

Crack detection Using deep learning approach

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Problem statement

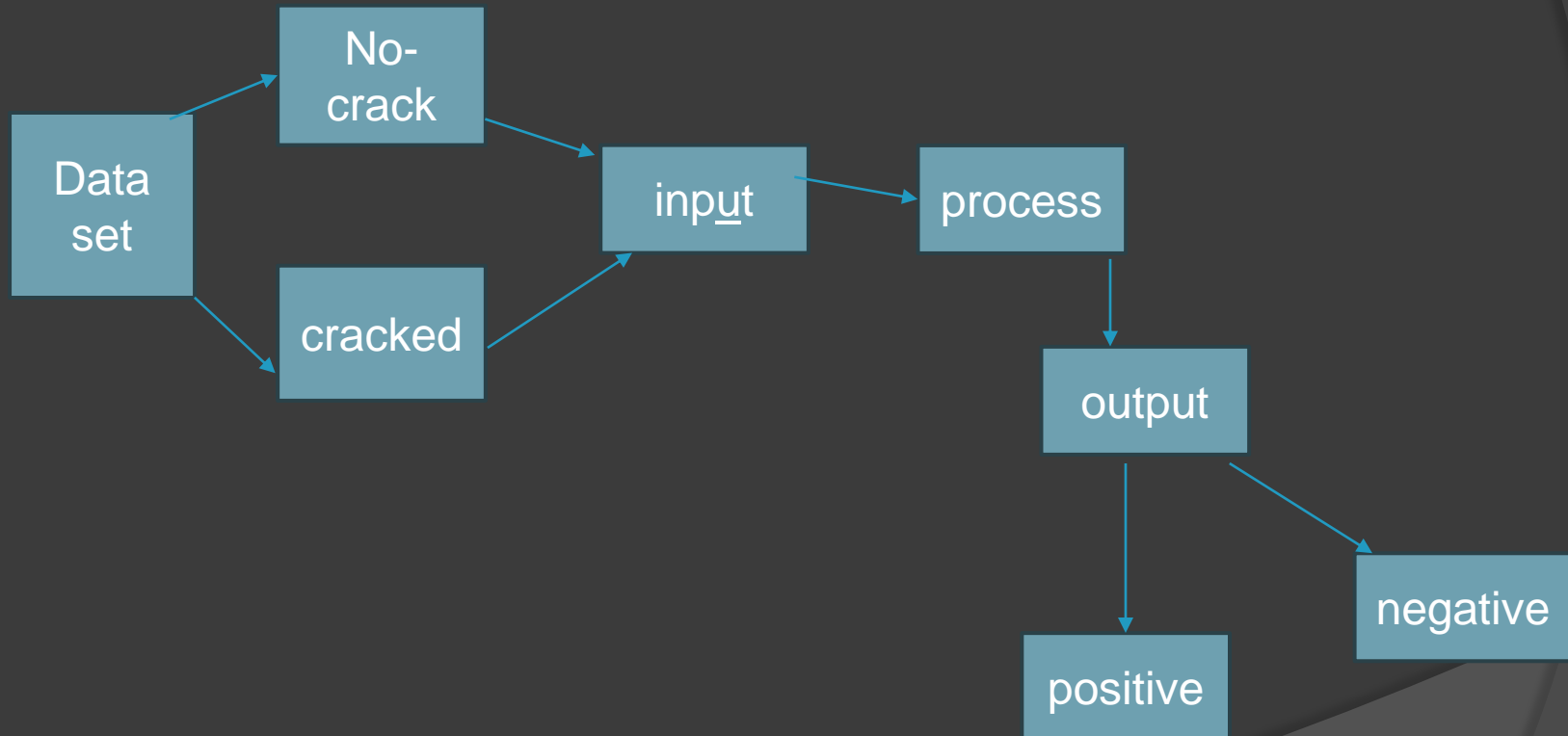
- The problem is to develop an effective and efficient system for the detection of cracks in structures, such as buildings or bridges.
- This involves creating a model capable of accurately identifying and localizing cracks in images or sensor data.
- The goal is to automate the detection process, providing a reliable tool for structural health monitoring to prevent potential failures and ensure the safety and integrity of infrastructure.
- ⦿ Manual crack detection is laborious, time-consuming, and prone to subjective judgments from inspectors.
- ⦿ Particularly challenging for tall buildings and bridges, manual inspection becomes impractical.

Introduction

- Detecting cracks is a crucial aspect of monitoring the structural integrity of concrete structures and other surface structures
- The goal of this project is to develop a robust crack detection system using deep learning techniques.
- The system will analyse images of surfaces to identify and localize crack
- Automated methods offer a more efficient and objective solution to identify and analyze surface cracks in concrete structures.

Methodology:

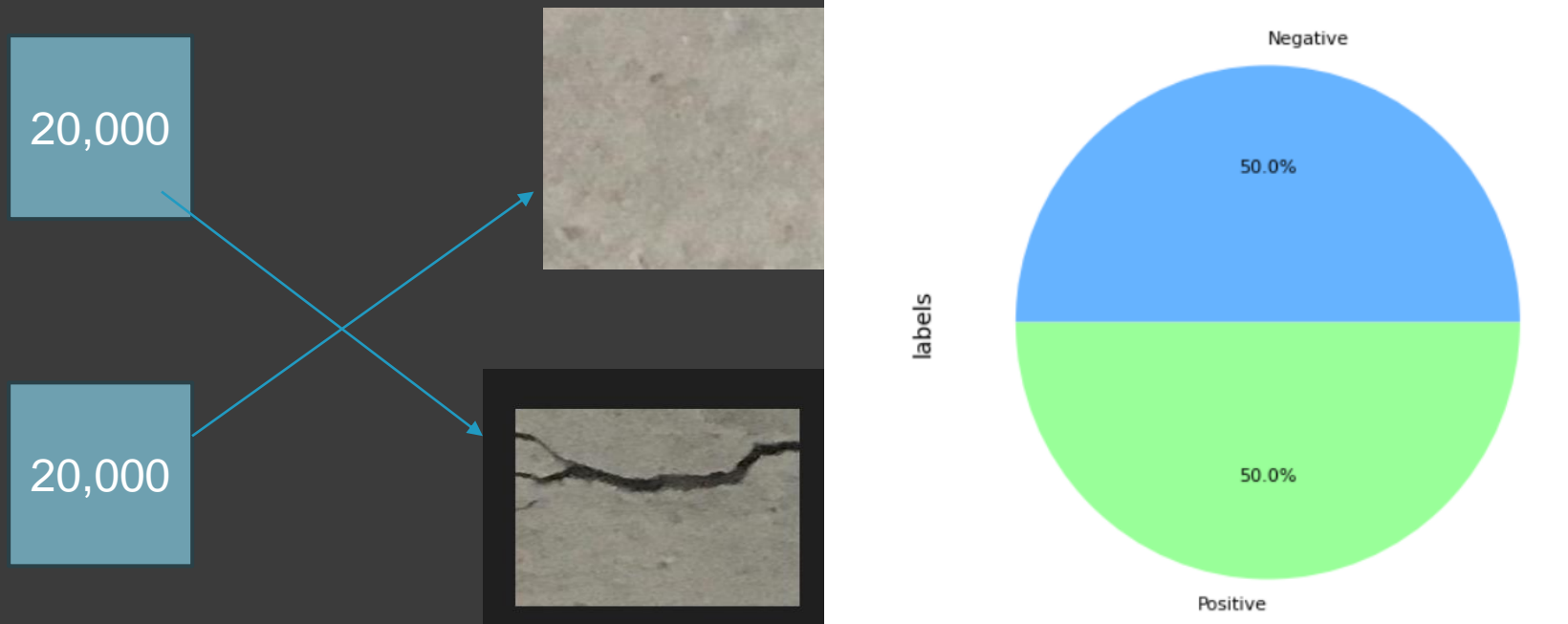
1 using deep learning approach



2 using non max suppression approach and edge detector

Dataset

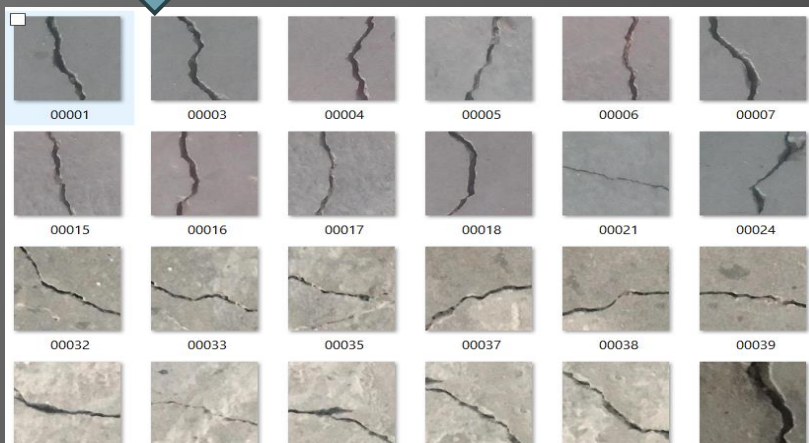
Data set consist of 40000 images



positive

Both
NAP

Negative



```
x,y = next(train_generator)|  
plot_images(x,y)
```



Negative



Negative



Negative



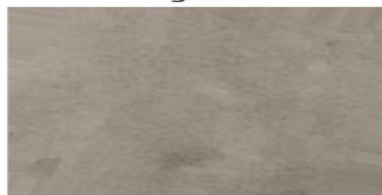
Positive



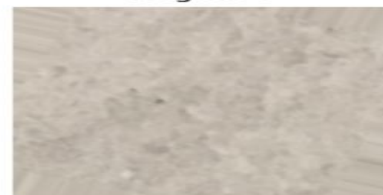
Positive



Negative



Negative



Positive



Positive

Positive

Negative

Positive

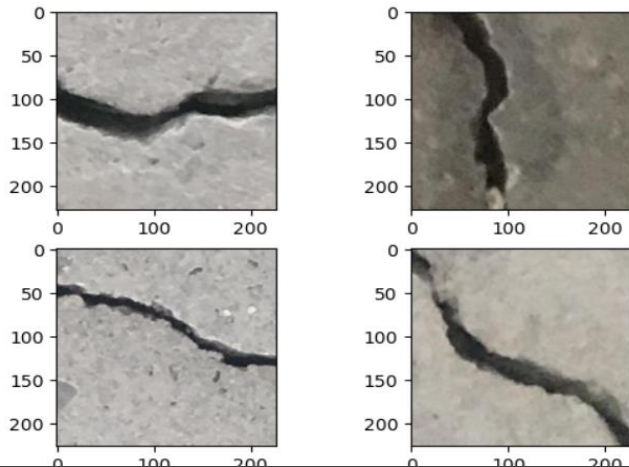
preprocessing

crack

Non
crack

image with cracks

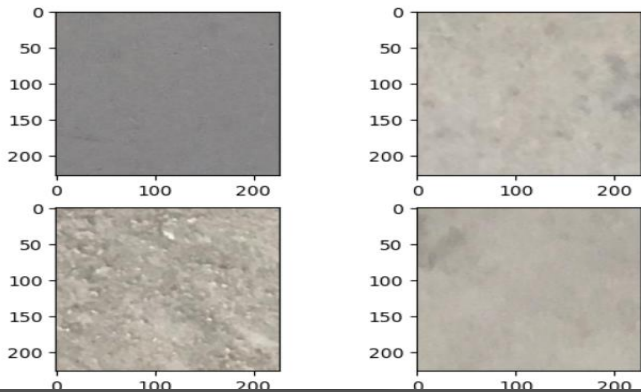
Out[12]: <matplotlib.image.AxesImage at 0x27918ccaac0>



```
axarr[1, 0].imshow(mping.imread(os.path.join(image_directory, img[2])))  
axarr[1, 1].imshow(mping.imread(os.path.join(image_directory, img[3])))
```

images with out cracks

Out[11]: <matplotlib.image.AxesImage at 0x27918a84670>



Out[14]:

	Filepath	Label
0	C:\Users\HP\Downloads\archive (4)\Positive\038...	Positive
1	C:\Users\HP\Downloads\archive (4)\Positive\128...	Positive
2	C:\Users\HP\Downloads\archive (4)\Positive\150...	Positive
3	C:\Users\HP\Downloads\archive (4)\Negative\167...	Negative
4	C:\Users\HP\Downloads\archive (4)\Positive\092...	Positive
...
39995	C:\Users\HP\Downloads\archive (4)\Positive\078...	Positive
39996	C:\Users\HP\Downloads\archive (4)\Negative\125...	Negative
39997	C:\Users\HP\Downloads\archive (4)\Positive\051...	Positive
39998	C:\Users\HP\Downloads\archive (4)\Positive\121...	Positive
39999	C:\Users\HP\Downloads\archive (4)\Negative\130...	Negative

40000 rows × 2 columns

Split the DataSet

```
In [46]: train_df, test_df = train_test_split(all_df.sample(30000, random_state=1),
                                             train_size=0.7,
                                             shuffle=True,
                                             random_state=42)
```

```
In [48]: train_df.shape
```

```
Out[48]: (21000, 2)
```

```
In [49]: test_df.shape
```

```
Out[49]: (9000, 2)
```

Data augmentation and pre-processing

```
gen = ImageDataGenerator(rescale      = 1./255.,  
                          horizontal_flip = True,  
                          vertical_flip   = True,  
                          zoom_range     = 0.05,  
                          rotation_range = 25)
```

modeling

- 1. Input Layer:
 - `tf.keras.Input(shape=(120, 120, 3))`
 - Defines the input layer with a shape of (120, 120, 3), indicating an input image size of 120x120 pixels with 3 color channels (RGB).
- 2. Convolutional Layers:
 - `x = tf.keras.layers.Conv2D(filters=16, kernel_size=(3, 3), activation='relu')(inputs)`
 - `x = tf.keras.layers.MaxPool2D(pool_size=(2, 2))(x)`
 - `x = tf.keras.layers.Conv2D(filters=32, kernel_size=(3, 3), activation='relu')(x)`
 - `x = tf.keras.layers.MaxPool2D(pool_size=(2, 2))(x)`
 -
 - Applies two convolutional layers with 16 and 32 filters, respectively, each using a 3x3 kernel.
 - Applies max pooling with a 2x2 pool size after each

Conti.....

3. Global Average Pooling Layer:

- `x=tf.keras.layers.GlobalAveragePooling2D()(x)`
- ⦿ Performs global average pooling to reduce the spatial dimensions to a single value per channel, creating a flat vector.

4. Output Layer:

- ⦿ `outputs = tf.keras.layers.Dense(1, activation='sigmoid')(x)`
- ⦿ Connects the output of the global average pooling layer to a dense layer with a single neuron (for binary classification) and a sigmoid activation function.

Training from scratch

Training model ¶

```
In [53]: inputs = tf.keras.Input(shape=(128,128,3))
x = tf.keras.layers.Conv2D(filters=16, kernel_size=(3,3), activation='relu')(inputs)
x = tf.keras.layers.MaxPool2D(pool_size=(2,2))(x)
x = tf.keras.layers.Conv2D(filters=32, kernel_size=(3,3), activation='relu')(x)
x = tf.keras.layers.MaxPool2D(pool_size=(2,2))(x)
x = tf.keras.layers.Conv2D(filters=64, kernel_size=(3,3), activation='relu')(x)
x = tf.keras.layers.MaxPool2D(pool_size=(2,2))(x)
x = tf.keras.layers.Conv2D(filters=128, kernel_size=(3,3), activation='relu')(x)
x = tf.keras.layers.MaxPool2D(pool_size=(2,2))(x)
x = tf.keras.layers.GlobalAveragePooling2D()(x)
outputs = tf.keras.layers.Dense(1, activation='sigmoid')(x)
```

Model summary of
training from
scratch

Layer (type)	Output Shape	Param #
input_4 (InputLayer)	[(None, 128, 128, 3)]	0
conv2d_11 (Conv2D)	(None, 126, 126, 16)	448
max_pooling2d_11 (MaxPooling2D)	(None, 63, 63, 16)	0
conv2d_12 (Conv2D)	(None, 61, 61, 32)	4640
max_pooling2d_12 (MaxPooling2D)	(None, 30, 30, 32)	0
conv2d_13 (Conv2D)	(None, 28, 28, 64)	18496
max_pooling2d_13 (MaxPooling2D)	(None, 14, 14, 64)	0
conv2d_14 (Conv2D)	(None, 12, 12, 128)	73856
max_pooling2d_14 (MaxPooling2D)	(None, 6, 6, 128)	0
global_average_pooling2d_3 (GlobalAveragePooling2D)	(None, 128)	0

For 15000
sample

Epoch 1/10

280/280 [=====] - 97s 342ms/step - loss: 0.1775 - accuracy: 0.9312 - val_loss: 0.0585 - val_accuracy: 0.9790

Epoch 2/10

280/280 [=====] - 35s 124ms/step - loss: 0.0738 - accuracy: 0.9795 - val_loss: 0.0388 - val_accuracy: 0.9862

Epoch 3/10

280/280 [=====] - 33s 118ms/step - loss: 0.0626 - accuracy: 0.9824 - val_loss: 0.0461 - val_accuracy: 0.9853

Epoch 4/10

280/280 [=====] - 33s 118ms/step - loss: 0.0539 - accuracy: 0.9839 - val_loss: 0.0475 - val_accuracy: 0.9839

Epoch 5/10

280/280 [=====] - 33s 118ms/step - loss: 0.0533 - accuracy: 0.9844 - val_loss: 0.0439 - val_accuracy: 0.9857

Cont.....

For 30,000 sample

```
Epoch 1/10
525/525 [=====] - 213s 404ms/step - loss: 0.1291 - accuracy: 0.9573 - val_loss: 0.0600 - val_accuracy: 0.9807
Epoch 2/10
525/525 [=====] - 151s 287ms/step - loss: 0.0779 - accuracy: 0.9779 - val_loss: 0.0860 - val_accuracy: 0.9705
Epoch 3/10
525/525 [=====] - 70s 133ms/step - loss: 0.0659 - accuracy: 0.9826 - val_loss: 0.0460 - val_accuracy: 0.9886
Epoch 4/10
525/525 [=====] - 68s 129ms/step - loss: 0.0428 - accuracy: 0.9870 - val_loss: 0.0554 - val_accuracy: 0.9879
Epoch 5/10
525/525 [=====] - 68s 130ms/step - loss: 0.0540 - accuracy: 0.9851 - val_loss: 0.0406 - val_accuracy: 0.9862
Epoch 6/10
525/525 [=====] - 68s 129ms/step - loss: 0.0359 - accuracy: 0.9889 - val_loss: 0.0258 - val_accuracy: 0.9924
Epoch 7/10
525/525 [=====] - 68s 129ms/step - loss: 0.0352 - accuracy: 0.9898 - val_loss: 0.0352 - val_accuracy: 0.9912
Epoch 8/10
525/525 [=====] - 69s 131ms/step - loss: 0.0333 - accuracy: 0.9901 - val_loss: 0.0505 - val_accuracy: 0.9829
Epoch 9/10
525/525 [=====] - 69s 131ms/step - loss: 0.0303 - accuracy: 0.9908 - val_loss: 0.0417 - val_accuracy: 0.9900
```


Using Resnet_v2

Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/inception_resnet_v2/inception_resnet_v2_weights_tf_dim_ordering_tf_kernels_notop.h5

219055592/219055592 [=====] - 43s 0us/step

Unfreezing number of layers in base model = 0

Epoch 1/3

WARNING:tensorflow:From C:\Users\HP\AppData\Roaming\Python\Python39\site-packages\keras\src\utils\tf_utils.py:492: The name tf.ragged.RaggedTensorValue is deprecated. Please use tf.compat.v1.ragged.RaggedTensorValue instead.

WARNING:tensorflow:From C:\Users\HP\AppData\Roaming\Python\Python39\site-packages\keras\src\engine\base_layer_utils.py:384: The name tf.executing_eagerly_outside_functions is deprecated. Please use tf.compat.v1.executing_eagerly_outside_functions instead.

750/750 [=====] - 4655s 6s/step - loss: 0.0448 - accuracy: 0.9855 - val_loss: 0.0096 - val_accuracy: 0.9965

Epoch 2/3

750/750 [=====] - 5218s 7s/step - loss: 0.0250 - accuracy: 0.9920 - val_loss: 0.0094 - val_accuracy: 0.9965

Epoch 3/3

750/750 [=====] - 4653s 6s/step - loss: 0.0211 - accuracy: 0.9932 - val_loss: 0.0103 - val_accuracy: 0.9965

Performance metric

$$\text{True Positive Rate (TPR)} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

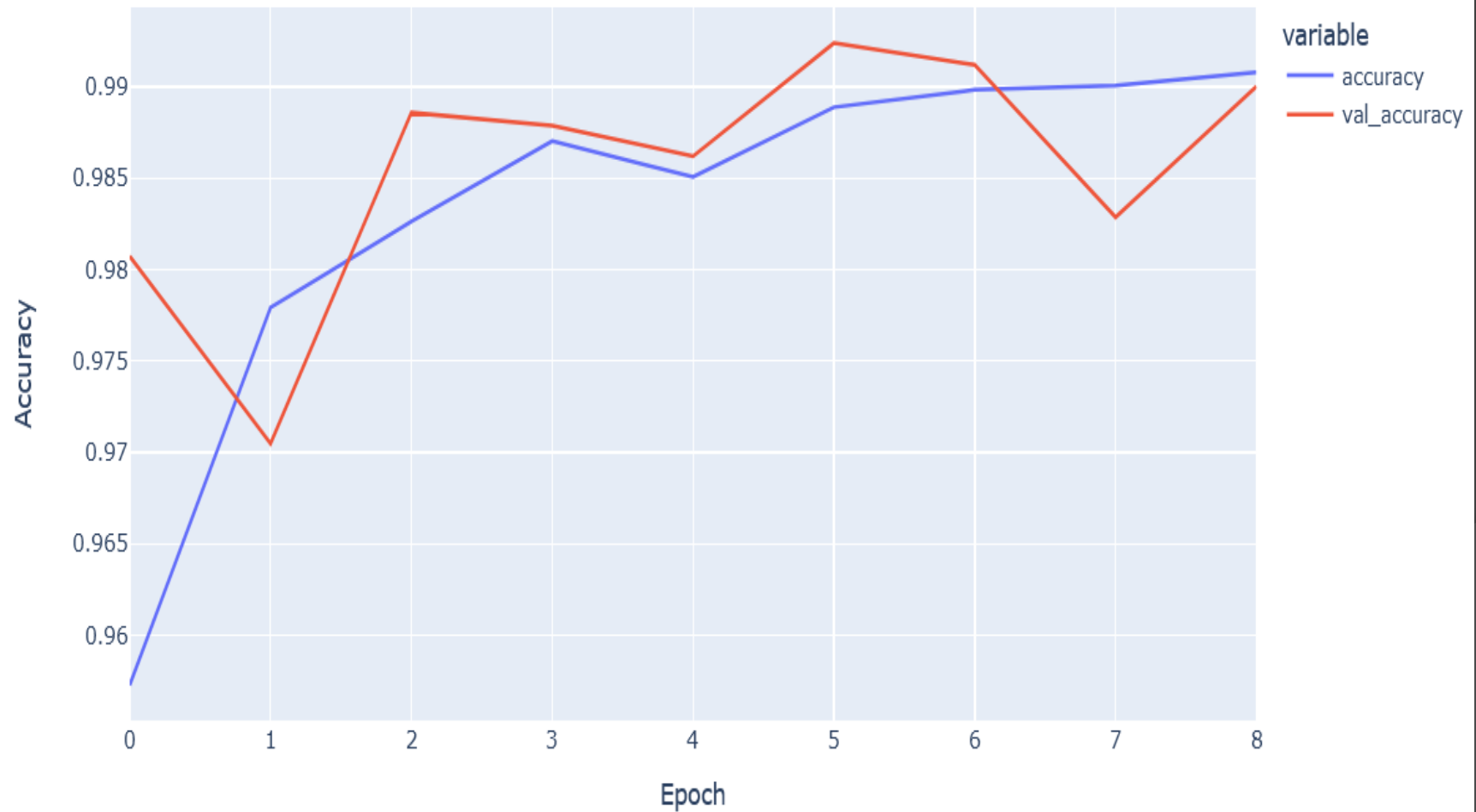
$$\text{False Positive Rate (FPR)} = \frac{\text{FP}}{\text{FP} + \text{TN}}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{FP} + \text{TN}}$$

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FN} + \text{TN} + \text{FP}}$$

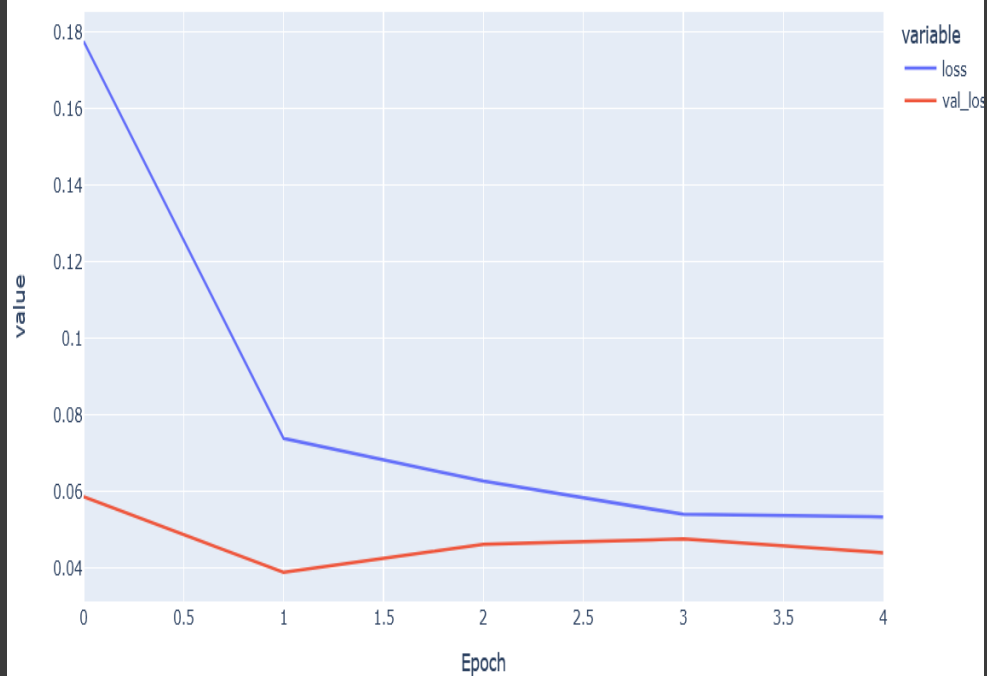
$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Training and Validation Accuracy Over Time

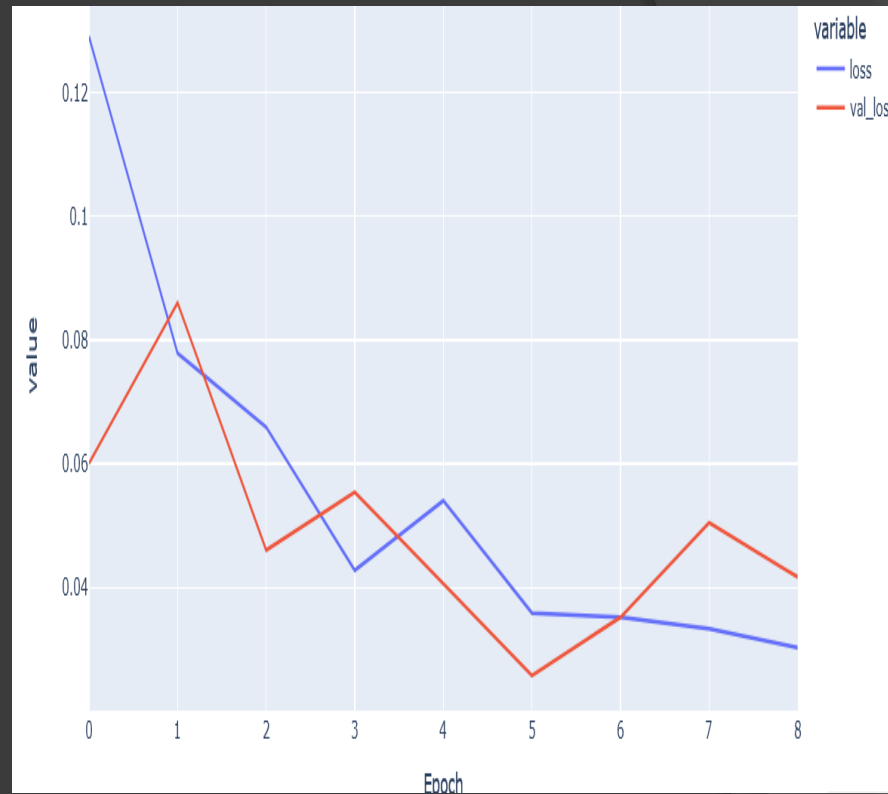


Result

Training and Validation Loss over Time



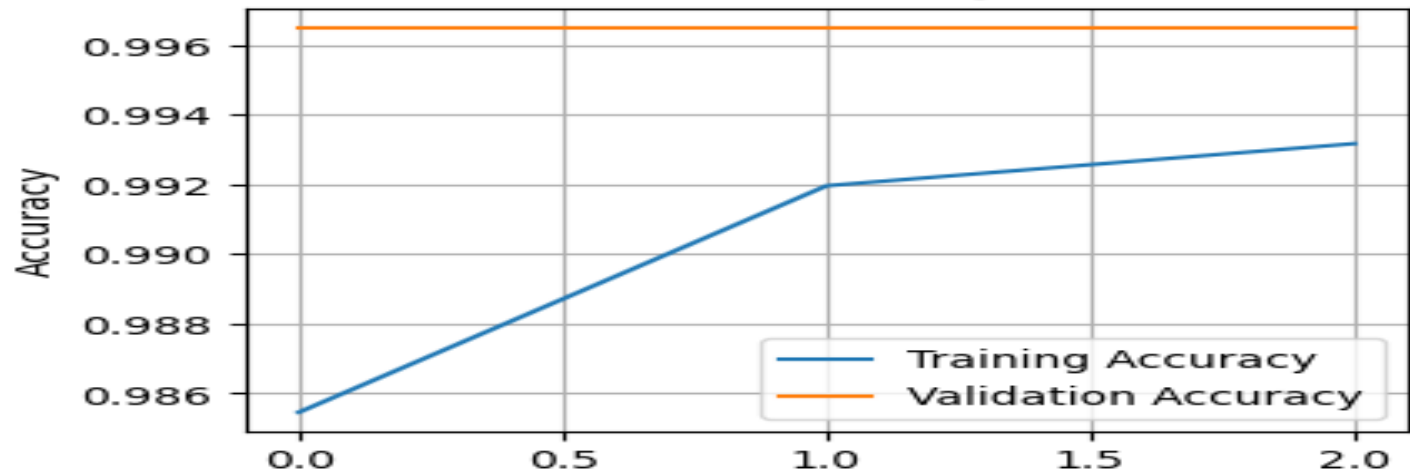
For 15000
sample



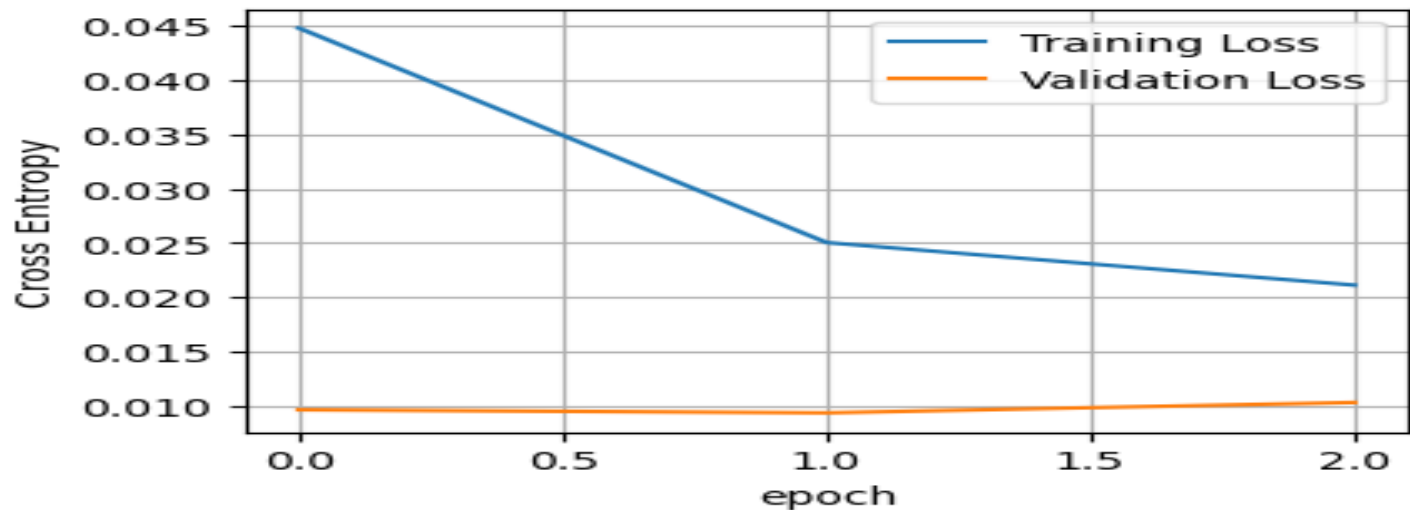
For 30000
sample

Using
pretrained
model

Training and Validation Accuracy.
Train Accuracy: 0.993
Validation Accuracy: 0.997



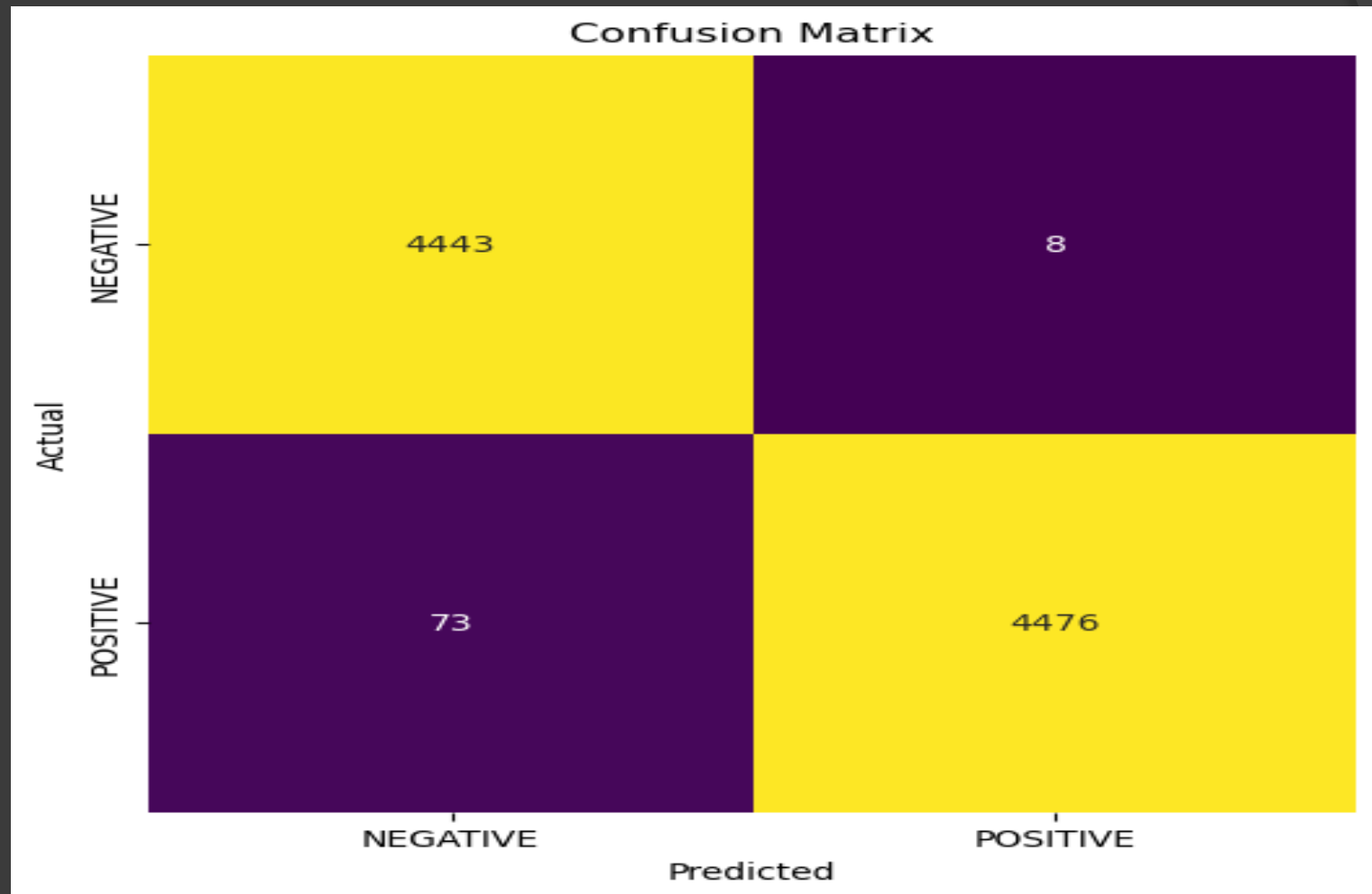
Training and Validation Loss.
Train Loss: 0.021
Validation Loss: 0.01



Result

```
0]: ▶ def evaluate_model(model, test_data):  
  
    results = model.evaluate(test_data, verbose=0)  
    loss = results[0]  
    acc = results[1]  
  
    print("    Test Loss: {:.5f}".format(loss))  
    print("Test Accuracy: {:.2f}%".format(acc * 100))  
  
1]: ▶ evaluate_model(model, test_data)  
  
    Test Loss: 0.02858  
    Test Accuracy: 99.10%
```

Confusion matrix



Cont.....

Classification Report:

	precision	recall	f1-score	support
NEGATIVE	0.98	1.00	0.99	4451
POSITIVE	1.00	0.98	0.99	4549
accuracy			0.99	9000
macro avg	0.99	0.99	0.99	9000
weighted avg	0.99	0.99	0.99	9000

Predicted
output

Positive
Positive 100.0%



Negative
Negative 100.0%



Negative
Negative 100.0%



Negative
Negative 99.4%



Positive
Positive 100.0%



Positive
Positive 100.0%



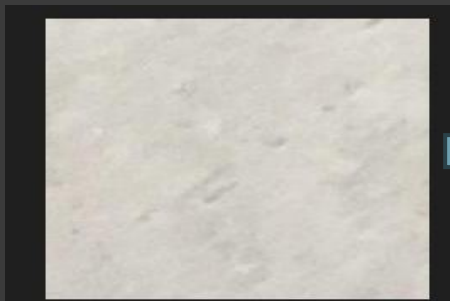
Positive
Positive 100.0%



Positive
Positive 100.0%



Using non max suppression and edge detector



input

output

Conclusion

- By comparing result of using pretrained model and training from scratch
- Utilizing pre-trained model is better than training from scratch in terms of accuracy.
-

Challenges and future work

- ⦿ When I reduce the number of sample, overfitting happened
- ⦿ Incorporate better accurate model to hard ware .make it more real time.
 - ⦿ Applying non max suppression with deep learning



Thank
you