JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

DETECTION OF NON-MELANOMA SKIN CANCER

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Abstract : — **Skin cancer is one of the deadliest types of cancer. If it is not diagnosed and treated early on, it is likely to spread to other areas of the body. It is primarily caused by abnormal skin cell development, which occurs often when the body is exposed to sunlight. The Surveillance Furthermore, identifying skin malignant development in its early stages is an expensive and difficult process. It is graded according to where it grows and what type of cell it is. The classification of lesions necessitates a high level of precision and recall. The MNIST HAM-10000 dataset containing dermoscopy images will be included in this article. The aim is to propose a method that uses a Convolution Neural Network to diagnose skin cancer and classify it into various groups. Image recognition and a deep learning algorithm are used in the diagnosis process. The noise and picture resolution were removed from the dermoscopy shot of skin cancer that was taken. Using different image augmentation methods, the image count may also be improved. Finally, the Transfer Learning approach is used to improve the image recognition accuracy even further. The weighted average Precision of our CNN model was 0.88, the weighted average Recall was 0.74, and the weighted f1-score was 0.77. The accuracy of the transfer learning method using the ResNet model was 90.51 percent.**

I. INTRODUCTION

There were over a million cases of skin cancer worldwide [1]. One of the fastest-growing diseases on the planet is skin cancer. The susceptibility to ultraviolet radiation released by the Sun is the primary cause of skin cancer. Early diagnosis of skin cancer is critical with the scarce services available. In general, for skin cancer prevention strategy, accurate diagnosis and identification viability are crucial. And dermatologists face difficulty in detecting skin cancer in the early stages. Deep learning has been widely used in both supervised and unsupervised learning challenges in recent years. Convolution Neu- ral Networks (CNN) is one of these models that has outperformed all others in object detection and classification tasks. By mastering highly discriminative features when being practiced end-to-end in a controlled manner, CNNs remove the need for manually handcrafting features. Recently, Convolutional Neural Networks (CNNs) have been used to classify Lesions in skin cancer In the classification of skin cancers, some CNN models have outperformed qualified human specialists. Several approaches, such as transfer learning, are available. The performance of these simulations has increased even further thanks to the use of massive datasets. VGG-16 is a convolutional neural network that has been trained on over a million images. images from the ImageNet collection. The framework has 16 layers which can be configured in a variety of ways. Pictures are divided into 1000 different categories, such as console, mouse, pencil, and various animals. As a result, the machine has studied detailed component representations for a variety of objects a broad range of images The image information scale on the system is 224 by 224 pixels. The definition of the model In ImageNet, a dataset with over a million images, it achieves 92.7 percent top5 test precision. There are 14 million pictures in 1000 schools. In this paper, we have generated a CNN model that analyses the skin pigment lesions and categorizes them using a publicly available dataset and a variety of methods. techniques for deep learning By using CNN and transfer learning models, we were able to increase classification accuracy. The HAM10000 dataset, which is freely available, was used to validate our model.

II. LITERATURE SURVEY

An enhanced technique of skin cancer classification using deep convolutional neural network with transfer learning models. Skin cancer is one of the top three perilous types of cancer caused by damaged DNA that can cause death. This damaged DNA begins cells to grow uncontrollably and nowadays it is getting increased speedily. There exist some researches for the computerized analysis of malignancy in skin lesion images. However, analysis of these images is very challenging having some troublesome factors like light reflections from the skin surface, variations in color illumination, different shapes, and sizes of the lesions. As a result, evidential automatic recognition of skin cancer is valuable to build up the accuracy and proficiency of pathologists in the early stages. In this paper, we propose a deep convolutional neural network (DCNN) model based on deep learning approach for the accurate classification between benign and malignant skin lesions. In preprocessing we firstly, apply filter or kernel to remove noise and artifacts; secondly, normalize the input images and extract features that help for accurate classification; and finally, data augmentation increases the number of images that improves the accuracy of classification rate. To evaluate the performance of our proposed, DCNN model is compared with some transfer learning models such as AlexNet, ResNet, VGG-16, DenseNet, MobileNet, etc. The model is evaluated on the HAM10000 dataset and ultimately we obtained the highest 93.16% of training and 91.93% of testing accuracy respectively. The final outcomes of our proposed DCNN model define it as more reliable and robust when compared with existing transfer learning models.

Melanoma skin cancer detection using deep learning and classical machine learning techniques: A hybrid approach Melanoma is considered as one of the fatal cancer in the world, this form of skin cancer may spread to other parts of the body in case that it has not been diagnosed in an early stage. Thus, the medical field has known a great evolution with the use of automated diagnosis systems that can help doctors and even normal people to determine a certain kind of disease. In this matter, we introduce a hybrid method for melanoma skin cancer detection that can be used to examine any suspicious lesion. Our proposed system rely on the prediction of three different methods: A convolutional neural network and two classical machine learning classifiers trained with a set of features describing the borders, texture and the color of a skin lesion. These methods are then combined to improve their performances using majority voting. The experiments have shown that using the three methods together, gives the highest accuracy level. Melanoma the deadliest form of skin cancer, is considered as the less common form of skin cancers but it is the most fatal. As mentioned above, it can quickly spread to other parts of the body. Melanoma arises through malignant transformation of melanocytes which are derived from the neural crest neoplasia. Melanoma causes 55 500 cancer deaths annually which is 0.7% of all cancer deaths. The incidence and mortality rates of melanoma differ from one country to another due to the variation of ethnic and racial groups . Established risk factors for melanoma include ultraviolet radiation, life in low geographic latitudes, high alcohol consumption, consuming fatty foods, the presence of melanocytic or dysplastic naevi, a family or personal history of melanoma, phenotypic charac teristics including fair hair, eye, and skin colors . The incidence and mortality of melanoma are related to the development index (HDI), The increase in the HDI index increases access to health services and early detection of disease and treatment of the disease at an early stage, thereby reducing mortality. Yet , statistics shows that the 5-year relative survival rate for people who has been diagnosed with melanoma in an early stage is about 98%. However, about 20% to 50% of people having melanoma in advanced stage will be alive 5 years after diagnosis . Since, it is important that the melanoma is caught at an early stage. Self examination is so vital even if you have carefully protected your skin from ultraviolet radiations. Thus, people should examine their skins head to toe regularly, looking for any lesions that might be turned into melanoma.

III. Existing System

The existing system is human based system to be controlled and monitored by the human. This causes a drawback in the system it requires time for result of data analysed from the sample. Skin diseases are one of the most rapidly increasing and deadliest cancers in the world, which accounts for 75% of skin cancer deaths. Early diagnosis is of great importance for treating this disease as it can be cured easily at early stages. To improve the diagnosis of this disease, dermoscopy has been introduced to assist dermatologists in clinical examination since it is a non-invasive skin imaging technique that provides clinicians. The realtime monitoring of the disease is not done using this system. It only helps to diagnosis the disease at some predicted time by Medical advisories.

IV. Proposed System

The disadvantages of the existing system are overcome by this system. This system enables the use of Machine learning for real time monitoring and data history of patients have maintained. Deep learning methods such as deep convolutional neural networks (CNNs) have established an overwhelming presence in image recognition tasks in the past few years. The main advantage of CNN is that it is endowed with an impressive visual representation capability for the recognition or detection task depending on the given training dataset. We present our proposed framework in details. We first introduce the deep residual neural network applied in our method, followed by the extraction of local dense activations as deep convolutional features in our framework. Then we elaborate how FV (fisher vector) encoding strategy is utilized to aggregate these deep features for more discriminative and robust representations. Finally, the classification method of the FV representations is present.

4.1 System Architecture

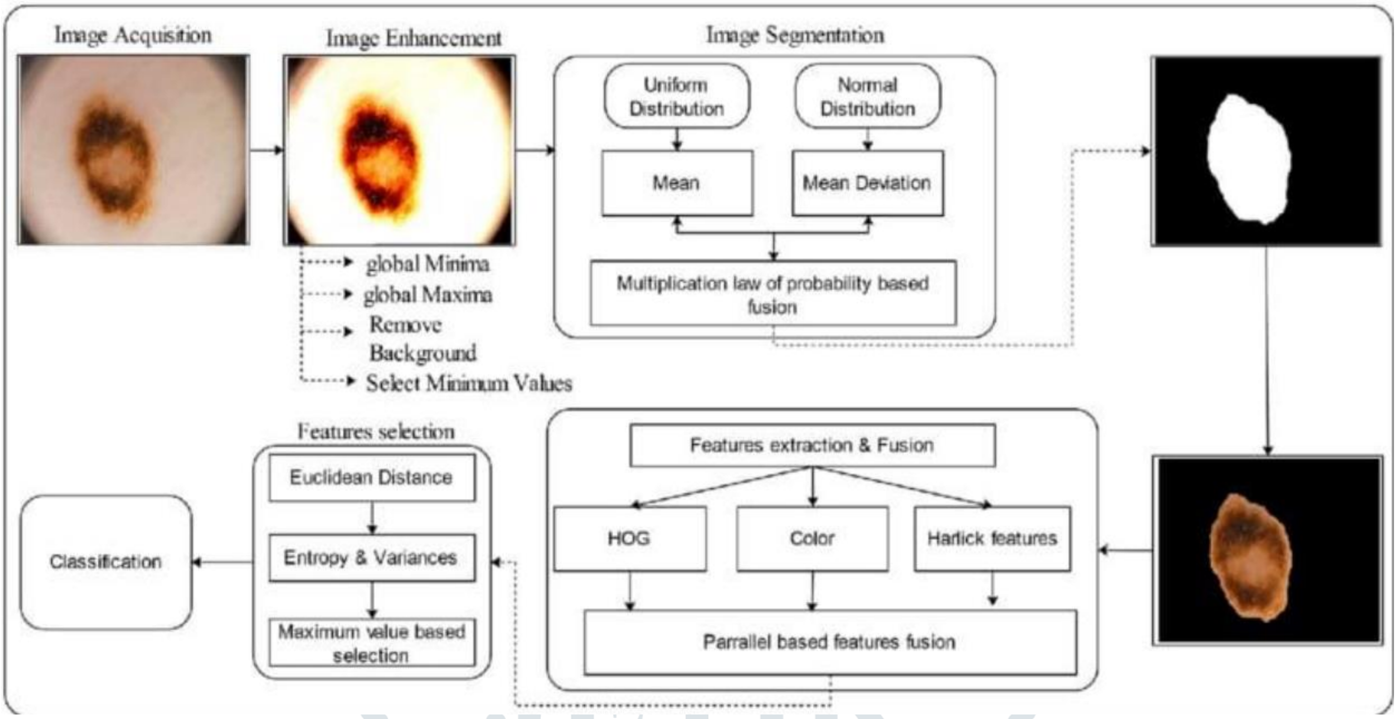

Fig 1 System Architecture

4.2 Algorithm Used- Convoluted Neural Network (DNN)

CNNs are regularized versions of multilayer perceptrons. Multilayer perceptrons usually mean fully connected networks, that is, each neuron in one layer is connected to all neurons in the next layer. The "full connectivity" of these networks make them prone to overfitting data. Typical ways of regularization, or preventing overfitting, include: penalizing parameters during training (such as weight decay) or trimming connectivity (skipped connections, dropout, etc.) CNNs take a different approach towards regularization: they take advantage of the hierarchical pattern in data and assemble patterns of increasing complexity using smaller and simpler patterns embossed in their filters. Therefore, on a scale of connectivity and complexity, CNNs are on the lower extreme.

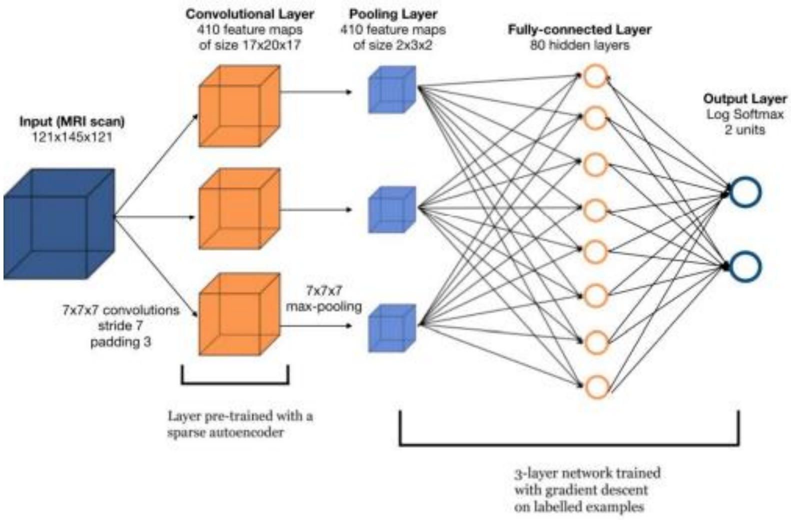

Fig 5.2.4 CNN

V. IMPLEMENTATION

To do efficient training on our CNN model, a backpropagation algorithm is set to adjust the rate of learning and stop the model automatically once it reaches maximum accuracy. Since the learning rate is one of the hyperparameters that decides model accuracy and time to process the model. OASIS-3 dataset consisted of 2168 independent MRI scanners. Among the given images, 1,734 are used for training and 434 were used for validation purposes. Because of the large image dataset, 10- fold cross-validation has been used and we have used each fold 70% as training, 10% as validation, and 20% images are used testing. The distribution of the dataset is presented in Table 1. Table 1: Total image distribution. Total Images: 2168 Type Percentage Trained images 1517 (70%) Testing images 434 (20%) Validation images 217 (10%) The model-fitting has to be done on a sample of 100 epochs and to prevent model overfitting we stop the model early at the 80th iteration. The model took a run time of 138 min to process the trained images.

Table 1: Total image distribution.

Total Images: 2168	
Type	***Percentage***
Trained images	1517 (70%)
Testing images	434 (20%)
Validation images	217 (10%)

AUC and loss metrics after each iteration on both training and validation image data.

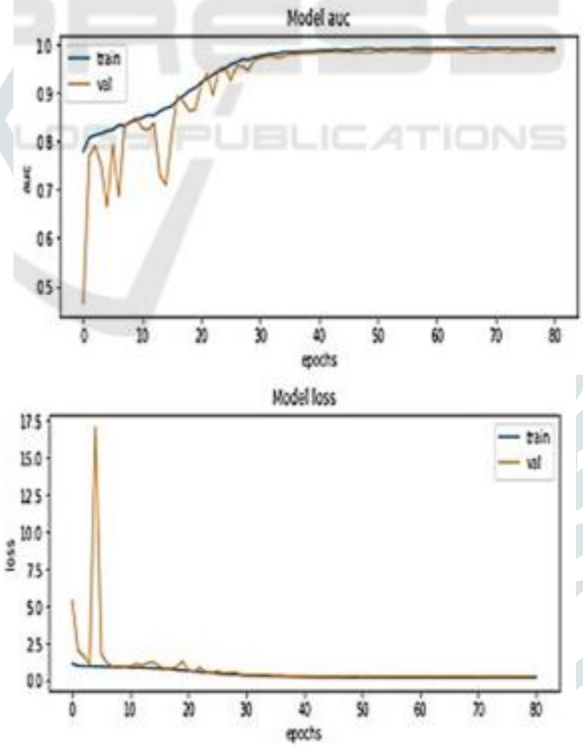

Figure 5: Model AUC and loss metric outcomes.

Though the model evaluation has been done on the validation dataset, we also perform the experiments on the testing dataset. The testing dataset model AUC curve outcome has presented in Figure 6 and the model achieved a ROC of 83.3% which is considered as an optimal classifier for AD image detection and this value is significantly higher than traditional ML approaches (Battineni, Chintalapudi, en Amenta 2019; A. Khan en Zubair 2020)

VI. CONCLUSION

This system provides a real time analysis of cancer cell based on Convolutional Neural Networks which helps in diagnosing the impact of disease and monitor it on realtime process. In this paper we simulate the result based on the data received from the MATLAB and found the types of disease. This system not only stimulates the sample but it sends the results to the Iota to store the result. In future this system can be enhanced by using a camera to capture the real time image and identifying the type of cancer cell image.

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