PROJECT REPORT

1.Introduction:

1.1.project overview:

Skin Diseases are a common problem among young adults. There is pacity of data about it among medical students. This study aimed to find out the pattern of various types of skin diseases and to describe their perspective solution for various type of skin disorders. people suffering from Atopic Dermatitis, also called eczema is a chronic, relapsing inflammatory disease that leads to itching and risk for skin infection. It is the most common skin disease in children about 10% to 20% of children in the United states and Western Europe have atopic dermatitis. If the skin diseases are not treated properly in an earlier stage itself, then it may lead to complication in the body including spreading of the infection from one person to another.

To overcome this skin disease caused by bacteria usually can be cured with antibiotics, though some bacteria have become resistant to the drugs and are harder to kill . Medication or presciription creams can stop most fungal infections and are several ways to treat skin disease

1.2 Purpose:

The diseases are not considered skin diseases, and skin tone is majorly suffered from the ultraviolet rays from the sun. However, dermatologists perform the majority of non-invasive screening tests simply with the naked eye, even though skin illness is a frequent disease for which early detection and classification are essential for patient success and recovery. The characteristic of the skin images is diversified so that it is a challenging job to devise an efficient and robust algorithm for automatic detection of skin disease and its severity. Automatic processing of such images for skin analysis requires quantitative discriminator to differentiate the diseases.

2 .Literature Survey:

2.1.Existing problem:

some of the most common skin diseases include Acne, blocked skin follicles that lead to oil, bacteria and dead skin buildup in your pores. Alopecia areata, losing your hair in small patches. Atopic dermatitis, dry, itchy skin leads to swelling, cracking or scaliness.

2.2.References:

- 1."Skin Disease and Conditions among Students of a Medical College in South India"

 ' Nitin Joseph ','Ganesh S Kumar',' Maria Nelliyanil' Jan 2014" Indian Dermatology

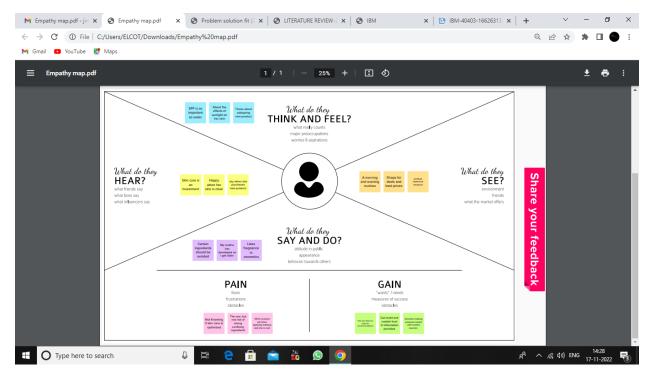
 Journal"CAD- Computer Aided Diagnosis Convenient Sampling Method
- 2."Al Based Localization And Classification Of Skin Disease with Erythema." Ha Min Son', 'Wooho Jeon', 'Tai-Myoung Chung' March 5 2021" Nature Publishing Group. "CAD-Computer Aided Diagnosis
- 3."Global Burden Of Skin Disease Inequities and Innovations." 'Divya Seth, Ab, Khatiya Cheldize, 'Esther F.Freeman' August 2017 HHS publication Healthy Equity Task Shifting.

2.3. Problem Statement Definition

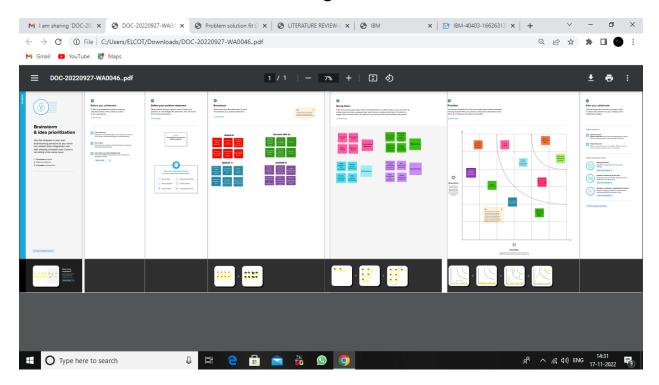
We are trying to find a solution to identify Skin Disease but Developed model is under training because given an image of skin, we can decompose, segment, and classify in a sequential manner which takes to Early detection of skin cancer, psoriasis Ecezma.

3.Ideation and proposed solution:

3.1. Empathy Map Canvas:



3.2. Ideation and BrainStroming:



3.3 Proposed Solution

Two-phase analysis model. The original image primarily enters a pre-processing stage, where normalization and decomposition occur. Afterwards, the first step is segmentation, where cluster of abnormal skin are segmented and cropped. The second step is classification, where each cluster is classified into its corresponding class. Developed Model is Still under training.

3.4 Problem Solution fit

Skin disease can appear in virtually any part of body and there is a lack of data required to form an association between the probability of a skin disease based on the body part. A Solution model used for the prevention and early detection of skin cancer and psoriasis by image analyses to detect whether the person is having skin disease or not. The location of the disease that is present in an image and improved performance by CNN model to focus on particular subsections of the images.

4. Requirement Analysis

4.1 Functional requirements

Image Acquisition, Pre-processing Steps such as Colour gradient generator on an

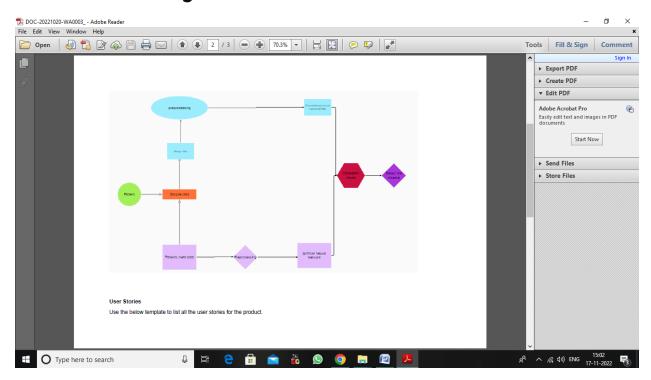
image, Cropping and isolating region of interest and Thresholding and Clustering on image, Visual feature extraction, System Training YOLO Model for Skin disease classification with deep learning and CNN, Separate access of application for admin, Diagnosis of Skin disease and Data retrieval and Data manipulation.

4.2 Non-Functional requirements

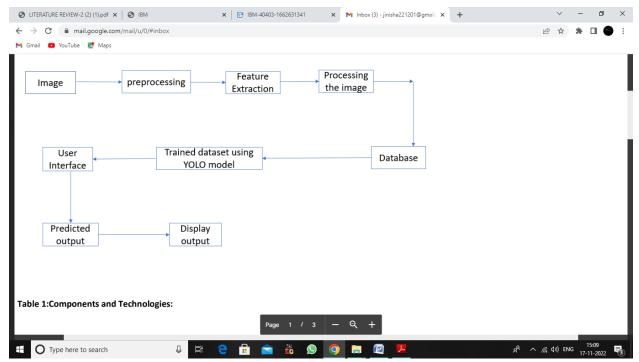
Software Quality Attributes, Prediction, Accuracy, usability, Security, Reliability, Performance, Availability, Scalability.

5. Project Design

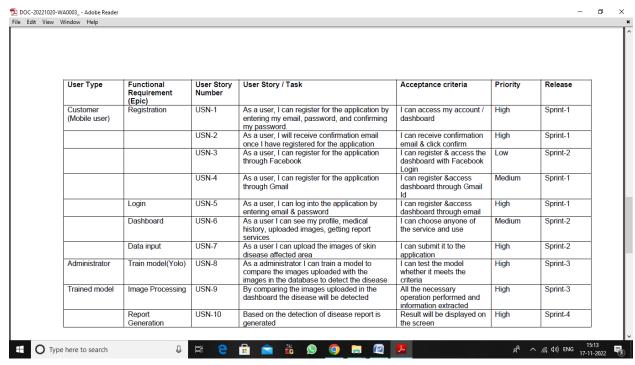
5.1 Data Flow Diagram



5.2 Solution and Technical Architecture

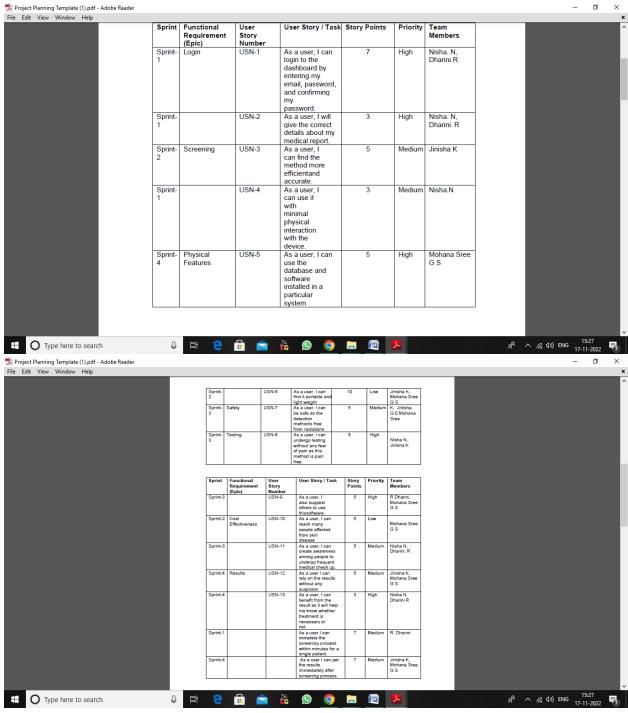


5.3. User Stories:

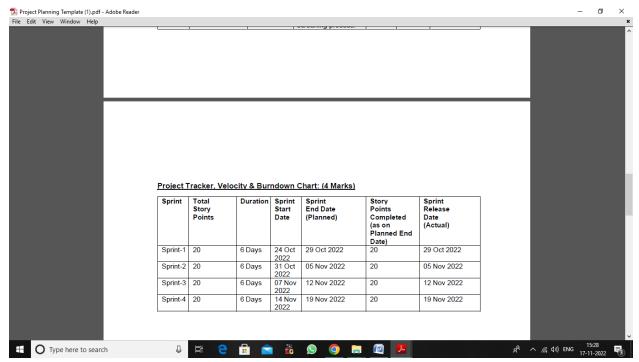


6. Project planning and Scheduling:

6.1.sprint planning and estimation:



6.2. Sprint delievery schedule:



7. Coding and Solutioning

pip3 install tensorflow tensorflow_hub matplotlib seaborn numpy pandas sklearn imblearn

import tensorflow as tf import
tensorflow_hub as hub import
matplotlib.pyplot as plt import
numpy as np import pandas as
pd import seaborn as sns
from tensorflow.keras.utils import get_file
from sklearn.metrics import roc_curve, auc, confusion_matrix
from imblearn.metrics import sensitivity_score, specificity_score

import os import glob import zipfile import random

to get consistent results after multiple runs tf.random.set_seed(7) np.random.seed(7) random.seed(7)

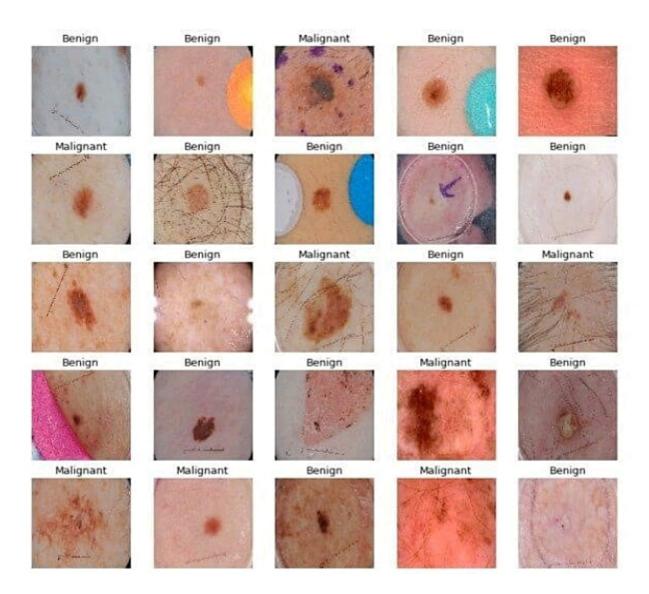
```
# 0 for benign, 1 for malignant
class_names = ["benign", "malignant"]
Preparing the Dataset
def download_and_extract_dataset():
# dataset from https://github.com/udacity/dermatologist-ai
# 5.3GB
train_url = "https://s3-us-west-1.amazonaws.com/udacity-dlnfd/datasets/skin-
cancer/train.zip"
# 824.5MB
valid_url = "https://s3-us-west-1.amazonaws.com/udacity-dlnfd/datasets/skin-
cancer/valid.zip"
# 5.1GB test_url = "https://s3-us-west-1.amazonaws.com/udacity-
dlnfd/datasets/skin-
cancer/test.zip" for i, download_link in enumerate([valid_url, train_url, test_url]):
temp_file =
f"temp{i}.zip"
data_dir = get_file(origin=download_link, fname=os.path.join(os.getcwd(), temp_file))
print("Extracting", download_link) with zipfile.ZipFile(data_dir, "r")
as z:
z.extractall("data") # remove the temp file
 os.remove(temp_file)
# comment the below line if you already downloaded the dataset
download_and_extract_dataset()
# preparing data
# generate CSV metadata file to read img paths and labels from it def
generate_csv(folder, label2int): folder_name =
os.path.basename(folder) labels = list(label2int) # generate CSV
file df = pd.DataFrame(columns=["filepath", "label"]) i = 0 for
label in labels: print("Reading", os.path.join(folder, label, "*"))
for filepath in glob.glob(os.path.join(folder, label, "*")):
         df.loc[i] = [filepath, label2int[label]]
i += 1
  output_file = f"{folder_name}.csv" print("Saving",
```

```
output_file)
   df.to_csv(output_file)
# generate CSV files for all data portions, labeling nevus and seborrheic keratosis
# as 0 (benign), and melanoma as 1 (malignant)
# you should replace "data" path to your extracted dataset path # don't
replace if you
used download_and_extract_dataset() function generate_csv("data/train",
{"nevus":
0, "seborrheic_keratosis": 0, "melanoma": 1})
generate_csv("data/valid", {"nevus": 0,
"seborrheic_keratosis": 0, "melanoma": 1})
generate_csv("data/test", {"nevus": 0,
"seborrheic_keratosis": 0, "melanoma": 1})
# loading data
train_metadata_filename = "train.csv" valid_metadata_filename =
"valid.csv" # load CSV
files as DataFrames df_train = pd.read_csv(train_metadata_filename) df_valid =
pd.read_csv(valid_metadata_filename) n_training_samples = len(df_train)
n_validation_samples = len(df_valid) print("Number of training samples:",
n_training_samples) print("Number of validation samples:",
n_validation_samples)
train_ds = tf.data.Dataset.from_tensor_slices((df_train["filepath"],
df_train["label"]))
valid_ds = tf.data.Dataset.from_tensor_slices((df_valid["filepath"],
df_valid["label"]))
Output:
Number of training samples: 2000 Number of validation samples: 150
# preprocess data def
decode_img(img):
# convert the compressed string to a 3D uint8 tensor img =
tf.image.decode_ipeg(img, channels=3)
# Use `convert_image_dtype` to convert to floats in the [0,1] range.
img = tf.image.convert_image_dtype(img, tf.float32) # resize the image
to the desired size. return tf.image.resize(img, [299, 299])
```

```
def process_path(filepath, label): # load the
raw data from the file as a string img =
tf.io.read_file(filepath) img = decode_img(img)
return img, label
valid_ds = valid_ds.map(process_path) train_ds =
train_ds.map(process_path)
# test_ds = test_ds for image, label in
train_ds.take(1): print("Image
shape:", image.shape) print("Label:",
label.numpy())
Image shape: (299, 299, 3)
Label: 0
# training parameters
batch_size = 64 optimizer =
"rmsprop" def
prepare_for_training(ds,
cache=True, batch_size=64,
shuffle_buffer_size=1000):
if cache: if
isinstance(cache, str): ds
= ds.cache(cache) else:
ds = ds.cache() #
shuffle the dataset
ds = ds.shuffle(buffer_size=shuffle_buffer_size)
# Repeat forever ds =
 ds.repeat() # split to
batches ds =
ds.batch(batch_size)
#`prefetch` lets the dataset fetch batches in the background while the model # is
training.
ds = ds.prefetch(buffer_size=tf.data.experimental.AUTOTUNE) return ds
valid_ds = prepare_for_training(valid_ds, batch_size=batch_size, cache="valid-
cached-data") train_ds =
prepare_for_training(train_ds, batch_size=batch_size, cache="train-cached-
```

```
data") batch =
next(iter(valid_ds))

def show_batch(batch):
plt.figure(figsize=(12,12)) for
n in range(25): ax =
plt.subplot(5,5,n+1)
plt.imshow(batch[0][n])
plt.title(class_names[batch[1][n].numpy()].title())
plt.axis('off')
show_batch(batch)
```



```
0.8708 Epoch 00027: val loss improved from 0.40253 to 0.38991, saving model
to benign-vsmalignant_64_rmsprop_0.390.h5
0.8684 - val_loss: 0.3899 - val_accuracy: 0.8359
<..SNIPED..>
Epoch 41/100
Epoch 00041: val_loss did not improve from 0.38991
0.8790 - val_loss: 0.3948 - val_accuracy: 0.8281
Epoch 42/100
Epoch 00042: val loss did not improve from 0.38991
0.8831 - val_loss: 0.4572 - val_accuracy: 0.8047
Model Evaluation:
# evaluation#
load testing
set
test metadata filename = "test.csv"
df_test=pd.read_csv(test_metadata_filename)n_tes
ting samples = len(df test)print("Number of testing
samples:", n_testing_samples)
test_ds = tf.data.Dataset.from_tensor_slices((df_test["filepath"],
df_test["label"]))defprepare_for_testing(ds, cache=True,
shuffle_buffer_size=1000): if cache: if isinstance(cache, str): ds =
ds.cache(cache)
else:
ds = ds.cache() ds =
ds.shuffle(buffer_size=shuffle_buffer_size)
return ds
test_ds = test_ds.map(process_path)test_ds =
prepare_for_testing(test_ds, cache="test-cached-data")
Number of testing samples: 600
```

#

```
evaluation#
load testing
set
test_metadata_filename =
"test.csv"df_test =
pd.read_csv(test_metadata_filename)n
_testing_samples = len(df_test)
print("Number of testing samples:", n_testing_samples)test_ds =
tf.data.Dataset.from_tensor_slices((df_test["filepath"],
df test["label"]))
defprepare_for_testing(ds, cache=True,
shuffle buffer size=1000): if cache:
ifisinstance(cache, str):
ds = ds.cache(cache)
else:
ds = ds.cache()
ds = ds.shuffle(buffer_size=shuffle_buffer_size)
return ds
test_ds = test_ds.map(process_path)test_ds =
prepare_for_testing(test_ds, cache="test-cached-
data")
# load the weights with the least loss
m.load_weights("benign-vs-malignant_64_rmsprop_0.390.h5")
print("Evaluating the model...")
loss, accuracy = m.evaluate(X_test, y_test, verbose=0)
print("Loss:", loss, " Accuracy:", accuracy)
Output:
Evaluating the model...
Loss: 0.4476394319534302 Accuracy: 0.8
defget_predictions(threshold=None):
Returns predictions for binary classification given 'threshold'
```

```
For instance, if threshold is 0.3, then it'll output 1 (malignant) for that
sample if the probability of 1 is 30% or more (instead of 50%)
y_pred = m.predict(X_test) if
not threshold: threshold = 0.5
result =
np.zeros((n_testing_samples,))
for i in
range(n testing samples):
test melanoma probability if
y_pred[i][0] >= threshold:
result[i] = 1 #
else, it's 0
(benign)
return result
threshold = 0.23
# get predictions with 23% threshold
# which means if the model is 23% sure or more that is malignant,
# it's assigned as malignant, otherwise it's
benign y_pred =
get predictions(threshold)
defplot_confusion_matrix(y_test,
y_pred): cmn = confusion_matrix(y_test,
y pred)
# Normalise
cmn = cmn.astype('float') / cmn.sum(axis=1)[:, np.newaxis]
# print it
print(cmn)
fig, ax = plt.subplots(figsize=(10,10))
sns.heatmap(cmn, annot=True, fmt='.2f',
xticklabels=[f"pred {c}" for c in class names],
yticklabels=[f"true_{c}" for c in class_names],
cmap="Blues"
plt.ylabel('Actual')
plt.xlabel('Predicted')
# plot the resulting confusion matrix
plt.show()
plot_confusion_matrix(y_test, y_pred)
Output:
# InceptionV3 model & pre-trained weights
module_url = "https://tfhub.dev/google/tf2-preview/inception_v3/feature_vector/4"
```

```
m = tf.keras.Sequential([
hub.KerasLayer(module_url, output_shape=[2048], trainable=False),
tf.keras.layers.Dense(1, activation="sigmoid")
])
m.build([None, 299, 299, 3])
m.compile(loss="binary_crossentropy", optimizer=optimizer, metrics=["accuracy"])
m.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #	
keras_layer (Keras	Layer) multiple	21802784	
dense (Dense)	multiple	2049	

===========Total params:

21,804,833

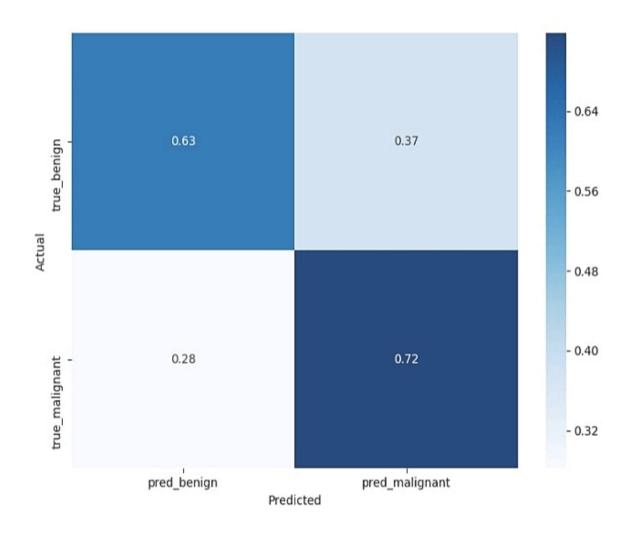
Trainable params: 2,049

Non-trainable params: 21,802,784

Training the Model

```
model_name = f"benign-vs-malignant_{batch_size}_{optimizer}"
tensorboard = tf.keras.callbacks.TensorBoard(log_dir=os.path.join("logs", model_name))
# saves model checkpoint whenever we reach better weights
modelcheckpoint = tf.keras.callbacks.ModelCheckpoint(model_name + "_{val_loss:.3f}.h5",
save_best_only=True, verbose=1)
```

```
history = m.fit(train_ds, validation_data=valid_ds,
steps_per_epoch=n_training_samples // batch_size,
validation_steps=n_validation_samples // batch_size, verbose=1, epochs=100,
callbacks=[tensorboard, modelcheckpoint])
```

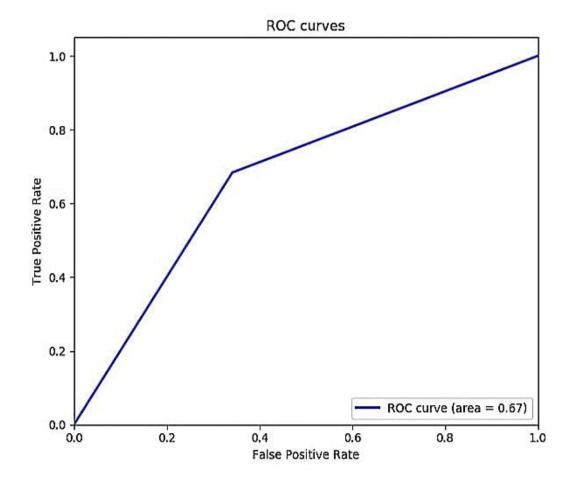


sensitivity = sensitivity_score(y_test, y_pred) specificity = specificity_score(y_test, y_pred) print("Melanoma Sensitivity:", sensitivity) print("Melanoma Specificity:", specificity) Output:

Melanoma Sensitivity: 0.717948717948718 Melanoma Specificity: 0.6252587991718427

defplot_roc_auc(y_true, y_pred):

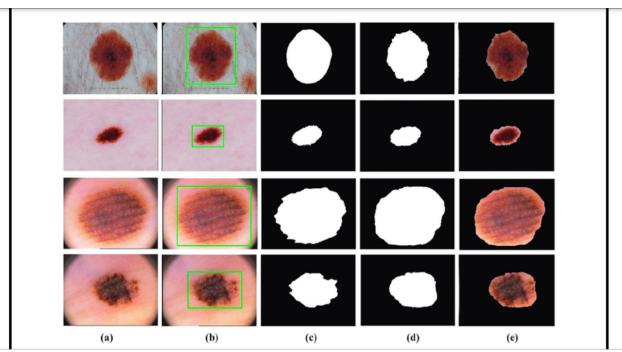
.....



ROC AUC:0.671

8.Result:

The final results are based on the accuracy results in the form of melanoma and the non-melanoma skin diseases classification.



9. Advantages and Disadvantages:

9.1.Advantages:

High Enhancement, No therapeutic limitation, Easily incorporate depot, Delivery not majorly affected by diseased state of skin.

9.2.Disadvantages:

High cost, Security concern

10.Conclusion:

Skin diseases are a bit like the common cold. They vary enormously from mild conditions which may affect only the appearance of the skin to severe disease which are totally incapacitating. The degree of treatment required or even sought varies accordinglyIn addition, we have shown that current state-of-the-art CNN models can outperform models created by previous research, through proper data pre-processing, self-supervised learning, transfer learning, and special CNN architecture techniques. Furthermore, with accurate segmentation, we gain knowledge of the location of the disease, which is useful in the pre-processing of data used in classification, as it allows the CNN model to focus on the area of interest. Lastly, unlike previous studies, our method provides a solution to classify multiple diseases within a single image. With higher quality and a larger quantity of data, it will be viable to use state-of-the-art models to enable the use of CAD in the field of dermatology.

11.Future Scope:

In future, this machine learning model may bind with a variouswebsite which can provide real-time data for skin disease prediction. Also, we may add large historical data on skin diseasewhich can help to improve theaccuracy of the machine learning model. We can build an android app as a userinterface for interacting with the user. For better performance, we plan to judiciously design deep learning network structures, use adaptive learning rates, and train it on clusters of data ratherthan the whole dataset.

12.Appendix:

Github link:

IBM-Project-40403-1660629006

Team ID:PNT2022TMID34161