Neural_Network_EDA,_Model_and_Prediction_on_Wine_Data

April 30, 2023

1 Brief

Welcome to the EDA, Model and Prediction of wine data. One of the ways to determine wine quality is by its physiocochemistry. The purpose of this study was to look at the physicochemical properties of the wine and analyze which model, of the ones we learned in the course, can give us the best fit, prediction and accuracy score of the quality of the wine.

2 Introduction

Ever wondered if a wine is good based on it's phsicochemical measurements? We will look into building a set of models to analyze exactly that!

In this project, the data consisted of 6497 observations across 11 physicochemical properties and the corresponding quality. The datasets were cleaned and explored. Then, we build a deep neural network and predict the quality of wine based on the model built.

After that, the accuracy test showed how well the model did at predicting the wine quality based on the physicochemical properties of the wine.

3 The Data

3.1 Sources

Data Set Source: > "Wine Quality Data Set." UCI Machine Learning Repository, 7 Oct. 2009, https://archive.ics.uci.edu/ml/datasets/Wine+Quality

Data Set Research: > P. Cortez, A. Cerdeira, F. Almeida, T. Matos and J. Reis. Modeling wine preferences by data mining from physicochemical properties. In Decision Support Systems, Elsevier, 47(4):547-553, 2009.

Further Research on Wine properties: > Mor, Nuriel S., et al. "Wine Quality and Type Prediction from Physicochemical Properties Using Neural Networks for Machine Learning: A Free Software for Winemakers and Customers." AgriRxiv, vol. 2022, 30 Jan. 2022, https://doi.org/10.31220/agrirxiv.2022.00125.

Further Research on Winemaking > “Winemaking.” Wikipedia: The Free Encyclopedia. Wikimedia Foundation, Inc, 22 July 2004, https://en.wikipedia.org/wiki/Winemaking. Accessed 7 Dec. 2022.

3.2 Description of Data

The data, acquired from UCI, is related with wine physicochemical inputs and sensory outputs for a Portuguese “Vinho Verde” wine.

3.2.1 Physicochemical Properties

In this dataset, the wine quality is determined by 11 physicochemical qualities: fixed acidity, volatile acidity, citric acid, residual sugar, chlorides, free sulfur dioxide, total sulfur dioxide, density, pH, sulphates, and alcohol. I did some outside research to understand what these qualities are and what their values mean.

Fixed Acidity: The fixed acids found in wines are tartaric, malic, citric, and succinic. Values are how much acid is in the wine based on the type of acid.

Volatile acidity: This is a measure of the low molecular weight of fatty acids.

Critic Acid: This is an organic acid, added to give wine its sour taste amongst other things.

Residual Sugar: The sugar that is leftover after the fermentation process.

Chlorides: This measures how much salt is in the wine.

Free Sulfur Dioxide: These are another type of salty additive generally used for oxidation. A fraction of this will react with sugars and fraction will not. This is the fraction that did not react.

Total Sulfur Dioxide: The total of reacted and free sulfur dioxide.

Density: The measure of mass per unit volume.

pH: The scale used to measure acidity and basicity of wine.

Sulfites: The chemical compounds that contain sulfite ions for preservation.

Alcohol: The Alcohol by Volume of wine.

3.2.2 Other Variables

Aside from the physicochemcial properties, there are a couple other variables in this dataset.

Quality: This is a score or grade given to a wine in part based on the above physicochemical properties.

Color: Red wine or White wine.

3.3 Data Import

To start building models, the data must be first imported.

3.3.1 Import Python Libraries

Begin by importing all the libraries that will be used.

[26]:
```
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import numpy as np
import math
import seaborn as sns
sns.set()

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score
from sklearn import preprocessing, model_selection
import sklearn.metrics as metrics
from sklearn.metrics import roc_auc_score, roc_curve, confusion_matrix,␣
↪classification_report

from tensorflow import keras
from tensorflow.keras import layers, optimizers, regularizers
from tensorflow.keras.models import Model, Sequential
from tensorflow.keras.layers import Dense, Dropout, Input, Add,␣
↪BatchNormalization, \
                                    Softmax, Activation
from tensorflow.keras.optimizers import Adam

from keras.utils import plot_model
#from kt_utils import *
import keras.backend as K

# Ignore Future Warnings
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
```

3.3.2 Import Wine Quality Data

Next, There are 2 CSV files to import that identify the quality of wines: one for red wines and one for white wines. These will be concatenated and this forms our complete DataFrame.

Since ‘color’ is a string label, it can be encoded of using the label as a number so it can be used for analysis.

Finally, the column names are updated with underscores to enable easier coding.

[27]:

```
# Import red wines
df_red = pd.read_csv('https://archive.ics.uci.edu/ml/machine-learning-databases/
↪wine-quality/winequality-red.csv', sep=';')
df_red['color'] = "red"

# # Import white wines
df_white = pd.read_csv('https://archive.ics.uci.edu/ml/
↪machine-learning-databases/wine-quality/winequality-white.csv', sep=';')
df_white['color'] = "white"

# # Combine red and white
df = pd.concat([df_red, df_white], ignore_index=True)
df.reindex()

# # Encode color label
df['color'] = df['color'].astype('category')
df['color_enc'] = df['color'].cat.codes

# Use underscores instead of spaces in column names
df.columns = [c.replace(' ', '_') for c in df.columns]

df
```

[27]:

```
      fixed_acidity  volatile_acidity  citric_acid  residual_sugar  chlorides  \
0               7.4              0.70         0.00             1.9      0.076
1               7.8              0.88         0.00             2.6      0.098
2               7.8              0.76         0.04             2.3      0.092
3              11.2              0.28         0.56             1.9      0.075
4               7.4              0.70         0.00             1.9      0.076
…               …                …              …                …       …
6492            6.2              0.21         0.29             1.6      0.039
6493            6.6              0.32         0.36             8.0      0.047
6494            6.5              0.24         0.19             1.2      0.041
6495            5.5              0.29         0.30             1.1      0.022
6496            6.0              0.21         0.38             0.8      0.020

      free_sulfur_dioxide  total_sulfur_dioxide  density    pH  sulphates  \
0                    11.0                  34.0  0.99780  3.51       0.56
1                    25.0                  67.0  0.99680  3.20       0.68
2                    15.0                  54.0  0.99700  3.26       0.65
3                    17.0                  60.0  0.99800  3.16       0.58
4                    11.0                  34.0  0.99780  3.51       0.56
…                     …                     …      …     …      …
6492                 24.0                  92.0  0.99114  3.27       0.50
6493                 57.0                 168.0  0.99490  3.15       0.46
6494                 30.0                 111.0  0.99254  2.99       0.46
6495                 20.0                 110.0  0.98869  3.34       0.38
```

```
6496                  22.0                 98.0  0.98941  3.26       0.32

      alcohol  quality  color  color_enc
0         9.4        5    red          0
1         9.8        5    red          0
2         9.8        5    red          0
3         9.8        6    red          0
4         9.4        5    red          0
…         …        …    …          …
6492     11.2        6  white          1
6493      9.6        5  white          1
6494      9.4        6  white          1
6495     12.8        7  white          1
6496     11.8        6  white          1

[6497 rows x 14 columns]
```

The data has been imported into a DataFrame and is now ready for cleaning and analysis.

4 Cleaning the Data and Exploratory Data Analysis

Conduct some exploratory data analysis to understand the data a little better.

First, the shape of the dataset.

[28]:
```python
print(f"Shape of Dataset: {df.shape}")
```

```
Shape of Dataset: (6497, 14)
```

To understand the spread of the data in the columns, look at the column ranges (min and max).

[29]:
```python
# Print min and max for each column
for c in df.columns:
    # color is a Categorical column and doesn't have a min and max
    if c == "color":
        continue

    print(f"{c:<22}: (min, max) = ({df[c].min():.2f}, {df[c].max():.2f})")
```

```
fixed_acidity         : (min, max) = (3.80, 15.90)
volatile_acidity      : (min, max) = (0.08, 1.58)
citric_acid           : (min, max) = (0.00, 1.66)
residual_sugar        : (min, max) = (0.60, 65.80)
chlorides             : (min, max) = (0.01, 0.61)
free_sulfur_dioxide   : (min, max) = (1.00, 289.00)
total_sulfur_dioxide  : (min, max) = (6.00, 440.00)
density               : (min, max) = (0.99, 1.04)
pH                    : (min, max) = (2.72, 4.01)
```

```
sulphates              : (min, max) = (0.22, 2.00)
alcohol                : (min, max) = (8.00, 14.90)
quality                : (min, max) = (3.00, 9.00)
color_enc              : (min, max) = (0.00, 1.00)
```

And then lets take a look at how many unique values are in each column.

[30]:
```
df.nunique()
```

[30]:
```
fixed_acidity           106
volatile_acidity        187
citric_acid              89
residual_sugar          316
chlorides               214
free_sulfur_dioxide     135
total_sulfur_dioxide    276
density                 998
pH                      108
sulphates               111
alcohol                 111
quality                   7
color                     2
color_enc                 2
dtype: int64
```

The data is then visually observed to check for any missing data or any values that should not be there. Any unknowns are converted to NA values and depending on how many NAs there are, those cells or features are dropped or imputed. Here is a tally of how many `null` values are in the data.

[31]:
```
a = [np.nan, None, [], {}, 'NaN', 'Null','NULL','None','NA','?','-', '.','', '␣
 ↪', '   ']
row_str = "{:<22}{:<15}{:<15}"
print(row_str.format("Column Name", "Real Nulls", "Null-like"))
print("----------------------------------------------")
for c in df.columns:
    string_null = np.array([x in a[2:] for x in df[c]])
    print(row_str.format(c, str(df[c].isnull().sum()), str(string_null.sum())))
```

```
Column Name           Real Nulls     Null-like
----------------------------------------------
fixed_acidity         0              0
volatile_acidity      0              0
citric_acid           0              0
residual_sugar        0              0
chlorides             0              0
free_sulfur_dioxide   0              0
total_sulfur_dioxide  0              0
density               0              0
```

```
pH                    0          0
sulphates             0          0
alcohol               0          0
quality               0          0
color                 0          0
color_enc             0          0
```

There are certain columns that do not affect the quality of wine. For example "color". Whether a wine is white or red by itself has no bearing on its quality.

As a note sometimes the color of the grape does have a different average for a particular physico-chemical property than the other.

Therefore, before we start analyzing the data, the color column. the encoded color column can be used instead, allowing for some forms of analysis.

[32]:
```
df = df.drop('color', axis=1)
df = df.drop('color_enc', axis=1)

df
```

[32]:
```
      fixed_acidity  volatile_acidity  citric_acid  residual_sugar  chlorides  \
0               7.4              0.70         0.00             1.9      0.076
1               7.8              0.88         0.00             2.6      0.098
2               7.8              0.76         0.04             2.3      0.092
3              11.2              0.28         0.56             1.9      0.075
4               7.4              0.70         0.00             1.9      0.076
…                 …                 …            …               …        …
6492            6.2              0.21         0.29             1.6      0.039
6493            6.6              0.32         0.36             8.0      0.047
6494            6.5              0.24         0.19             1.2      0.041
6495            5.5              0.29         0.30             1.1      0.022
6496            6.0              0.21         0.38             0.8      0.020

      free_sulfur_dioxide  total_sulfur_dioxide  density    pH  sulphates  \
0                    11.0                  34.0  0.99780  3.51       0.56
1                    25.0                  67.0  0.99680  3.20       0.68
2                    15.0                  54.0  0.99700  3.26       0.65
3                    17.0                  60.0  0.99800  3.16       0.58
4                    11.0                  34.0  0.99780  3.51       0.56
…                       …                     …      …     …          …
6492                 24.0                  92.0  0.99114  3.27       0.50
6493                 57.0                 168.0  0.99490  3.15       0.46
6494                 30.0                 111.0  0.99254  2.99       0.46
6495                 20.0                 110.0  0.98869  3.34       0.38
6496                 22.0                  98.0  0.98941  3.26       0.32

      alcohol  quality
0         9.4        5
```

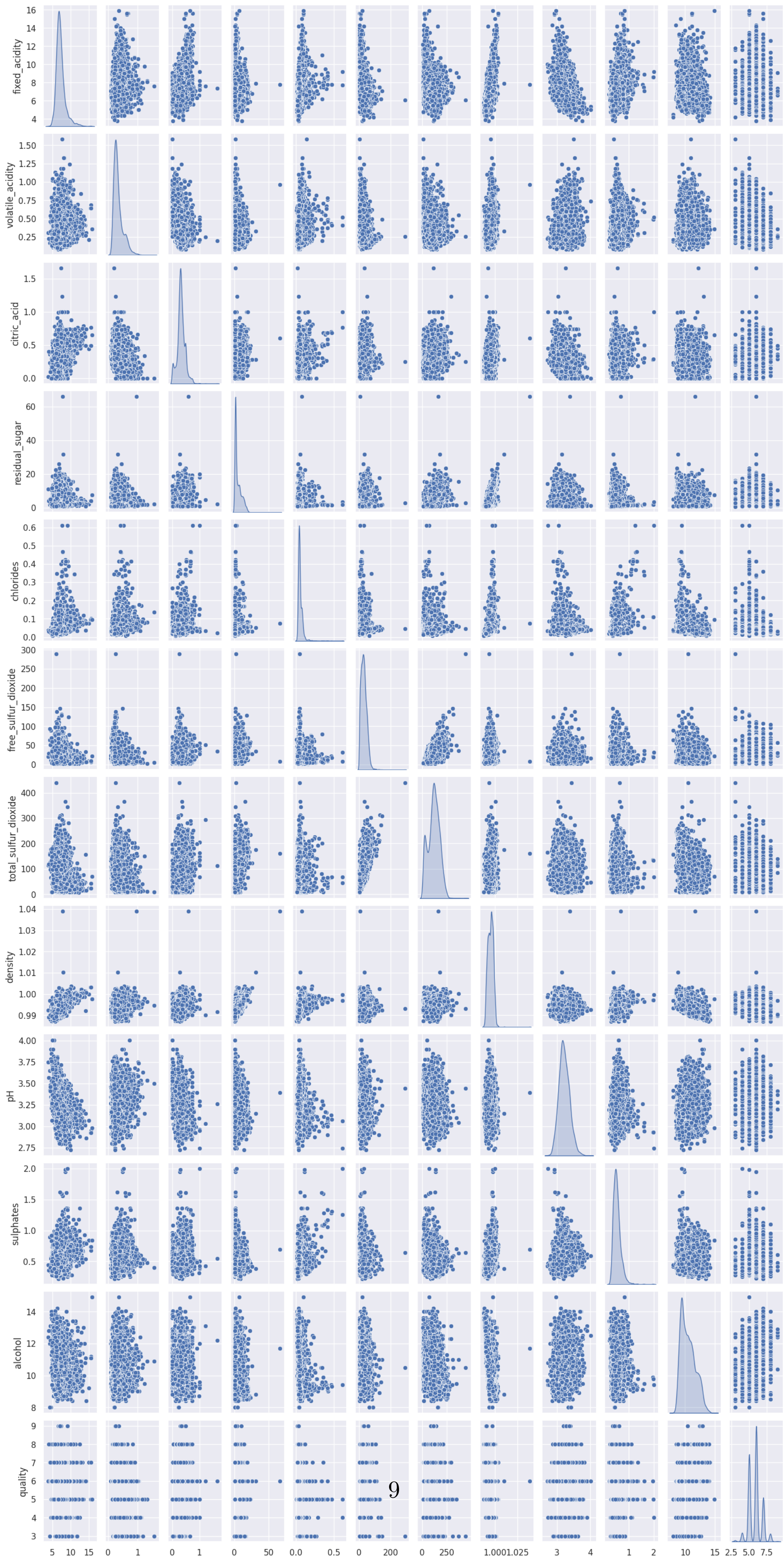
```
1          9.8        5
2          9.8        5
3          9.8        6
4          9.4        5
…        …       …
6492      11.2        6
6493       9.6        5
6494       9.4        6
6495      12.8        7
6496      11.8        6

[6497 rows x 12 columns]
```

Inspecting the relationships between the features or components using a pair plot and a heatmap

[33]:
```
# pair plot
sns.pairplot(df, aspect=0.5 , diag_kind='kde')
```

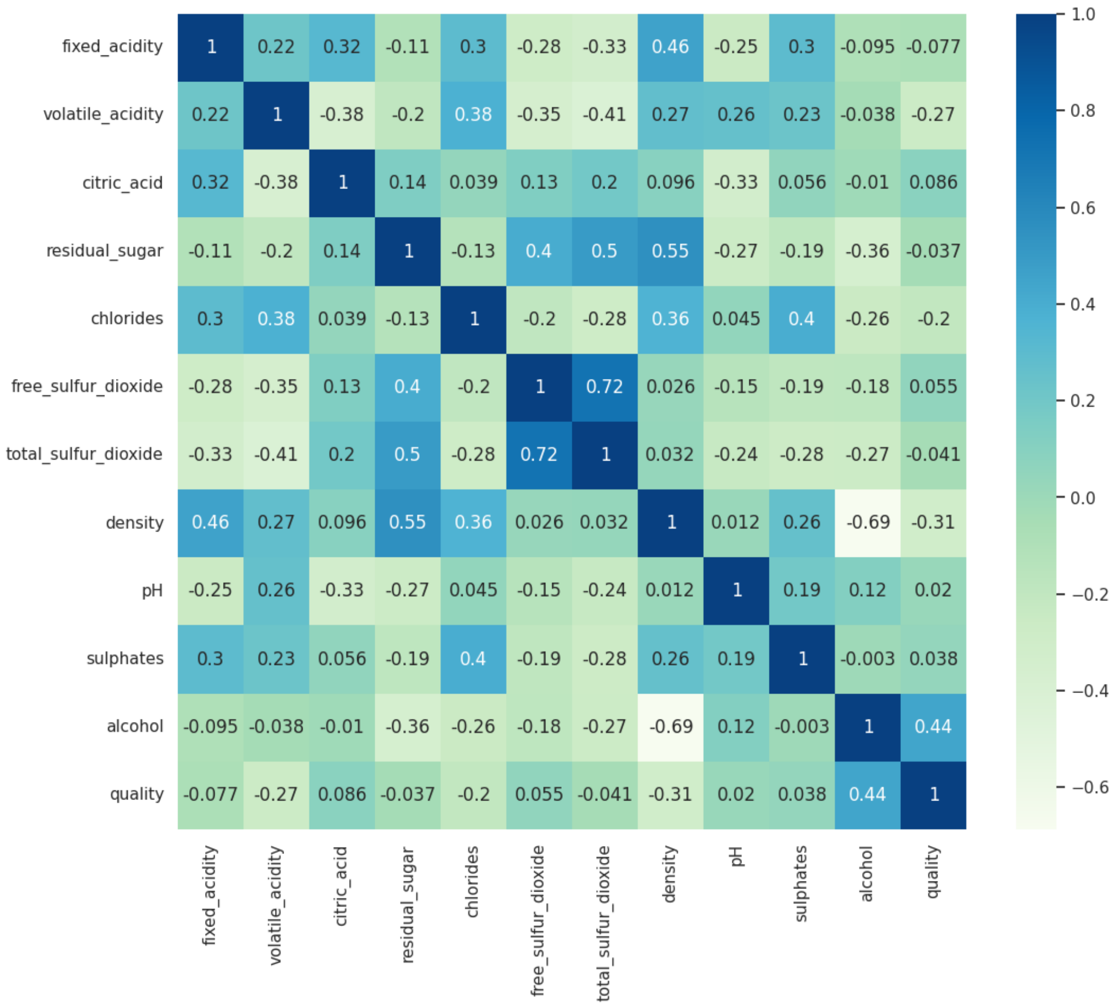
[33]:
```
<seaborn.axisgrid.PairGrid at 0x7f57c79521a0>
```


fixed_acidity
volatile_acidity
citric_acid
residual_sugar
chlorides
free_sulfur_dioxide
total_sulfur_dioxide
density
pH
sulphates
alcohol
quality

This is a histogram pairplot of quality vs each individual property. The chemical property is on the x-axis, while the quality is on the y-axis. This histogram pairplot shows the count of a particular rank at a particular value of the property. For example for fixed acidity, there are a of quality=6 wines in the range of 5 to 10 for fixed acidity vs, the range of 10 to 15. As the wine quality increases, more the lower range of the fixed acidity has more points than the upper range.

Next, plot a heatmap to visualize features are correlated with each other.

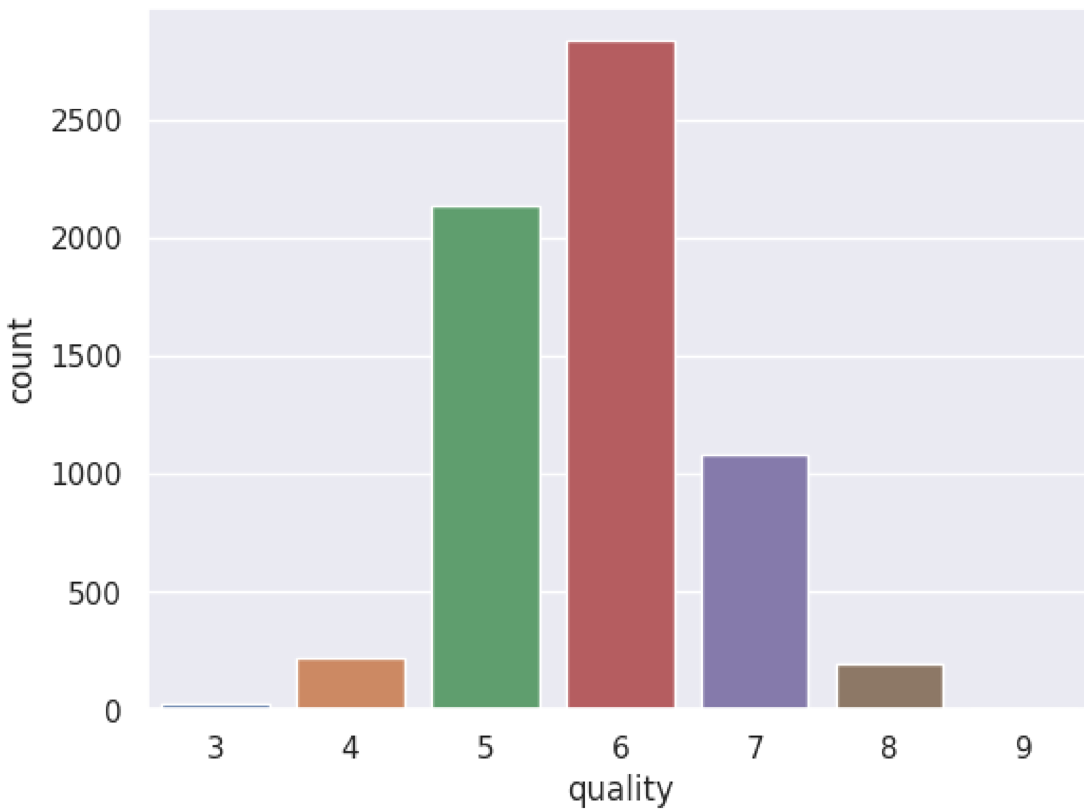
[34]:
```python
# Heatmap
plt.figure(figsize=(12,10))
cor = df.corr()
sns.heatmap(cor, annot=True, cmap=plt.cm.GnBu)
plt.show()
```



The Heat map shows the correlation between each of the properties. The highest correlation seems to be between total sulfur dioxide and the color. This could mean that a particular color of wine has more total sulfur dioxide than the other color. For determining, which factor affects the quality the most, the highest correlation seems to be between quality and alcohol content.

[35]:
```
sns.countplot(x=df["quality"])
```

[35]: `<Axes: xlabel='quality', ylabel='count'>`



Here is is distribution of the wines by quality. They are centered around 5, 6 and 7. This could be a downside for our model building.

[36]:
```
df["quality"] =df["quality"].astype(int)
df = pd.get_dummies(df, columns=["quality"])

df.head(5)
```

[36]:

	fixed_acidity	volatile_acidity	citric_acid	residual_sugar	chlorides	\
0	7.4	0.70	0.00	1.9	0.076	
1	7.8	0.88	0.00	2.6	0.098	
2	7.8	0.76	0.04	2.3	0.092	
3	11.2	0.28	0.56	1.9	0.075	
4	7.4	0.70	0.00	1.9	0.076	

```
   free_sulfur_dioxide  total_sulfur_dioxide  density    pH  sulphates  \
0                 11.0                  34.0   0.9978  3.51       0.56
1                 25.0                  67.0   0.9968  3.20       0.68
2                 15.0                  54.0   0.9970  3.26       0.65
3                 17.0                  60.0   0.9980  3.16       0.58
4                 11.0                  34.0   0.9978  3.51       0.56

   alcohol  quality_3  quality_4  quality_5  quality_6  quality_7  quality_8  \
0      9.4          0          0          1          0          0          0
1      9.8          0          0          1          0          0          0
2      9.8          0          0          1          0          0          0
3      9.8          0          0          0          1          0          0
4      9.4          0          0          1          0          0          0

   quality_9
0          0
1          0
2          0
3          0
4          0
```

5 Modeling the Data

5.1 Preparing the Data

First we prepare the data so that we do not have bias later. We will also split the data into training and test set. The training set will be 75% and the test set will be 25%.

[37]:
```python
X = df.iloc[:,0:11].values # first columns
Y = df.iloc[:,12:].values # last columns

X = preprocessing.normalize(X, axis = 0)

X_train,X_test,Y_train,Y_test = model_selection.train_test_split(X,Y,test_size=0.25)

print(X_train.shape,Y_train.shape,X_test.shape,Y_test.shape)
```

```
(4872, 11) (4872, 6) (1625, 11) (1625, 6)
```

5.2 Method

1. **Evaluate Models** Build a model

2. **Make Predictions or Plot the Accuracy** Make predictions and find accuracy or metrics of the model.
3. **Analyze** Analyze and make conclusion about the fit and accuracy of the model.

5.2.1 Model Architecture

With a stronger sense of the training data and the goal, the next discussion is which model architecture to use and train for best results. Selecting the right model architecture is important because it will use the right amount of resources for the task, will not overfit the data, and will give accurate classification results.

5.2.2 Options for Architecture

The loss function must be selected, with possible choices including mean absolute error (mae), mean squared error (mse), and Huber loss for regression loss calculations. This problem is a categorical classification problem so there are the options of using Categorical Cross Entropy.

Additionally the activation function for the linear units must be selected. Choices here include Sigmoid, TanH, and ReLU. Since ReLU has shown great promise with training Neural Network models and since it also can increase the speed of the model learning, that will be one of the activation function selected here.

Additionally, it is possible to select strategies to optimize the hyperparameters of an Neural Network model and one of the most popular and effective strategies is Stochastic Gradient Descent. This will be the selected strategy for optimizing the Neural Network to reduce loss.

[38]:
```
def model_performance_graphs(classifier, acc):


    fig, axes = plt.subplots(1, 2, figsize = (8, 3))

    axes[0].plot(classifier.epoch, classifier.history[acc], label = 'acc')
    axes[0].set_title('Accuracy vs Epochs', fontsize = 12)
    axes[0].set_xlabel('Epochs', fontsize = 10)
    axes[0].set_ylabel('Accuracy', fontsize = 10)
    axes[0].legend()

    axes[1].plot(classifier.epoch, classifier.history['loss'], label = 'loss')
    axes[1].set_title("Loss Curve",fontsize=12)
    axes[1].set_xlabel("Epochs",fontsize=10)
    axes[1].set_ylabel("Loss",fontsize=10)
    axes[1].legend()

    plt.show()
```

5.3 Basic Stochastic Gradient Descent

Stochastic gradient descent (SGD) is a method for finding a minimum of a function by iteratively taking steps in the direction of the negative gradient of the function at the current point. The steps are chosen randomly, hence the name "stochastic". SGD is a popular algorithm for training neural networks.

SGD works by repeatedly taking steps in the direction of the negative gradient of the loss function. The loss function is a measure of how well the model fits the training data. The gradient of the loss function is a vector that points in the direction of greatest increase in the loss function. By taking steps in the opposite direction of the gradient, SGD can find a minimum of the loss function.

[39]:
```
mod1 = keras.Sequential([
    layers.Dense(512, activation='relu', input_shape=[11]),
    layers.Dense(512, activation='relu'),
    layers.Dense(512, activation='relu'),
    layers.Dense(1),
])
```

[40]:
```
mod1.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_4 (Dense)             (None, 512)               6144

 dense_5 (Dense)             (None, 512)               262656

 dense_6 (Dense)             (None, 512)               262656

 dense_7 (Dense)             (None, 1)                 513

=================================================================
Total params: 531,969
Trainable params: 531,969
Non-trainable params: 0
_________________________________________________________________
```

[41]:
```
mod1.compile(
    optimizer='adam',
    loss='mae',
    metrics = ["accuracy"]
)
```

[42]:
```
history1 = mod1.fit(
    X_train, Y_train,
    validation_data=(X_test, Y_test),
```

```
    batch_size=256,
    epochs=100,
)
```

```
Epoch 1/100
20/20 [==============================] - 2s 37ms/step - loss: 0.1703 - accuracy:
0.8340 - val_loss: 0.1664 - val_accuracy: 0.8344
Epoch 2/100
20/20 [==============================] - 1s 28ms/step - loss: 0.1666 - accuracy:
0.8340 - val_loss: 0.1658 - val_accuracy: 0.8344
Epoch 3/100
20/20 [==============================] - 1s 43ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1656 - val_accuracy: 0.8344
Epoch 4/100
20/20 [==============================] - 1s 45ms/step - loss: 0.1664 - accuracy:
0.8340 - val_loss: 0.1664 - val_accuracy: 0.8344
Epoch 5/100
20/20 [==============================] - 1s 47ms/step - loss: 0.1665 - accuracy:
0.8340 - val_loss: 0.1662 - val_accuracy: 0.8344
Epoch 6/100
20/20 [==============================] - 1s 36ms/step - loss: 0.1664 - accuracy:
0.8340 - val_loss: 0.1659 - val_accuracy: 0.8344
Epoch 7/100
20/20 [==============================] - 1s 27ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 8/100
20/20 [==============================] - 1s 27ms/step - loss: 0.1663 - accuracy:
0.8340 - val_loss: 0.1659 - val_accuracy: 0.8344
Epoch 9/100
20/20 [==============================] - 1s 29ms/step - loss: 0.1663 - accuracy:
0.8340 - val_loss: 0.1660 - val_accuracy: 0.8344
Epoch 10/100
20/20 [==============================] - 1s 27ms/step - loss: 0.1662 - accuracy:
0.8340 - val_loss: 0.1660 - val_accuracy: 0.8344
Epoch 11/100
20/20 [==============================] - 1s 26ms/step - loss: 0.1662 - accuracy:
0.8340 - val_loss: 0.1659 - val_accuracy: 0.8344
Epoch 12/100
20/20 [==============================] - 1s 28ms/step - loss: 0.1662 - accuracy:
0.8340 - val_loss: 0.1659 - val_accuracy: 0.8344
Epoch 13/100
20/20 [==============================] - 1s 27ms/step - loss: 0.1662 - accuracy:
0.8340 - val_loss: 0.1658 - val_accuracy: 0.8344
Epoch 14/100
20/20 [==============================] - 1s 27ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1658 - val_accuracy: 0.8344
Epoch 15/100
```

```
20/20 [==============================] - 1s 28ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1658 - val_accuracy: 0.8344
Epoch 16/100
20/20 [==============================] - 1s 28ms/step - loss: 0.1662 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 17/100
20/20 [==============================] - 1s 27ms/step - loss: 0.1663 - accuracy:
0.8340 - val_loss: 0.1661 - val_accuracy: 0.8344
Epoch 18/100
20/20 [==============================] - 1s 27ms/step - loss: 0.1666 - accuracy:
0.8340 - val_loss: 0.1662 - val_accuracy: 0.8344
Epoch 19/100
20/20 [==============================] - 1s 27ms/step - loss: 0.1665 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 20/100
20/20 [==============================] - 1s 28ms/step - loss: 0.1660 - accuracy:
0.8340 - val_loss: 0.1658 - val_accuracy: 0.8344
Epoch 21/100
20/20 [==============================] - 1s 28ms/step - loss: 0.1660 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 22/100
20/20 [==============================] - 1s 27ms/step - loss: 0.1660 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 23/100
20/20 [==============================] - 1s 26ms/step - loss: 0.1660 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 24/100
20/20 [==============================] - 1s 33ms/step - loss: 0.1660 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 25/100
20/20 [==============================] - 1s 43ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1659 - val_accuracy: 0.8344
Epoch 26/100
20/20 [==============================] - 1s 44ms/step - loss: 0.1662 - accuracy:
0.8340 - val_loss: 0.1661 - val_accuracy: 0.8344
Epoch 27/100
20/20 [==============================] - 1s 47ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 28/100
20/20 [==============================] - 1s 32ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 29/100
20/20 [==============================] - 1s 28ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 30/100
20/20 [==============================] - 1s 26ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1660 - val_accuracy: 0.8344
Epoch 31/100
```

```
20/20 [==============================] - 1s 27ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1658 - val_accuracy: 0.8344
Epoch 32/100
20/20 [==============================] - 1s 27ms/step - loss: 0.1662 - accuracy:
0.8340 - val_loss: 0.1660 - val_accuracy: 0.8344
Epoch 33/100
20/20 [==============================] - 1s 27ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 34/100
20/20 [==============================] - 1s 26ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1658 - val_accuracy: 0.8344
Epoch 35/100
20/20 [==============================] - 1s 27ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 36/100
20/20 [==============================] - 1s 27ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1658 - val_accuracy: 0.8344
Epoch 37/100
20/20 [==============================] - 1s 27ms/step - loss: 0.1662 - accuracy:
0.8340 - val_loss: 0.1656 - val_accuracy: 0.8344
Epoch 38/100
20/20 [==============================] - 1s 25ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1659 - val_accuracy: 0.8344
Epoch 39/100
20/20 [==============================] - 1s 27ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1658 - val_accuracy: 0.8344
Epoch 40/100
20/20 [==============================] - 1s 27ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1658 - val_accuracy: 0.8344
Epoch 41/100
20/20 [==============================] - 1s 26ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1658 - val_accuracy: 0.8344
Epoch 42/100
20/20 [==============================] - 1s 28ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1658 - val_accuracy: 0.8344
Epoch 43/100
20/20 [==============================] - 1s 28ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 44/100
20/20 [==============================] - 1s 26ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 45/100
20/20 [==============================] - 1s 28ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 46/100
20/20 [==============================] - 1s 31ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 47/100
```

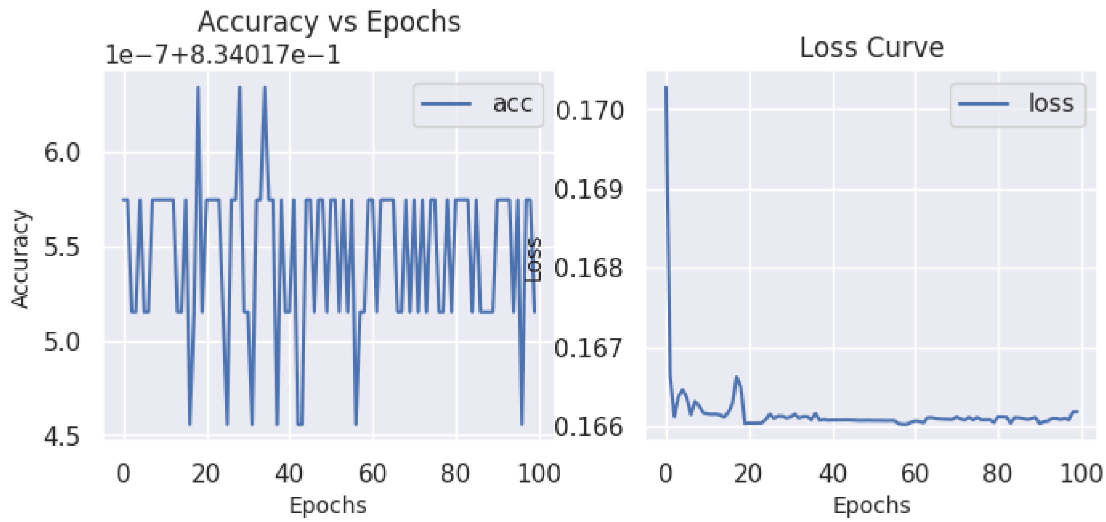
```
20/20 [==============================] - 1s 43ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 48/100
20/20 [==============================] - 1s 44ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 49/100
20/20 [==============================] - 1s 48ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 50/100
20/20 [==============================] - 1s 30ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 51/100
20/20 [==============================] - 1s 28ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 52/100
20/20 [==============================] - 1s 27ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 53/100
20/20 [==============================] - 1s 27ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 54/100
20/20 [==============================] - 1s 27ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 55/100
20/20 [==============================] - 1s 26ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 56/100
20/20 [==============================] - 1s 27ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 57/100
20/20 [==============================] - 1s 25ms/step - loss: 0.1660 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 58/100
20/20 [==============================] - 1s 28ms/step - loss: 0.1660 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 59/100
20/20 [==============================] - 1s 26ms/step - loss: 0.1660 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 60/100
20/20 [==============================] - 1s 28ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1659 - val_accuracy: 0.8344
Epoch 61/100
20/20 [==============================] - 1s 27ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 62/100
20/20 [==============================] - 1s 27ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1658 - val_accuracy: 0.8344
Epoch 63/100
```

```
20/20 [==============================] - 1s 28ms/step - loss: 0.1660 - accuracy:
0.8340 - val_loss: 0.1658 - val_accuracy: 0.8344
Epoch 64/100
20/20 [==============================] - 1s 26ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1658 - val_accuracy: 0.8344
Epoch 65/100
20/20 [==============================] - 1s 26ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1658 - val_accuracy: 0.8344
Epoch 66/100
20/20 [==============================] - 1s 27ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1658 - val_accuracy: 0.8344
Epoch 67/100
20/20 [==============================] - 1s 28ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1658 - val_accuracy: 0.8344
Epoch 68/100
20/20 [==============================] - 1s 35ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1658 - val_accuracy: 0.8344
Epoch 69/100
20/20 [==============================] - 1s 43ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1658 - val_accuracy: 0.8344
Epoch 70/100
20/20 [==============================] - 1s 48ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 71/100
20/20 [==============================] - 1s 48ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1658 - val_accuracy: 0.8344
Epoch 72/100
20/20 [==============================] - 1s 27ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 73/100
20/20 [==============================] - 1s 26ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1658 - val_accuracy: 0.8344
Epoch 74/100
20/20 [==============================] - 1s 26ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 75/100
20/20 [==============================] - 1s 26ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1658 - val_accuracy: 0.8344
Epoch 76/100
20/20 [==============================] - 1s 27ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 77/100
20/20 [==============================] - 1s 27ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1658 - val_accuracy: 0.8344
Epoch 78/100
20/20 [==============================] - 1s 27ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1658 - val_accuracy: 0.8344
Epoch 79/100
```

```
20/20 [==============================] - 1s 27ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1658 - val_accuracy: 0.8344
Epoch 80/100
20/20 [==============================] - 1s 29ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 81/100
20/20 [==============================] - 1s 28ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 82/100
20/20 [==============================] - 1s 28ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 83/100
20/20 [==============================] - 1s 28ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 84/100
20/20 [==============================] - 1s 27ms/step - loss: 0.1660 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 85/100
20/20 [==============================] - 1s 28ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 86/100
20/20 [==============================] - 1s 28ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 87/100
20/20 [==============================] - 1s 28ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 88/100
20/20 [==============================] - 1s 25ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1656 - val_accuracy: 0.8344
Epoch 89/100
20/20 [==============================] - 1s 26ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 90/100
20/20 [==============================] - 1s 39ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1656 - val_accuracy: 0.8344
Epoch 91/100
20/20 [==============================] - 1s 46ms/step - loss: 0.1660 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 92/100
20/20 [==============================] - 1s 47ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1659 - val_accuracy: 0.8344
Epoch 93/100
20/20 [==============================] - 1s 39ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1658 - val_accuracy: 0.8344
Epoch 94/100
20/20 [==============================] - 1s 26ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 95/100
```

```
20/20 [==============================] - 1s 28ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1656 - val_accuracy: 0.8344
Epoch 96/100
20/20 [==============================] - 1s 26ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 97/100
20/20 [==============================] - 1s 28ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 98/100
20/20 [==============================] - 0s 25ms/step - loss: 0.1661 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
Epoch 99/100
20/20 [==============================] - 1s 30ms/step - loss: 0.1662 - accuracy:
0.8340 - val_loss: 0.1658 - val_accuracy: 0.8344
Epoch 100/100
20/20 [==============================] - 1s 26ms/step - loss: 0.1662 - accuracy:
0.8340 - val_loss: 0.1657 - val_accuracy: 0.8344
```

[43]:
```
model_performance_graphs(history1, "accuracy")
```



[44]:
```
train1_acc = mod1.evaluate(x = X_train, y = Y_train)
print()
print ("Train Accuracy = " + str(train1_acc[1]))
print()
test1_acc = mod1.evaluate(x = X_test, y = Y_test)
print()
print ("Loss = " + str(test1_acc[0]))
print ("Test Accuracy = " + str(test1_acc[1]))
```

```
153/153 [==============================] - 1s 3ms/step - loss: 0.1660 -
```

```
accuracy: 0.8340

Train Accuracy = 0.8340182900428772

51/51 [==============================] - 0s 4ms/step - loss: 0.1657 - accuracy:
0.8344

Loss = 0.165687695145607
Test Accuracy = 0.8343589305877686
```

The accuracy of our model is pretty high. We can attempt to improve the accuracy by utilizing other techniques

5.4 Dropout and Batch Normalization

Dropout and batch normalization are two techniques used to improve the performance of neural networks. Dropout works by randomly dropping out (setting to zero) a certain percentage of neurons during each training epoch. This forces the network to learn more robust features that are not dependent on any single neuron. Batch normalization works by normalizing the inputs to each layer of the network, which helps to prevent the values from becoming too large or too small.

[45]:
```
mod2 = Sequential()
# layer 1
mod2.add(Dense(30, input_dim=11, activation='relu',␣
 ↪name='fc0',kernel_regularizer=regularizers.l2(0.01)))
mod2.add(BatchNormalization(momentum=0.99, epsilon=0.001))
#layer 2
mod2.add(Dense(50, name='fc1',bias_initializer='zeros'))
mod2.add(Activation('tanh'))
mod2.add(BatchNormalization(momentum=0.99, epsilon=0.001))
mod2.add(Dropout(0.5))
#layer 3
mod2.add(Dense(100, name='fc2',bias_initializer='zeros'))
mod2.add(Activation('relu'))
mod2.add(BatchNormalization(momentum=0.99, epsilon=0.001))
mod2.add(Dropout(0.5))
#layer 4
mod2.add(Dense(6, name='fc3',bias_initializer='zeros'))
mod2.add(Activation('softmax'))
mod2.add(BatchNormalization(momentum=0.99, epsilon=0.001))
```

[46]:
```
mod2.summary()
```

```
Model: "sequential_3"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 fc0 (Dense)                 (None, 30)                360
```

```
 batch_normalization_4 (Batc  (None, 30)               120
 hNormalization)

 fc1 (Dense)                 (None, 50)                1550

 activation_3 (Activation)   (None, 50)                0

 batch_normalization_5 (Batc  (None, 50)               200
 hNormalization)

 dropout_2 (Dropout)         (None, 50)                0

 fc2 (Dense)                 (None, 100)               5100

 activation_4 (Activation)   (None, 100)               0

 batch_normalization_6 (Batc  (None, 100)              400
 hNormalization)

 dropout_3 (Dropout)         (None, 100)               0

 fc3 (Dense)                 (None, 6)                 606

 activation_5 (Activation)   (None, 6)                 0

 batch_normalization_7 (Batc  (None, 6)                24
 hNormalization)

=================================================================
Total params: 8,360
Trainable params: 7,988
Non-trainable params: 372
_________________________________________________________________
```

[47]:
```python
Adam = optimizers.Adam(learning_rate=0.001, beta_1=0.9, beta_2=0.999,␣
 ↪epsilon=1e-08)
mod2.compile(optimizer = Adam, loss = "mae", metrics = ["accuracy"])
```

[48]:
```python
history2 = mod2.fit(x = X_train, y = Y_train, epochs = 100,verbose=1,␣
 ↪batch_size = 64,validation_data=(X_test, Y_test))
```

```
Epoch 1/100
77/77 [==============================] - 3s 8ms/step - loss: 0.9232 - accuracy:
0.1882 - val_loss: 0.3982 - val_accuracy: 0.1631
Epoch 2/100
77/77 [==============================] - 0s 5ms/step - loss: 0.7745 - accuracy:
0.2377 - val_loss: 0.3616 - val_accuracy: 0.1729
```

```
Epoch 3/100
77/77 [==============================] - 0s 5ms/step - loss: 0.6275 - accuracy:
0.2917 - val_loss: 0.3279 - val_accuracy: 0.4215
Epoch 4/100
77/77 [==============================] - 0s 5ms/step - loss: 0.4973 - accuracy:
0.3502 - val_loss: 0.3253 - val_accuracy: 0.4215
Epoch 5/100
77/77 [==============================] - 0s 5ms/step - loss: 0.4119 - accuracy:
0.3890 - val_loss: 0.2613 - val_accuracy: 0.4215
Epoch 6/100
77/77 [==============================] - 0s 5ms/step - loss: 0.3449 - accuracy:
0.4438 - val_loss: 0.2515 - val_accuracy: 0.4289
Epoch 7/100
77/77 [==============================] - 0s 5ms/step - loss: 0.2929 - accuracy:
0.4516 - val_loss: 0.2518 - val_accuracy: 0.4843
Epoch 8/100
77/77 [==============================] - 0s 5ms/step - loss: 0.2496 - accuracy:
0.4645 - val_loss: 0.2365 - val_accuracy: 0.4720
Epoch 9/100
77/77 [==============================] - 0s 5ms/step - loss: 0.2230 - accuracy:
0.4750 - val_loss: 0.2075 - val_accuracy: 0.5058
Epoch 10/100
77/77 [==============================] - 1s 9ms/step - loss: 0.2091 - accuracy:
0.4873 - val_loss: 0.2112 - val_accuracy: 0.4751
Epoch 11/100
77/77 [==============================] - 1s 7ms/step - loss: 0.2003 - accuracy:
0.4971 - val_loss: 0.2494 - val_accuracy: 0.4185
Epoch 12/100
77/77 [==============================] - 1s 7ms/step - loss: 0.1957 - accuracy:
0.4984 - val_loss: 0.2180 - val_accuracy: 0.4412
Epoch 13/100
77/77 [==============================] - 1s 8ms/step - loss: 0.1879 - accuracy:
0.5082 - val_loss: 0.1904 - val_accuracy: 0.4929
Epoch 14/100
77/77 [==============================] - 1s 7ms/step - loss: 0.1846 - accuracy:
0.5064 - val_loss: 0.1846 - val_accuracy: 0.4862
Epoch 15/100
77/77 [==============================] - 0s 6ms/step - loss: 0.1797 - accuracy:
0.5101 - val_loss: 0.1884 - val_accuracy: 0.4609
Epoch 16/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1775 - accuracy:
0.5080 - val_loss: 0.1873 - val_accuracy: 0.4695
Epoch 17/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1750 - accuracy:
0.5113 - val_loss: 0.1799 - val_accuracy: 0.4837
Epoch 18/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1716 - accuracy:
0.5226 - val_loss: 0.1684 - val_accuracy: 0.5182
```

```
Epoch 19/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1706 - accuracy:
0.5205 - val_loss: 0.1763 - val_accuracy: 0.4917
Epoch 20/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1687 - accuracy:
0.5261 - val_loss: 0.1622 - val_accuracy: 0.5329
Epoch 21/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1697 - accuracy:
0.5168 - val_loss: 0.1657 - val_accuracy: 0.5255
Epoch 22/100
77/77 [==============================] - 1s 7ms/step - loss: 0.1655 - accuracy:
0.5287 - val_loss: 0.1687 - val_accuracy: 0.5108
Epoch 23/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1665 - accuracy:
0.5220 - val_loss: 0.1686 - val_accuracy: 0.5175
Epoch 24/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1672 - accuracy:
0.5174 - val_loss: 0.1839 - val_accuracy: 0.4597
Epoch 25/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1643 - accuracy:
0.5255 - val_loss: 0.1599 - val_accuracy: 0.5274
Epoch 26/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1631 - accuracy:
0.5277 - val_loss: 0.1902 - val_accuracy: 0.2849
Epoch 27/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1642 - accuracy:
0.5244 - val_loss: 0.1879 - val_accuracy: 0.2154
Epoch 28/100
77/77 [==============================] - 0s 6ms/step - loss: 0.1632 - accuracy:
0.5271 - val_loss: 0.1669 - val_accuracy: 0.5108
Epoch 29/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1646 - accuracy:
0.5189 - val_loss: 0.1599 - val_accuracy: 0.5286
Epoch 30/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1592 - accuracy:
0.5308 - val_loss: 0.1855 - val_accuracy: 0.4505
Epoch 31/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1624 - accuracy:
0.5086 - val_loss: 0.1647 - val_accuracy: 0.5040
Epoch 32/100
77/77 [==============================] - 0s 6ms/step - loss: 0.1600 - accuracy:
0.5216 - val_loss: 0.1697 - val_accuracy: 0.4228
Epoch 33/100
77/77 [==============================] - 0s 6ms/step - loss: 0.1611 - accuracy:
0.5183 - val_loss: 0.1700 - val_accuracy: 0.4234
Epoch 34/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1602 - accuracy:
0.5193 - val_loss: 0.1698 - val_accuracy: 0.4209
```

```
Epoch 35/100
77/77 [==============================] - 0s 6ms/step - loss: 0.1617 - accuracy:
0.5129 - val_loss: 0.1691 - val_accuracy: 0.4332
Epoch 36/100
77/77 [==============================] - 0s 6ms/step - loss: 0.1625 - accuracy:
0.5109 - val_loss: 0.1556 - val_accuracy: 0.5440
Epoch 37/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1609 - accuracy:
0.5170 - val_loss: 0.1706 - val_accuracy: 0.4295
Epoch 38/100
77/77 [==============================] - 0s 6ms/step - loss: 0.1599 - accuracy:
0.5226 - val_loss: 0.1758 - val_accuracy: 0.4215
Epoch 39/100
77/77 [==============================] - 1s 9ms/step - loss: 0.1597 - accuracy:
0.5195 - val_loss: 0.1692 - val_accuracy: 0.3520
Epoch 40/100
77/77 [==============================] - 1s 9ms/step - loss: 0.1606 - accuracy:
0.5148 - val_loss: 0.1746 - val_accuracy: 0.4178
Epoch 41/100
77/77 [==============================] - 1s 8ms/step - loss: 0.1607 - accuracy:
0.5150 - val_loss: 0.1659 - val_accuracy: 0.4732
Epoch 42/100
77/77 [==============================] - 1s 7ms/step - loss: 0.1609 - accuracy:
0.5148 - val_loss: 0.1563 - val_accuracy: 0.5372
Epoch 43/100
77/77 [==============================] - 0s 6ms/step - loss: 0.1592 - accuracy:
0.5236 - val_loss: 0.1684 - val_accuracy: 0.5028
Epoch 44/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1595 - accuracy:
0.5181 - val_loss: 0.1556 - val_accuracy: 0.5311
Epoch 45/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1585 - accuracy:
0.5209 - val_loss: 0.1695 - val_accuracy: 0.4283
Epoch 46/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1597 - accuracy:
0.5135 - val_loss: 0.1703 - val_accuracy: 0.4166
Epoch 47/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1616 - accuracy:
0.5041 - val_loss: 0.1690 - val_accuracy: 0.4222
Epoch 48/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1595 - accuracy:
0.5156 - val_loss: 0.1686 - val_accuracy: 0.4437
Epoch 49/100
77/77 [==============================] - 0s 6ms/step - loss: 0.1584 - accuracy:
0.5222 - val_loss: 0.1654 - val_accuracy: 0.4615
Epoch 50/100
77/77 [==============================] - 0s 6ms/step - loss: 0.1593 - accuracy:
0.5113 - val_loss: 0.1614 - val_accuracy: 0.5200
```

```
Epoch 51/100
77/77 [==============================] - 0s 6ms/step - loss: 0.1567 - accuracy:
0.5195 - val_loss: 0.1802 - val_accuracy: 0.4597
Epoch 52/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1599 - accuracy:
0.5142 - val_loss: 0.1984 - val_accuracy: 0.4037
Epoch 53/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1603 - accuracy:
0.5096 - val_loss: 0.1634 - val_accuracy: 0.5083
Epoch 54/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1588 - accuracy:
0.5105 - val_loss: 0.1673 - val_accuracy: 0.4997
Epoch 55/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1582 - accuracy:
0.5154 - val_loss: 0.1553 - val_accuracy: 0.5397
Epoch 56/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1598 - accuracy:
0.5160 - val_loss: 0.1672 - val_accuracy: 0.5034
Epoch 57/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1593 - accuracy:
0.5181 - val_loss: 0.1557 - val_accuracy: 0.5323
Epoch 58/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1589 - accuracy:
0.5156 - val_loss: 0.1686 - val_accuracy: 0.4295
Epoch 59/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1576 - accuracy:
0.5142 - val_loss: 0.1605 - val_accuracy: 0.5225
Epoch 60/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1585 - accuracy:
0.5099 - val_loss: 0.1583 - val_accuracy: 0.5182
Epoch 61/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1570 - accuracy:
0.5203 - val_loss: 0.1555 - val_accuracy: 0.5262
Epoch 62/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1592 - accuracy:
0.5049 - val_loss: 0.1863 - val_accuracy: 0.4418
Epoch 63/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1580 - accuracy:
0.5150 - val_loss: 0.1596 - val_accuracy: 0.5286
Epoch 64/100
77/77 [==============================] - 0s 6ms/step - loss: 0.1583 - accuracy:
0.5160 - val_loss: 0.1528 - val_accuracy: 0.5391
Epoch 65/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1583 - accuracy:
0.5117 - val_loss: 0.1652 - val_accuracy: 0.4812
Epoch 66/100
77/77 [==============================] - 1s 8ms/step - loss: 0.1598 - accuracy:
0.5099 - val_loss: 0.1609 - val_accuracy: 0.4991
```

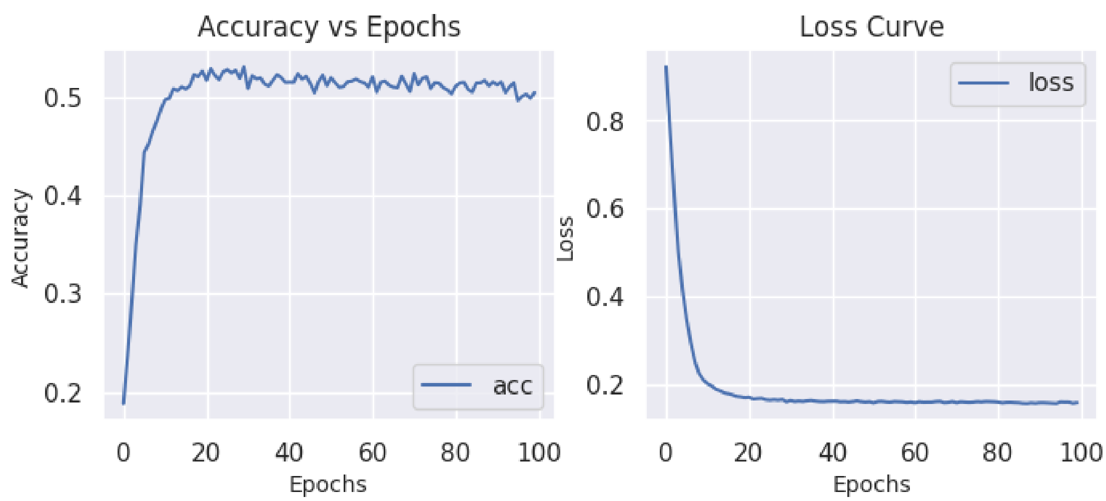
```
Epoch 67/100
77/77 [==============================] - 1s 8ms/step - loss: 0.1603 - accuracy:
0.5092 - val_loss: 0.1690 - val_accuracy: 0.3458
Epoch 68/100
77/77 [==============================] - 1s 8ms/step - loss: 0.1571 - accuracy:
0.5209 - val_loss: 0.1569 - val_accuracy: 0.5385
Epoch 69/100
77/77 [==============================] - 1s 9ms/step - loss: 0.1578 - accuracy:
0.5131 - val_loss: 0.1559 - val_accuracy: 0.5372
Epoch 70/100
77/77 [==============================] - 1s 7ms/step - loss: 0.1596 - accuracy:
0.5055 - val_loss: 0.1888 - val_accuracy: 0.4369
Epoch 71/100
77/77 [==============================] - 0s 6ms/step - loss: 0.1570 - accuracy:
0.5238 - val_loss: 0.1523 - val_accuracy: 0.5397
Epoch 72/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1591 - accuracy:
0.5123 - val_loss: 0.1531 - val_accuracy: 0.5446
Epoch 73/100
77/77 [==============================] - 0s 6ms/step - loss: 0.1584 - accuracy:
0.5189 - val_loss: 0.1554 - val_accuracy: 0.5194
Epoch 74/100
77/77 [==============================] - 0s 6ms/step - loss: 0.1577 - accuracy:
0.5203 - val_loss: 0.1684 - val_accuracy: 0.4985
Epoch 75/100
77/77 [==============================] - 0s 6ms/step - loss: 0.1583 - accuracy:
0.5084 - val_loss: 0.1600 - val_accuracy: 0.5132
Epoch 76/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1595 - accuracy:
0.5144 - val_loss: 0.1699 - val_accuracy: 0.4794
Epoch 77/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1588 - accuracy:
0.5140 - val_loss: 0.1576 - val_accuracy: 0.5372
Epoch 78/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1599 - accuracy:
0.5092 - val_loss: 0.1674 - val_accuracy: 0.4978
Epoch 79/100
77/77 [==============================] - 0s 6ms/step - loss: 0.1597 - accuracy:
0.5072 - val_loss: 0.1623 - val_accuracy: 0.5243
Epoch 80/100
77/77 [==============================] - 0s 6ms/step - loss: 0.1593 - accuracy:
0.5031 - val_loss: 0.1565 - val_accuracy: 0.5323
Epoch 81/100
77/77 [==============================] - 0s 6ms/step - loss: 0.1585 - accuracy:
0.5107 - val_loss: 0.1567 - val_accuracy: 0.5298
Epoch 82/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1567 - accuracy:
0.5142 - val_loss: 0.1645 - val_accuracy: 0.4862
```

```
Epoch 83/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1577 - accuracy:
0.5148 - val_loss: 0.1613 - val_accuracy: 0.4991
Epoch 84/100
77/77 [==============================] - 0s 6ms/step - loss: 0.1579 - accuracy:
0.5076 - val_loss: 0.1617 - val_accuracy: 0.4898
Epoch 85/100
77/77 [==============================] - 0s 6ms/step - loss: 0.1573 - accuracy:
0.5049 - val_loss: 0.1563 - val_accuracy: 0.5120
Epoch 86/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1570 - accuracy:
0.5142 - val_loss: 0.1548 - val_accuracy: 0.5274
Epoch 87/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1557 - accuracy:
0.5142 - val_loss: 0.1551 - val_accuracy: 0.5169
Epoch 88/100
77/77 [==============================] - 0s 6ms/step - loss: 0.1553 - accuracy:
0.5168 - val_loss: 0.1541 - val_accuracy: 0.5225
Epoch 89/100
77/77 [==============================] - 0s 6ms/step - loss: 0.1567 - accuracy:
0.5111 - val_loss: 0.1596 - val_accuracy: 0.5095
Epoch 90/100
77/77 [==============================] - 0s 6ms/step - loss: 0.1558 - accuracy:
0.5152 - val_loss: 0.1545 - val_accuracy: 0.5243
Epoch 91/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1570 - accuracy:
0.5121 - val_loss: 0.1540 - val_accuracy: 0.5231
Epoch 92/100
77/77 [==============================] - 0s 6ms/step - loss: 0.1570 - accuracy:
0.5152 - val_loss: 0.1529 - val_accuracy: 0.5243
Epoch 93/100
77/77 [==============================] - 0s 6ms/step - loss: 0.1565 - accuracy:
0.5043 - val_loss: 0.1610 - val_accuracy: 0.4985
Epoch 94/100
77/77 [==============================] - 1s 8ms/step - loss: 0.1560 - accuracy:
0.5101 - val_loss: 0.1516 - val_accuracy: 0.5323
Epoch 95/100
77/77 [==============================] - 1s 8ms/step - loss: 0.1553 - accuracy:
0.5144 - val_loss: 0.1631 - val_accuracy: 0.4948
Epoch 96/100
77/77 [==============================] - 1s 8ms/step - loss: 0.1588 - accuracy:
0.4963 - val_loss: 0.1639 - val_accuracy: 0.4874
Epoch 97/100
77/77 [==============================] - 1s 9ms/step - loss: 0.1584 - accuracy:
0.5006 - val_loss: 0.1587 - val_accuracy: 0.5286
Epoch 98/100
77/77 [==============================] - 0s 6ms/step - loss: 0.1585 - accuracy:
0.5027 - val_loss: 0.1567 - val_accuracy: 0.5120
```

```
Epoch 99/100
77/77 [==============================] - 0s 6ms/step - loss: 0.1558 - accuracy:
0.4986 - val_loss: 0.1739 - val_accuracy: 0.4695
Epoch 100/100
77/77 [==============================] - 0s 5ms/step - loss: 0.1572 - accuracy:
0.5043 - val_loss: 0.1520 - val_accuracy: 0.5311
```

[49]:

```
model_performance_graphs(history2, "accuracy")
```



[50]:

```
train2_acc = mod2.evaluate(x = X_train, y = Y_train)
print()
print ("Train Accuracy = " + str(train2_acc[1]))
print()
test2_acc = mod2.evaluate(x = X_test, y = Y_test)
print()
print ("Loss = " + str(test2_acc[0]))
print ("Test Accuracy = " + str(test2_acc[1]))
```

```
153/153 [==============================] - 0s 2ms/step - loss: 0.1566 -
accuracy: 0.5230

Train Accuracy = 0.522988498210907

51/51 [==============================] - 0s 3ms/step - loss: 0.1520 - accuracy:
0.5311

Loss = 0.15203529596328735
Test Accuracy = 0.5310769081115723
```

Unfortunately, the accuracy of our model reduced when utilizing dropout and batch normalization. When the network is small relative to the dataset, regularization is usually unnecessary. If the model capacity is already low, lowering it further by adding regularization will hurt performance. Additionally, there are some cases where Batch Normalization can actually hurt the performance of a neural network. For example, if the batch size is too small, Batch Normalization can introduce noise into the training process. Additionally, if the network is very deep, Batch Normalization can make it difficult for the network to learn long-range dependencies.

6 Conclusion

In conclusion, I first used a basic stochastic gradient descent algorithm with our wine data. We got an accuracy of nearly 85%. When I introduced dropout and batch normalization, I saw a decrease in our accuracy.

This is the best I could obtain without overfitting. The algorithm might perform better with a better distribution among the different scores. An other explanation might be that wine testing is strongly subjective.

Neural network models are a powerful tool for machine learning. They can be used to solve a wide variety of problems, including classification. However, neural network models can be difficult to train and can be prone to overfitting.

Overfitting is a phenomenon in machine learning where a model performs well on the training data but poorly on the test data. This happens when the model learns the noise in the training data instead of the underlying patterns. While there was a disparity in the accuracies of the two different models, there was little to no difference between the training and testing accuracies of each model.

Overall, neural network models are a powerful tool for machine learning. However, it is important to be aware of their limitations and to use them carefully.

6.0.1 References

- https://www.kaggle.com/code/ryanholbrook/a-single-neuron
- https://www.kaggle.com/code/davidzarebski/a-neural-net-for-red-wine-quality-estimation -https://www.kaggle.com/code/rprkh15/red-wine-quality-xgboost-optuna-neural-networks#Prediction-Using-Neural-Networks