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COMPARITIVE STUDY OF DCNN WITH TRANSFER LEARNING TECHNIQUES FOR SKIN CANCER CLASSIFICATION

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Abstract

Skin cancer is one of the top three perilous types of cancer caused by damaged DNA that can cause death. Cells start to expand out of control as a result of this damaged DNA, and this growth is happening more quickly these days. A few research on the automatic identification of cancer in skin lesion photographs have been carried out. However, it is quite challenging to analyze these images because of a variety of problematic factors, such as light reflections from the skin's surface, variations in color illumination, and varied sizes and patterns of lesions. Consequently, the development of evidence automatic recognition of skin cancer is beneficial in enhancing pathologists' early diagnostic precision and expertise. In this work, we propose a Deep Convolution Neural Network (DCNN) model based on deep learning for accurate classification of benign and malignant skin lesions. Initially, we use a filter or kernel to remove noise and artifacts from the input images. After normalizing the photos, we identify characteristics that help with precise classification. Lastly, we enrich the data with more images to boost the accuracy of the classification rate. To evaluate its performance, our proposed DCNN model is compared with many Transfer learning techniques, such as MobileNet, AlexNet, and DenseNet. Ultimately, we were able to obtain training and testing accuracy, respectively. The final results of our proposed DCNN model show that it is more reliable and robust than other transfer learning techniques.

Keywords: Skin Cancer, Deep Convolutional Neural Network, DenseNet201, MobileNetV2 and AlexNet

I. Introduction

Cancer is a serious threat to human life. Occasionally, it might lead to someone's death. Although there are many other types of cancer that can harm a person's body, skin cancer spreads the fastest and has the biggest potential for death. Contributing variables may include the use of alcohol, smoking, allergies, illnesses, viruses, physical activity, changing weather patterns, exposure to ultraviolet (UV) light, and more. UV rays from the sun have the power to completely damage the DNA found in skin cells. Furthermore, abnormal body enlargements can potentially lead to skin cancer. The four most common forms of skin cancer are actinic keratoses, squamous cell carcinoma, basal cell carcinoma, and melanoma. The World Health Organization (WHO) estimates that skin cancer accounts for one in three cases of cancer diagnoses. In the US, Canada, and Australia, the number of cases of skin cancer has been rising rather regularly over the past few decades. It is projected that the United States will diagnose 5.4 million instances of skin cancer annually. Every day, there is an increasing need for rapid and efficient clinical testing. Strong cancer that begins in the melanocytes found in the skin's epidermis is called malignant melanoma. This type of cancer spreads quickly and is more challenging to treat. Therefore, early detection of skin cancer may result in a diagnosis and course of therapy that improves prognosis. Many computer-aided diagnosis (CAD) systems have been introduced in the last few decades for the diagnosis of skin cancer. In order to diagnose cancer, conventional computer vision techniques are mostly employed as a classifier to extract several factors, such as shape, size, color, and texture. AI is being utilized more and more as a solution to solve these issues.

The medical domain uses the most commonly used deep-learning architectures, such as recurrent neural networks (RNN), long short-term memory (LSTM), convolutional neural networks (CNN), and deep neural networks (DNN), to identify cancer cells. The categorization of skin cancer is another useful application for these models. Furthermore, CNN—more precisely, a DNN—has already produced outstanding outcomes in this area. CNN is the most widely used model; it consists of multiple machine learning algorithms for object classification and feature extraction. Furthermore, transfer learning is used to massive data sets from these businesses, increasing the accuracy of the outcomes.

II. Literature Review

Al-Masni, et.al [1] has discussed a novel use of full resolution convolution networks (FrCN) for segmentation. By learning the full resolution features of each individual pixel in the input data immediately, the FrCN technique eliminates the need for pre- or post-processing processes such as low contrast correction, artifact removal, or additional optimization of the segmented skin lesion boundaries.

Alfed.N, et.al [2] has discussed an effective method for identifying skin cancer using dermoscopic pictures. It has been demonstrated that the dermoscopic image's statistical properties of the pigment network might be effectively employed as distinguishing features for cancer detection. 200 dermoscopic photos from the Hospital Pedro Hispano were used to evaluate the suggested method, and the cross-validation results demonstrated high detection accuracy.

Aljanabi, et.al [3] has discussed a novel method of melanoma identification using digital photos that uses the artificial bee colony, or ABC algorithm. This algorithm, in contrast to others, is quick, easy to use, adaptable, and requires less parameters. Applications for this methodology include datasets from Dermis, PH2, and the ISBI 2016 and 2017 challenges. Several anomalies affect the pictures of these bases. The photographs that make up the databases are from a range of sources; they are based with various lighting conditions, resolutions, and other attributes.

Biessmann, et.al [4] has discussed a reliable and scalable method for imputation that works with non-numerical tables and unstructured text data in a variety of languages. Tests conducted on publicly available data sets and data sets drawn from an extensive product catalogue in two distinct languages (Japanese and English) show that this method is both scalable and produces imputations that are more accurate.

Ech-Cherif, et.al [5] has discussed Transfer Learning resource-constrained CNN model known as MobileNetV2 separates skin lesions into two categories: benign and malignant. The trained model produced an overall accuracy of 91.33% with a batch size of 32. A mobile application for iOS devices was subsequently created using the trained model and the Core ML framework. After that, the mobile application's functionality was evaluated with a fresh dataset on an untested picture library.

III. Proposed Method

The goal of this research is to develop a system that can discriminate between regular and pothole-filled road photographs. Deep learning methods that are helpful for image analysis and classification are called convolutional neural networks. Using manually gathered pothole and non-pothole (normal) photos as well as images from Kaggle's online repository, we trained a deep convolutional neural network (DCNN). For the purpose of comparing outcomes, several pre-trained neural network models, including DenseNet201, MobileNet, and AlexNet, are tested. The block diagram and system architecture for the suggested system are shown in Figures 1 and 2, respectively.

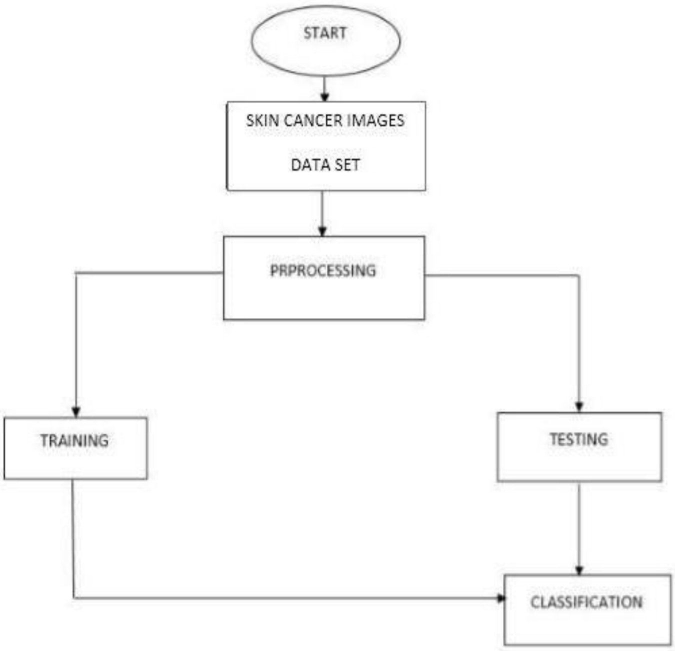

Figure 1: Block Diagram of Proposed System

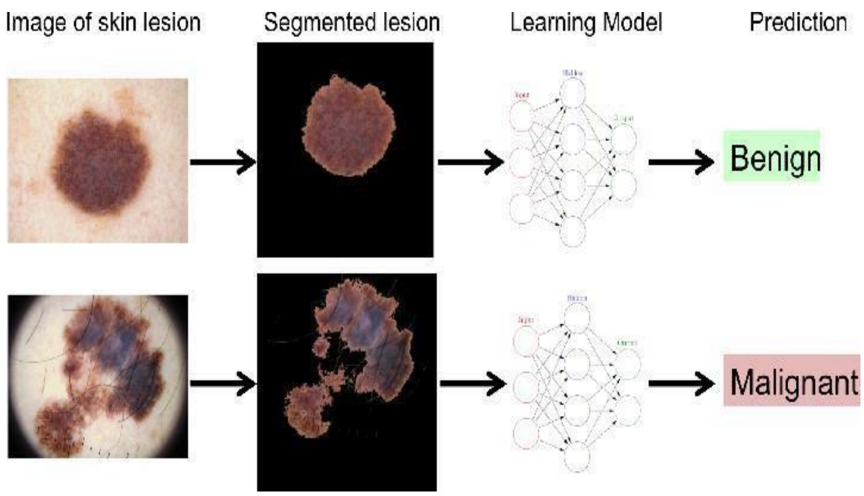

Figure 2: Architecture of Proposed System

The various pre-trained neural network models likeDenseNet201, MobileNet and AlexNet are discussed here:

DenseNet201:

The Dense Convolution Network (DenseNet) architecture establishes a feed-forward mechanism that connects every layer to every other layer. On the other hand, the conventional Convolution Neural Network (CNN) with the L layer exhibits an L relationship, wherein the mutual relationship is directly related to L (L + 1) / 2. Dense Net has a very thin layer (12 filters per layer), and the overall collective information of the network is composed of only a small number of feature maps.

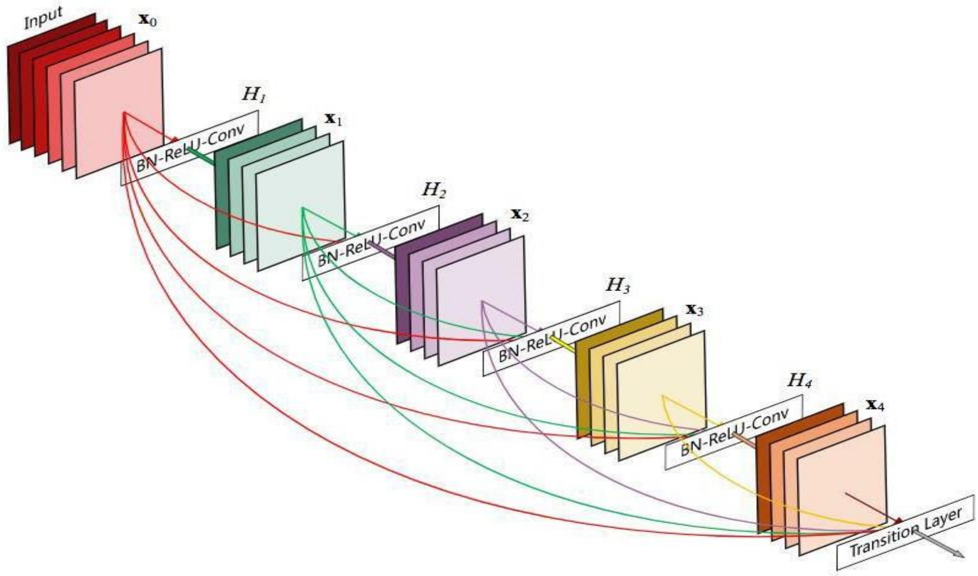

Figure 3: DenseNet201 Architecture

AlexNet:

The 2012 ImageNet ILSVRC deep learning algorithm challenges were comfortably won by the AlexNet CNN architecture, with a top-5 error rate of 17% and a second-best achievement of 26%! Convolution layers were first stacked directly on top of one another in CN networks, rather than with a pooling layer layered on top of each one. The inventor of it was Alex Krizhevsky. LeNet-5 and the models developed by Ilya Sutskever and Geoffrey Hinton are very comparable, albeit larger and deeper. AlexNet consists of eight layers, three completely connected and five convolution, with a total of sixty million parameters. AlexNet first implements Rectified Linear Units, or ReLUs, as activation functions. It was the first CNN architecture that uses GPU to increase performance.

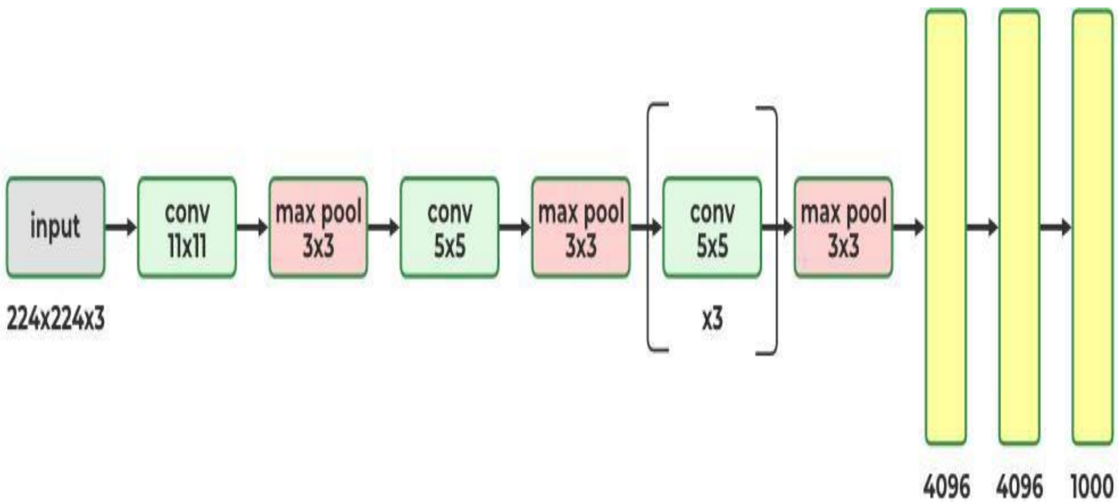

Figure 4: AlexNet Architecture

MobileNet:

Compared to MobileNetV1, accuracy is greater when using the ImageNet dataset, which is used by MobileNetV2. The depth- and point-wise convolution from MobileNetV1 is still used in the MobileNetV2 architecture. Linear bottlenecks and shortcut links between bottlenecks are two further aspects of MobileNetV2.Between the models is the input and output portions of the bottleneck component. The inner layer of the model contains the ability to concurrently transfer input from a lower-level idea (pixels) to a higher-level descriptor (picture classification).Shortcuts between bottlenecks will consequently expedite and enhance the training process, much like residual connections in traditional CNN systems.

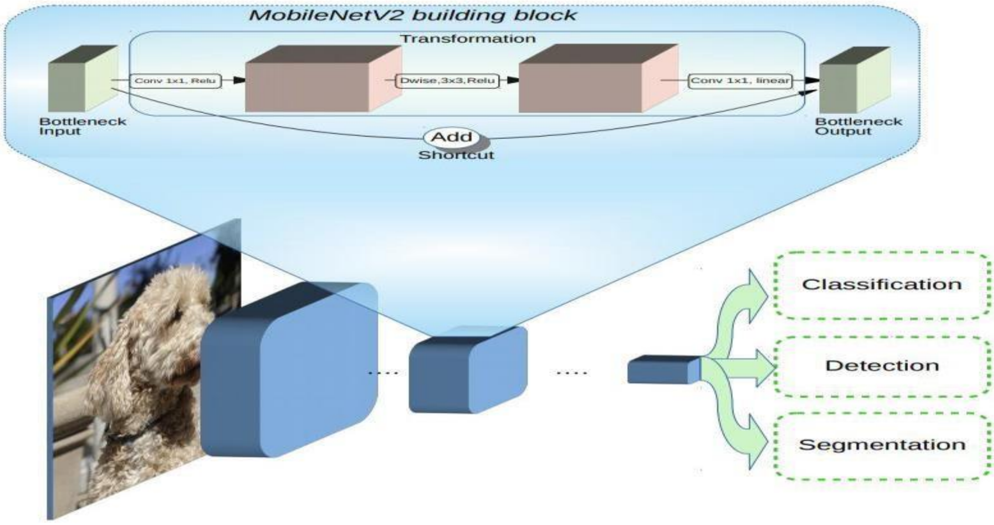

Figure 5: MobileNet Architecture

IV. RESULTS

Home Page:

The user's home page for the online application Skin Cancer Classification Using Deep Convolutional Neural Network is shown in Figure 6 below.

Figure 6: Homepage of Skin Cancer Classification using DCNN

Login:

The login page for Skin Cancer Classification Using Deep Convolution Neural Network is shown in Figure 7 below.

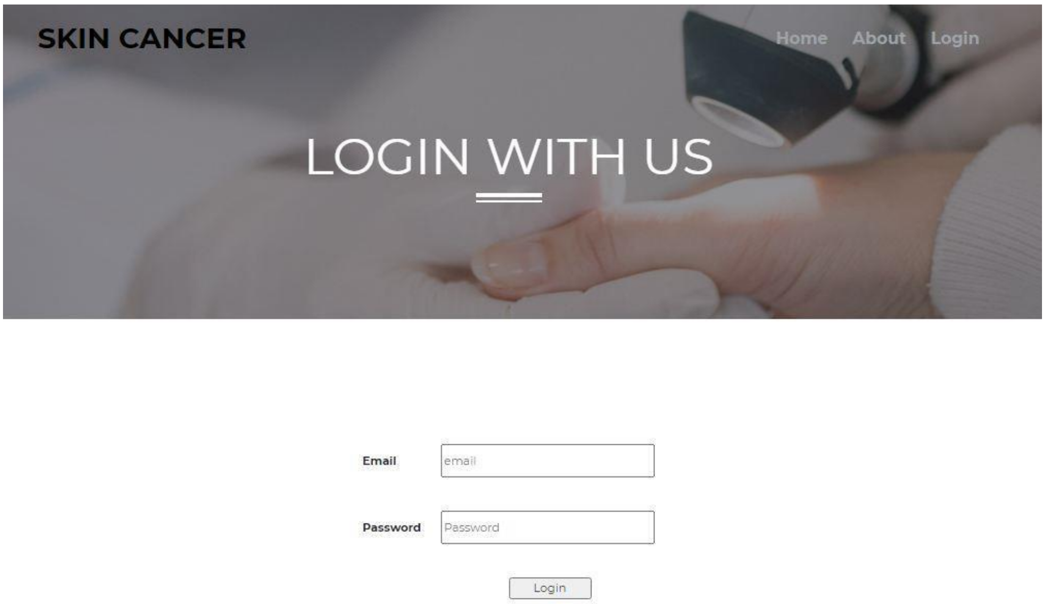

Figure 7: Login page of Skin Cancer Classification using DCNN

Register:

The registration process for the Skin Cancer Classification Using Deep Convolution Neural Network is shown in Figure 8 below.

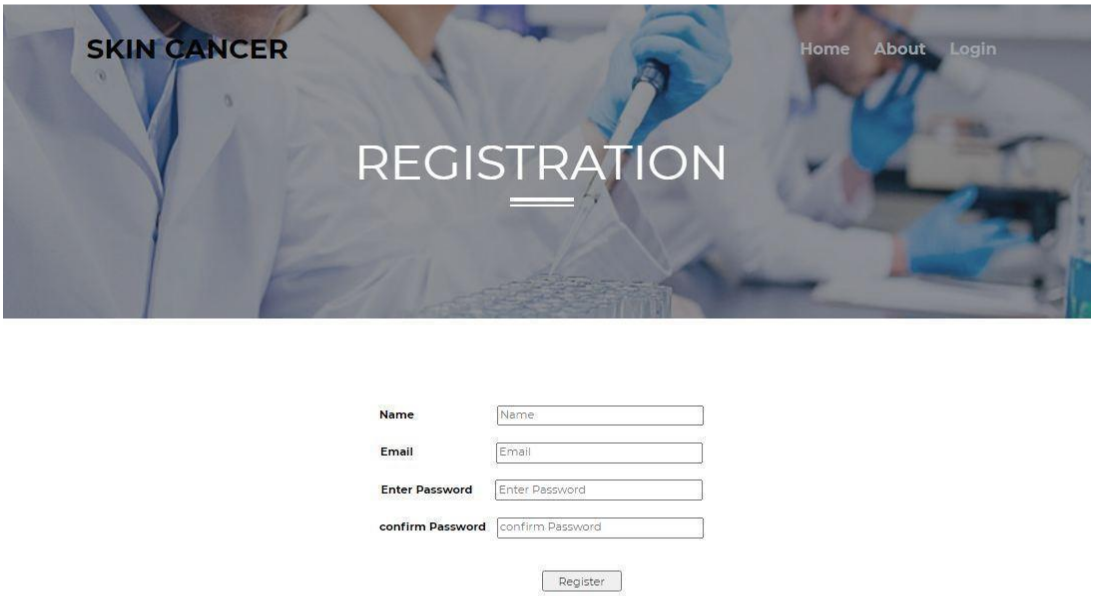

Figure 8: Register page of Skin Cancer Classification using DCNN

Upload Image:

The upload area where people can submit photos of skin cancer is shown in Figure 9 below.

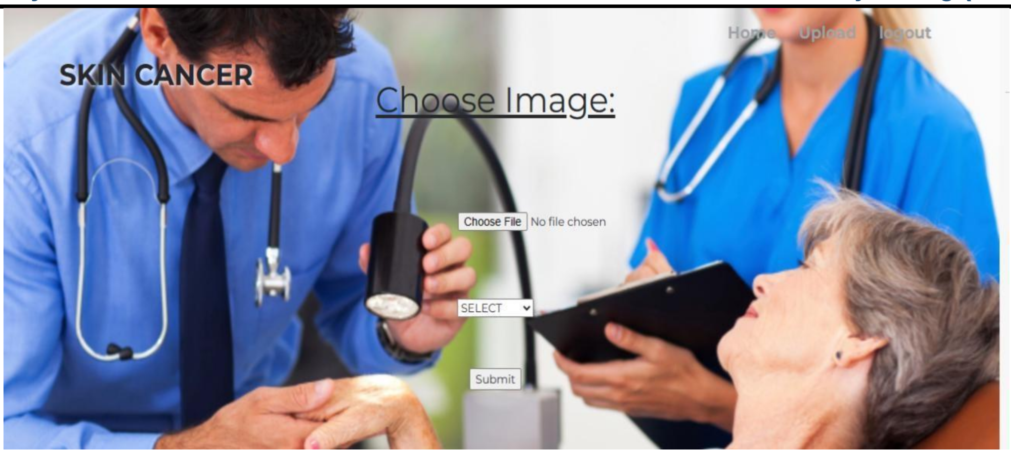

Figure 9: Upload image page of Skin Cancer Classification using DCNN

Final Result:

The visitor may see the submitted image in Figure 10 below, which could be benign or cancerous.

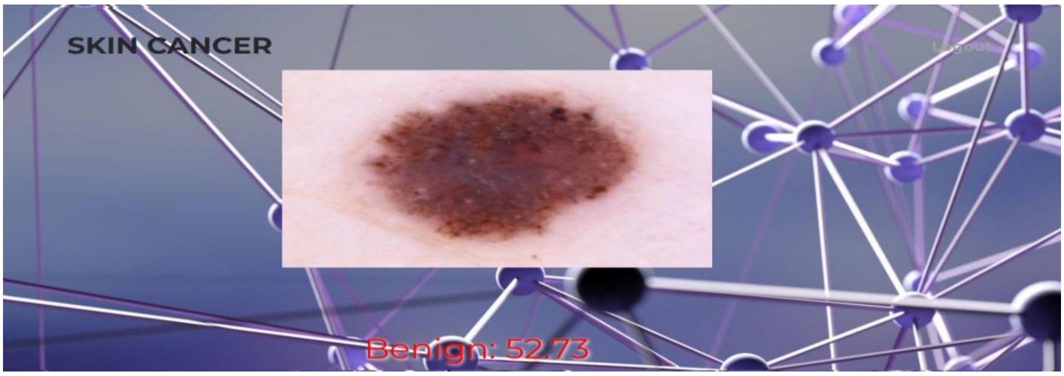

Figure 10: Final Result image of Skin Cancer Classification using DCNN

V. RESULT ANALYSIS

Input	Output	Result
Features of Input	Tested for various characteristics specified by the customer on various models .	Achieved
DenseNet201 Classification	Tested for various user-provided input features on various model features are generated using various algorithms and data.	Achieved
Forecasting Prices	The many models constructed from the algorithms will be used to predict prices.	Achieved

Table 1: Test Cases

S.NO	Test cases	I/O	Expected O/T	Actual O/T	P/F
1	Examine the datasets.	Dataset's path.	The datasets must read correctly.	Datasets successfully retrieved	It gave rise to P. If not, F will appear.
2	Confirming the Skin Cancer Extraction produces a result.	Skin Cancer Extraction classification	Output as either in Skin Cancer Extraction	Output is classified image it is Benign are Malignant.	It gave rise to P. If not, it will experience F
3	Confirming the Skin Cancer Extraction produces a result.	Skin Cancer Extraction classification	Output is Benign (or) Malignant.	Output is classified as image it is Benign (or) Malignant.	P was the result. If not, it will travel through F
4	Confirming the Skin Cancer Extraction produces a result.	Skin Cancer picture as input for Image prediction	Need to predict the image it is Benign (or) Malignant.	Model successfully predicted type of Cancer.	It brought forth P. Should this not be the case, F

Table 2: Test Cases Model Building

VI. CONCLUSION

The proposed DCNN model in this research achieves a higher classification rate than other transfer learning techniques. It may be possible to distinguish between skin cancer and healthy skin using the suggested method. Lesions by changing the output activation layer to a sigmoid. A binary classification exists. Furthermore, the proposed methodology was assessed, which enabled us to generate more accurate models for training and testing, respectively, when compared to other currently employed transfer learning methods. Furthermore, several images threw off the dataset's imbalance and prevented the model from using a big enough sample size to increase accuracy. To get the best prediction and classification accuracy, we will work on a larger dataset in the future that has more labeled skin lesions in order to successfully develop a DNN, including pre-processing procedures. The CAD, which is robust and user-friendly for all acquired image situations, may also identify skin cancer. Thus, we will also attempt to create a DNN that can use CAD systems to identify different kinds of skin lesions.

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