



Model Development Phase Template

Date	7th July 2025
Team ID	SWTID1750822736
Project Title	Fault detection using transfer learning
Maximum Marks	4 Marks

Initial Model Training Code, Model Validation and Evaluation Report

The following section contains the initial model training code extracted from the Jupyter notebook, including data loading, preprocessing, model configuration, and training.

Initial Model Training Code:

Code Block 1

```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import os
import pathlib
import PIL
import cv2
import skimage
from IPython.display import Image, display
from matplotlib.image import imread
import matplotlib.cm as cm
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras.models import Sequential
from tensorflow.keras.preprocessing import image
import random
seed = 0
random.seed(seed)
np.random.seed(seed)
tf.random.set seed(seed)
Code Block 2
# import dataset
dataset url = "/kaggle/input/real-life-industrial-dataset-of-casting-
product/casting 512x512/casting 512x512/"
data dir = pathlib.Path(dataset url)
data dir
Output:
PosixPath('/kaggle/input/real-life-industrial-dataset-of-casting-
product/casting 512x512/casting 512x512')
```





Code Block 3

```
# check the number of rows / number of .jpeg files
image_count = len(list(data_dir.glob('*/*.jpeg')))
print(image_count)
Output:
1300
```

Code Block 4

```
# open the image using the PIL library => for defective_front
def_front = list(data_dir.glob('def_front/*'))
PIL.Image.open(def_front[0])
```

Output:

<PIL.JpegImagePlugin.JpegImageFile image mode=RGB size=512x512>

Code Block 5

```
# ok_front list of products
ok_front = list(data_dir.glob('ok_front/*'))
PIL.Image.open(ok_front[0])
```

Output:

<PIL.JpegImagePlugin.JpegImageFile image mode=RGB size=512x512>

Code Block 6

```
sample1= imread(ok_front[0])
sample1.shape
```

Output:

(512, 512, 3)

Code Block 7

```
batch_size = 64
epochs = 200
img_height = 299
img_width = 299
img_size = (img_height, img_width)
```

Code Block 8

```
train_set = tf.keras.utils.image_dataset_from_directory(
   data_dir,
   validation_split=0.2,
   class_names = ['ok_front', 'def_front'],
   subset="training",
   seed=seed,
   image_size=(img_height, img_width),
   batch_size=batch_size)
```

Output:

Found 1300 files belonging to 2 classes. Using 1040 files for training.

Code Block 9

```
val_set = tf.keras.utils.image_dataset_from_directory(
   data_dir,
   validation_split=0.2,
   class_names = ['ok_front', 'def_front'],
   subset="validation",
   seed=seed,
   image_size=(img_height, img_width),
   batch_size=batch_size)
```

Output:

Found 1300 files belonging to 2 classes. Using 260 files for validation.

Code Block 10

```
class_names = train_set.class_names
print(class_names)
```

Output:

['ok front', 'def front']





```
Code Block 11
plt.figure(figsize=(10, 10))
for images, labels in train set.take(1):
  for i in range(9):
    ax = plt.subplot(3, 3, i + 1)
    plt.imshow(images[i].numpy().astype("uint8"))
    plt.title(class names[labels[i]])
    plt.axis("off")
Code Block 12
for images, labels in train set:
  print(images.shape)
  print(labels.shape)
  break
Output:
(64, 299, 299, 3)
(64,)
Code Block 13
AUTOTUNE = tf.data.AUTOTUNE
train ds = train set.cache().shuffle(1300).prefetch(buffer size=AUTOTUNE)
val ds = val set.cache().prefetch(buffer size=AUTOTUNE)
Code Block 14
data augmentation = keras. Sequential (
  [
layers.RandomFlip("horizontal and vertical", input shape=(img height, img width, 3),
seed = seed),
    layers.RandomZoom(0.1, seed = seed),
    layers.RandomContrast(0.3, seed = seed )
Code Block 15
custom model = Sequential([
  layers. Rescaling (1./255),
  data augmentation,
  layers.Conv2D(64, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Conv2D(64, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Conv2D(64, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Conv2D(32, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Flatten(),
  layers.Dense(128, activation='relu'),
  layers.Dense(1, activation = 'sigmoid')
Code Block 16
custom model.compile(optimizer='adam',
                     loss='binary crossentropy',
                     metrics=['accuracy'])
Code Block 17
class myCallback(tf.keras.callbacks.Callback):
    def on epoch end(self, epoch, logs={}):
        if logs.get('accuracy') == 1.0 and logs.get('val accuracy') == 1.0 :
            print("\nReached 100% accuracy so cancelling training!")
```

self.model.stop training = True





```
terminate callback = myCallback()
Code Block 18
# why reduceLROnPlateau() => takes bigger steps
reduce lr = tf.keras.callbacks.ReduceLROnPlateau(monitor='val loss', factor=0.5,
verbose=1, min delta=0.01,
               patience=5, min lr=0.000001)
Code Block 19
history1 = custom model.fit(train ds,
              validation data=val ds,
              epochs=epochs,
              callbacks= [reduce lr, terminate callback]
)
Output:
Epoch 1/200
0.6279 - val loss: 0.5668 - val accuracy: 0.6885
Epoch 2/200
0.6875 - val loss: 0.5353 - val accuracy: 0.7615
Epoch 3/200
0.7356 - val loss: 0.5108 - val accuracy: 0.7615
Epoch 4/200
0.7510 - val loss: 0.4686 - val accuracy: 0.8000
Epoch 5/200
0.7308 - val loss: 0.4757 - val accuracy: 0.7923
Epoch 6/200
0.7750 - val loss: 0.4346 - val accuracy: 0.8038
Epoch 7/200
0.7942 - val loss: 0.4125 - val accuracy: 0.8038
Epoch 8/200
0.8202 - val loss: 0.3537 - val_accuracy: 0.8346
Epoch 9/200
0.8010 - val loss: 0.4009 - val accuracy: 0.8192
Epoch 10/200
0.8048 - val loss: 0.3221 - val accuracy: 0.8654
Epoch 11/200
0.8298 - val loss: 0.2866 - val accuracy: 0.8423
Epoch 12/200
0.8673 - val loss: 0.2613 - val accuracy: 0.8769
Epoch 13/200
0.8769 - val loss: 0.2180 - val accuracy: 0.9038
Epoch 14/200
0.8673 - val loss: 0.3209 - val accuracy: 0.8692
Epoch 15/200
0.8894 - val_loss: 0.1932 - val_accuracy: 0.9077
Epoch 16/200
```





```
0.8365 - val loss: 0.1875 - val accuracy: 0.9385
Epoch 17/200
0.8625 - val loss: 0.2613 - val accuracy: 0.9038
Epoch 18/200
0.8875 - val_loss: 0.1857 - val accuracy: 0.8923
Epoch 19/200
0.9029 - val loss: 0.1262 - val accuracy: 0.9615
Epoch 20/200
0.9404 - val loss: 0.1176 - val accuracy: 0.9654
Epoch 21/200
0.9404 - val loss: 0.1377 - val accuracy: 0.9231
Epoch 22/200
0.9433 - val loss: 0.0983 - val accuracy: 0.9577
Epoch 23/200
0.9212 - val loss: 0.1117 - val accuracy: 0.9615
Epoch 24/200
0.9500 - val loss: 0.0821 - val accuracy: 0.9731
Epoch 25/200
0.9413 - val loss: 0.1631 - val accuracy: 0.9269
Epoch 26/200
0.9346 - val loss: 0.1512 - val accuracy: 0.9269
Epoch 27/200
0.9615 - val_loss: 0.0542 - val_accuracy: 0.9846
Epoch 28/200
0.9663 - val loss: 0.0430 - val accuracy: 0.9885
Epoch 29/200
0.9692 - val_loss: 0.0578 - val_accuracy: 0.9731
Epoch 30/200
0.9596 - val loss: 0.1289 - val accuracy: 0.9462
Epoch 31/200
0.9769 - val loss: 0.0233 - val_accuracy: 0.9962
Epoch 32/200
0.9692 - val loss: 0.0342 - val accuracy: 0.9846
Epoch 33/200
0.9827 - val loss: 0.0321 - val accuracy: 0.9846
Epoch 34/200
0.9856 - val loss: 0.0172 - val accuracy: 0.9962
Epoch 35/200
0.9798 - val loss: 0.0180 - val accuracy: 0.9962
Epoch 36/200
0.9404 - val loss: 0.1020 - val accuracy: 0.9423
```





```
Epoch 00036: ReduceLROnPlateau reducing learning rate to 0.0005000000237487257.
Epoch 37/200
0.9731 - val loss: 0.0434 - val accuracy: 0.9846
Epoch 38/200
0.9885 - val_loss: 0.0301 - val_accuracy: 0.9885
Epoch 39/200
0.9875 - val loss: 0.0156 - val accuracy: 0.9962
Epoch 40/200
0.9913 - val loss: 0.0064 - val accuracy: 1.0000
Epoch 41/200
0.9875 - val loss: 0.0132 - val accuracy: 0.9962
Epoch 42/200
0.9865 - val loss: 0.0074 - val accuracy: 0.9962
Epoch 43/200
0.9923 - val loss: 0.0038 - val accuracy: 1.0000
Epoch 44/200
0.9904 - val loss: 0.0228 - val accuracy: 0.9923
Epoch 45/200
0.9942 - val loss: 0.0034 - val accuracy: 1.0000
Epoch 00045: ReduceLROnPlateau reducing learning rate to 0.0002500000118743628.
Epoch 46/200
0.9971 - val loss: 0.0023 - val accuracy: 1.0000
Epoch 47/200
0.9971 - val loss: 0.0027 - val accuracy: 1.0000
Epoch 48/200
0.9981 - val loss: 0.0015 - val accuracy: 1.0000
Epoch 49/200
0.9971 - val loss: 0.0019 - val accuracy: 1.0000
Epoch 50/200
0.9942 - val loss: 0.0015 - val accuracy: 1.0000
Epoch 00050: ReduceLROnPlateau reducing learning rate to 0.0001250000059371814.
Epoch 51/200
0.9990 - val loss: 0.0019 - val accuracy: 1.0000
Epoch 52/200
0.9971 - val loss: 0.0013 - val_accuracy: 1.0000
Epoch 53/200
0.9981 - val loss: 0.0011 - val accuracy: 1.0000
Epoch 54/200
1.0000 - val loss: 0.0011 - val accuracy: 1.0000
```





Code Block 20

custom model.summary()

Output:

Model: "sequential 5"

Layer (type)	Output	Shape	Param #
rescaling_4 (Rescaling)	(None,	299, 299, 3)	0
sequential_4 (Sequential)	(None,	299, 299, 3)	0
conv2d_16 (Conv2D)	(None,	299, 299, 64)	1792
max_pooling2d_8 (MaxPooling2	(None,	149, 149, 64)	0
conv2d_17 (Conv2D)	(None,	149, 149, 64)	36928
max_pooling2d_9 (MaxPooling2	(None,	74, 74, 64)	0
conv2d_18 (Conv2D)	(None,	74, 74, 64)	36928
max_pooling2d_10 (MaxPooling	(None,	37, 37, 64)	0
conv2d_19 (Conv2D)	(None,	37, 37, 32)	18464
max_pooling2d_11 (MaxPooling	(None,	18, 18, 32)	0
flatten_4 (Flatten)	(None,	10368)	0
dense_8 (Dense)	(None,	128)	1327232
dense_9 (Dense)	(None,	1)	129
Total params: 1,421,473 Trainable params: 1,421,473	=====		=======

Non-trainable params: 0

Code Block 21

```
acc = history1.history['accuracy']
val acc = history1.history['val accuracy']
loss = history1.history['loss']
val loss = history1.history['val loss']
epochs range = range(len(acc))
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.plot(epochs range, acc, label='Training Accuracy')
plt.plot(epochs_range, val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')
plt.subplot(1, 2, 2)
plt.plot(epochs range, loss, label='Training Loss')
plt.plot(epochs range, val loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.show()
```





```
Code Block 22
base model = keras.applications.Xception(
  weights='imagenet', # Load weights pre-trained on ImageNet.
  input shape=(img height, img width, 3),
  include top=False)
Code Block 23
base model.trainable = False
# Create new model on top
inputs = keras.Input(shape=(img height, img width, 3))
x = data augmentation(inputs) # Apply random data augmentation
x = keras.layers.Rescaling(scale=1 / 255.0)(x)
x = base model(x, training=False)
x = keras.layers.Flatten()(x)
x = keras.layers.Dense(128, activation = 'relu')(x)
outputs = keras.layers.Dense(1, activation = 'sigmoid')(x)
pretrained model = keras.Model(inputs, outputs)
Code Block 24
pretrained model.compile(optimizer='adam',
         loss='binary crossentropy',
         metrics=['accuracy'])
Code Block 25
history2 = pretrained model.fit(
  train ds,
  validation data=val ds,
  epochs=epochs,
  callbacks= [reduce lr, terminate callback]
)
Output:
Epoch 1/200
0.7125 - val loss: 1.6489 - val accuracy: 0.7769
Epoch 2/200
0.8740 - val loss: 0.6319 - val accuracy: 0.8577
Epoch 3/200
0.9212 - val loss: 0.0494 - val accuracy: 0.9808
Epoch 4/200
0.9683 - val loss: 0.0866 - val_accuracy: 0.9692
Epoch 5/200
0.9808 - val loss: 0.0141 - val accuracy: 0.9962
Epoch 6/200
0.9933 - val loss: 0.0146 - val accuracy: 0.9962
Epoch 7/200
0.9981 - val_loss: 0.0062 - val_accuracy: 1.0000
Epoch 8/200
0.9990 - val loss: 0.0037 - val accuracy: 1.0000
Epoch 9/200
0.9981 - val loss: 0.0058 - val accuracy: 1.0000
Epoch 10/200
```



plt.show()



```
0.9990 - val loss: 0.0092 - val accuracy: 0.9962
Epoch 11/200
1.0000 - val loss: 0.0054 - val_accuracy: 0.9962
Epoch 12/200
0.9990 - val loss: 0.0081 - val accuracy: 0.9962
Epoch 13/200
0.9981 - val loss: 0.0259 - val accuracy: 0.9846
Epoch 00013: ReduceLROnPlateau reducing learning rate to 0.0005000000237487257.
Epoch 14/200
0.9990 - val loss: 0.0037 - val accuracy: 1.0000
Epoch 15/200
0.9981 - val loss: 0.0107 - val accuracy: 0.9962
Epoch 16/200
0.9990 - val loss: 0.0034 - val accuracy: 1.0000
Epoch 17/200
0.9990 - val loss: 0.0044 - val accuracy: 1.0000
Epoch 18/200
0.9990 - val loss: 0.0068 - val accuracy: 0.9962
Epoch 00018: ReduceLROnPlateau reducing learning rate to 0.0002500000118743628.
Epoch 19/200
0.9981 - val loss: 0.0033 - val accuracy: 1.0000
Epoch 20/200
1.0000 - val loss: 0.0042 - val accuracy: 1.0000
Reached 100% accuracy so cancelling training!
Code Block 26
acc = history2.history['accuracy']
val acc = history2.history['val accuracy']
loss = history2.history['loss']
val loss = history2.history['val loss']
epochs range = range(len(acc))
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.plot(epochs range, acc, label='Training Accuracy')
plt.plot(epochs range, val acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')
plt.subplot(1, 2, 2)
plt.plot(epochs range, loss, label='Training Loss')
plt.plot(epochs range, val loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
```





Code Block 27

pretrained_model.summary()

Output:

Model: "model_2"

Layer (type)	Output Shape	Param #
input_6 (InputLayer)	[(None, 299, 299, 3)]	0
sequential_4 (Sequential)	(None, 299, 299, 3)	0
rescaling_5 (Rescaling)	(None, 299, 299, 3)	0
xception (Functional)	(None, 10, 10, 2048)	20861480
flatten_5 (Flatten)	(None, 204800)	0
dense_10 (Dense)	(None, 128)	26214528
dense_11 (Dense)	(None, 1)	129

Total params: 47,076,137
Trainable params: 26,214,657
Non-trainable params: 20,861,480