

## Model Optimization and Tuning Phase

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Project Title	Rice Type Classification using CNN
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
Model 1	<p>MobileNET</p> <p>Hyperparam1: Two Conv2D Layers</p> <p>This model incorporates two additional Conv2D layers to deepen the network. The extra convolutional layers aim to capture more intricate features from the images, potentially improving accuracy</p>

```
0s # Build fifth CNN Model: by two Conv2D layer
model_5 = tf.keras.Sequential(
    [
        tf.keras.layers.Rescaling(1./255, input_shape=(150, 150, 3)),
        tf.keras.layers.Conv2D(filters=32, kernel_size=3, activation='relu',
                                kernel_regularizer=tf.keras.regularizers.l2(0.001)),
        tf.keras.layers.Conv2D(filters=64, kernel_size=3, activation='relu',
                                kernel_regularizer=tf.keras.regularizers.l2(0.001)),
        tf.keras.layers.MaxPool2D(pool_size=2, strides=2),
        tf.keras.layers.Flatten(),
        tf.keras.layers.Dense(units=300, activation='relu',
                                kernel_regularizer=tf.keras.regularizers.l2(0.001)),
        tf.keras.layers.Dense(units=100, activation='relu',
                                kernel_regularizer=tf.keras.regularizers.l2(0.001)),
        tf.keras.layers.Dropout(0.5),
        tf.keras.layers.Dense(units=5),
    ]
)

model_5.summary()
```

## Hyperparam2: Regularization with L2

This model aims to reduce overfitting by adding L2 regularization to the convolutional and dense layers. L2 regularization penalizes large weights in the network, encouraging the model to keep the weights small and thus reducing overfitting.

```
# Build third CNN Model to prevent overffiting: by add regularization-L2
model_3 = tf.keras.Sequential(
    [
        tf.keras.layers.Rescaling(1./255, input_shape=(224, 224, 3)),
        tf.keras.layers.Conv2D(filters=32, kernel_size=3, activation='relu',
                                kernel_regularizer=tf.keras.regularizers.l2(0.001)),
        tf.keras.layers.MaxPool2D(pool_size=2, strides=2),
        tf.keras.layers.Flatten(),
        tf.keras.layers.Dense(units=300, activation='relu',
                                kernel_regularizer=tf.keras.regularizers.l2(0.001)),
        tf.keras.layers.Dropout(0.5),
        tf.keras.layers.Dense(units=5),
    ]
)

model_3.summary()
```

Model 2

ALEXNET;

Hyperparam1:

Increase Epoch from 3 to 5

Model: "model"

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 240, 240, 3)]	0
conv2d (Conv2D)	(None, 58, 58, 96)	34944
batch_normalization (Batch Normalization)	(None, 58, 58, 96)	384
max_pooling2d (MaxPooling2D)	(None, 28, 28, 96)	0
conv2d_1 (Conv2D)	(None, 24, 24, 256)	614656
batch_normalization_1 (Batch Normalization)	(None, 24, 24, 256)	1024
max_pooling2d_1 (MaxPooling2D)	(None, 11, 11, 256)	0
conv2d_2 (Conv2D)	(None, 9, 9, 384)	885120
conv2d_3 (Conv2D)	(None, 7, 7, 384)	1327488
conv2d_4 (Conv2D)	(None, 5, 5, 256)	884992
max_pooling2d_2 (MaxPooling2D)	(None, 2, 2, 256)	0
flatten (Flatten)	(None, 1024)	0
dense (Dense)	(None, 4096)	4198400
dropout (Dropout)	(None, 4096)	0
dense_1 (Dense)	(None, 4096)	16781312
dropout_1 (Dropout)	(None, 4096)	0
dense_2 (Dense)	(None, 5)	20485

```
# Assuming 'Alex_model' is the history object from your model training
training_acc_alex = Alex_model.history['accuracy']
val_acc_alex = Alex_model.history['val_accuracy']

best_training_acc = max(training_acc_alex)
best_val_acc = max(val_acc_alex)

# Converting to percentage and rounding off to 2 decimal places
best_training_acc_percentage = round(best_training_acc * 100, 2)
best_val_acc_percentage = round(best_val_acc * 100, 2)

print("Best Training Accuracy: ", best_training_acc_percentage, "%")
print("Best Validation Accuracy: ", best_val_acc_percentage, "%")
```

Best Training Accuracy: 97.61 %  
Best Validation Accuracy: 97.99 %

Model 3

CGGNET;

Hyperparam1:

## Increase Epoch 3 to 5

Model: "model\_1"

Layer (type)	Output Shape	Param #
input_2 (InputLayer)	[(None, 240, 240, 3)]	0
conv2d_5 (Conv2D)	(None, 238, 238, 64)	1792
conv2d_6 (Conv2D)	(None, 236, 236, 64)	36928
batch_normalization_2 (Batch Normalization)	(None, 236, 236, 64)	256
max_pooling2d_3 (Max Pooling 2D)	(None, 118, 118, 64)	0
conv2d_7 (Conv2D)	(None, 116, 116, 128)	73856
conv2d_8 (Conv2D)	(None, 114, 114, 128)	147584
batch_normalization_3 (Batch Normalization)	(None, 114, 114, 128)	512
max_pooling2d_4 (Max Pooling 2D)	(None, 57, 57, 128)	0
conv2d_9 (Conv2D)	(None, 55, 55, 256)	295168
conv2d_10 (Conv2D)	(None, 53, 53, 256)	590080

```

0s # Assuming 'VGG_model' is the history object from your model training
training_acc_alex = VGG_model.history['accuracy']
val_acc_alex = VGG_model.history['val_accuracy']

best_training_acc = max(training_acc_alex)
best_val_acc = max(val_acc_alex)

# Converting to percentage and rounding off to 2 decimal places
best_training_acc_percentage = round(best_training_acc * 100, 2)
best_val_acc_percentage = round(best_val_acc * 100, 2)

print("Best Training Accuracy: ", best_training_acc_percentage, "%")
print("Best Validation Accuracy: ", best_val_acc_percentage, "%")

```

Best Training Accuracy: 98.39 %  
Best Validation Accuracy: 98.66 %

**Final Model Selection Justification (2 Marks):**

Final Model	Reasoning
Model 1 MobileNet CNN	The MobileNet model has demonstrated higher accuracy compared to other models like VGG-Net and AlexNet, which is why I selected this project.