between time efficiency and accuracy, dropping computational costs, and surging computing power. In our model, after preprocessing step, we passed with segmentation step to extract the affected area. Then, we used the deep convolutional neural network (CNN) for the classification part. And about the Reinforcement Learning part, we used the Deep Q_Learning algorithm to train and retrain our model until we find the best result. After extensive experiments, we obtained good results in comparison to some approaches presented in related work. we were able to achieve better classification accuracy by 80%, these results show the effectiveness of our approach.

We conclude to our model is among the best solution to make the decision in the healthcare domain especially medical image applications: in the case of skin cancer. Additionally, there is still a possibility for improvement if we supply additional data using specific and clean datasets and exploit the potential of deep reinforcement learning algorithms for the classification task.

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