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Embedded artificial intelligence system using deep learning and raspberrypi for the detection and classification of melanoma

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ABSTRACT

Melanoma is a kind of skin cancer that originates in melanocytes responsible for producing melanin, it can be a severe and potentially deadly form of cancer because it can metastasize to other regions of the body if not detected and treated early. To facilitate this process, Recently, various computer-assisted low-cost, reliable, and accurate diagnostic systems have been proposed based on artificial intelligence (AI) algorithms, particularly deep learning techniques. This work proposed an innovative and intelligent system that combines the internet of things (IoT) with a Raspberry Pi connected to a camera and a deep learning model based on the deep convolutional neural network (CNN) algorithm for real-time detection and classification of melanoma cancer lesions. The key stages of our model before serializing to the Raspberry Pi: Firstly, the preprocessing part contains data cleaning, data transformation (normalization), and data augmentation to reduce overfitting when training. Then, the deep CNN algorithm is used to extract the features part. Finally, the classification part with applied Sigmoid Activation Function. The experimental results indicate the efficiency of our proposed classification system as we achieved an accuracy rate of 92%, a precision of 91%, a sensitivity of 91%, and an area under the curve- receiver operating characteristics (AUC-ROC) of 0.9133.

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1. INTRODUCTION

Currently, cancer remains a significant global health challenge [1], [2], especially skin cancer [3], which is considered a leading cause of death in many cases if not detected early and diagnosed correctly. To ensure the success of the diagnosis process, oncologists in general must possess a comprehensive knowledge of the skin's primary layers, including the epidermis, dermis, and subcutaneous fat [4]. When abnormal growth occurs and irregular in the uppermost skin layer, it can give rise to mutations that form tumors, which may be either benign or malignant [5]. Melanoma is considered among the most harmful and deadly kinds of skin cancer that often looks like moles. It's a dangerous, and deadly variety it grows rapidly and can influence and spread in all areas of the human body [6]. Diagnosing it in its early stages is vitally important, as it can contribute to minimizing the risk factor in patients, improving the prognosis of malignant melanoma, and treating it more easily [7], [8].

Dermoscopy is widely recognized as a common technique for the detection of skin lesions [9]. Nevertheless, the automatic detection of these tumors from dermoscopy images remains a major challenge for public health [10] due to the substantial similarities between melanoma and non-melanoma lesions. Consequently, there is a great demand for the scientific research community's development of new and innovative technologies to automatically analyze dermatoscopy images and assist oncologists [11], [12]. It is considered the most effective approach for early detection and involves promoting and facilitating more efficient skin monitoring systems through the utilization of advanced internet of things (IoT) techniques [13] and artificial intelligence algorithms [14] to develop automated systems to aid doctors for early and real-time detection.

Computer vision is a field of artificial intelligence that focuses on enabling computers to interpret and understand visual information. In this area, the detection and classification of objects are crucial tasks, serving as fundamental building blocks for a wide range of applications. Due to the rise in the capabilities of computing facilities, deep learning [15] is revolutionizing computer vision and contains a set of algorithms based on the human brain's structure such as the neural networks. Deep learning techniques have several advantages for this have emerged as a powerful tool in image segmentation and classification tasks principally in the medical domain of the early diagnosis of melanoma [16]–[18]. We cite, for example the convolutional neural networks (CNN) [19]–[21], are inspired by the human visual cortex used especially in image identification and classification.

This research primarily concentrates on the automated detection of melanoma cancer by combining advanced technologies: The IoT and deep learning. To achieve this objective, we have proposed an intelligent and embedded system with a Raspberry Pi designed for the real-time identification and classification of skin lesions captured using an embedded Pi camera and processed by a deep convolutional neural network model as containing an important number and varying types of layers including convolutional layers, pooling layers, and dense layers were meticulously trained using a dataset collected by the international skin imaging collaboration (ISIC) archive, which comprises two distinct classes: benign and malignant. The model is implemented in python using keras and tensorflow frameworks and was created firstly on a computer and after serialized to Raspberry Pi for real-time execution. The main steps of our proposed deep learning model before serializing to the Raspberry Pi are: 1) Passing the input dermoscopy images to the preprocessing step: data cleaning, data transformation (Normalization), and data augmentation to reduce overfitting when training; 2) Extract the features by applying the deep CNN algorithm; and 3) The classification part with the use of a Sigmoid Activation Function. Our experiment results show an accuracy rate of 92%, a precision of 91%, a sensitivity of 91%, and an area under the curve- receiver operating characteristics (AUC-ROC) of 0.9133. We hope our proposed system will help to diagnose, detect, and classify this melanoma cancer more efficiently way than other methods that have already been used. The major contributions of this study include: 1) A novel automated system is suggested for the classification of skin cancer in real-time, utilizing a combination of an Internet of Things device (Raspberry Pi) attached to a camera and an artificial intelligence model precise and optimized (deep CNN); 2) We improved the model efficiently with an increase in the dermoscopy images using augmentation techniques; 3) The architecture provides high accuracy (92%) with the best performance metrics obtained using a deep algorithm containing many layers with different parameters and a Sigmoid function for classification.

The rest of the article is organized as follows: In section 2 We presented the proposed method with a brief overview of the dataset, hardware, and software system used in this paper. Section 3 contains the experiment results and evaluation with a little discussion. Finally, section 4 describes the conclusion, followed by the references.

2. METHOD

2.1. Dataset

To implement our CNN model, we need the data for training. In this research, a skin cancer dataset [22] consisting of a balanced number of dermoscopic images of benign skin cancer moles and malignant ones was compiled from the ISIC archive. The dataset is segmented into 2,637 images in the training set and 660 images in the test. After collecting the dataset, we preprocessed all images by sizes of 128×128 pixels to obtain the same size as all the images. The dataset details are illustrated in Table 1.

Table 1. Dataset description

Class	Benign/malignant
Number of images class (benign)	1,800
Number of images class (malignant)	1,497
Total number of images	3.297
Dimension after preprocessing	128×128 pixels

2.2. Hardware system

The hardware used for this research is the Raspberry Pi, a miniature personal computer, approximately the size of a credit card, introduced first time in the year 2012 [23], with an SD Card as a hard disk to stock the features of our model. The camera module is connected to the camera port of the Raspberry Pi for capturing an image of the lesion and a power cable for the power supply, as well as, a keyboard, HDMI display, and LCD display to view the result of our model.

2.3. Software design

The software in this research consists firstly of preparing the operating system we have used Raspbian which is optimized for Raspberry Pi hardware and is based on debian linux. secondly, to build a detection skin cancer system using a Raspberry Pi, supporting software is needed with jupyter notebook to write the scripts in python, one of the commonly languages used for deep learning tasks with open-source frameworks: tensorflow. we have used the open-source computer vision library OpenCV which includes a large selection of algorithms that can help us to apply our model. Other libraries are used like scikit-learn.

About the skin cancer model detection and classification system that has been trained on a laptop and serialized after to the Raspberry Pi, we have applied deep learning [24] is a part of the family of artificial intelligence [25] uses a multilayer approach; these layers are connected to extract features from the source data [26]. Every artificial neural network has layers, the higher the number of this layers, the deeper and more powerful the network. Recently, deep learning has been used frequently in various areas of computer vision including image classification, voice recognition, object detection, semantic segmentation [27]–[29], and other tasks [30] and achieved the best results in detection and classification tasks, particularly for the classification of medical images. For these reasons, we used it in this study specifically convolutional neural networks, which are a kind of neural network applied in deep learning mostly to analyze image or visual data [31]. The CNN was first proposed by LeCun *et al.* [32]. The CNN architecture has multiple layers [33], (see details in section 2.4 about our deep CNN proposed).

2.4. Proposed methodology

The principal goal of this study is the production of an automatic system-friendly, lightweight, and simplified setup with low hardware resources for reduced cost and energy and facilitated connection, that will be applied in all aspects of healthcare specifically for the detection and classification of skin diseases. The main idea of our work is to implement the basic embedded system to aid doctors in melanoma cancer detection and make better medical decisions in real time. This system proposed applied an innovative combination: artificial intelligence specifically the deep learning algorithm and the IoT devices. This combination is a state-of-the-art and attractive solution for building a melanoma skin cancer classification system. The novelty of this research is evident in:

- Among the first research that as far as i know used an approach that combined artificial intelligence (AI) and the IoT to implement a complete, intelligent, and automatic melanoma classification system.
- Developing an efficient deep learning model with multiple layers deployed on an IoT device Raspberry Pi for skin cancer classification into 'melanoma' and 'benign' classes.
- Since the ISIC archive is one of the most extensive open source databases accessible, this paper addresses evaluating the performance of dermoscopic images with our model CNN.

The process of our methodology goes through three main steps each step consists of several tasks: artificial intelligence part, Raspberry Pi part, and deployment of the model on Raspberry Pi. In this section, we will present the key elements of our AI model for detecting and classifying skin cancer using dermoscopy images. We have built a model using the CNN algorithm with various layers for extracting the maximum of features and tried a collection of activation functions in the classification layer to get the best accuracy. As illustrated in Figure 1, our proposed model contains a preprocessing step including resizing images, data cleaning, data transformation (normalization), and data augmentation to increase accuracy. Additionally, we employed the deep CNN algorithm to extract the features of the lesion. After that, three activation functions (softmax, sigmoid, switch) have been tried to classify the image into: benign and melanoma until we found the best result. In the end, we have trained our model with optimal hyper-parameters.

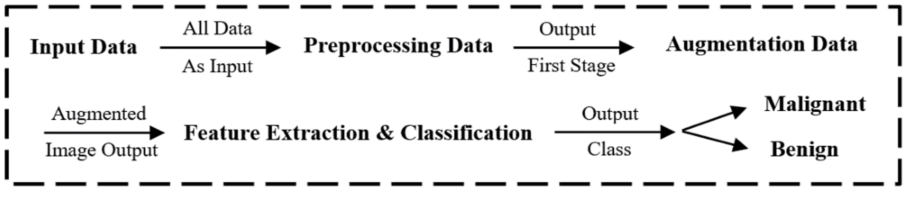


Figure 1. The architecture of the proposed method

The proposed methodology is illustrated in Figure 1 and has been described in detail below:

a. Input image: Our model is trained by using a dataset contains of 3,297 images separated into two classes.
b. Preprocessing: After loading and reading the data all images were resized to 128×128 pixels to make the computation and training faster. The major steps of the preprocessing are image improvement and noise removal. we have used a median filter to reduce the amount of intensity variation between one pixel and the other pixel. Islam *et al*. [34] then, we normalized the pixel values to a [0,1] range to reduce the space of variation of the values of a feature. Finally, we apply the Train_Test_Split technique to randomly split data. Where 80% are used for training, and 20% are used for testing.
c. Data augmentation: is an AI technique for generating new data from existing data this technique is used to train a model properly, increase the classifier's efficiency and the accuracy, also to addressing class imbalance problems, reducing overfitting problems, and improving convergence [35]. In the absence of a large number of datasets, and since we are working with a finite quantity of data to train our CNN model we have used the augmentation techniques to augment our data using the Keras library with the ImageDataGenerator function. We applied: Rotation_range=30, Width_shift_range=0.1, Height_shift_range=0.1, Horizontal_flip=True, Vertical_flip=True, Zoom_range=0.1.
d. Feature extraction & classification: After the preprocessing step, we used the deep CNN algorithm to extract features and classify the skin cancer. About the feature extraction task, the first part of the algorithm is used to split the image's points into several subsets such as area, points [36] our proposed system uses the deep CNN network to extract the features and classify them. This network is trained from scratch to learn the optimal weights of the network. The second part of our CNN model aims to perform classification among two types of skin lesions with applied different kinds of activation functions in the dense layer as classifiers including softmax, sigmoid, and swish. In the proposed method a CNN model from scratch was applied. The scratch model provides good performance and accuracy. We have used the multiple convolution layers to detect more complex features, each of the convolution layers when fed with an image will produce many activation maps, which emphasize important image features. After, the output of the initial layer is given to the next layer as input, where complex features are extracted. A batch normalization and a max-pooling layers were used to prevent initial random weight bias. We applied the filters with different parameters. Finally, we combined these features to make the classification. After that, there are four fully-connected layers used for classification by testing numerous activation functions: the softmax, sigmoid, and swish functions. The proposed deep CNN model illustrated in Figure 2.

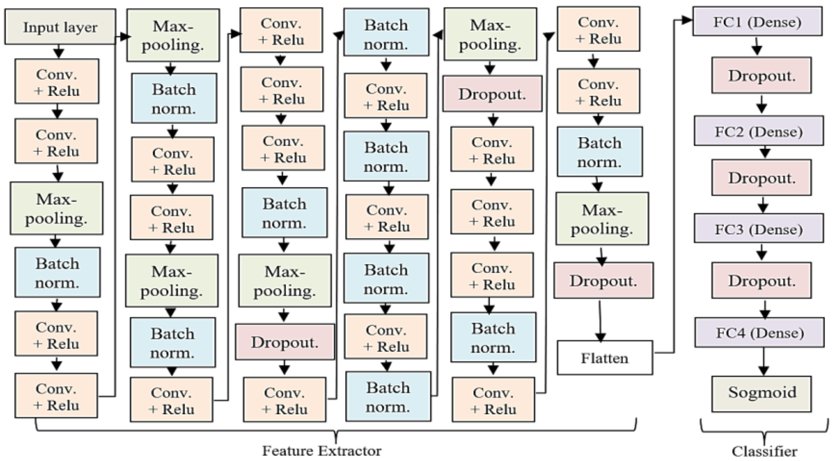


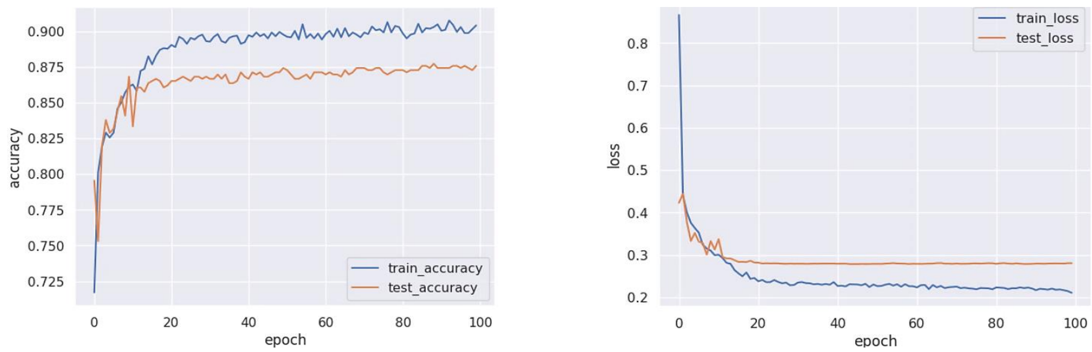
Figure 2. Proposed deep CNN model architecture

3. RESULTS AND DISCUSSION

3.1. Experiments and results

For measuring our architecture's performance was evaluated and validated using several metrics: Accuracy, Recall/ Sensitivity, Precision, F1 Score [37]. Also, the performance is assessed for this binary classification problem using the AUC and ROC-AUC metrics [38]. The receiver operating characteristic (ROC) curve is a graphical representation that plots the sensitivity against the specificity at various classification thresholds. The AUC is the measure of the performance of a binary classification model, often in the context of a ROC curve.

We trained our model with used the google colab platform graphics processing unit (GPU). The model was implemented on the TensorFlow framework with open-source Keras packages. For training, we used the technique Train_Test_Split to randomly split data. And, we compiled our model many times with several hyperparameters such as ADAM, RMSprop, and stochastic gradient descent, Nadam as optimizer with a learning rate of 0.001, 0.0001, 0.00001, the batch size was 32, 64, 128, and epohs of 50, 100, and 150 with "binary_crossentropy" as the loss function until we find a good result. Figure 3(a) illustrates the training and test accuracy of our model, while Figure 3(b) describes the training and test loss. Following the completion of training, we observed a slight overfitting pattern, which can be attributed to the characteristics of the dataset used. The following Table 2 shows the results obtained from the model proposed.



(a) (b)

Figure 3. The test resulf of the proposed method on: (a) accuracy, and (b) loss graph

Table 2. Results of model proposed

Algorithm	Optimizer	LR	F1 Score	Precision	Accuracy
DeepCNN	Adam	0.01	0.8944	0.8934	0.8958
	RMSProp	0.0001	0.8808	0.8802	0.8826
	SGD	0.00001	0.9076	0.9073	0.91
	Adam	0.00001	0.9129	0.9125	0.92

After multiple and several times of tunings, we achieved the accuracy of 92% with the following hyperparameters: Optimizer: Adam, Learning rate: 0.00001, Dropout: 0.5, Batch size: 32, Epochs: 100. The idea is to decide lesion cancer by using the embedded system, for this, the classification model obtained was serialized and copied to the Raspberry Pi. Then, these results show the effective power of utilizing a deep learning model, especially deep CNN Integrate in IOT systems. Figure 4 presents the confusion matrix of our model, the size of our confusion matrix 2×2. The accuracy of classification is 92% and the AUC value obtained is 0.9133 (shown in Figure 5). In comparison to models found in other research as illustrated in Table 3 (details available in section 3.2), our proposed method has the best accuracy metrics due to our great and efficient choice of the number of layers and convolutional filters and pooling layers to extract sufficient features, and also the delicate chooses the right activation function as a classifier to obtain in end highly-accurate skin lesion classifier.

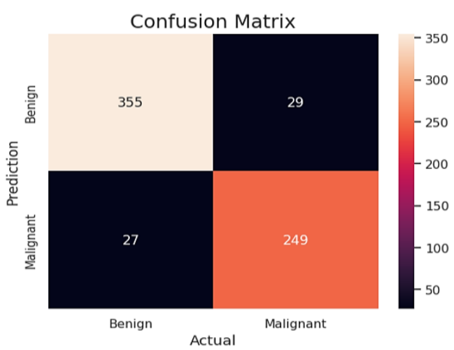


Figure 4. Confusion matrix

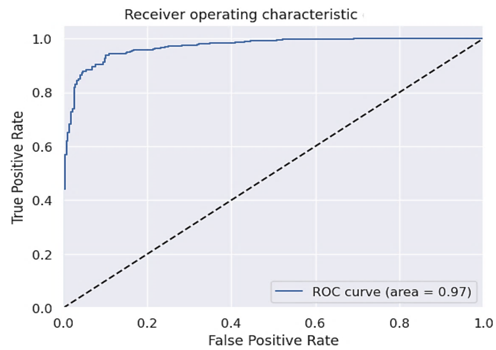


Figure 5. The ROC curve of our model

Table 3. Comparison with the existing work

Reference	Model	Accuracy (%)
[39]	CNN with 9 layers	80.52
[40]	Modified GoogleNet	81
[41]	CNN+SVM	89.52
[42]	CNN	87.82
[43]	MobilenetV2-LSTM	90.72
[44]	DenseNet-EfficientNet	85.80
Proposed	Deep CNN	92

3.2. Discussion

There is a several works published in the context of melanoma diagnosis using different techniques among them: In this article, the advanced technologies based on the IoT and deep learning are proposed. This deep learning architecture proposed is based on the deep CNN algorithm implemented from scratch with an important number and varying types of layers (see details in section 2.4). After the training step, this model is serialized to the Raspberry Pi to facilitate diagnosis of skin cancer in real-time. we achieved an accuracy of 92%. We compared the results that we obtained with those obtained by other authors using other techniques. Jianu *et al.* [39] proposed a system for classification melanoma using cnn algorithm with great architecture containing nine layers. Two steps are important: Preprocessing and CNN Architecture. This model gives a robust result of 80.52%. Kassem *et al.* [40] for classification skin lesions the authors presented a GoogleNet model with some modification at the level of filters and layers (add and replace layer by another layer). Their proposed model gives 81% accuracy compared with the original GoogleNet which achieved 63% accuracy. Haghighi *et al.* [41] a system for melanoma recognition is proposed based on fusion with CNN and support vector machine (SVM). The CNN architecture is used to extract features and a SVM is used as a classifier. In this study, the author first applied data augmentation. Secondly, extract features with CNN architecture.

After that, a fully connected layer, a dropout layer, and a rectified linear unit (ReLU) layer are added. Finally, the classification stage used the SVM classifier. The authors obtained an accuracy of 89.52%. Guarnizo *et al.* [42] proposed a model for diagnosis skin cancer using the deep learning algorithm CNN. This CNN model contains a lot of hidden layers. In this work, the authors applied the rectified linear activation function (ReLU) to every convolutional layer. And about the classification part, they used the activation function sigmoid, they found an average accuracy of 87.82 %. Srinivasu *et al.* [43] the authors proposed an efficient model that can work on lightweight computational devices based on Mobile Net V2 and long short-term memory (LSTM) to classify skin disease. They obtained an accuracy of more than 85%. Huang *et al.* [44] the authors presented a deep learning method for the classification of skin cancer based with Dense Net and Efficient Net. They obtained an accuracy of 85.8%.

4. CONCLUSION

Skin diseases have become increasingly prevalent in many regions. This paper aims to create an intelligent system based on the combination of the Internet of Things and deep learning algorithms for the real-time diagnosis of melanoma lesions where it was applied the data augmentation method for increasing the number of images, reducing the overfitting problem, and improving convergence. We have found the best result with an accuracy of 92% and can refine the system's performance by expanding the dataset size and exploring advanced preprocessing techniques. Through comparing this study with previous empirical studies, (see section discussion), our findings suggest that our model represents one of the most effective solutions for decision-making quickly in the healthcare sector, particularly in medical image applications, such as the diagnosis of skin cancer. Furthermore, there is room for further enhancement by incorporating more specific and meticulously curated datasets and developing new layers in deep learning algorithms.

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