

# Predicting the Rings (Age) of abalone

## Final Project for MATH 156

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```
In [ ]: import pandas as pd
import matplotlib.pyplot as plt
```

### Exploratory Data Analysis

```
In [ ]: df = pd.read_csv("abalone.csv")
df.head()
```

```
Out[ ]:
```

	Sex	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings
0	M	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150	15
1	M	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070	7
2	F	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210	9
3	M	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155	10
4	I	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.055	7

```
In [ ]: print("Rows: " + str(df.shape[0]))
print("Cols: " + str(df.shape[1]))
```

Rows: 4177  
Cols: 9

```
In [ ]: print("unique ring values:", len(df.value_counts("Rings").index))
print("Highest number of rings:", max(df["Rings"]))
```

unique ring values: 28  
Highest number of rings: 29

28 different abalone Ring values are represented in the dataset. The largest one is 29.

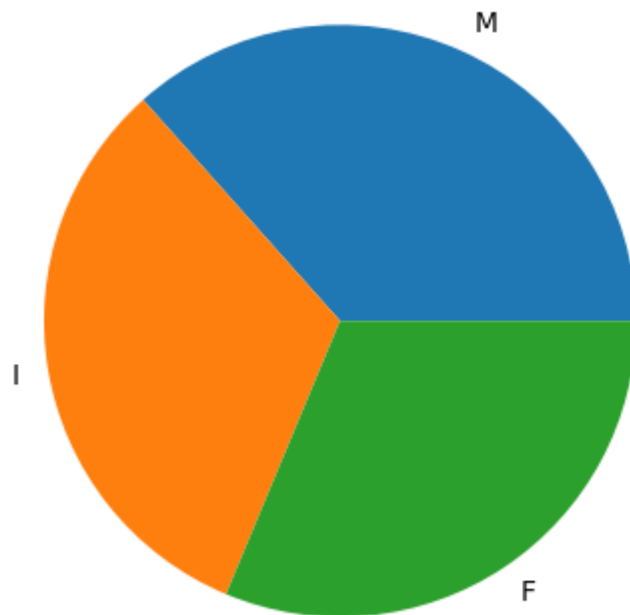
```
In [ ]: round(df.describe(), 2)
```

Out[ ]:

	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings
<b>count</b>	4177.00	4177.00	4177.00	4177.00	4177.00	4177.00	4177.00	4177.00
<b>mean</b>	0.52	0.41	0.14	0.83	0.36	0.18	0.24	9.93
<b>std</b>	0.12	0.10	0.04	0.49	0.22	0.11	0.14	3.22
<b>min</b>	0.08	0.06	0.00	0.00	0.00	0.00	0.00	1.00
<b>25%</b>	0.45	0.35	0.12	0.44	0.19	0.09	0.13	8.00
<b>50%</b>	0.55	0.42	0.14	0.80	0.34	0.17	0.23	9.00
<b>75%</b>	0.62	0.48	0.16	1.15	0.50	0.25	0.33	11.00
<b>max</b>	0.82	0.65	1.13	2.83	1.49	0.76	1.00	29.00

```
In [ ]: gender_nums = df["Sex"].value_counts()
labels = gender_nums.index
values = gender_nums.values
plt.pie(values, labels = labels)
plt.show()

round(df.groupby("Sex").mean(), 2)
```

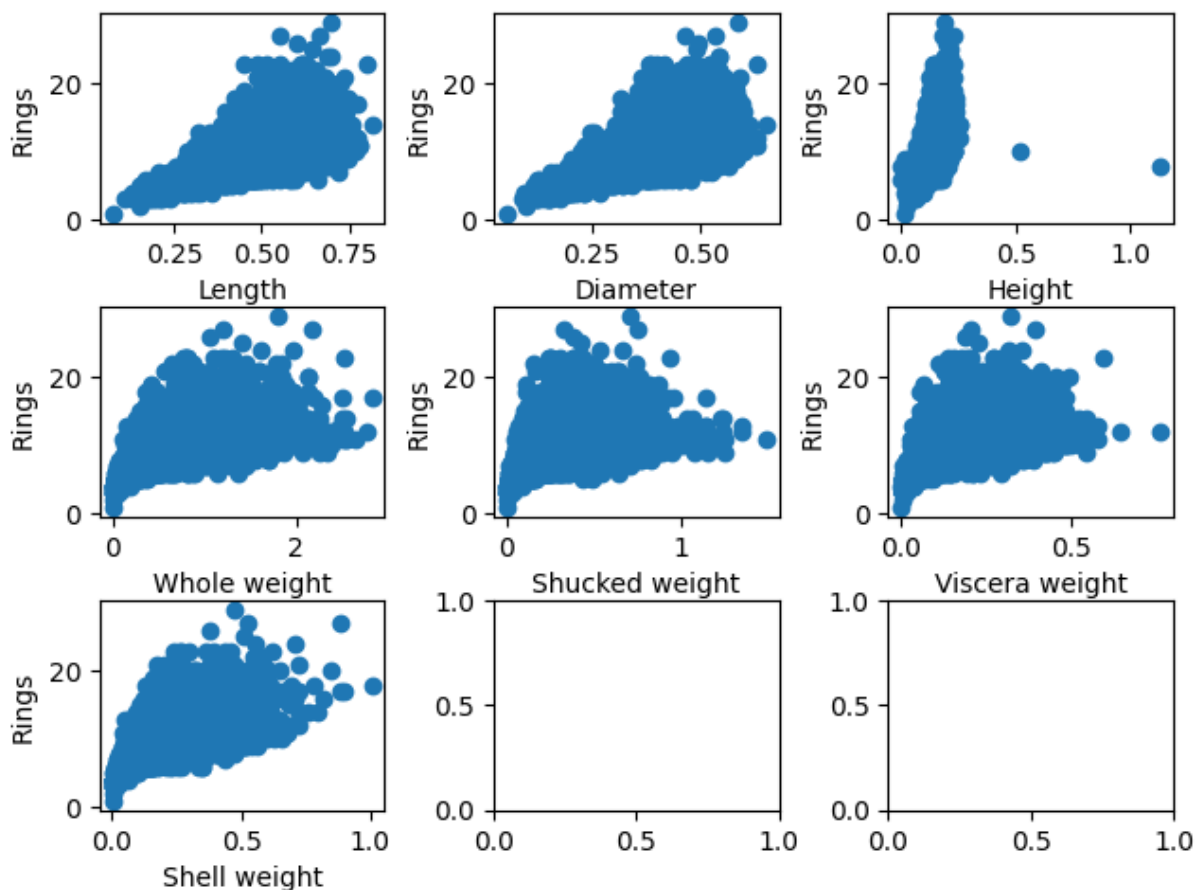


Out[ ]:

	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings
Sex								
F	0.58	0.45	0.16	1.05	0.45	0.23	0.30	11.13
I	0.43	0.33	0.11	0.43	0.19	0.09	0.13	7.89
M	0.56	0.44	0.15	0.99	0.43	0.22	0.28	10.71

Data is evenly distributed between M = Male, F = Female, I = Infant. Generally, it seems that all measurements are on average lowest for Infant, in the middle for Male, and highest for Female.

```
In [ ]: fig, ax = plt.subplots(3, 3)
fig.tight_layout()
explanatory_vars = df.drop(["Sex", "Rings"], axis = 1)
for i, col in enumerate(explanatory_vars.columns):
    ax[i // 3, i % 3].scatter(explanatory_vars[col], df["Rings"])
    ax[i // 3, i % 3].set_xlabel(col)
    ax[i // 3, i % 3].set_ylabel("Rings")
    #plt.scatter(df[col], df["Age"])
    #plt.show()
plt.show()
```



```
In [ ]: #df.boxplot("Rings", "Sex")
```

There is generally a positive correlation between the variables and the Ring number. The correlation seems to be the strongest for Height vs Rings.

## Data Preprocessing

Sex must be one hot encoded.

```
In [ ]: cat_list = pd.get_dummies(df["Sex"], prefix = "Sex", dtype = float)
df = df.join(cat_list)
df = df.drop("Sex", axis = 1)
df.head()
```

```
Out[ ]:
```

	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings	Sex_F	Sex_I	Sex
0	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150	15	0.0	0.0	
1	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070	7	0.0	0.0	
2	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210	9	1.0	0.0	
3	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155	10	0.0	0.0	
4	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.055	7	0.0	1.0	

We are predicting the Rings value, and in order to use the multi-class classification functionality of a neural network as learned in class, we must treat the Rings value as a categorical variable. However, our model may face accuracy issues because if predictions are 6 and 1000 when the true number of Rings is 7, both inaccurate predictions are penalized equally because 6 and 1000 are different categories than 7. However, we want to take into account that 6 is close to 7, and this prediction would have value. Therefore, we will turn the output into classes of groups of 4, so label 0 represents 0-3 Rings, 1 represents 4-7 Rings, 2 represents 8 to 11 rings, and so on. This way, our accuracy is improved while still generating useful predictions.

```
In [ ]: #transform y as described above.
df["group"] = df["Rings"] // 4
df.head()
```

Out[ ]:

	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings	Sex_F	Sex_I	Sex
0	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150	15	0.0	0.0	
1	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070	7	0.0	0.0	
2	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210	9	1.0	0.0	
3	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155	10	0.0	0.0	
4	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.055	7	0.0	1.0	

A min max scaler is applied to each column to standardize measurements.

```
In [ ]: df = df.drop("Rings", axis = 1)
x = df.iloc[:, df.columns != "group"].values
y = df.iloc[:, df.columns == "group"].values

from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
x = sc.fit_transform(x)
```

```
In [ ]: from tensorflow.keras.utils import to_categorical
import numpy as np
groups_present = np.unique(y)
num_groups = len(groups_present)
y = to_categorical(y, num_classes = num_groups)
```

## Training the model

```
In [ ]: from keras.models import Sequential
from keras.layers import Dense

from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2)

model = Sequential()
model.add(Dense(15, input_dim=10, activation="relu"))
model.add(Dense(12, activation="relu"))
model.add(Dense(num_groups, activation="softmax"))
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
history = model.fit(x_train, y_train, validation_data = (x_test, y_test), epochs=50)
```

Epoch 1/50  
53/53 [=====] - 7s 34ms/step - loss: 1.7624 - accuracy: 0.5391 - val\_loss: 1.5190 - val\_accuracy: 0.5825  
Epoch 2/50  
53/53 [=====] - 0s 9ms/step - loss: 1.3836 - accuracy: 0.5660 - val\_loss: 1.2092 - val\_accuracy: 0.5825  
Epoch 3/50  
53/53 [=====] - 1s 13ms/step - loss: 1.1524 - accuracy: 0.6438 - val\_loss: 1.0425 - val\_accuracy: 0.6663  
Epoch 4/50  
53/53 [=====] - 1s 14ms/step - loss: 1.0346 - accuracy: 0.6630 - val\_loss: 0.9547 - val\_accuracy: 0.6758  
Epoch 5/50  
53/53 [=====] - 1s 14ms/step - loss: 0.9734 - accuracy: 0.6648 - val\_loss: 0.9096 - val\_accuracy: 0.6770  
Epoch 6/50  
53/53 [=====] - 1s 9ms/step - loss: 0.9392 - accuracy: 0.6657 - val\_loss: 0.8785 - val\_accuracy: 0.6770  
Epoch 7/50  
53/53 [=====] - 1s 12ms/step - loss: 0.9151 - accuracy: 0.6699 - val\_loss: 0.8582 - val\_accuracy: 0.6818  
Epoch 8/50  
53/53 [=====] - 1s 18ms/step - loss: 0.8952 - accuracy: 0.6702 - val\_loss: 0.8431 - val\_accuracy: 0.6830  
Epoch 9/50  
53/53 [=====] - 0s 8ms/step - loss: 0.8800 - accuracy: 0.6735 - val\_loss: 0.8306 - val\_accuracy: 0.6794  
Epoch 10/50  
53/53 [=====] - 1s 22ms/step - loss: 0.8680 - accuracy: 0.6752 - val\_loss: 0.8220 - val\_accuracy: 0.6794  
Epoch 11/50  
53/53 [=====] - 0s 9ms/step - loss: 0.8582 - accuracy: 0.6797 - val\_loss: 0.8136 - val\_accuracy: 0.6782  
Epoch 12/50  
53/53 [=====] - 0s 7ms/step - loss: 0.8492 - accuracy: 0.6806 - val\_loss: 0.8062 - val\_accuracy: 0.6794  
Epoch 13/50  
53/53 [=====] - 0s 9ms/step - loss: 0.8400 - accuracy: 0.6827 - val\_loss: 0.8008 - val\_accuracy: 0.6866  
Epoch 14/50  
53/53 [=====] - 0s 6ms/step - loss: 0.8312 - accuracy: 0.6845 - val\_loss: 0.7945 - val\_accuracy: 0.6794  
Epoch 15/50  
53/53 [=====] - 0s 8ms/step - loss: 0.8242 - accuracy: 0.6860 - val\_loss: 0.7905 - val\_accuracy: 0.6818  
Epoch 16/50  
53/53 [=====] - 0s 7ms/step - loss: 0.8180 - accuracy: 0.6866 - val\_loss: 0.7827 - val\_accuracy: 0.6878  
Epoch 17/50  
53/53 [=====] - 0s 9ms/step - loss: 0.8123 - accuracy: 0.6863 - val\_loss: 0.7778 - val\_accuracy: 0.6854  
Epoch 18/50  
53/53 [=====] - 0s 8ms/step - loss: 0.8067 - accuracy: 0.6839 - val\_loss: 0.7733 - val\_accuracy: 0.6866  
Epoch 19/50  
53/53 [=====] - 0s 8ms/step - loss: 0.8025 - accuracy: 0.68

48 - val\_loss: 0.7734 - val\_accuracy: 0.6938  
Epoch 20/50  
53/53 [=====] - 0s 9ms/step - loss: 0.7970 - accuracy: 0.68  
39 - val\_loss: 0.7725 - val\_accuracy: 0.6926  
Epoch 21/50  
53/53 [=====] - 0s 8ms/step - loss: 0.7944 - accuracy: 0.68  
93 - val\_loss: 0.7663 - val\_accuracy: 0.6962  
Epoch 22/50  
53/53 [=====] - 1s 11ms/step - loss: 0.7903 - accuracy: 0.6  
896 - val\_loss: 0.7672 - val\_accuracy: 0.6914  
Epoch 23/50  
53/53 [=====] - 1s 13ms/step - loss: 0.7854 - accuracy: 0.6  
926 - val\_loss: 0.7636 - val\_accuracy: 0.6914  
Epoch 24/50  
53/53 [=====] - 1s 12ms/step - loss: 0.7845 - accuracy: 0.6  
911 - val\_loss: 0.7605 - val\_accuracy: 0.6974  
Epoch 25/50  
53/53 [=====] - 1s 20ms/step - loss: 0.7794 - accuracy: 0.6  
929 - val\_loss: 0.7582 - val\_accuracy: 0.6950  
Epoch 26/50  
53/53 [=====] - 1s 12ms/step - loss: 0.7780 - accuracy: 0.6  
899 - val\_loss: 0.7586 - val\_accuracy: 0.7045  
Epoch 27/50  
53/53 [=====] - 1s 12ms/step - loss: 0.7742 - accuracy: 0.6  
932 - val\_loss: 0.7577 - val\_accuracy: 0.7033  
Epoch 28/50  
53/53 [=====] - 1s 14ms/step - loss: 0.7730 - accuracy: 0.6  
956 - val\_loss: 0.7595 - val\_accuracy: 0.7057  
Epoch 29/50  
53/53 [=====] - 0s 7ms/step - loss: 0.7710 - accuracy: 0.69  
44 - val\_loss: 0.7535 - val\_accuracy: 0.6890  
Epoch 30/50  
53/53 [=====] - 1s 13ms/step - loss: 0.7671 - accuracy: 0.6  
995 - val\_loss: 0.7521 - val\_accuracy: 0.6962  
Epoch 31/50  
53/53 [=====] - 0s 8ms/step - loss: 0.7674 - accuracy: 0.68  
72 - val\_loss: 0.7516 - val\_accuracy: 0.6914  
Epoch 32/50  
53/53 [=====] - 0s 9ms/step - loss: 0.7643 - accuracy: 0.69  
62 - val\_loss: 0.7515 - val\_accuracy: 0.6938  
Epoch 33/50  
53/53 [=====] - 1s 14ms/step - loss: 0.7637 - accuracy: 0.6  
956 - val\_loss: 0.7532 - val\_accuracy: 0.6998  
Epoch 34/50  
53/53 [=====] - 0s 9ms/step - loss: 0.7618 - accuracy: 0.69  
32 - val\_loss: 0.7537 - val\_accuracy: 0.6986  
Epoch 35/50  
53/53 [=====] - 1s 28ms/step - loss: 0.7584 - accuracy: 0.6  
956 - val\_loss: 0.7502 - val\_accuracy: 0.6986  
Epoch 36/50  
53/53 [=====] - 1s 19ms/step - loss: 0.7592 - accuracy: 0.6  
974 - val\_loss: 0.7478 - val\_accuracy: 0.6950  
Epoch 37/50  
53/53 [=====] - 1s 13ms/step - loss: 0.7568 - accuracy: 0.6  
968 - val\_loss: 0.7490 - val\_accuracy: 0.6998  
Epoch 38/50

```

53/53 [=====] - 1s 22ms/step - loss: 0.7556 - accuracy: 0.6
977 - val_loss: 0.7487 - val_accuracy: 0.6986
Epoch 39/50
53/53 [=====] - 1s 12ms/step - loss: 0.7537 - accuracy: 0.7
001 - val_loss: 0.7510 - val_accuracy: 0.6926
Epoch 40/50
53/53 [=====] - 1s 11ms/step - loss: 0.7542 - accuracy: 0.6
965 - val_loss: 0.7498 - val_accuracy: 0.6986
Epoch 41/50
53/53 [=====] - 1s 16ms/step - loss: 0.7502 - accuracy: 0.6
977 - val_loss: 0.7510 - val_accuracy: 0.6998
Epoch 42/50
53/53 [=====] - 1s 12ms/step - loss: 0.7504 - accuracy: 0.6
992 - val_loss: 0.7481 - val_accuracy: 0.7010
Epoch 43/50
53/53 [=====] - 1s 10ms/step - loss: 0.7497 - accuracy: 0.6
959 - val_loss: 0.7517 - val_accuracy: 0.6938
Epoch 44/50
53/53 [=====] - 2s 37ms/step - loss: 0.7485 - accuracy: 0.6
983 - val_loss: 0.7465 - val_accuracy: 0.6950
Epoch 45/50
53/53 [=====] - 3s 66ms/step - loss: 0.7480 - accuracy: 0.6
950 - val_loss: 0.7462 - val_accuracy: 0.6962
Epoch 46/50
53/53 [=====] - 2s 32ms/step - loss: 0.7461 - accuracy: 0.6
971 - val_loss: 0.7469 - val_accuracy: 0.6962
Epoch 47/50
53/53 [=====] - 1s 21ms/step - loss: 0.7451 - accuracy: 0.6
977 - val_loss: 0.7494 - val_accuracy: 0.6962
Epoch 48/50
53/53 [=====] - 1s 15ms/step - loss: 0.7452 - accuracy: 0.6
998 - val_loss: 0.7467 - val_accuracy: 0.6974
Epoch 49/50
53/53 [=====] - 1s 19ms/step - loss: 0.7445 - accuracy: 0.7
019 - val_loss: 0.7503 - val_accuracy: 0.7045
Epoch 50/50
53/53 [=====] - 1s 21ms/step - loss: 0.7442 - accuracy: 0.7
001 - val_loss: 0.7460 - val_accuracy: 0.6950

```

In this first model, the accuracy peaks around 70% after 50 epochs. A different combination of layers might work better

```

In [ ]: model2 = Sequential()
model2.add(Dense(15, input_dim=10, activation="relu"))
model2.add(Dense(13, activation="relu"))
model2.add(Dense(11, activation="relu"))
model2.add(Dense(9, activation="relu"))
model2.add(Dense(num_groups, activation="softmax"))
model2.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
history2 = model2.fit(x_train, y_train, validation_data = (x_test, y_test), epochs=

```



Epoch 1/100  
14/14 [=====] - 9s 129ms/step - loss: 2.0082 - accuracy: 0.3349 - val\_loss: 1.9406 - val\_accuracy: 0.4737  
Epoch 2/100  
14/14 [=====] - 0s 17ms/step - loss: 1.8843 - accuracy: 0.5459 - val\_loss: 1.8066 - val\_accuracy: 0.5825  
Epoch 3/100  
14/14 [=====] - 0s 17ms/step - loss: 1.7397 - accuracy: 0.5660 - val\_loss: 1.6572 - val\_accuracy: 0.5825  
Epoch 4/100  
14/14 [=====] - 0s 19ms/step - loss: 1.5872 - accuracy: 0.5660 - val\_loss: 1.5121 - val\_accuracy: 0.5825  
Epoch 5/100  
14/14 [=====] - 1s 52ms/step - loss: 1.4461 - accuracy: 0.5660 - val\_loss: 1.3621 - val\_accuracy: 0.5825  
Epoch 6/100  
14/14 [=====] - 1s 67ms/step - loss: 1.2982 - accuracy: 0.5705 - val\_loss: 1.2031 - val\_accuracy: 0.6663  
Epoch 7/100  
14/14 [=====] - 0s 27ms/step - loss: 1.1472 - accuracy: 0.6609 - val\_loss: 1.0645 - val\_accuracy: 0.6555  
Epoch 8/100  
14/14 [=====] - 0s 20ms/step - loss: 1.0490 - accuracy: 0.6450 - val\_loss: 0.9952 - val\_accuracy: 0.6567  
Epoch 9/100  
14/14 [=====] - 1s 38ms/step - loss: 0.9978 - accuracy: 0.6606 - val\_loss: 0.9520 - val\_accuracy: 0.6770  
Epoch 10/100  
14/14 [=====] - 1s 60ms/step - loss: 0.9633 - accuracy: 0.6645 - val\_loss: 0.9176 - val\_accuracy: 0.6794  
Epoch 11/100  
14/14 [=====] - 1s 53ms/step - loss: 0.9373 - accuracy: 0.6696 - val\_loss: 0.8916 - val\_accuracy: 0.6806  
Epoch 12/100  
14/14 [=====] - 0s 31ms/step - loss: 0.9170 - accuracy: 0.6699 - val\_loss: 0.8744 - val\_accuracy: 0.6746  
Epoch 13/100  
14/14 [=====] - 1s 61ms/step - loss: 0.9020 - accuracy: 0.6684 - val\_loss: 0.8614 - val\_accuracy: 0.6818  
Epoch 14/100  
14/14 [=====] - 1s 75ms/step - loss: 0.8891 - accuracy: 0.6705 - val\_loss: 0.8527 - val\_accuracy: 0.6818  
Epoch 15/100  
14/14 [=====] - 0s 24ms/step - loss: 0.8810 - accuracy: 0.6696 - val\_loss: 0.8450 - val\_accuracy: 0.6806  
Epoch 16/100  
14/14 [=====] - 0s 15ms/step - loss: 0.8717 - accuracy: 0.6761 - val\_loss: 0.8375 - val\_accuracy: 0.6818  
Epoch 17/100  
14/14 [=====] - 1s 49ms/step - loss: 0.8635 - accuracy: 0.6764 - val\_loss: 0.8314 - val\_accuracy: 0.6818  
Epoch 18/100  
14/14 [=====] - 0s 37ms/step - loss: 0.8577 - accuracy: 0.6851 - val\_loss: 0.8240 - val\_accuracy: 0.6890  
Epoch 19/100  
14/14 [=====] - 0s 18ms/step - loss: 0.8495 - accuracy: 0.6

815 - val\_loss: 0.8190 - val\_accuracy: 0.6842  
Epoch 20/100  
14/14 [=====] - 0s 19ms/step - loss: 0.8437 - accuracy: 0.6  
827 - val\_loss: 0.8144 - val\_accuracy: 0.6866  
Epoch 21/100  
14/14 [=====] - 0s 15ms/step - loss: 0.8442 - accuracy: 0.6  
752 - val\_loss: 0.8118 - val\_accuracy: 0.6854  
Epoch 22/100  
14/14 [=====] - 1s 38ms/step - loss: 0.8361 - accuracy: 0.6  
824 - val\_loss: 0.8064 - val\_accuracy: 0.6914  
Epoch 23/100  
14/14 [=====] - 1s 78ms/step - loss: 0.8279 - accuracy: 0.6  
893 - val\_loss: 0.8036 - val\_accuracy: 0.6926  
Epoch 24/100  
14/14 [=====] - 1s 57ms/step - loss: 0.8235 - accuracy: 0.6  
887 - val\_loss: 0.8003 - val\_accuracy: 0.6902  
Epoch 25/100  
14/14 [=====] - 0s 31ms/step - loss: 0.8219 - accuracy: 0.6  
845 - val\_loss: 0.7961 - val\_accuracy: 0.6926  
Epoch 26/100  
14/14 [=====] - 0s 34ms/step - loss: 0.8172 - accuracy: 0.6  
872 - val\_loss: 0.7931 - val\_accuracy: 0.6902  
Epoch 27/100  
14/14 [=====] - 1s 65ms/step - loss: 0.8145 - accuracy: 0.6  
875 - val\_loss: 0.7921 - val\_accuracy: 0.6902  
Epoch 28/100  
14/14 [=====] - 0s 19ms/step - loss: 0.8111 - accuracy: 0.6  
842 - val\_loss: 0.7901 - val\_accuracy: 0.6938  
Epoch 29/100  
14/14 [=====] - 0s 21ms/step - loss: 0.8076 - accuracy: 0.6  
902 - val\_loss: 0.7884 - val\_accuracy: 0.6962  
Epoch 30/100  
14/14 [=====] - 1s 51ms/step - loss: 0.8056 - accuracy: 0.6  
869 - val\_loss: 0.7866 - val\_accuracy: 0.6902  
Epoch 31/100  
14/14 [=====] - 1s 42ms/step - loss: 0.8019 - accuracy: 0.6  
878 - val\_loss: 0.7832 - val\_accuracy: 0.6926  
Epoch 32/100  
14/14 [=====] - 1s 53ms/step - loss: 0.7996 - accuracy: 0.6  
884 - val\_loss: 0.7813 - val\_accuracy: 0.6986  
Epoch 33/100  
14/14 [=====] - 0s 21ms/step - loss: 0.7962 - accuracy: 0.6  
896 - val\_loss: 0.7808 - val\_accuracy: 0.6986  
Epoch 34/100  
14/14 [=====] - 1s 42ms/step - loss: 0.7944 - accuracy: 0.6  
902 - val\_loss: 0.7786 - val\_accuracy: 0.6962  
Epoch 35/100  
14/14 [=====] - 1s 101ms/step - loss: 0.7939 - accuracy: 0.  
6896 - val\_loss: 0.7795 - val\_accuracy: 0.6914  
Epoch 36/100  
14/14 [=====] - 0s 36ms/step - loss: 0.7933 - accuracy: 0.6  
884 - val\_loss: 0.7774 - val\_accuracy: 0.6950  
Epoch 37/100  
14/14 [=====] - 1s 44ms/step - loss: 0.7897 - accuracy: 0.6  
911 - val\_loss: 0.7724 - val\_accuracy: 0.7010  
Epoch 38/100

14/14 [=====] - 1s 78ms/step - loss: 0.7887 - accuracy: 0.6  
932 - val\_loss: 0.7738 - val\_accuracy: 0.7033  
Epoch 39/100  
14/14 [=====] - 0s 36ms/step - loss: 0.7870 - accuracy: 0.6  
914 - val\_loss: 0.7741 - val\_accuracy: 0.7010  
Epoch 40/100  
14/14 [=====] - 0s 21ms/step - loss: 0.7848 - accuracy: 0.6  
947 - val\_loss: 0.7749 - val\_accuracy: 0.6998  
Epoch 41/100  
14/14 [=====] - 0s 22ms/step - loss: 0.7816 - accuracy: 0.6  
920 - val\_loss: 0.7719 - val\_accuracy: 0.6986  
Epoch 42/100  
14/14 [=====] - 0s 34ms/step - loss: 0.7821 - accuracy: 0.6  
893 - val\_loss: 0.7700 - val\_accuracy: 0.6974  
Epoch 43/100  
14/14 [=====] - 0s 15ms/step - loss: 0.7794 - accuracy: 0.6  
926 - val\_loss: 0.7696 - val\_accuracy: 0.7010  
Epoch 44/100  
14/14 [=====] - 0s 15ms/step - loss: 0.7774 - accuracy: 0.6  
935 - val\_loss: 0.7709 - val\_accuracy: 0.6974  
Epoch 45/100  
14/14 [=====] - 0s 27ms/step - loss: 0.7772 - accuracy: 0.6  
914 - val\_loss: 0.7698 - val\_accuracy: 0.7010  
Epoch 46/100  
14/14 [=====] - 1s 50ms/step - loss: 0.7765 - accuracy: 0.6  
932 - val\_loss: 0.7667 - val\_accuracy: 0.7057  
Epoch 47/100  
14/14 [=====] - 0s 30ms/step - loss: 0.7737 - accuracy: 0.6  
941 - val\_loss: 0.7691 - val\_accuracy: 0.7057  
Epoch 48/100  
14/14 [=====] - 0s 28ms/step - loss: 0.7724 - accuracy: 0.6  
926 - val\_loss: 0.7651 - val\_accuracy: 0.7045  
Epoch 49/100  
14/14 [=====] - 0s 17ms/step - loss: 0.7715 - accuracy: 0.6  
929 - val\_loss: 0.7638 - val\_accuracy: 0.6998  
Epoch 50/100  
14/14 [=====] - 0s 14ms/step - loss: 0.7722 - accuracy: 0.6  
956 - val\_loss: 0.7641 - val\_accuracy: 0.7045  
Epoch 51/100  
14/14 [=====] - 1s 46ms/step - loss: 0.7688 - accuracy: 0.6  
929 - val\_loss: 0.7637 - val\_accuracy: 0.7022  
Epoch 52/100  
14/14 [=====] - 0s 26ms/step - loss: 0.7692 - accuracy: 0.6  
944 - val\_loss: 0.7627 - val\_accuracy: 0.7033  
Epoch 53/100  
14/14 [=====] - 0s 27ms/step - loss: 0.7681 - accuracy: 0.6  
935 - val\_loss: 0.7607 - val\_accuracy: 0.7069  
Epoch 54/100  
14/14 [=====] - 0s 24ms/step - loss: 0.7673 - accuracy: 0.6  
947 - val\_loss: 0.7619 - val\_accuracy: 0.7057  
Epoch 55/100  
14/14 [=====] - 0s 35ms/step - loss: 0.7656 - accuracy: 0.6  
923 - val\_loss: 0.7616 - val\_accuracy: 0.7045  
Epoch 56/100  
14/14 [=====] - 1s 49ms/step - loss: 0.7630 - accuracy: 0.6  
956 - val\_loss: 0.7623 - val\_accuracy: 0.7033

Epoch 57/100  
14/14 [=====] - 0s 13ms/step - loss: 0.7647 - accuracy: 0.6923 - val\_loss: 0.7604 - val\_accuracy: 0.7057  
Epoch 58/100  
14/14 [=====] - 0s 29ms/step - loss: 0.7622 - accuracy: 0.7001 - val\_loss: 0.7621 - val\_accuracy: 0.7033  
Epoch 59/100  
14/14 [=====] - 0s 36ms/step - loss: 0.7622 - accuracy: 0.6995 - val\_loss: 0.7589 - val\_accuracy: 0.7117  
Epoch 60/100  
14/14 [=====] - 0s 31ms/step - loss: 0.7610 - accuracy: 0.6947 - val\_loss: 0.7585 - val\_accuracy: 0.7081  
Epoch 61/100  
14/14 [=====] - 0s 22ms/step - loss: 0.7606 - accuracy: 0.6956 - val\_loss: 0.7573 - val\_accuracy: 0.7045  
Epoch 62/100  
14/14 [=====] - 0s 29ms/step - loss: 0.7591 - accuracy: 0.6935 - val\_loss: 0.7577 - val\_accuracy: 0.7081  
Epoch 63/100  
14/14 [=====] - 0s 35ms/step - loss: 0.7582 - accuracy: 0.6989 - val\_loss: 0.7579 - val\_accuracy: 0.7069  
Epoch 64/100  
14/14 [=====] - 0s 29ms/step - loss: 0.7577 - accuracy: 0.6968 - val\_loss: 0.7562 - val\_accuracy: 0.7022  
Epoch 65/100  
14/14 [=====] - 0s 17ms/step - loss: 0.7588 - accuracy: 0.6974 - val\_loss: 0.7588 - val\_accuracy: 0.7093  
Epoch 66/100  
14/14 [=====] - 0s 22ms/step - loss: 0.7573 - accuracy: 0.6962 - val\_loss: 0.7554 - val\_accuracy: 0.7033  
Epoch 67/100  
14/14 [=====] - 1s 58ms/step - loss: 0.7594 - accuracy: 0.6944 - val\_loss: 0.7578 - val\_accuracy: 0.7069  
Epoch 68/100  
14/14 [=====] - 0s 31ms/step - loss: 0.7555 - accuracy: 0.6953 - val\_loss: 0.7565 - val\_accuracy: 0.7010  
Epoch 69/100  
14/14 [=====] - 0s 14ms/step - loss: 0.7546 - accuracy: 0.6941 - val\_loss: 0.7550 - val\_accuracy: 0.7093  
Epoch 70/100  
14/14 [=====] - 0s 22ms/step - loss: 0.7533 - accuracy: 0.6995 - val\_loss: 0.7546 - val\_accuracy: 0.6974  
Epoch 71/100  
14/14 [=====] - 1s 38ms/step - loss: 0.7531 - accuracy: 0.6971 - val\_loss: 0.7577 - val\_accuracy: 0.7033  
Epoch 72/100  
14/14 [=====] - 0s 30ms/step - loss: 0.7522 - accuracy: 0.6977 - val\_loss: 0.7552 - val\_accuracy: 0.7045  
Epoch 73/100  
14/14 [=====] - 0s 33ms/step - loss: 0.7527 - accuracy: 0.6962 - val\_loss: 0.7538 - val\_accuracy: 0.7093  
Epoch 74/100  
14/14 [=====] - 1s 55ms/step - loss: 0.7524 - accuracy: 0.6956 - val\_loss: 0.7530 - val\_accuracy: 0.7081  
Epoch 75/100  
14/14 [=====] - 2s 132ms/step - loss: 0.7503 - accuracy: 0.

6974 - val\_loss: 0.7539 - val\_accuracy: 0.7069  
Epoch 76/100  
14/14 [=====] - 0s 22ms/step - loss: 0.7501 - accuracy: 0.6  
983 - val\_loss: 0.7515 - val\_accuracy: 0.7093  
Epoch 77/100  
14/14 [=====] - 0s 26ms/step - loss: 0.7494 - accuracy: 0.6  
977 - val\_loss: 0.7529 - val\_accuracy: 0.7033  
Epoch 78/100  
14/14 [=====] - 0s 15ms/step - loss: 0.7489 - accuracy: 0.6  
989 - val\_loss: 0.7552 - val\_accuracy: 0.7093  
Epoch 79/100  
14/14 [=====] - 1s 37ms/step - loss: 0.7499 - accuracy: 0.6  
980 - val\_loss: 0.7558 - val\_accuracy: 0.7045  
Epoch 80/100  
14/14 [=====] - 1s 61ms/step - loss: 0.7493 - accuracy: 0.6  
992 - val\_loss: 0.7523 - val\_accuracy: 0.7105  
Epoch 81/100  
14/14 [=====] - 0s 22ms/step - loss: 0.7482 - accuracy: 0.7  
028 - val\_loss: 0.7517 - val\_accuracy: 0.7153  
Epoch 82/100  
14/14 [=====] - 0s 23ms/step - loss: 0.7493 - accuracy: 0.6  
986 - val\_loss: 0.7525 - val\_accuracy: 0.7022  
Epoch 83/100  
14/14 [=====] - 0s 31ms/step - loss: 0.7473 - accuracy: 0.6  
947 - val\_loss: 0.7508 - val\_accuracy: 0.7081  
Epoch 84/100  
14/14 [=====] - 2s 174ms/step - loss: 0.7463 - accuracy: 0.  
6980 - val\_loss: 0.7525 - val\_accuracy: 0.7081  
Epoch 85/100  
14/14 [=====] - 2s 149ms/step - loss: 0.7471 - accuracy: 0.  
6983 - val\_loss: 0.7512 - val\_accuracy: 0.7093  
Epoch 86/100  
14/14 [=====] - 1s 73ms/step - loss: 0.7444 - accuracy: 0.7  
010 - val\_loss: 0.7512 - val\_accuracy: 0.7093  
Epoch 87/100  
14/14 [=====] - 0s 37ms/step - loss: 0.7463 - accuracy: 0.6  
977 - val\_loss: 0.7514 - val\_accuracy: 0.7093  
Epoch 88/100  
14/14 [=====] - 0s 37ms/step - loss: 0.7445 - accuracy: 0.7  
013 - val\_loss: 0.7504 - val\_accuracy: 0.7069  
Epoch 89/100  
14/14 [=====] - 1s 41ms/step - loss: 0.7450 - accuracy: 0.6  
986 - val\_loss: 0.7507 - val\_accuracy: 0.7081  
Epoch 90/100  
14/14 [=====] - 1s 69ms/step - loss: 0.7432 - accuracy: 0.7  
016 - val\_loss: 0.7502 - val\_accuracy: 0.7081  
Epoch 91/100  
14/14 [=====] - 0s 20ms/step - loss: 0.7446 - accuracy: 0.6  
980 - val\_loss: 0.7535 - val\_accuracy: 0.7045  
Epoch 92/100  
14/14 [=====] - 0s 25ms/step - loss: 0.7450 - accuracy: 0.7  
028 - val\_loss: 0.7523 - val\_accuracy: 0.7057  
Epoch 93/100  
14/14 [=====] - 0s 15ms/step - loss: 0.7433 - accuracy: 0.6  
983 - val\_loss: 0.7504 - val\_accuracy: 0.7105  
Epoch 94/100

```

14/14 [=====] - 0s 11ms/step - loss: 0.7427 - accuracy: 0.7
034 - val_loss: 0.7513 - val_accuracy: 0.7057
Epoch 95/100
14/14 [=====] - 0s 27ms/step - loss: 0.7425 - accuracy: 0.7
007 - val_loss: 0.7505 - val_accuracy: 0.7057
Epoch 96/100
14/14 [=====] - 0s 13ms/step - loss: 0.7418 - accuracy: 0.7
028 - val_loss: 0.7496 - val_accuracy: 0.7093
Epoch 97/100
14/14 [=====] - 0s 20ms/step - loss: 0.7423 - accuracy: 0.6
998 - val_loss: 0.7493 - val_accuracy: 0.7093
Epoch 98/100
14/14 [=====] - 0s 12ms/step - loss: 0.7424 - accuracy: 0.7
004 - val_loss: 0.7497 - val_accuracy: 0.7129
Epoch 99/100
14/14 [=====] - 0s 12ms/step - loss: 0.7410 - accuracy: 0.7
028 - val_loss: 0.7501 - val_accuracy: 0.7117
Epoch 100/100
14/14 [=====] - 0s 14ms/step - loss: 0.7534 - accuracy: 0.6
962 - val_loss: 0.7510 - val_accuracy: 0.7093

```

```

In [ ]: model3 = Sequential()
        model3.add(Dense(15, input_dim=10, activation="relu"))
        model3.add(Dense(256, activation="relu"))
        model3.add(Dense(128, activation="relu"))
        model3.add(Dense(64, activation="relu"))
        model3.add(Dense(num_groups, activation="softmax"))
        model3.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
        history3 = model3.fit(x_train, y_train, validation_data = (x_test, y_test), epochs=

```

Epoch 1/50  
14/14 [=====] - 2s 27ms/step - loss: 1.7800 - accuracy: 0.5  
397 - val\_loss: 1.3006 - val\_accuracy: 0.5825  
Epoch 2/50  
14/14 [=====] - 0s 10ms/step - loss: 1.1451 - accuracy: 0.6  
154 - val\_loss: 0.9551 - val\_accuracy: 0.6699  
Epoch 3/50  
14/14 [=====] - 0s 11ms/step - loss: 0.9348 - accuracy: 0.6  
603 - val\_loss: 0.8525 - val\_accuracy: 0.6782  
Epoch 4/50  
14/14 [=====] - 0s 12ms/step - loss: 0.8817 - accuracy: 0.6  
779 - val\_loss: 0.8226 - val\_accuracy: 0.6926  
Epoch 5/50  
14/14 [=====] - 0s 12ms/step - loss: 0.8431 - accuracy: 0.6  
872 - val\_loss: 0.8009 - val\_accuracy: 0.6986  
Epoch 6/50  
14/14 [=====] - 0s 10ms/step - loss: 0.8156 - accuracy: 0.6  
926 - val\_loss: 0.7865 - val\_accuracy: 0.6914  
Epoch 7/50  
14/14 [=====] - 0s 12ms/step - loss: 0.7994 - accuracy: 0.6  
890 - val\_loss: 0.7855 - val\_accuracy: 0.7010  
Epoch 8/50  
14/14 [=====] - 0s 10ms/step - loss: 0.7986 - accuracy: 0.6  
884 - val\_loss: 0.7760 - val\_accuracy: 0.6962  
Epoch 9/50  
14/14 [=====] - 0s 10ms/step - loss: 0.7740 - accuracy: 0.6  
935 - val\_loss: 0.7747 - val\_accuracy: 0.7081  
Epoch 10/50  
14/14 [=====] - 0s 12ms/step - loss: 0.7673 - accuracy: 0.6  
968 - val\_loss: 0.7739 - val\_accuracy: 0.7045  
Epoch 11/50  
14/14 [=====] - 0s 11ms/step - loss: 0.7662 - accuracy: 0.6  
965 - val\_loss: 0.7684 - val\_accuracy: 0.7117  
Epoch 12/50  
14/14 [=====] - 0s 12ms/step - loss: 0.7566 - accuracy: 0.6  
986 - val\_loss: 0.7604 - val\_accuracy: 0.7153  
Epoch 13/50  
14/14 [=====] - 0s 11ms/step - loss: 0.7575 - accuracy: 0.6  
965 - val\_loss: 0.7588 - val\_accuracy: 0.7010  
Epoch 14/50  
14/14 [=====] - 0s 10ms/step - loss: 0.7522 - accuracy: 0.6  
923 - val\_loss: 0.7548 - val\_accuracy: 0.7129  
Epoch 15/50  
14/14 [=====] - 0s 11ms/step - loss: 0.7585 - accuracy: 0.6  
962 - val\_loss: 0.7605 - val\_accuracy: 0.7081  
Epoch 16/50  
14/14 [=====] - 0s 15ms/step - loss: 0.7487 - accuracy: 0.6  
962 - val\_loss: 0.7612 - val\_accuracy: 0.7022  
Epoch 17/50  
14/14 [=====] - 0s 13ms/step - loss: 0.7519 - accuracy: 0.6  
974 - val\_loss: 0.7506 - val\_accuracy: 0.7010  
Epoch 18/50  
14/14 [=====] - 0s 9ms/step - loss: 0.7371 - accuracy: 0.70  
31 - val\_loss: 0.7563 - val\_accuracy: 0.7141  
Epoch 19/50  
14/14 [=====] - 0s 14ms/step - loss: 0.7405 - accuracy: 0.6

980 - val\_loss: 0.7567 - val\_accuracy: 0.6974  
Epoch 20/50  
14/14 [=====] - 0s 12ms/step - loss: 0.7370 - accuracy: 0.7  
019 - val\_loss: 0.7629 - val\_accuracy: 0.6998  
Epoch 21/50  
14/14 [=====] - 0s 9ms/step - loss: 0.7371 - accuracy: 0.70  
25 - val\_loss: 0.7523 - val\_accuracy: 0.7022  
Epoch 22/50  
14/14 [=====] - 0s 9ms/step - loss: 0.7329 - accuracy: 0.69  
65 - val\_loss: 0.7576 - val\_accuracy: 0.7045  
Epoch 23/50  
14/14 [=====] - 0s 15ms/step - loss: 0.7365 - accuracy: 0.6  
977 - val\_loss: 0.7544 - val\_accuracy: 0.7057  
Epoch 24/50  
14/14 [=====] - 0s 9ms/step - loss: 0.7289 - accuracy: 0.70  
07 - val\_loss: 0.7507 - val\_accuracy: 0.7057  
Epoch 25/50  
14/14 [=====] - 0s 15ms/step - loss: 0.7249 - accuracy: 0.7  
046 - val\_loss: 0.7557 - val\_accuracy: 0.7093  
Epoch 26/50  
14/14 [=====] - 0s 9ms/step - loss: 0.7275 - accuracy: 0.70  
31 - val\_loss: 0.7507 - val\_accuracy: 0.7105  
Epoch 27/50  
14/14 [=====] - 0s 15ms/step - loss: 0.7331 - accuracy: 0.6  
986 - val\_loss: 0.7543 - val\_accuracy: 0.7093  
Epoch 28/50  
14/14 [=====] - 0s 9ms/step - loss: 0.7346 - accuracy: 0.69  
50 - val\_loss: 0.7504 - val\_accuracy: 0.7022  
Epoch 29/50  
14/14 [=====] - 0s 14ms/step - loss: 0.7253 - accuracy: 0.7  
103 - val\_loss: 0.7680 - val\_accuracy: 0.6938  
Epoch 30/50  
14/14 [=====] - 0s 13ms/step - loss: 0.7358 - accuracy: 0.6  
953 - val\_loss: 0.7634 - val\_accuracy: 0.7069  
Epoch 31/50  
14/14 [=====] - 0s 14ms/step - loss: 0.7222 - accuracy: 0.7  
037 - val\_loss: 0.7491 - val\_accuracy: 0.7069  
Epoch 32/50  
14/14 [=====] - 0s 14ms/step - loss: 0.7184 - accuracy: 0.7  
082 - val\_loss: 0.7500 - val\_accuracy: 0.6998  
Epoch 33/50  
14/14 [=====] - 0s 17ms/step - loss: 0.7301 - accuracy: 0.6  
962 - val\_loss: 0.7531 - val\_accuracy: 0.6974  
Epoch 34/50  
14/14 [=====] - 0s 13ms/step - loss: 0.7189 - accuracy: 0.7  
046 - val\_loss: 0.7558 - val\_accuracy: 0.7057  
Epoch 35/50  
14/14 [=====] - 0s 13ms/step - loss: 0.7208 - accuracy: 0.7  
076 - val\_loss: 0.7535 - val\_accuracy: 0.6986  
Epoch 36/50  
14/14 [=====] - 0s 10ms/step - loss: 0.7156 - accuracy: 0.7  
094 - val\_loss: 0.7477 - val\_accuracy: 0.7117  
Epoch 37/50  
14/14 [=====] - 0s 9ms/step - loss: 0.7160 - accuracy: 0.71  
36 - val\_loss: 0.7797 - val\_accuracy: 0.6926  
Epoch 38/50



```

14/14 [=====] - 0s 15ms/step - loss: 0.7200 - accuracy: 0.7
049 - val_loss: 0.7549 - val_accuracy: 0.6998
Epoch 39/50
14/14 [=====] - 0s 17ms/step - loss: 0.7129 - accuracy: 0.7
061 - val_loss: 0.7496 - val_accuracy: 0.7022
Epoch 40/50
14/14 [=====] - 0s 18ms/step - loss: 0.7175 - accuracy: 0.7
076 - val_loss: 0.7528 - val_accuracy: 0.7069
Epoch 41/50
14/14 [=====] - 0s 17ms/step - loss: 0.7215 - accuracy: 0.7
025 - val_loss: 0.7591 - val_accuracy: 0.7022
Epoch 42/50
14/14 [=====] - 0s 17ms/step - loss: 0.7123 - accuracy: 0.7
049 - val_loss: 0.7517 - val_accuracy: 0.7105
Epoch 43/50
14/14 [=====] - 0s 16ms/step - loss: 0.7110 - accuracy: 0.7
088 - val_loss: 0.7588 - val_accuracy: 0.7033
Epoch 44/50
14/14 [=====] - 0s 17ms/step - loss: 0.7140 - accuracy: 0.7
097 - val_loss: 0.7572 - val_accuracy: 0.6998
Epoch 45/50
14/14 [=====] - 0s 17ms/step - loss: 0.7325 - accuracy: 0.7
004 - val_loss: 0.7870 - val_accuracy: 0.6974
Epoch 46/50
14/14 [=====] - 0s 16ms/step - loss: 0.7202 - accuracy: 0.7
121 - val_loss: 0.7558 - val_accuracy: 0.6986
Epoch 47/50
14/14 [=====] - 0s 15ms/step - loss: 0.7181 - accuracy: 0.7
058 - val_loss: 0.7550 - val_accuracy: 0.6950
Epoch 48/50
14/14 [=====] - 0s 14ms/step - loss: 0.7216 - accuracy: 0.7
061 - val_loss: 0.7679 - val_accuracy: 0.6962
Epoch 49/50
14/14 [=====] - 0s 15ms/step - loss: 0.7259 - accuracy: 0.7
031 - val_loss: 0.7564 - val_accuracy: 0.6986
Epoch 50/50
14/14 [=====] - 0s 12ms/step - loss: 0.7086 - accuracy: 0.7
097 - val_loss: 0.7504 - val_accuracy: 0.7057

```

## Analyzing the results

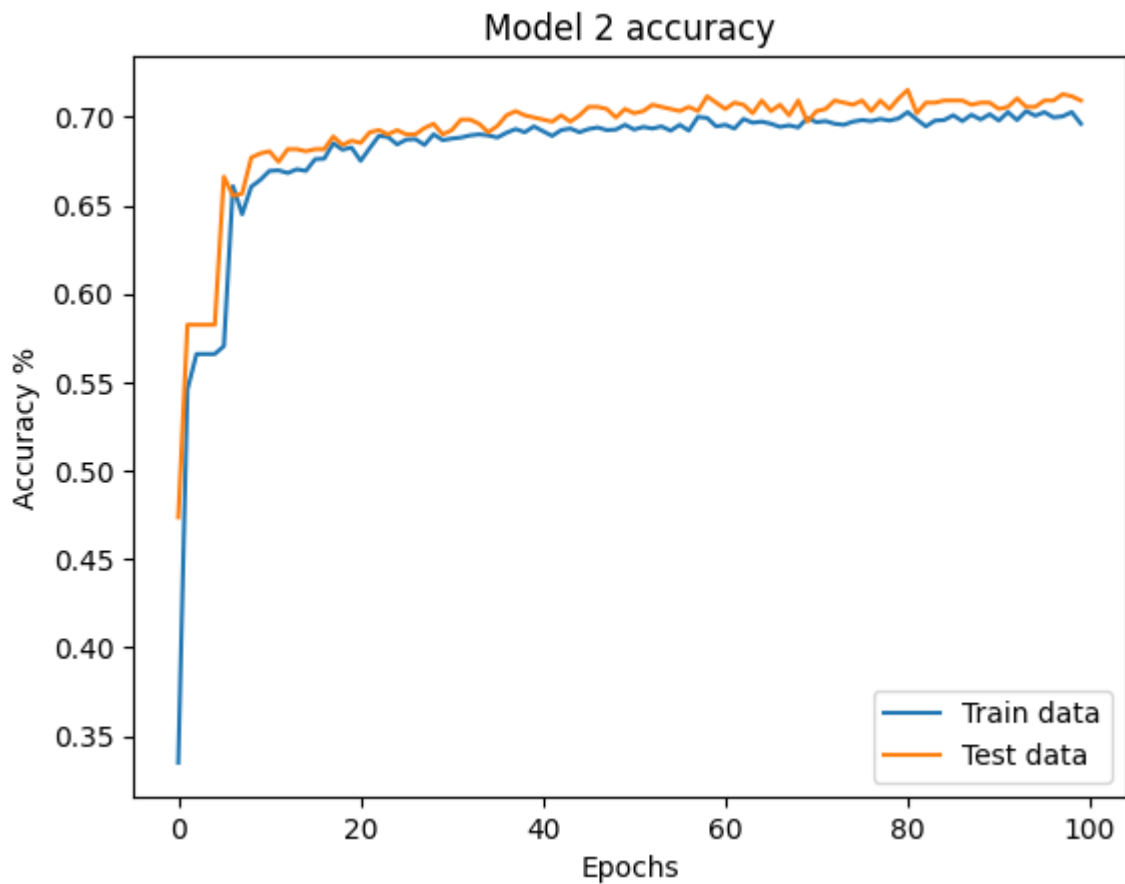
```
In [ ]: num_groups
```

```
Out[ ]: 8
```

The accuracy has not improved. 70% accuracy is still good, because since there are 8 possible groups, picking at random would result in a 12.5% accuracy, so 70% accuracy means the model is giving meaningful predictions.

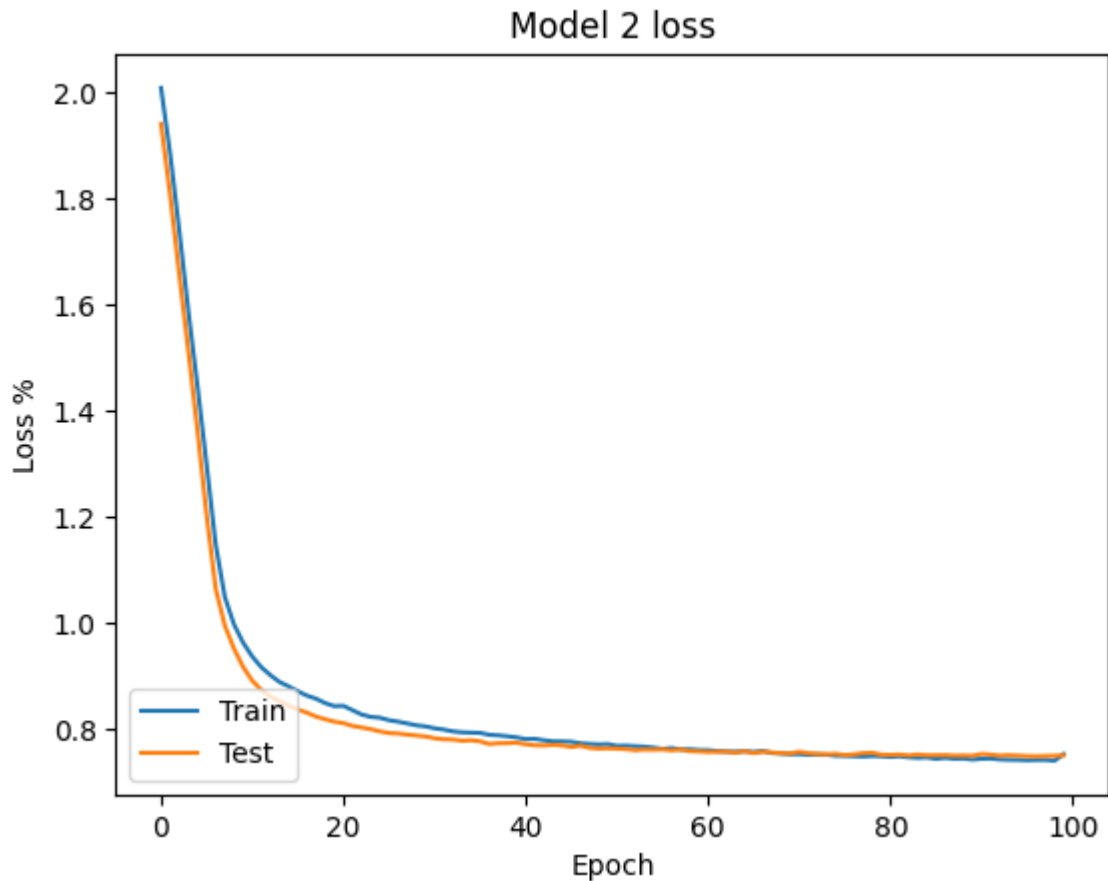
```
In [ ]: plt.plot(history2.history["accuracy"])
plt.plot(history2.history["val_accuracy"])
plt.title("Model 2 accuracy")
plt.ylabel('Accuracy %')
```

```
plt.xlabel('Epochs')
plt.legend(['Train data', 'Test data'], loc='lower right')
plt.show()
```



The accuracy of this model goes seems to plateau at around 70%, which is significantly better than random guessing. The train and test accuracy moved together, so that means it did not overfit.

```
In [ ]: plt.plot(history2.history['loss'])
plt.plot(history2.history['val_loss'])
plt.title('Model 2 loss')
plt.ylabel('Loss %')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='lower left')
plt.show()
```



The loss of the model is decreasing, which means that the error of the model is decreasing, which is good. The train and test loss also are similar which means the model did not overfit.

The below cell demonstrates the model predicting a high percentage of accurate Ring value groups.

```
In [ ]: predictions_raw = model2.predict(x)
predictions = [np.argmax(probs_arr) for probs_arr in predictions_raw]
df["predicted group"] = predictions
df.head()
```

131/131 [=====] - 1s 6ms/step

```
Out[ ]:
```

	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Sex_F	Sex_I	Sex_M	grc
0	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150	0.0	0.0	1.0	
1	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070	0.0	0.0	1.0	
2	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210	1.0	0.0	0.0	
3	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155	0.0	0.0	1.0	
4	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.055	0.0	1.0	0.0	