PRINCIPLES OF ARTIFICIAL INTELLIGENCE (ISB 46703)

PROJECT SUBMISSION

GROUP MEMBERS

1. AHMAD SUFIAN BIN AHMAD SYAHRIZAL(52215121160) L01-B03
2. MUHAMMAD SYAFIQ IKHWAN BIN MOHD NORHISHAM (52215121121) - L01-B02
3. MOHAMAD SYAZWAN BIN MOHD SHUKRI (52215121161) L01-B03

Loading Data & Splitting

In [1]:

```
import os
import shutil
import random
from sklearn.model_selection import train_test_split
from PIL import Image
```

In [3]:

```
# Dataset's path
base_path = r"C:\Users\User\Downloads\Mini Project\Mini Project\Dataset\combined dataset 21"

# loading dataset and removing corrupted files
def load_dataset(base_path):
    dataset = []
    try:
        subspecies = os.listdir(base_path)
        for subspecies_name in subspecies:
            subspecies_path = os.path.join(base_path, subspecies_name)
            if os.path.isdir(subspecies_path):
                for img_name in os.listdir(subspecies_path):
                    img_path = os.path.join(subspecies_path, img_name)
                    try:
                        with Image.open(img_path) as img:
                            dataset.append((img_path, subspecies_name))
                    except (IOError, OSError) as e:
                        print(f"Removing corrupted file {img_path}: {e}")
                        os.remove(img_path)
    except FileNotFoundError as e:
        print(f"Error: {e}")
    return dataset

# Saving images
def save_images(dataset, base_path):
    for img_path, subspecies_name in dataset:
        subspecies_dir = os.path.join(base_path, subspecies_name)
        os.makedirs(subspecies_dir, exist_ok=True)
        shutil.copy(img_path, subspecies_dir)


dataset = load_dataset(base_path)


random.shuffle(dataset)


# Split dataset
train_val_split = 0.7
val_test_split = 0.5

labels = [label for _, label in dataset]
train_val, test = train_test_split(dataset, train_size=train_val_split, stratify=labels)
train_labels = [label for _, label in train_val]
train, val = train_test_split(train_val, test_size=val_test_split, stratify=train_labels)

# Paths to save splitted datasets
test_path = r"C:\Users\User\Downloads\Mini Project\Mini Project\Dataset\Dataset 21\test"
train_path = r"C:\Users\User\Downloads\Mini Project\Mini Project\Dataset\Dataset 21\train"
val_path = r"C:\Users\User\Downloads\Mini Project\Mini Project\Dataset\Dataset 21\val"

# Save splitted datasets
save_images(train, train_path)
save_images(val, val_path)
save_images(test, test_path)

print("Datasets have been split and saved successfully!")
```

```
Datasets have been split and saved successfully!
```

Buil and Train Models

In [5]:
```
import numpy as np
import tensorflow as tf
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.applications import ResNet50, DenseNet121, MobileNetV3Small
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, GlobalAveragePooling2D
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint
```

```
WARNING:tensorflow:From C:\Users\User\AppData\Local\Programs\Python\Python311\Lib\site-packages\keras\src\losses
.py:2976: The name tf.losses.sparse_softmax_cross_entropy is deprecated. Please use tf.compat.v1.losses.sparse_s
oftmax_cross_entropy instead.
```

In [8]:
```
test_path = r"C:\Users\User\Downloads\Mini Project\Mini Project\Dataset\Dataset 21\test"
train_path = r"C:\Users\User\Downloads\Mini Project\Mini Project\Dataset\Dataset 21\train"
val_path = r"C:\Users\User\Downloads\Mini Project\Mini Project\Dataset\Dataset 21\val"

# Image data generators
train_datagen = ImageDataGenerator(rescale=1./255, horizontal_flip=True, zoom_range=0.2, shear_range=0.2)
val_datagen = ImageDataGenerator(rescale=1./255)
test_datagen = ImageDataGenerator(rescale=1./255)

train_generator = train_datagen.flow_from_directory(train_path, target_size=(224, 224), batch_size=32, class_mod
val_generator = val_datagen.flow_from_directory(val_path, target_size=(224, 224), batch_size=32, class_mode='ca
test_generator = test_datagen.flow_from_directory(test_path, target_size=(224, 224), batch_size=32, class_mode=

# Model build
def build_model(base_model):
    model = Sequential([
        base_model,
        GlobalAveragePooling2D(),
        Dense(256, activation='relu'),
        Dense(train_generator.num_classes, activation='softmax')
    ])
    return model
```

```
Found 1245 images belonging to 10 classes.
Found 1246 images belonging to 10 classes.
Found 1068 images belonging to 10 classes.
```

In [11]:
```
# ResNet50
resnet50_base = ResNet50(weights='imagenet', include_top=False, input_shape=(224, 224, 3))
resnet50_model = build_model(resnet50_base)
resnet50_model.compile(optimizer=Adam(), loss='categorical_crossentropy', metrics=['accuracy'])

# DenseNet121
densenet121_base = DenseNet121(weights='imagenet', include_top=False, input_shape=(224, 224, 3))
densenet121_model = build_model(densenet121_base)
densenet121_model.compile(optimizer=Adam(), loss='categorical_crossentropy', metrics=['accuracy'])

# MobileNetV3
mobilenetv3_base = MobileNetV3Small(weights='imagenet', include_top=False, input_shape=(224, 224, 3))
mobilenetv3_model = build_model(mobilenetv3_base)
mobilenetv3_model.compile(optimizer=Adam(), loss='categorical_crossentropy', metrics=['accuracy'])

# Callbacks
callbacks = [
    EarlyStopping(monitor='val_loss', patience=20, restore_best_weights=True),
    ModelCheckpoint('model_checkpoint.h5', save_best_only=True)
]
```

In [12]:
```
# Training ResNet50
resnet50_history = resnet50_model.fit(train_generator, validation_data=val_generator, epochs=25, callbacks=call
```

```
Epoch 1/25
WARNING:tensorflow:From C:\Users\User\AppData\Local\Programs\Python\Python311\Lib\site-packages\keras\src\utils\
tf_utils.py:492: The name tf.ragged.RaggedTensorValue is deprecated. Please use tf.compat.v1.ragged.RaggedTensor
Value instead.

WARNING:tensorflow:From C:\Users\User\AppData\Local\Programs\Python\Python311\Lib\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.

39/39 [==============================] - ETA: 0s - loss: 2.3253 - accuracy: 0.2819
```

```
C:\Users\User\AppData\Local\Programs\Python\Python311\Lib\site-packages\keras\src\engine\training.py:3103: UserW
arning: You are saving your model as an HDF5 file via `model.save()`. This file format is considered legacy. We
recommend using instead the native Keras format, e.g. `model.save('my_model.keras')`.
  saving_api.save_model(
```

```
39/39 [==============================] - 597s 14s/step - loss: 2.3253 - accuracy: 0.2819 - val_loss: 135.0009 - val_accuracy: 0.1316
Epoch 2/25
39/39 [==============================] - 460s 12s/step - loss: 1.8739 - accuracy: 0.3470 - val_loss: 62.1717 - val_accuracy: 0.1565
Epoch 3/25
39/39 [==============================] - 310s 8s/step - loss: 1.7240 - accuracy: 0.4305 - val_loss: 16.6345 - val_accuracy: 0.1565
Epoch 4/25
39/39 [==============================] - 214s 5s/step - loss: 1.5162 - accuracy: 0.4900 - val_loss: 3.0389 - val_accuracy: 0.1372
Epoch 5/25
39/39 [==============================] - 220s 6s/step - loss: 1.3960 - accuracy: 0.5149 - val_loss: 3.2155 - val_accuracy: 0.0875
Epoch 6/25
39/39 [==============================] - 226s 6s/step - loss: 1.2571 - accuracy: 0.5815 - val_loss: 3.0382 - val_accuracy: 0.1372
Epoch 7/25
39/39 [==============================] - 219s 6s/step - loss: 1.1388 - accuracy: 0.6305 - val_loss: 4.3557 - val_accuracy: 0.0875
Epoch 8/25
39/39 [==============================] - 219s 6s/step - loss: 1.0612 - accuracy: 0.6506 - val_loss: 4.6917 - val_accuracy: 0.0875
Epoch 9/25
39/39 [==============================] - 224s 6s/step - loss: 0.9544 - accuracy: 0.6739 - val_loss: 7.9989 - val_accuracy: 0.0875
Epoch 10/25
39/39 [==============================] - 225s 6s/step - loss: 0.9251 - accuracy: 0.7028 - val_loss: 12.1049 - val_accuracy: 0.0875
Epoch 11/25
39/39 [==============================] - 226s 6s/step - loss: 0.8260 - accuracy: 0.7333 - val_loss: 10.7120 - val_accuracy: 0.0875
Epoch 12/25
39/39 [==============================] - 225s 6s/step - loss: 0.7385 - accuracy: 0.7622 - val_loss: 8.0050 - val_accuracy: 0.0875
Epoch 13/25
39/39 [==============================] - 224s 6s/step - loss: 0.6154 - accuracy: 0.7952 - val_loss: 7.0444 - val_accuracy: 0.0875
Epoch 14/25
39/39 [==============================] - 220s 6s/step - loss: 0.5867 - accuracy: 0.7984 - val_loss: 9.0535 - val_accuracy: 0.0875
Epoch 15/25
39/39 [==============================] - 228s 6s/step - loss: 0.5386 - accuracy: 0.8193 - val_loss: 7.5728 - val_accuracy: 0.0891
Epoch 16/25
39/39 [==============================] - 229s 6s/step - loss: 0.4839 - accuracy: 0.8450 - val_loss: 10.8754 - val_accuracy: 0.0875
Epoch 17/25
39/39 [==============================] - 218s 6s/step - loss: 0.4422 - accuracy: 0.8466 - val_loss: 4.8511 - val_accuracy: 0.0979
Epoch 18/25
39/39 [==============================] - 218s 6s/step - loss: 0.4224 - accuracy: 0.8699 - val_loss: 5.8708 - val_accuracy: 0.0987
Epoch 19/25
39/39 [==============================] - 214s 6s/step - loss: 0.3614 - accuracy: 0.8884 - val_loss: 4.6610 - val_accuracy: 0.1172
Epoch 20/25
39/39 [==============================] - 223s 6s/step - loss: 0.2905 - accuracy: 0.9052 - val_loss: 5.4242 - val_accuracy: 0.1180
Epoch 21/25
39/39 [==============================] - 217s 6s/step - loss: 0.3658 - accuracy: 0.8731 - val_loss: 4.3447 - val_accuracy: 0.1404
Epoch 22/25
39/39 [==============================] - 217s 6s/step - loss: 0.3072 - accuracy: 0.9028 - val_loss: 3.6633 - val_accuracy: 0.2352
Epoch 23/25
39/39 [==============================] - 218s 6s/step - loss: 0.3263 - accuracy: 0.8996 - val_loss: 2.5611 - val_accuracy: 0.3796
Epoch 24/25
39/39 [==============================] - 221s 6s/step - loss: 0.2357 - accuracy: 0.9213 - val_loss: 3.5514 - val_accuracy: 0.3307
Epoch 25/25
39/39 [==============================] - 220s 6s/step - loss: 0.1945 - accuracy: 0.9406 - val_loss: 2.4750 - val_accuracy: 0.4591
```

In [13]:

```
# Training DenseNet121
densenet121_history = densenet121_model.fit(train_generator, validation_data=val_generator, epochs=25, callbacks
```

```
Epoch 1/25
39/39 [==============================] - 223s 5s/step - loss: 1.9971 - accuracy: 0.3502 - val_loss: 3.8028 - val
_accuracy: 0.2063
Epoch 2/25
39/39 [==============================] - 195s 5s/step - loss: 1.4940 - accuracy: 0.4908 - val_loss: 5.4440 - val
_accuracy: 0.1388
Epoch 3/25
39/39 [==============================] - 195s 5s/step - loss: 1.3029 - accuracy: 0.5639 - val_loss: 7.3014 - val
_accuracy: 0.1894
Epoch 4/25
39/39 [==============================] - 195s 5s/step - loss: 1.1587 - accuracy: 0.6129 - val_loss: 4.0196 - val
_accuracy: 0.2994
Epoch 5/25
39/39 [==============================] - 193s 5s/step - loss: 1.0049 - accuracy: 0.6675 - val_loss: 2.5154 - val
_accuracy: 0.3860
Epoch 6/25
39/39 [==============================] - 195s 5s/step - loss: 0.8635 - accuracy: 0.7108 - val_loss: 2.5069 - val
_accuracy: 0.4157
Epoch 7/25
39/39 [==============================] - 196s 5s/step - loss: 0.7284 - accuracy: 0.7542 - val_loss: 2.7301 - val
_accuracy: 0.3547
Epoch 8/25
39/39 [==============================] - 194s 5s/step - loss: 0.6985 - accuracy: 0.7687 - val_loss: 3.0963 - val
_accuracy: 0.3973
Epoch 9/25
39/39 [==============================] - 195s 5s/step - loss: 0.6226 - accuracy: 0.7920 - val_loss: 2.8191 - val
_accuracy: 0.3242
Epoch 10/25
39/39 [==============================] - 196s 5s/step - loss: 0.5198 - accuracy: 0.8233 - val_loss: 2.7497 - val
_accuracy: 0.4310
Epoch 11/25
39/39 [==============================] - 194s 5s/step - loss: 0.4739 - accuracy: 0.8434 - val_loss: 7.5717 - val
_accuracy: 0.1998
Epoch 12/25
39/39 [==============================] - 196s 5s/step - loss: 0.4789 - accuracy: 0.8337 - val_loss: 2.1701 - val
_accuracy: 0.4944
Epoch 13/25
39/39 [==============================] - 194s 5s/step - loss: 0.3946 - accuracy: 0.8755 - val_loss: 2.2019 - val
_accuracy: 0.5008
Epoch 14/25
39/39 [==============================] - 193s 5s/step - loss: 0.3952 - accuracy: 0.8763 - val_loss: 2.8921 - val
_accuracy: 0.4486
Epoch 15/25
39/39 [==============================] - 200s 5s/step - loss: 0.3522 - accuracy: 0.8932 - val_loss: 2.8147 - val
_accuracy: 0.4543
Epoch 16/25
39/39 [==============================] - 194s 5s/step - loss: 0.3423 - accuracy: 0.8948 - val_loss: 3.0593 - val
_accuracy: 0.4703
Epoch 17/25
39/39 [==============================] - 193s 5s/step - loss: 0.2971 - accuracy: 0.9052 - val_loss: 3.6738 - val
_accuracy: 0.3780
Epoch 18/25
39/39 [==============================] - 192s 5s/step - loss: 0.3243 - accuracy: 0.8956 - val_loss: 3.8058 - val
_accuracy: 0.3403
Epoch 19/25
39/39 [==============================] - 196s 5s/step - loss: 0.2221 - accuracy: 0.9269 - val_loss: 1.9778 - val
_accuracy: 0.5642
Epoch 20/25
39/39 [==============================] - 195s 5s/step - loss: 0.1625 - accuracy: 0.9462 - val_loss: 2.9602 - val
_accuracy: 0.4912
Epoch 21/25
39/39 [==============================] - 192s 5s/step - loss: 0.1800 - accuracy: 0.9390 - val_loss: 2.3609 - val
_accuracy: 0.5706
Epoch 22/25
39/39 [==============================] - 192s 5s/step - loss: 0.1550 - accuracy: 0.9446 - val_loss: 3.0023 - val
_accuracy: 0.4856
Epoch 23/25
39/39 [==============================] - 192s 5s/step - loss: 0.2386 - accuracy: 0.9116 - val_loss: 2.8329 - val
_accuracy: 0.4390
Epoch 24/25
39/39 [==============================] - 191s 5s/step - loss: 0.2490 - accuracy: 0.9157 - val_loss: 2.7637 - val
_accuracy: 0.4936
Epoch 25/25
39/39 [==============================] - 192s 5s/step - loss: 0.2127 - accuracy: 0.9317 - val_loss: 2.2843 - val
_accuracy: 0.5201
```

In [48]:
```
# Training MobileNetV3
mobilenetv3_history = mobilenetv3_model.fit(train_generator, validation_data=val_generator, epochs=25, callback:
```

```
Epoch 1/25
39/39 [==============================] - 33s 847ms/step - loss: 0.0265 - accuracy: 0.9904 - val_loss: 10.5303 -
val_accuracy: 0.0875
Epoch 2/25
39/39 [==============================] - 32s 816ms/step - loss: 0.0339 - accuracy: 0.9904 - val_loss: 12.1344 -
val_accuracy: 0.1372
Epoch 3/25
39/39 [==============================] - 34s 863ms/step - loss: 0.0471 - accuracy: 0.9871 - val_loss: 11.8139 -
val_accuracy: 0.1372
Epoch 4/25
39/39 [==============================] - 32s 828ms/step - loss: 0.0610 - accuracy: 0.9799 - val_loss: 13.6072 -
val_accuracy: 0.0875
Epoch 5/25
39/39 [==============================] - 32s 832ms/step - loss: 0.0605 - accuracy: 0.9847 - val_loss: 12.4035 -
val_accuracy: 0.0875
Epoch 6/25
39/39 [==============================] - 33s 836ms/step - loss: 0.0334 - accuracy: 0.9904 - val_loss: 13.5851 -
val_accuracy: 0.0875
Epoch 7/25
39/39 [==============================] - 33s 835ms/step - loss: 0.0269 - accuracy: 0.9888 - val_loss: 20.2545 -
val_accuracy: 0.0875
Epoch 8/25
39/39 [==============================] - 33s 834ms/step - loss: 0.0206 - accuracy: 0.9928 - val_loss: 15.4031 -
val_accuracy: 0.0875
Epoch 9/25
39/39 [==============================] - 32s 821ms/step - loss: 0.0434 - accuracy: 0.9807 - val_loss: 10.8022 -
val_accuracy: 0.1372
Epoch 10/25
39/39 [==============================] - 34s 873ms/step - loss: 0.0505 - accuracy: 0.9823 - val_loss: 8.8078 - v
al_accuracy: 0.1372
Epoch 11/25
39/39 [==============================] - 35s 901ms/step - loss: 0.1124 - accuracy: 0.9735 - val_loss: 10.9642 -
val_accuracy: 0.1372
Epoch 12/25
39/39 [==============================] - 32s 821ms/step - loss: 0.0861 - accuracy: 0.9735 - val_loss: 6.3209 - v
al_accuracy: 0.0875
Epoch 13/25
39/39 [==============================] - 32s 810ms/step - loss: 0.0542 - accuracy: 0.9831 - val_loss: 4.1024 - v
al_accuracy: 0.1276
Epoch 14/25
39/39 [==============================] - 32s 820ms/step - loss: 0.0422 - accuracy: 0.9880 - val_loss: 4.9970 - v
al_accuracy: 0.0995
Epoch 15/25
39/39 [==============================] - 33s 853ms/step - loss: 0.0310 - accuracy: 0.9888 - val_loss: 4.8454 - v
al_accuracy: 0.0875
Epoch 16/25
39/39 [==============================] - 33s 836ms/step - loss: 0.0371 - accuracy: 0.9871 - val_loss: 5.2326 - v
al_accuracy: 0.0875
Epoch 17/25
39/39 [==============================] - 33s 841ms/step - loss: 0.0307 - accuracy: 0.9912 - val_loss: 7.2674 - v
al_accuracy: 0.0987
Epoch 18/25
39/39 [==============================] - 33s 857ms/step - loss: 0.0514 - accuracy: 0.9831 - val_loss: 6.6696 - v
al_accuracy: 0.0875
Epoch 19/25
39/39 [==============================] - 33s 845ms/step - loss: 0.0441 - accuracy: 0.9880 - val_loss: 4.9771 - v
al_accuracy: 0.1372
Epoch 20/25
39/39 [==============================] - 33s 857ms/step - loss: 0.1021 - accuracy: 0.9663 - val_loss: 4.3816 - v
al_accuracy: 0.1372
Epoch 21/25
39/39 [==============================] - 34s 867ms/step - loss: 0.0755 - accuracy: 0.9759 - val_loss: 6.4491 - v
al_accuracy: 0.1372
Epoch 22/25
39/39 [==============================] - 32s 821ms/step - loss: 0.0310 - accuracy: 0.9936 - val_loss: 6.1616 - v
al_accuracy: 0.1404
Epoch 23/25
39/39 [==============================] - 34s 879ms/step - loss: 0.0561 - accuracy: 0.9847 - val_loss: 12.1572 -
val_accuracy: 0.0875
Epoch 24/25
39/39 [==============================] - 32s 820ms/step - loss: 0.0465 - accuracy: 0.9863 - val_loss: 7.9483 - v
al_accuracy: 0.0875
Epoch 25/25
39/39 [==============================] - 39s 993ms/step - loss: 0.0604 - accuracy: 0.9831 - val_loss: 5.5911 - v
al_accuracy: 0.0987
```

Model Accuracy

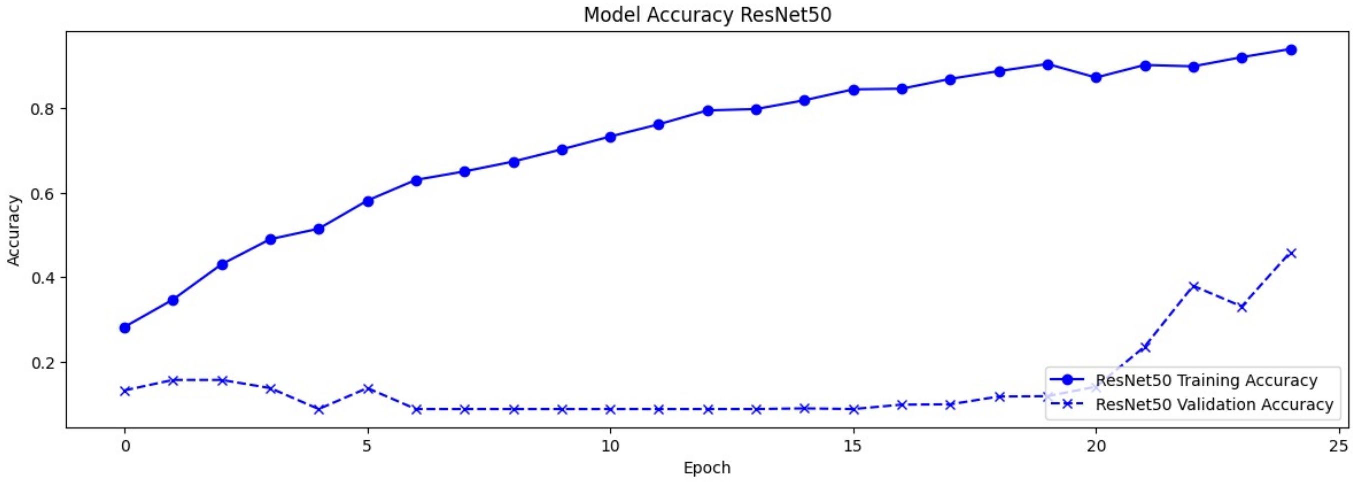
In [18]:

```
import matplotlib.pyplot as plt
```

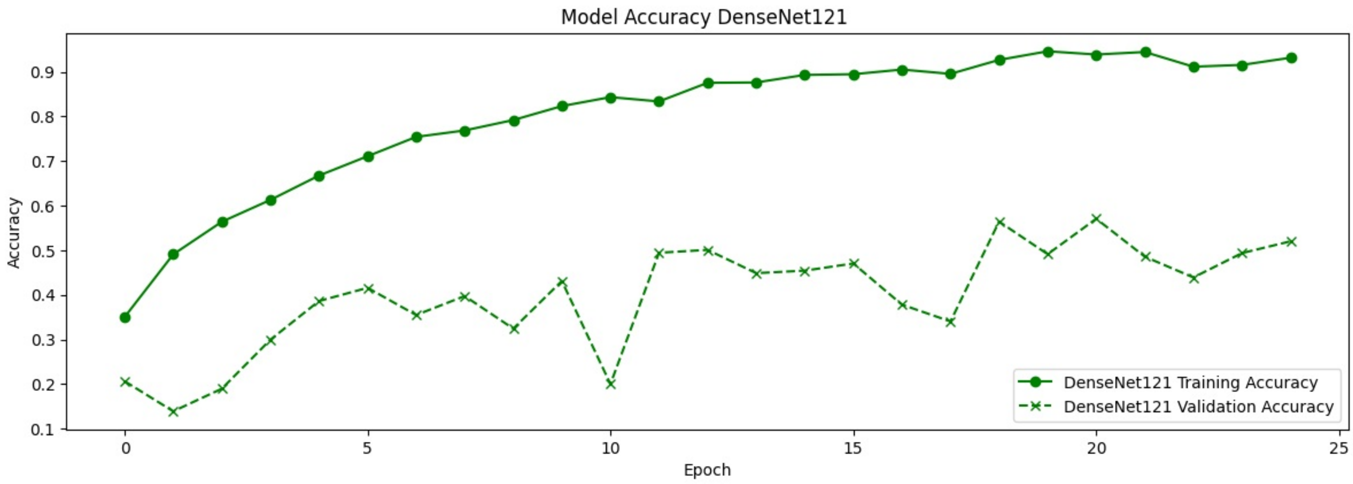
In [45]:

```
# Plotting model accuracy
plt.figure(figsize=(12, 8))
```

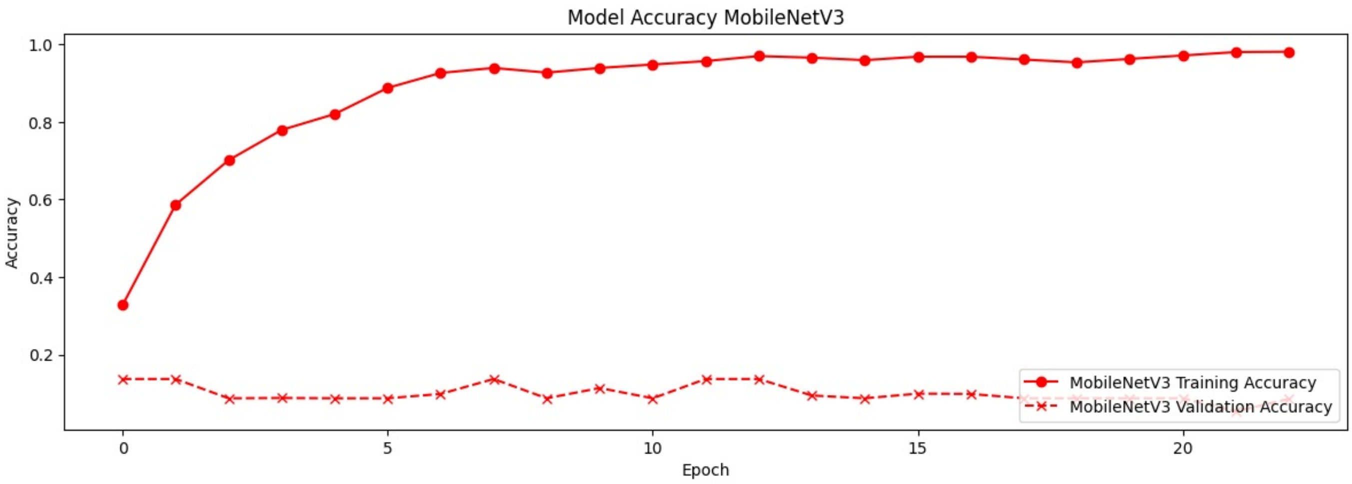
```
plt.subplot(2, 1, 1)
plt.plot(resnet50_history.history['accuracy'], label='ResNet50 Training Accuracy', linestyle='-', marker='o', c
plt.plot(resnet50_history.history['val_accuracy'], label='ResNet50 Validation Accuracy', linestyle='--', marker
plt.title('Model Accuracy ResNet50')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(loc='lower right')

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



In [44]:
```
# Plotting model accuracy
plt.figure(figsize=(12, 8))
plt.subplot(2, 1, 1)
plt.plot(densenet121_history.history['accuracy'], label='DenseNet121 Training Accuracy', linestyle='-', marker=
plt.plot(densenet121_history.history['val_accuracy'], label='DenseNet121 Validation Accuracy', linestyle='--', 
plt.title('Model Accuracy DenseNet121 ')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(loc='lower right')

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



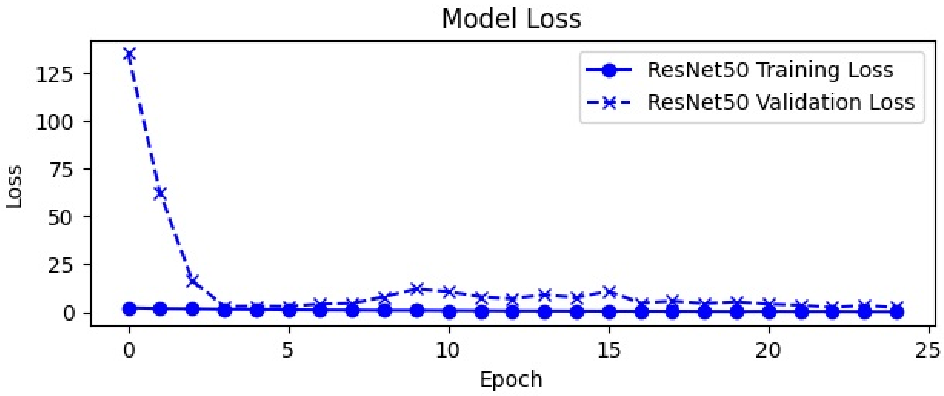
In [62]:
```
# Plotting model accuracy
plt.figure(figsize=(12, 8))
plt.subplot(2, 1, 1)
plt.plot(mobilenetv3_history.history['accuracy'], label='MobileNetV3 Training Accuracy', linestyle='-', marker=
plt.plot(mobilenetv3_history.history['val_accuracy'], label='MobileNetV3 Validation Accuracy', linestyle='--', 
plt.title('Model Accuracy MobileNetV3')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(loc='lower right')

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



Model Loss

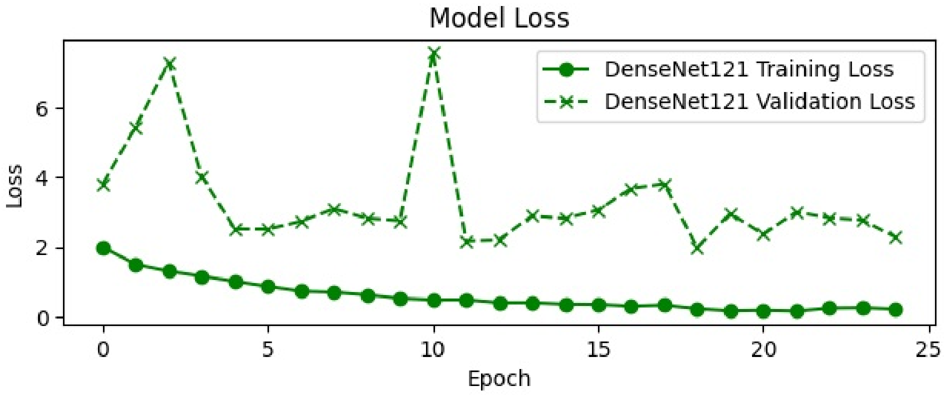
In [42]:

```
# Plotting model loss
plt.subplot(2, 1, 2)
plt.plot(resnet50_history.history['loss'], label='ResNet50 Training Loss', linestyle='-', marker='o', color='b'
plt.plot(resnet50_history.history['val_loss'], label='ResNet50 Validation Loss', linestyle='--', marker='x', co
plt.title('Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend(loc='upper right')

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



In [64]:

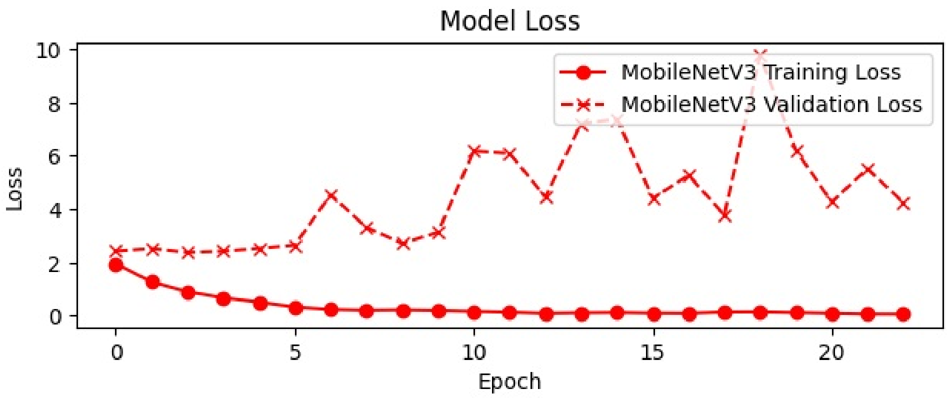
```
# Plotting model loss
plt.subplot(2, 1, 2)
plt.plot(densenet121_history.history['loss'], label='DenseNet121 Training Loss', linestyle='-', marker='o', col
plt.plot(densenet121_history.history['val_loss'], label='DenseNet121 Validation Loss', linestyle='--', marker='
plt.title('Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend(loc='upper right')

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



In [63]:

```
# Plotting model loss
plt.subplot(2, 1, 2)
plt.plot(mobilenetv3_history.history['loss'], label='MobileNetV3 Training Loss', linestyle='-', marker='o', col
```

```
plt.plot(mobilenetv3_history.history['val_loss'], label='MobileNetV3 Validation Loss', linestyle='--', marker='
plt.title('Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend(loc='upper right')

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



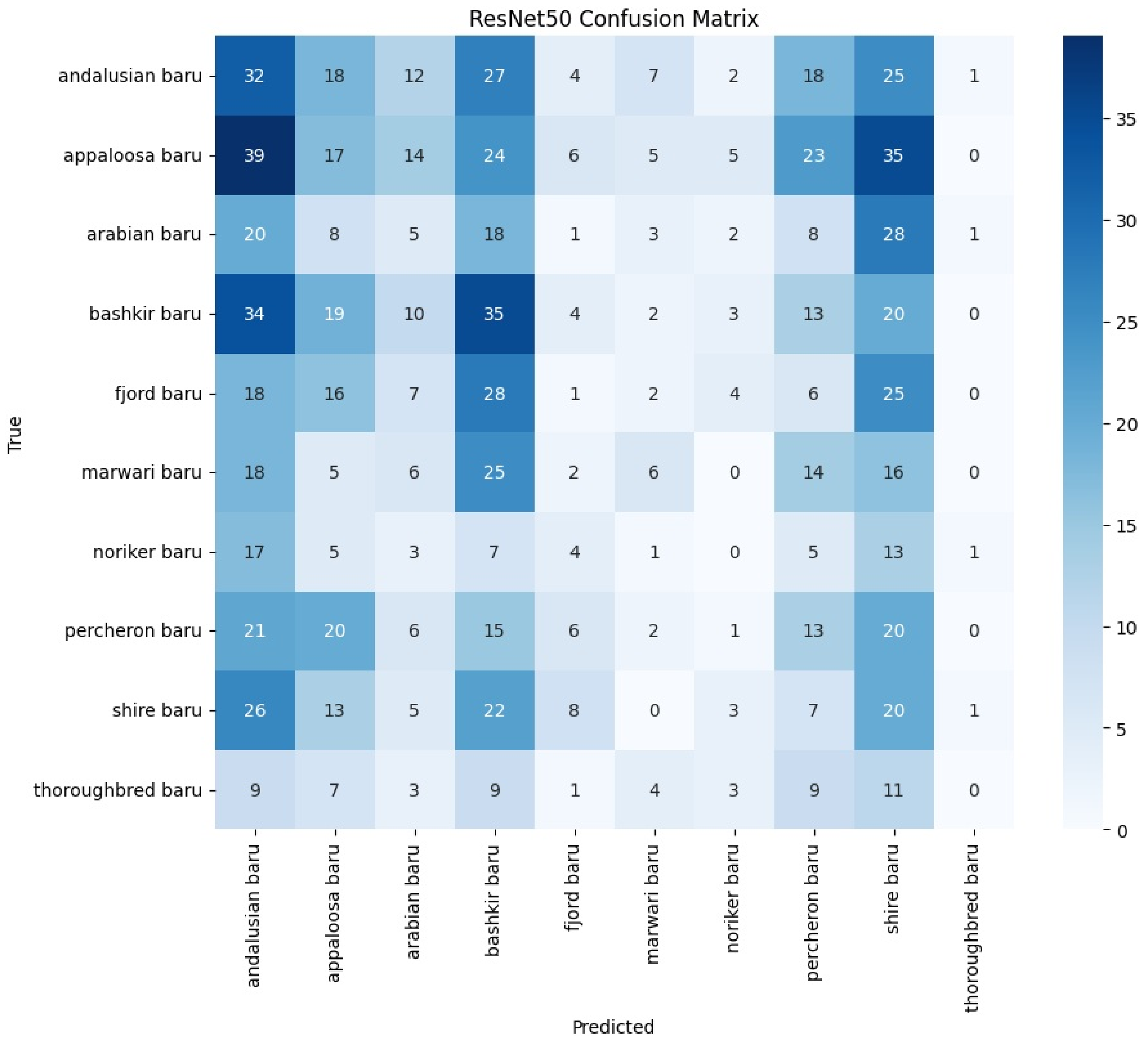
Evaluate Models (Visualize)

In [25]:
```
from sklearn.metrics import confusion_matrix, classification_report
import seaborn as sns
import matplotlib.pyplot as plt
```

In [28]:
```
def evaluate_model(model, test_generator, model_name):
    test_loss, test_acc = model.evaluate(test_generator)
    print(f"Test Accuracy: {test_acc:.4f}")
    print(f"Test Loss: {test_loss:.4f}")

    # Confusion matrix
    Y_pred = model.predict(test_generator)
    y_pred = np.argmax(Y_pred, axis=1)
    y_true = test_generator.classes

    cm = confusion_matrix(y_true, y_pred)
    cr = classification_report(y_true, y_pred, target_names=test_generator.class_indices.keys())

    plt.figure(figsize=(10, 8))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=test_generator.class_indices.keys(), yticklal
    plt.xlabel('Predicted')
    plt.ylabel('True')
    plt.title(f'{model_name} Confusion Matrix')
    plt.show()

    print("Classification Report:\n", cr)
```

In [29]:
```
# Evaluate ResNet50
print("ResNet50 Evaluation")
evaluate_model(resnet50_model, test_generator, 'ResNet50')
```

```
ResNet50 Evaluation
34/34 [==============================] - 40s 1s/step - loss: 2.4507 - accuracy: 0.4551
Test Accuracy: 0.4551
Test Loss: 2.4507
34/34 [==============================] - 41s 1s/step
```

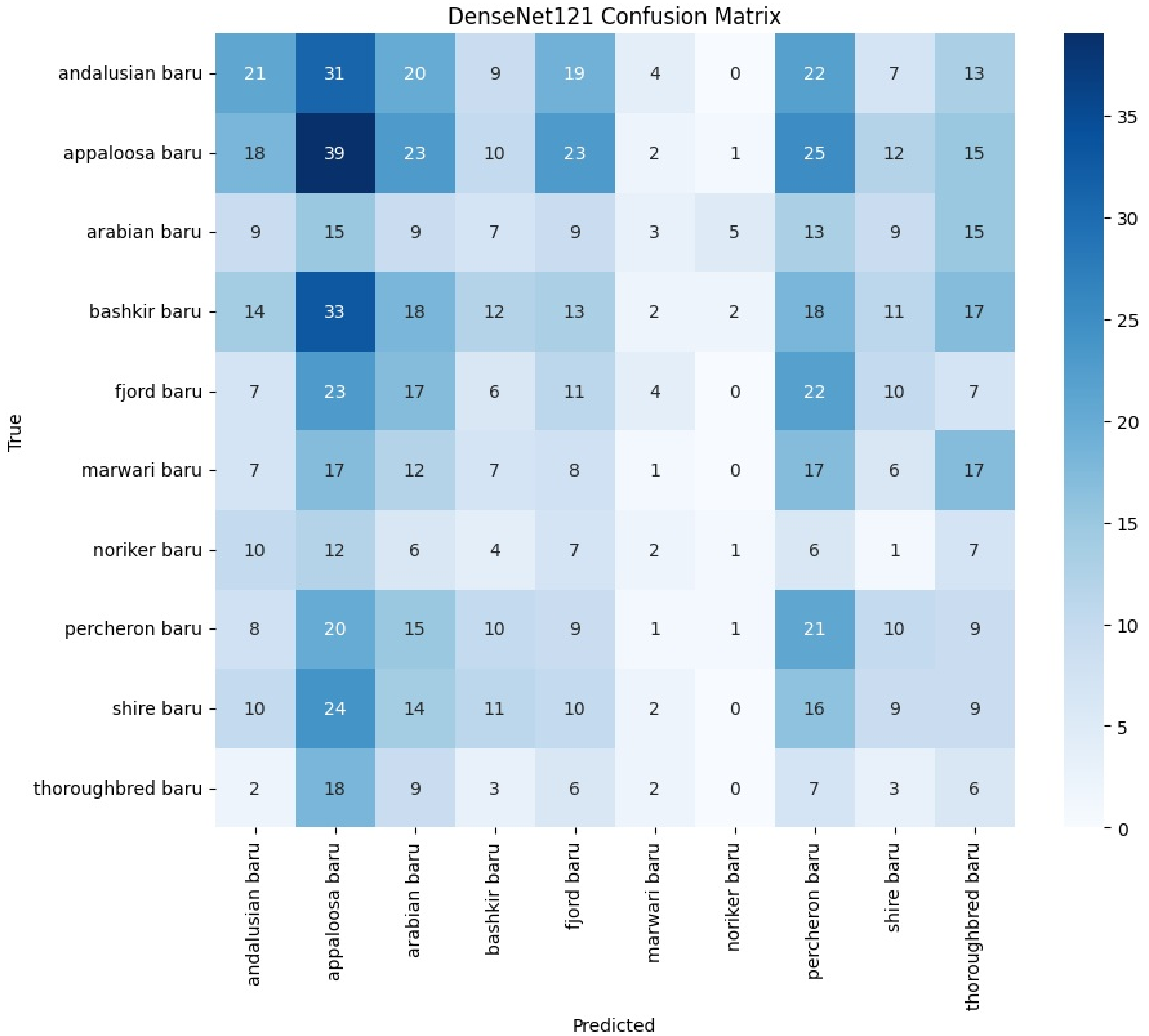

ResNet50 Confusion Matrix
True
Predicted
andalusian baru
appaloosa baru
arabian baru
bashkir baru
fjord baru
marwari baru
noriker baru
percheron baru
shire baru
thoroughbred baru
32 18 12 27 4 7 2 18 25 1
39 17 14 24 6 5 5 23 35 0
20 8 5 18 1 3 2 8 28 1
34 19 10 35 4 2 3 13 20 0
18 16 7 28 1 2 4 6 25 0
18 5 6 25 2 6 0 14 16 0
17 5 3 7 4 1 0 5 13 1
21 20 6 15 6 2 1 13 20 0
26 13 5 22 8 0 3 7 20 1
9 7 3 9 1 4 3 9 11 0
35
30
25
20
15
10
5
0

```
Classification Report:
                   precision    recall  f1-score   support

  andalusian baru       0.14      0.22      0.17       146
   appaloosa baru       0.13      0.10      0.11       168
     arabian baru       0.07      0.05      0.06        94
     bashkir baru       0.17      0.25      0.20       140
       fjord baru       0.03      0.01      0.01       107
     marwari baru       0.19      0.07      0.10        92
     noriker baru       0.00      0.00      0.00        56
   percheron baru       0.11      0.12      0.12       104
       shire baru       0.09      0.19      0.13       105
thoroughbred baru       0.00      0.00      0.00        56

         accuracy                           0.12      1068
        macro avg       0.09      0.10      0.09      1068
     weighted avg       0.11      0.12      0.11      1068
```

In [30]:

```python
# Evaluate DenseNet121
print("DenseNet121 Evaluation")
evaluate_model(densenet121_model, test_generator, 'DenseNet121')
```

```
DenseNet121 Evaluation
34/34 [==============================] - 36s 1s/step - loss: 2.2014 - accuracy: 0.5243
Test Accuracy: 0.5243
Test Loss: 2.2014
34/34 [==============================] - 36s 1s/step
```

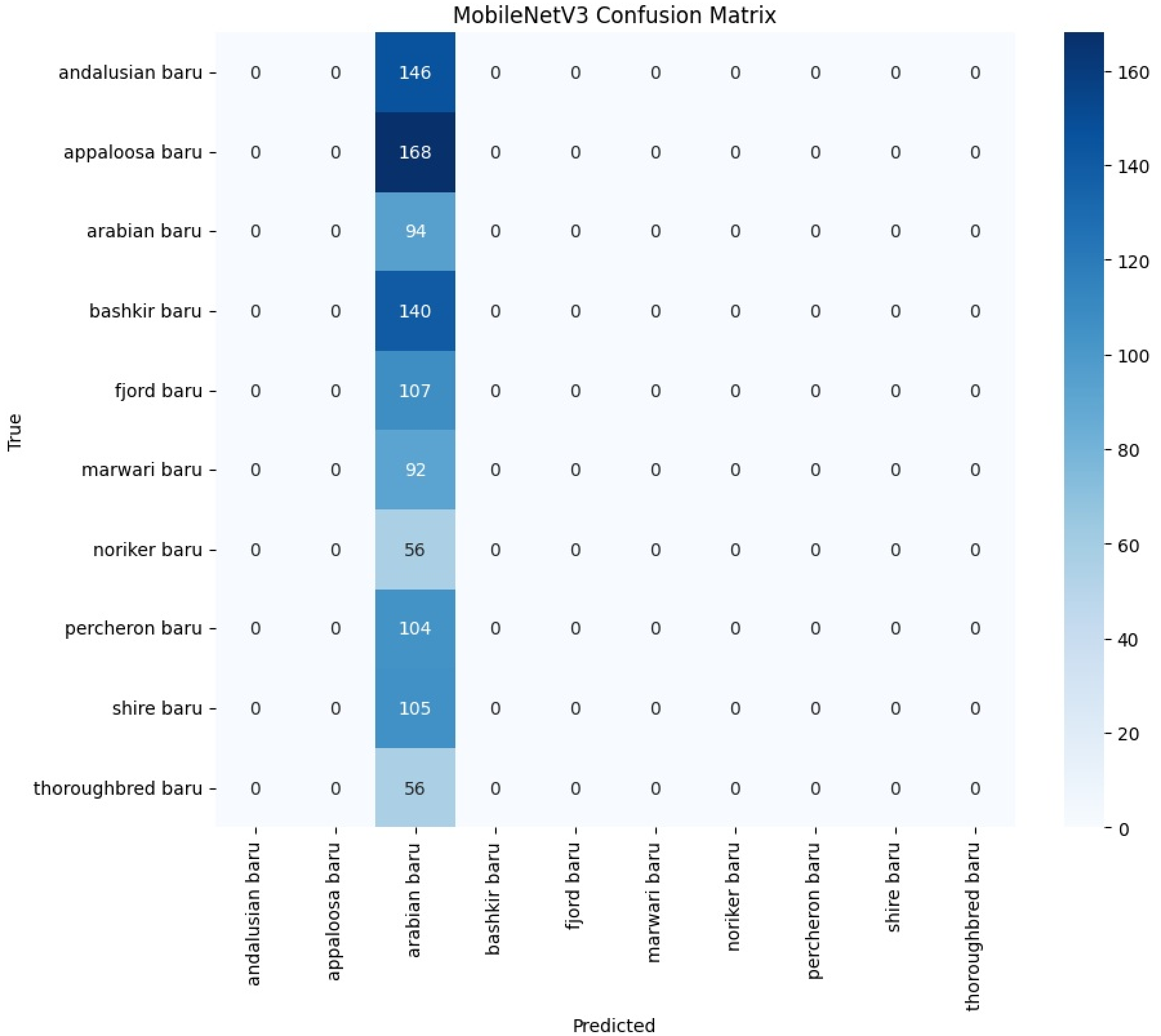


```
Classification Report:
                      precision    recall  f1-score   support

  andalusian baru       0.20      0.14      0.17       146
   appaloosa baru       0.17      0.23      0.20       168
     arabian baru       0.06      0.10      0.08        94
     bashkir baru       0.15      0.09      0.11       140

       fjord baru       0.10      0.10      0.10       107
     marwari baru       0.04      0.01      0.02        92
     noriker baru       0.10      0.02      0.03        56
   percheron baru       0.13      0.20      0.15       104
       shire baru       0.12      0.09      0.10       105
thoroughbred baru       0.05      0.11      0.07        56

         accuracy                           0.12      1068
        macro avg       0.11      0.11      0.10      1068
     weighted avg       0.12      0.12      0.12      1068
```

In [65]:

```python
# Evaluate MobileNetV3
print("MobileNetV3 Evaluation")
evaluate_model(mobilenetv3_model, test_generator, 'MobileNetV3')
```

```
MobileNetV3 Evaluation
34/34 [==============================] - 7s 206ms/step - loss: 2.3736 - accuracy: 0.0880
MobileNetV3 Test Accuracy: 0.0880
MobileNetV3 Test Loss: 2.3736
34/34 [==============================] - 7s 217ms/step
```



```
MobileNetV3 Classification Report:
                    precision    recall  f1-score   support

  andalusian baru       0.00      0.00      0.00       146
   appaloosa baru       0.00      0.00      0.00       168
     arabian baru       0.09      1.00      0.16        94
     bashkir baru       0.00      0.00      0.00       140
       fjord baru       0.00      0.00      0.00       107
     marwari baru       0.00      0.00      0.00        92
     noriker baru       0.00      0.00      0.00        56
   percheron baru       0.00      0.00      0.00       104
       shire baru       0.00      0.00      0.00       105
thoroughbred baru       0.00      0.00      0.00        56

         accuracy                           0.09      1068
        macro avg       0.01      0.10      0.02      1068
     weighted avg       0.01      0.09      0.01      1068
```

Conclusion

Analysist

Based on the evaluation results of DenseNet121, ResNet50, and MobileNetV3 for classifying horse breeds, we can draw several conclusions.

- DenseNet121 achieved an accuracy of 12% and demonstrated slightly better precision and recall for certain classes compared to the other models. Notably, it had higher precision for "andalusian baru" and "appaloosa baru," and better recall for "percheron baru."
- ResNet50 also reached an accuracy of 12%. However, it showed lower precision and recall than DenseNet121 for most classes. For instance, it struggled significantly with the "fjord baru" and "noriker baru" classes, having almost negligible precision and recall.
- MobileNetV3 had the poorest performance with an accuracy of only 10%. Its precision and recall were very low across nearly all classes, except for "shire baru," where it managed to achieve a recall of 100% but with a low precision of 10%. This indicates that while MobileNetV3 could identify "shire baru" instances, it also misclassified a large number of other breeds as "shire baru."

Summary

- DenseNet121: Best overall performance with the highest precision and recall in several key classes. ResNet50: Similar accuracy to DenseNet121 but lower overall precision and recall.
- MobileNetV3: Lowest accuracy and generally poor performance across most classes.

Given these results, DenseNet121 stands out as the best model among the three. Its superior precision and recall in multiple classes indicate it is more reliable for this classification task. Although the overall accuracy for both DenseNet121 and ResNet50 is the same, DenseNet121's better handling of individual class predictions makes it the preferred choice.

Improvements

1. Increase Dataset Size: Expanding the dataset beyond the current 3551 images could provide the models with more diverse examples to learn from, potentially improving the prediction accuracy.
2. Balance Class Distribution: Ensuring an equal representation of each horse subspecies in the dataset can prevent the models from favoring more prevalent classes, thereby enhancing overall accuracy.
3. Fine-tune Hyperparameters: Adjusting parameters like learning rate, batch size, and epochs through systematic tuning can optimize model training, potentially leading to better convergence and higher accuracy.

By implementing these recommendations is expected to improve model performance, increasing both accuracy and reliability in classifying horse subspecies. By addressing these aspects, we aim to develop a more robust and effective model for future classification tasks in this domain.