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Skin Cancer Lesions Classification Using Deep Learning Techniques

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Abstract:- According to World Health Organization, one of the most prevalent types of cancer is skin cancer of human malignancy. Skin Cancer is more likely to be cured and treated more inexpensively if detected early. Melanoma, the deadliest variety of skin cancer, can manifest itself in a variety of ways. Early melanoma detection can increase the number of people who survive the disease. The main contributor to the development of skin cancer is sun exposure (ultraviolet). In this article, a variety of deep learning algorithms for skin cancer detection are introduced. The aim of this essay is to give a newbie a better understanding of the various methods for spotting skin cancer.

Keywords: *Skin Cancer, Melanoma, Human Malignancy, Deep Learning.*

I. INTRODUCTION

Tomography Skin cancer is a fatal condition resulting from aberrant cell proliferation that can spread to other body regions. Skin cancer most usually appears on parts that receive direct sunlight. Other variables, such the environment and genetic anomalies, can also cause it. During the course of a few decades, its frequency of incidence dramatically increases. A computer-aided diagnostic is suggested in order to reduce the expense of diagnosing skin cancer. The primary layer of the skin is made up of squamous cells, the second layer is made up of basal cells, and the third layer is made up of melanocyte cells. Non-melanoma skin cancers include those with basal cells and those with pavement epithelium cells. Sarcoma, lymphoma, Merkel cell malignancies, and cancers of the hair and sweat organs are some more unusual forms of skin illness. Melanoma poses a greater risk than other types of skin conditions. It quickly spreads to other parts of the body if it isn't found in its initial stages. Some risk factors include fair skin, a history of sunburns, prolonged sun exposure, sunny or high-altitude locations, moles, and other skin problems. Hereditary, radiation, exposure, and a weakened immune system all contribute to skin cancer.

A biopsy approach is a formal method for detecting skin cancer. In this technique, tests are sent to various research institutes for testing. This is a difficult cycle that can spread to different areas of your body. The proposed skin cancer detection system helps avoid the drawbacks of conventional techniques such as a biopsy. There are two ways to detect skin cancer. The dermoscopy image is captured with high zoom by a specialized dedicated system at a pathology center and must be interpreted by a skilled dermatologist (E.g.20x). Sadly, this method has costs and time limitations. The victim can administer the test whenever they want, even at home, if there is computer software that can detect skin cancer automatically from a digital image captured by any digital image-capturing device with minimum attention to the area of concern.

➢ *Software and Dataset:*

- *Software:*

Collaboratory, sometimes known as "colab" is a machine learning platform that enables you to mix rich text, charts, photos, executable python code, HTML and more into a single google drive document. It is a data analysis tool that is depicted in Fig- 1. By linking to a robust Google cloud platform runtime, it enables you to collaborate and share your work easily.

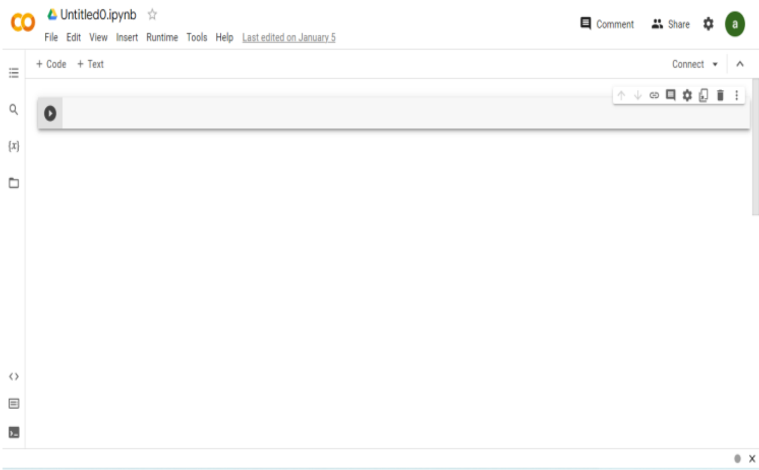

Fig 1 Google Colab Environment

- *Datasets:*

The dataset is used to simulate the suggested model comes from an open source called Kaggle. Skin Cancer photos from the ISIC Archive have been processed and included in the benign vs. malignant dataset. The dataset contains a balanced image set of benign and malignant tumors. The dataset is divided into two folders: one for training photos and another for testing. Each folder is divided into two folders, one with photographs of benign moles and the other with pictures of cancerous moles.

The train folder has a total of 2637 photographs, 1440 of which are benign and 1197 of which are malignant. These training images are used to train the methodology's suggested PNN model. The test folder contains 360 benign photographs and 300 malignant images, for a total of 660 images. These test photographs are fed into the pre-trained classifier to determine the model's accuracy. Fig- 2 depicts the first 15 datasets.

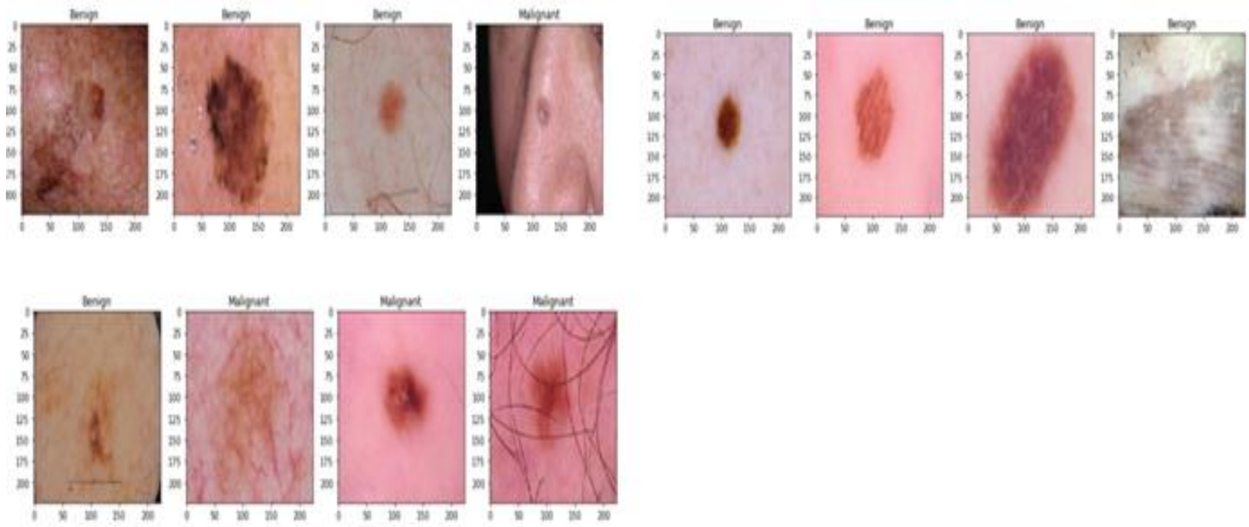

Fig 2 Data Sets

II. METHODOLOGY

The fundamental purpose of this project is to use image processing and Convolutional neural networks to identify skin cancer as benign or malignant (efficient B0).

The flow of work can be seen in Fig- 3. Getting a digital camera image of the probable skin area to diagnose is the first step in classifying skin cancer. The acquired image is pre-processed, including hair removal, unnecessary data removal, and image scaling to the required size. Segmentation is applied to the pre-processed image after the pre-processing stage. Even though we can split up the data and analyze it separately to produce better findings, we often find that doing so is more efficient. Later we get to classify the images to malignant or benign.

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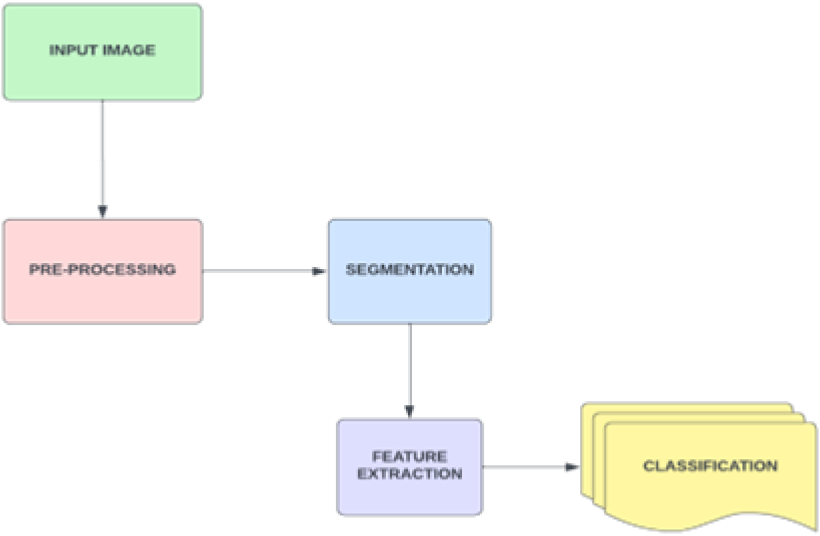

Fig 3 Flow of Work

➢ *Input Data:*

A convolution neural network (CNN) analyzes an image's three color planes to determine the color space it belongs to-for example, RGB, CMYK, or grayscale. For example, in an RGB image, the colors are based on three color planes: red, green, and blue. The CNN then measures the dimensions of the image, which can be a time-consuming task for large images like an 8K image (7680x4320 pixels). However, one of the key advantages of CNNs is their ability to reduce the dimensionality of images while still retaining all the important features. This process allows the CNN to efficiently process large images while maintaining the necessary information for accurate analysis. Overall, CNN's ability to analyze images based on their color planes, color spaces, and dimensions makes it a valuable tool in image recognition and processing tasks.

➢ *Pre-Processing:*

Before feeding image data to a model, it is essential to pre-process it to ensure compatibility with the model's input requirements. For instance, fully connected layers in convolutional neural networks necessitate images to be in arrays of identical sizes. Proper pre-processing can not only improve model accuracy but also accelerate model training and inference times. We can see some pre-processed images in below Fig- 4.

- *Steps Involved in it:*

Image pre-processing involves several steps to prepare the image data for model input. The four major categories of image pre-processing techniques are as follows:

✓ Pixel brightness alterations or corrections, which entail changing picture brightness and contrast to improve its characteristics.
✓ Geometric transformations, which include scaling, rotation, and the translation of the images to standardize their size and orientation.
✓ Image filtering and segmentation, which involve smoothing, sharpening, and edge detection to reduce noise and highlight relevant information.
✓ Fourier transform and image restoration, which involves frequency domain analysis and the restoration of images by removing distortions and artifacts.

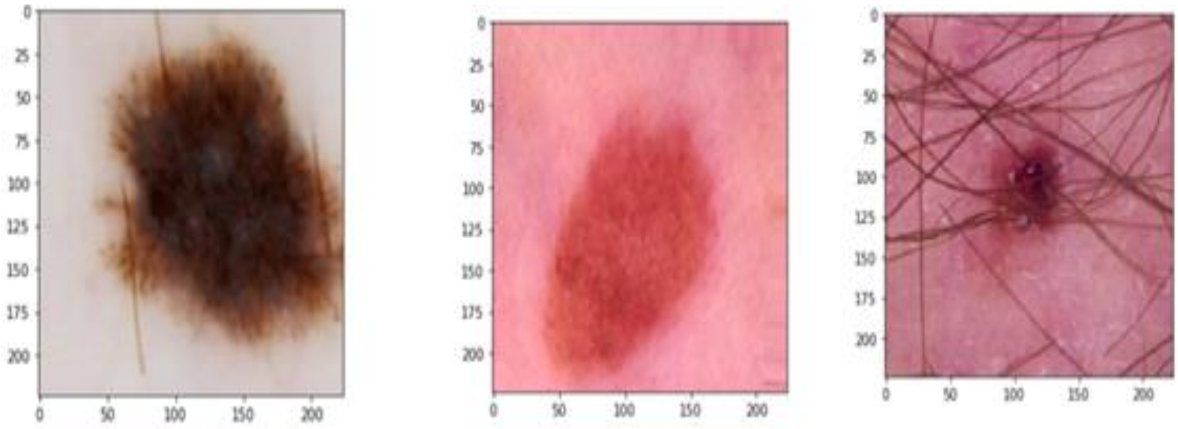

Fig 4 Pre-Processed Images

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➢ *Segmentation:*

Deep learning segmentation is a technique that involves categorizing pixels based on their similarity, which can be utilized in various applications. In this method, a neural network is employed to earn how to divide an image into distinct segments.

The network is trained using a set of annotated images, where each image is tagged with the appropriate segmentation. Image segmentation often employs Convolutional Neural Networks (CNNs or ConvNets), a type of neural network primarily utilized in image and speech recognition. CNNs feature a convolutional layer that is capable of reducing image dimensionality while preserving essential information. This makes CNNs an excellent choice for image segmentation tasks.

➢ *Feature Extraction:*

In machine learning, feature extraction involves converting raw data into numerical features that can be analyzed and processed, while still retaining the key information from the original dataset. This method is typically more effective than applying machine learning algorithms directly to raw data. In image processing, feature extraction is crucial for detecting patterns and structures within an image, enabling more efficient and accurate analysis.

Feature extraction involves identifying the most informative and concise set of features or patterns to enhance the efficiency of a classifier. Its primary objective is to extract features from the original signal, ensuring accurate and reliable classification. By selecting the most relevant features, feature extraction enables efficient processing and analysis of large datasets in machine learning, image processing, and other fields.

➢ *Convolutional Neural:*

- *Networks (CNNS):*

Convolutional Neural Networks (CNNs) are a type of deep learning algorithm primarily used in image and video processing applications. They consist of multiple layers that perform different tasks, such as convolutions, pooling, and classification. CNNs are designed to automatically detect features within an image or video, such as edges, curves, and other shapes, which allows them to classify and recognize objects accurately its layers can be shown in below fig-5. Unlike traditional neural networks, CNNs can process data with a grid-like topology, which makes them ideal for image analysis. One of the key advantages of CNNs is their ability to reduce the amount of preprocessing required. Instead of manually identifying features, such as edges or corners, CNNs can learn to identify them on their own through a process of trial and error. This makes them highly efficient and effective in analyzing large volumes of image data. Overall, CNNs are a powerful tool in the field of deep learning and have a wide range of applications in various industries, including healthcare, autonomous vehicles, and robotics.

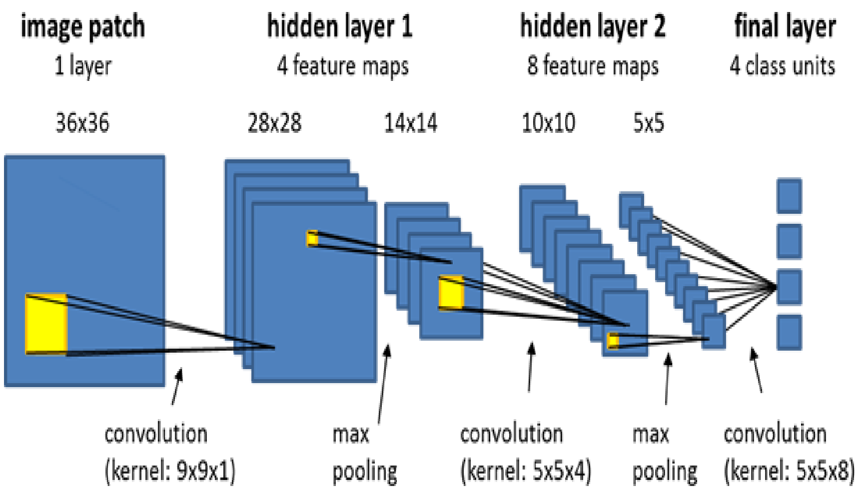

Fig 5 CNN Architecture

- *EFFICIENT B0:*

EfficientNet architecture shown in below Fig- 6 is based on a highly effective baseline network that was developed using a neural architecture search approach through the AutoML MNAS framework. This framework is capable of optimizing both accuracy and efficiency, measured in FLOPS(floating-point operations per second).The EfficientNet design, like other popular architectures like as MobileNetV2 and MnasNet, incorporates mobile inverted bottleneck convolution (MBConv). The EfficientNet design, on the other hand, is slightly bigger than these models, allowing it to make greater use of the given FLOP budget. EfficientNet is able to build a variety of models with varied sizes and computing requirements by scaling up the baseline network. This method enables EfficientNet to deliver cutting-edge picture recognition performance while staying very efficient and scalable.

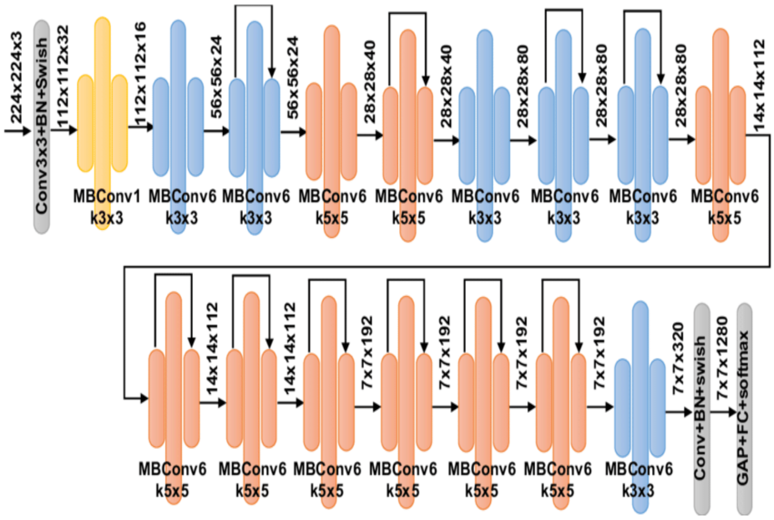

Fig 6 B0 Architecture

III. LITERATURE SURVEY

The use of CNNs (convolution neural networks) for the diagnosis of skin cancer has been suggested in [1]. In this study, the authors used the fundamental CNN architecture to forecast the output. Patch extraction, convolution, activation, pooling, and fully connected layers of CNN architecture are present. In the algorithm, they used the Rectified Linear Unit (Re Lu) activation layer. With a precision of 0.8375, this suggested approach had successfully identified skin cancer.

In [2], In general, the CNN approach necessitates a powerful computer and a lot of memory, which makes it challenging to use on a smart phone. In this study, an Android-based application that may identify skin cancer employs the MobileNet v2 and Faster R-CNN algorithms. An Android app was created in this study to use the smart phone camera for skin cancer screening. Faster R-CNN achieved higher accuracy when testing using the Jupyter notebook, while MobileNet v2 achieved the same high accuracy when applying on a smart phone, with an accuracy of 86.3%. Two testing techniques, the Android camera and Jupyter notebook, were used in this study.

In [3], Four separate categories of data augmentation techniques—geometrical modification, noise addition, color transformation, and picture mix—were used in a research described in this study. Furthermore, investigated is the several layer's data augmentation strategy. In this study, the ROI image mix performed the best when compared to other techniques, and single-layer augmentation outperformed multiple-layer augmentation approaches. Moreover, CNN has a classification accuracy of 82.9% for benign and malignant tumours.

The categorization of dermoscopy pictures to determine the type of Skin lesion, whether it is benign or malignant, is the main topic of [4]. A Convolutional Neural Network (CNN) model is developed to classify the images for lesion identification. To further improve classification accuracy, a batch normalised convolutional neural network (BN-CNN) is advised. The custom CNN model is similar to the proposed model except that Batch normalisation is not applied and Dropout is present at the Fully Connected layer.

[5] Makes a suggestion for using image processing methods to identify skin cancer. In this study, the patient provides a color image of the afflicted skin area, which is then processed using a variety of digital image processing methods. In the preprocessing stage, noise is removed using a median filter, and the resulting image is transformed into a Grey image and a HSI(hue, saturation, intensity) image. For boundary detection, active segmentation and texture segmentation are performed, and the grey level co-occurrence matrix (GLCM) approach is used to extract the necessary features. The classification of the skin lesion as benign or malignant is done using a probabilistic neural network (PNN) classifier and the grey level co-occurrence matrix (GLCM) approach is used to extract the necessary features. The classification of the skin lesion as benign or malignant is done using a probabilistic neural network (PNN) classifier.

In [6], analysis of various ANN architecture and the application of SVM for the classification of skin cancer images, together with the accuracy outcomes and performance, are reviewed. This paper mentions that the initial phase is obtaining images from datasets and for Dull Razor SOFTWARE is used to remove hairs from photographs during preprocessing, and contrast enhancement is a technique employed in this case to enhance the aesthetic appeal of images. Several segmentation algorithms, including ROI (Region of Interest) clustering and k-means clustering, were used in this study. Wavelet transform and GLCM functions are utilized for feature extraction. The techniques used for image classification include Artificial Neural Networks (ANN), Feed Forward Artificial Neural Network, Back Propagation Neural Network (BPN), Evaluation Metric of Classification Algorithm, and Usage of SVM. A basic description of how melanoma operates and is detected aids in the classification of normal and malignant skin cells.

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The PNN classifier in [7] uses segmentation utilizing thresholding and unique features retrieved to classify into melanoma, BCC, and SCC with an accuracy of 80%. This system improves image analysis using various pre-processing approaches for noise reduction and picture improvement.

IV. RESULTS

The lesion was successfully classified as benign or malignant using the suggested strategy, which utilised an efficientB0 classifier based on features retrieved. The dataset includes 300 malignant pictures and 360 test photos that are benign. With different train and test images, the classifier is trained or educated. By employing CNN (efficient B0), we were able to classify skin cancer with an accuracy of 87% after few modifications we got an accuracy of 90%. Also, the outcomes from the dataset for both benign and cancerous photos are as follows:

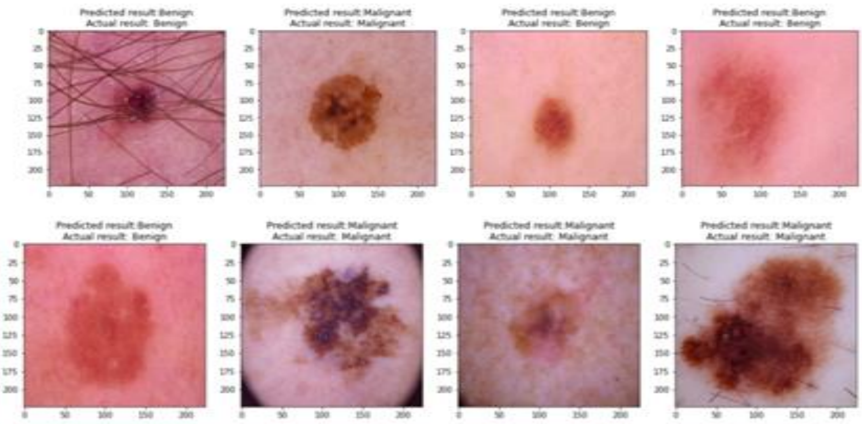

Fig 7 Results of Detecting the Type

- *Accuracy :*

```
[ ] accuracy_score(np.argmax(Y_test, axis=1), np.argmax(Y_pred, axis=1))

    0.8787878787878788

[ ] accuracy_score(np.argmax(Y_test, axis=1), np.argmax(Y_pred_tta, axis=1))

    0.9015151515151515
```

Fig 8 Accuracy

- *ROC Curve:*

A ROC curve (receiver operating characteristic curve) is a graphical representation of a classification model's ability to discriminate between positive and negative classes across all possible decision thresholds.

Sensitivity (True Positive Rate) and Specificity are two metrics that describe it (True Negative Rate).

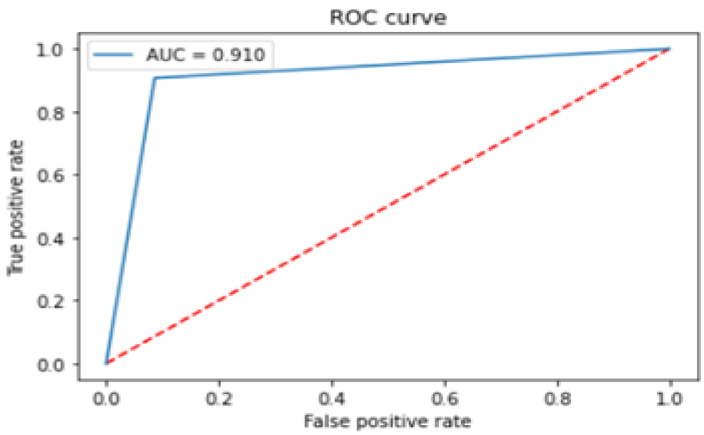

Fig 9 ROC Curve

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➢ *Confusion Matrix:*

A classification model's performance on a specific set of test data is assessed using a tabular representation known as the confusion matrix. Prior knowledge of the test data's actual values is necessary. The matrix, which clearly and orderly illustrates the model's faults, is also known as an error matrix. While the matrix itself is simple to understand, the related language might be more difficult. Fig- 10 and Fig- 11 below illustrate the confusion matrix before and after the adjustments.

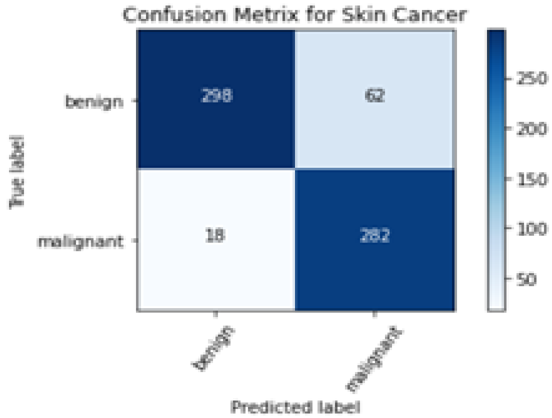

Fig 10 Before Modification

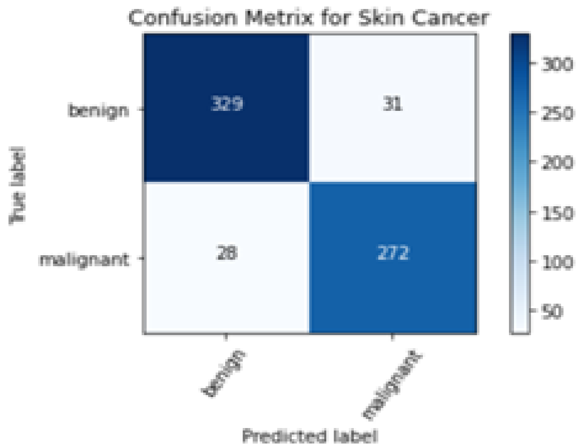

Fig 11 After Modification

V. CONCLUSION

This study outlined the distinction between benign and malignant skin cancer lesions. The suggested strategy helps to overcome the drawbacks of conventional techniques like a biopsy and lower the cost of diagnosing skin cancer. The suggested method can be used by both patients and doctors to distinguish skin tumors more accurately. In remote, rural areas where there may not be access to medical personnel, thistechnology may be more beneficial.

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