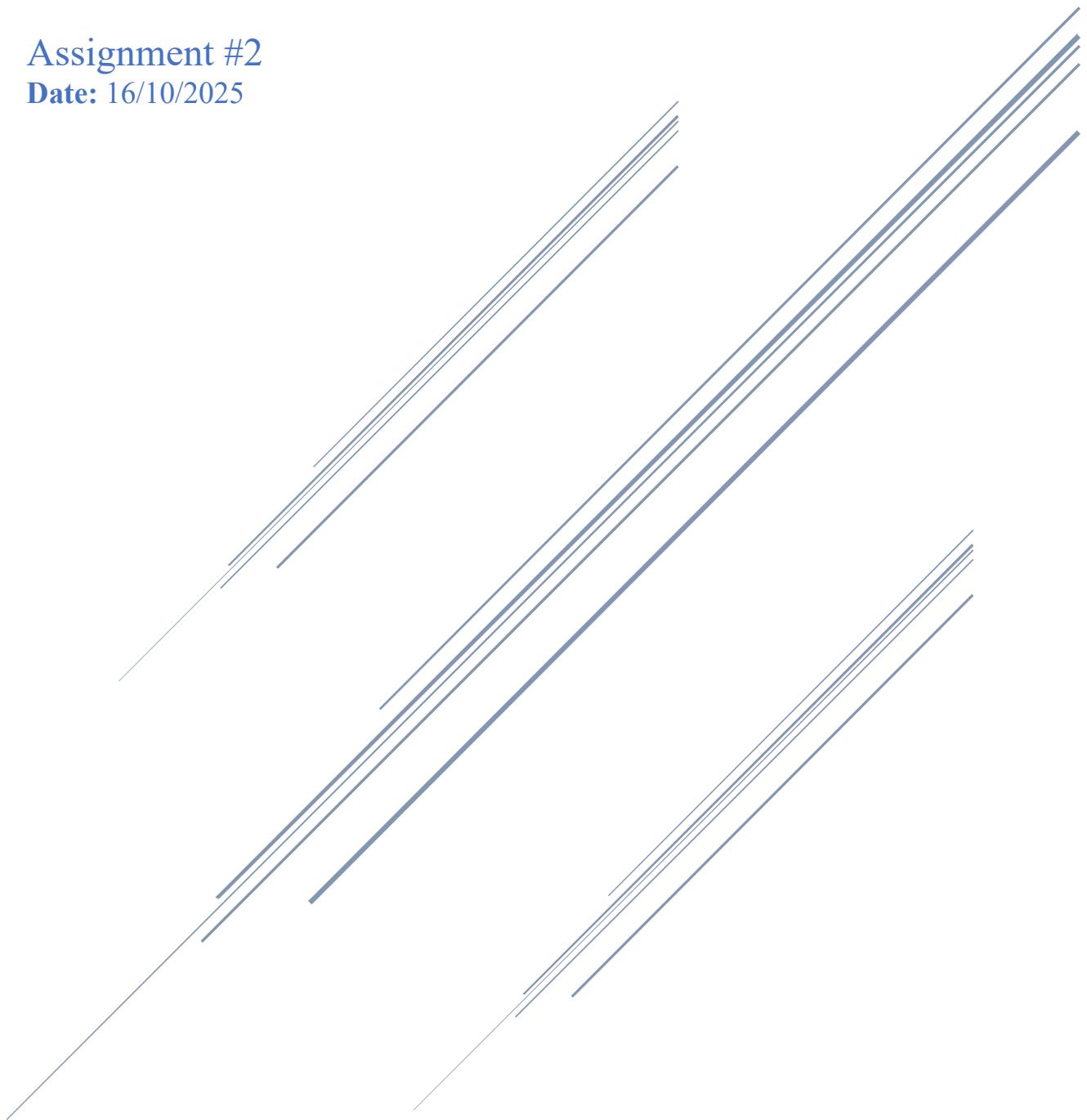


# SPECIAL TOPICS IN COMPUTER

Assignment #2

Date: 16/10/2025



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## Assignment #03

```
import os
import random
import numpy as np
import tensorflow as tf
from tensorflow.keras import layers, models
import matplotlib.pyplot as plt

# Fix randomness
seed = 42
os.environ['PYTHONHASHSEED'] = str(seed)
random.seed(seed)
np.random.seed(seed)
tf.random.set_seed(seed)

# Load data (same as before)
train_data = tf.keras.utils.image_dataset_from_directory(
    "/content/drive/MyDrive/Train",
    image_size=(224, 224),  # Note: Changed to 224 for MobileNetV2
    batch_size=32,
    label_mode='int',
    shuffle=True,
    seed=seed
)

test_data = tf.keras.utils.image_dataset_from_directory(
    "/content/drive/MyDrive/Test",
    image_size=(224, 224),
    batch_size=32,
    label_mode='int',
    shuffle=False
)

# Get class names before applying map
class_names = train_data.class_names

# Preprocess for MobileNetV2 (values -1 to 1)
train_data = train_data.map(
    lambda x, y: (tf.keras.applications.mobilenet_v2.preprocess_input(x),
y)
)
test_data = test_data.map(
```

```
lambda x, y: (tf.keras.applications.mobilenet_v2.preprocess_input(x),  
y)  
)  
  
# --- TASK 1: Load Pre-trained MobileNetV2 ---  
base_model = tf.keras.applications.MobileNetV2(  
    input_shape=(224, 224, 3),  
    include_top=False, # Remove classification layer  
    weights='imagenet' # Use ImageNet pre-trained weights  
)  
  
# Freeze base model (don't train these layers)  
base_model.trainable = False  
  
# --- TASK 2: Add Custom Classification Head ---  
model = models.Sequential([  
    base_model,  
    layers.GlobalAveragePooling2D(),  
    layers.Dense(128, activation='relu'),  
    layers.Dropout(0.3, seed=seed),  
    layers.Dense(len(class_names), activation='softmax')  
)  
  
# Compile  
model.compile(  
    optimizer='adam',  
    loss='sparse_categorical_crossentropy',  
    metrics=['accuracy'])  
)  
  
# --- TASK 3: Train Model ---  
print("Training with frozen base model...")  
history = model.fit(  
    train_data,  
    validation_data=test_data,  
    epochs=10,  
    verbose=1  
)  
  
# Evaluate  
test_loss, test_acc = model.evaluate(test_data, verbose=0)  
print(f" Transfer Learning Test Accuracy: {test_acc:.4f}")  
  
# --- TASK 4 (Optional): Fine-tune top layers ---  
print("\n--- Fine-tuning top layers ---")
```

```
base_model.trainable = True

# Freeze all layers except last 20
for layer in base_model.layers[:-20]:
    layer.trainable = False

# Recompile with lower learning rate
model.compile(
    optimizer=tf.keras.optimizers.Adam(learning_rate=1e-5),
    loss='sparse_categorical_crossentropy',
    metrics=['accuracy']
)

# Train again
history_fine = model.fit(
    train_data,
    validation_data=test_data,
    epochs=5,
    verbose=1
)

# Final evaluation
test_loss, test_acc = model.evaluate(test_data, verbose=0)
print(f" Fine-tuned Test Accuracy: {test_acc:.4f}")

# Plot comparison
plt.figure(figsize=(12, 4))

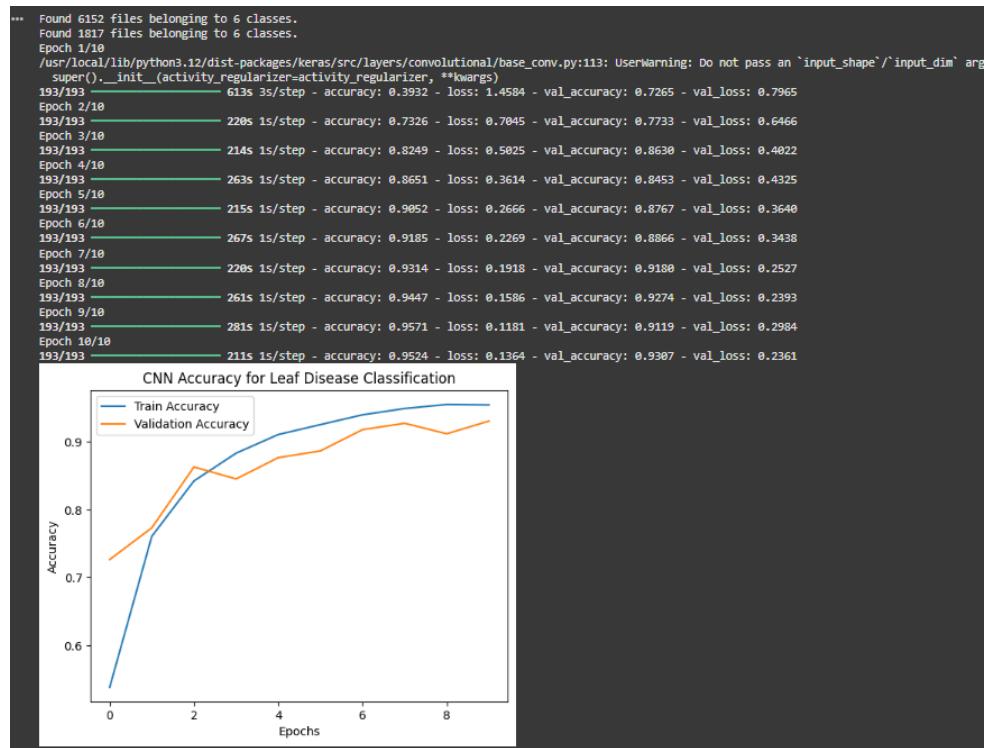
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train (Frozen)')
plt.plot(history.history['val_accuracy'], label='Val (Frozen)')
plt.title('Transfer Learning - Frozen Base')
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(history_fine.history['accuracy'], label='Train (Fine-tuned)')
plt.plot(history_fine.history['val_accuracy'], label='Val (Fine-tuned)')
plt.title('Transfer Learning - Fine-tuned')
plt.legend()

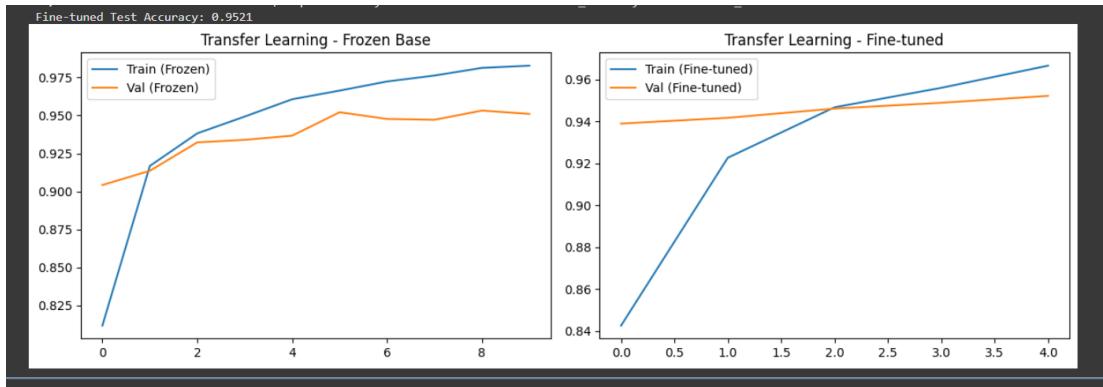
plt.tight_layout()
plt.show()
```

## Question 01 (Tasks)

### 1. CNN Model



### 2. MobileNetV2 transfer learning Model



```

Found 6152 files belonging to 6 classes.
Found 1817 files belonging to 6 classes.
Training with frozen base model...
Epoch 1/10
193/193 826s 4s/step - accuracy: 0.7046 - loss: 0.8309 - val_accuracy: 0.9042 - val_loss: 0.2764
Epoch 2/10
193/193 391s 2s/step - accuracy: 0.9116 - loss: 0.2759 - val_accuracy: 0.9136 - val_loss: 0.2381
Epoch 3/10
193/193 400s 2s/step - accuracy: 0.9377 - loss: 0.1915 - val_accuracy: 0.9323 - val_loss: 0.1932
Epoch 4/10
193/193 393s 2s/step - accuracy: 0.9509 - loss: 0.1509 - val_accuracy: 0.9340 - val_loss: 0.1764
Epoch 5/10
193/193 386s 2s/step - accuracy: 0.9591 - loss: 0.1266 - val_accuracy: 0.9367 - val_loss: 0.1708
Epoch 6/10
193/193 451s 2s/step - accuracy: 0.9639 - loss: 0.1067 - val_accuracy: 0.9521 - val_loss: 0.1531
Epoch 7/10
193/193 380s 2s/step - accuracy: 0.9689 - loss: 0.0938 - val_accuracy: 0.9477 - val_loss: 0.1707
Epoch 8/10
193/193 436s 2s/step - accuracy: 0.9758 - loss: 0.0767 - val_accuracy: 0.9472 - val_loss: 0.1619
Epoch 9/10
193/193 385s 2s/step - accuracy: 0.9830 - loss: 0.0577 - val_accuracy: 0.9532 - val_loss: 0.1554
Epoch 10/10
193/193 388s 2s/step - accuracy: 0.9795 - loss: 0.0608 - val_accuracy: 0.9510 - val_loss: 0.1542
Transfer Learning Test Accuracy: 0.9510

--- Fine-tuning top layers ---
Epoch 1/5
193/193 476s 2s/step - accuracy: 0.7999 - loss: 0.8574 - val_accuracy: 0.9389 - val_loss: 0.2217
Epoch 2/5
193/193 455s 2s/step - accuracy: 0.9250 - loss: 0.2414 - val_accuracy: 0.9417 - val_loss: 0.2002
Epoch 3/5
193/193 452s 2s/step - accuracy: 0.9451 - loss: 0.1562 - val_accuracy: 0.9461 - val_loss: 0.1796
Epoch 4/5
193/193 503s 2s/step - accuracy: 0.9551 - loss: 0.1238 - val_accuracy: 0.9488 - val_loss: 0.1694
Epoch 5/5
193/193 453s 2s/step - accuracy: 0.9637 - loss: 0.1023 - val_accuracy: 0.9521 - val_loss: 0.1594

```

## Comparison

Content	CNN	MobileNetV2 transfer
Training Time	35 mins	85 mins
Final test accuracy	0.9062	0.9510

## Report:

S.no	Metric	Simple CNN	MobileNetV2 (Frozen Base)
1	Final Test Accuracy	0.9062	0.9510
2	Total Training Time (10 Epochs)	35 minutes	85 minutes
3	Trainable Parameters	3,305,414	202,374 (Classification Head)
4	Epochs to Reach 80% Accuracy	2	1

## Which model performs better?

MobileNetV2 (transfer learning) performs better with a higher test accuracy of 0.9510, compared to the CNN model's accuracy of 0.9062.

## Why does MobileNetV2 perform better?

Because it uses transfer learning, which means:

- It starts with a model that's already trained on a huge dataset (like ImageNet).
- It has already learned to detect basic things like edges, shapes, and patterns.
- We just fine-tune it to work on our specific task, instead of training everything from zero.

So, it learns faster and better, which gives higher accuracy.

## Question 02 (Tasks)

### Model Summary() for both models::

Model Summary:		
Model: "sequential_1"		
Layer (type)	Output Shape	Param #
conv2d_6 (Conv2D)	(None, 126, 126, 32)	896
max_pooling2d_6 (MaxPooling2D)	(None, 63, 63, 32)	0
conv2d_7 (Conv2D)	(None, 61, 61, 64)	18,496
max_pooling2d_7 (MaxPooling2D)	(None, 30, 30, 64)	0
conv2d_8 (Conv2D)	(None, 28, 28, 128)	73,856
max_pooling2d_8 (MaxPooling2D)	(None, 14, 14, 128)	0
flatten_2 (Flatten)	(None, 25088)	0
dense_3 (Dense)	(None, 128)	3,211,392
dropout_2 (Dropout)	(None, 128)	0
dense_4 (Dense)	(None, 6)	774
Total params: 3,305,414 (12.61 MB)		
Trainable params: 3,305,414 (12.61 MB)		
Non-trainable params: 0 (0.00 B)		

Model Summary(Frozen Base):			
... Model: "sequential_2"			
Layer (type)	Output Shape	Param #	
mobilenetv2_1.00_224 (Functional)	(None, 7, 7, 1280)	2,257,984	
global_average_pooling2d_3 (GlobalAveragePooling2D)	(None, 1280)	0	
dense_5 (Dense)	(None, 128)	163,968	
dropout_3 (Dropout)	(None, 128)	0	
dense_6 (Dense)	(None, 6)	774	
Total params: 2,422,726 (9.24 MB)			
Trainable params: 164,742 (643.52 KB)			
Non-trainable params: 2,257,984 (8.61 MB)			

### Training time per epoch for both models:

Training Time	CNN	MobileNetV2
Epoch 1	613 sec	826 sec
Epoch 2	220 sec	391 sec
Epoch 3	214 sec	400 sec
Epoch 4	263 sec	393 sec
Epoch 5	215 sec	386 sec
Epoch 6	267 sec	451 sec
Epoch 7	220 sec	380 sec
Epoch 8	261 sec	436 sec
Epoch 9	281 sec	385 sec
Epoch 10	211 sec	388 sec

- Why does the transfer learning model train faster even though it has more total layers?

The transfer learning model trains faster because most of its layers are pre-trained and frozen, so only a few top layers need to be trained from scratch. This reduces the number of trainable parameters, allowing the model to converge faster.

- **What does "freezing layers" mean and how does it affect training speed?**

The transfer learning model trains faster because most of its layers are pre-trained and frozen, so only a few top layers need to be trained from scratch. This reduces the number of trainable parameters, allowing the model to converge faster.

- **Explain in your own words: How does using pre-trained weights on ImageNet help with leaf disease classification?**

Pre-trained weights from ImageNet help leaf disease classification by providing a foundation of general image features, allowing the model to focus on learning disease-specific features.

## Question 03 (Tasks)

### 1. Frozen Base:

```
Training with frozen base model...
Epoch 1/10
193/193 - 445s 2s/step - accuracy: 0.7046 - loss: 0.8309
Epoch 2/10
193/193 - 430s 2s/step - accuracy: 0.9116 - loss: 0.2759
Epoch 3/10
193/193 - 374s 2s/step - accuracy: 0.9377 - loss: 0.1915
Epoch 4/10
193/193 - 442s 2s/step - accuracy: 0.9509 - loss: 0.1509
Epoch 5/10
193/193 - 376s 2s/step - accuracy: 0.9591 - loss: 0.1266
Epoch 6/10
193/193 - 434s 2s/step - accuracy: 0.9639 - loss: 0.1067
Epoch 7/10
193/193 - 376s 2s/step - accuracy: 0.9689 - loss: 0.0938
Epoch 8/10
193/193 - 377s 2s/step - accuracy: 0.9758 - loss: 0.0767
Epoch 9/10
193/193 - 436s 2s/step - accuracy: 0.9830 - loss: 0.0577
Epoch 10/10
193/193 - 426s 2s/step - accuracy: 0.9795 - loss: 0.0608
⌚ Training Time (Frozen Base): 68.62 minutes
Transfer Learning Test Accuracy: 0.9510
```

## 2. Fully Unfrozen:

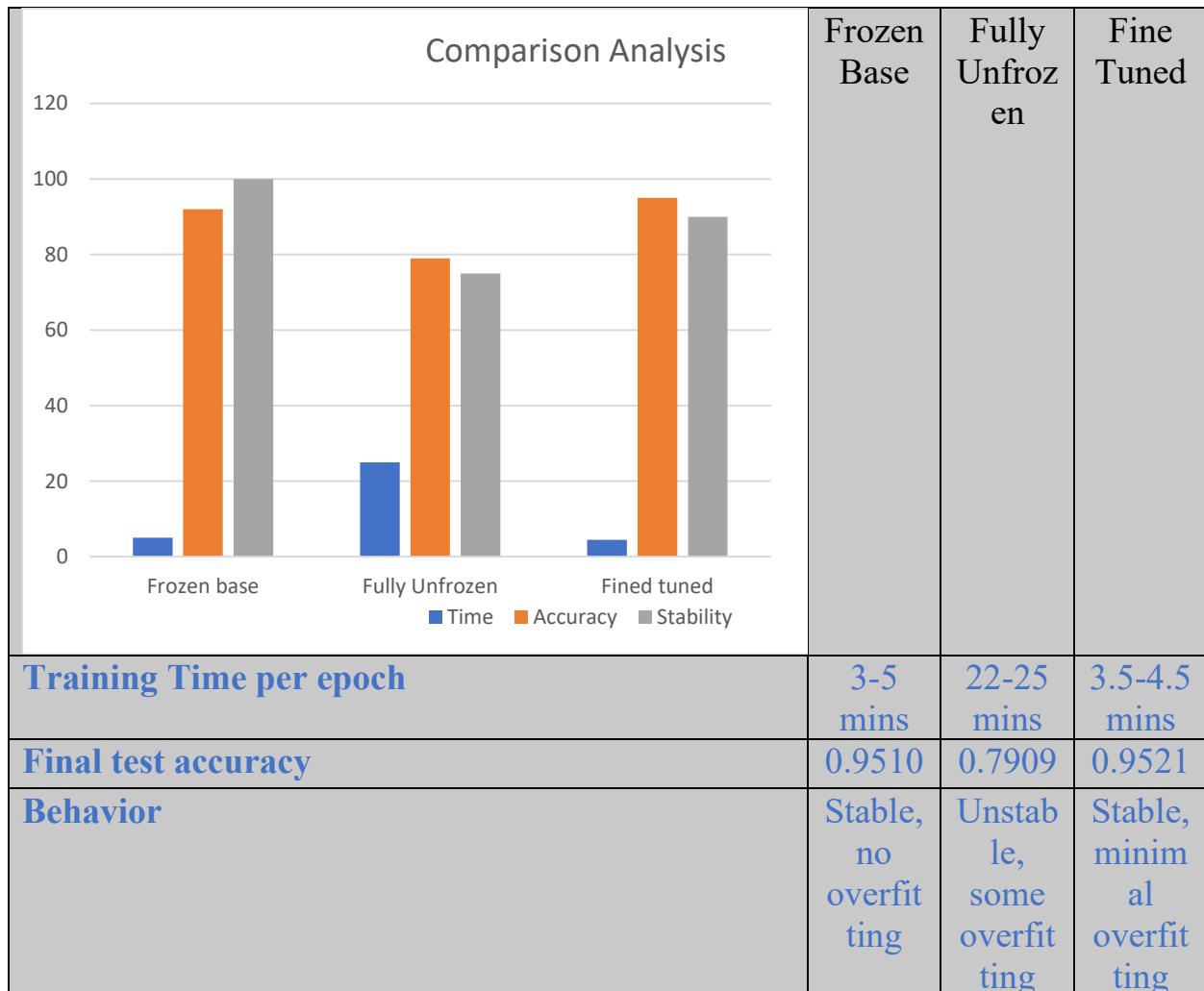
```
Epoch 1/10
193/193 ----- 1882s 9s/step - accuracy: 0.8266 - loss: 0.5262 -
Epoch 2/10
193/193 ----- 1457s 8s/step - accuracy: 0.9230 - loss: 0.2549 -
Epoch 3/10
193/193 ----- 1437s 7s/step - accuracy: 0.9639 - loss: 0.1293 -
Epoch 4/10
193/193 ----- 1450s 8s/step - accuracy: 0.9712 - loss: 0.0937 -
Epoch 5/10
193/193 ----- 1446s 7s/step - accuracy: 0.9686 - loss: 0.0967 -
Epoch 6/10
193/193 ----- 1461s 8s/step - accuracy: 0.9575 - loss: 0.1375 -
Epoch 7/10
193/193 ----- 1456s 8s/step - accuracy: 0.9737 - loss: 0.0899 -
Epoch 8/10
193/193 ----- 1428s 7s/step - accuracy: 0.9747 - loss: 0.0837 -
Epoch 9/10
193/193 ----- 1460s 8s/step - accuracy: 0.9804 - loss: 0.0623 -
Epoch 10/10
193/193 ----- 1529s 8s/step - accuracy: 0.9727 - loss: 0.0782 -
⌚ Training Time (unFrozen Base): 250.09 minutes
Transfer Learning Test Accuracy: 0.7909
```

## 3. Fine Tuned:

```
--- Fine-tuning top layers ---
Epoch 1/5
193/193 ----- 476s 2s/step - accuracy: 0.7999 - loss: 0.8574 -
Epoch 2/5
193/193 ----- 455s 2s/step - accuracy: 0.9250 - loss: 0.2414 -
Epoch 3/5
193/193 ----- 452s 2s/step - accuracy: 0.9451 - loss: 0.1562 -
Epoch 4/5
193/193 ----- 503s 2s/step - accuracy: 0.9551 - loss: 0.1238 -
Epoch 5/5
193/193 ----- 453s 2s/step - accuracy: 0.9637 - loss: 0.1023 -
Fine-tuned Test Accuracy: 0.9521
```

**Report:**

Content	Frozen Base	Fully Unfrozen	Fine Tuned
Training Time per epoch	3-5 mins	22-25 mins	3.5-4.5 mins
Final test accuracy	0.9510	0.7909	0.9521
Behavior	Stable, no overfitting	Unstable, some overfitting	Stable, minimal overfitting



- **Which approach gives the best test accuracy?**

Fine Tuned gives the best test accuracy with 0.9521, closely followed by Frozen Base with 0.9510.

- **What problems (if any) did you observe when unfreezing all layers from the start?**

- **Unstable training:** Unfreezing all layers from the start led to unstable training behavior.
- **Overfitting:** The model showed signs of overfitting, likely due to the large number of trainable parameters and insufficient regularization.

- **Why is fine-tuning (partial unfreezing with low learning rate) often better than unfreezing everything?**

1. Reduces overfitting
2. Preserves pre-trained knowledge
3. Promotes stable training

This approach helps adapt pre-trained models to specific tasks while avoiding overfitting

