Convolutional Neural Network with the cifar10 Dataset

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Explanation of Project

I will be creating a basic convolutional neural network (CNN) using the cifar10 dataset. Then I will use Keras Tuner to tune it to hopefully achieve better results.

Techniques Employed

- CNN
- Hyperparameter Tuning

Import Statements

In [1]:
```
#General libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings("ignore")

#Keras and TensorFlow
import keras
import tensorflow as tf
from keras.utils import to_categorical

#cifar10 dataset
from keras.datasets import cifar10

#Model building libraries
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten
from keras.layers import Conv2D, MaxPooling2D
from keras.optimizers import SGD

#Hyperparameter tuning
import os
import shutil
import keras_tuner as kt
from sklearn.metrics import mean_absolute_error

#Output visualisation and analysis
from collections import Counter
from sklearn.metrics import confusion_matrix
import itertools
```

```
Using TensorFlow backend
```

Exploratory Data Analysis

Load data and examine

In [2]:
```
(X_train, y_train), (X_valid, y_valid) = cifar10.load_data()
```

In [3]:
```
#Reformatting for examination
X_train_df = pd.DataFrame(X_train.reshape(X_train.shape[0], -1))
y_train_df = pd.DataFrame(y_train, columns=["Label"])

X_valid_df = pd.DataFrame(X_valid.reshape(X_valid.shape[0], -1))
y_valid_df = pd.DataFrame(y_valid, columns=["Label"])
```

In [4]:
```
print("The shape of X_train is: ", X_train.shape)
print("The shape of y_train is: ", y_train.shape)
print("The shape of X_valid is: ", X_valid.shape)
print("The shape of y_valid is: ", y_valid.shape)
```

```
The shape of X_train is:  (50000, 32, 32, 3)
The shape of y_train is:  (50000, 1)
The shape of X_valid is:  (10000, 32, 32, 3)
The shape of y_valid is:  (10000, 1)
```

In [5]:
```
X_train_df.describe()
```

Out[5]:

	0	1	2	3	4	5	
count	50000.000000	50000.00000	50000.000000	50000.00000	50000.000000	50000.000000	50000.00
mean	130.710740	136.05614	132.553800	130.14036	135.442380	131.853580	131.05
std	73.412873	72.90798	80.449751	72.44259	71.901316	79.598048	72.24
min	0.000000	0.00000	0.000000	0.00000	0.000000	0.000000	0.00
25%	71.000000	77.00000	61.000000	71.00000	78.000000	61.000000	73.00
50%	128.000000	135.00000	127.000000	127.00000	135.000000	127.000000	129.00
75%	189.000000	195.00000	207.000000	188.00000	193.000000	206.000000	188.00
max	255.000000	255.00000	255.000000	255.00000	255.000000	255.000000	255.00

8 rows × 3072 columns

In [6]:
```
X_train_df.head()
```

Out[6]:

	0	1	2	3	4	5	6	7	8	9	...	3062	3063	3064	3065	3066	3067
0	59	62	63	43	46	45	50	48	43	68	...	104	216	184	140	151	118
1	154	177	187	126	137	136	105	104	95	102	...	136	143	133	139	143	134
2	255	255	255	253	253	253	253	253	253	253	...	79	78	85	83	79	85
3	28	25	10	37	34	19	38	35	20	42	...	38	54	47	28	63	56
4	170	180	198	168	178	196	177	185	203	183	...	78	75	79	82	71	75

5 rows × 3072 columns

In [7]:
```
X_train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50000 entries, 0 to 49999
Columns: 3072 entries, 0 to 3071
dtypes: uint8(3072)
memory usage: 146.5 MB
```

In [8]:
```
y_train_df.describe()
```

Out[8]:

	Label
count	50000.00000
mean	4.50000
std	2.87231
min	0.00000
25%	2.00000
50%	4.50000
75%	7.00000
max	9.00000

In [9]:
```
y_train_df.head()
```

Out[9]:

	Label
0	6
1	9
2	9
3	4
4	1

In [10]:
```
y_train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50000 entries, 0 to 49999
Data columns (total 1 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   Label   50000 non-null  uint8
dtypes: uint8(1)
memory usage: 49.0 KB
```

In [11]:
```
X_valid_df.describe()
```

Out[11]:

	0	1	2	3	4	5	
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.00000	10000.0
mean	130.535400	136.046200	132.830000	129.993900	135.511300	132.23110	131.1
std	73.333214	72.690423	80.134163	72.397388	71.740927	79.18629	72.2
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.00000	0.0
25%	70.000000	78.000000	62.000000	71.000000	79.000000	62.00000	73.0
50%	127.000000	135.000000	128.000000	127.000000	135.000000	128.00000	128.0
75%	188.000000	195.000000	207.000000	187.000000	193.000000	205.00000	189.0
max	255.000000	255.000000	255.000000	255.000000	255.000000	255.00000	255.0

8 rows × 3072 columns

In [12]:
```
X_valid_df.head()
```

Out[12]:

	0	1	2	3	4	5	6	7	8	9	...	3062	3063	3064	3065	3066	3067
0	158	112	49	159	111	47	165	116	51	166	...	145	24	77	124	34	84
1	235	235	235	231	231	231	232	232	232	232	...	163	168	183	178	180	195
2	158	190	222	158	187	218	139	166	194	132	...	37	5	6	8	4	5
3	155	156	149	167	176	187	176	179	193	190	...	53	60	63	50	64	65
4	65	68	50	70	81	64	48	64	46	30	...	147	143	179	136	154	185

5 rows × 3072 columns

In [13]:
```
X_valid_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Columns: 3072 entries, 0 to 3071
dtypes: uint8(3072)
memory usage: 29.3 MB
```

In [14]:
```
y_valid_df.describe()
```

Out[14]:

	Label
count	10000.000000
mean	4.500000
std	2.872425
min	0.000000
25%	2.000000
50%	4.500000
75%	7.000000
max	9.000000

In [15]:

```
y_valid_df.head()
```

Out[15]:

	Label
0	3
1	8
2	8
3	0
4	6

In [16]:

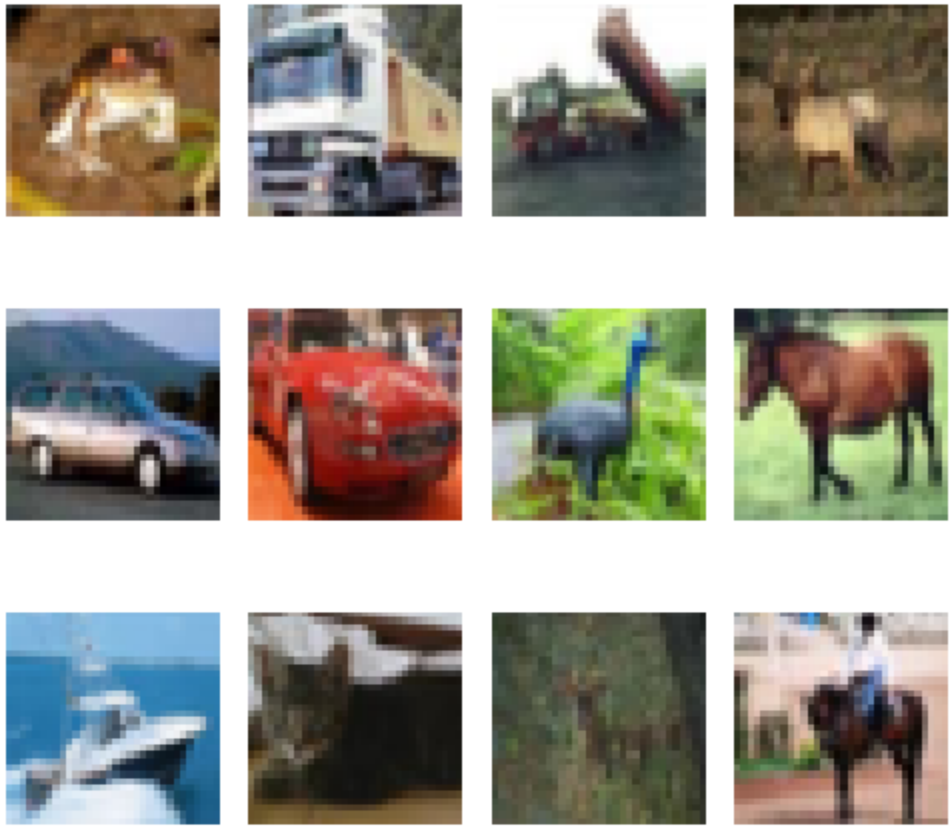
```
y_valid_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 1 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   Label   10000 non-null  uint8
dtypes: uint8(1)
memory usage: 9.9 KB
```

Visualization

In [17]:

```
plt.figure(figsize=(5, 5))
for k in range(12):
    plt.subplot(3, 4, k+1)
    plt.imshow(X_train[k], cmap="Greys")
    plt.axis("off")
plt.tight_layout()
plt.show()
```



Data Transformation

In [18]:
```
class_names = ["airplane", "automobile", "bird", "cat", "deer", "dog", "frog", "hor
n_classes = 10
```

In [19]:
```
X_train[0]
```

Out[19]:
```
array([[[ 59,  62,  63],
        [ 43,  46,  45],
        [ 50,  48,  43],
        ...,
        [158, 132, 108],
        [152, 125, 102],
        [148, 124, 103]],

       [[ 16,  20,  20],
        [  0,   0,   0],
        [ 18,   8,   0],
        ...,
        [123,  88,  55],
        [119,  83,  50],
        [122,  87,  57]],

       [[ 25,  24,  21],
        [ 16,   7,   0],
        [ 49,  27,   8],
        ...,
        [118,  84,  50],
        [120,  84,  50],
        [109,  73,  42]],

       ...,

       [[208, 170,  96],
        [201, 153,  34],
        [198, 161,  26],
        ...,
        [160, 133,  70],
        [ 56,  31,   7],
        [ 53,  34,  20]],

       [[180, 139,  96],
        [173, 123,  42],
        [186, 144,  30],
        ...,
        [184, 148,  94],
        [ 97,  62,  34],
        [ 83,  53,  34]],

       [[177, 144, 116],
        [168, 129,  94],
        [179, 142,  87],
        ...,
        [216, 184, 140],
        [151, 118,  84],
        [123,  92,  72]]], dtype=uint8)
```

In [20]:
```
print(y_train[0])
print(f"A value of {y_train[0]} refers to the class of 'frog'.")
```

```
[6]
A value of [6] refers to the class of 'frog'.
```

In [21]:
```
y_train = to_categorical(y_train)
y_valid = to_categorical(y_valid)

X_train = X_train.astype("float32")
X_valid = X_valid.astype("float32")

X_train = X_train / 255
X_valid = X_valid / 255
```

Tuning Hyperparameters

This is a basic model, with guesses and assumptions for hyperparameter values

In [22]:
```
#Instatiate the model
model = Sequential()

#Input layer
model.add(Conv2D(32, kernel_size=(3, 3), activation="relu", input_shape=(32, 32, 3)

#Convolutional and Pooling layers
model.add(Conv2D(64, kernel_size=(3, 3), activation="relu"))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))
model.add(Flatten())

#Dense hidden layer
model.add(Dense(128, activation="relu"))
model.add(Dropout(0.5))

#Output layer
model.add(Dense(n_classes, activation="softmax"))
```

In [23]:
```
#Model summary
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 30, 30, 32)        896

 conv2d_1 (Conv2D)           (None, 28, 28, 64)        18496

 max_pooling2d (MaxPooling2D  (None, 14, 14, 64)       0
 )

 dropout (Dropout)           (None, 14, 14, 64)        0

 flatten (Flatten)           (None, 12544)             0

 dense (Dense)               (None, 128)               1605760

 dropout_1 (Dropout)         (None, 128)               0

 dense_1 (Dense)             (None, 10)                1290

=================================================================
Total params: 1,626,442
Trainable params: 1,626,442
Non-trainable params: 0
_________________________________________________________________
```

In [24]:
```
model.compile(loss="categorical_crossentropy", optimizer="adam", metrics=["Accuracy
```

In [25]:
```
model.fit(X_train, y_train, batch_size=128, epochs=10, verbose=1, validation_data=(
```

```
Epoch 1/10
391/391 [==============================] - 43s 109ms/step - loss: 1.7031 - Accurac
y: 0.3773 - val_loss: 1.3507 - val_Accuracy: 0.5368
Epoch 2/10
391/391 [==============================] - 40s 101ms/step - loss: 1.3700 - Accurac
y: 0.5060 - val_loss: 1.1647 - val_Accuracy: 0.5946
Epoch 3/10
391/391 [==============================] - 39s 100ms/step - loss: 1.2284 - Accurac
y: 0.5617 - val_loss: 1.0662 - val_Accuracy: 0.6287
Epoch 4/10
391/391 [==============================] - 40s 101ms/step - loss: 1.1491 - Accurac
y: 0.5889 - val_loss: 1.0005 - val_Accuracy: 0.6523
Epoch 5/10
391/391 [==============================] - 39s 101ms/step - loss: 1.0991 - Accurac
y: 0.6098 - val_loss: 1.0159 - val_Accuracy: 0.6493
Epoch 6/10
391/391 [==============================] - 40s 101ms/step - loss: 1.0489 - Accurac
y: 0.6289 - val_loss: 0.9522 - val_Accuracy: 0.6675
Epoch 7/10
391/391 [==============================] - 39s 101ms/step - loss: 1.0002 - Accurac
y: 0.6443 - val_loss: 0.9290 - val_Accuracy: 0.6736
Epoch 8/10
391/391 [==============================] - 39s 101ms/step - loss: 0.9639 - Accurac
y: 0.6570 - val_loss: 0.9188 - val_Accuracy: 0.6804
Epoch 9/10
391/391 [==============================] - 40s 101ms/step - loss: 0.9287 - Accurac
y: 0.6697 - val_loss: 0.9027 - val_Accuracy: 0.6886
Epoch 10/10
391/391 [==============================] - 39s 100ms/step - loss: 0.8912 - Accurac
y: 0.6815 - val_loss: 0.9039 - val_Accuracy: 0.6800
```

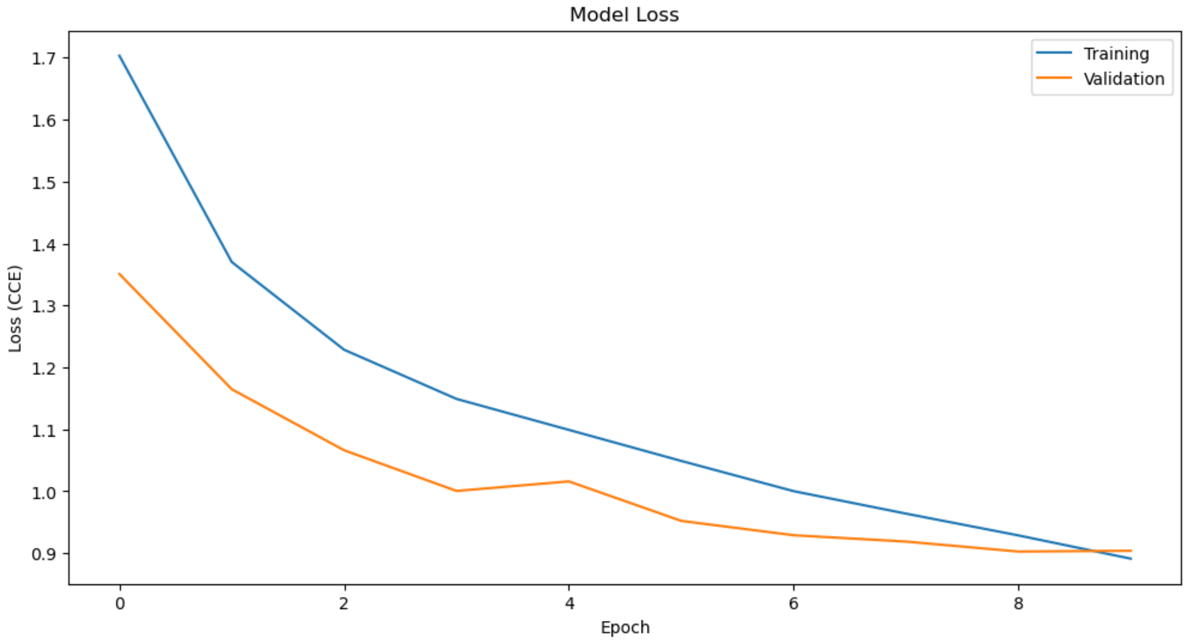
Out[25]: <keras.callbacks.History at 0x1c1ddae65b0>

In [ ]:

In [26]:

```
plt.figure(figsize=(12, 6))
plt.plot(model.history.history["loss"][:])
plt.plot(model.history.history["val_loss"][:])
plt.title("Model Loss")
plt.xlabel("Epoch")
plt.ylabel("Loss (CCE)")
plt.legend(["Training", "Validation"], loc="upper right")
```

Out[26]: <matplotlib.legend.Legend at 0x1c1e98748e0>



In [27]:
```
basic_loss, basic_accuracy = model.evaluate(X_valid, y_valid)
```

```
313/313 [==============================] - 2s 7ms/step - loss: 0.9039 - Accuracy:
0.6800
```

In [28]:
```
print(f"The basic model's loss is: {basic_loss:.2f}")
print(f"The basic model's accuracy is: {basic_accuracy:.2f}")
```

```
The basic model's loss is: 0.90
The basic model's accuracy is: 0.68
```

Applying Deep Learning Techniques

Hyperparameter tuning with Keras Tuner

In [30]:
```
#Clearing existing data for previous trials
folder_path = "hyperparameter_tuning/CISB62_Midterm"

if os.path.exists(folder_path):
    shutil.rmtree(folder_path)
    print(f"The folder '{hyperparameter_tuning}' has been deleted.")
else:
    print(f"The folder '{folder_path}' does not exist.")
```

```
The folder 'hyperparameter_tuning/CISB62_Midterm' does not exist.
```

In [31]:
```
#Function to create a model
def model_builder(hp):
    model = Sequential()

    hp_filters = hp.Int("filters", min_value=4, max_value=20, step=4)

    #Input layer
    model.add(Conv2D(filters=hp_filters, kernel_size=(3, 3), activation="relu", inp

    #Convolutional and Pooling layer
    model.add(Conv2D(64, kernel_size=(3, 3), activation="relu"))
    model.add(MaxPooling2D(pool_size=(2, 2)))
    model.add(Dropout(0.25))
    model.add(Flatten())

    #Dense hidden layer
    model.add(Dense(128, activation="relu"))
    model.add(Dropout(0.5))

    #Output layer
    model.add(Dense(n_classes, activation="softmax"))

    #Compiling the model
    model.compile(loss="categorical_crossentropy", optimizer="adam", metrics=["accu

    return model
```

In [32]:
```
#Hyperparameter tuner
tuner = kt.Hyperband(model_builder, objective="val_accuracy", max_epochs=10, factor
```

In [33]:
```
#Early stopping variable
stop_early = tf.keras.callbacks.EarlyStopping(monitor="val_loss", patience=5)
```

In [34]:
```
#Searching for optimal values: Filters
tuner.search(X_train, y_train, epochs=10, validation_split=0.2, callbacks=[stop_ear

best_hps = tuner.get_best_hyperparameters(num_trials=1)[0]

print(f"The hyperparameter search is complete. The optimal number of filters in the
```

```
Trial 5 Complete [00h 01m 19s]
val_accuracy: 0.6191999912261963

Best val_accuracy So Far: 0.6191999912261963
Total elapsed time: 00h 09m 15s
The hyperparameter search is complete. The optimal number of filters in the first d
ense layer is 12
```

In [36]:
```
#Searching for optimal values: Epochs
model = tuner.hypermodel.build(best_hps)
history = model.fit(X_train, y_train, epochs=20, validation_split=0.2)

val_acc_per_epoch = history.history["val_accuracy"]
best_epoch = val_acc_per_epoch.index(max(val_acc_per_epoch)) + 1

print("Best epoch: %d" % (best_epoch,))
```

```
Epoch 1/20
1250/1250 [==============================] - 41s 32ms/step - loss: 1.6280 - accurac
y: 0.4054 - val_loss: 1.2995 - val_accuracy: 0.5405
Epoch 2/20
1250/1250 [==============================] - 35s 28ms/step - loss: 1.3224 - accurac
y: 0.5273 - val_loss: 1.1215 - val_accuracy: 0.6093
Epoch 3/20
1250/1250 [==============================] - 35s 28ms/step - loss: 1.1988 - accurac
y: 0.5750 - val_loss: 1.0312 - val_accuracy: 0.6331
Epoch 4/20
1250/1250 [==============================] - 36s 29ms/step - loss: 1.1074 - accurac
y: 0.6052 - val_loss: 0.9821 - val_accuracy: 0.6574
Epoch 5/20
1250/1250 [==============================] - 35s 28ms/step - loss: 1.0353 - accurac
y: 0.6306 - val_loss: 0.9585 - val_accuracy: 0.6661
Epoch 6/20
1250/1250 [==============================] - 34s 27ms/step - loss: 0.9743 - accurac
y: 0.6528 - val_loss: 0.9706 - val_accuracy: 0.6594
Epoch 7/20
1250/1250 [==============================] - 35s 28ms/step - loss: 0.9247 - accurac
y: 0.6717 - val_loss: 0.9541 - val_accuracy: 0.6691
Epoch 8/20
1250/1250 [==============================] - 34s 27ms/step - loss: 0.8762 - accurac
y: 0.6876 - val_loss: 0.9854 - val_accuracy: 0.6652
Epoch 9/20
1250/1250 [==============================] - 36s 29ms/step - loss: 0.8399 - accurac
y: 0.6993 - val_loss: 0.9129 - val_accuracy: 0.6898
Epoch 10/20
1250/1250 [==============================] - 37s 30ms/step - loss: 0.8008 - accurac
y: 0.7152 - val_loss: 0.9115 - val_accuracy: 0.6841
Epoch 11/20
1250/1250 [==============================] - 36s 29ms/step - loss: 0.7668 - accurac
y: 0.7260 - val_loss: 0.9164 - val_accuracy: 0.6846
Epoch 12/20
1250/1250 [==============================] - 37s 29ms/step - loss: 0.7211 - accurac
y: 0.7386 - val_loss: 0.9229 - val_accuracy: 0.6916
Epoch 13/20
1250/1250 [==============================] - 33s 26ms/step - loss: 0.6990 - accurac
y: 0.7430 - val_loss: 0.9270 - val_accuracy: 0.6913
Epoch 14/20
1250/1250 [==============================] - 36s 29ms/step - loss: 0.6742 - accurac
y: 0.7559 - val_loss: 0.9312 - val_accuracy: 0.6881
Epoch 15/20
1250/1250 [==============================] - 35s 28ms/step - loss: 0.6436 - accurac
y: 0.7655 - val_loss: 0.9566 - val_accuracy: 0.6925
Epoch 16/20
1250/1250 [==============================] - 36s 29ms/step - loss: 0.6233 - accurac
y: 0.7721 - val_loss: 0.9905 - val_accuracy: 0.6891
Epoch 17/20
1250/1250 [==============================] - 35s 28ms/step - loss: 0.6048 - accurac
y: 0.7778 - val_loss: 0.9919 - val_accuracy: 0.6882
Epoch 18/20
1250/1250 [==============================] - 35s 28ms/step - loss: 0.5862 - accurac
y: 0.7861 - val_loss: 0.9976 - val_accuracy: 0.6919
Epoch 19/20
1250/1250 [==============================] - 34s 27ms/step - loss: 0.5635 - accurac
y: 0.7908 - val_loss: 1.0369 - val_accuracy: 0.6893
Epoch 20/20
1250/1250 [==============================] - 36s 29ms/step - loss: 0.5525 - accurac
```

```
y: 0.7942 - val_loss: 0.9979 - val_accuracy: 0.6959
Best epoch: 20
```

In [37]:
```
#Building a model using the optimal values
hypermodel = tuner.hypermodel.build(best_hps)
hypermodel.fit(X_train, y_train, epochs=best_epoch, validation_split=0.2)
```

```
Epoch 1/20
1250/1250 [==============================] - 35s 28ms/step - loss: 1.6227 - accurac
y: 0.4080 - val_loss: 1.2489 - val_accuracy: 0.5692
Epoch 2/20
1250/1250 [==============================] - 37s 29ms/step - loss: 1.3053 - accurac
y: 0.5304 - val_loss: 1.0890 - val_accuracy: 0.6127
Epoch 3/20
1250/1250 [==============================] - 34s 27ms/step - loss: 1.1712 - accurac
y: 0.5827 - val_loss: 1.0288 - val_accuracy: 0.6409
Epoch 4/20
1250/1250 [==============================] - 33s 27ms/step - loss: 1.0762 - accurac
y: 0.6145 - val_loss: 1.0061 - val_accuracy: 0.6496
Epoch 5/20
1250/1250 [==============================] - 34s 27ms/step - loss: 1.0099 - accurac
y: 0.6375 - val_loss: 0.9461 - val_accuracy: 0.6675
Epoch 6/20
1250/1250 [==============================] - 33s 27ms/step - loss: 0.9398 - accurac
y: 0.6626 - val_loss: 0.9759 - val_accuracy: 0.6558
Epoch 7/20
1250/1250 [==============================] - 34s 27ms/step - loss: 0.8903 - accurac
y: 0.6795 - val_loss: 0.9702 - val_accuracy: 0.6687
Epoch 8/20
1250/1250 [==============================] - 35s 28ms/step - loss: 0.8435 - accurac
y: 0.6954 - val_loss: 0.9262 - val_accuracy: 0.6806
Epoch 9/20
1250/1250 [==============================] - 36s 29ms/step - loss: 0.7996 - accurac
y: 0.7097 - val_loss: 0.9431 - val_accuracy: 0.6775
Epoch 10/20
1250/1250 [==============================] - 36s 29ms/step - loss: 0.7666 - accurac
y: 0.7212 - val_loss: 0.9394 - val_accuracy: 0.6854
Epoch 11/20
1250/1250 [==============================] - 35s 28ms/step - loss: 0.7210 - accurac
y: 0.7387 - val_loss: 0.9549 - val_accuracy: 0.6752
Epoch 12/20
1250/1250 [==============================] - 35s 28ms/step - loss: 0.6941 - accurac
y: 0.7470 - val_loss: 0.9419 - val_accuracy: 0.6835
Epoch 13/20
1250/1250 [==============================] - 33s 27ms/step - loss: 0.6661 - accurac
y: 0.7594 - val_loss: 0.9471 - val_accuracy: 0.6873
Epoch 14/20
1250/1250 [==============================] - 34s 27ms/step - loss: 0.6317 - accurac
y: 0.7716 - val_loss: 0.9425 - val_accuracy: 0.6912
Epoch 15/20
1250/1250 [==============================] - 36s 29ms/step - loss: 0.6102 - accurac
y: 0.7768 - val_loss: 0.9693 - val_accuracy: 0.6878
Epoch 16/20
1250/1250 [==============================] - 34s 27ms/step - loss: 0.5915 - accurac
y: 0.7824 - val_loss: 1.0213 - val_accuracy: 0.6781
Epoch 17/20
1250/1250 [==============================] - 35s 28ms/step - loss: 0.5738 - accurac
y: 0.7885 - val_loss: 1.0386 - val_accuracy: 0.6829
Epoch 18/20
1250/1250 [==============================] - 37s 29ms/step - loss: 0.5518 - accurac
y: 0.7969 - val_loss: 1.0299 - val_accuracy: 0.6852
Epoch 19/20
1250/1250 [==============================] - 37s 30ms/step - loss: 0.5414 - accurac
y: 0.8020 - val_loss: 1.0054 - val_accuracy: 0.6893
Epoch 20/20
1250/1250 [==============================] - 38s 30ms/step - loss: 0.5136 - accurac
```

```
y: 0.8098 - val_loss: 1.0283 - val_accuracy: 0.6920
```

Out[37]:

```
<keras.callbacks.History at 0x1c1f2d48790>
```

Evaluating the hypermodel on test data.

In [38]:

```
eval_result = hypermodel.evaluate(X_train, y_train)

print("[Test Loss, Test, Accuracy]:", eval_result)
```

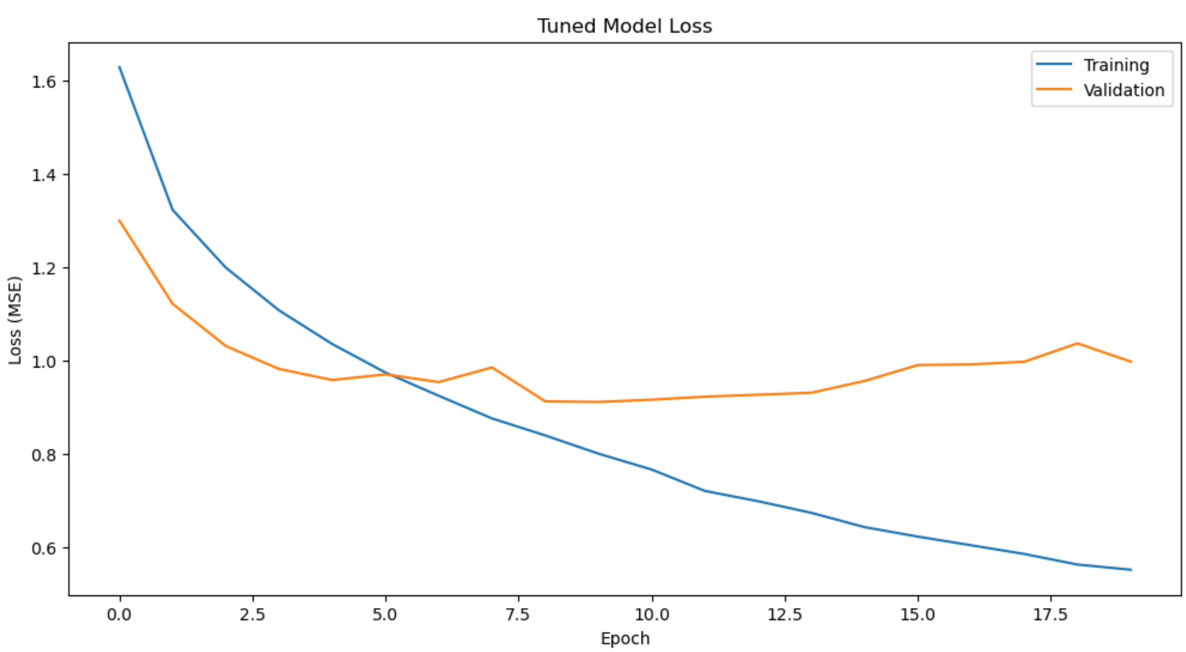
```
1563/1563 [==============================] - 11s 7ms/step - loss: 0.3614 - accurac
y: 0.9029
[Test Loss, Test, Accuracy]: [0.3613594174385071, 0.9028800129890442]
```

In [39]:

```
plt.figure(figsize=(12, 6))
plt.plot(model.history.history["loss"][:])
plt.plot(model.history.history["val_loss"][:])
plt.title("Tuned Model Loss")
plt.xlabel("Epoch")
plt.ylabel("Loss (MSE)")
plt.legend(["Training", "Validation"], loc="upper right")
```

Out[39]:

```
<matplotlib.legend.Legend at 0x1c1f38725b0>
```



In [40]:

```
y_pred = model.predict(X_valid)
mae = mean_absolute_error(y_valid, y_pred)

y_pred[0:5]
```

```
313/313 [==============================] - 2s 5ms/step
```

Out[40]:
```
array([[2.16775061e-05, 1.01118516e-04, 9.30281414e-04, 9.42361116e-01,
        3.14277495e-05, 5.36066517e-02, 2.34575011e-03, 4.32498346e-04,
        1.29223074e-04, 4.01980833e-05],
       [8.62683926e-04, 2.69109309e-01, 4.57840918e-11, 2.02925459e-12,
        8.61710811e-16, 2.32569646e-15, 8.26927614e-16, 3.44548565e-19,
        7.29989409e-01, 3.85104613e-05],
       [1.30412787e-01, 1.71356648e-02, 2.59456516e-04, 1.97324829e-04,
        7.39778261e-05, 1.86343118e-06, 1.94123731e-06, 1.48028118e-06,
        8.50921214e-01, 9.94337723e-04],
       [7.32468784e-01, 1.01485327e-01, 1.00839057e-03, 4.64276563e-05,
        3.29479553e-05, 4.44122776e-07, 5.01559271e-06, 1.09159066e-06,
        1.39624804e-01, 2.53268443e-02],
       [2.84187198e-08, 2.82258810e-07, 5.00642927e-05, 3.88244420e-01,
        1.82053372e-02, 9.96706635e-03, 5.83532453e-01, 3.68916545e-07,
        1.03449060e-09, 2.14433946e-08]], dtype=float32)
```

In [41]:
```
print(f"The Mean Absolute Error is: {mae}")
```

```
The Mean Absolute Error is: 0.07360576093196869
```

Comparing prediction values and actual values

In [42]:
```
y_pred[42]
```

Out[42]:
```
array([1.3196096e-05, 4.0640148e-06, 4.0570949e-04, 6.6787854e-02,
       6.7576630e-06, 9.2672271e-01, 1.8823856e-08, 6.0563381e-03,
       2.6731841e-09, 3.3439558e-06], dtype=float32)
```

In [43]:
```
model.predict(np.reshape(X_valid[42], [1, 14]))
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
Cell In[43], line 1
----> 1 model.predict(np.reshape(X_valid[42], [1, 14]))

File ~\anaconda3\envs\p3918\lib\site-packages\numpy\core\fromnumeric.py:285, in res
hape(a, newshape, order)
    200 @array_function_dispatch(_reshape_dispatcher)
    201 def reshape(a, newshape, order='C'):
    202     """
    203     Gives a new shape to an array without changing its data.
    204
   (...)
    283            [5, 6]])
    284     """
--> 285     return _wrapfunc(a, 'reshape', newshape, order=order)

File ~\anaconda3\envs\p3918\lib\site-packages\numpy\core\fromnumeric.py:59, in _wra
pfunc(obj, method, *args, **kwds)
     56     return _wrapit(obj, method, *args, **kwds)
     58 try:
---> 59     return bound(*args, **kwds)
     60 except TypeError:
     61     # A TypeError occurs if the object does have such a method in its
     62     # class, but its signature is not identical to that of NumPy's. This
   (...)
     66     # Call _wrapit from within the except clause to ensure a potential
     67     # exception has a traceback chain.
     68     return _wrapit(obj, method, *args, **kwds)

ValueError: cannot reshape array of size 3072 into shape (1,14)
```

Summary and Conclusion

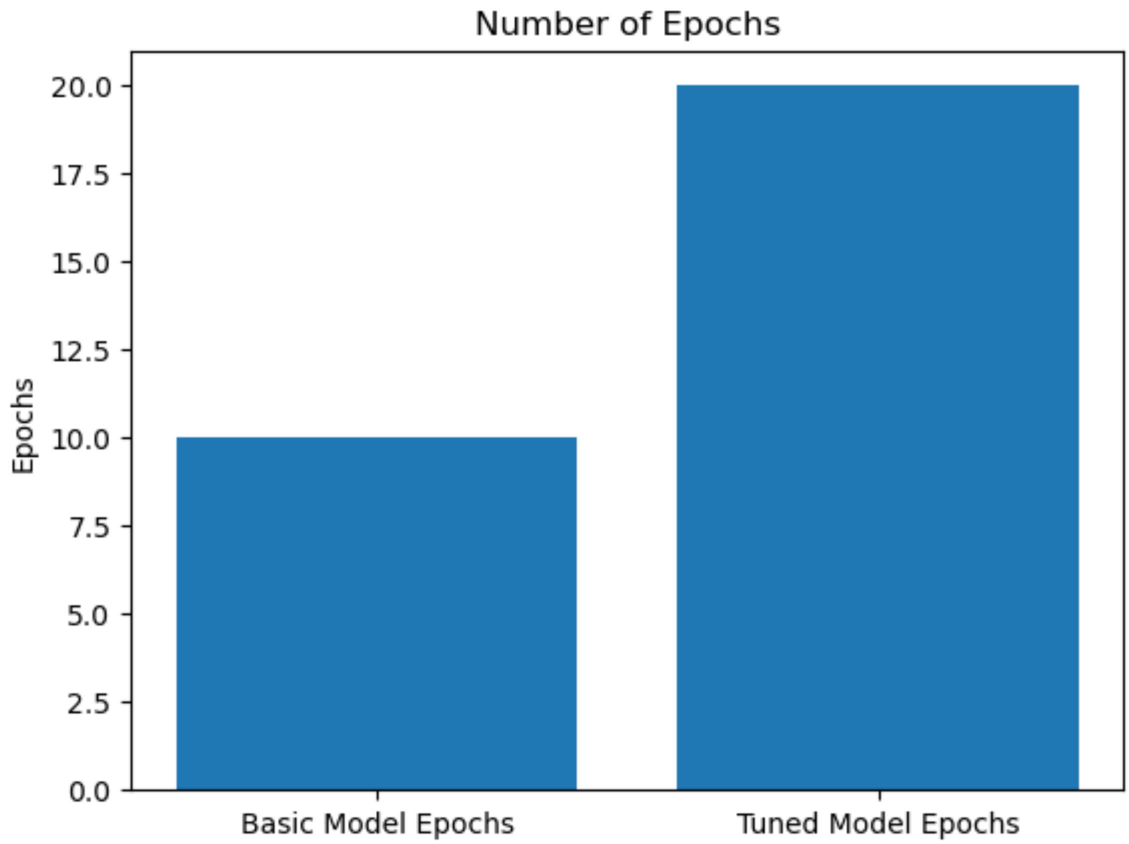
Summary

In [45]:
```
epoch_num = ["Basic Model Epochs", "Tuned Model Epochs"]
epoch_times = ["Basic Model Time", "Tuned Model Time"]
loss_value = ["Basic Model Loss", "Tuned Model Loss"]
accuracy_values = ["Basic Model Accuracy", "Tuned Model Accuracy"]

basic_epoch_num = 10

basic_epoch_times = np.array([43, 40, 39, 40, 39, 40, 39, 39, 40, 40])
basic_epoch_avg = np.mean(basic_epoch_times)

tuned_epoch_num = 20

tuned_epoch_times = np.array([35, 37, 34, 33, 34, 33, 34, 35, 36, 36, 35, 35, 33, 3
tuned_epoch_avg = np.mean(tuned_epoch_times)

print(f"Basic Loss: {basic_loss:2f}")
print(f"Basic Accuracy: {basic_accuracy:2f}")

print("Tuned Loss", eval_result[0])
print("Tuned Accuracy", eval_result[1])

epochs = [basic_epoch_num, tuned_epoch_num]
times = [basic_epoch_avg, tuned_epoch_avg]
losses = [basic_loss, eval_result[0]]
accuracies = [basic_accuracy, eval_result[1]]
```

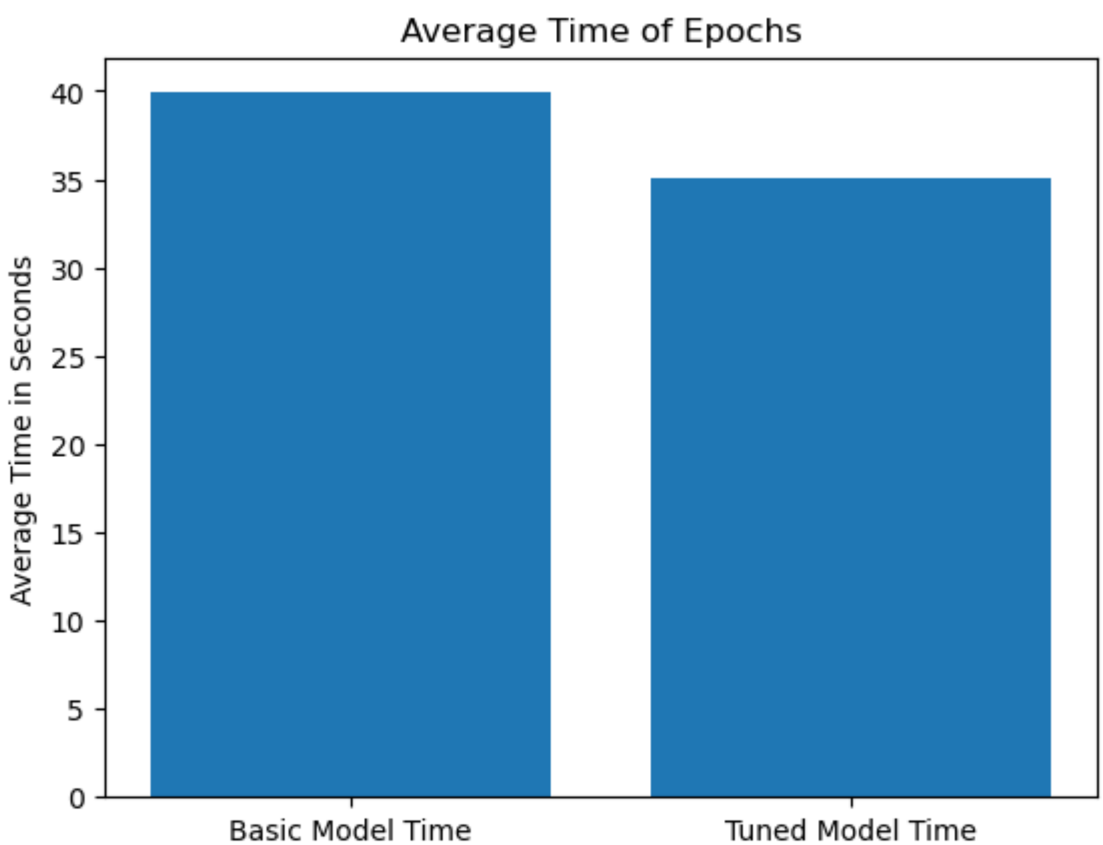
```
Basic Loss: 0.903936
Basic Accuracy: 0.680000
Tuned Loss 0.3613594174385071
Tuned Accuracy 0.9028800129890442
```

In [46]:
```
def plot_values(data_labels, data_points, ylabel, title):
    fig, ax = plt.subplots()
    ax.bar(data_labels, data_points)
    ax.set_ylabel(ylabel)
    ax.set_title(title)
    plt.show()
```

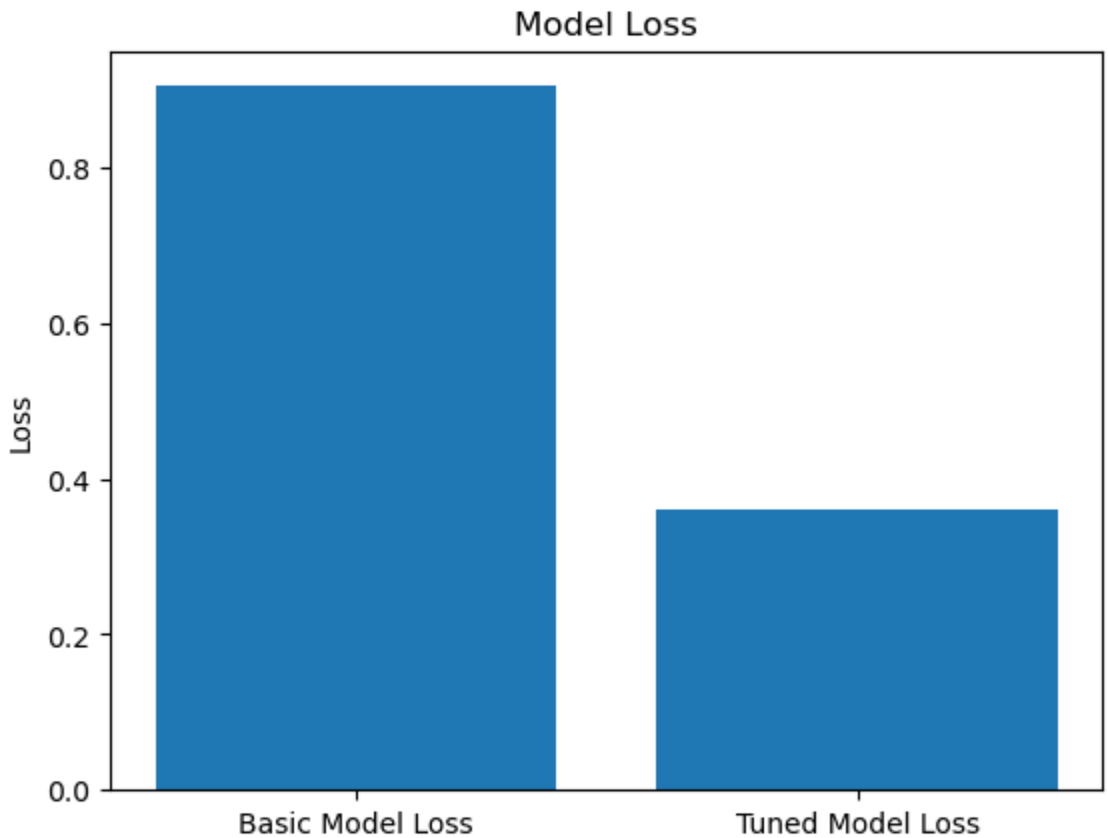
In [47]:
```
#Number of epochs
plot_values(epoch_num, epochs, ylabel="Epochs", title="Number of Epochs")
```



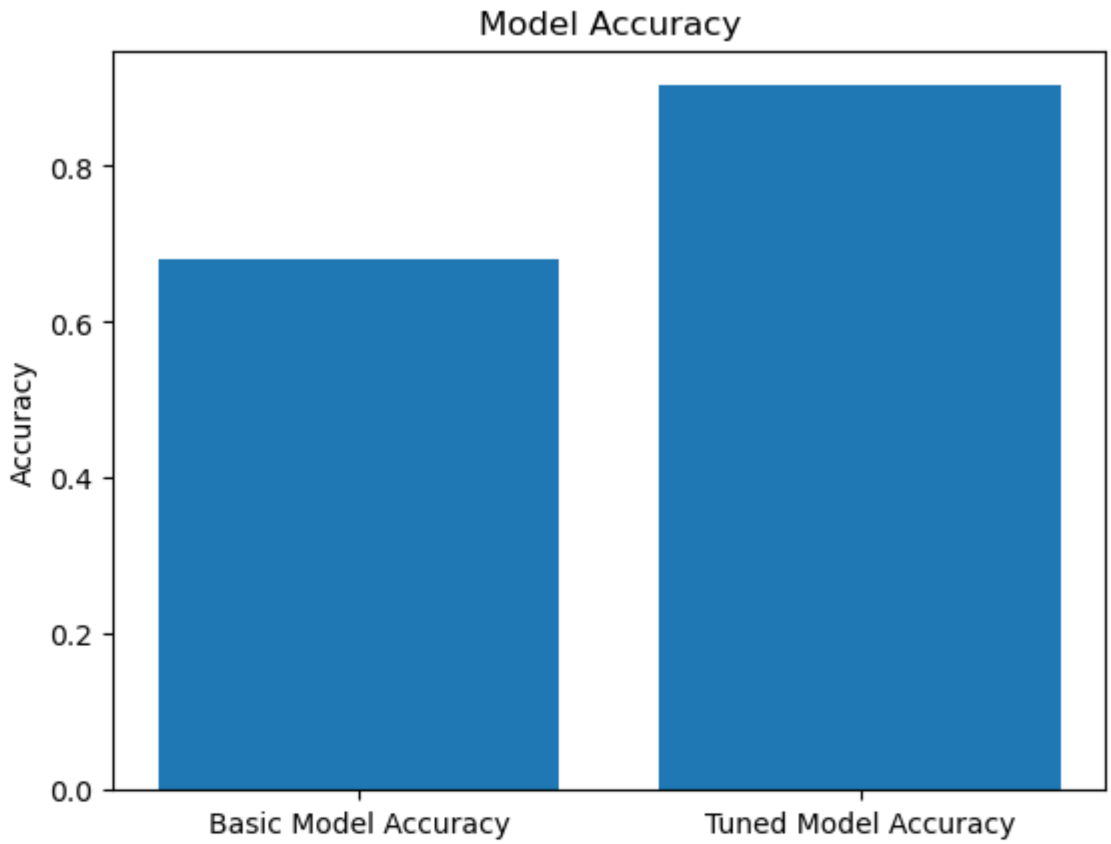
In [48]:
```
#Average time of epochs
plot_values(epoch_times, times, ylabel="Average Time in Seconds", title="Average Ti
```



In [49]:
```
#Loss
plot_values(loss_value, losses, ylabel="Loss", title="Model Loss")
```



In [50]:
```
#Accuracy
plot_values(accuracy_values, accuracies, ylabel="Accuracy", title="Model Accuracy")
```

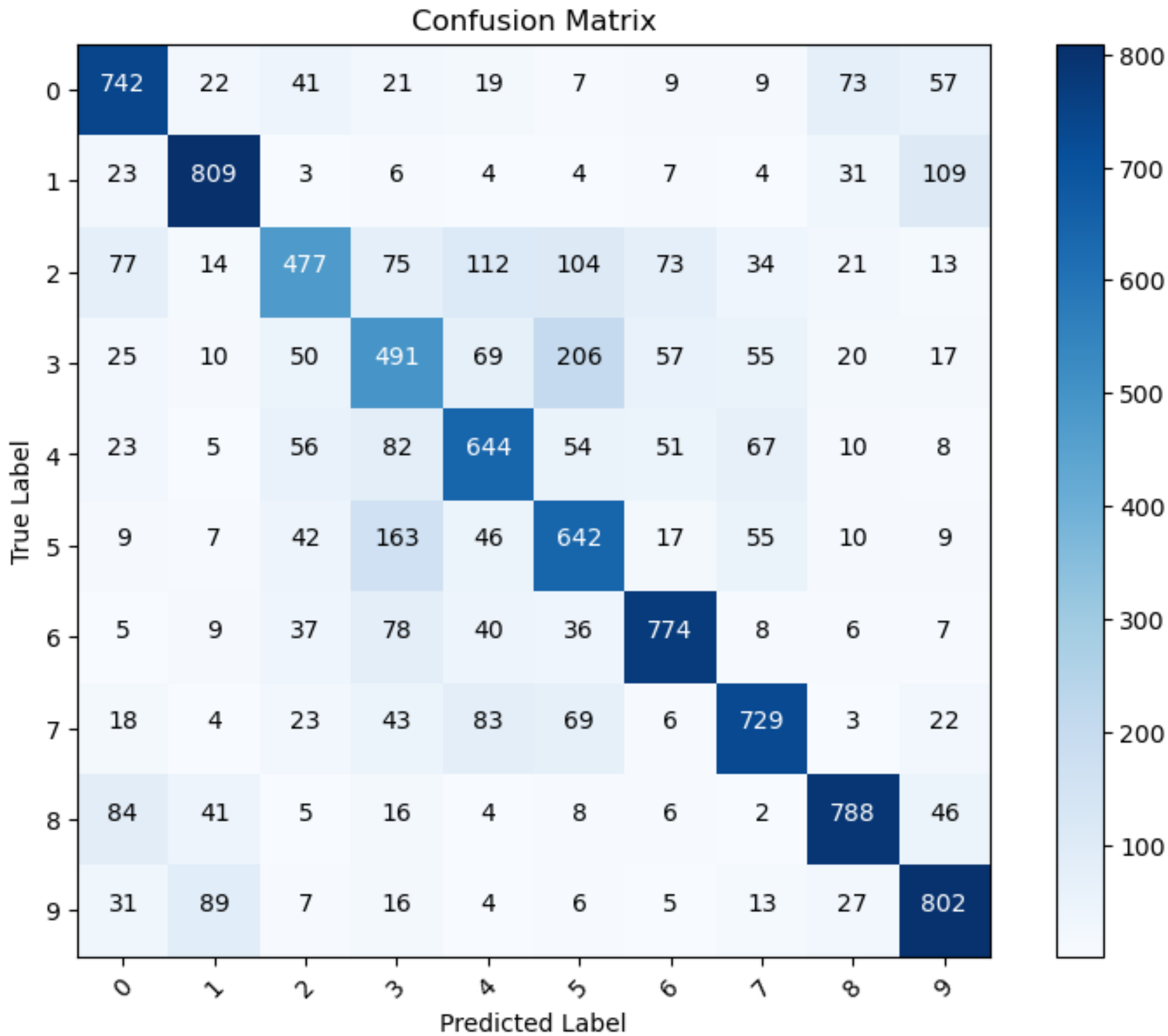


Confusion Matrix

In [51]:
```
#Confusion Matrix
def plot_confusion_matrix(y_true, y_pred, classes, normalize=False, title="Confusio
    cm = confusion_matrix(y_true, y_pred)

    if normalize:
        cm = cm.astype("float") / cm.sum(axis=1)[:, np.newaxis]
        print("Normalized Confusion Matrix")
    else:
        print("Confusion Matrix, without Normalization")

    plt.figure(figsize=(8, 6))
    plt.imshow(cm, interpolation="nearest", cmap=cmap)
    plt.title(title)
    plt.colorbar()

    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    fmt = ".2f" if normalize else "d"
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt), horizontalalignment="center", color="

    plt.tight_layout()
    plt.xlabel("Predicted Label")
    plt.ylabel("True Label")
    plt.show()
```

In [52]:
```
Y_pred = model.predict(X_valid)
Y_pred_classes = np.argmax(Y_pred, axis=1)
Y_true = np.argmax(y_valid, axis=1)

plot_confusion_matrix(Y_true, Y_pred_classes, classes=range(n_classes), normalize=F
```

```
313/313 [==============================] - 2s 6ms/step
Confusion Matrix, without Normalization
```



Conclusions

While the Tuned Model had twice the number of epochs in this run of the program, it took a shorter time per epoch on average. This is due to the better tuning on the number of filters in the Input Layer. In addition, both the Loss and Accuracy of the tuned model were better (lower and higher, respectively), with the Tuned Model's Accuracy reaching 90%.

In the Confusion Matrix, we can see that the model had some issues distinguishing cats and dogs (labels 3 and 5), but generally was clear on each prediction.

If I were to continue to work on this specific project, I would try adding more convolutional layers, to try to increase the accuracy, with a goal being 97% Accuracy. I would also like to possibly attempt to use the cifar100 dataset, but I might need a dedicated computer with a discrete gpu for that.

While preparing this midterm, I tried both Adam and SGD optimizers. Interestingly, the Adam optimizer provided better results on loss and accuracy. I found conflicting reports online, but the general concensus was that Adam is a worse performer for CNN tasks.

I ran into an issue with the model predictions at the end, and could not easily find a way to fix it. Any guidance would be appreciated.

I would like to thank my partner for the use of their computer for this assignment. It would have taken me much longer to actually run the code outside of testing if I had used my own.

In [ ]:

```

```