MONITORING AND ANALYZING DIABETIC FOOT ULCER USING RESNET50 IN DEEP LEARNING

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Abstract

This paper introduces a deep learning approach using the ResNet50 algorithm within Google Colab to detect diabetic foot ulcers. Early identification of these ulcers is crucial to prevent leg amputations. Leveraging a diverse dataset, the model exhibits high accuracy and sensitivity, offering a cost-effective solution for timely intervention in diabetic foot ulcers, there by improving patient outcomes.

I) INTRODUCTION

Diabetic foot ulcers are a pervasive and serious complication among individuals with diabetes, often culminating in lower limb amputations. The timely identification of these ulcers is imperative to prevent such life-altering outcomes. This paper introduces a novel approach utilizing deep learning and the ResNet50 algorithm within the Google Colab environment to detect diabetic foot ulcers. Our research focuses on enhancing patient outcomes by enabling early intervention and treatment, thereby mitigating the need for amputations in diabetic patients.

II) PROPOSED SYSTEM

Proposed Methodology

The proposed method uses deep convolutional neural network models that includes different stages like the preprocessing augmentation, training the models applying different DL models & validation, and prediction

Augmentation of training patch

To function effectively, CNN needs a lot of labeled training data Furthermore, collecting a lot of medical data is expensive and challenging. To Get better performance and prevent overfitting, we used data augmentation approaches. In data augmentation, we used a variety of image processing techniques, including rotation, flipping, employing multiple color models, contrast improvement, and random scaling to create the desired effect.

Classification Models

Deep learning is the key technology behind a lot of high-end advancements like driverless cars, voice control in gadgets like tablets, smartphones, hands-free speakers, sensors, etc., and many more. The issue dealing with the current models is that the depth, width, and resolution are interdependent, and their values fluctuate depending on the available resources. ConvNets are difficult to scale, hence most traditional methods scale them in one of these dimensions.It is observed that all the models use Rectified Linear Unit (ReLU) as the activation function The ReLU activation function is a Straight for- ward calculation that gives an immediate response of the value entered or 0.0 ifthe input is 0.0 or less.

Train the modified ResNet-50 model on your labeled dataset. Use a suitable loss function, like categorical cross-entropy, to optimize the model's parameters.Monitor the training process with validation data to prevent overfitting. You can also consider techniques like early stopping to prevent training from continuing when validation performance starts to degrade.After training, evaluate the model's performance on a separate test dataset that it hasn't seen during training. Use metrics like accuracy , precision, recall, and F1-score to assess its performance.

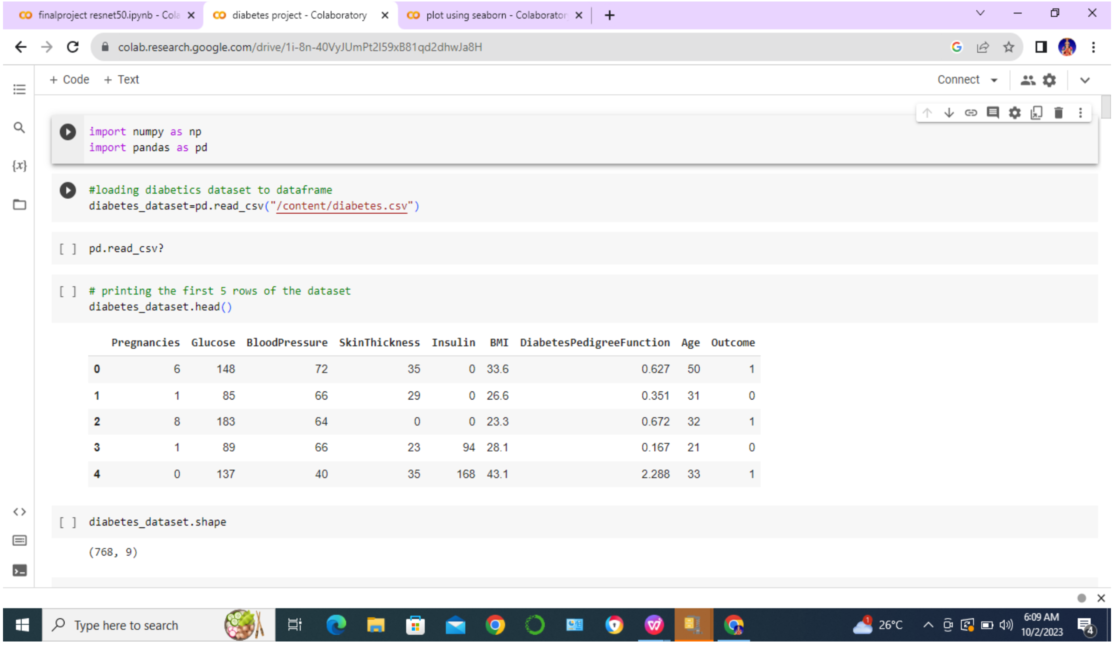
Fine-Tuning and Optimization:

Depending on the performance, you might consider fine-tuning the model by adjusting hyperparameters, modifying the architecture, experimenting with different optimizers.

Deployment and Real-Time Inference:

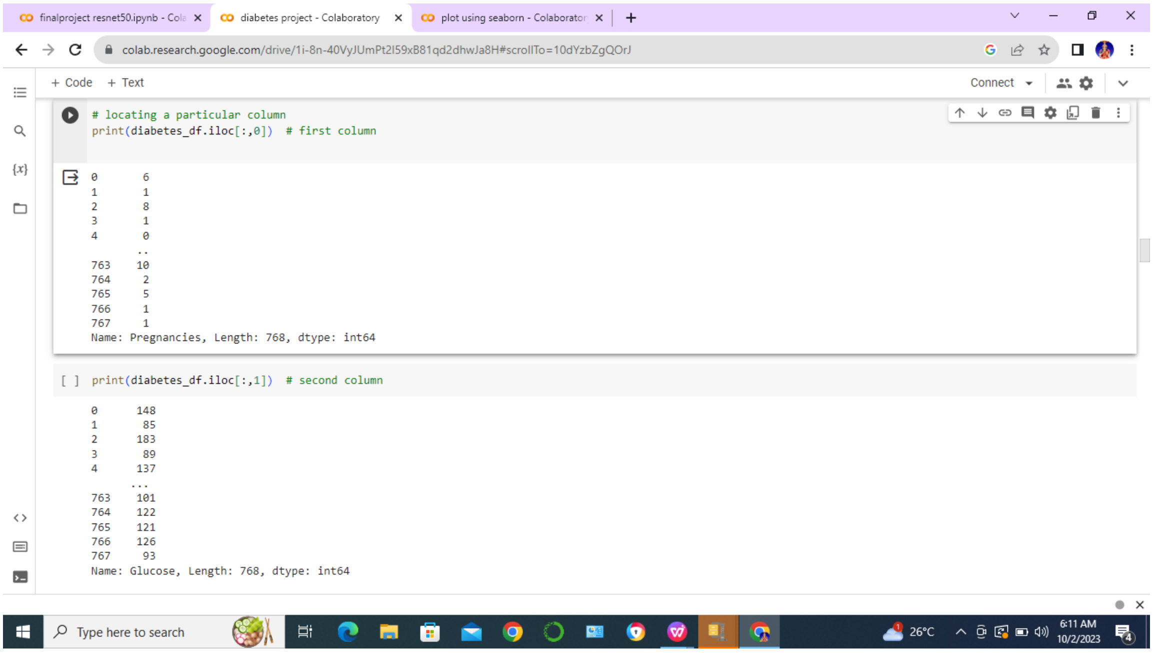
Once you have a trained model, optimize it for deployment on mobile devices or in real-time scenarios. Techniques like quantization and model compression can help reduce model size and improve inference speed. Remember that while ResNet-50 is a powerful architecture, success depends on having a diverse and representative dataset, thoughtful preprocessing, and effective fine-tuning. Additionally, explain ability and interpretability are important considerations, especially in medical applications, so it's valuable to visualize and understand how the model is making its decisions.

FIGURE 1



The above chart shows the Diabetic Dataset to display its head which shows the few rows of dataset it includes columns like patient information and health metrics such as BMI,Blood pressure,Age,Pregancies,Insulin and Outcomes.

FIGURE 2



The chart shows the location of rows and column of particular field of diabetic patient history

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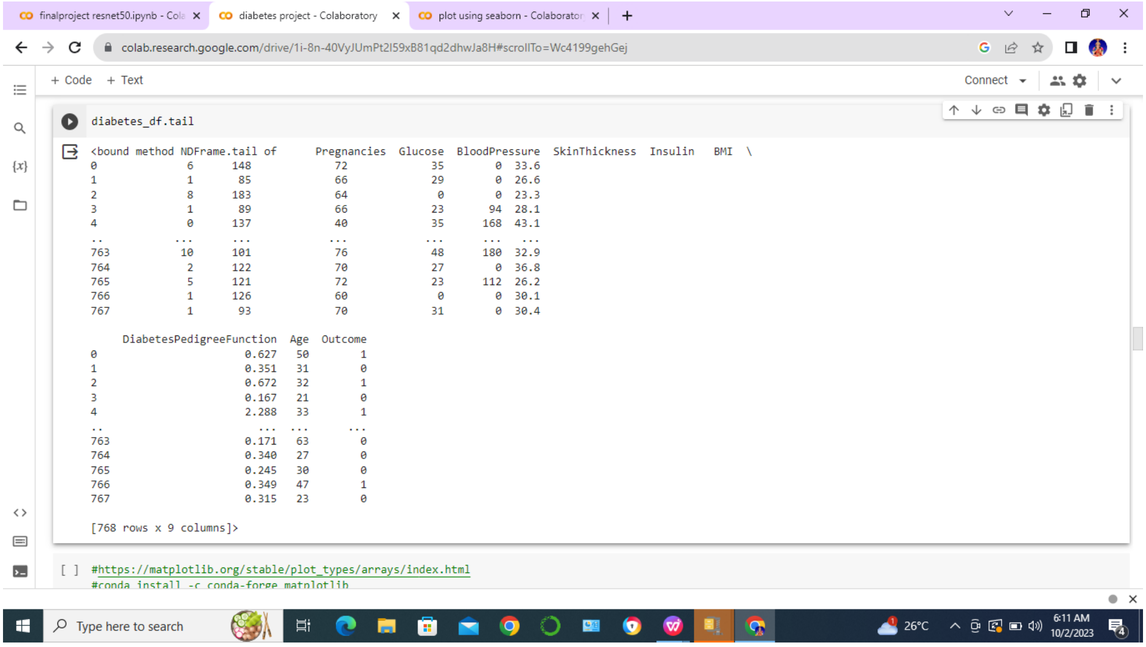
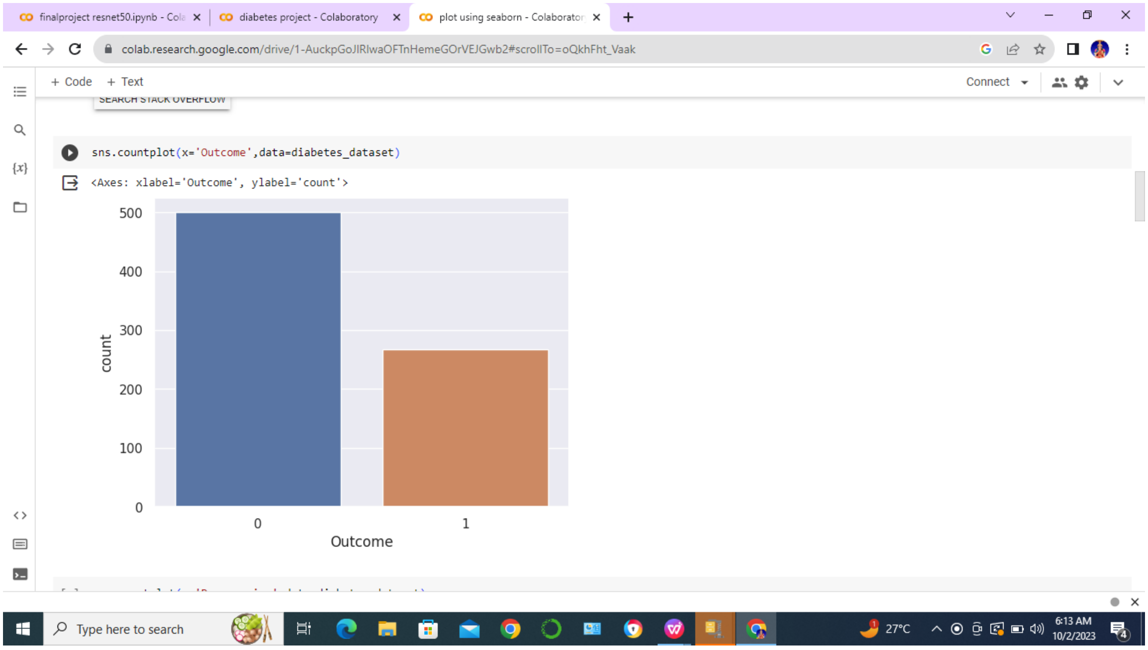
FIGURE 3



The above chart shows the tail of diabetic dataset which includes Pregnancies, Glucose Blood Pressure, Skin,Thickness, Insulin, BMI,Diabetes,Pedigree Function ,Age and Outcome

FIGURE 4



The above chart shows the Diabetic dataset using Seaborn function for using bar chart in calculating Outcome and count for Diabetic dataset taken from kaggle .

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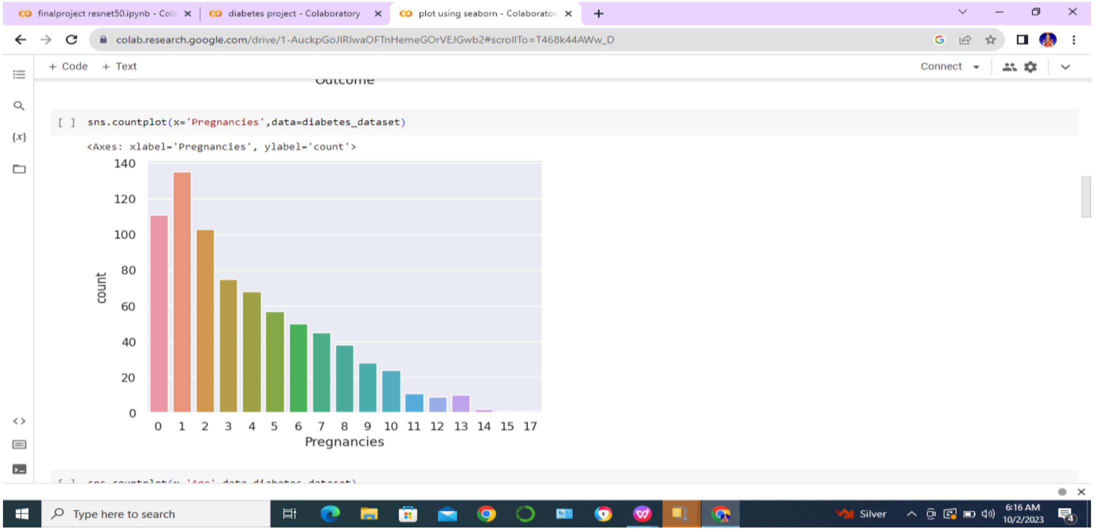
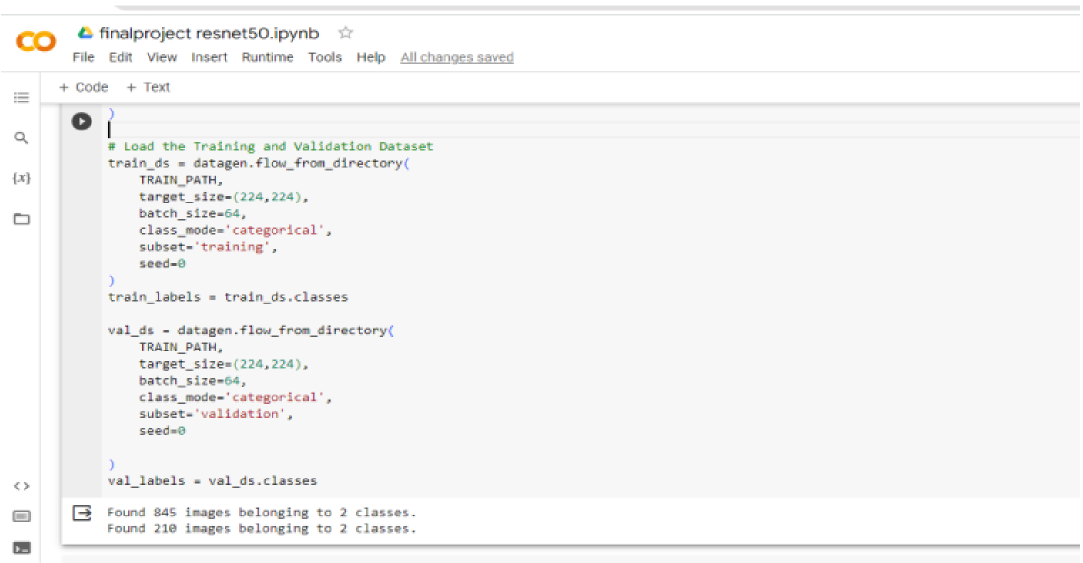
FIGURE 5



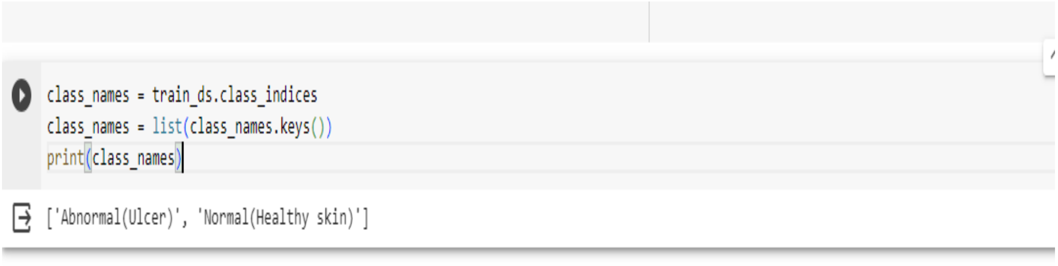
The above chart shows the metrics like Pregancies and count are calculated using seaborn function in mat plot libraries.

FIGURE 6



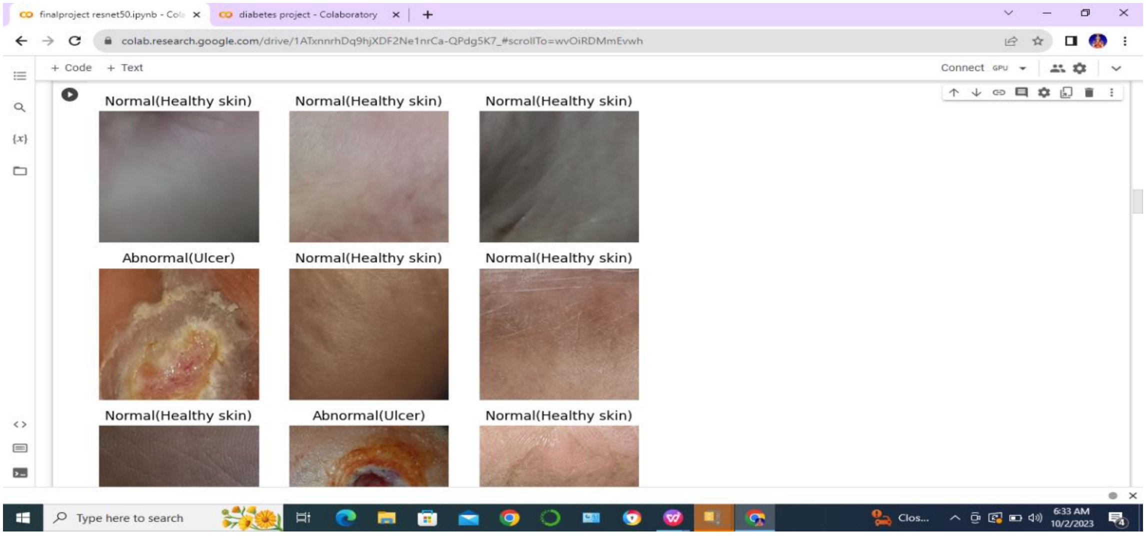
The above image shows the training and validation categorical of dataset using tensorflow for coding it show how many images belongs to which classes.

FIGURE 7



The above figure shows the class names of diabetic foot ulcer in which they are dealing with two types of classes Abnormal (Ulcer) and Normal ulcer (Healthy skin).

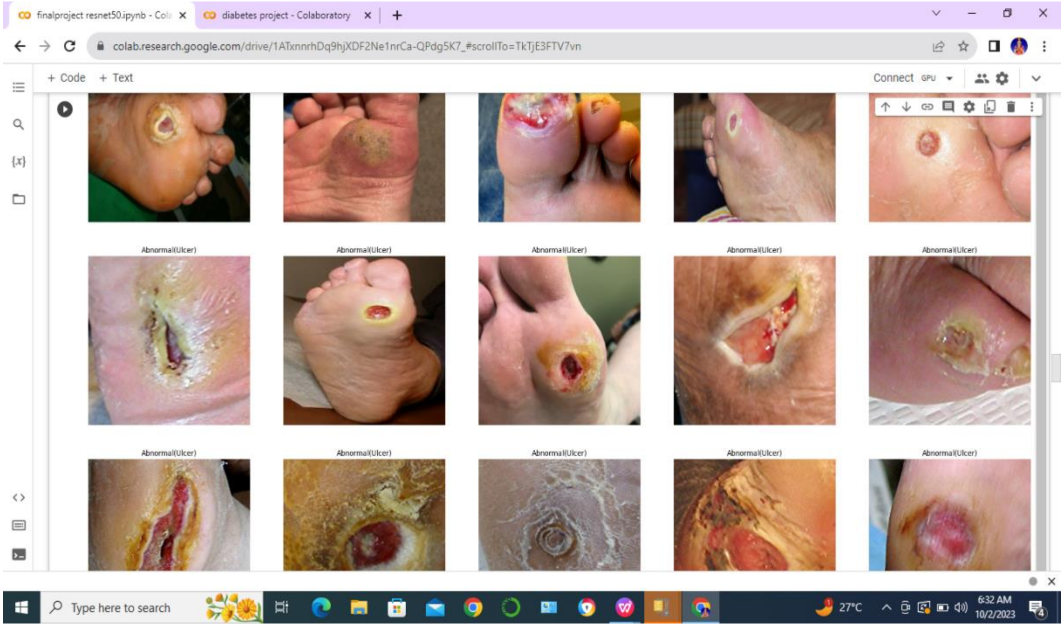
FIGURE 8



The above figure show Visualize the training dataset by using following tensorflow

```
Plt.figure(figsize=(7, 7))
for images, labels in train_ds:
for i in range(9):
ax = plt.subplot(3, 3, i + 1)
plt.imshow(images[i])
plt.title(class_names[labels[i].argmax()])
plt.axis('off')
break  # Only show the first batch of images
plt.tight_layout()
plt.show()
```

FIGURE 9



The figure shows the Visualize the testing dataset of Diabetic foot ulcer

plt.figure(figsize = (7, 7))

i = 0;

for images in test_ds.take(6):

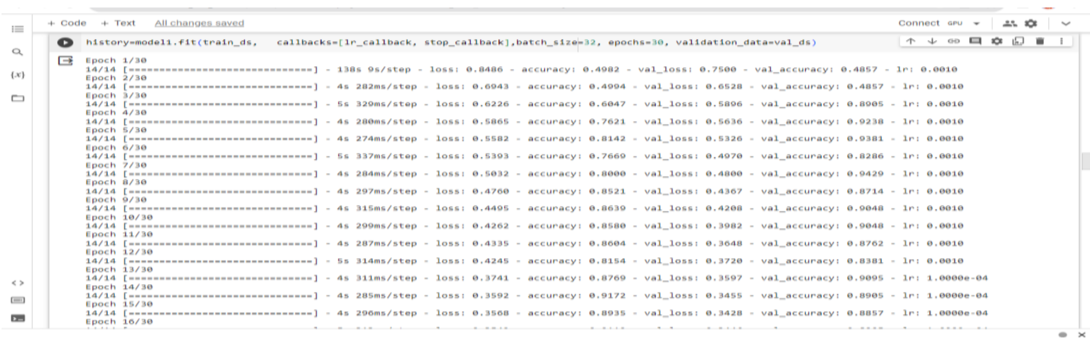
ax = plt.subplot(3, 3, i + 1)

plt.imshow(images.numpy().astype("uint8"))

plt.axis("off")

I += 1

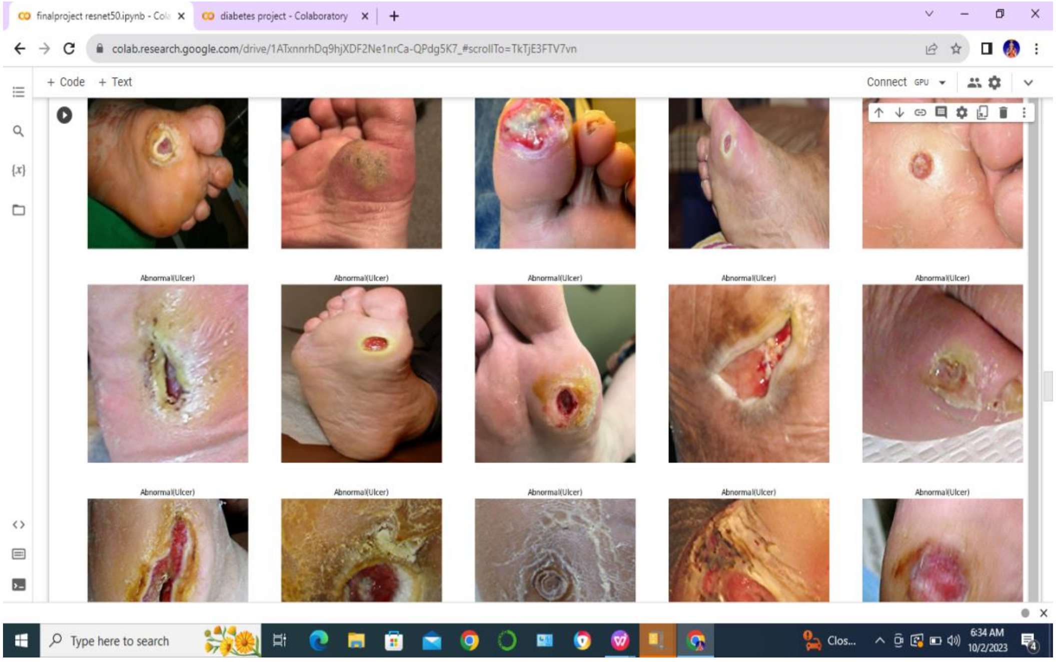
FIGURE 10



The image shows that Define Callbacks function

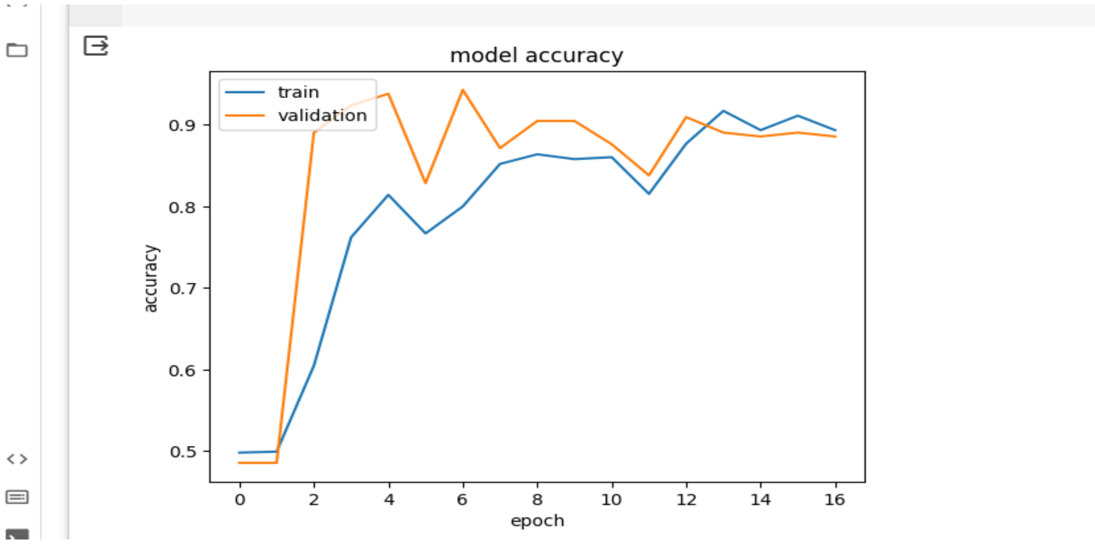
lr_callback = callbacks.ReduceLROnPlateau(monitor='val_accuracy', factor=0.1, patience=5)

stop_callback = callbacks.EarlyStopping(monitor='val_accuracy', patience=10)FIGURE 11



The above figure shows the testing on test dataset using ResNet50 algorithm and finding all diabetic abnormal ulcer .

FIGURE 12



The above chart shows the history model accuracy on epoch and accuracy on basis of training and validation of diabetic foot ulcer.

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FIGURE 13

```
output_class=class_names[np.argmax(pred)]
print("The predicted class is", output_class)
plt.imshow(img)
```

```
The predicted class is Abnormal(Ulcer)
<matplotlib.image.AxesImage at 0x79a5d7f512d0>
```

The above figure shows the segmenting of diabetic foot ulcer an predicting wheather normal or abnormal ulcer .

III) Conculsion:

Diabetic foot ulcer can be frequently monitor avoid amputation of leg by using deep learning approach using ResNet50 algorithm . Deep neural network models are explored for the automatic classification of diabetic foot images into normal (healthy skin) and abnormal (DFU). ResNet50 based model has better than other CNN models like Google Net, Alex Net, VGG16, VGG19 on diabetes foot ulcer image set.

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