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Advancing Melanoma Diagnosis: A Computer-Aided Diagnostic Approach for Enhanced Precision

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***Abstract:** Melanoma, a dangerous type of skin cancer, is now the ninth most common cancer. Detecting it early is crucial for easier treatment. Dermoscopy, a common method that magnifies skin lesions for examination, relies on the skill of trained professionals. This limits its use to those with extensive training. To overcome this, our research suggests using a Computer-Aided Diagnostic (CAD) system. This system has a user-friendly interface, making it accessible for dermatologists with limited training. Unlike traditional methods, our study shows that CAD not only supports skilled professionals but also provides a reliable second opinion in identifying melanoma. This research aims to improve the accuracy of melanoma diagnosis, making it more accessible and precise for better patient outcomes.*
***Keywords:** Melanoma, Dermoscopy, Computer-Aided Diagnostic, Cancer Diagnosis, Skin Cancer, Imaging Procedures, Diagnostic Tools, Precision Medicine, Early Detection*

I. INTRODUCTION

Melanoma is the most dangerous kind of skin cancer. It is now placed ninth on the list of cancers that affect the most people. If indeed the melanoma is caught at an early stage, there is a potential that it may be treated with a more straightforward surgical procedure [1]. One of the most common imaging procedures used by dermatologists is known as dermoscopy. It amplifies the surface of the skin lesion, making its structure more obvious to the dermatologist so that they may examine it. Because the success of this method is entirely dependent on the visual acuity and expertise of the practitioner [1], it can only be utilised successfully by medical professionals who have received enough training. Because of these limitations, the scientific community is motivated to find novel methods for visualising melanoma and diagnosing it. Melanoma cancer may be diagnosed more accurately with the use of a computer-aided diagnostic (CAD) system. The CAD programme offers a comfortable and intuitive interface for dermatologists with little to no prior training [1]. In the process of identifying melanoma cancer, evidence from a CAD diagnostic tool could serve as a second opinion.

A. Background

These days, skin cancer is quite frequent. According to the information provided by the American Cancer Society, Inc., Surveillance Studies in 2020, it is anticipated that there will be a total of 100,350 new cases of skin cancer with melanoma [2]. Of these, there will be 60,350 male instances and 43,070 female instances. A total of 6,850 people will lose their lives to skin cancer this year, with 8,030 men and 3,450 women succumbing to the disease. This figure is projected to climb by roughly 2.5% [2]. On average, there are three different forms of skin cancer:

1) Basal Cell Carcinoma (BCC): It begins to develop at the base of the epidermal in regions of the skin that are exposed to sunlight for extended periods. Since the progression of skin cancer is gradual, the disease is fairly simple to diagnose. Visually, a basal cell carcinoma may seem like a small, waxy, smooth, glossy, or light lump. Additionally, it may be red and have rough, dry, or scaly regions.
2) Squamous Cell Carcinoma (also known as SCC) is an additional kind of skin cancer. As is the case with basal cell carcinoma, it begins to form at the topmost layer of the skin. At an early stage, it had already spread to other parts of the skin. The primary distinction between BCC and SCC lies along these lines. Squamous Cell Carcinoma might seem to the naked eye as minuscule, smooth, microscopic lumps that are either brown or real.

The third and most serious kind of skin cancer is known as malignant melanoma (MM). It takes place in the cells known as melanocytes. Melanoma is a kind of skin cancer that may be identified by its visibly asymmetrical shape, uneven borders, and unusual colour [3]. There has been a sharp increase in the incidence of skin cancer. A melanoma is a kind of skin cancer that may be identified optically by a dermatologist utilizing dermoscopy.

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The dermoscopy method is an imaging technology that does not include any invasive procedures and is used to diagnose melanoma skin disorders. Melanoma is the most lethal kind of skin cancer, which is why it is the most common. Melanoma is the most deadly form of skin cancer, and its mortality rate is much higher than that of other forms of skin cancer disorders. Dermatologists are the primary medical professionals responsible for making diagnoses of skin cancer (Skin specialist doctor). Visual examination of dermoscopy [4] pictures enables dermatologists to make diagnoses of disorders related to skin cancer. Although he can identify the kind of skin cancer based on his years of knowledge, it is not possible to detect melanoma with a hundred per cent certainty, and there is a possibility that doing so might sometimes cause serious damage. In this context, the term "possible damage" refers to the performance of an unwanted procedure, such as taking a skin sample to examine lesions; however, the findings of such biopsies may not always point to the presence of skin cancer. And there are situations when doctors do not recommend having a skin biopsy, which may lead to death. Early identification of skin cancer results in a lower mortality rate and also reduces the amount of time needed for diagnosis, which speeds up the process of providing patients with more effective therapy [4].
For the purpose of melanoma automated detection, There are a variety of treatments available for skin cancer [3] because of advances in medical research. These days, however, the decision-making computerised automated skin cancer diagnosis is more beneficial. A survey is offered on several ancient and contemporary methods of skin cancer diagnosis in its early stages. The research community may benefit from this poll by learning more about the efforts of diverse researchers.

B. *Literature Review*

An automated melanoma diagnosis might be a beneficial tool for clinicians in their daily jobs by providing quick and cheap access to potentially lifesaving discoveries [5]. As a result of all of these challenges, the machine-learning community as a whole has come to the conclusion that melanoma classification is an area where significant progress has to be made [6]. A key component of modern machine learning is the application of statistical models to the task of education. These algorithms first adapt the parameters of the program to "train" the data, and then test the data under those conditions [6]. Prior to 2016, most studies focused on the standard machine learning pipeline, which consists of pre-processing, classification, feature extraction, and classification [5]. In addition, a fair level of understanding is always required for the extraction of features from cancerous photographs. The accuracy of classification may suffer as a result of improper segmentation, which can then lead to inaccurate feature selection [6].
2016 marks the beginning of a transitional period in the field of approaches for classifying skin lesions. This trend may be seen in the many techniques that were discussed during the 2016 International Symposium on Biomedical Imaging (ISBI). Instead of using conventional machine learning techniques, all of the writers in the research relied on convolution neural networks (CNNs) [7], a kind of deep learning. Tang et al. [8] summarise the few options for visual skin cancer diagnosis. This study's findings are applicable beyond the diagnosis of melanoma to the photographic documentation of many other cancer types. The number of studies examining how to detect melanoma in this publication was rather low. Moreover, Dang et al. [9] have released a work where they introduce many deep learning methods and analyse several benchmark datasets. Nevertheless, it lacked details on datasets that had not been made public and could not be downloaded from the web. Brinker et al. [10] have also performed a thorough review of the literature on the issue of utilising CNNs to detect skin lesions. This piece offers a concise summary of the various approaches to deep learning. The fact that this research did not disclose any information regarding the datasets was, however, the most significant weakness of the study.

II. METHODOLOGY

A. *Part 1 – Skin cancer images dataset*

The set of models that are used in this research is mentioned below:

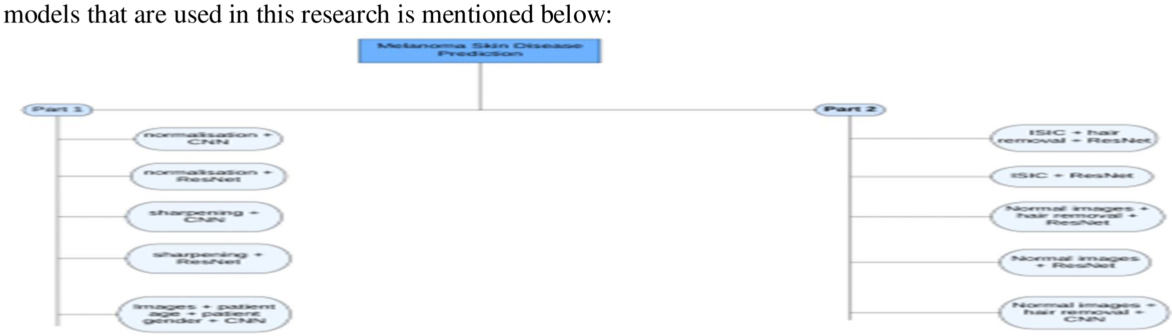

Figure 1: Models flow

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Set 1
Dataset: ISIC
Model 1: normalisation + CNN
Model 2: normalisation + ResNet
Model 3: sharpening + CNN
Model 4: sharpening + ResNet
Model 5: Images + patient age + patient gender + CNN
CNN Model
Here, in figure 1, the structure and flow of CNN model is displayed.

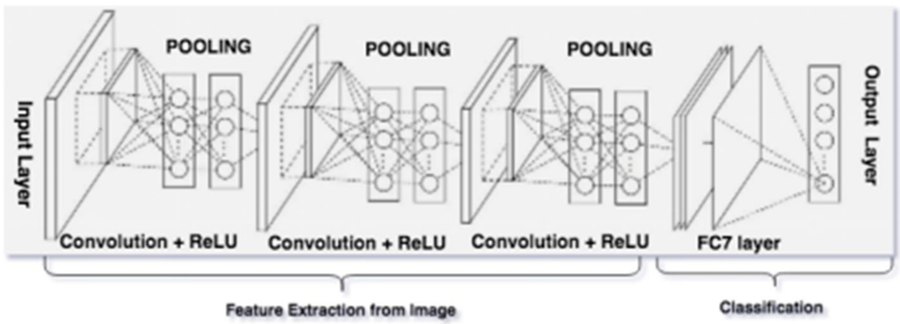

Figure 2: CNN working

ResNet Working
Here, in Figure 1, the structure and flow of ResNet model is displayed.

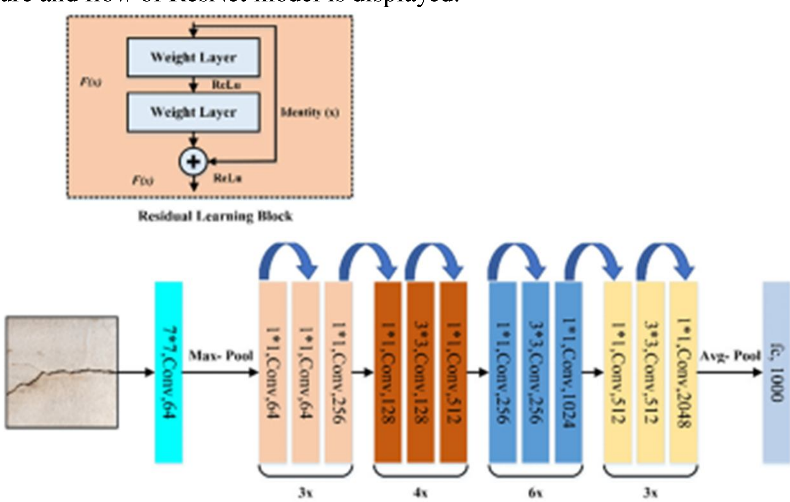

Figure 3: ResNet Working

Now all the steps leading up to creating these above models will be discussed. The dataset that was used here is https://www.cs.rug.nl/~imaging/databases/melanoma_naevi/, which is a normal image dataset. Contains 70 melanoma and 100 naevus photos from the digital image archive of the Department of Dermatology at the University Medical Centre Groningen and was used in the creation of the MED-NODE system for skin cancer detection from macroscopic photographs (UMCG). There are a total of 170 photos (70 melanoma and 100 nevi) in the 24KB complete mednode dataset.zip file.

Following is a presentation of the fundamental process that underpins conventional technologies based on the categorization of skin cancer images.

1) Image Acquisition: An image may be obtained by utilising a dermoscopy or any other digital camera. Several different databases are provided for the collecting of photographs of various kinds of skin cancer.
2) Image post-processing: Photo post-processing is the process of improving the form of an image as well as scaling an image [6]. To accomplish the post-processing of a picture, the sharpening of images is done.

Normalization was the next process that was carried out. Used in image processing, normalisation adjusts the range of image intensity to create a more visually appealing image. The term "normalisation" is used to describe the process of transforming an input image into a range of neighbouring pixels that are more sensory-typical. This is the normal goal of the tool. Picture normalisation is a procedure in computer vision in which the intensity values of an image are adjusted to a certain range, often to [0,1] or [-1,1]. Image normalisation is an important step in the creation of high-quality images. This guarantees that all the photos included within a dataset have the same scale, which may enhance the performance of machine learning models that use image data as input. The objective is to eliminate inconsistencies in size, lighting, and contrast to make it possible to precisely study and compare the aspects of a picture.

Sharpening of images is done to get clear images. The sharpening of photos may be accomplished in Python using a variety of methods including unsharp masked, high-pass filtering, and image convolution. One of the more common methods for sharpening a picture in Python is to conduct convolution with such a sharpening kernel. This increases the high-frequency elements of the image, which gives the impression that the image is sharper. Image sharpening is a technique used in machine learning (ML) to enhance the visual quality of images by improving their sharpness and clarity. Sharpening can be particularly useful when dealing with low-quality or noisy images, which can result from various factors such as low resolution, compression, or poor lighting conditions.

The process of image sharpening involves enhancing the edges and contrast of an image, which makes the image appear more detailed and distinct. It is common practice to do this by applying a filter to the picture, which boosts the high-frequency elements of the image while attenuating the low-frequency components of the image. The result is an image with more pronounced edges and clearer features. In ML, image sharpening can be used to improve the performance of image recognition and classification models. By enhancing the features of an image, the model can better distinguish between objects and patterns, which can lead to more accurate and reliable predictions.

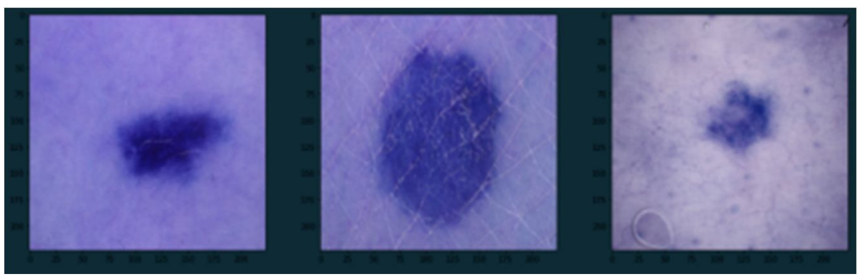

Figure 4: Image before sharpening

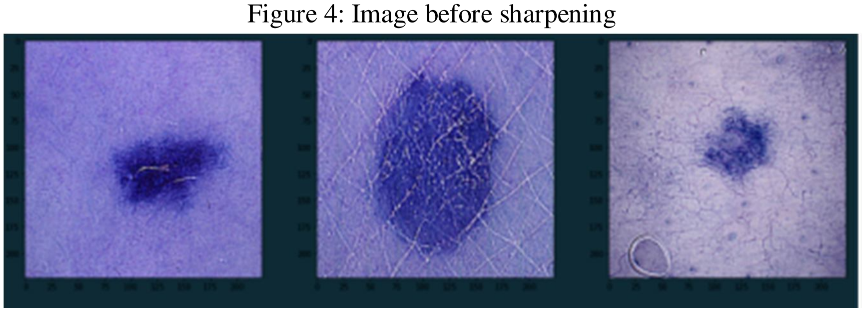

Figure 5: Image after sharpening

Additionally, image sharpening can also be used in image pre-processing and data augmentation, which are common techniques used in ML to improve the performance of image models. By sharpening the images in the training set, the model can be trained on high-quality images, which can improve its ability to generalize to new data. Overall, image sharpening is an important technique in ML for improving the quality and performance of image models. However, it should be used with caution, as over-sharpening can lead to artefacts and loss of information. Therefore, it is important to carefully evaluate the effect of image sharpening on the model performance and choose the appropriate parameters and techniques for the specific application.

B. Part 2 – Dermatology database

Set 2

Model 1: ISIC + hair removal + ResNet

Model 2: ISIC + ResNet

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Volume 11 Issue XI Nov 2023- Available at www.ijraset.com

Model 3: Normal images + hair removal + ResNet
Model 4: Normal images + ResNet
Model 5: Normal images + hair removal + CNN
In the second part of the code, the dataset was taken from https://www.cs.rug.nl/~imaging/databases/melanoma_naevi/ , the process that was followed was using hair removal from the images and then image augmentation to feed these images into the model. In part 2 of the code as well there are 5 models which are listed above.
In Figure 3, the images that are shown contain hair in them which will be removed using hair removal technique and augmentation.

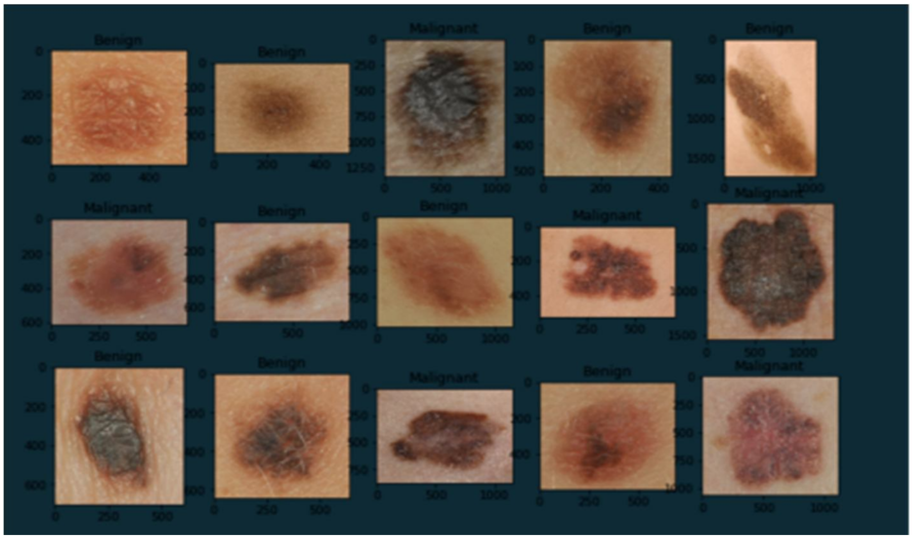

Figure 6: Images with hair

In Figure 4, the images obtained after hair removal of the skin disease images shown above in Figure 3. The image is clearly better now, and no hair can be seen in the images.

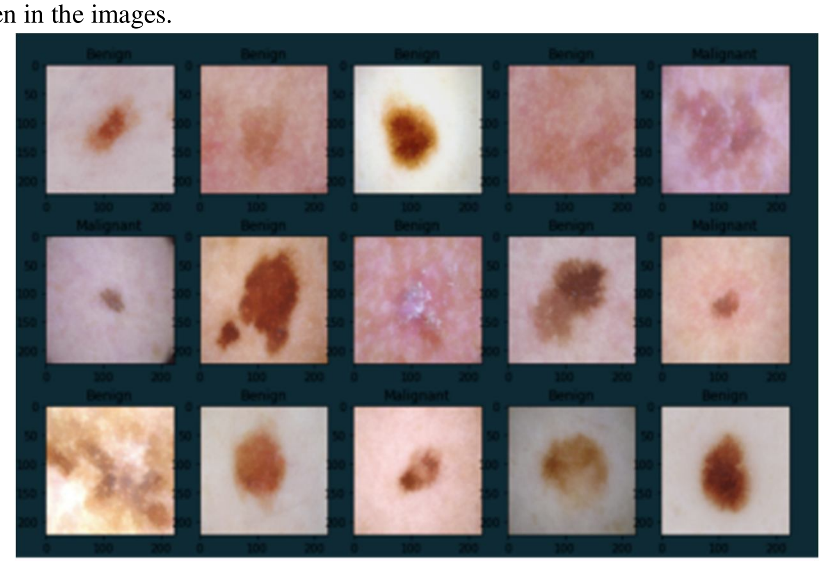

Figure 7: After hair removal

III. IMPLEMENTATION

To begin with the implementation process, the following set of models will be discussed:
Model 1: normalisation + CNN
Model 2: normalisation + ResNet
Model 3: sharpening + CNN
Model 4: sharpening + ResNet
Model 5: Images + patient age + patient gender + CNN

1) Model 1 – Normalisation + CNN

Convolutional neural networks, often known as CNNs, are a form of deep learning model that are frequently used in the field of machine learning for tasks including image identification, classification, and segmentation (ML). A convolutional neural network (CNN) is made up of many layers, including pooling layers, fully connected layers, and convolutional layers. In the convolutional layers, filters are used to identify features in the input pictures, and in the pooling layers, the features are downsampled in order to lower the dimensionality of those features. The predictions made by the fully connected layers are based on the characteristics that were retrieved.

Feeding a large batch of labelled pictures into the network and modifying the weights of the filters and layers is required in order to train a CNN. The goal of this procedure is to reduce the amount of variance that exists between the predicted labels and the actual labels. Backpropagation, which entails spreading the mistake across the network and modifying the weights appropriately, is the method that is commonly used to accomplish this task. In comparison to more conventional machine learning models for image processing, CNNs provide a number of significant benefits. One of the benefits is that they are able to automatically learn features from the photos, which decreases the need for manually designing characteristics. Another benefit is that they are able to handle pictures of varying sizes and shapes, which renders them more adaptable for a broad variety of image processing jobs. This ability to handle images of varying sizes and forms is an advantage. In general, convolutional neural networks (CNNs) are a strong and extensively used technology for image processing in machine learning (ML), and they have proven state-of-the-art performance in a variety of applications. Nevertheless, they may be computationally costly and need a considerable quantity of labelled data for training, therefore it is crucial to thoroughly analyse the cost and utility of employing CNNs for a particular application before deciding whether or not to use them.

Figure 3 shows that the CNN model is currently being constructed with the optimiser represented as "Adam," loss represented as "binary cross-entropy," and accuracy serving as the metrics. Twenty epochs have been allotted for use by the CNN model in total. Throughout the process of training a neural network, a neural network will make many passes over its training dataset. Each of these passes is referred to as an epoch. Iteratively, during the course of each epoch, the network will adjust its weights and biases in accordance with the deviation that exists between the output that was anticipated and the output that actually occurred. This mistake is intended to be reduced during the course of the training of the neural network, and each epoch represents a step in the direction of accomplishing that objective.

```
model.compile(
    optimizer = 'adam',
    loss = 'binary_crossentropy',
    metrics = ['accuracy']
)

history = model.fit(
    train,
    epochs=20,
    validation_data=val
)

model.save('../models1/cnn/with-sharpening.h5')
```

Figure 8: CNN model

An accuracy score is a statistic that is used in the field of machine learning to assess the effectiveness of a classification model. It does this by calculating the proportion of accurate predictions that the model produced based on a given test set. The ratio of the number of cases that were properly categorised to the total number of examples that were included in the test set is what is used to determine the accuracy score. The final accuracy of the CNN + normalisation model is 0.83 and the validation accuracy is 0.80.

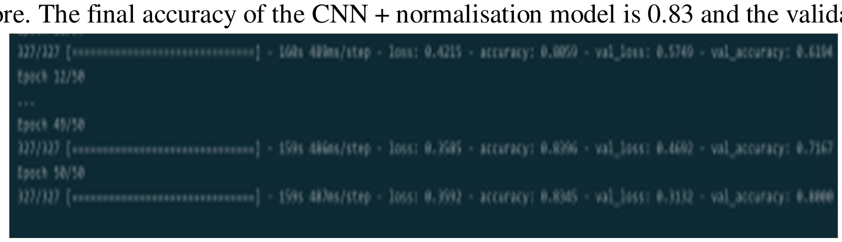

Figure 9: CNN accuracy

2) Model 2: Normalisation + ResNet

A deep neural network architecture called ResNet was first developed in 2015 by Microsoft researchers. It was designed to address the issue of sluggish convergence or even performance impairment due to disappearing gradients in deep neural networks. The ResNet architecture is based on the concept of residual learning, which allows information to be directly propagated from one layer to another without being transformed. The idea is to add shortcut connections (also called skip connections) between some layers in the network so that the input to a layer can be directly added to its output. This helps to mitigate the vanishing gradient problem, as the gradient can be easily propagated through the shortcut connections.

Here, in Figure 5, the ResNet model is being built with optimiser as ‘Adam’ loss as ‘binary cross-entropy, and accuracy as metrics. The total number of epochs set for the CNN model is 20.

```
model.compile(
    optimizer = 'adam',
    loss = 'binary_crossentropy',
    metrics = ['accuracy']
)

history = model.fit(
    train,
    epochs=20,
    validation_data=val
)

model.save('../models1/resnet/with-normalization.h5')
```

Figure 10: ResNet

The final accuracy of the ResNet + normalisation model is 0.75 and the validation accuracy is 0.58. These scores are very poor, and this model performs badly as compared to Model 1.

```
...
Epoch 19/20
327/327 [==============================] - 859s 3s/step - loss: 0.6267 - accuracy: 0.7521 - val_loss: 0.5887 - val_accuracy: 0.7361
Epoch 20/20
327/327 [==============================] - 876s 3s/step - loss: 0.5954 - accuracy: 0.7518 - val_loss: 0.6937 - val_accuracy: 0.5889
```

Figure 11: Accuracy

3) Model 4: Sharpening + ResNet

Here, in Figure 7, the ResNet model is being built with optimiser as ‘Adam’ loss as ‘binary cross-entropy, and accuracy as metrics. The total number of epochs set for the CNN model is 15.

```
model.compile(
    optimizer = 'adam',
    loss = 'binary_crossentropy',
    metrics = ['accuracy']
)

history = model.fit(
    train,
    epochs=15,
    validation_data=val
)

model.save('../models1/resent/with-sharpening.h5')
```

Figure 12: ResNet + Sharpening

The final accuracy of the ResNet + sharpening model is 0.88 and the validation accuracy is 0.88. This is much better as compared to other ResNet models.

Figure 13: Accuracy score

4) Model 5: Images + patient age + patient gender + CNN

This is the most important model as it is the most unique one. This model has included images along with patient age, and patient gender as attributes to be supplied to the CNN model. The structure of the model can be seen in Figure 9, it is evident that the layers of CNN start with Input later which is only one input and one output. It further goes to functional and then dense 6 input layer and finally, an output layer is formed at the end.

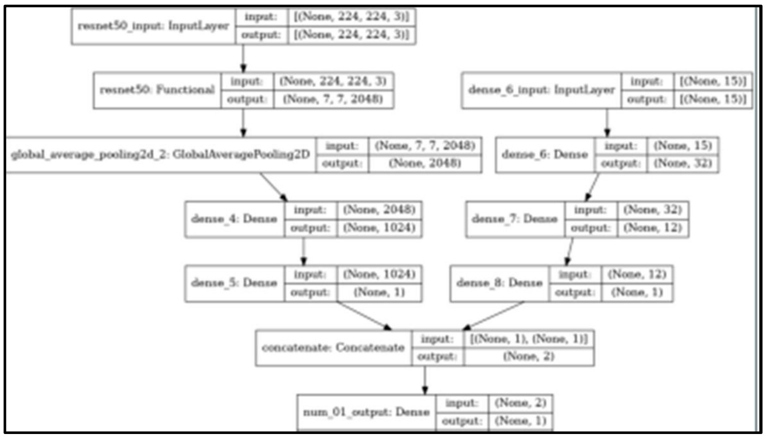

Figure 14: Model structure

From Figure 10, the model 5 accuracy score can be seen, it is 0.96 or 96% which is the highest score amongst the other 4 models. This model performs the best in terms of predicting skin disease not just with images but with additional features as well.

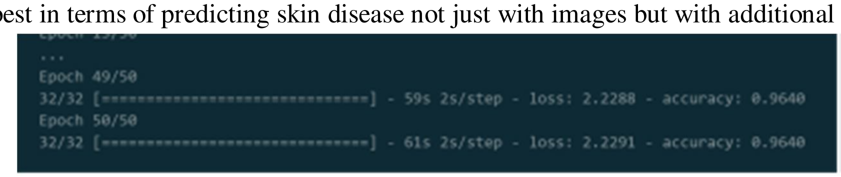

Figure 15: Model 5 Accuracy

Part 2 – Dermatology database

1) Model 1: ISIC + ResNet

Here the Resnet model is being implemented, the accuracy of this model is 0.98 or 98% which is quite good. But this model does not include the hair removal images which makes it less efficient.

Figure 16: Model 1 Accuracy

2) Model 2: Normal images + hair removal + ResNet

From Figure 14, the model 4 accuracy scores can be seen, it is 0.98 or 98% and validation accuracy is 1.00 which can signify that the model is overfitting, and it does not perform well.

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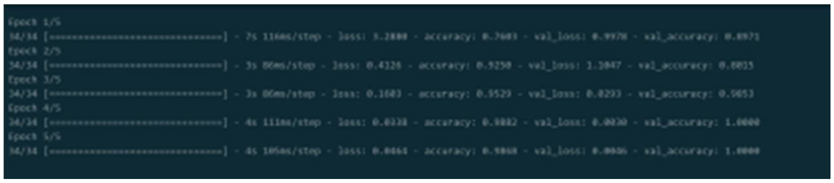

Figure 17: Model 2 accuracy

In machine learning, there are two approaches to gauge a model's efficacy: during training, accuracy is assessed via training, and during evaluation, accuracy is measured through validation. Training accuracy refers to how well a model performs on the data set it was trained on. Throughout the training phase, the model is given several opportunities to interact with the training data set, and its weights are adjusted in order to minimise the quantity of data that is lost as a direct consequence of the training procedure. The accuracy of the training is evaluated by comparing the outputs that are predicted by the model to the outputs that are actually generated by the training data set. This helps to establish whether or not the training was successful.

When referring to a model's "validation accuracy," one should understand that this word refers to the accuracy of the model when it is applied to a validation data set, which is a data set that is separate from the training data set. The validation data set is used to validate the performance of the model on data that has not previously been seen and to prevent overfitting. This is done in order to avoid the model becoming too specific to the data. During training, the performance of the model is evaluated based on how well it fits the validation data set. This helps ensure that the model does not inappropriately match the training data. Comparison of the model's projected outputs to the validation data set's actual outputs is another method for determining the correctness of the validation.

In an ideal scenario, the training accuracy and the validation accuracy should both be quite high. This would indicate that the model is correctly predicting the outputs for both the training data set and the validation data set. If the accuracy of the model in training is high but the accuracy of the model in validation is low, this may be an indication that the model is overfitting the training data and is not generalising well to new data. If the accuracy of the model is poor during both training and validation, this might be an indication that the model is not sophisticated enough to understand the patterns that are present in the data.

In Figure 15, the graph for training and validation accuracy is depicted to show what is the difference between both. It is clear from the graph that both training and validation accuracies are close to each other.

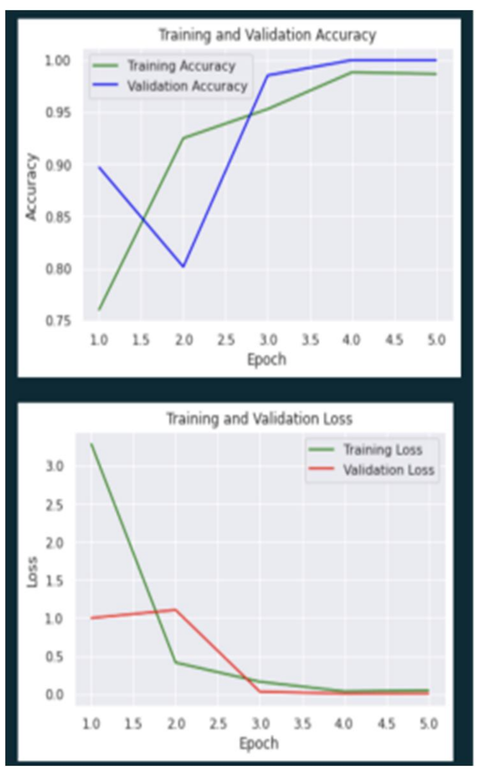

Figure 18: Accuracy graphs

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3) Model 3: Normal images + hair removal + CNN

From Figure 16, the model 3 accuracy scores can be seen, it is 0.98 or 98% which is the highest score amongst the other 4 models. This model performs the best in terms of predicting skin disease not just with images after hair removal.

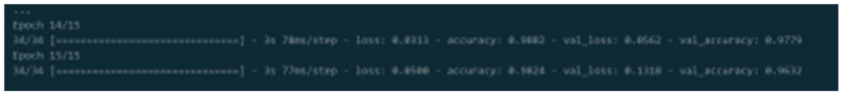

Figure 19: Model accuracy

In Figure 17, the graph for training and validation accuracy is depicted to show what is the difference between both. It is clear from the graph that both training and validation accuracies are not so close to each other.

Figure 20: Graphs

IV. CONCLUSION

From the given information, it can be concluded that different models were developed to predict skin diseases using various deep learning techniques such as ResNet and CNN. The ResNet architecture was used to address the problem of vanishing gradients in deep neural networks, and shortcut connections were added to the network to mitigate this problem. Among the five models developed, model 5, which included images along with patient age and gender as attributes, performed the best in terms of predicting skin diseases. This model achieved an accuracy score of 0.96 or 96%, which is the highest among all the models.

In the Dermatology database, model 3, which used normal images along with hair removal and a CNN architecture, performed the best, achieving an accuracy score of 0.98 or 98%. Model 2, which used normal images along with hair removal and a ResNet architecture, showed overfitting as the validation accuracy was 1.00, indicating that the model may not perform well on unseen data. Overall, the use of deep learning techniques such as ResNet and CNN in predicting skin diseases can be beneficial. However, the choice of model architecture and inclusion of additional attributes such as patient age and gender can significantly impact the performance of the model. It is important to carefully evaluate different models and select the one that performs the best on unseen data.

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