

Import necessary library dependencies

```
In [1]: import tensorflow as tf
        from tensorflow.keras import layers, models
        from tensorflow.keras.applications import EfficientNetV2B0
        from tensorflow.keras.applications.efficientnet import preprocess_input
        from sklearn.metrics import confusion_matrix, classification_report
        import matplotlib.pyplot as plt
        import seaborn as sns
        import numpy as np
```

Import datasets

```
In [2]: #Dataset paths
        trainpath = r'/content/drive/MyDrive/modified-dataset/train'
        validpath = r'/content/drive/MyDrive/modified-dataset/val'
        testpath = r'/content/drive/MyDrive/modified-dataset/test'
```

Understand the Data

```
In [3]: # 1EXPLORE AND UNDERSTAND THE DATA
        IMG_SIZE = (128, 128)
        BATCH_SIZE = 32

        datatrain = tf.keras.utils.image_dataset_from_directory(trainpath, shuffle=True,
        datavalid = tf.keras.utils.image_dataset_from_directory(validpath, shuffle=True,
        datatest = tf.keras.utils.image_dataset_from_directory(testpath, shuffle=False,

        class_names = datatrain.class_names
        print(f"Classes: {class_names}")
```

Found 2410 files belonging to 10 classes.
Found 300 files belonging to 10 classes.
Found 310 files belonging to 10 classes.
Classes: ['Battery', 'Keyboard', 'Microwave', 'Mobile', 'Mouse', 'PCB', 'Player', 'Printer', 'Television', 'Washing Machine']

Visualize samples

```
In [4]: # Visualize samples
        plt.figure(figsize=(10,10))
        for images, labels in datatrain.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")
plt.show()
```

Printer



PCB



Player



Television



Television



Microwave



Microwave



Washing Machine



Keyboard

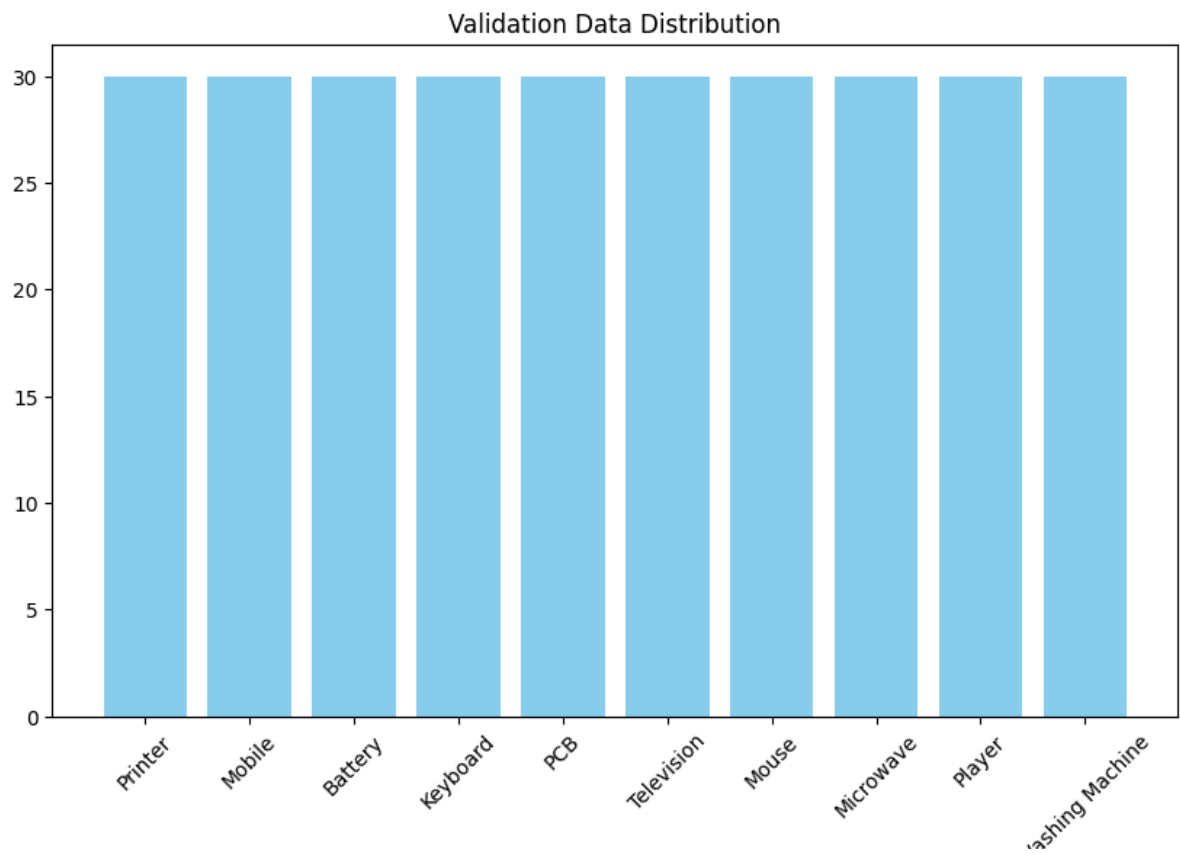
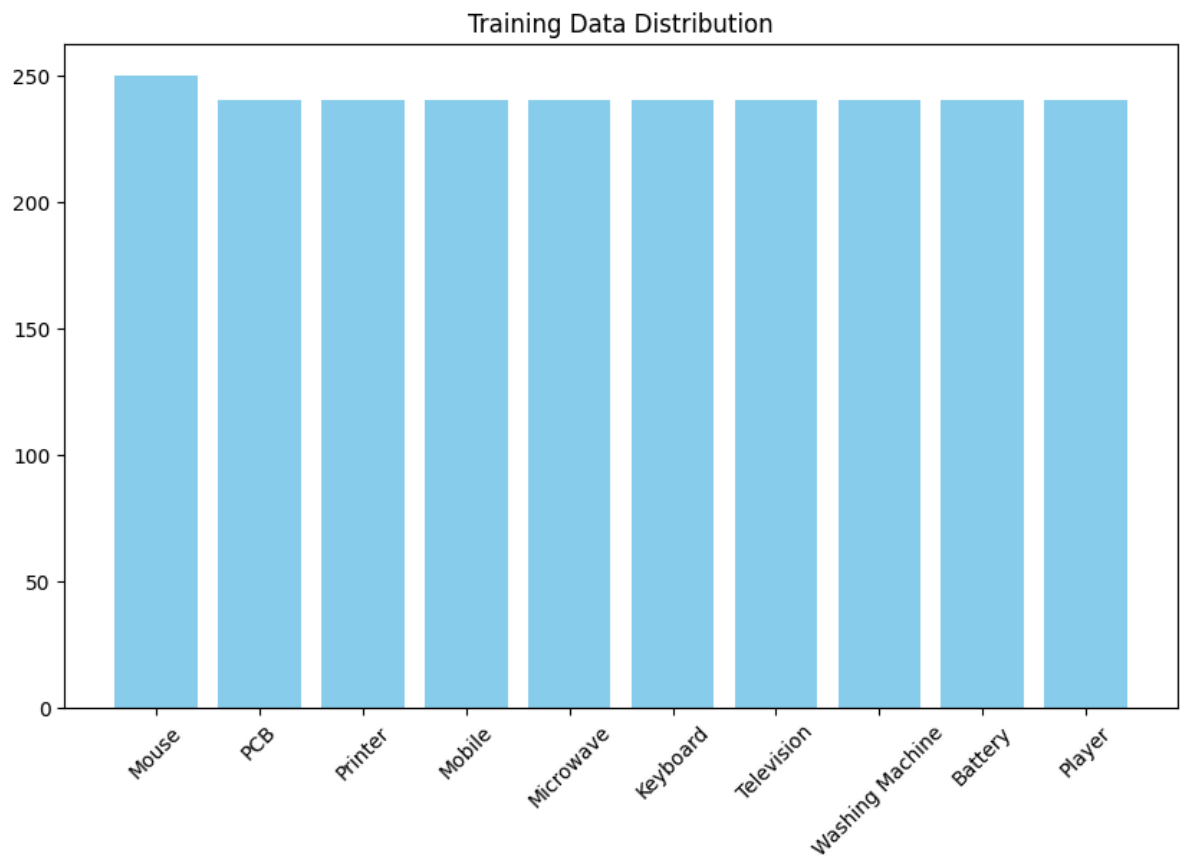


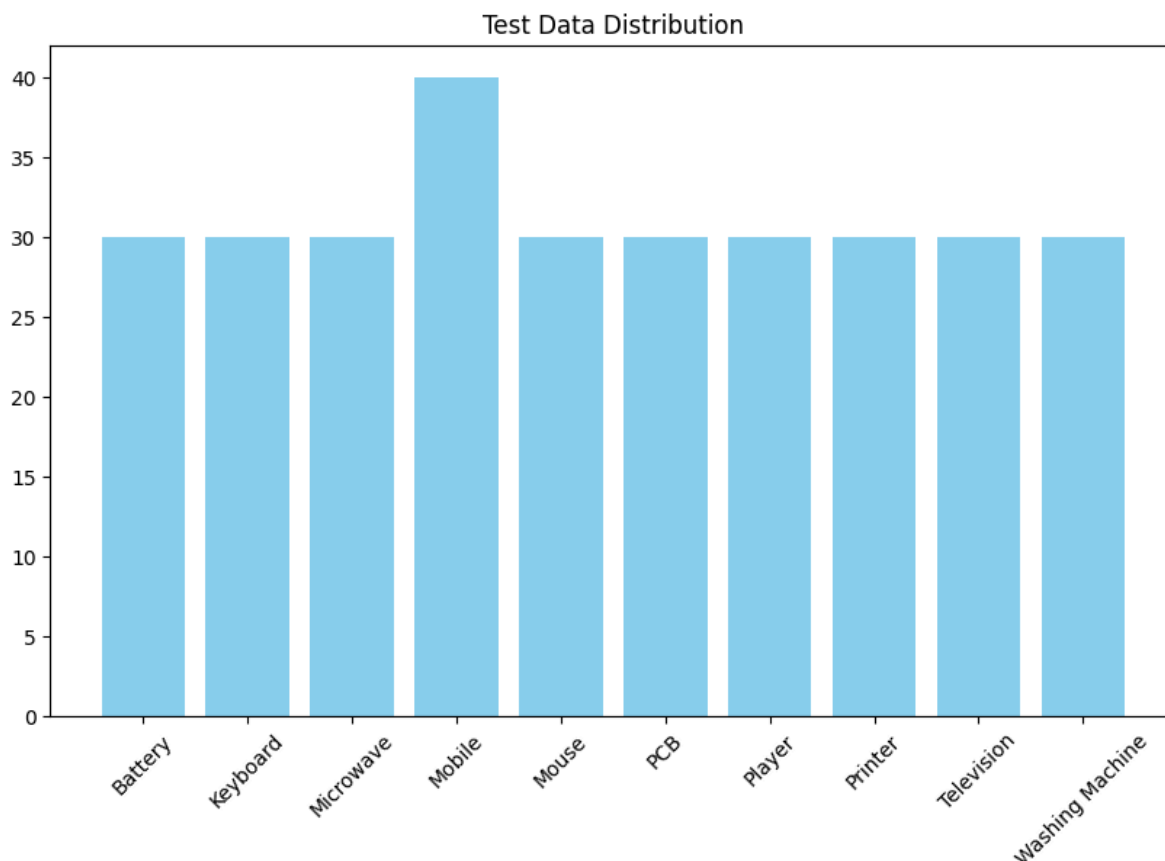
Plot class distribution

```
In [5]: # Plot class distribution
def plot_class_distribution(dataset, title):
    counts = {}
    for _, labels in dataset:
        for label in labels.numpy():
            class_name = dataset.class_names[label]
            counts[class_name] = counts.get(class_name, 0) + 1
    plt.figure(figsize=(10,6))
    plt.bar(counts.keys(), counts.values(), color='skyblue')
    plt.title(title)
    plt.xticks(rotation=45)
```

```
plt.show()
```

```
plot_class_distribution(data_train, "Training Data Distribution")  
plot_class_distribution(data_valid, "Validation Data Distribution")  
plot_class_distribution(data_test, "Test Data Distribution")
```





DATA PREPROCESSING

```
In [6]: # DATA PREPROCESSING / PREPARATION
data_augmentation = tf.keras.Sequential([
    layers.RandomFlip("horizontal"),
    layers.RandomRotation(0.1),
    layers.RandomZoom(0.1),
])

datatrain = datatrain.prefetch(tf.data.AUTOTUNE)
datavalid = datavalid.prefetch(tf.data.AUTOTUNE)
datatest = datatest.prefetch(tf.data.AUTOTUNE)
```

MODEL SELECTION USING EFFICIENTNET

```
In [7]: # MODEL SELECTION
base_model = EfficientNetV2B0(input_shape=IMG_SIZE+(3,), include_top=False, weights='imagenet')
for layer in base_model.layers[:100]:
    layer.trainable = False

inputs = layers.Input(shape=IMG_SIZE+(3,))
x = data_augmentation(inputs)
x = preprocess_input(x)
x = base_model(x, training=False)
```

```
x = layers.GlobalAveragePooling2D()(x)
x = layers.Dropout(0.2)(x)
outputs = layers.Dense(10, activation='softmax')(x)
model = models.Model(inputs, outputs)
```

Downloading data from https://storage.googleapis.com/tensorflow/keras-application-s/efficientnet_v2/efficientnetv2-b0_notop.h5
 24274472/24274472 ————— 0s 0us/step

MODEL TRAINING

In [9]:

```
# MODEL TRAINING
from tensorflow.keras.callbacks import EarlyStopping, ReduceLRonPlateau
model.compile(optimizer=tf.keras.optimizers.Adam(1e-4),
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

early_stop = EarlyStopping(monitor='val_loss', patience=3, restore_best_weights=True)
reduce_lr = ReduceLRonPlateau(monitor='val_loss', factor=0.5, patience=2)

history = model.fit(data_train, validation_data=data_valid, epochs=15, callbacks=[early_stop, reduce_lr])
```

Epoch 1/15

76/76 ————— 52s 180ms/step - accuracy: 0.2598 - loss: 2.1305 - val_accuracy: 0.7967 - val_loss: 1.1384 - learning_rate: 1.0000e-04

Epoch 2/15

76/76 ————— 10s 137ms/step - accuracy: 0.7977 - loss: 0.9845 - val_accuracy: 0.9033 - val_loss: 0.5048 - learning_rate: 1.0000e-04

Epoch 3/15

76/76 ————— 20s 123ms/step - accuracy: 0.8681 - loss: 0.4941 - val_accuracy: 0.9333 - val_loss: 0.3257 - learning_rate: 1.0000e-04

Epoch 4/15

76/76 ————— 11s 140ms/step - accuracy: 0.9202 - loss: 0.3001 - val_accuracy: 0.9300 - val_loss: 0.2432 - learning_rate: 1.0000e-04

Epoch 5/15

76/76 ————— 20s 130ms/step - accuracy: 0.9412 - loss: 0.2134 - val_accuracy: 0.9500 - val_loss: 0.1960 - learning_rate: 1.0000e-04

Epoch 6/15

76/76 ————— 10s 125ms/step - accuracy: 0.9487 - loss: 0.1866 - val_accuracy: 0.9433 - val_loss: 0.1804 - learning_rate: 1.0000e-04

Epoch 7/15

76/76 ————— 10s 123ms/step - accuracy: 0.9540 - loss: 0.1712 - val_accuracy: 0.9533 - val_loss: 0.1624 - learning_rate: 1.0000e-04

Epoch 8/15

76/76 ————— 11s 142ms/step - accuracy: 0.9671 - loss: 0.1273 - val_accuracy: 0.9500 - val_loss: 0.1550 - learning_rate: 1.0000e-04

Epoch 9/15

76/76 ————— 19s 123ms/step - accuracy: 0.9703 - loss: 0.1106 - val_accuracy: 0.9500 - val_loss: 0.1546 - learning_rate: 1.0000e-04

Epoch 10/15

76/76 ————— 9s 121ms/step - accuracy: 0.9827 - loss: 0.0785 - val_accuracy: 0.9567 - val_loss: 0.1511 - learning_rate: 1.0000e-04

Epoch 11/15

76/76 ————— 11s 124ms/step - accuracy: 0.9785 - loss: 0.0710 - val_accuracy: 0.9567 - val_loss: 0.1511 - learning_rate: 1.0000e-04

```

76/76 ————— 11s 134ms/step - accuracy: 0.9703 - loss: 0.0713 - val_
accuracy: 0.9600 - val_loss: 0.1248 - learning_rate: 1.0000e-04
Epoch 12/15
76/76 ————— 10s 133ms/step - accuracy: 0.9772 - loss: 0.0771 - val_
accuracy: 0.9567 - val_loss: 0.1306 - learning_rate: 1.0000e-04
Epoch 13/15
76/76 ————— 10s 131ms/step - accuracy: 0.9863 - loss: 0.0611 - val_
accuracy: 0.9633 - val_loss: 0.1198 - learning_rate: 1.0000e-04
Epoch 14/15
76/76 ————— 10s 123ms/step - accuracy: 0.9917 - loss: 0.0386 - val_
accuracy: 0.9600 - val_loss: 0.1251 - learning_rate: 1.0000e-04
Epoch 15/15
76/76 ————— 11s 142ms/step - accuracy: 0.9923 - loss: 0.0323 - val_
accuracy: 0.9700 - val_loss: 0.1191 - learning_rate: 1.0000e-04

```

MODEL TUNING AND OPTIMIZATION

```

In [10]: # MODEL TUNING AND OPTIMIZATION (optional fine-tune)
for layer in base_model.layers[100:]:
    layer.trainable = True
model.compile(optimizer=tf.keras.optimizers.Adam(1e-5),
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
model.fit(datatrain, validation_data=datavalid, epochs=5, callbacks=[early_stop,

```

```

Epoch 1/5
76/76 ————— 47s 181ms/step - accuracy: 0.9923 - loss: 0.0303 - val_
accuracy: 0.9633 - val_loss: 0.1201 - learning_rate: 1.0000e-05
Epoch 2/5
76/76 ————— 10s 134ms/step - accuracy: 0.9875 - loss: 0.0374 - val_
accuracy: 0.9633 - val_loss: 0.1144 - learning_rate: 1.0000e-05
Epoch 3/5
76/76 ————— 11s 138ms/step - accuracy: 0.9941 - loss: 0.0353 - val_
accuracy: 0.9633 - val_loss: 0.1188 - learning_rate: 1.0000e-05
Epoch 4/5
76/76 ————— 19s 121ms/step - accuracy: 0.9895 - loss: 0.0435 - val_
accuracy: 0.9633 - val_loss: 0.1256 - learning_rate: 1.0000e-05
Epoch 5/5
76/76 ————— 11s 135ms/step - accuracy: 0.9950 - loss: 0.0286 - val_
accuracy: 0.9700 - val_loss: 0.1140 - learning_rate: 5.0000e-06

```

```

Out[10]: <keras.src.callbacks.history.History at 0x7d08ecd52850>

```

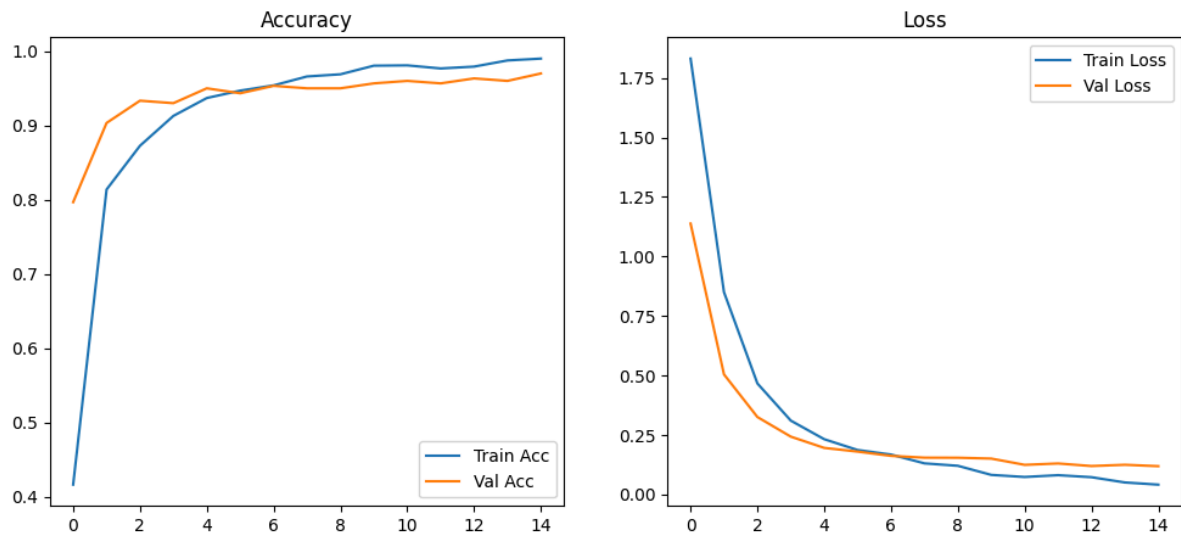
MODEL PERFORMANCE VISUALIZATION

```

In [11]: # MODEL PERFORMANCE VISUALIZATION
plt.figure(figsize=(12,5))
plt.subplot(1,2,1)
plt.plot(history.history['accuracy'], label='Train Acc')
plt.plot(history.history['val_accuracy'], label='Val Acc')
plt.title('Accuracy')
plt.legend()
plt.subplot(1,2,2)
plt.plot(history.history['loss'], label='Train Loss')

```

```
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Val Loss')
plt.title('Loss')
plt.legend()
plt.show()
```



MODEL EVALUATION AND CONFUSION MATRIX

In [12]:

```
# MODEL EVALUATION
test_loss, test_acc = model.evaluate(datatest)
print(f"Test Accuracy: {test_acc:.4f}, Test Loss: {test_loss:.4f}")

y_true = np.concatenate([y.numpy() for _, y in datatest], axis=0)
y_pred = np.argmax(model.predict(datatest), axis=1)

cm = confusion_matrix(y_true, y_pred)
print(classification_report(y_true, y_pred, target_names=class_names))

plt.figure(figsize=(10,8))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=class_names, yticklabels=class_names)
plt.xlabel("Predicted")
plt.ylabel("True")
plt.title("Confusion Matrix")
plt.show()
```

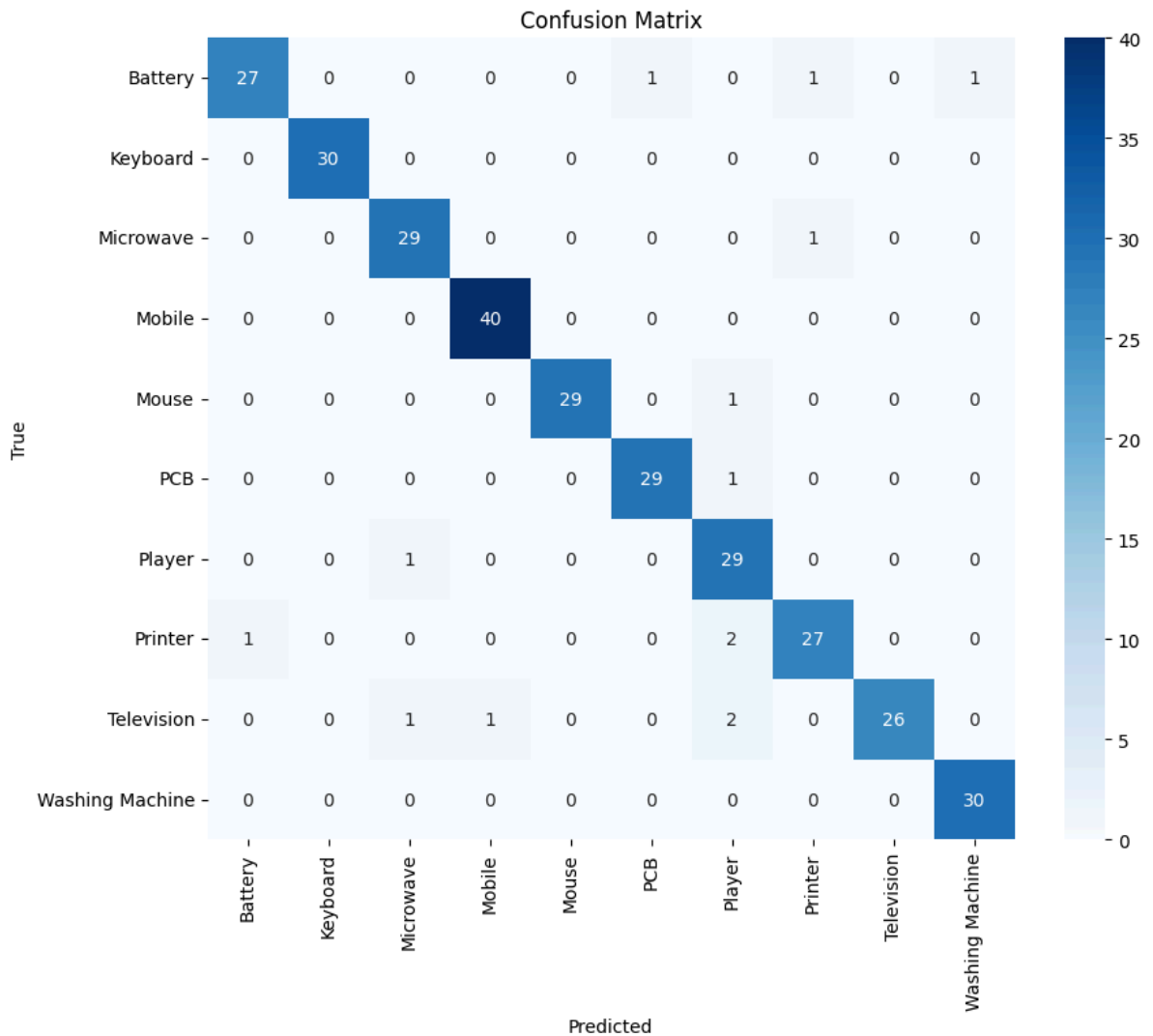
10/10 ————— 1s 128ms/step - accuracy: 0.9555 - loss: 0.1602

✓ Test Accuracy: 0.9548, Test Loss: 0.1317

10/10 ————— 7s 393ms/step

	precision	recall	f1-score	support
Battery	0.96	0.90	0.93	30
Keyboard	1.00	1.00	1.00	30
Microwave	0.94	0.97	0.95	30
Mobile	0.98	1.00	0.99	40
Mouse	1.00	0.97	0.98	30

House	1.00	0.97	0.98	30
PCB	0.97	0.97	0.97	30
Player	0.83	0.97	0.89	30
Printer	0.93	0.90	0.92	30
Television	1.00	0.87	0.93	30
Washing Machine	0.97	1.00	0.98	30
accuracy			0.95	310
macro avg	0.96	0.95	0.95	310
weighted avg	0.96	0.95	0.95	310



FINAL TESTING AND SAVE THE MODEL

```
In [18]: # FINAL TESTING AND SAVE THE MODEL
model.save('efficientnetv2b0_ewaste_final.keras')
print("Keras model saved")
```

Keras model saved

Save TFLite


```

In [19]: # Save TFLite
converter = tf.lite.TFLiteConverter.from_keras_model(model)
converter.optimizations = [tf.lite.Optimize.DEFAULT]
tflite_model = converter.convert()
with open('efficientnetv2b0_ewaste_final.tflite', 'wb') as f:
    f.write(tflite_model)
print("TFLite model saved")

```

Saved artifact at '/tmp/tmpodr7su2v'. The following endpoints are available:

* Endpoint 'serve'

args_0 (POSITIONAL_ONLY): TensorSpec(shape=(None, 128, 128, 3), dtype=tf.float32, name='keras_tensor_270')

Output Type:

TensorSpec(shape=(None, 10), dtype=tf.float32, name=None)

Captures:

137479627293328: TensorSpec(shape=(1, 1, 1, 3), dtype=tf.float32, name=None)
137479627293136: TensorSpec(shape=(1, 1, 1, 3), dtype=tf.float32, name=None)
137480611166160: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627293712: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627296208: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627295824: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627295440: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627296016: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627297360: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627298320: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627297552: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627296784: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627297744: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627301008: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627300048: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627300432: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627300240: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627298128: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627302928: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627303888: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627303120: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627299472: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627304848: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627303312: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627305616: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627304080: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627302160: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627307152: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627306768: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627308112: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627307344: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627305232: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627304464: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627620816: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627621776: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627308304: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627620624: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627622736: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627622352: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627623696: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627622928: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627621584: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627621008: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479627624848: TensorSpec(shape=(), dtype=tf.resource, name=None)

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

```
137479625579152: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479625583184: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479625583376: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479625581648: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479625583760: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479625579728: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479625584912: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479625585680: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479625584528: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479625584336: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479625585104: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479625587024: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479625587984: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479625587216: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479625585872: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479625586832: TensorSpec(shape=(), dtype=tf.resource, name=None)
137479624263248: TensorSpec(shape=(), dtype=tf.resource, name=None)
TFLite model saved
```

Predictions on sample test images

```
In [15]: # Show predictions on sample test images
for images, labels in datatest.take(1):
    preds = model.predict(images)
    pred_classes = tf.argmax(preds, axis=1)
    for i in range(8):
        plt.imshow(images[i].numpy().astype("uint8"))
        plt.title(f"True: {class_names[labels[i]]}, Pred: {class_names[pred_classes[i]]}")
        plt.axis("off")
    plt.show()
```

1/1 ————— 2s 2s/step

True: Battery, Pred: Battery



True: Battery, Pred: Printer



True: Battery, Pred: Battery



True: Battery, Pred: Battery





True: Battery, Pred: Battery



True: Battery, Pred: Battery





True: Battery, Pred: PCB



True: Battery, Pred: Battery



Using CNN Model

In [16]:

```
# Normal CNN Model
normal_model = tf.keras.Sequential([
    tf.keras.layers.Rescaling(1./255, input_shape=IMG_SIZE+(3,)), # Simple rescaling
    tf.keras.layers.Conv2D(32, 3, activation='relu'),
    tf.keras.layers.MaxPooling2D(),
    tf.keras.layers.Conv2D(64, 3, activation='relu'),
    tf.keras.layers.MaxPooling2D(),
    tf.keras.layers.Conv2D(128, 3, activation='relu'),
    tf.keras.layers.GlobalAveragePooling2D(),
    tf.keras.layers.Dropout(0.2),
    tf.keras.layers.Dense(10, activation='softmax')
])

normal_model.compile(optimizer='adam',
                    loss='sparse_categorical_crossentropy',
                    metrics=['accuracy'])
normal_history = normal_model.fit(data_train,
                                validation_data=data_valid,
                                epochs=15,
                                callbacks=[early_stop, reduce_lr])
```

Epoch 1/15

/usr/local/lib/python3.11/dist-packages/keras/src/layers/preprocessing/tf_data_layer.py:19: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.

```
super().__init__(**kwargs)
```

76/76 ————— 13s 126ms/step - accuracy: 0.1479 - loss: 2.2522 - val_accuracy: 0.2133 - val_loss: 2.1031 - learning_rate: 0.0010

Epoch 2/15

76/76 ————— 6s 79ms/step - accuracy: 0.2411 - loss: 2.0616 - val_accuracy: 0.2833 - val_loss: 2.0063 - learning_rate: 0.0010

Epoch 3/15

76/76 ————— 11s 87ms/step - accuracy: 0.3085 - loss: 1.9544 - val_accuracy: 0.2500 - val_loss: 1.9843 - learning_rate: 0.0010

Epoch 4/15

76/76 ————— 10s 84ms/step - accuracy: 0.3229 - loss: 1.8475 - val_accuracy: 0.3400 - val_loss: 1.7361 - learning_rate: 0.0010

Epoch 5/15

76/76 ————— 11s 96ms/step - accuracy: 0.3549 - loss: 1.7743 - val_accuracy: 0.4300 - val_loss: 1.6915 - learning_rate: 0.0010

Epoch 6/15

76/76 ————— 6s 79ms/step - accuracy: 0.3797 - loss: 1.7258 - val_accuracy: 0.4267 - val_loss: 1.6392 - learning_rate: 0.0010

Epoch 7/15

76/76 ————— 7s 96ms/step - accuracy: 0.4125 - loss: 1.6638 - val_accuracy: 0.4700 - val_loss: 1.6006 - learning_rate: 0.0010

Epoch 8/15

76/76 ————— 9s 82ms/step - accuracy: 0.4091 - loss: 1.6414 - val_accuracy: 0.4433 - val_loss: 1.6227 - learning_rate: 0.0010

Epoch 9/15

76/76 ————— 11s 91ms/step - accuracy: 0.4209 - loss: 1.6662 - val_a

```

ccuracy: 0.4767 - val_loss: 1.4897 - learning_rate: 0.0010
Epoch 10/15
76/76 ----- 10s 91ms/step - accuracy: 0.4577 - loss: 1.5337 - val_a
ccuracy: 0.4933 - val_loss: 1.4748 - learning_rate: 0.0010
Epoch 11/15
76/76 ----- 7s 98ms/step - accuracy: 0.4625 - loss: 1.4887 - val_ac
curacy: 0.5267 - val_loss: 1.4806 - learning_rate: 0.0010
Epoch 12/15
76/76 ----- 6s 83ms/step - accuracy: 0.4660 - loss: 1.4985 - val_ac
curacy: 0.5167 - val_loss: 1.4915 - learning_rate: 0.0010
Epoch 13/15
76/76 ----- 11s 89ms/step - accuracy: 0.4701 - loss: 1.4690 - val_a
ccuracy: 0.5567 - val_loss: 1.3467 - learning_rate: 5.0000e-04
Epoch 14/15
76/76 ----- 11s 95ms/step - accuracy: 0.5041 - loss: 1.3938 - val_a
ccuracy: 0.5433 - val_loss: 1.3434 - learning_rate: 5.0000e-04
Epoch 15/15
76/76 ----- 6s 81ms/step - accuracy: 0.5215 - loss: 1.3725 - val_ac
curacy: 0.5800 - val_loss: 1.2799 - learning_rate: 5.0000e-04

```

Plot between CNN and EfficientNet

```

In [17]: import matplotlib.pyplot as plt

plt.figure(figsize=(14, 5))

# Accuracy Comparison
plt.subplot(1, 2, 1)
plt.plot(normal_history.history['accuracy'], label='Normal CNN - Training')
plt.plot(normal_history.history['val_accuracy'], label='Normal CNN - Validation')
plt.plot(history.history['accuracy'], label='EfficientNetV2B0 - Training')
plt.plot(history.history['val_accuracy'], label='EfficientNetV2B0 - Validation')
plt.title('Training and Validation Accuracy Comparison')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.grid(True)

# Loss Comparison
plt.subplot(1, 2, 2)
plt.plot(normal_history.history['loss'], label='Normal CNN - Training')
plt.plot(normal_history.history['val_loss'], label='Normal CNN - Validation')
plt.plot(history.history['loss'], label='EfficientNetV2B0 - Training')
plt.plot(history.history['val_loss'], label='EfficientNetV2B0 - Validation')
plt.title('Training and Validation Loss Comparison')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.grid(True)

plt.show()

```



