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A Deep Neural Network Approach to Detect and Classify Skin Cancer

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ABSTRACT- Among all cancers, skin cancer is one of the serious disease which effects major population across the globe. If the detection and diagnosis would not happen in early stages it can be spread to other body parts rapidly from sunlight because the tissues and skin cells get effected when exposed to sunlight. Although there are many systems available with the medical industry but this research is proposed to improve the performance of existing system by employing deep learning feature of Artificial Intelligence (AI) using Convolution Neural Networks (CNN), where Convolution Neural Networks (CNN) has been implemented using 3x3 and 5x5 matrix along with Graphical User Interface (GUI) generation so to provide better user experience (UX). This research accomplished the desired parameters with values to achieve 80.55% accuracy and 0.63% loss while training and testing the model. The research has been supported with the datasets from kaggle and International Symposium on Biomedical Imaging (ISBI) 2019 contest collection with 6,594 RGB photos. The data set contains nine clinical types skin cancer, such as actinic keratosis, basal cell carcinoma, benign keratosis, dermatofibroma, melanoma, nevus, seborrheic keratosis, squamous cell carcinoma, vascular lesions. The performance of the proposed research has been correlated and compared with the existing techniques i.e. Visual Geometry Group 16 (VGG16) and VGG19.

KEYWORDS- Skin Cancer, CNN, Deep Learning, Kaggle, Python.

I. INTRODUCTION

As an essential organelle in our body, the skin regulates our temperature as well as protect us from extreme temperatures and UV rays. Since the skin is the body's largest organ, the point here is that skin cancer is the most common type of cancer among humans [1]. As a result of overexposure to infrared rays (Ultraviolet), skin cancer begins while the derma cells remain destroyed. With 10,000 diagnoses and 1,250 deaths each year, skin cancer is now increasingly prevalent not only in the USA but also in other nations with a majority of Caucasians, such as the UK and Canada [2]. One of the most serious problems with skin in the body is the risk of disease, which can lead to skin cancer. Skin cancer grows in the skin's cells, which are the most integral elements.

A. Skin Cancer Classification

All skin tones, including those with darker complexions, are susceptible to developing skin cancer. People with dark skin tones are more prone to develop melanoma on the palms of their hands and soles of their feet, which are often not exposed to the sun. Overexposure to sunlight, especially when it causes sunburn and blistering, is the primary cause of skin cancer. The skin's DNA is harmed by ultraviolet (UV) radiation from the sun, which leads to the formation of aberrant cells [3,4]. These aberrant cells divide quickly and erratically to produce a mass of cancer cells. Skin cancer can affect people of various skin tones
It is generally classified into two major categories: melanoma and non-melanoma skin cancer. Melanoma is a dangerous, rare, and deadly type of skin cancer. According to statistics from the American Cancer Society, melanoma skin cancer cases are only 1% of total cases, but they result in a higher death rate. Early diagnosis is therefore crucial for skin cancer treatment. The biopsy approach is typically used by doctors to find skin cancer. Through this treatment, a sample of a potentially malignant skin lesion is retrieved for testing by a doctor. This process is painful, slow, and time-consuming. Skin cancer signs can now be quickly, comfortably, and more economically diagnosed thanks to computer-based technology. Several non-invasive approaches are suggested to investigate the symptoms of skin cancer to determine whether they are caused by melanoma or non-melanoma [5].

B. Skin Imaging Technique

Skin cancer is 90% curable in the early stages if it is discovered, compared to 50% in the late stages [6]. The accuracy of in-situ skin cancer or skin lesion diagnosis has grown with the development of non-invasive and high-resolution imaging techniques [7]. The main cause of overtreatment (resulting from false positive diagnosis) or under treatment for melanoma is the decreased diagnostic accuracy for the disease (caused by false negative diagnosis). False positive diagnoses are a major factor in the rise in treatment costs because they force surgeons to remove an excessive number of benign lesions for biopsy and pathological analysis. High-resolution imaging techniques, on the other hand, have the potential to greatly enhance diagnostic specificity, which opens the door to the prospect of causing a decrease in unnecessary excisions and associated costs.

- **Reflectance Confocal Microscopy (RCM):** Confocal microscopy is a non-invasive imaging technique that employs a laser focused on a particular area of the skin and allows in-vivo visualization of the cellular structure of the skin.
- **Optical Coherence Tomography (OCT):** OCT has the ability to discern between healthy and malignant tissue and can be used to examine microscopic structures (few mm) in vivo. The OCT, however, is unable to see the membrane and subcellular components, making it impossible to spot a tumour in its earliest stages.
- **Ultrasound:** One of the most popular non-invasive methods is ultrasound since it is adaptable, painless, and low risk. The ultrasonic waves that are reflected back from the tissue during this process can be used to see the morphology of the skin.
- **Dermoscopy:** A non-invasive, in-person technique for the early diagnosis of malignant melanoma and other pigmented lesions is dermoscopy, commonly referred to as epilumence microscopy (EM). It enables users to take pictures of the skin's hues and subsurface structures to find melanoma in its earliest stages.

C. Convolution Neural Network (CNN)

A crucial kind of deep neural network that is successfully applied in computer vision is the convolution neural network. It is employed for picture classification, gathering a collection of input images, and image recognition. CNN is a fantastic tool for collecting and learning global data as well as local data by gathering more straightforward features such as curves and edges to produce complex features such as shapes and corners. CNNs are employed in computer vision issues for two basic causes. First off, it can be difficult to solve the computer vision problem using typical NNs, even for very small images. A 750x563 monochrome image, for instance, has 422,250 pixels. This image would contain 1,266,750 pixels and the same number of weights if it were polychrome, in which case the number of pixels is normally multiplied by three, the usual number of colour channels. As a result, the total number of free parameters in NN rapidly increases, leading to overfitting and decreased performance. Additionally, compared to other image classification algorithms, CNNs require comparably little image pre-processing, which enables CNNs to learn the filters on their own.

As seen in Figure 1 various input and output layers, as well as numerous hidden layers, make up the CNN. Convolutional, pooling, and completely linked layers are frequently used as the hidden layers [8].

- **Convolutional Layers:** These layers pass the results of the input to the next layer. It simulates the response of a neuron to visual stimuli.
- **Pooling Layers:** These layers merge the neuron cluster outputs from the previous layer into a single neuron in the following layer. This layer's goal is to simplify network calculations and parameters.
- **Fully-connected Layers:** These layers link every neuron in one layer with every other layer's neuron.

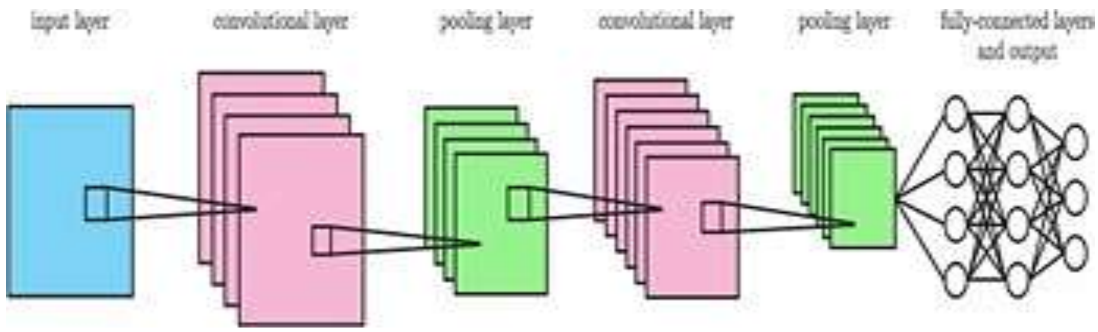

Figure 1: Example of a convolutional neural network

D. Real Time Implementation with GUI

The addition of a Human Machine Interface (HMI) enhances the model’s appeal to all users. It had a complicated helping page that let members to post photos in real time. As provided as the single image file is in.jpeg style, the image that must be provided can originate from any technique that focuses on the connectors on the flesh. The input picture is initially given to the framework, where it is obtained, before being sent to the Neural Networks. The system’s expertise is applied to that same result during the training cycle. The GUI then displays the following message: ‘The image submitted shows no signs of malignancy.’ Have no fear!’ If the picture is considered to be benign, say something like, “The image provided reveals some cancer signs!” Say something like, "The supplied image displays some cancer indicators!" if the image is deemed to be benign. If the model appears to be cancerous, one should get professional assistance. A website’s front-end the user interface was built with Bootstrap, a CSS toolkit that makes building web sites with Python straightforward. technique that focuses on the connectors on the flesh.

II. LITERATURE REVIEW

On this subject, a substantial quantity of study has been conducted. As a result, gathering and interpreting information, classifying it, and summarizing prior studies' results is critical. For a complete evaluation of recurrent convolution network-based collection skin cancer detection algorithms, relevant keywords are devised to discover anything that is useful.

D.Gutman et al (2016) [9] in the paper titled “Skin Lesion Analysis toward Melanoma Detection” proposed a research for automated diagnosis of melanoma, from dermoscopic images. Each image analysis task, such as lesion segmentation, dermoscopic feature recognition within a lesion, and melanoma classification, was broken down into a separate challenge.

Kawahara et al (2016) [10] in the paper titled "Deep Features To Classify Skin Lesions" used a linear classifier to classify 10 different skin lesions. Feature extraction was also performed using an AlexNet, whose last fully connected layer was replaced with a convolutional layer. This slightly modified AlexNet was tested using the public Dermofit Image Library which contains 1300 clinical images of 10 skin lesions. An accuracy of 81.8% was achieved based on the entire dataset of 10 different types of skin lesions.

Nasr-Esfahani et al. (2016) [11] in the paper titled "Melanoma Detection by Analysis of Clinical Images Using Convolutional Neural Network" implemented a two-layer CNN was trained from scratch for the differentiation of melanoma versus benign nevi based on clinical images. Only 136 images were used to train the model and the test dataset contained only 34 images. The images were all from the public image archive of the Department of Dermatology of the University Medical Center Groningen. The method achieved a sensitivity of 81%, a specificity of 80%, and an accuracy of 81%.

DeVries et al. (2017) [12] in the paper titled "Skin Lesion Classification Using Deep Multi-Scale Convolutional Neural Networks" proposed a multi-scale convolution neural network CNN using the concept of v3 deep neural network that was trained on an ImageNet dataset. For skin cancer classification, the pre-trained inception v3 was further fined-tuned on two resolution scales of input lesion images: coarse-scale and finer scale. The coarse-scale was used to capture shape, characteristics and overall contextual information of lesions. In comparison, the finer scale gathered textual detail of lesion for differentiation between various types of skin lesions.

Esteva A et al. (2017) [13] in the paper titled "Dermatologist-level classification of skin cancer with deep neural networks" has presented a landmark publication. For the first time, a CNN model was trained with a large amount of data, specifically 129,450 images, of which 3374 were obtained from dermatoscopic devices and represented 2032 different skin lesions. He proposed a new methodology of classification and detection of Melanoma/benign Keratinocyte carcinomas/benign SK using Deep Convolution Neural Network (CNN). The last classification differentiation was performed for both clinical and dermatoscopic images. The data sets where in the order of ISIC-Dermoscopic Archive. He studied Expert-l evel performance against 21 certified dermatologists. With his keen knowledge and testing the accuracy of this model turned out to be 72.1% of the order.

Noortaz R. (2020) [14] in the paper titled "Detection and Classification of Skin Cancer by Using a Parallel CNN Model" has suggested an automated technique for skin cancer classification. The study classified nine different forms of skin cancer and examined the effectiveness and prowess of deep convolutional neural networks (CNN). The goal was to create a model that uses a convolution neural network to identify skin cancer and categorise it into several classifications. Deep learning and image processing concepts were applied in the diagnosing methodology. The quantity of images has also increased through the use of various image enhancement techniques. The transfer learning strategy is then utilised to further increase the classification tasks' accuracy. The suggested CNN approach demonstrated accuracy of 79.45 percent, 0.76 weighted average precision, 0.78 weighted average recall, and 0.76 weighted average f1-score.

III. PROBLEM FORMULATION AND METHODOLOGY

A. Research Gap

Many studies have been conducted on the use of computer vision to identify skin cancer. Existing technology uses subjective, moderately, or automatic guns border detection approaches to split skin lesions in input images. The previous procedures for identifying this condition were done by hand and did not include any technology.

AI algorithms are now widely used for categorizing medical images, which is crucial for the diagnosis of many diseases. Currently available CAD systems rely heavily on high-quality, well-annotated data collected by specialized medical equipment. Therefore, the proposed methodology of classification and detection of skin cancer is done by using Python version 3.110 and Anaconda Navigator 2.2.0. There are various parameters on which the accuracy depends, such as number of training images, number of epochs, size of training images, hidden layers of CNN used, matrix, etc. However, the more the number of training images, the better accuracy is obtained.

Early skin cancer detection requires the deployment of efficient models and further research into the applicability of machine learning in healthcare environments. By using CNN to identify and categorize skin cancer, cases can then be sent to human experts for review, reducing their workload, saving their time and preventing further complications by starting treatment right away.

B. Objectives

- To study and analyze the cutting-edge photo classification technology to enhance people's lives by reducing the morality rate caused by skin cancer.
- To enhance the performance of skin cancer detection and classification system by implementing CNN.

C. Methodology

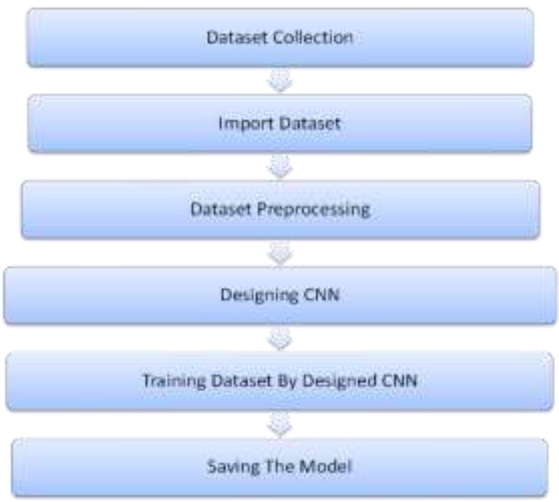

Figure 2: Flow diagram of training phase of the model

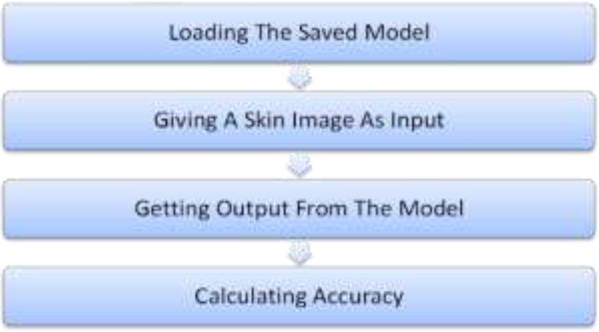

Figure 3: Flow Diagram of testing phase of the model

Figure 2 depicts the steps that are involved in training phase of the model and Figure 3 depicts the steps that are involved in testing phase of the model. The methodology of classification and detection of skin cancer using deep learning are as follows:

- **Collection of data set**: The dataset needed to train the model must be gathered. There are two ways to collect it. One entails taking pictures using a camera and compiling personal information. A different choice is to get information directly from a website or the internet. Even though both of these techniques are reliable, it might be challenging and time-consuming to obtain data on one's own.
- **Importing the Libraries:** It is necessary to create an environment that can run the code without causing issues before beginning the programming portion. The required libraries are downloaded, then imported into the code to establish the environment. The primary goal of developing and designing models is made easier by libraries.
- **Determining the path of dataset**: The dataset must be imported into the code for additional processing after it has been gathered and stored. In some situations, the obtained data must be processed before being used to train the model. The processing could involve image scaling, color adjustment, etc.
- **Pre-processing of data set:** The image acquisition method must be non-uniform in a number of ways. As a result, the primary objective of the pre-processing step is to improve image attributes like quality, clarity, etc. by deleting or minimising the undesired portions of the image or the background. The key pre-processing procedures are noise removal, image enhancement, and grayscale conversion. Figure 4 shows various stages involved in pre-processing step. All of the photographs in this suggested system are first made grayscale. Then, for image improvement and noise removal, two filter i.e. the Gaussian filter and the median filter are employed. The Dull Razor Method is employed along with filters to get rid of the unwanted hair from the skin lesion.

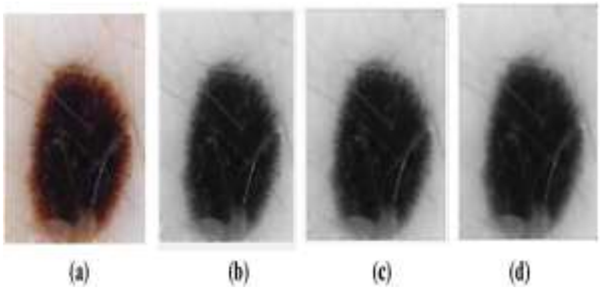

Figure 4: Pre-processing stage results, (a) Dull razor image, (b) Gray scale image, (c) Gaussian filter, (d) Median filter

- **Data Augmentation:** To start maximising our desired goals for training sessions and enhancing the classification outcomes, the ISIC sample was augmented with a range of impromptu alterations. Among the datasets used were size down sampling, tilting rotations, two vertical shifts, picture enlargement, and two vertical flips. In Figure 5 various skin images are altered via data augmentation.

Figure 5: Data augmented preview

- **Segmentation:** Segmentation is the process of dividing the image's region of interest. By assigning a comparable characteristic to each pixel in the image, this separation can be achieved. The key benefit is that, rather than processing the entire image, it is broken into manageable portions. The most popular method is to mark the boundaries of the specific area. The other methods, including thresholding, clustering, and region expanding, make use of similarity detection in the targeted area. Figure 6 shows various steps involved in clustering. Clustering is used in this instance using color-based k means.

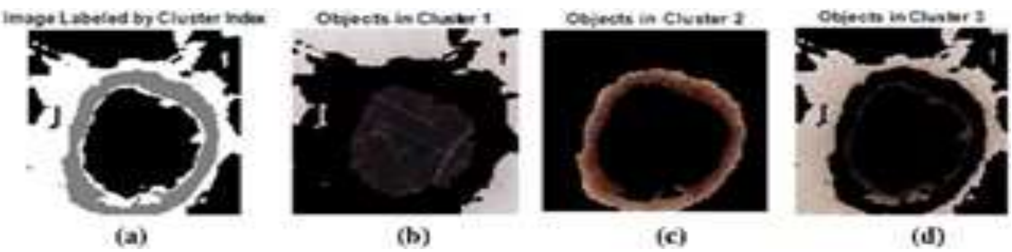

Figure 6: Segmentation results, (a) Image labelled by cluster index, (b) objects in cluster 1, (c) objects in cluster 2, (d) objects in cluster 3

- **Feature Extraction:** The most important step in the classification process is regarded as feature extraction. Feature extraction is the process of extracting pertinent features from the input dataset for use in subsequent computations like detection and classification. The features from the skin lesions are extracted by our suggested system using two techniques, ABCD and GLCM, and the results are merged. For further categorization purposes, features such the asymmetry index, diameter, standard vector, mean colour channel values, energy, entropy, autocorrelation, correlation, homogeneity, and contrast are generated.
- **Adding the pretrained ImageNet model:** The CNN model that was utilized in this study calls for a sizable dataset. However, the dataset gathered does not contain enough photos, necessitating the use of ImageNet, a pre-trained collection of photographs. It aids in feature extraction from the dataset but has no adverse effects on model training.
- **Visualizing the designed model**: To clearly understand all the layers involved into the model architecture, the CNN model is created and shown.
- **Training the model:** The model must now be trained after being designed. The dataset is fed into the CNN layers numerous times using a number of epochs, and in this method a suitable learning mechanism is developed and used.
- **Saving the model:** With regard to epochs, the pattern of losses and accuracy in training and validation is saved. The training process is ended and the model is saved if the training parameters and validation parameters, such as training loss, training accuracy, validation loss, and validation accuracy, do not improve as the number of epochs increases.
- **Testing the model:** By receiving a skin image (of any kind) as input and then confirming the image, the model that was previously saved is now tested on the testing dataset that has been given to it. The type of skin cancer is determined by the verification of the skin image. The output is obtained, and the corresponding accuracy and loss are assessed.
- **Plotting the graph:** The pattern of losses and accuracy in training and validation is depicted with regard to epochs. If the training parameters and validation parameters, such as training loss, training accuracy, validation loss, and validation accuracy, do not improve as the number of epochs grows, the training process is terminated and the model is saved.

IV. IMPLEMENTATION AND RESULTS

A. Implementation

Deep learning is the most common type of machine learning used to classify images using CNN. For this, the best library in Python is Keras, which makes it pretty simple to build a CNN model. Keras is also used in designing, training and testing. The other library used in this model is PyQt5, which helps to develop Graphical User Interface (GUI) for a desktop application in Python. The basic key elements of PyQt5 are widgets, layouts, labels, UI files, etc. Matplotlib is the other one which has been used. It is used to plot graphs. Numpy is used for performing arithmetic operation and transform data into arrays. Scikit-Learn is used to plot confusion matrix which is shown in the results section. After importing the libraries the function of each block is explained below.

Step 1: Initiate Generator

In the first step, “Initiate Generator” is used to provide the path for dataset.

Step 2: Setup UI

The second step “Setup UI” helps us to know about Graphical User Interface (GUI). This setup is used to set the location of various buttons of Graphical User Interface (GUI) software.

Step 3: Retranslate UI

In the next step, “Retranslate UI” takes the number of classes as input. It translates images and classes of the model and thus makes the model trainable.

Step4: Load Image

Then “Load Image” block takes the class names, model and learning rate as input.

Step5: Training Function

Further “Training function” helps to design Convolution Neural Networks (CNN). It takes the model, checkpoint, number of epochs and batch size as inputs.

Step6: Classify Function

In the next step, “Classify function” helps with the classification of various classes of the model.

Step 7: Plot Function

In the final step, “Plot function” takes model history, class names and number of epochs as input.

B. Results

The CNN depicted that reached accuracy of 97.70% with the validation accuracy of 80.55%. As the number of images being trained is increasing, the loss is decreasing and the accuracy is improving steadily. The completion of an epoch updates weights. The training was complete with an accuracy of 97.70%. Below is the testing result for different Epochs.

Table 1: For 5 Epochs and 8 classes

No. of Epochs	Time/ Step	Accuracy	Loss	Val Accuracy	Val Loss
1.	25s 613ms	58.31	6.24	62.48	0.9
2.	29s 700ms	65.08	0.77	71.06	0.68
3.	30s 725ms	73.47	0.66	76.72	0.63
4.	35s 861ms	76.80	0.58	77.49	0.56
5.	38s 938ms	78.14	0.49	79.48	0.48

Table 1 shows various parameters for training the model for 5 epochs and 8 classes. The parameters include time per step, accuracy, loss, validation accuracy and validation loss.

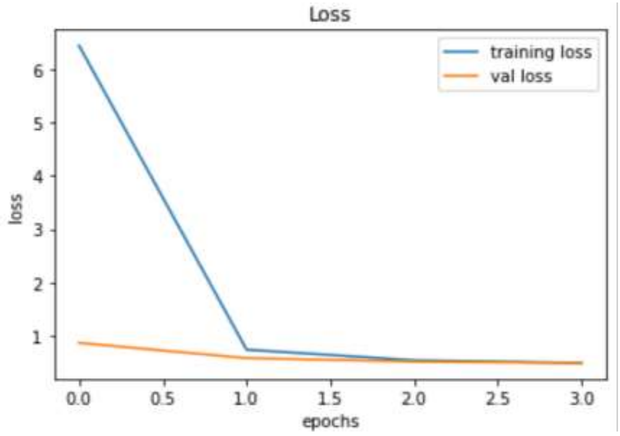

Figure 7: Graph showing accuracy and loss for 5 epochs

Figure 7 represents the graphs for training and validation loss for 5 epochs for 8 classes. X-axis represents the epochs and Y-axis represents loss percentage. The blue line represents the training loss and the orange line represents the validation loss. It is clear from the graph that the training and validation loss decreases as the epochs increase. However, the overall accuracy of the Test Set is 77%

Table 2: For10 Epochs and 8 classes

No. of Epochs	Time per step	Accuracy	Loss	Validation Accuracy	Validation Loss
1.	27s 650ms	59.34	11.57	62.48	0.77
2.	28s 678ms	67.15	0.74	74.73	0.65
3.	30s 733ms	74.92	0.62	77.34	0.56
4.	32s 777ms	76.76	0.52	75.34	0.55
5.	32s 772ms	76.84	0.55	78.10	0.51
6.	32s 770ms	74.89	0.57	77.79	0.53
7.	32s 782ms	79.99	0.45	77.03	0.51
8.	33s 795ms	79.90	0.41	78.56	0.48
9.	32s 769ms	78.37	0.49	75.37	0.52
10.	31s 762ms	82.73	0.39	77.18	0.49

Table 2 shows various parameters for training the model for 10 epochs and 8 classes. The parameters include time per step, accuracy, loss, validation accuracy and validation loss.

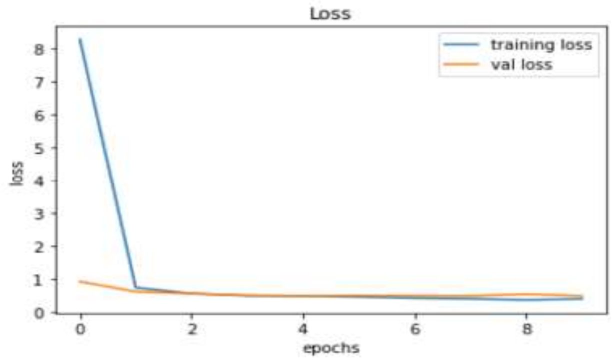

Figure 8: Graph showing accuracy and loss for 10 epochs

Figure 8 represents training and validation loss for 10 epochs for 8 classes. The Validation loss decreases over the increasing epochs. However, Validation loss increases slightly over increasing epochs. The overall accuracy on the Test Set is 78.56%

Table 3: for 20 Epochs and 8 Classes

Number of Epochs	Time per step	Accuracy	Loss	Validation Accuracy	Validation Loss
1.	30s 741ms	60.34	0.62	62.48	0.91
2.	32s 769ms	65.54	0.79	73.97	0.91
3.	32s 770ms	75.46	0.58	77.95	0.51
4.	32s 775ms	75.96	0.56	77.03	0.51
5.	32s 770ms	78.02	0.50	73.66	0.68
6.	34s 818ms	77.64	0.51	77.95	0.52
7.	31s 766ms	79.48	0.45	78.56	0.48
8.	32s 786ms	81.39	0.40	78.56	0.51
9.	32s 784ms	82.31	0.39	79.63	0.47
10.	33s 800ms	83.73	0.35	77.49	0.48
11.	32s 786ms	85.38	0.32	77.3	0.50
12.	32s 784ms	87.37	0.30	80.55	0.48
13.	33s 804ms	88.59	0.27	77.34	0.52
14.	32s 790ms	88.51	0.27	79.94	0.50
15.	35s 849ms	90.93	0.23	79.02	0.51
16.	36s 871ms	92.19	0.19	77.34	0.62
17.	35s 863ms	92.27	0.19	79.17	0.56
18.	35s 863ms	93.99	0.15	78.10	0.57
19.	35s 859ms	94.03	0.15	77.49	0.58
20.	37s 896ms	94.18	0.15	77.95	0.61

Table 3 shows various parameters for training the model for 20 epochs and 8 classes. The parameters include time per step, accuracy, loss, validation accuracy and validation loss.

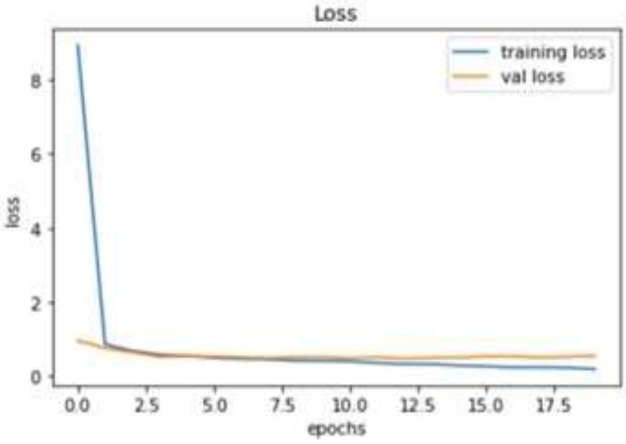

Figure 9: Graph showing accuracy and loss for 20 epochs

Figure 9 represents the graphs for training and validation loss for 20 epochs for 4 classes. X-axis represents the epochs and Y-axis represents loss percentage. The blue line represents the training loss and the orange line represents the validation loss. It is clear from the graph that the training and validation loss decreases as the epochs increase. However, the overall accuracy of the Test Set is 80.55%

Figure 10: GUI representation of skin cancer (Melanoma)

Figure 11: GUI representation of skin cancer (Basal Cell Carcinoma)

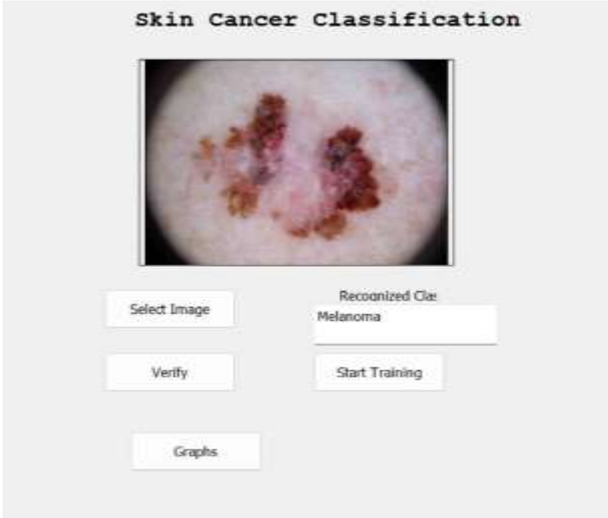

Figure 12: GUI representation of skin cancer (Melanoma)

Figure 13: GUI representation of skin cancer (Dermatofibroma)

In the past, models like VGG16, Support Vector Machine (SVM), ResNet50, and self-built models (sequential) have all been used to study how CNN models are formed. This system is based on CNN and GUI representation. Various results of GUI are shown in Figure 10, 11, 12 and 13 which display different types of skin cancer. It demonstrated the best accuracy and the least loss in the majority of the models. These designs perform differently as a result of the variations in layer counts. Based on their layers and working techniques, some features perform better than others.

The highest accuracy was noted to be over 80.55%, and the lowest accuracy was noted to be above 71%.

C. Comparison of results for various epochs

Table 4: Comparison of results for various epochs

Epochs	Accuracy	Loss	Val. Acc	Val. Loss
5	78.14%	0.49%	79.48%	0.48%
10	82.73%	0.39%	78.56%	0.48%
20	94.18%	0.15%	80.55%	0.48%
30	92.42%	0.18%	78.56%	0.47%
50	97.70%	0.06%	79.02%	0.48%

D. Comparison of Existing and Proposed Model

Table 5: Comparison of results for various epochs

S. No.	**Comparison on the basis of**	**Paper 1**	**Paper 2**	**Paper 3**	**Proposed paper**
1.	Model Used	SVM	VGG16	VGG19	CNN
2.	Output	Histogram of Oriented Gradients (HOG)	Bar charts	Bar charts	Graphical User Interface (GUI)
3.	Types of Skin cancer	7 types	7 types	7 types	8 types
4.	Accuracy	76%	69.57 %	71.19 %	80.55%

V. CONCLUSION AND FUTURE SCOPE

An increasing number of people in countries like Algeria are being affected by skin cancer, which is on the increase globally. One of the most lethal cancers is melanoma. However, malignant melanoma can be successfully treated if discovered in its early stages. If they receive treatment sooner rather than later, more patients will live. An algorithmic approach can help with early diagnosis because a malignancy's study area is prone to human error. This study suggests that dermatologists could diagnose skin lesions using Deep Learning technology. It investigated how to improve the performance of a multi-class classifier for spotting early skin lesions by using CNN to average an ensemble of binary models. Because there were so many uneven classes in the skin lesions dataset, a technique for creating fake pictures was developed.

In the suggested paradigm, skin cancer is detected using CNN and a user-friendly GUI. Later, this model compares the model with SVM, VGG16, VGG19 which has an accuracy of 76%, 69% and 71% respectively and discovers that CNN and GUI have discovered an accuracy of around 80.55%. Consequently, it was discovered that CNN performed better than SVM and other methods.

It may be worthwhile to look at squeeze-and-excitation blocks in the design as well as excess neural networks (RNNs), which have recently been shown to perform well on computer vision tests by recommending networks that are far deeper and simpler to modify.

The second issue is data; since CNNs need a lot of training data and the ISIC data set is uneven, it is believed that employing a Deep Rule-Based (DRB) technique to improve the performance of the classifier would be beneficial.

The effect of imbalanced data on model performance is reduced when the loss function is changed to Focal loss, leading to a more stable model.

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