# Skin Cancer Detection Using Convolutional Neural Network

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***Abstract:*** This research focuses on intelligent skin cancer diagnosis based on a balanced dataset of benign and malignant skin moles images. Skin cancer is a typical kind of cancer that grows abnormally on skin cells, and studies found that the early detection of skin cancer increases survival by a large margin. The main aim of this research is to detect skin cancer. Considering the seriousness of skin cancer, If people could detect cancer in the early stage, it can be diagnosed comparatively easily. It most often occurs on skin that is commonly exposed to the sun, But it is also a common form of cancer that can also occur on areas of your skin not ordinarily exposed to sunlight. This paper presents a detailed review of skin cancer detection using a convolutional neural network. Research results are shown with different graphs, images and tables for better understanding.

## I. INTRODUCTION

Early detection of skin cancer is crucial as it is a dangerous form of cancer spreading vigorously among humans[1]. With the progress of Machine learning, Machine learning-enabled skin cancer detection systems are demanding. Still, very few real-time skin cancer detection systems are available for the general public and primarily available are the paid. Recently, Convolutional Neural Network (CNN) based methods advanced cancer detection. The proposed method is developed using computer vision and image processing techniques combined with a convolutional neural network algorithm. Each year in the USA alone, approximately 5.4 million new cases of skin cancer are recorded[2][3]. The mortality rate of this condition is expected to increase in the next decade. The survival rate is less than 14% [4], [5], [6]. if diagnosed in later stages. However, if skin cancer is detected at early stages, the survival rate is nearly 97% [7]. This demands the early detection of skin cancer. This research addresses the issue of early diagnosis with improved accuracy.

To diagnose skin cancer speedily at the earliest stage and solve some of the problems mentioned above, there have been extensive research solutions by developing computer image analysis algorithms. The dataset used for this research is taken from the International Skin Image Collaboration (ISIC) archive. It consists of a total of three thousand five hundred pictures. These pictures include 1800 pictures of benign moles and 1497 pictures of malignant classified moles. The high definition pictures are modified to low-resolution pictures to improve the performance, and pictures have all been resized to low resolution (224x224x3) RGB. The dataset is pretty balanced, and the model will be tested with accuracy.

In this paper, we address developing deep learning-based image classification models to identify skin cancer without prior programming knowledge. The main objective of this paper is:
1. To classify the cell images into two types of Cancer and identify Cancer with improved accuracy using Convolution Neural Network.

The two types of skin cancers focussed here are:
1. Benign
2. Malignant

## II. RELATED WORK

With the vast advancement of Machine learning, similar research is happening around cancer detection using machine learning. For the last five years, the research in this domain multiplied due to various reasons. Rehman Ashraf and the team introduced an approach[8], 'Region-of-Interest Based Transfer Learning Assisted Framework for Skin Cancer Detection. In his study, he focuses on Melanoma. Melanoma is considered the most severe kind of skin cancer. All over the world, the mortality rate is much high for Melanoma in contrast with other cancer. There are various computer-aided solutions proposed to identify melanoma cancer correctly. Nevertheless, it is complicated to design a reliable Computer-Aided Diagnosis (CAD) system for accurate melanoma detection because of the difficult visual appearance of the nevus makes. Existing approaches either use traditional machine learning models and focus on handpicked suitable features or deep learning-based methods that use complete images for feature learning. The ROI based approach helps to identify discriminative features as the images containing only melanoma cells are used to train system. They further use a Convolutional Neural Network (CNN) based transfer learning model with data augmentation for ROI images of DermIS

and DermQuest datasets. Their proposed system gives 97.9% and 97.4% accuracy for DermIS and DermQuest respectively. The proposed ROI based transfer learning approach outperforms existing methods that use complete images for classification.

Mohammad Ali Kadampur and their team introduced deep learning-based model-driven architecture in the cloud for classifying dermal cell images for skin cancer detection[9]. The main objective of his studies is a way to enable researchers and practitioners to develop deep learning models by simple plug and play art. This also classifies the cell images and identify Cancer with an improved degree of accuracy using deep learning. The DLS, Model Driven Architecture Tool provides Neural Network Modeling components as a stack of drag-drop & develop art. The models built using DLS were tested against the benchmark machine learning databases (HAM 10000), and the results are promising. A higher value of ROC suggests that the classifier model rarely fails to diagnose Cancer classification as Cancer or non Cancer. From the main pre-trained models, squeeznet, densenet, and inception v3, inception v3 models have a higher ROC than the resnet model. These observations suggest that the models built using DLS produce better results than many of the findings in the related work.This study introduced a tool in which a non-programming background person can develop complex deep learning models. It opened the options of flexibility in designing deep learning classifiers by hinting at the general procedures and looping patterns in developing deep learning models The DLS models achieved an AUC of 99.77% in detecting cancer cells from the images of cancer cells. The paper pointed at obtaining the programming code for the model for further exploration by the programming specialist. The provision to download the trained model and develop enterprise-level applications is the best seed-level research this paper observes for future work.

Praveen Banasode and team had introduced a technique to Melanoma Skin Cancer Detection Using Machine Learning Technique mainly, Support Vector Machine. They used one of the most commonly used classification algorithms, the support vector machine (SVM). First, they analyzed the skin image and then converted it into BGR-Gray and BGR-HSV for the computer to understand and enable it to read binary codes. The training set of images is used to test the SVM, which classifies the affected skin area as melanoma. A feature like asymmetric behaviour, colour, and border irregularity are extracted. Finally, this feature vector is given as input to the SVM classifier, classifying the skin lesions. By using a support vector machine, the performance evaluation was found t be very high. The sensitivity, specificity and Accuracy were found to be 95%, 90% and 96%.

## III. METHODOLOGY

The steps used in this research are pictured in figure 1. The first step is to load all the essential functions that we are using in this project. The framework used is a jupyter notebook. The dataset is taken from the International Skin Image Collaboration Archive. It consists of three thousand images containing 1800 and 1500 pictures of benign moles and malignant classified moles, respectively. The pictures have all been resized to low-resolution RGB to have a better performance. The task is to create a model, which can classify a mole visually into benign and malignant. In this research, we tried to detect two different classes of moles using Convolution Neural Network with Keras TensorFlow in the backend and then analyze the result to see how the model can be helpful in a practical scenario. The next is to load the pictures and turn them into NumPy arrays using the RGB values. The photos have already been resized to low resolution. As the pictures do not have labels, The next step is to create that labels. Lastly, the images are added together to an extensive training set and shuffled.
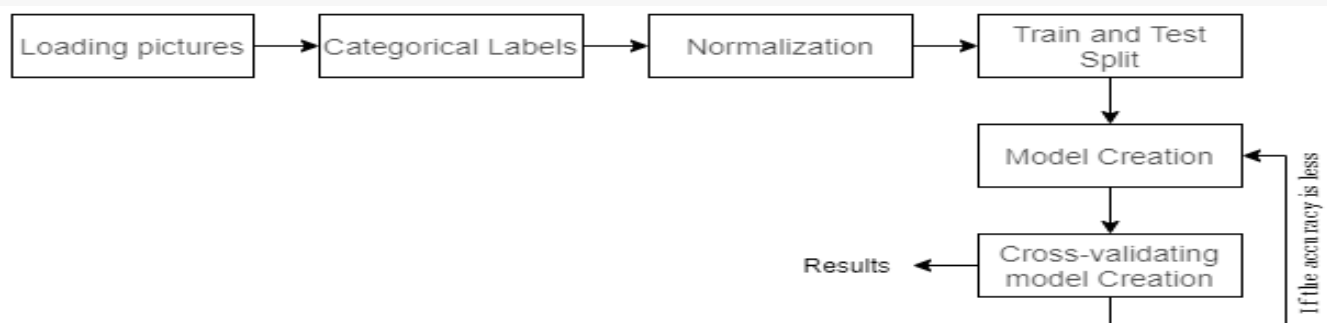


**fig -1**: Process Diagram

The next step is to turn labels into one-hot encoding followed by Normalizing all pictures' values by dividing all the images RGB values by 255. Here I used Keras Sequential API, where you have to add each layer one by one starting from the input layer. The first is the convolutional 2D layer. I chose to set 64 filters for the two firsts conv2D layers. The CNN can separate features that are useful everywhere from these transformed images. The second important layer in CNN is the pooling layer. This layer acts as a downsampling filter. These are used to reduce the computational cost, and to some extent, also decrease overfitting. We have to choose the pooling size more the pooling dimension is high, the

more the downsampling is essential. The next step is the dropout method. The figure two shows images of the moles and how they are classified.
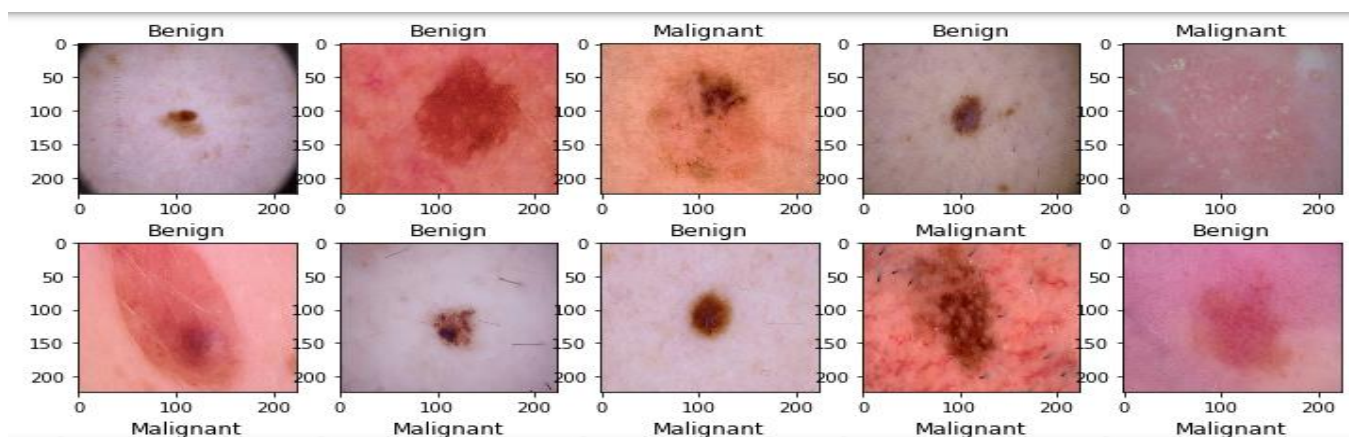


**fig -2**: Images of moles, and how they are classified

Dropout is a regularization method, where a proportion of nodes in the layer are randomly ignored for every training sample. This drops the balance of the network randomly and forces it to learn features in a distributed way. This technique also improves generalization and reduces overfitting. First, the model has to be fitted with all the data, such that no data is left out.

## IV. RESULTS AND DISCUSSION

After model creation, The first step was testing the accuracy against different performance metrics. The dataset was balanced equally; therefore, the accuracy is the performance metric used. The initial CNN we used only got 70% accuracy, and Thus the resnet50, is also tried. And we got the accuracy as 92%.

## V. CONCLUSION

This project introduces a method to detect skin cancer using the deep learning method. In our proposed system, the CNN can combine local features and learn characteristics of the image by combining convolutional and pooling layers. The proposed method includes images from International Skin Imaging Collaboration preprocessing to extract the region of interest in the image and then augment some pictures to produce a more extensive dataset containing images. The resulting dataset has been applied to the CNN model to train the model, which comprises different layers, including pooling, convolutional, classification layer, etc. Testing the model produced promising results with an accuracy of 70%. To improve the accuracy, I used another variation of the convolutional neural network, which is resnet50. The results are promising. The results were enhanced from 70 to 92%. Unlike other methods, the proposed method based on neural networks shows the best results, and different machine learning techniques can improve the results.

## VI. REFERENCES

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