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Deep Learning Skin Disease Diagnosis and Prognosis Based on Artificial Intelligence

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Abstract: One of the most common disorder spread between people is dermatology, which have heavily touched to peoples live, these diseases can result from various factors (bacteria, infection or radiation), Identifying these diseases in the initial phase ensure improvement in healing likelihood. In this research, an artificial intelligence system represented by deep learning is used, the model built based on an architecture of Convolutional Neural Network (CNN) along with Visual Geometry Group (VGG16) network to detect three kinds of diseases, identified by "nevus, melanoma and seborrheic keratosis". A total of 1,403 dataset sourced from Kaggle were used for training and testing. An accurate result of 99.31% were gained, in order to estimate the performance of the methodology suggested. These findings revealed the robustness of CNN-based system to classify the dataset in high accuracy. The presented model main objective is to distinguish between unusual kind of skin disease categories, employing several performance valuations, involving (accuracy, precision, f1-score, recall, and support, and highlighting on most related methodologies in this field.

Keywords: Artificial Intelligence, CNN, Deep Learning, Melanoma, Skin Diseases, VGG16.

1. Introduction

Dermatology can be defined as a skin condition that may spread among people for all ranges of ages, and it has the ability to transfer from person to person. Since the skin one of most sensitive organs that cover all around the human body with weight of (3.6 kg) and area of (2 square meters). It very important to detect and identify any disorder occur in the skin of the body, considering the critical purpose that skin plays in keeping the healthy life of humans. Some types of skin disease can be an outcome from many factors like "environmental represented by highly exposing to sun-light" the most popular of these diseases are (nevi and melanoma) [1].

Across (91,270) cases are diagnosis with melanoma in 2018, with the increase of skin cancer Cases occurring each year for various type of cancer like (prostate, breast, colon, lung and gland) [2]. One of the prime problems in dermatology image classification is the constantly changing in the effected skin area, as there are many identical factors for different types of disease, thus can be led to misdiagnosis and treatment made by the human eye. The change in skin type represented by human age, beside the colour of the skin can add more complicacy for machine learning to make the right diagnosis. So, extraction the proper feature is highly essential process in computer-aid systems to make the right predication. Therefore, in order to have a successful system give an accurate diagnosis with less time consuming and can be operates remotely, a robustness image processing along with the tasks of machine learning which can lead to acceleration and improvement in diagnosis [3]. The advance in deep learning in computer vision areas, speech and image recognition etc., through the last decades have accomplish a wide success. Since 2013 deep learning have been glorify as one of the most important technologies due to the vital role its play in data analysis, which considered a simulating method to the neural network in human. These development technologies in machine learning including “deep learning” have a wide influence in medical image classification as artificial intelligence anticipation gradually raising resulting in continuously progress in medical application [4].

Deep learning architectures have been investigated in several literature researches, one of the main topics CNN image classifications in medical fields. As CNN considered a kind of Artificial Neural Network (ANN), that make use of “multiple perceptron” for input image analysis which make use of learnable weights and bases to several parts of images. CNN basically consisting of group of layers (convolutional, pooling and flatten) with receptive fields and a trainable weight that work on reducing the size of the input image. Large number of data-set are required for training [5-6], it depend on the impact of using “local spatial coherence” for the input images, this step permits to share certain characteristics as less weight are used. The size of the memory and network complicity are highly affected by this process, resulting in an improving in the system performance.

Various algorithm and methodologies are utilized in dermatology diagnosis such as; Asymmetry Border irregularity Colour patterns, and Diameter (ABCD) rule [7], melanoma detection method using a GPU equipped server [8], a joint architecture consist of CNN Recurrent Neural Network (RNN) for skin melanoma segmentation [9], also a CNN along with “Error-Correcting Output Codes (ECOC) and Support Vector Machine (SVM)” are utilized to diagnosis multi-class skin diseases [10], a fine-tuned pre-trained, VGG16-CNN with logistic regression and a Deep Neural Network (DNN) models are proposed for vision-based skin cancer classification [11]. While another study investigates techniques for skin cancer diagnosis using two types of features. Also explored the use of clinical features for skin cancer detection these methods are (ABCD, Menzies, seven-point detection, Gabor filters, visual textures (GRC), oriental histography, fractal dimension, random fields of Markov and local binary patterns) [12].

This paper proposed a CNN for skin disease diagnosis using VGG-16 model. The data were tested on the network are taken from publicly accessible dermatology website “Kaggle”, consisting of three types of diseases, identified as nevus, melanoma and seborrheic keratosis. The final results are compared to other researches implementations.

The article is organized as follow. The related work is detailed in topic 2. The methodology of the suggested work is demonstrated in topic 3. In Section 4, we describe the results obtained. Based on the experimental results. Eventually, topic 5, include the final finding and future work.

2. RELATED WORK

Numerous research papers aim to identify the challenges of skin disease detection, with many showcasing enhancements to existing models. This paper endeavors to analyze these papers to gain a nuanced understanding of the solutions employed and explore the potential for developing a new model. The table1, below categorizes the latest research based on methodology, datasets utilized, type of disease, accuracies and some other details.

Table 1: Review for most related works

Year/Ref.	Diagnosis	Method	Data	Accuracy	others
2015 [11]	Benign/Melanoma	CNN-VGG16	International Skin Imaging Collaboration (ISIC)	78%	Three separate models were used
2016 [8]	Benign/Melanoma	CNN	170 Non-demoscopic image	81%	Clinical images by digital camera were used
2017 [9]	Melanoma	CNN/RNN	ISBI 2016	98%	900 image trained and 375 image were tested
2018 [10]	Acne/Eczema/ Benign/Malignant	DCNN/SVM	9144 image	86.21%	An hybrid approach of DCNN-ECOC are employed
2018 [13]	Melanoma/ Common and typical Nevus	DCNN with AlexNet	PH2	98.61%	Model were evaluated using 4 quantitive measure
2019 [14]	(SK/AK/ROS/LE/BCC/SCC)*	CNN	2656 image	92.9%	Xiangya-Derm clinical images for 543 different skin diseases were used.
2019 [15]	Melanoma/Eczema/Leprosy	(GLCM/IQ)**	45 image	87%	The images were pre-processed using "Global Thresholding" technique
2019 [16]	Benign/Melanoma	ABCD-(GLRLM/LBP/HOG)***	PH2	97.79%	"Particle Swarm Optimization (PSO)" models are used
2019 [17]	Acne/Lichen/Sjs-ten/Planus	Random forest, naive bayes, logistic regression, kernel SVM and CNN	N/A	99.05%	The skin image dataset is originally preprocessed (80 – instruction/20-testing)
2019 [18]	Eczema/Melanoma/Psoriasis Normal	CNN-AlexNet/SVM	80 image	100%	20 image for every disease
2020 [19]	Melanoma/Non-Melanoma	CNN-VGG19	ISIC 2016/ ISIC 2019/ PH2	97.5%	classification performance improved by "Kernel Principal Component Analysis (KPCA)"
2020 [20]	Benign/Melanoma	SVM/ABCD/GLCM-HOG	ISIC 2017	97.8%	328 image for benign 672 for melanoma
2020 [21]	(Akiec, Bcc, Bkl, Df, Mel, Nv, Vasc)****	CNN/One Versus All (OVA)	HAM10000	92.90%	ISIC data consisting of 10015 image
2020 [22]	Akiec, Bcc, Bkl, Df, Mel, Nv, Vasc	CNN/VGG11/ ResNet50/DenseNet21	HAM10000	90%	CNN and by using Keras Sequential API
2020 [23]	Akiec, Bcc, Bkl, Df, Mel, Nv, Vasc	DCNN/VGG19/VGG16	HAM10000	99%	Data after augmentation consist of 7182 image
2021 [24]	Benign/Malignant	CNN/VGG19/ReseNet/Inceptionv3	ISIC 2019-2020	86.90%	Data consist of 24000 skin cancer images
2021 [25]	Nv, Bcc and Mel	LSTM/MobileNetv2	HAM10000	85.34%	The performance evaluation are presented. (Sensitivity, Specificity, Accuracy, Jaccard Similarity Index (JSI), and Mathew Coefficient Correlation (MCC))
2021 [26]	Melanoma	CNN	https://dermnetnz.org/.	88.83%	Data consist 936 superficial spreading Mel, 756 nodular Mel and 783 lentigo malignant Mel.
2021 [27]	Melanoma	Efficient-B6 VGG16/VGG19	ISIC 2020	91.7%	Dataset were divided as training, validation and test sub dataset in proportion of 7:2:1.
2022 [28]	Melanoma/Non-Melanoma/ Nevus Seborrheic Keratosis	CNN	Kaggle 2750 image	82.90%	Test accuracy in Jupyter notebook 77.25% While 96.19% in glob Google drive
2022 [29]	Diverse data of skin disease	CNN	75665 image	57.9%	Dermatology image from different atlas Websits
2022 [30]	Acne/athlete foot/chickenpox/ Eczema/skin cancer/Vitiligo	DCNN	3000 images	81.75%	Data were collected from online datasets and internet
2023 [31]	Eight most common skin disorders	ResNet152/VGG19/ VGG16…	25000 Kaggle	95.78%	11 different network algorithms were used
2023 [32]	Melanoma/Benign/Malignant	CNN	10000 image	91%	9600 image used for training and 1000 for evaluation
2024 [33]	Various types of eczema /acne to diverse cancerous conditions	CNN	6584 image	86.34%	Data set covered various factors, like sex age, disease site (head, hand, feet,, nail), skin color (white, yellow, brown, black), lesions periods (early, middle, or late).
2024 [34]	Diverse collection of dermoscopic images	tuned EfficientNetV2L	ISIC 2018	98,04%	10000 images labeled with a specific category of skin disease

*: Rosacea (ROS), Seborrheic Keratosis (SK), Actinic Keratosis (AK),), Squamous Cell Carcinoma (SCC) Lupus Erythematosus (LE) and Basal Cell Carcinoma (BCC).

**: Grey Level Co-occurrence Matrix (GLCM), Image Quality Assessment (IQA).

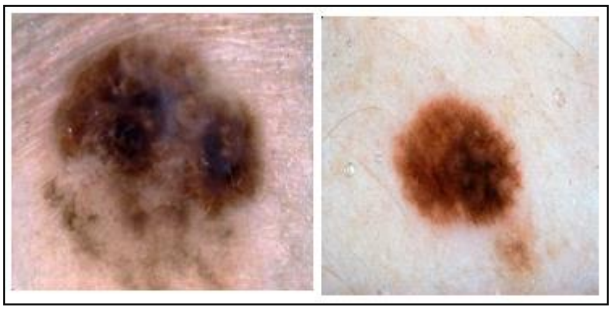
***: Grey Level Run Length Matrix (GLRLM), Histogram of Oriented Gradients (HOG) and Local Binary Patterns (LBP)

****: benign keratosis (Bkl), Actinic keratoses and intraepithelial carcinoma (Akiec), Dermatofibroma (Df), Melanoma (Mel), Vascular lesions (Vasc) and Melanocytic type (Nv).

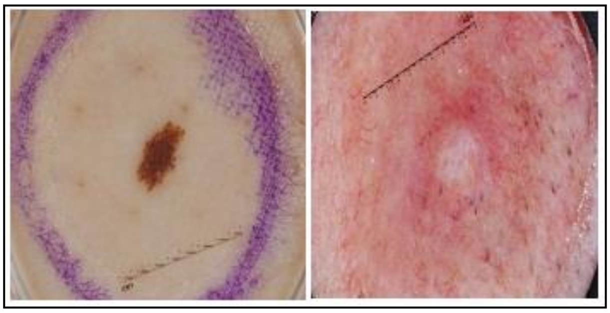
3. METHODOLOGY

A. *Data collection*

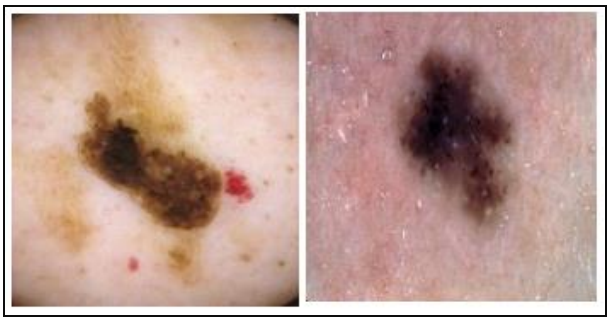
The data consist of 1,403 images for three disease nevus, melanoma and seborrheic keratosis as evidence in Fig1. The data-set can be used for various algorithms, models, and systems. These images were taken from Kaggle [35] data-sets for the current proposed work, which concentrate on various skin disease types. We have divided the data-set into (training, validation and testing) and made plotting for dataset as shown in Fig. 2 shows the sample representation of the dataset.



(a)

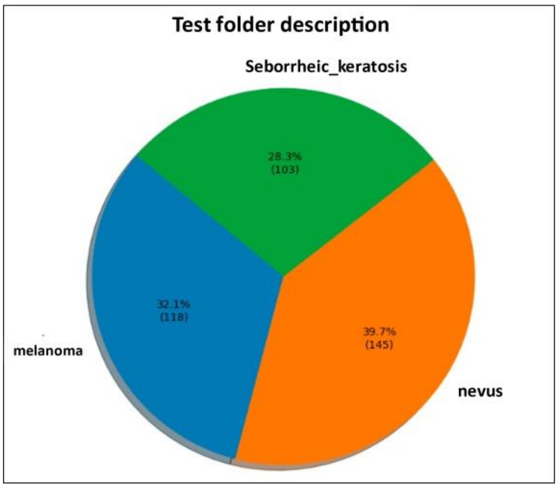


(b)

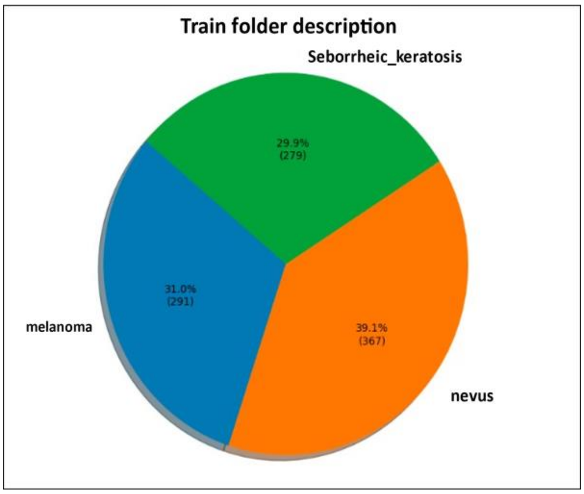


(c)

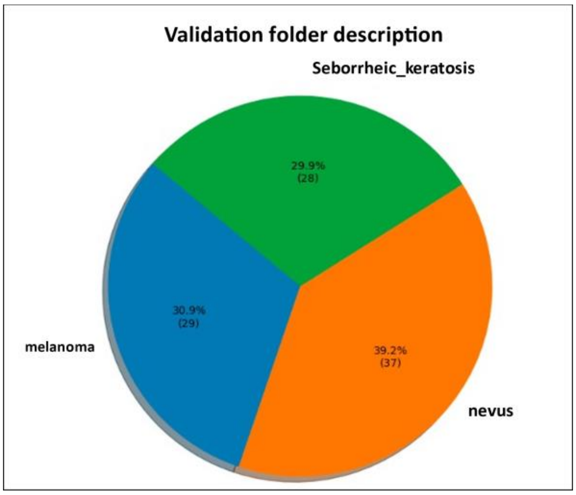
Fig. 1 Examples of some skin lesions cases including (a) Melanoma (b) Nevus (c) Keratosis [35].



(a)



(b)



(c)

Fig. 2: Samples representation of the dataset (a)test folder description (b)train folder description (c)validation folder description.

B. *CNN Architecture*

Initially, the Convolutional neural network is utilized where the input images are cross through a series of layers: convolutional, pooling, flattening and fully connected layers, and then the output of CNN is generated which classify images. This procedure includes loading images inside the column from the (image folder's) with the path of the desired image. The initial dimensions of the images are (224 X 224 x 3). While the used labels are consisted of 3 different categorize of skin disease types ranging from (0 to 2), thus the output of CNN is generated which capable of classifying images using special model image augmentation technique. A pre-trained model VGG-16 are employed to identify the images and examine the accuracy for "training and validation" data. Fig3. Shows the architecture flow chart for the proposed CNN.

Fig. 3 A flow chart for the suggested CNN.

C. *VGG16*

Researchers of VGG at "the University of Oxford" have established the current network. It characterizes by its structure which is similar to pyramid. It contains a set of layers constructed of (convolutional, pooling and bundling) layers. These bounding layers allow to create a form of a narrower layer. The advantage involves in providing quite well infrastructure to benchmark each particular mission [36-38]. Although of the general use of the pre-trained VGG networks, the need to implement a huge number of computational which it extremely slows in practical work [39]. A transfer learning for VGG16 model is utilized; transfer learning machine learning technique task represent by training a numerous size of data-sets employing all the important factors which are available in neural networks. This are accomplished by pre-training the last four layer of VGG16 neural network and adding three denes layer and using a flatten layer with a SoftMax as an activation function, Since the output layer conveys three different types.

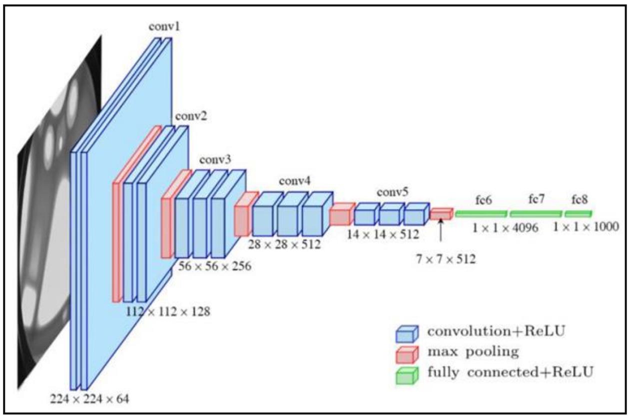


Fig. 4 The architecture of VGG16 [40].

The scheme of the VGG16 employed includes a couple of two convolutional layers with 64 filter and 128 filter with a max-pooling layer repetitive for two times, the previous layers are connected to three convolutional layers followed by three layers of max-pooling layer, in the end of the network, three densely fully connected layers are connected. The kernel size for all convolutional layers were used is (3 × 3) and the stride rate is one, while the kernel size of (2 × 2) are used for all the rest of max pooling layers along with a stride rate equal to two. Lastly ReLu activation function is utilized in the hidden layers.

Multiple parameters are utilized to be configured in the suggested VGG16 model represented by:

- Train Batch size =64 (No. of images that are processed in each repetition)**.**
- Validation frequencies =8 (No. of repetition between "evaluations of the validation metrics").
- Initial learning rate =0.0001
- epochs number (80)
- Adam optimizer.

The Architecture of our presented model are displayed in Fig.5

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 vgg16 (Functional)          (None, 7, 7, 512)         14714688

 flatten (Flatten)           (None, 25088)             0

 dense (Dense)               (None, 256)               6422784

 dropout (Dropout)           (None, 256)               0

 dense_1 (Dense)             (None, 128)               32896

 dropout_1 (Dropout)         (None, 128)               0

 dense_2 (Dense)             (None, 3)                 387

=================================================================
Total params: 21170755 (80.76 MB)
Trainable params: 13535491 (51.63 MB)
Non-trainable params: 7635264 (29.13 MB)
_________________________________________________________________
```

Fig. 5 Architecture of the proposed Model.

4. RESULT

We use 1,403 images from kaggle datasets in order to evaluate our proposed model, the overall accuracy achieved was 99.31% for 80 epochs. The final results of the system are displayed below.

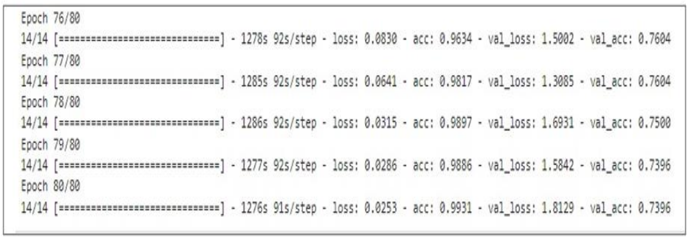

```
Epoch 76/80
14/14 [==============================] - 1278s 92s/step - loss: 0.0830 - acc: 0.9634 - val_loss: 1.5002 - val_acc: 0.7604
Epoch 77/80
14/14 [==============================] - 1285s 92s/step - loss: 0.0641 - acc: 0.9817 - val_loss: 1.3085 - val_acc: 0.7604
Epoch 78/80
14/14 [==============================] - 1286s 92s/step - loss: 0.0315 - acc: 0.9897 - val_loss: 1.6931 - val_acc: 0.7500
Epoch 79/80
14/14 [==============================] - 1277s 92s/step - loss: 0.0286 - acc: 0.9886 - val_loss: 1.5842 - val_acc: 0.7396
Epoch 80/80
14/14 [==============================] - 1276s 91s/step - loss: 0.0253 - acc: 0.9931 - val_loss: 1.8129 - val_acc: 0.7396
```

Fig. 6 Accuracy, loss, validation accuracy (VA) and validation loss (VL) for VGG16.

While Fig. 7 demonstrate the training accuracy and validation accuracy (VA) in VGG16 model, and the training loss and validation loss (VL) in VGG16 model is illustrated in Fig.8

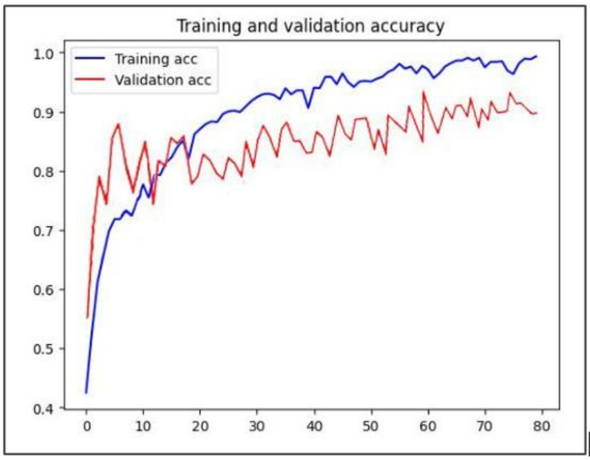


Fig. 7 The training accuracy and VA in VGG16

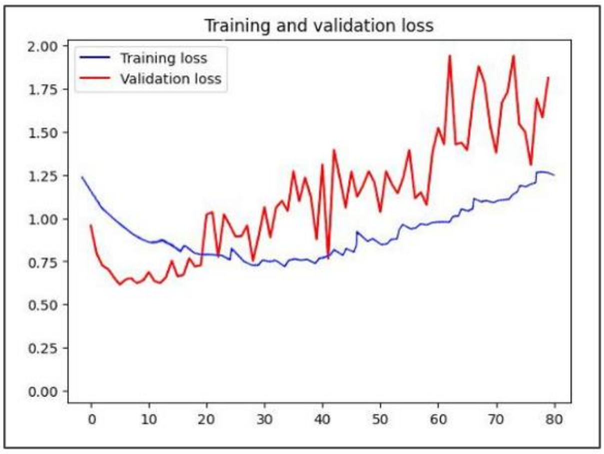


Fig. 8 The training loss and VL in VGG16 model.

A convolution matrix is a tabulated form that revels the calculation and how much it is predicting correct. There are two measured true and predicted Fig.9 below shows the confusion matrix of VGG16, for the 3 types of diseases (melanoma, nevus and keratosis) of the proposed model.

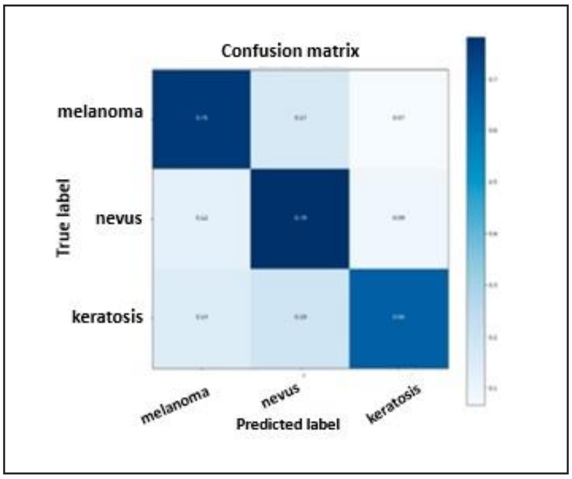
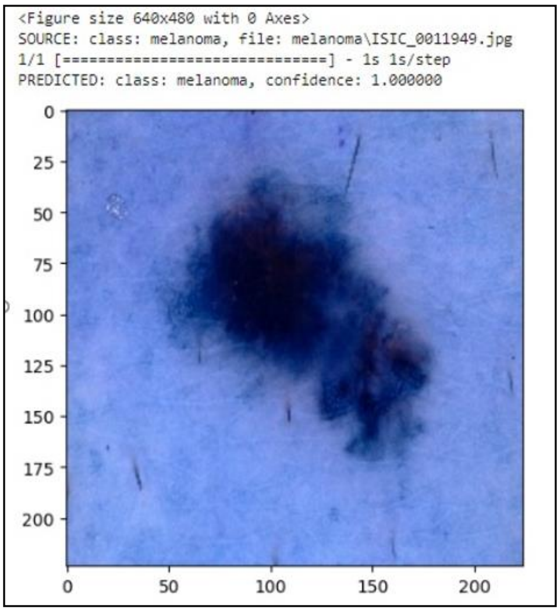
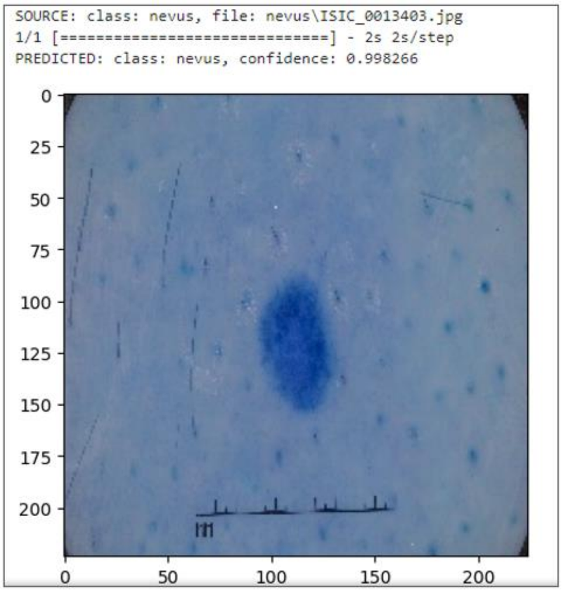


Fig.9 Confusion matrix for 3 classes of disease.

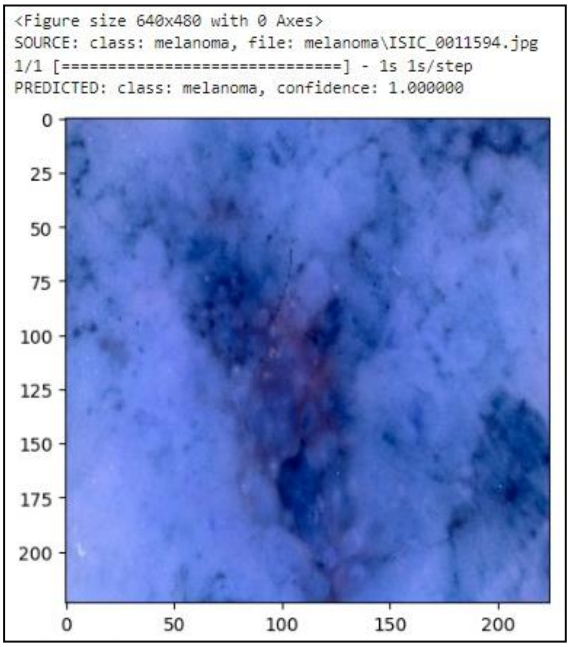
The Final predication for some of the dataset used are displayed in figure below, these finding are the final output of the proposed system shown in Fig. 10. Which it reveals the capability of the system to identifying three classes of disease which are melanoma, nevus, and keratosis.



(a)



(b)



(c)

Fig. 10 The results of some datasets for 3 classes (a) melanoma, (b) nevus, (c) melanoma.

There are other methods to evaluate the proposed beside the resulting accuracy represented by precision, recall, f1 score and support which are illustrated in the Fig.11 below.

	precision	recall	f1-score	support
melanoma	0.73	0.76	0.75	118
nevus	0.74	0.79	0.76	146
seborrheic_keratosis	0.77	0.66	0.71	104
accuracy			0.74	368
macro avg	0.75	0.74	0.74	368
weighted avg	0.75	0.74	0.74	368

Fig. 11 The precision, recall, F1 score and support for VGG16after 80 epochs.

5. CONCLUSIONS

This paper discusses deep learning method to diagnose three kinds of skin disorder including (melanoma, nevus and keratosis), utilizing CNN based method with employing a pre-trained VGG16 model. For this model we used 80 epochs to train and evaluate the dataset taken from kaggle website. The results for evaluation produced by the system represented by figures of loss and accuracy, confusion matrix, and the calculation of precision, support, F1 score and recall are made. The system was capable of detecting 99.31% accurately.

The study also promotes various problems for automatic visual identification of clinical dermatology images. It's clear that old fashion methods are not enough or effective. So, building and developing an automatic computer assisted system which capable of diagnoses various type of skin diseases problems are needed, the system consists of datasets taken from the real world and categorized it into 3 classes which, represent three types of diseases in order to facilitate the prediction of images that can be benefit to work in multiple areas. Where the model we provided can be efficient in detection in comparison with human eyes. Many factors can influence the efficiency of the model, like increasing the dataset in the CNN-VGG16 model would highly effect on the accuracy resulting into increasing, and minimizing the loss function.

The future plan is to use this model to facilities the process of detecting skin diseases in a real life, which can be alternative way for manually diagnosis that might be individual, required more time and additional human exertion are required. It can be very helpful for those who have receiving a little medical help.

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