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Early detection of skin cancer using deep learning approach

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Abstract: Skin cancer is a worldwide epidemic. A computerised instrument allows spotting small shifts to change the skin's functionality in an early stage. This paper utilises Convolutional Neural Network (CNN) to identify skin cancers Theattained results demonstrate that the CNN method can effectively identify melanoma and benign cases from X-ray images. This work can help doctors to diagnose cancer in the skin in an initial stage and treat it successfully.

Keywords*: Skin cancer;image classification;Deep learning; CNN; Machine learning*

I. INTRODUCTION:

Cancer is an uncontrolled division of pathological cells that can invade distant sections of the body. The skin can play a substantial role in the human body by shielding muscles and bones in all parts of the body. If the skin's functionalities diverge slightly, the entire body structure becomes disturbed, affecting all the body's crucial functions. Skin cancer, among other cancers, is the most prevalent and damaging cancer type. Cancer of the skin may only be curable when it is discovered at an early phase. The lesion region is known as the sick skin mark. A large variety of skin lesions are available. Any lesion is fragmented from the skin cell form that induces the genesis. Melanocytic lesions arising from melanocytes such as melanoma are essential for developing a protein pigment named melanin [1].

Some skin cell forms, such as basal or squamous cells, are responsible for non-melanocytic lesions. A difference is created between two forms of lesions based on whether a series of dermoscopic components, such as a pigment network, are present or not [2].

There are twelve million individuals who have cancer, and skin cancer is the most significant concern for western countries, especially the USA, with strong sunshine exposure. Around 1 million new skin cancer patients are expected in the USA in 2020 [3]. The basic diagnosis approach for detecting cancerous cell or skin cancer is to visually examine the skin by an expert dermatologist [4].Providing specialised dermatologists and experienced medical assistance to each individual is difficult, and in many cases, people do not go to specialists until the condition deteriorates.

Physicians usually detect the biopsy procedure for diagnosing diseases. The skin is scrapped or detached in the biopsy process, and specific laboratory experiments can be conducted on these skin samples. This process is time-intensive and often frustrating because of this. Computer-aided screening allows early-stage diagnosis of skin cancer [5]. Typically, macroscopic photographs are branded as quantifiable images that are generally used for computer processing, and these images are captured utilising a typical digital camera and video[6]. Medical photographs have many problems, such as low lighting and the appearance of artifacts such as skin lines, highlights, repetitions and hair in the pictures. Researching skin lesions is very difficult because of these complications. Several measures are involved in detecting skin cancer at the computational level, such as pre-processing, recognizing trends, selecting features, and extraction of features and identification.

The first step to erase imagery is to eliminate distinctive elements. Characteristics explain the way lesions are classed. Properties may be extracted and then divided into global and local function extraction techniques. As a function extractor, neural networks may also do. Then, the special features will be extracted, which will align with the type of the file. Proper function selection results in good precision and stability and leads to the classifier's performance [7].

There are many ways to derive functions of dermoscopic and non-dermoscopic objects through computer vision [8-11]. Several efforts in the area of medical technology have been recently made to investigate deep learning approaches for image segmentation and classification [12, 13]. In [14], the authors employed a CNN model to facilitate skin cancer diagnosis and used a large collection of skin lesions images to classify them into cancerous or non-cancerous. The authors included the CNN model into an online platform to help doctors identify high priority patients.

In [15], the CNN model is used as an identification system to identify skin cancer in dermoscopy images of the HAM10000 dataset. The results exhibited that the CNN model can achieve excellent accuracy by utilising this dataset for training and testing. In another work, the authors [16], the authors evaluated the performance of some Machine Learning (ML) algorithms for sin cancer diagnosis using datasets obtained from the UCI ML repository. They used information-gain and relief as feature selection methods to improve the classification process and used selected features as inputs to Support Vector Machines (SVM), Random Forest (RF), Recurrent Neural Network (RNN) and CNN methods. The results revealed that deep learning algorithms, especially RNN, achieved the best performance compared to other algorithms and efficiently diagnosed cancer.

In this work, CNN is applied to classify melanoma and benign cases from X-ray images. The skin cancer dataset is used as input in the CNN technique. The reliability and performance of CNN are assessed based on the statistical accuracy measure. This work will assist and provide additional aids for doctors in the healthcare domain to detect a slight change in skin functionality in the initial stages.

This paper offers an overview of the used materials and methods in section 2, section 3 presents the evaluation metric which is used to assess CNN model, section 4 provides the results and analysis of the experimental research and finally, section 5 provides the conclusions and future work of this paper.

II. Material and Method

2.1 Used Dataset

This work uses the dataset obtained from Kaggle and consists of skin-cancer images of the ISIC archive [17]. The skin-cancer dataset has a total of 3297 images, 2637 as training and 660 testing images. It has two main classes, including melanoma and benign cases, and in order to remove clutter, an initial sharpening filter is applied for image pre-processing. In this paper, the skin cancer dataset is divided into 2077 images as training, 560 as validation and 660 as testing images. Data augmentation is also performed with a rotation range of 40 degrees, a zooming range, and a shearing range of 0.2. The images are flipped horizontally and vertically in order to increase diversity and to avoid model overfitting. A sample of the resulted images after the data augmentation phase is shown in figure 1.

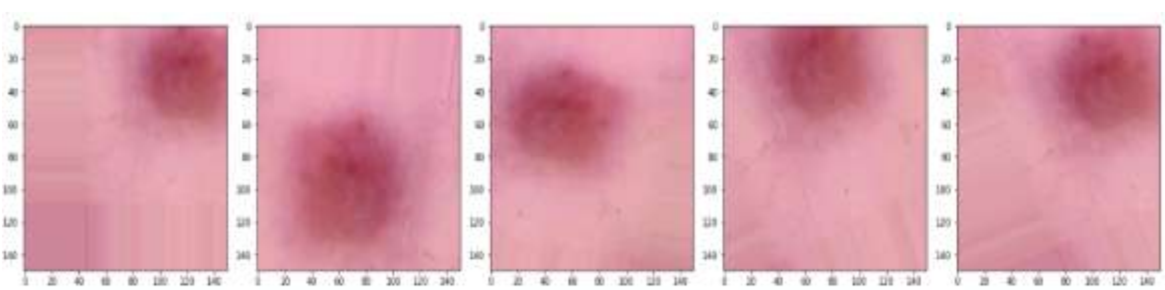

Figure 1. Some labeled images taken from the dataset after data-augmentation

2.2. CNN

A deep learning approach is widely applied to extract features in datasets such as video, image and extract valuable information from the original datasets, which can be used in medical decision making. CNN became popular due to its ability to extract features and provide great support in the healthcare domain and makes it widely applied in medical- image analysis [18]. It can also process a high volume of unstructured data with high accuracy and less computational costs. CNN architecture includes convolution, pooling, and fully connected layers, as shown in figure 2 [20].

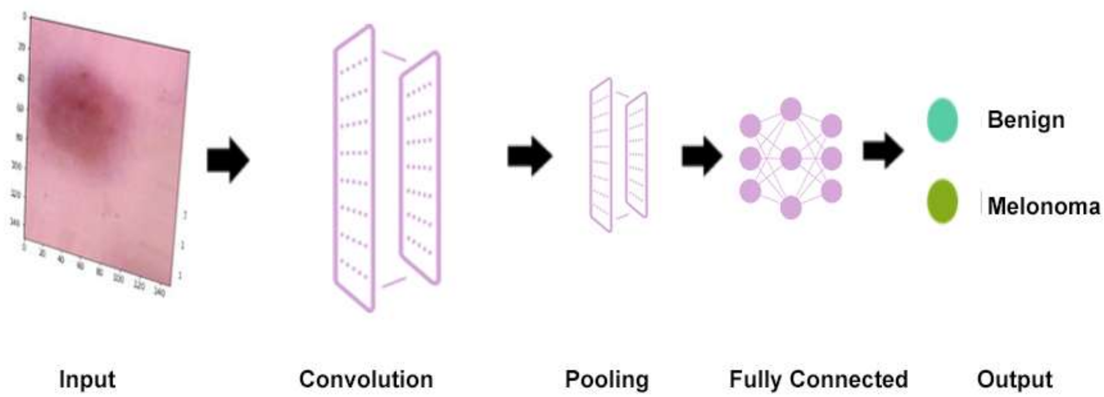

Figure2. Basic architecture of CNN for the detection of skin cancer

The convolution layer receives X-ray images as input and then computes each iamge image's convolution with each filter. Then, the pooling layer aims to reduce the number of factors and calculations in the network, resulting in improving network efficiency. In this layer, the 2x2 adjacent cell is used to divide skin cancer images into cells and keep the maximum value within each of them. Finally, the fully connected layer classifies the skin cancer image as an input to the network. This layer returns a vector of melanoma and benign classes, where each element of the vector specifies the probability for the skin cancer images either to be melanoma or benign cases.

III. Evaluation metric

In order to assess the CNN model, a Confusion Matrix (CM) is employed to find out the training accuracy. The CMcontains four parameters,and they are True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN).

In this work, the accuracy measure is used for evaluating classification models. model's accuracy refers to the percentage of c classes in the test phase by a given classifier. The classification accuracy can be measured using the following equation:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FN + FP}$$

IV. RESULTS AND DISCUSSION

The CNN model was applied and trained on the skin cancer dataset to classify melanoma and benign cases. For the training CNN model, 30 epochs, the learning rate is set to be 0.0001and Adam optimiser is used. The training and validation accuracy is examined to study the impacts of the network training with two different types of data, while the test dataset. is used for assessing the CNN model's overall performance. Training and validation accuracy levels are shown in figure 3.

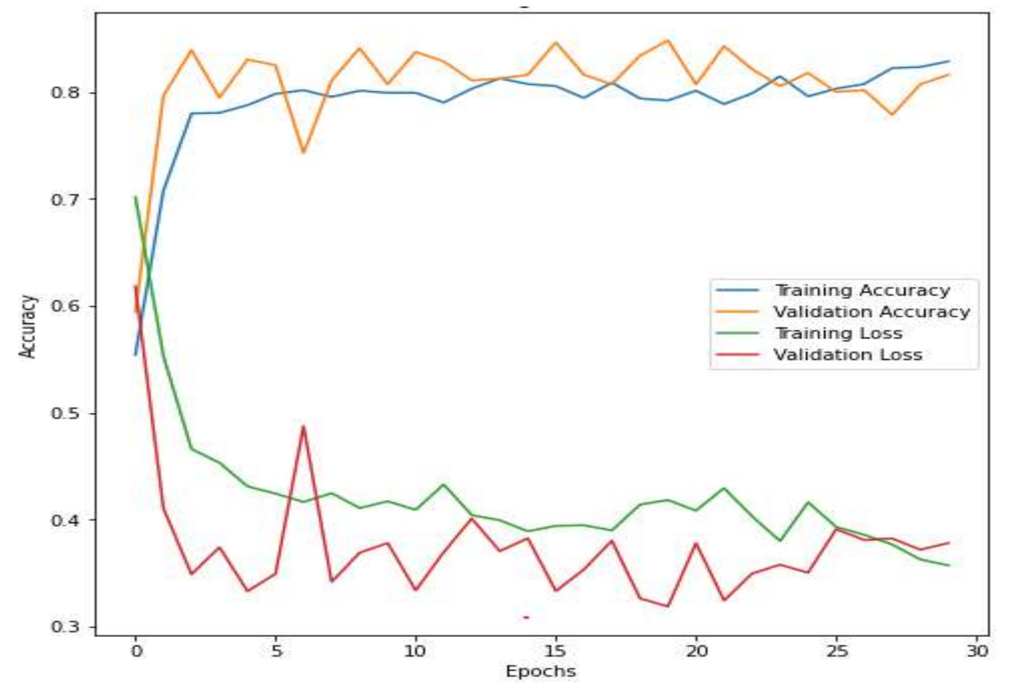

Figure 3. Training curve of loss for the accuracy and validation for the CNN models

It can be seen in figure 2 that the validation accuracy attain better than training results, and also the validation loss rate is decreased compared to the training loss rate.

Therefore, an improvement is attained by using the CNN model. The model is also evaluated on the test data to assess the model's overall effectiveness. The model achieved an accuracy of 0.824 and a test loss of 0.381. It indicates that the CNN approach can help classify both classes from X-Ray images with good accuracy.

V. CONCLUSION AND FUTURE WORK

This work employed a CNN approach for classifying skin cancer from a dataset obtained from Kaggle. The results indicate that the CNN approach can help classify both classes from X-Ray images with good accuracy. It can help categorize both classes from X-Ray images effectively. For future improvements, we are planning to train CNN on more data and include clinical images for skin cancer diagnosis and use transfer learning models such as VGG16 [20], Xception [21], ResNetXt101 [22].

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