



Model Optimization and Tuning Phase Template

Date	15 july 2024
Team ID	SWTID1720093035
Project Title	TechPart Vision: Personal Computer Parts Image Classification Using EfficientNet Transfer Learning
Maximum Marks	10 Marks

Model Optimization and Tuning Phase

The Model Optimization and Tuning Phase involves refining neural network models for peak performance. It includes optimized model code, fine-tuning hyperparameters, comparing performance metrics, and justifying the final model selection for enhanced predictive accuracy and efficiency.

Hyperparameter Tuning Documentation (8 Marks):

Model	Tuned Hyperparameters	
	Convolutional Layers	
	• Number of Filters: 32	
	• Kernel Size: 3 (first layer), 2 (second layer)	
CNN	Activation Function: ReLU	
CININ	Padding: Same	
	Pooling Layers	
	• Pooling Size: 2	
	Regularization	





• **Dropout Rate**: 0.5

Dense Layers

• Units: 128

Kernel Initializer: HeNormal

Output Layer

• Units: 14

Training Parameters

• Batch Size: 32

• Number of Epochs: 10

```
from keras.models import Sequential
from keras.layers import Dense, Activation, Dropout, Flatten
from keras.layers import Convolution2D, MaxPooling2D
initializer = tf.keras.initializers.HeNormal()
model=Sequential()
model.add(Convolution2D(filters=32, kernel_size=3, padding='same', activation="relu",
                            input_shape=(255,_255, 3)))
model.add(MaxPooling2D(strides=2, pool_size=2, padding= "valid"))
model.add(Convolution2D(filters=32, kernel_size=2, padding='same', activation="relu"))
model.add(MaxPooling2D(strides=2, pool_size=2, padding="valid"))
model.add(Dropout(0.5))
model.add(Flatten())
model.add(Dense(128, activation='relu', kernel initializer=initializer))
model.add(Dropout(0.5))
model.add(Dense(14, activation='softmax'))
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
history = model.fit(train gen, validation data= val gen, batch size= 32, epochs = 10, verbose = 1)
```





Tuned Hyperparameters:

Base Model: EfficientNetV2B1

Base Model

• **Base Model**: EfficientNetV2B1 (pretrained on ImageNet, used as a feature extractor)

Pooling

• **Pooling**: Max (global max pooling applied to the output of the base model)

Batch Normalization

EfficientNetV2

B1 Model

Initialisation

• **Axis**: -1

• **Momentum**: 0.99

• **Epsilon**: 0.001

Dense Layer

• Units: 256

Regularization

• Kernel Regularization: 12(0.016)

• Activity Regularization: 11(0.006)

• **Bias Regularization**: 11(0.006)

Activation

• Activation Function: ReLU





Dropout

• **Rate**: 0.4

Output Layer

• Units: 14 (softmax activation for multi-class classification)

Optimizer

• Optimizer: Adamax

• Learning Rate: 0.001

Callbacks

• ReduceLROnPlateau:

o **Monitor**: "val_loss"

• **Factor**: 0.4

o Patience: 2

o **Min LR**: 0.0

• EarlyStopping:

o Monitor: "val_loss"

o **Patience**: 2

o Restore Best Weights: True

Training Parameters

• Number of Epochs: 5





	base_model=tf.keras.applications.EfficientNetVzB1(include_top=False, weights="imagenet",input_shape=(255,255,3), pooling='max') print('Created EfficientNetV2 B1 model') Python
	ownloading data from https://storage.googleapis.com/tensorflow/keras-applications/efficientnet_v2/efficientnetv2-b1_notop_h5 8456088/28456088 [
	N
	base_model.trainable=True x-base_model.output x=BatchNormalization(axis=-1, momentum=0.99, epsilon=0.001](x) x = Dense(256, kernel_regularizer = regularizers.12(1 = 0.016),activity_regularizer-regularizers.11(0.006),
	bia_regularizer-regularizers.il(0.000), activation='relu')(x) x=0ropout(rate-4, seed=123)(x) output-benez(d, activation='softmax')(x)
	model=Model(inputs=base_model.input, outputs=output) model.compile(Adamax(learning_rate=0.001), loss='categorical_crossentropy', metrics=['accuracy']) Python
	rlronp=keras.callbacks.ReducelROnPlateau(monitor="val_loss", factor=0.4, patience=2, verbose=1, mode="auto", min_delta=0.00001, cooldown=0, min_lr=0.0
	estop-keras.callbacks.Earlystopping(monitor="val_loss", min_delta=0, patienc=2, verbose=1, mode="auto", baseline=hone, restore_best_weights=irue) callbacks=[rironp, estop]
	Python
	history=model.fit(x=train gen, epochs=5, verbose=1, callbacks=callbacks, validation data=val gen,
	validation_steps=None, shuffle=True)
	Hyperparameter Tuning:
	Tryperparameter running.
	Base Model
Vgg19	Base Model: VGG19 (pretrained on ImageNet, used as a feature)
	extractor)
	• Input Shape: (224, 224, 3)
	Pooling
	Toomig
	Pooling: Global Average Pooling
	Dense Layers
	• Units: 1024
	• Units: 1024
	 Units: 1024 Activation Function: ReLU
	Activation Function: ReLU
	Activation Function: ReLU





• Activation Function: Softmax

Optimizer

• **Optimizer**: Adam

• Learning Rate: 0.001

Loss Function

• Loss Function: Categorical Crossentropy

Metrics

• Metrics: Accuracy

Freezing Layers

• Freezing Layers: Initially freeze all base model layers

```
from tensorflow.keras.applications import VGG19
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Dense, GlobalAveragePooling2D
from tensorflow.keras.optimizers import Adam
base_model = VGG19(weights='imagenet', include_top=False, input_shape=(224, 224, 3))

x = base_model.output
x = GlobalAveragePooling2D()(x)
x = Dense(1024, activation='relu')(x)
predictions = Dense(len(train_gen.class_indices), activation='softmax')(x)

model = Model(inputs=base_model.input, outputs=predictions)

for layer in base_model.layers:
    layer.trainable = False

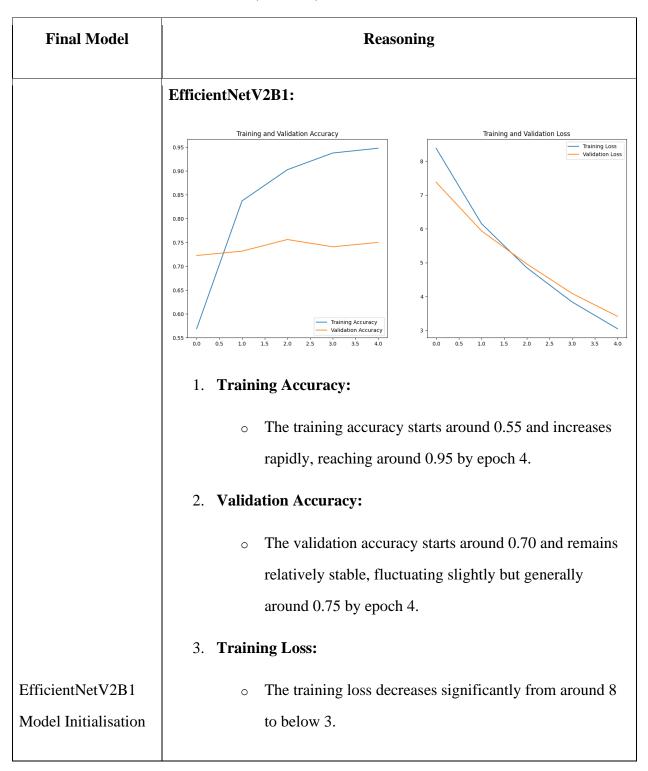
model.compile(optimizer=Adam(learning_rate=0.001),
    loss='categorical_crossentropy',
    metrics=['accuracy'])

model.summary()
```





Final Model Selection Justification (2 Marks):



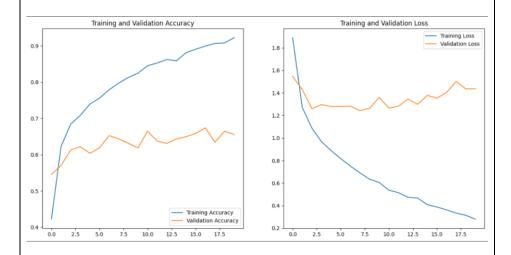




4. Validation Loss:

 The validation loss also decreases from around 7 to slightly above 3.

VGG19:



1. Training Accuracy:

 The training accuracy starts around 0.4 and increases steadily, reaching around 0.9 by epoch 17.5.

2. Validation Accuracy:

 The validation accuracy starts around 0.4 and shows fluctuations, peaking around 0.7 but generally staying lower than the training accuracy.

3. Training Loss:

 The training loss decreases significantly from around 2 to nearly 0.2.

4. Validation Loss:





 The validation loss decreases initially from around 1.8 to around 1.2 but then fluctuates and increases slightly.

Comparison:

• Training Accuracy:

 EfficientNetV2B1 reaches higher training accuracy more quickly than VGG19.

• Validation Accuracy:

 EfficientNetV2B1 maintains a relatively stable validation accuracy around 0.75, while VGG19's validation accuracy fluctuates and generally stays lower.

• Training Loss:

Both models show a significant decrease in training loss,
 but EfficientNetV2B1 starts with a higher value and
 decreases more sharply initially.

• Validation Loss:

 EfficientNetV2B1 has a more consistent decrease in validation loss, whereas VGG19's validation loss fluctuates after the initial decrease.

Conclusion:

EfficientNetV2B1 seems to perform better overall, with higher and more stable validation accuracy and a consistent decrease in validation loss compared to VGG19. While both models improve over time,





EfficientNetV2B1 shows quicker and more consistent improvements in the metrics provided.

