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Melanoma Skin Cancer Detection and Classification using Deep Learning

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Abstract: Melanoma is caused by abnormal growth of skin cells which is most often devloped on skin exposed to UV rays. It is less common but one of the most dangerous diseases in the world. Classifying skin lesions correctly at an early stage could avoid some types of skin cancers like melanoma and increases the chances of cure before cancer spreads. One of the efficient methods to accurately identify Melanoma is using deep learning. Deep learning methods such as AlexNet, Inception V3 were proposed in the past. In this project, other methods like MobileNet, CNN, ensemble method, ReNet, VGG16 will be used to detect the type of cancer using dermoscopic image data. Layers of these models are applied for fine-tuning which allows us to differentiate between different classes of skin lesions. There are two kinds of Melanoma, malignant and benign and we will also perform grading to early diagnose the disease which will ultimately increase the survival rate.
Keywords: MobileNet, Hybrid, CNN, TensorFlow

I. INTRODUCTION

Unchecked development of skin pigmented cells is one of the characteristics of skin cancer melanoma. It is one of the most lethal types of skin cancer and, if not found and treated quickly, can cause severe health issues. Using deep learning models is one potential method for melanoma detection and classification. Artificial neural networks are used in deep learning, a type of machine learning, to evaluate and learn from large datasets. Deep learning models can be taught to correctly identify and classify various types of melanomas by training them on large datasets of medical images of melanoma. Deep learning models can also be used to assess the severity of melanoma, which can assist medical professionals in making better treatment choices. The classification of melanoma skin diseases has been an active topic of research, with numerous studies suggesting various strategies to increase the precision and understandability of the classification models.

Deep learning model development for melanoma detection and classification is still an active research field, though. The need for big and diverse datasets. the interpretability of the models, and validation in actual clinical settings are just a few of the unresolved issues. Deep learning models have the potential to increase the precision and effectiveness of melanoma identification and classification in spite of these difficulties. If these models are successful, they could have a significant influence on melanoma early detection and treatment, improving patient outcomes. Convolutional neural networks (CNNs), for example, are a deep learning technology that may be used to automatically extract features from input photos. The performance of CNNs in melanoma classification tasks has been demonstrated to be very high, with many research obtaining accuracy rates above 90%.

II. LITERATURE REVIEW

The categorization of melanoma skin diseases has become a prominent research area in recent years, with numerous publications offering various techniques to increase the precision of classification models.

Scalability, computational power, and storage capacity are just a few benefits that cloud computing can provide for melanoma detection. Researchers have effectively processed massive volumes of data and trained intricate deep learning models by using cloud technology. Real-time analysis, remote access, and collaboration among healthcare experts are also made possible by cloud-based technologies[1]. The Dataset for ISIC 2019 which consisting of 25331 dermatoscopy pictures of skin lesions, was used by the authors to train and assess their models. There are two stages to the suggested hybrid strategy. In the first step, features from the input photos are obtained by employing a deep CNN model. In the second stage, the collected features are used to categorize skin lesions into benign or malignant using a traditional machine 4 earning method like support vector machines (SVMs).

The suggested method outperforms the current approaches with area under the receiver operating characteristic curve, sensitivity, specificity, and accuracy of 93.78%, 89.27%, and 0.975, respectively [2].

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Three most common types of skin cancer: melanoma, squamous cell carcinoma, and basal cell carcinoma the scientists trained a deep convolutional neural network (CNN) model. The International Skin Imaging Collaboration (ISIC) and the University of Heidelberg, among other clinics and sources, provided the dataset. The trained model's effectiveness in identifying skin cancer was compared to a panel of 21 board-certified dermatologists using a separate dataset of 514 dermatoscopic images of skin lesions. In contrast to dermatologists, the area under the receiver operating characteristic curve for the CNN model was 0.91 [3].

The ISIC 2017 dataset was used by the authors to train and test a CNN model, and they used approaches for data augmentation to increase the training dataset. Using metrics for accuracy, sensitivity, specificity, and AUC-ROC, they assessed the model's performance and contrasted it with other deep learning models. When compared to other machine learning techniques, the suggested CNN model performed better at melanoma detection and attained high accuracy and sensitivity rates. The model achieved 88%, 84%, and 89%, respectively, for accuracy, sensitivity, specificity, and AUC- ROC values. The authors also contrasted their CNN model with cutting-edge deep learning models like ResNet50, VGG16, and Inception V3 [4]. The dataset was subsequently processed using both conventional image processing methods, such as color-based segmentation and feature extraction, and modern methods, such as deep learning algorithms. The findings demonstrated that when compared to conventional methods, deep learning algorithms had a greater level of melanoma detection accuracy. The maximum accuracy, 94%, was attained by the deep learning method utilizing the Inception V3 model [10].

Deep learning methods including explainable deep learning. transfer learning, and CNNs have showed considerable potential in this field. A paper published by using a hybrid approach-2020 used technique to detect hair lines from the dermoscopic images is done based on the 2-D derivatives of Gaussian (DOG) of the blue component of the images. Otsu method is used for separating hair lines. For the lesion segmentation, we used morphological snakes. After extracting the texture features SVM, KNN and CNN are used. Compound coefficient method is used to enhance the ability to capture richer and much more complex features for melanoma recognition and transfer learning h3 ped the model to find better model weights for inference. EfficientNet on ImageNet to a new skin lesion image has been used for classification domain.

III. SYSTEM DESIGN AND IMPLEMENTATION

A. Data Set

The SIIM-ISIC Melanoma Classification dataset is a sizable, openly accessible dataset of skin lesion images that is frequently used in studies for the classification of melanoma skin diseases. It includes both benign and malignant skin lesions in its 33,126 photos. The dataset, which is accessible 12 for download on the ISIC website, was assembled by the International Skin Imaging Collaboration (ISIC) and 4he Society for Imaging Informatics in Medicine (SIIM).The images in the dataset were obtained using a variety of tools and imaging modalities, and they range in size and quality. The collection also contains meta-data that can be utilised to further analyse the photos, such as patient age, sex, and lesion location. With 22,934 photos in the 15 training set and 10,192 images in the validation set, the dataset is divided into training and validation sets. Out of these we have taken 1440 for testing and 8164 for testing.

B. Methods

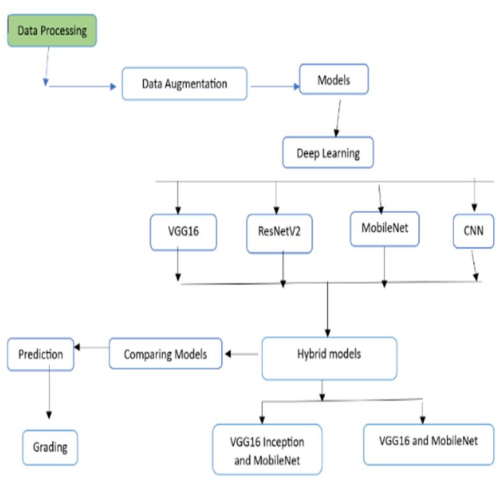

Figure 1: Architectural Implementation

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To create a reliable classification system for melanoma skin diseases, various procedures must be taken. First and foremost, gathering reliable data is crucial to the system's performance. To prepare the data for the model training process, it must be resized, normalised, and enhanced with additional data. The best model for classifying skin lesions has proven to be CNNs, and once chosen, the model must be trained using the preprocessed data. To make sure the model is accurate, its performance on a different set of data must be assessed. The model can be used to categorise skin lesions in a web-based application, once it has been reviewed and found to be satisfactory. By retraining the model on new data, performance may be continuously improved.

After building few models such as VGG16, Inception, Mobilenett, ResNetV2 and comparing it with Ensemble methods such as VGG16 and Mobilenett, VGG16, inception and Mobilenett. It was observed that mobilenett have achieved the greatest accuracy i.e., 92% among all the models built. Due to its minimal processing demands, MobileNet is a well- known CNN architecture for deep learning models. The initial stage in using MobileNet for the classification of melanoma skin diseases is to gather a high-quality dataset and preprocess it by scaling the photos to a particular size, normalising the pixel values, and carrying out data augmentation to enhance the dataset size. Next, the preprocessed data must be used to train the MobileNet model using methods like transfer learning or fine-tuning. Transfer learning entails utilising the MobileNet model's pre-trained weights on a sizable dataset like ImageNet before retraining the model's final few layers using the melanoma skin disease dataset. The entire model must be fine-tuned, and it must be retrained.

Our proposed method consists of the steps starting with data pre-processing followed by data augmentation then the model has been trained the data with different deep learning and ensemble models by compared the accuracies and by providing the testing images to the models in which the model will be predicting whether the predicted image as malignant or benign. Then the model which gave the highest accuracy i.e., Mobile net has been chosen as a base model to perform grading. By using the base model, the stage of cancer is predicted i.e., Stage 1 to 3.

The architectural implementation of our model is given below:

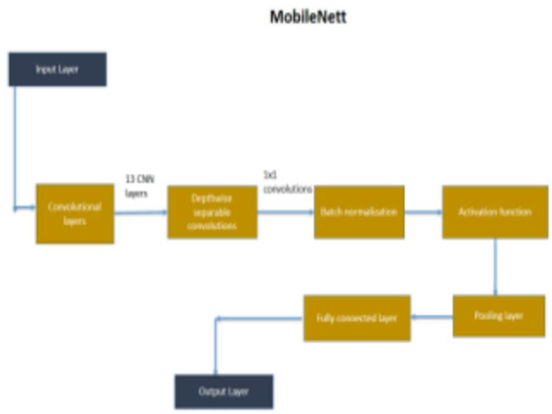

Figure 2-MobileNett

A convolutional neural network with a basic MobileNet architecture, also called MobileNetV1, is made up of a number of convolutional layers with depth wise separable convolutions. The fundamental design of MobileNet is as follows:

In Input layer 224x224 RGB images are commonly used as the input image for this layer and in the convolutional layer the input image is processed by 13 convolutional layers, each of which has a different number of filters and kernel sizes. The input tensor is halved in size in the first layer, which has a stride of 2. A stride of 1 is used in the other convolutional layers. D 15h wise separable convolutions: MobileNetV1 employs depth wise separable convolutions, which are made up of a pointwise convolution and a depth wise convolution. The pointwise convolution combines the result of the depth wise convolution using 1x1 convolutions, whereas the depth wise convolution applies a single filter to each input channel independently. Batch Normalizations: MobileNet employs batch normalization after each convolutional layer, which helps to normalize the layer's output and enhances the network's accuracy. Activation function: A ReLU activation function, which introduces non-linearity into the network and aids in the capture of more complex features in the input data, is applied to the out 14 of each batch normalization layer and in poolinng layer a global average pooling layer, which calculates the average value of each feature map in the output tensor, is applied after the last convolutional layer's output. Fully connected layer: The network's ultimate output is created by flattening and passing the output of the pooling layer via a fully connected lay.

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The MobileNet ModelNet parameters used are same as VGG16 and that of activation function I.e., Relu, the output activation functions were taken as softmax and sigmoid. All the top layers were trained with imagenet dataset, and the last layers are trained with our dataset. While training the model it is trained using adgard optimizer at a learning rate of 0.01. We took 10 epochs to train the model and defined all the parameters which are to be included for training the images. As a result, the validation loss was improved from epoch 1 to 7, for the 8th and 9th epoch the validation loss did not improve so on the 9th epoch learning rate was reduced. After that the validation loss did not improve for the 9th and 10th epoch and finally, we got an accuracy of 0.916 and a loss of 0.1987. Using the MobileNet model we have predicted whether the skin lesions images are malignant or benign. Out of 25 images only one image was incorrectly predicted.

Figure 3:prediction-1

By using ngrok tool for building secure tunnels to nearby development environments. streamlit have been used for building the website in which It takes the input of a skin lesion image and gives the output whether the image is benign or malignant and gives in which stage the cancer is.

With the help of the Python package Streamlit, interactive web applications can be easily made. Its user-friendly interface enables developers to quickly prototype and launch their apps, which is intended to streamline the process of creating data-driven applications. Web applications for data visualisation, machine learning, and other data-related tasks can be created by developers using Streamlit.

Figure 4:Prediction-2

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IV. RESULTS

S.NO.	Model name	Number of epochs	Validation loss	Validation on accuracy
1	VGG16	10	0.33	0.854
2	Mobile Net	10	0.19	0.921
3	Resnet	10	0.69	0.52
4	VGG16 and Mobile Net	10	0.21	0.90
5	VGG16 Mobile Net and Inception	10	0.26	0.88

From the above table we can analyze how well the models have performed on predicting the data. ResNet has performed the worst out of all the models it has misclassified most of the predictions which gave a loss value of 0.69 and the accuracy of 0.52. Other than MobileNet the other models have given decent results accuracy ranging from 0.85 to 0.90. MobileNet has given better results out of all the models with a validation accuracy of 0.921.

Figure 5:Confusion matrix of MobileNet model

The accuracy achieved was 92% after enabling early stopping and dropout regularization, with a precision of 0.95 recall of 0.88, and F1 score of 0.92. These metrics show that the MobileNet model is successfully identifying malignant melanoma from benign melanoma in melanoma picture classification.

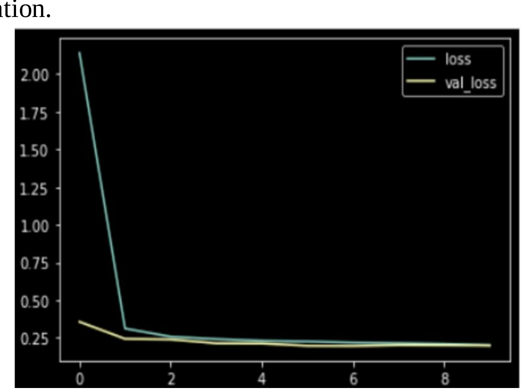

Figure 6:Loss curves of MobileNet

The loss curve in the provided loss graph begins at a rather high value and steadily declines over the duration of training epochs, as can be seen. This suggests that the model is evolving and making predictions that are more accurate with time. A positive indication that the model is successfully identifying patterns in the data is the decreasing trend. When we compare the training loss and validation loss curves, we can see that they both have a similar downward tendency.

Given that the validation loss is similarly falling and is not considerably larger than the training loss, this suggests that the model is not overfitting the training set. This may indicate that the model generalizes effectively to fresh, untested data.

Last but not least, while training goes on, the loss curve gradually flattens out at a low value, demonstrating that the model has converged and improved in performance. This is a good result since it indicates that the model is successfully identifying the underlying patterns in the data. We see a consistent rise in accuracy over the training epochs in the accuracy curve that is supplied. This shows that as the model gains knowledge from the training data, it performs better and generates predictions that are more accurate.The accuracy curve initially begins at a low value and steadily increases. This implies that the model could initially have trouble making accurate predictions but eventually improves as training goes on. The increasing trend shows how the model can identify underlying patterns in the data over time and produce more accurate predictions.

The accuracy curve achieves a high value plateau as the training epochs go on. This suggests that the model has stabilized its performance and is operating at its highest level of accuracy. The plateau means that the model has made good progress in generalization and is reliably producing precise predictions on both the training and validation data.

V. CONCLUSION & FUTURE SCOPE

Melanoma is a form of skin cancer that, if not found and treated quickly, can be incurable. Dermatologists employ a variety of methods, such as clinical examination, ceroscopy, and histology, to recognize and classify skin lesions.

The models generated in this project have produced encouraging results, with good accuracy in identifying benign and malignant skin lesions as well as in identifying the stage of the disease by using MobileNett. To create deep learning models for the classification of melanoma, numerous studies have been undertaken. These models used a variety of clinical, dermoscopic, and histological features that are derived from skin lesions. By identifying and categorizing skin lesions as benign or malignant using image analysis techniques, deep learning algorithms can compete in overcoming these constraints. To understand the visual patterns and traits that distinguish between benign and malignant lesions, these algorithms are trained on massive datasets of skin lesion photos with dermatologist annotations

The future scope for deep learning in melanoma classification is promising, and there are several potential directions for further research and development like, incorporating more representative and diverse datasets can help deep learning models perform better and be more generalizable.

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