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Skin Cancer Classification Using CNN

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Abstract: One of the most common illnesses on the planet is cancer. Cancer comes in many forms and affects different areas of the human body. Cancer kills nearly 5 million people each year, with skin cancer accounting for a significant proportion. The aberrant cell proliferation of the human body produced by the steady progression of physical, chemical, or biological carcinogens is known as skin cancer. Skin cancer is defined as aberrant skin cell proliferation that leads in neoplastic skin cell growth. There are four main types of skin cancer: actinic keratosis, basal cell carcinoma, squamous cell carcinoma, and melanoma. The mortality rate from melanoma skin cancer is significantly higher than that from non-melanoma skin cancer. There has been a consistent increase in both the incidence of melanoma and the number of cases analysed of non-melanoma skin cancers. Thus, skin cancer detection in its early stages is crucial for improving life expectancies. The goal is to use various forms of image processing and image recognition technologies such as segmentation and convolutional neural networks to create highly accurate and optimized versions of classifiers for various forms of skin cancer the categorization of skin problems is another highlight of this study.

Keywords: Skin Cancer, CNN, Mel, Histogram, Conv2D, MaxPool2D.

1. Introduction

Skin cancers is an uncommon improvement of pores and skin cells and has been beneath a big take a look at for decades. It, for the maximum part, creates in regions which can be provided to the solar, but it is able to be in likewise form in locations that don't normally gets solar openness. Two major styles of Skin most cancers are Melanoma and Keratinocyte Carcinoma. We would be using Neural networks for the detection of such cells. Companies using convolutional neural networks have several layers of artificial neurons. Synthetic neurons are a severe mimicry of their natural counterparts; they are numerical capacity that can evaluate the relative importance of various data sets and provide an initiation rating.

A visual inspection of a worrisome skin region is the first step in evaluating malignant lesions. The commonality of several lesion types necessitates accurate identification; also, diagnostic accuracy correlates. Without technology assistance, the dermatologist has a cure rate of 65-80% in melanoma diagnosis. Dermoscopy photographs, obtained with a specialised high-resolution magnifying lens, will be utilised to back up the visual evaluation if there is any doubt. During the recording, the lights are turned on. Skin reflexes are reduced by using controlled filters, which allows you to view a deeper layer of skin. Support can enhance the accuracy of skin lesion diagnosis by another 49% using this technology. An absolute melanoma detection is achieved by combining optic examination with dermatoscopy pictures. Typically, the CNN's initial (or base) layer recognizes important characteristics including flat, vertical, and sloping edges. Extra complex highlights, such as corners and an aggregation of edges, are extracted in the second layer, whose output is then sorted as a contribution to the primary layer's result. More advanced layers of the convolutional neural network can recognize more complex scene features, such as objects, faces, and more.

To pre-method the statistics and run our CNN version, we need a dataset. Skin cancer growth datasets ordinarily come in various formats and shapes including clinical pictures, henceforth, the information requires enormous endeavors for pre-processing before the auto-diagnostic assignment itself.

The **HARVARD HAM10000** data set was used for the analysis presented in this study. We will run our version in this and depict, with images, how pores and skin most cancers detection is executed the usage of photo processing. The consequences will inspire and encourage for destiny development and studies on line diagnosing of pores and skin most cancers in early stages.

2. Literature Review

Adaptive main curvature was used to detect and remove hair from images, colour normalisation was used to segment skin lesions, and the ABCD rule was used to extract characteristics for melanoma diagnosis. When it comes to recognizing hairs, the adaptive main curvature comes in help. To diagnose low-intensity skin lesions and lessen the effects of shadow and shade, colour normalisation is highly helpful. Melanoma is diagnosed by analysing the TDS score using the ABCD criteria. Each task, including hair detection, segmentation of skin lesions, and melanoma identification, as well as the overall recommended technique, is quite accurate and works well. The suggested approach has a flaw in that it was only tested on one individual, and the width of skin lesions is difficult to see throughout the shot. As a result, the information must be mined for the diameter

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of the skin lesions.

In this study, researchers R. S. Sanketh, M. Madhu Bala, P. V. Narendra Reddy, and G. V. S. Phani Kumar (2020) created a method for detecting cancer more quickly and accurately. A method for identifying and differentiating cancer. We were able to diagnose malignant and benign skin cancer with 91 percent accuracy using ISIC data. A specialist with years of expertise is a more realistic model. Fewer epochs are employed due to a shortage of hardware resources. Increase the number of epochs utilized to enhance efficiency. The total number of epochs and transitions that have occurred. Future work could involve integrating this approach with web-based or mobile paradigms. Without needing to go to the hospital, an application may be evaluated remotely.

D. C. Malo, M. M. Rahman, J. Mahbub and M. M. Khan (2022) The purpose of this research was to examine how well sophisticated convolutional neural architectures can distinguish between benign and malignant skin cancers. To assist specialists, these styles may be effortlessly integrated in dermoscopy frameworks or even on cellphones. To inspire change, extra various datasets (different categories, different ages) with numerous additional dermoscopy photographs and altered 6 checks according to lesson are required. It could be good to use the information of each image to increase the model's accuracy. 5636 is the new structured check range. The lookupset's accuracy is 0.875757576118816. The findings show that in the binary class of star freckle versus skin cancer, a CNN constructed using the approach presented in would not perform worse.

S. Pande et al (2018) analysed and evaluated CNN's most recent iteration, known as the capsule network, which is used for many different jobs.

Titus Josef Brinker (2018) using CNN which is already trained using some large dataset in which optimizes the performance of the neural network by tuning and optimizing the parameters and hyper parameters. This approach of optimization of a currently employed CNN is one of the most accurate and powerful system on the market. The downside in this case remains the lack of memory. In the future, we will be able to work in a hybrid network that includes CNN and LSTM performance, achieving skin cancer detection model accuracy as close as possible to a complete model.

S. Pande et al (2022) presented a shape and texture-based approach using KNN for classification of general images. The IDM and shape features used here are helpful for effective classification of the images.

Vedanti Chintawar and Jignyasa Sanghav (2018) Bolster Support Vector Machine (SVM) calculation and GLCM system. The proposed technique successfully detects the Skin cancer from images but more precise outcomes are possible. Deep convolutional neural networks (CNNs) indicate potential.

Cpsule Network based technique for medicinal leaf retrieval was developed by S. Pande et al. (2021).

Using images from several dermatological collections, A. Ech-Cherif, M. Misbhauddin, and M. Ech-Cherif (2019) developed a deep neural network architecture that is both efficient and suitable for usage on mobile devices. The created model was evaluated with various learning rates and stack size to determine the near-optimal hyperparameters that could be used in the prototype application. The total accuracy is 91.33 percent with a stack size of 32. Usingthe CoreML framework, the model was then converted to an iOS mobile application.

3. Proposed Methodology

(Fig 1) The primary emphasis of the skin cancer detection method is image enhancement and thresholding segmentation. While each of these approaches has its benefits, the accuracy of the final product is much improved when pre- and post-processing techniques are utilised in tandem with the basic algorithms.

Data Pre-processing- 1) Each individual image is resized. 2)Image will be converted into grayscale.

3)The features and labels are then separated into 2 different lists.

Image Processing - 1) Add gauss or salt-and-pepper noise based on the parameters passed.

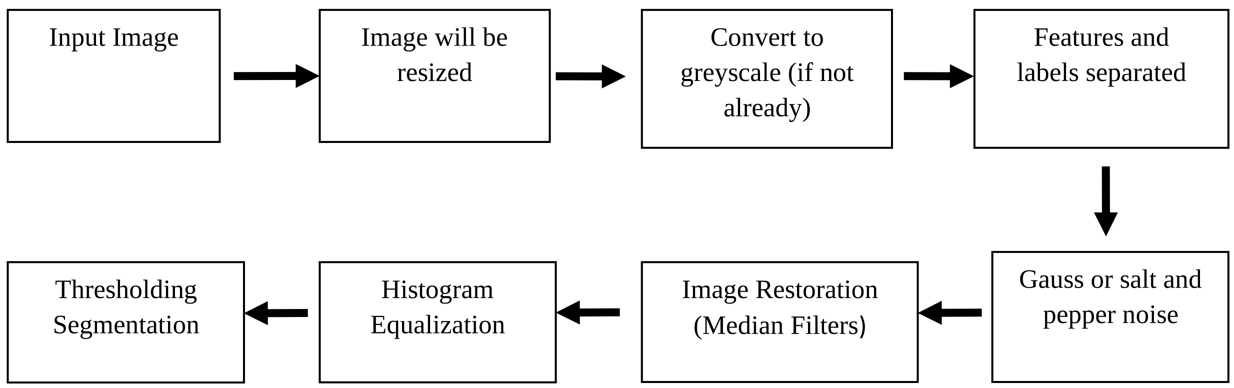

Fig. 1. Methodology Flowchart

Image Restoration- 1) Median filters might work the best from the three provided
noises. 2)Median filters are a type of non-linear digital filter that is often used to reduce noise in images and signals.

Image enhancement- 1) To improve contrast, histogram equalization is performed
to modify picture intensities. 2)An image may be represented by the function f as a mr * mc matrix of integer pixel intensities in the range 0 to L-1, where L is the maximum number of intensities that can be utilised in the image (which is 256).

Image Segmentation- 1) Thresholding segmentation will be used. 2)The dataset contains images having distinct tumor regions and background skin.

4. CNN Model

Convolutional Neural Networks (CNN) are a more advanced kind of neural network. With its use of normalisation, backpropagation, and gradient descent, CNN is a mathematical mastery technique worth studying. A convolutional layer, a pooling layer, and a fully connected layer make up a convolutional neural network (CNN). Because of their great overall performance, synthetic neural networks are recognized as appropriate responses to a variety of tough issues in photo processing and system vision. Gradient descent was used to minimize the error between the executed reaction from the community and the intended value in multilayer perceptron designs and other equivalent networks, which is a shortcoming of these networks. However, when gradient descent is utilized, the outcome is typically confined within the local minimum, resulting in a poor-quality international solution. When it comes to handling difficult circumstances, CNN has the power to be exceedingly green.

- **CNN Layers**

1) (Fig 2) Input Layer: As large images will require exponentially huge computation power in order to train. Therefore, we will resize the image to a 28x28x3 image.
2) The dropout layer ignores (randomly) a set of neurons. This is usually used to prevent the mesh from becoming too large.
3) The high-density layer is the conventional fully linked layer in a neural network. A dense layer fully connects the neurons in the neural network.
4) The flatten function takes a pooled feature map and converts it into a single column that can be sent to a fully linked layer. When you have a multidimensional output and want to make it linear so you can feed it onto a Dense layer, you utilize Flatten layers.
5) When training a deep neural network, the inputs to each layer are normalised on a mini-batch basis using a technique called batch normalisation. This helps to stabilize the learning process and drastically reduces the number of epochs of training needed to construct deep networks.
6) Conv2D class. 2D convolution layer- A tensor of outputs is produced by the 2D convolution layer by convolving a convolution kernel created by this layer with the input of the layer. When utilise bias is set to True, a bias vector is created and attached to the outputs. Finally, if activation is not None, it will be applied to the outputs too though.

When utilising this layer as the first in a model, provide the input shape (tuple of integers, excluding the sample axis) using the keyword parameter, for instance, input shape=(128, 128, 3) for 128x128 RGB images in data format="channels last".

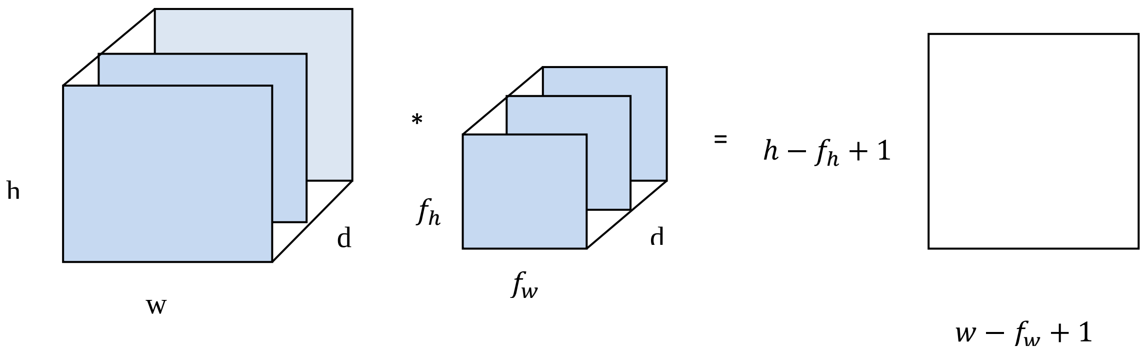

Fig. 2. Layers

- **Sequential Model**

A machine learning model called a sequence model accepts a sequence of data as input or output. Time series data, audio clips, and video sequences are all instances of sequential data. Recurrent neural networks (RNNs) are a standard technique for sequence modelling.

5. CNN Architecture

In feature extraction, a convolutional technique is used to isolate and catalog a wide variety of a picture's features for further examination.

An image's class may be predicted with the help of the characteristics recovered in the previous step and the output of the convolution layer, which is a fully connected layer.

It consists of -

1) Convolutional Layer-

This layer is the starting point for extracting features from the given image.

In this layer, we do arithmetic on the convolution between the input image and a filter with a size of MxM. Moving the filter across the input picture results in an inner product between the filter and the region of the input picture that is proportional to the size of the filter (MxM). The end result is a "feature map," which details the image by highlighting things like edges and corners.

2) Pooling Layer-

Usually, the pooling layer is placed after the convolutional layer. This layer's primary function is to reduce the size of the convolutional feature map for the sake of economy and efficiency.

In order to do this, we must disconnect the layers and handle each feature map separately. There is a wide variety of pooling processes available, each with its own set of benefits and drawbacks depending on the circumstances.

3) Fully Connected Layer-

Layers in the Densely Integrated (FC) layer are commonly connected using weights and biases to facilitate communication between neurons. In most CNN implementations, these layers are the final ones to be added before the output layer.

4) Dropout-

It's likely that the training dataset will be overfit if all features are connected to the FC layer.

When a model works well with the training data but not with the fresh data, it has overfitted. A dropout layer is used to address this issue.

5) Activation Function-

The activation function is a crucial part of the convolutional neural network (CNN) model. These are used to discover and measure a multitude of discrete and continuous relationships between network variables.Simply choose which model information to transmit and which information the network end will not boot.

ReLU, SoftMax, tanH, and Sigmoid are some of the most often utilised activation functions that impart nonlinearity onto a network. There is a specific purpose for each of these traits. Sigmoid and SoftMax functions are advised for usage in CNN models as binary classifiers, whereas SoftMax is often used for multi-class classification.

6. Optimizer Used

Adam Optimizer

Adaptive moment estimation is a method used in gradient descent optimization. When dealing with huge problems involving a significant number of data or parameters, this strategy is particularly effective. It is efficient and consumes little memory. It's a mix of the steepest descent method, the momentum algorithm, and the RMSP algorithm, on the surface.

The Adam Optimizer works in a similar way to a standard gradient descent algorithm. The distinction between Adam optimizer and gradient descent is that the learning rate in Adam optimizer is higher at first, but it drops as the number of completed epochs grows.

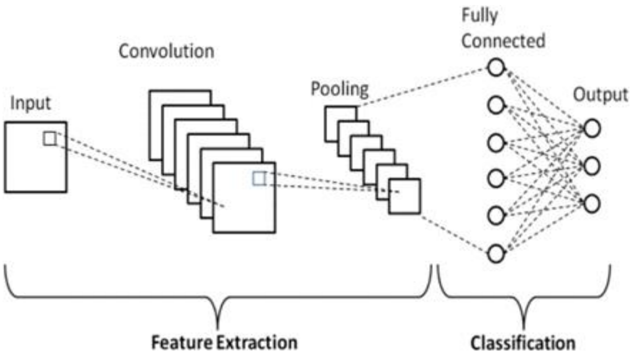

Fig. 2. Architecture

7. Plotting Loss and Accuracy

- **Model Accuracy**

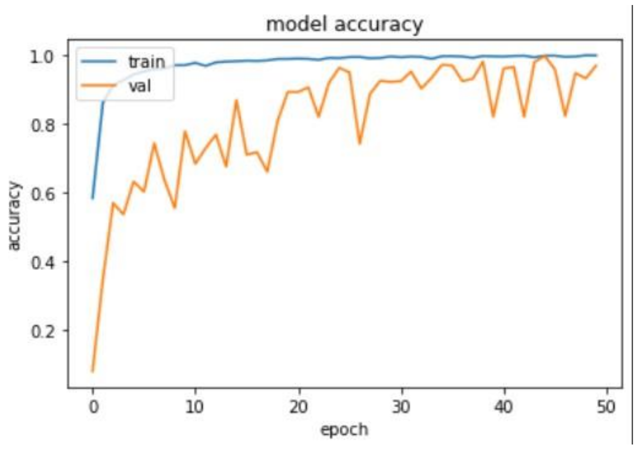

Fig. 4. Model Accuracy

We got the accuracy graph; in this we can see the model is been performing well and after every epoch the accuracy is increasing.

- **Model Loss**

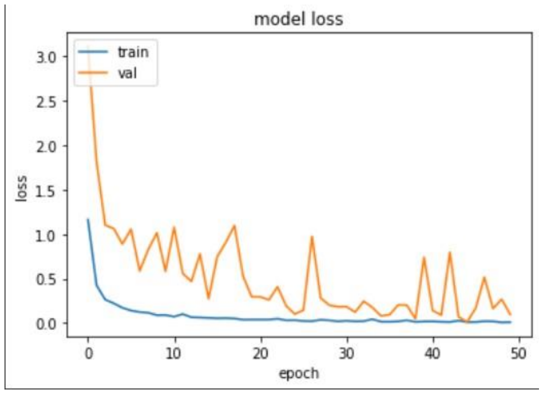

Fig. 5. Model Loss

As we can see in this graph the loss is continuously decreasing after every epoch, our model is performing well.

8. Results

1) We have created a web-based or mobile model. User can click a picture of his/her infected skin region and upload.

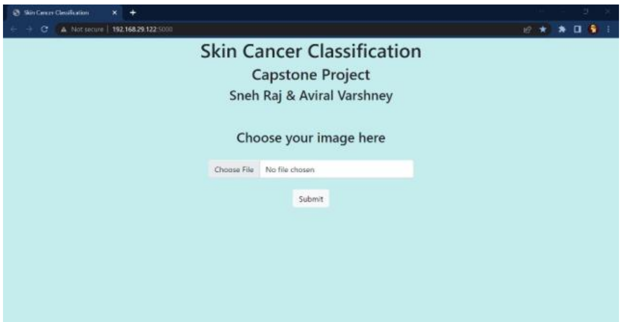

Fig. 6. Image upload page

Actinic keratoses and intraepithelial carcinoma, basal cell carcinoma, benign keratosis-like tumors, dermatofibroma, melanocytic nevi, pyogenic granulomas and haemorrhage, and melanoma are among diseases that may be recognized by this paradigm. After classifying the disease, the app can also show some information about the disease, and suggest the user to contact a dermatologist as soon as possible.

2) To check whether the person has skin cancer and which type of skin cancer we will take an image as an input and run it on our website.

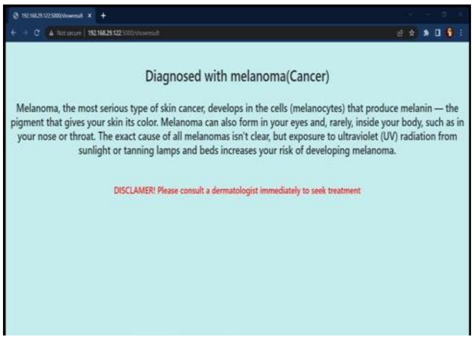

Fig. 7. Results

3) After uploading the input image, we got the result the results in the below figure as Diagnosed with melanoma.

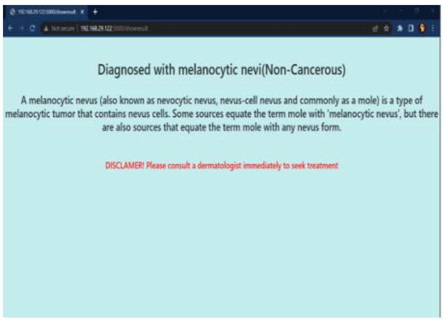

Fig. 8. Results

The image shows 2 of the 7 possible classes that our model can detect.

9. Test accuracy achieved

In this paper we have achieved test accuracy of 95.81%

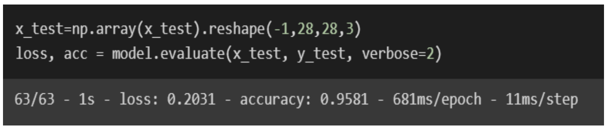

Fig. 9. Test Accuracy

10. Validation Accuracy

In this paper we have achieved 96.79% validation accuracy.

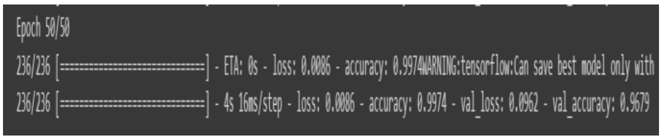

Fig. 10. Validation Accuracy

Initially, we discovered that the validation accuracy was too low after training our model (mid 50s). We then tried increasing the learning rate to see if it would help, but no luck. Then we came to know that the frequency of the classes was imbalanced (class melanocytic nevi had a far greater frequency than others).

To correct this, we used RandomOverSampler to equalize the frequency of the classes. The frequency of the classes before and after random over sampling is depicted in the graphs below.

Before Random Oversampling –

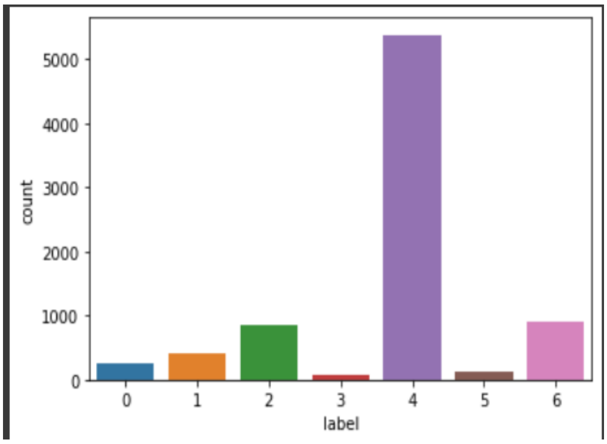

Fig. 11. Before Random over sampling

After Random Over Sampling

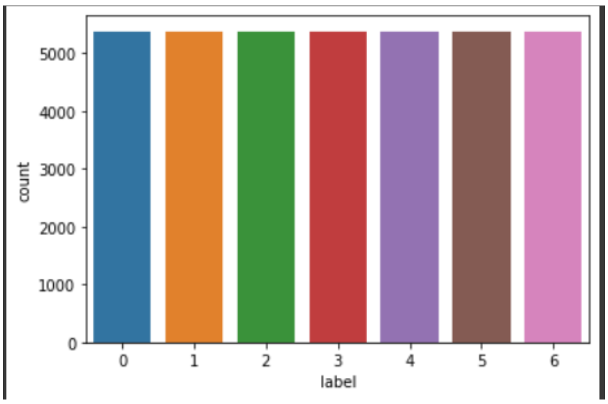

Fig. 12. After Random over sampling

11. Performance Evaluation

After making a reasonable front end and back end and considering the exactness of above 90 %, the result got has demonstrated to be correct and can be relied upon.
We have 7 classes of skin malignant growths thus far; the model has been performing especially well. Upon additional testing with various pictures, the precision ended up being something similar and the model gave right result.
The CNN layers utilized alongside sweeping data-set isolated into both, preparing and testing, can be credited for acquiring this high exactness. Besides the fact that the site analyzes precisely, expansion of highlights, for example, meaning of the sickness and how deadly it tends to be, gives an understanding to the clients that can help them towards the correct course to seeking the treatment they require.
R. S. Sanketh, et.al [2], has mentioned their accuracy is 85% but, in this method, we achieved the accuracy of 95%.

12. Conclusion and Future work

The paper's major objective was to create a highly accurate model that could detect different forms of skin cancer. We have created a superior skin cancer detection model using CNN along with a website. We could conclude that depending upon the training/validation, split and the accuracy of the paper was above the 95% mark.
For future work, we can incorporate several image processing models which will enhance the image quality and give even higher accuracies. Also, we can add more functionalities to the website to make it more user friendly such as giving the doctors contact details, name of the closest hospital etc. Not only this, we can expand our reach to different types of cancer and provide a common framework for all cancer diagnosed patients and help them overcome this lethal disease. However, despite all this, it is advised to get the doctors expert opinion irrespective of the model's diagnosis.

Conflicts of Interest

The authors state that they have no competing interests. The authors additionally certify that they have not submitted, and will not submit, any of the material included in this thesis for consideration in another journal.

Author Contributions

Conceptualization, Aviral and Sneh; Methodology, Aviral and Sneh; Software, Aviral and Sneh; Validation, Dr. Abhishek G; formal analysis, Sneh and Aviral; investigation, Sneh and Aviral; resources, Sneh and Aviral; data curation, Sneh and Aviral; writing—original draft prep, Sneh and Aviral; writing—review and editing, Sneh and Aviral; visualization, Sneh and Aviral; supervision, Dr. Abhishek G; project management, Dr. Abhishek G;

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