Seattle Bird Call Classification Using Neural Networks

Libraries

In [1]:
```
import numpy as np
import pandas as pd
import os
import h5py
import matplotlib.pyplot as plt
import seaborn as sns
import tensorflow as tf
import librosa
import librosa.display
import IPython.display as ipd
from matplotlib import image
from skimage.transform import resize
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression, LassoCV
from sklearn.preprocessing import LabelBinarizer, StandardScaler
from sklearn.metrics import mean_absolute_error, classification_report, confusion_matrix
from tensorflow.keras.preprocessing.image import load_img, img_to_array
from tensorflow.keras.preprocessing.sequence import pad_sequences
from keras.models import Sequential
from keras.layers import Dense, Dropout, Conv2D, MaxPooling2D, Flatten
from keras.datasets import mnist, cifar10
from keras.utils import to_categorical
from keras.applications.resnet50 import ResNet50
from tensorflow.keras.applications.resnet50 import decode_predictions, preprocess_input
from keras.applications import imagenet_utils
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.applications import ResNet50
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Dense, GlobalAveragePooling2D, Input
from tensorflow.keras.applications import MobileNetV2
from tensorflow.keras.layers import Lambda
from tensorflow.keras.applications.mobilenet import preprocess_input
```

Loading the dataset

In [2]:
```
# h5 file of Bird species data
species_data = h5py.File('spectrograms.h5', 'r')

# Keys for different species
species_keys = list(species_data.keys())

species_keys
```

Out[2]:
```
['amecro',
 'barswa',
 'bkcchi',
 'blujay',
 'daejun',
 'houfin',
 'mallar3',
 'norfli',
 'rewbla',
 'stejay',
 'wesmea',
 'whcspa']
```

In [3]:
```python
# Shape of the spectogram data
# Here, we selected one species out of 12 to see the shape
dset = species_data['stejay']

dset.shape
```

Out[3]:
```
(256, 343, 40)
```

Binary Classification Model

We will use Northern Flicker and Steller's Jay bird species for this model

In [4]:
```python
# Load data for the selected species
# norfli sound for Northern Flicker data and stejay for Steller's Jay data
norfli_data = species_data['norfli'][:]
stejay_data = species_data['stejay'][:]
```

In [5]:
```python
norfli_data.shape
```

Out[5]:
```
(256, 343, 59)
```

In [6]:
```python
# Now Let's label the selected species
# Using 0 for Northern Flicker birds and 1 for Steller's Jay birds
norfli_data_labels = np.zeros(norfli_data.shape[2])
stejay_data_labels = np.ones(stejay_data.shape[2])
```

In [7]:
```python
# After the above step, combining the data and labels
X_bin = np.concatenate((norfli_data, stejay_data), axis=2)
y_bin = np.concatenate((norfli_data_labels, stejay_data_labels), axis=0)
```

In [8]:
```python
# Normalizing the data
X_bin = X_bin / np.max(X_bin)

# Reshaping X to match the expected input shape for CNNs (frequency, timesteps, no. of s
X_bin = np.transpose(X_bin, (2, 0, 1))
X_bin = X_bin[..., np.newaxis]  # This will add a channel dimension
```

In [9]:
```python
# Now, Converting the labels to categorical data
y_bin = to_categorical(y_bin, 2)
```

In [10]:
```python
# Splitting the data into training and validation sets (70% training set and 30% validat
X_train, X_val, y_train, y_val = train_test_split(X_bin, y_bin, test_size=0.3, random_st
```

In [11]:
```python
print(X_train.shape, X_val.shape, y_train.shape, y_val.shape)
```

```
(69, 256, 343, 1) (30, 256, 343, 1) (69, 2) (30, 2)
```

In [12]:
```python
# Defining the CNN model for our Binary classification
Bin_model = Sequential([
    Conv2D(32, (3, 3), activation='relu', input_shape=(256, 343, 1)),
    MaxPooling2D((2, 2)),
    Dropout(0.25),
    Conv2D(64, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Dropout(0.25),
    Flatten(),
    Dense(128, activation='relu'),
    Dropout(0.5),
```

```
    Dense(2, activation='sigmoid')
])
```

```
C:\Users\hirshikesh\anaconda3\lib\site-packages\keras\src\layers\convolutional\base_con
v.py:107: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. Whe
n using Sequential models, prefer using an `Input(shape)` object as the first layer in t
he model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

In [13]:

```
# Model summary
Bin_model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 254, 341, 32)	320
max_pooling2d (MaxPooling2D)	(None, 127, 170, 32)	0
dropout (Dropout)	(None, 127, 170, 32)	0
conv2d_1 (Conv2D)	(None, 125, 168, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 62, 84, 64)	0
dropout_1 (Dropout)	(None, 62, 84, 64)	0
flatten (Flatten)	(None, 333312)	0
dense (Dense)	(None, 128)	42,664,064
dropout_2 (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 2)	258

Total params: 42,683,138 (162.82 MB)

Trainable params: 42,683,138 (162.82 MB)

Non-trainable params: 0 (0.00 B)

In [14]:

```
# Compiling the model
Bin_model.compile(optimizer=Adam(), loss='binary_crossentropy', metrics=['accuracy'])
```

In [15]:

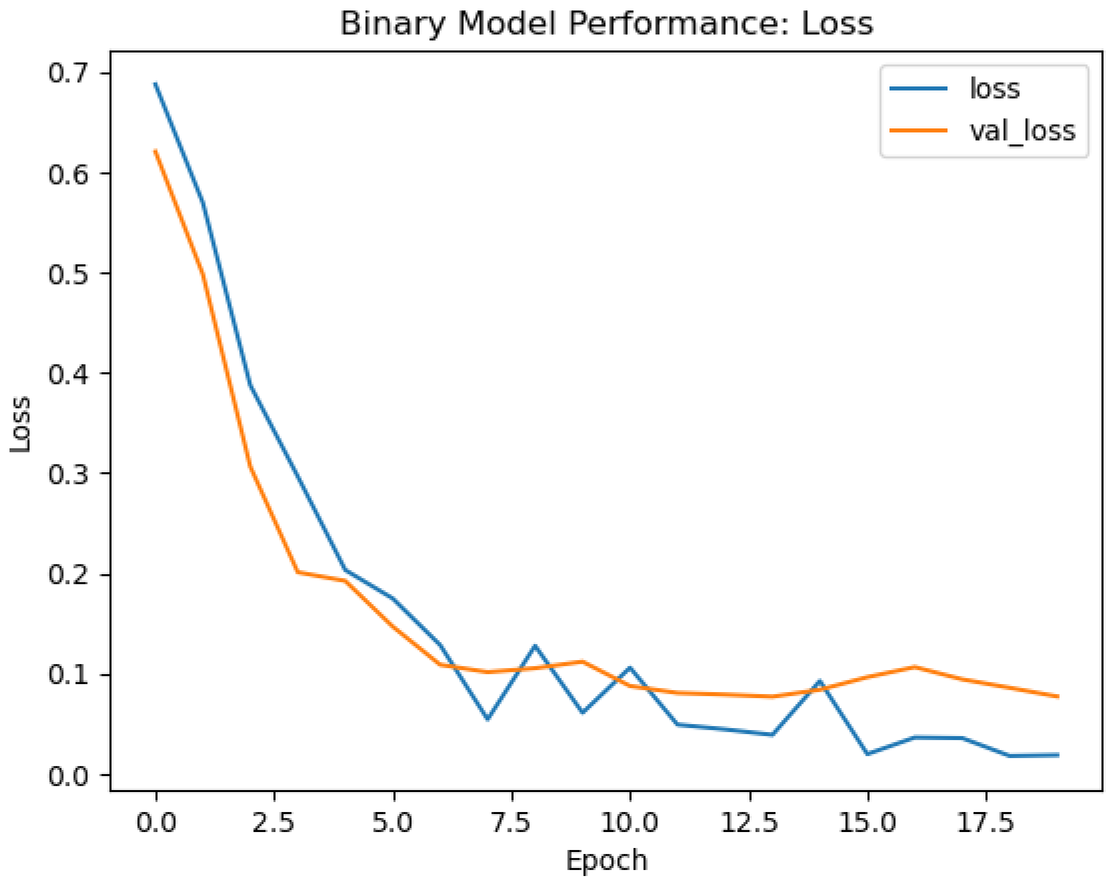
```
# Training the model
history = Bin_model.fit(X_train, y_train, epochs=20, validation_data=(X_val, y_val))
```

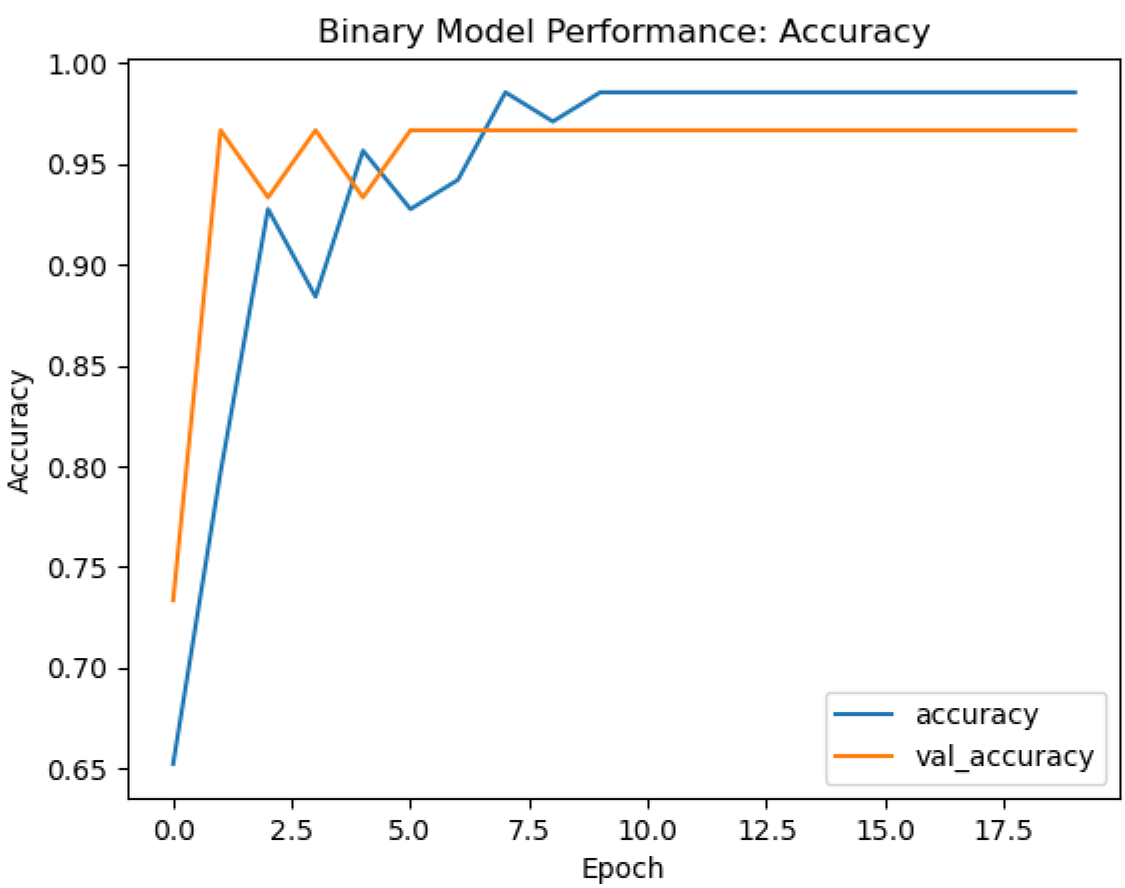
```
Epoch 1/20
3/3 ━━━━━━━━━━━━━━━━━━━━ 3s 630ms/step - accuracy: 0.6542 - loss: 0.6896 -
 val_accuracy: 0.7333 - val_loss: 0.6206
Epoch 2/20
3/3 ━━━━━━━━━━━━━━━━━━━━ 2s 591ms/step - accuracy: 0.7423 - loss: 0.5978 -
 val_accuracy: 0.9667 - val_loss: 0.4982
Epoch 3/20
3/3 ━━━━━━━━━━━━━━━━━━━━ 2s 599ms/step - accuracy: 0.9130 - loss: 0.3986 -
 val_accuracy: 0.9333 - val_loss: 0.3064
Epoch 4/20
3/3 ━━━━━━━━━━━━━━━━━━━━ 2s 578ms/step - accuracy: 0.9186 - loss: 0.2556 -
 val_accuracy: 0.9667 - val_loss: 0.2011
Epoch 5/20
3/3 ━━━━━━━━━━━━━━━━━━━━ 2s 564ms/step - accuracy: 0.9431 - loss: 0.2363 -
 val_accuracy: 0.9333 - val_loss: 0.1925
Epoch 6/20
```

```
3/3 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 2s 578ms/step - accuracy: 0.9364 - loss: 0.1697 -
 val_accuracy: 0.9667 - val_loss: 0.1470
Epoch 7/20
3/3 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 2s 589ms/step - accuracy: 0.9398 - loss: 0.1364 -
 val_accuracy: 0.9667 - val_loss: 0.1089
Epoch 8/20
3/3 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 2s 591ms/step - accuracy: 0.9810 - loss: 0.0622 -
 val_accuracy: 0.9667 - val_loss: 0.1015
Epoch 9/20
3/3 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 2s 577ms/step - accuracy: 0.9699 - loss: 0.1113 -
 val_accuracy: 0.9667 - val_loss: 0.1054
Epoch 10/20
3/3 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 2s 585ms/step - accuracy: 0.9888 - loss: 0.0523 -
 val_accuracy: 0.9667 - val_loss: 0.1119
Epoch 11/20
3/3 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 2s 583ms/step - accuracy: 0.9888 - loss: 0.0861 -
 val_accuracy: 0.9667 - val_loss: 0.0877
Epoch 12/20
3/3 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 2s 592ms/step - accuracy: 0.9810 - loss: 0.0596 -
 val_accuracy: 0.9667 - val_loss: 0.0807
Epoch 13/20
3/3 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 2s 589ms/step - accuracy: 0.9810 - loss: 0.0550 -
 val_accuracy: 0.9667 - val_loss: 0.0791
Epoch 14/20
3/3 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 2s 569ms/step - accuracy: 0.9810 - loss: 0.0452 -
 val_accuracy: 0.9667 - val_loss: 0.0770
Epoch 15/20
3/3 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 2s 588ms/step - accuracy: 0.9810 - loss: 0.1142 -
 val_accuracy: 0.9667 - val_loss: 0.0840
Epoch 16/20
3/3 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 2s 587ms/step - accuracy: 0.9810 - loss: 0.0241 -
 val_accuracy: 0.9667 - val_loss: 0.0965
Epoch 17/20
3/3 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 2s 585ms/step - accuracy: 0.9888 - loss: 0.0295 -
 val_accuracy: 0.9667 - val_loss: 0.1065
Epoch 18/20
3/3 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 2s 589ms/step - accuracy: 0.9810 - loss: 0.0454 -
 val_accuracy: 0.9667 - val_loss: 0.0943
Epoch 19/20
3/3 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 2s 587ms/step - accuracy: 0.9888 - loss: 0.0151 -
 val_accuracy: 0.9667 - val_loss: 0.0859
Epoch 20/20
3/3 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 2s 579ms/step - accuracy: 0.9888 - loss: 0.0154 -
 val_accuracy: 0.9667 - val_loss: 0.0772
```

In [16]:

```python
# Model Performance Plot
# Loss performance
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Binary Model Performance: Loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['loss', 'val_loss'], loc='upper right')
plt.show();

# Accuracy performance
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Binary Model Performance: Accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['accuracy', 'val_accuracy'], loc='lower right')
plt.show();
```





In [17]:
```
# Evaluating the model on the validation set
val_loss, val_accuracy = Bin_model.evaluate(X_val, y_val)

# Result
print(f'Validation Loss for Binary Model: {val_loss}')
print(f'Validation Accuracy for Binary Model: {val_accuracy}')
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 130ms/step - accuracy: 0.9667 - loss: 0.0772
```

```
Validation Loss for Binary Model: 0.07719671726226807
Validation Accuracy for Binary Model: 0.9666666388511658
```

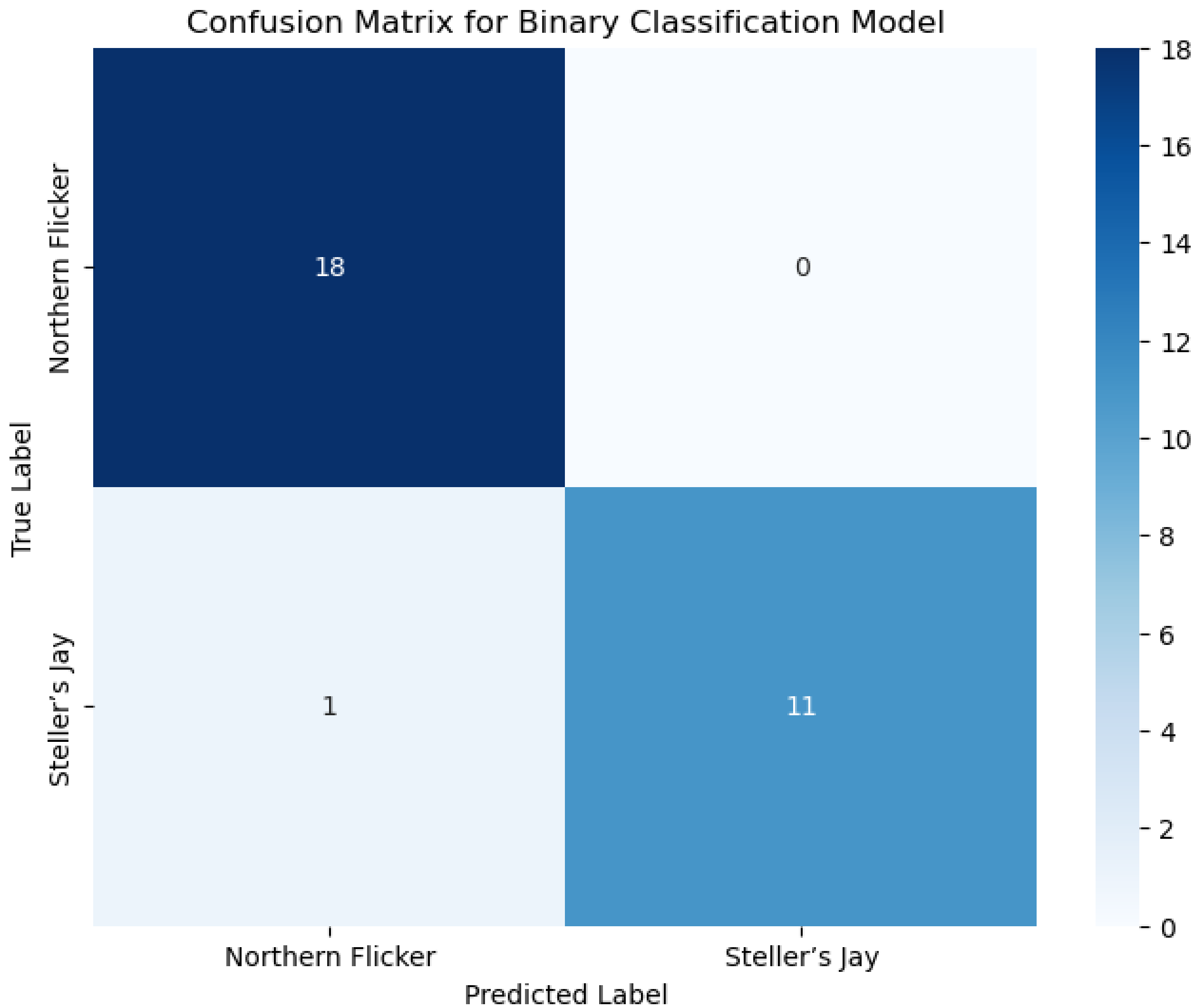
In [18]:
```
# Predicting new data
predictions = Bin_model.predict(X_val)

# Converting probabilities to class labels
predicted_classes = (predictions > 0.5).astype(int)
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 158ms/step
```

In [19]:
```
# Now, converting labels to integer labels
true_classes = np.argmax(y_val, axis=1)
predicted_classes = (predictions > 0.5).astype(int)
predicted_classes = np.argmax(predicted_classes, axis=1)

# Classification report
report = classification_report(true_classes, predicted_classes, target_names=['Northern
print(report)
```

```
                  precision    recall  f1-score   support

Northern Flicker       0.95      1.00      0.97        18
   Steller’s Jay       1.00      0.92      0.96        12

        accuracy                           0.97        30
       macro avg       0.97      0.96      0.96        30
    weighted avg       0.97      0.97      0.97        30
```

In [20]:
```
# Confusion Matrix
matrix = confusion_matrix(true_classes, predicted_classes)

# Heatmap For confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(matrix, annot=True, fmt="d", cmap="Blues",
            xticklabels=['Northern Flicker', 'Steller’s Jay'],
            yticklabels=['Northern Flicker', 'Steller’s Jay'])
plt.title('Confusion Matrix for Binary Classification Model')
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.show()
```



Multi-Class Classification Model for all 12 Bird Species

In [21]:
```
# Load data for all species and their labels
# We created a empty lists for data and their labels
# X_multi : data samples for all bird species
# y_multi : labels for all birds species
X_multi = []
y_multi = []

# Now, looping over each species key to load the for all species data
for index, key in enumerate(species_keys):
    data = species_data[key][:]
    # We created a label array to fill the species index
    labels = np.full(data.shape[2], index)
    X_multi.append(data)
    y_multi.append(labels)
```

In [22]:
```
# Now, combining the data and labels from all species
X_multi = np.concatenate(X_multi, axis=2)
y_multi = np.concatenate(y_multi, axis=0)
```

In [23]:
```
# Normalizing the data
X_multi = X_multi / np.max(X_multi)
```

In [24]:
```
# Reshaping X to match the expected input shape for CNNs (frequency, timesteps, samples)
X_multi = np.transpose(X_multi, (2, 0, 1))
X_multi = X_multi[..., np.newaxis]  # this will adds a channel dimension
```

In [25]:
```
# Converting the labels to categorical data
y_multi = to_categorical(y_multi, len(species_keys))
```

In [26]:
```
# Splitting the data into training and validation sets (70% training set and 30% validat
X_train, X_val, y_train, y_val = train_test_split(X_multi, y_multi, test_size=0.3, rando
```

In [27]:
```
# Defining the CNN model for Multi-class classification
Multi_class_model = tf.keras.Sequential([
    tf.keras.layers.Input(shape=(256, 343, 1)),
    tf.keras.layers.Conv2D(32, kernel_size=(3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(pool_size=(2,2)),
    tf.keras.layers.Conv2D(64, kernel_size=(3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(pool_size=(2,2)),
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(256, activation='relu'),
    tf.keras.layers.Dropout(0.5),
    tf.keras.layers.Dense(12, activation='softmax')
])
```

In [28]:
```
# Model summary
Multi_class_model.summary()
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv2d_2 (Conv2D)	(None, 254, 341, 32)	320
max_pooling2d_2 (MaxPooling2D)	(None, 127, 170, 32)	0
conv2d_3 (Conv2D)	(None, 125, 168, 64)	18,496
max_pooling2d_3 (MaxPooling2D)	(None, 62, 84, 64)	0
flatten_1 (Flatten)	(None, 333312)	0
dense_2 (Dense)	(None, 256)	85,328,128
dropout_3 (Dropout)	(None, 256)	0
dense_3 (Dense)	(None, 12)	3,084

Total params: 85,350,028 (325.58 MB)

Trainable params: 85,350,028 (325.58 MB)

Non-trainable params: 0 (0.00 B)

In [29]:
```
# Compiling the model
Multi_class_model.compile(optimizer=Adam(), loss='categorical_crossentropy', metrics=['a
```

In [30]:
```
# Training the model
history = Multi_class_model.fit(X_train, y_train, epochs=20, batch_size=128, validation_
```

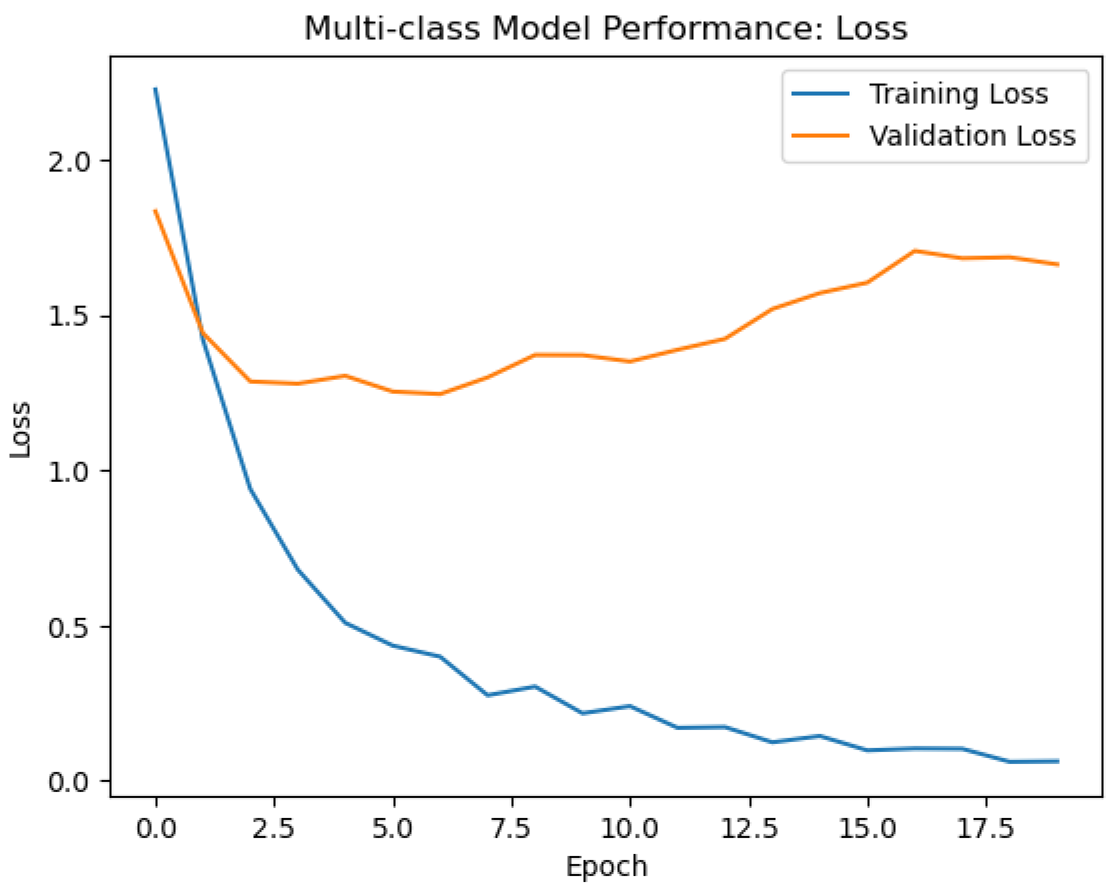
```
Epoch 1/20
4/4 ━━━━━━━━━━━━━━━━━━━━ 12s 3s/step - accuracy: 0.2160 - loss: 2.3056 - v
al_accuracy: 0.3908 - val_loss: 1.8335
Epoch 2/20
4/4 ━━━━━━━━━━━━━━━━━━━━ 9s 2s/step - accuracy: 0.5690 - loss: 1.4658 - va
l_accuracy: 0.5632 - val_loss: 1.4413
Epoch 3/20
4/4 ━━━━━━━━━━━━━━━━━━━━ 9s 2s/step - accuracy: 0.7315 - loss: 0.9518 - va
```

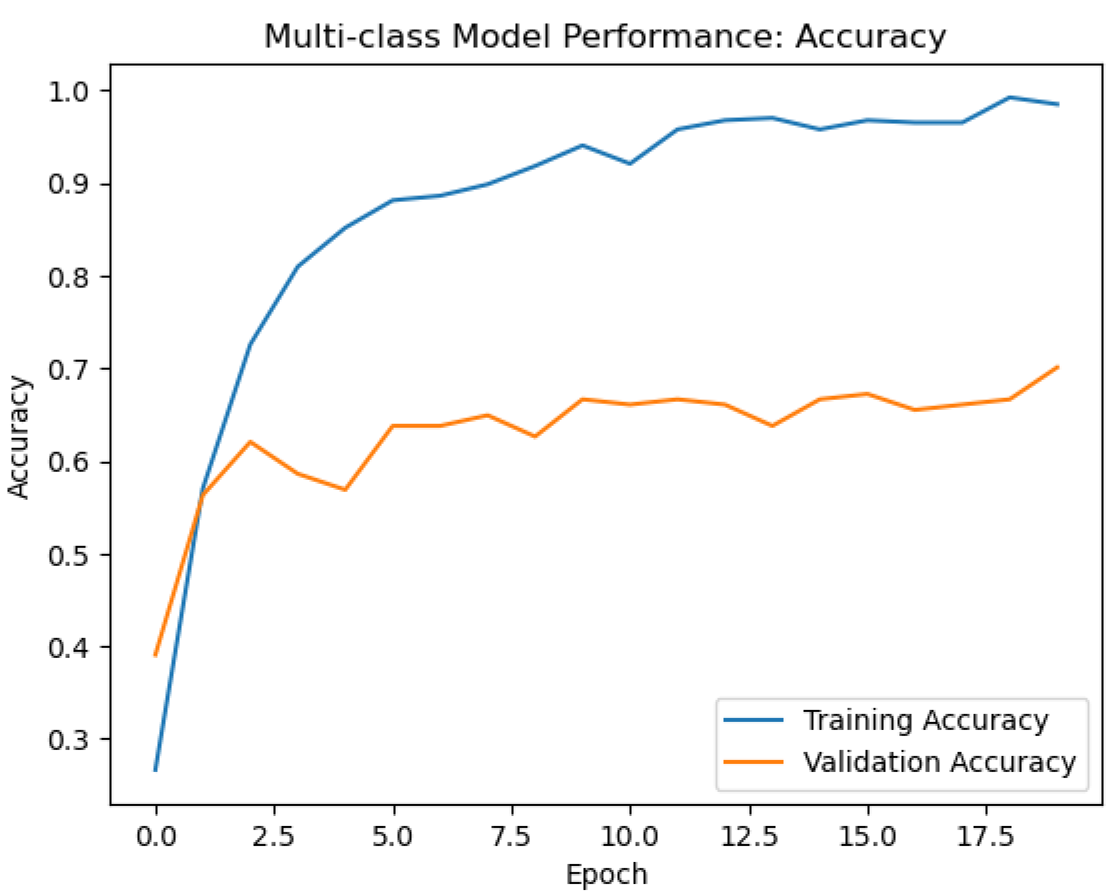
```
l_accuracy: 0.6207 - val_loss: 1.2854
Epoch 4/20
4/4 ━━━━━━━━━━━━━━━━━━━━ 9s 2s/step - accuracy: 0.8107 - loss: 0.7061 - va
l_accuracy: 0.5862 - val_loss: 1.2784
Epoch 5/20
4/4 ━━━━━━━━━━━━━━━━━━━━ 9s 2s/step - accuracy: 0.8374 - loss: 0.5553 - va
l_accuracy: 0.5690 - val_loss: 1.3036
Epoch 6/20
4/4 ━━━━━━━━━━━━━━━━━━━━ 9s 2s/step - accuracy: 0.8760 - loss: 0.4586 - va
l_accuracy: 0.6379 - val_loss: 1.2529
Epoch 7/20
4/4 ━━━━━━━━━━━━━━━━━━━━ 8s 2s/step - accuracy: 0.8879 - loss: 0.3946 - va
l_accuracy: 0.6379 - val_loss: 1.2448
Epoch 8/20
4/4 ━━━━━━━━━━━━━━━━━━━━ 9s 2s/step - accuracy: 0.9017 - loss: 0.2709 - va
l_accuracy: 0.6494 - val_loss: 1.2986
Epoch 9/20
4/4 ━━━━━━━━━━━━━━━━━━━━ 9s 2s/step - accuracy: 0.9174 - loss: 0.3122 - va
l_accuracy: 0.6264 - val_loss: 1.3708
Epoch 10/20
4/4 ━━━━━━━━━━━━━━━━━━━━ 9s 2s/step - accuracy: 0.9378 - loss: 0.2284 - va
l_accuracy: 0.6667 - val_loss: 1.3702
Epoch 11/20
4/4 ━━━━━━━━━━━━━━━━━━━━ 9s 2s/step - accuracy: 0.9267 - loss: 0.2211 - va
l_accuracy: 0.6609 - val_loss: 1.3496
Epoch 12/20
4/4 ━━━━━━━━━━━━━━━━━━━━ 9s 2s/step - accuracy: 0.9553 - loss: 0.1605 - va
l_accuracy: 0.6667 - val_loss: 1.3874
Epoch 13/20
4/4 ━━━━━━━━━━━━━━━━━━━━ 9s 2s/step - accuracy: 0.9700 - loss: 0.1815 - va
l_accuracy: 0.6609 - val_loss: 1.4226
Epoch 14/20
4/4 ━━━━━━━━━━━━━━━━━━━━ 8s 2s/step - accuracy: 0.9676 - loss: 0.1310 - va
l_accuracy: 0.6379 - val_loss: 1.5187
Epoch 15/20
4/4 ━━━━━━━━━━━━━━━━━━━━ 8s 2s/step - accuracy: 0.9587 - loss: 0.1405 - va
l_accuracy: 0.6667 - val_loss: 1.5700
Epoch 16/20
4/4 ━━━━━━━━━━━━━━━━━━━━ 8s 2s/step - accuracy: 0.9684 - loss: 0.0982 - va
l_accuracy: 0.6724 - val_loss: 1.6036
Epoch 17/20
4/4 ━━━━━━━━━━━━━━━━━━━━ 9s 2s/step - accuracy: 0.9612 - loss: 0.1144 - va
l_accuracy: 0.6552 - val_loss: 1.7058
Epoch 18/20
4/4 ━━━━━━━━━━━━━━━━━━━━ 9s 2s/step - accuracy: 0.9659 - loss: 0.0952 - va
l_accuracy: 0.6609 - val_loss: 1.6820
Epoch 19/20
4/4 ━━━━━━━━━━━━━━━━━━━━ 9s 2s/step - accuracy: 0.9900 - loss: 0.0659 - va
l_accuracy: 0.6667 - val_loss: 1.6854
Epoch 20/20
4/4 ━━━━━━━━━━━━━━━━━━━━ 9s 2s/step - accuracy: 0.9860 - loss: 0.0558 - va
l_accuracy: 0.7011 - val_loss: 1.6623
```

In [31]:

```python
# Model Performance Plot for Loss
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Multi-class Model Performance: Loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Training Loss', 'Validation Loss'], loc='upper right')
plt.show()

# Model Performance Plot for Accuracy
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
```

```
plt.title('Multi-class Model Performance: Accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Training Accuracy', 'Validation Accuracy'], loc='lower right')
plt.show()
```





In [32]:
```
# Evaluating the model on the validation set
val_loss, val_accuracy = Multi_class_model.evaluate(X_val, y_val)
```

```
# Result
print(f'Validation Loss for Multi-class Model: {val_loss}')
print(f'Validation Accuracy for Multi-class Model: {val_accuracy}')
```

```
6/6 ━━━━━━━━━━━━━━━━━━━━ 1s 127ms/step - accuracy: 0.6834 - loss: 1.6372
Validation Loss for Multi-class Model: 1.6622616052627563
Validation Accuracy for Multi-class Model: 0.7011494040489197
```

In [33]:

```
# Predicting new data
predictions = Multi_class_model.predict(X_val)

# Converting probabilities to class labels
predicted_classes = np.argmax(predictions, axis=1)
```

```
6/6 ━━━━━━━━━━━━━━━━━━━━ 1s 129ms/step
```

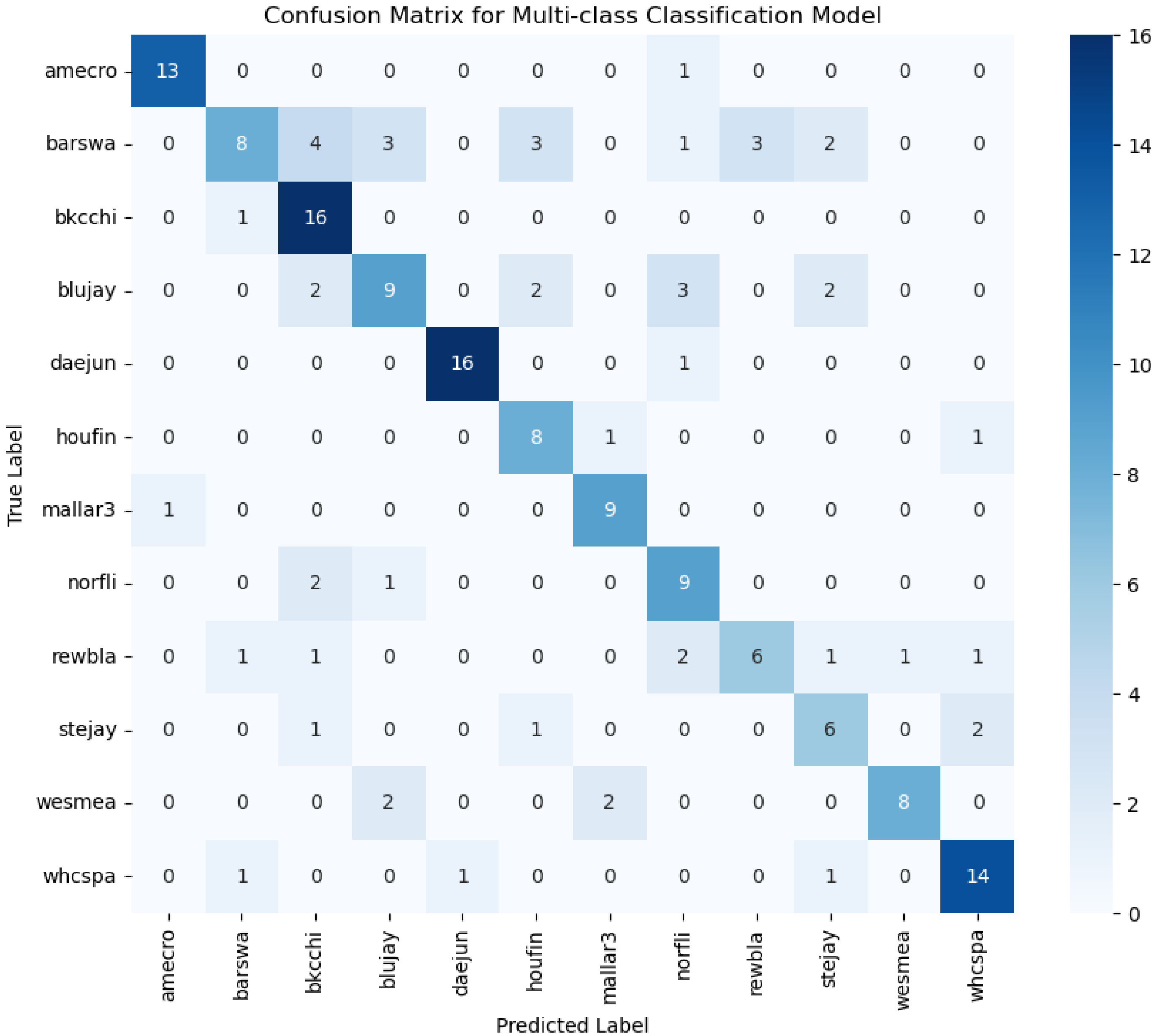
In [34]:

```
# Now, converting labels to integer labels
true_classes = np.argmax(y_val, axis=1)

# Classification report for multi-class model
report = classification_report(true_classes, predicted_classes, target_names = species_k
print(report)
```

```
              precision    recall  f1-score   support

      amecro       0.93      0.93      0.93        14
      barswa       0.73      0.33      0.46        24
      bkcchi       0.62      0.94      0.74        17
      blujay       0.60      0.50      0.55        18
      daejun       0.94      0.94      0.94        17
      houfin       0.57      0.80      0.67        10
     mallar3       0.75      0.90      0.82        10
      norfli       0.53      0.75      0.62        12
      rewbla       0.67      0.46      0.55        13
      stejay       0.50      0.60      0.55        10
      wesmea       0.89      0.67      0.76        12
      whcspa       0.78      0.82      0.80        17

    accuracy                           0.70       174
   macro avg       0.71      0.72      0.70       174
weighted avg       0.72      0.70      0.69       174
```

In [35]:

```
# Confusion Matrix for multi-class model
matrix = confusion_matrix(true_classes, predicted_classes)

# Heatmap For confusion matrix
plt.figure(figsize=(10, 8))
sns.heatmap(matrix, annot=True, fmt="d", cmap="Blues",
            xticklabels=species_keys,
            yticklabels=species_keys)
plt.title('Confusion Matrix for Multi-class Classification Model')
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.show()
```



In [36]:
```python
# Defining the 2nd CNN model for Multi-class classification
Multi_class_model2 = tf.keras.Sequential([
    tf.keras.layers.Input(shape=(256, 343, 1)),
    tf.keras.layers.Conv2D(32, kernel_size=(3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(pool_size=(2,2)),
    tf.keras.layers.Conv2D(64, kernel_size=(3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(pool_size=(2,2)),
    tf.keras.layers.Conv2D(128, kernel_size=(3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(pool_size=(2,2)),
    tf.keras.layers.Conv2D(256, kernel_size=(3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(pool_size=(2,2)),
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(256, activation='relu'),
    tf.keras.layers.Dropout(0.5),
    tf.keras.layers.Dense(12, activation='softmax')
])
```

In [37]:
```python
# Model summary
Multi_class_model2.summary()
```

Model: "sequential_2"

Layer (type)	Output Shape	Param #

conv2d_4 (Conv2D)	(None, 254, 341, 32)	320
max_pooling2d_4 (MaxPooling2D)	(None, 127, 170, 32)	0
conv2d_5 (Conv2D)	(None, 125, 168, 64)	18,496
max_pooling2d_5 (MaxPooling2D)	(None, 62, 84, 64)	0
conv2d_6 (Conv2D)	(None, 60, 82, 128)	73,856
max_pooling2d_6 (MaxPooling2D)	(None, 30, 41, 128)	0
conv2d_7 (Conv2D)	(None, 28, 39, 256)	295,168
max_pooling2d_7 (MaxPooling2D)	(None, 14, 19, 256)	0
flatten_2 (Flatten)	(None, 68096)	0
dense_4 (Dense)	(None, 256)	17,432,832
dropout_4 (Dropout)	(None, 256)	0
dense_5 (Dense)	(None, 12)	3,084

Total params: 17,823,756 (67.99 MB)

Trainable params: 17,823,756 (67.99 MB)

Non-trainable params: 0 (0.00 B)

In [38]:
```
# Compiling the model
Multi_class_model2.compile(optimizer=Adam(), loss='categorical_crossentropy', metrics=['
```

In [39]:
```
# Training the model
history2 = Multi_class_model2.fit(X_train, y_train, epochs=30, batch_size=64, validation
```

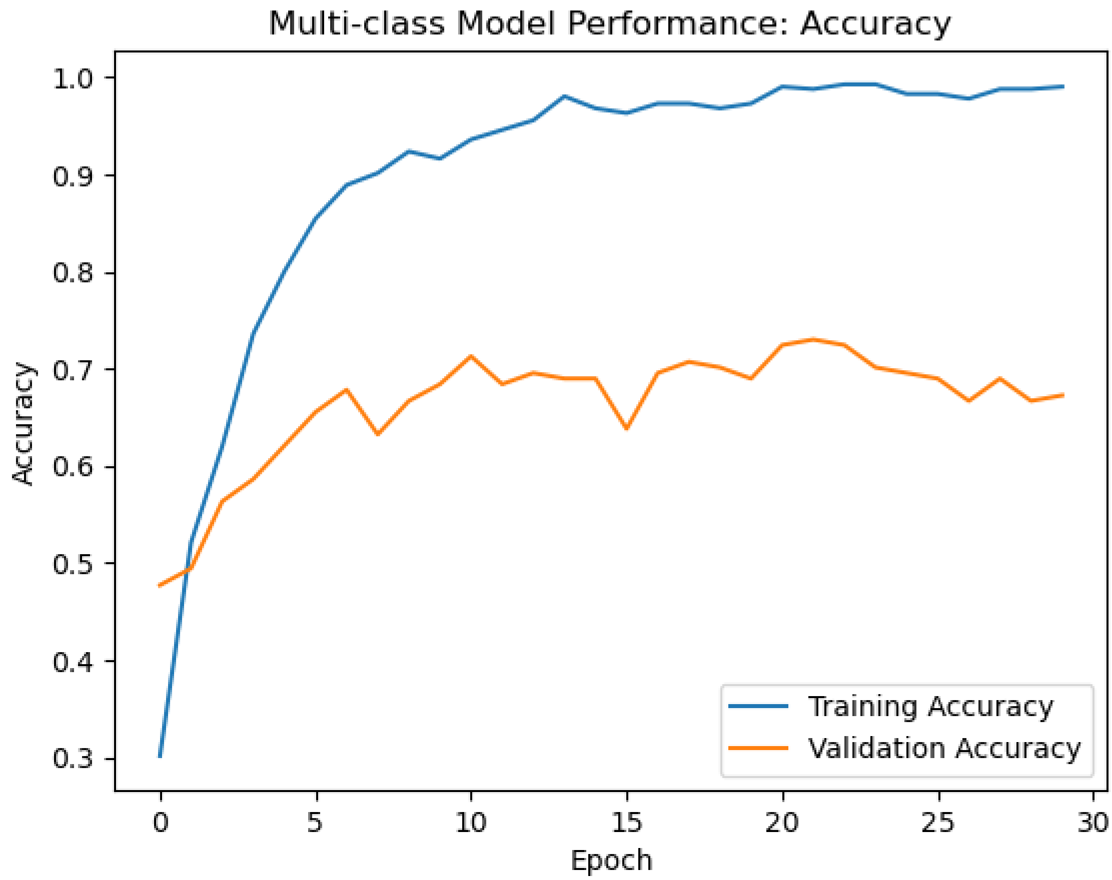
```
Epoch 1/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 12s 2s/step - accuracy: 0.2316 - loss: 2.2958 - v
al_accuracy: 0.4770 - val_loss: 1.7246
Epoch 2/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 11s 2s/step - accuracy: 0.5040 - loss: 1.6057 - v
al_accuracy: 0.4943 - val_loss: 1.4462
Epoch 3/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 11s 2s/step - accuracy: 0.5891 - loss: 1.1873 - v
al_accuracy: 0.5632 - val_loss: 1.3274
Epoch 4/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 11s 2s/step - accuracy: 0.7353 - loss: 0.8904 - v
al_accuracy: 0.5862 - val_loss: 1.2149
Epoch 5/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 10s 1s/step - accuracy: 0.7833 - loss: 0.6365 - v
al_accuracy: 0.6207 - val_loss: 1.2232
Epoch 6/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 11s 2s/step - accuracy: 0.8751 - loss: 0.4586 - v
al_accuracy: 0.6552 - val_loss: 1.2980
Epoch 7/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 11s 2s/step - accuracy: 0.8914 - loss: 0.3801 - v
al_accuracy: 0.6782 - val_loss: 1.3552
Epoch 8/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 12s 2s/step - accuracy: 0.8949 - loss: 0.3602 - v
al_accuracy: 0.6322 - val_loss: 1.5987
Epoch 9/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 11s 2s/step - accuracy: 0.9228 - loss: 0.2966 - v
al_accuracy: 0.6667 - val_loss: 1.6180
Epoch 10/30
```

```
7/7 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11s 2s/step - accuracy: 0.9102 - loss: 0.2689 - v
al_accuracy: 0.6839 - val_loss: 1.4741
Epoch 11/30
7/7 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 12s 2s/step - accuracy: 0.9461 - loss: 0.2141 - v
al_accuracy: 0.7126 - val_loss: 1.6364
Epoch 12/30
7/7 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11s 2s/step - accuracy: 0.9449 - loss: 0.1678 - v
al_accuracy: 0.6839 - val_loss: 1.9117
Epoch 13/30
7/7 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 12s 2s/step - accuracy: 0.9541 - loss: 0.1289 - v
al_accuracy: 0.6954 - val_loss: 2.1707
Epoch 14/30
7/7 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11s 2s/step - accuracy: 0.9870 - loss: 0.0925 - v
al_accuracy: 0.6897 - val_loss: 2.2550
Epoch 15/30
7/7 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 12s 2s/step - accuracy: 0.9681 - loss: 0.1350 - v
al_accuracy: 0.6897 - val_loss: 2.2391
Epoch 16/30
7/7 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11s 1s/step - accuracy: 0.9653 - loss: 0.0990 - v
al_accuracy: 0.6379 - val_loss: 2.4522
Epoch 17/30
7/7 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11s 2s/step - accuracy: 0.9645 - loss: 0.1239 - v
al_accuracy: 0.6954 - val_loss: 2.0301
Epoch 18/30
7/7 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11s 2s/step - accuracy: 0.9744 - loss: 0.0984 - v
al_accuracy: 0.7069 - val_loss: 1.9972
Epoch 19/30
7/7 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11s 2s/step - accuracy: 0.9656 - loss: 0.1064 - v
al_accuracy: 0.7011 - val_loss: 2.0504
Epoch 20/30
7/7 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 1s/step - accuracy: 0.9694 - loss: 0.0698 - v
al_accuracy: 0.6897 - val_loss: 2.1285
Epoch 21/30
7/7 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11s 2s/step - accuracy: 0.9849 - loss: 0.0465 - v
al_accuracy: 0.7241 - val_loss: 2.1781
Epoch 22/30
7/7 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11s 2s/step - accuracy: 0.9880 - loss: 0.0479 - v
al_accuracy: 0.7299 - val_loss: 2.3860
Epoch 23/30
7/7 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11s 2s/step - accuracy: 0.9912 - loss: 0.0298 - v
al_accuracy: 0.7241 - val_loss: 2.6870
Epoch 24/30
7/7 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11s 2s/step - accuracy: 0.9903 - loss: 0.0595 - v
al_accuracy: 0.7011 - val_loss: 2.7997
Epoch 25/30
7/7 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11s 2s/step - accuracy: 0.9898 - loss: 0.0383 - v
al_accuracy: 0.6954 - val_loss: 2.9740
Epoch 26/30
7/7 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 2s/step - accuracy: 0.9782 - loss: 0.1390 - v
al_accuracy: 0.6897 - val_loss: 2.5107
Epoch 27/30
7/7 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10s 1s/step - accuracy: 0.9773 - loss: 0.0799 - v
al_accuracy: 0.6667 - val_loss: 2.6212
Epoch 28/30
7/7 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 12s 2s/step - accuracy: 0.9854 - loss: 0.0429 - v
al_accuracy: 0.6897 - val_loss: 2.7523
Epoch 29/30
7/7 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 12s 2s/step - accuracy: 0.9896 - loss: 0.0493 - v
al_accuracy: 0.6667 - val_loss: 2.8336
Epoch 30/30
7/7 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 11s 2s/step - accuracy: 0.9869 - loss: 0.0573 - v
al_accuracy: 0.6724 - val_loss: 2.9570
```

In [40]:

```
# Model Performance Plot for Loss
plt.plot(history2.history['loss'])
plt.plot(history2.history['val_loss'])
```

```
plt.title('Multi-class Model Performance: Loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Training Loss', 'Validation Loss'], loc='upper right')
plt.show()

# Model Performance Plot for Accuracy
plt.plot(history2.history['accuracy'])
plt.plot(history2.history['val_accuracy'])
plt.title('Multi-class Model Performance: Accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Training Accuracy', 'Validation Accuracy'], loc='lower right')
plt.show()
```



In [41]:
```
# Evaluating the model on the validation set
val_loss2, val_accuracy2 = Multi_class_model2.evaluate(X_val, y_val)

# Result
print(f'Validation Loss for Multi-class Model2: {val_loss2}')
print(f'Validation Accuracy for Multi-class Model2: {val_accuracy2}')
```

```
6/6 ━━━━━━━━━━━━━━━━━━━━ 1s 168ms/step - accuracy: 0.6759 - loss: 3.1402
Validation Loss for Multi-class Model2: 2.9570038318634033
Validation Accuracy for Multi-class Model2: 0.6724137663841248
```

In [42]:
```
# Predicting new data
predictions2 = Multi_class_model2.predict(X_val)

# Converting probabilities to class labels
predicted_classes2 = np.argmax(predictions2, axis=1)
```

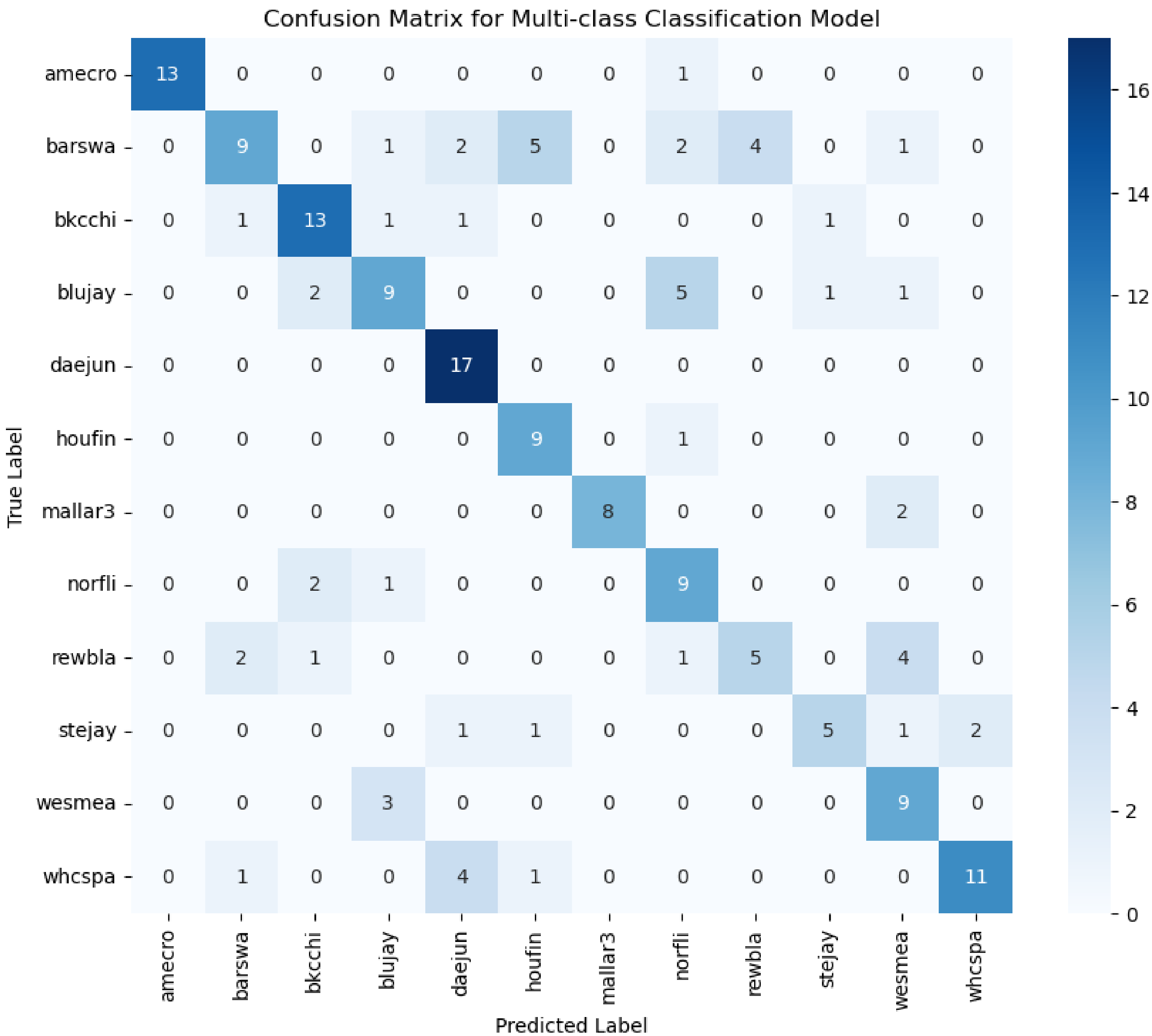
```
6/6 ━━━━━━━━━━━━━━━━━━━━ 1s 186ms/step
```

In [43]:
```
# Now, converting labels to integer labels
true_classes2 = np.argmax(y_val, axis=1)

# Classification report for multi-class model
report2 = classification_report(true_classes2, predicted_classes2, target_names = specie
print(report)
```

```
              precision    recall  f1-score   support

     amecro       0.93      0.93      0.93        14
     barswa       0.73      0.33      0.46        24
     bkcchi       0.62      0.94      0.74        17
     blujay       0.60      0.50      0.55        18
     daejun       0.94      0.94      0.94        17
     houfin       0.57      0.80      0.67        10
    mallar3       0.75      0.90      0.82        10
     norfli       0.53      0.75      0.62        12
     rewbla       0.67      0.46      0.55        13
```

```
      stejay       0.50      0.60      0.55        10
      wesmea       0.89      0.67      0.76        12
      whcspa       0.78      0.82      0.80        17

    accuracy                           0.70       174
   macro avg       0.71      0.72      0.70       174
weighted avg       0.72      0.70      0.69       174
```

In [44]:
```python
# Confusion Matrix for multi-class model
matrix2 = confusion_matrix(true_classes2, predicted_classes2)

# Heatmap For confusion matrix
plt.figure(figsize=(10, 8))
sns.heatmap(matrix2, annot=True, fmt="d", cmap="Blues",
            xticklabels=species_keys,
            yticklabels=species_keys)
plt.title('Confusion Matrix for Multi-class Classification Model')
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.show()
```



Multi-Class Model on External Test Data

In [52]:

```
# Function to preprocess the test audio files and generate spectrograms for the same
def preprocess_test_clips(clip_path):
    y, sr = librosa.load(clip_path, sr=None)
    y = librosa.resample(y, orig_sr=sr, target_sr=22050)
    intervals = librosa.effects.split(y, top_db=20)
    clips = [y[start:end] for start, end in intervals if (end - start) > 0.5 * sr]

    spectrograms = []
    for clip in clips:
        if len(clip) > 2 * sr:
            for i in range(0, len(clip) - 2 * sr, 2 * sr):
                window = clip[i:i + 2 * sr]
                S = librosa.feature.melspectrogram(y=window, sr=22050, n_mels=256, fmax=
                S_dB = librosa.power_to_db(S, ref=np.max)
                S_dB_resized = resize(S_dB, (256, 343))  # Resize to match input shape o
                spectrograms.append(S_dB_resized)
        else:
            window = librosa.util.fix_length(clip, 2 * sr)
            S = librosa.feature.melspectrogram(y=window, sr=22050, n_mels=256, fmax=8000
            S_dB = librosa.power_to_db(S, ref=np.max)
            S_dB_resized = resize(S_dB, (256, 343))  # Resize to match input shape of th
            spectrograms.append(S_dB_resized)

    return spectrograms
```

In [53]:

```
# Function to predict bird species from the test spectrograms
def predict(spectrograms, model, species_keys):
    predictions = []
    for spectrogram in spectrograms:
        spectrogram = np.expand_dims(spectrogram, axis=0)  # Adding the  batch dimension
        spectrogram = np.expand_dims(spectrogram, axis=-1)  # This is to add channel dim
        prediction = model.predict(spectrogram)
        predicted_class = np.argmax(prediction, axis=1)[0]
        predictions.append((species_keys[predicted_class], prediction[0]))
    return predictions
```

In [54]:

```
# Function to analyze predictions and format output
def analyze_preds(predictions, species_keys):
    detailed_predictions = []
    for species, probs in predictions:
        sorted_probs = sorted(zip(species_keys, probs), key=lambda x: x[1], reverse=True
        top_preds = sorted_probs[:3]
        detailed_predictions.append(top_preds)
    return detailed_predictions
```

In [55]:

```
# Load the trained model
model = Multi_class_model2

# Directory containing the test clips
test_clips = 'test_birds/'

# Processing each test file and storing the results
test_files = [os.path.join(test_clips, f) for f in os.listdir(test_clips) if f.endswith(
results = []

for test_file in test_files:
    spectrograms = preprocess_test_clips(test_file)
    predictions = predict(spectrograms, model, species_keys)
    detailed_predictions = analyze_preds(predictions, species_keys)

    results.append({
        'File': test_file,
        'Predictions': detailed_predictions
    })
```

```python
# Displaying results in a table
results_df = pd.DataFrame(results)
print(results_df)
print("\n")

# Checking the presence of multiple bird calls in each clip
for index, row in results_df.iterrows():
    multiple_bird_call = False
    for prediction in row['Predictions']:
        if len(prediction) > 1 and prediction[1][1] > 0.5:
            multiple_bird_call = True
            break
    if multiple_bird_call:
        print(f"{row['File']} may contain more than one bird call.")
    else:
        print(f"{row['File']} is likely to contain single bird call.")
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 26ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step
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1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 26ms/step
                    File                                         Predictions
0  test_birds/test1.mp3  [[(daejun, 1.0), (amecro, 0.0), (barswa, 0.0)]...
1  test_birds/test2.mp3    [[(daejun, 1.0), (amecro, 0.0), (barswa, 0.0)]]
2  test_birds/test3.mp3  [[(daejun, 1.0), (amecro, 0.0), (barswa, 0.0)]...


test_birds/test1.mp3 is likely to contain single bird call.
test_birds/test2.mp3 is likely to contain single bird call.
test_birds/test3.mp3 is likely to contain single bird call.
```

References

- 1) Lecture Notes
- 2) Ch10-1 and Ch10-2 Kereas files from the lecture materials
- 3) Keras and Tensorflow documentation: https://www.tensorflow.org/guide
- 4) Audio Classification model of CNN for constructing spectograms: https://github.com/jeffprosise/Deep-Learning/blob/master/Audio%20Classification%20(CNN).ipynb
- 5) Librosa documentation: https://librosa.org/doc/latest/index.html
- 6) Librosa API reference: https://librosa.org/doc/latest/api.html