

**PROJECT TITLE : SKIN FIT**

# Vityarthi Project

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## ● Introduction

I designed and implemented a machine-learning based system capable of distinguishing between vitiligo/leucoderma-affected skin and healthy skin with high accuracy.

The objective of this project is to classify skin images into 'vitiligo' or 'normal' using a Convolutional Neural Network. The early detection can support dermatological assessment for swift and effective intervention.

## ● Problem Statement

Vitiligo is a depigmentation skin disorder. Manual diagnosis involves much time and subjectivity. There exists a need for the development of an automated system to classify skin images that will support clinicians and improve early screening.

## ● Functional Requirements

1. Load image datasets from directories
2. Preprocess and augment images for model generalization.
3. Train a binary classification CNN
4. Validate accuracy during training
5. Predict class from a new image (vitiligo/normal)

## ● Non-Functional Requirements

1. Fast inference time on new images
2. Usable by non-experts - simple input/output
3. Compatibility with Google Drive for dataset storage
4. Model persistence for use later

## ● System Architecture

1. High-Level Flow
2. Data loading and preprocessing
3. Model training & validation
4. Model saving and prediction

## ● Diagrams Design

1. Use Case Diagram: It depicts the actors that interact with the system, and what the system does for those actors. That is, a user who uploads an image, and in response, gets results back.
2. Workflow Diagram: The linear flow is Image Loading → Preprocessing → Model Training → Evaluation → Prediction.
3. Sequence Diagram: User provides image → System loads & resizes image → CNN predicts label → Result shown
4. Class/Component Diagram: Key components/ classes: ImageDataGenerator, Model, Train/Validation Data
5. ER Diagram: If using database, represents the images table (id, path, label); not needed for in-memory/flat file workflows

## ● Design Decisions & Rationale

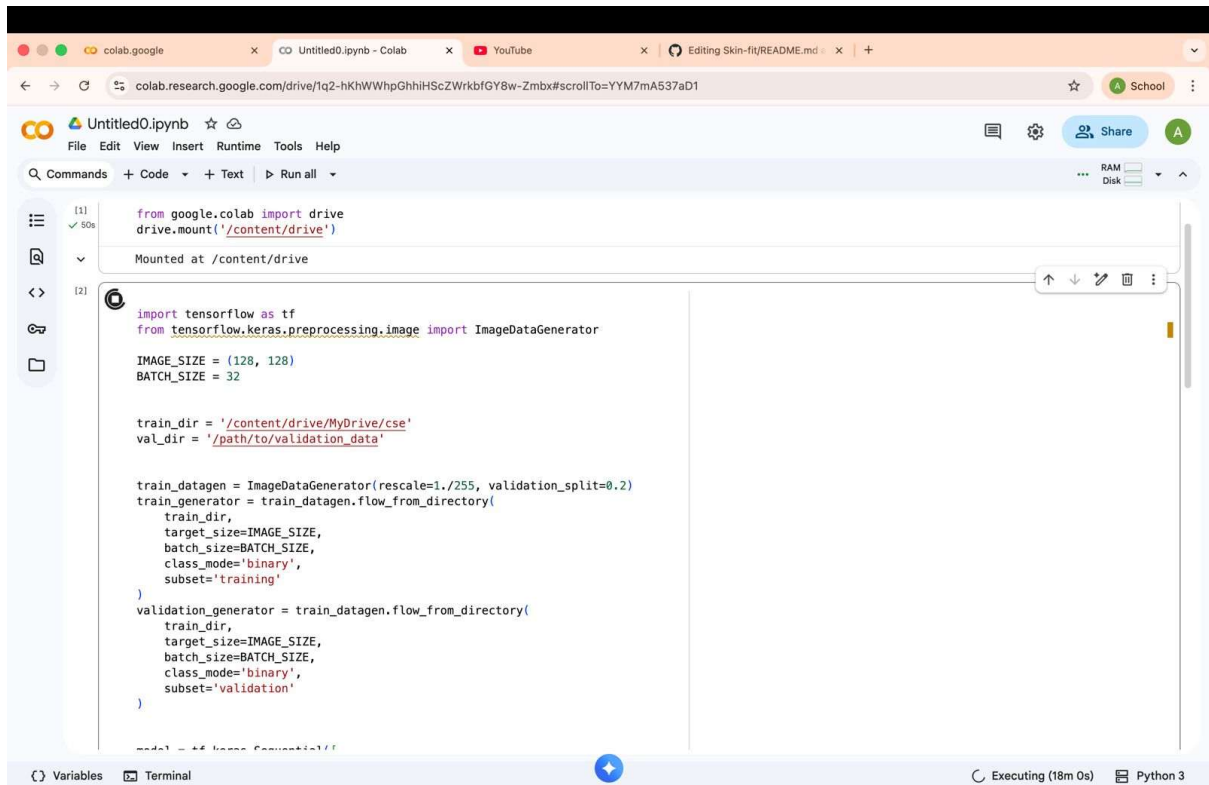
1. Chose CNN for image feature extraction and classification accuracy
2. Used Image Data Generator for augmentation to address overfitting.
3. Rescale the pixel values to normalize the input and enhance convergence.
4. Adopted binary cross-entropy as loss for two-class problem

## ● Implementation Details

1. Kera's Sequential model for modularity and simplicity

2. Directory structure: Different folders for 'vitiligo' and 'normal'
3. Output: trained model ('vitiligo\_detector\_model.h5')
4. Code compatible with Google Colab & Google Drive

## • Screenshots / Results



The screenshot shows a Google Colab notebook interface. The browser tabs at the top include 'colab.google', 'Untitled0.ipynb - Colab', 'YouTube', and 'Editing Skin-fit/README.md'. The address bar shows the Colab URL. The notebook has a menu bar with 'File', 'Edit', 'View', 'Insert', 'Runtime', 'Tools', and 'Help'. Below the menu is a toolbar with 'Commands', '+ Code', '+ Text', and 'Run all'. The left sidebar shows a file explorer with a folder icon. The main code area contains two code cells. Cell [1] imports 'drive' from 'google.colab' and mounts the drive at '/content/drive'. Cell [2] imports 'tensorflow as tf' and 'ImageDataGenerator' from 'tensorflow.keras.preprocessing.image'. It defines 'IMAGE\_SIZE = (128, 128)' and 'BATCH\_SIZE = 32'. It sets 'train\_dir' to '/content/drive/MyDrive/cse' and 'val\_dir' to '/path/to/validation\_data'. It creates a 'train\_datagen' object with 'rescale=1./255' and 'validation\_split=0.2', and a 'train\_generator' object using 'flow\_from\_directory'. It also creates a 'validation\_generator' object. The bottom status bar shows 'Executing (18m 0s)' and 'Python 3'.

```
[1] from google.colab import drive
drive.mount('/content/drive')

Mounted at /content/drive

[2] import tensorflow as tf
from tensorflow.keras.preprocessing.image import ImageDataGenerator

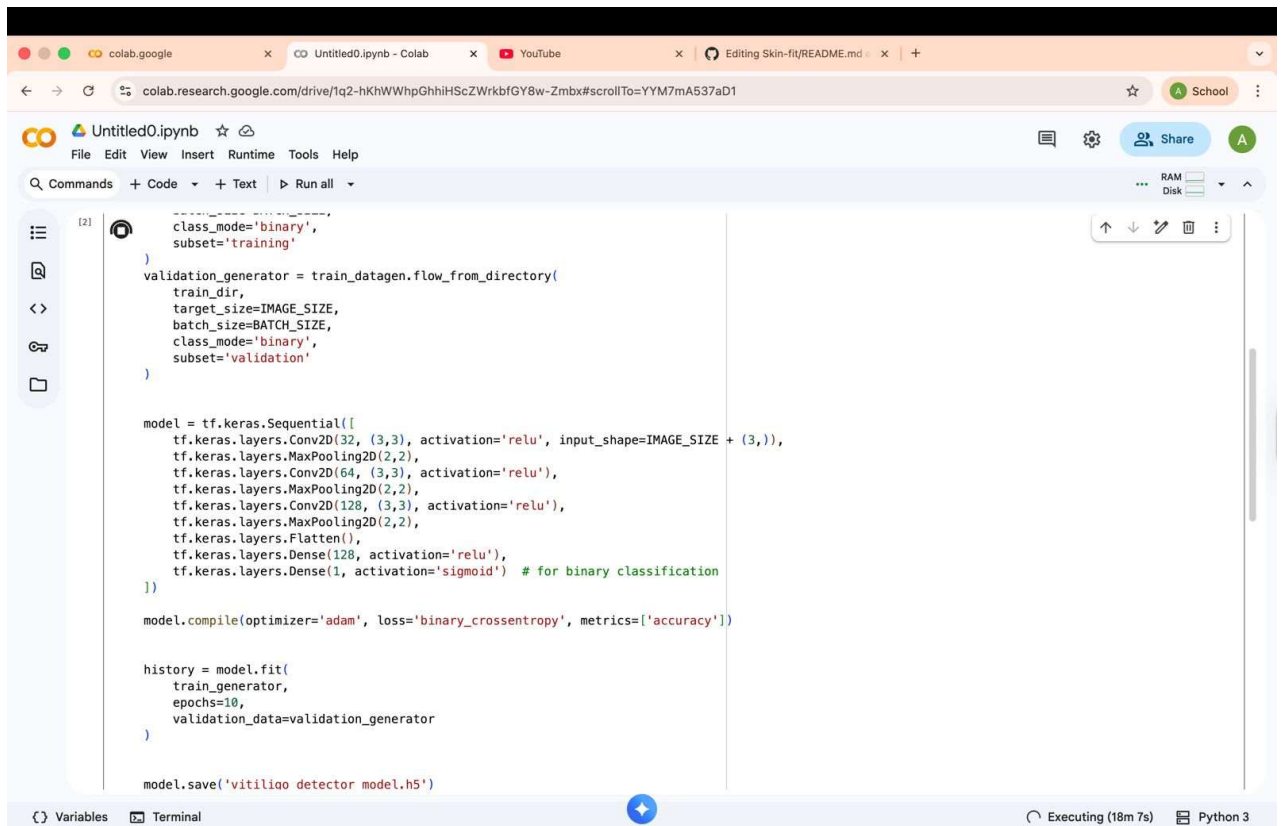
IMAGE_SIZE = (128, 128)
BATCH_SIZE = 32

train_dir = '/content/drive/MyDrive/cse'
val_dir = '/path/to/validation_data'

train_datagen = ImageDataGenerator(rescale=1./255, validation_split=0.2)
train_generator = train_datagen.flow_from_directory(
    train_dir,
    target_size=IMAGE_SIZE,
    batch_size=BATCH_SIZE,
    class_mode='binary',
    subset='training'
)

validation_generator = train_datagen.flow_from_directory(
    train_dir,
    target_size=IMAGE_SIZE,
    batch_size=BATCH_SIZE,
    class_mode='binary',
    subset='validation'
)

model = tf.keras.Sequential()
```



```
[2] class_model='binary',
subset='training'

validation_generator = train_datagen.flow_from_directory(
    train_dir,
    target_size=IMAGE_SIZE,
    batch_size=BATCH_SIZE,
    class_mode='binary',
    subset='validation'

)

model = tf.keras.Sequential([
    tf.keras.layers.Conv2D(32, (3,3), activation='relu', input_shape=IMAGE_SIZE + (3,)),
    tf.keras.layers.MaxPooling2D(2,2),
    tf.keras.layers.Conv2D(64, (3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(2,2),
    tf.keras.layers.Conv2D(128, (3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(2,2),
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.Dense(1, activation='sigmoid') # for binary classification
])

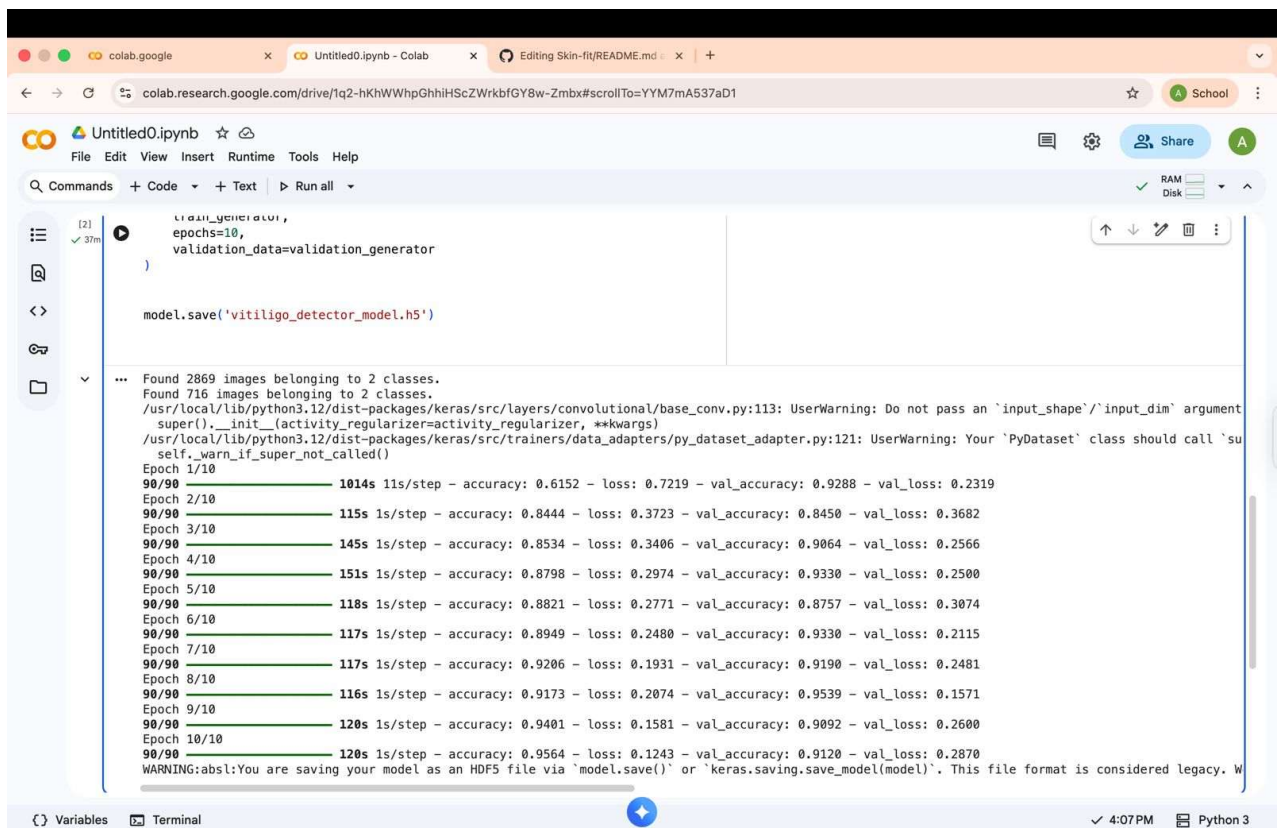
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

history = model.fit(
    train_generator,
    epochs=10,
    validation_data=validation_generator

)

model.save('vitiligo_detector_model.h5')
```

Executing (18m 7s) Python 3



```
[2] train_generator,
epochs=10,
validation_data=validation_generator

)

model.save('vitiligo_detector_model.h5')
```

Found 2869 images belonging to 2 classes.  
Found 716 images belonging to 2 classes.  
/usr/local/lib/python3.12/dist-packages/keras/src/layers/convolutional/base\_conv.py:113: UserWarning: Do not pass an 'input\_shape'/'input\_dim' argument to super().\_\_init\_\_(activity\_regularizer=activity\_regularizer, \*\*kwargs) from /usr/local/lib/python3.12/dist-packages/keras/src/trainers/data\_adapters/py\_dataset\_adapter.py:121: UserWarning: Your 'PyDataset' class should call 'self.\_warn\_if\_super\_not\_called()'

Epoch	Time	Step	Accuracy	Loss	Val Accuracy	Val Loss
1/10	1014s	11s/step	0.6152	0.7219	0.9288	0.2319
2/10	115s	1s/step	0.8444	0.3723	0.8450	0.3682
3/10	145s	1s/step	0.8534	0.3406	0.9064	0.2566
4/10	151s	1s/step	0.8798	0.2974	0.9330	0.2500
5/10	118s	1s/step	0.8821	0.2771	0.8757	0.3074
6/10	117s	1s/step	0.8949	0.2480	0.9330	0.2115
7/10	117s	1s/step	0.9206	0.1931	0.9190	0.2481
8/10	116s	1s/step	0.9173	0.2074	0.9539	0.1571
9/10	120s	1s/step	0.9401	0.1581	0.9092	0.2600
10/10	120s	1s/step	0.9564	0.1243	0.9120	0.2870

WARNING:absl:You are saving your model as an HDF5 file via 'model.save()' or 'keras.saving.save\_model(model)'. This file format is considered legacy. W

4:07 PM Python 3

## • Testing Approach

1. Used validation split in ImageDataGenerator for in-training evaluation
2. Test with unseen images to measure real world performance.

## • Challenges Faced

Limited and imbalanced training data

Tuning hyperparameters for best accuracy  
Managing image augmentation and directory formats  
Learnings & Key Takeaways  
Importance of clean, labeled data  
CNNs are able to model image classification problems in an efficient manner. Validation split helps to monitor overfitting.  
Future Enhancements  
Add multiclass classification for more skin conditions  
Integrate with databases for scalable storage.  
Develop web-mobile UIs for wider accessibility  
References  
Keras Documentation  
TensorFlow Tutorials  
Imaging for Diagnosis of Vitiligo: A Review

## • References

1. Keras Documentation
2. TensorFlow Tutorials
3. Research on Vitiligo Diagnosis via Imaging
4. Kaggle : <https://www.kaggle.com/datasets/shinynose/vitiligo>