SCDT64 – AI and Machine Learning

CW1: Practical and Presentation

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# Comparison of Selected Tools and Techniques

Python is the selected programming language for developing the machine learning algorithm and Flask application in. When comparing performance between Python and ML.NET, another popular tool used for machine learning classification, Torre (2019) states that ML.NET will usually provide better performance when running predictions with less time needing to be spent on optimising the code when deploying the machine learning models. Maryliya (2024) counters this by stating that the performance benefits ML.NET has over Python may not be significant enough to outweigh the benefits of using Python and in most cases will not lead to a significant difference in performance. This will be especially relevant in this instance, since the dataset is relatively small and therefore the time taken to perform the necessary stages of the CRISP-DM model on the data set will not result in a significant decrease in performance when using Python.

Scikit-learn will be the chosen tool for making data predictions and creating the model. Comparing the accuracy of Scikit-learn to ML.NET khan (2023) reveals that that they have a very similar accuracy rating with there only being a 1% difference in accuracy between them in ML.NET’s favour. Despite this Scikit-learn is easier to implement, with it being easer to install, import, and use. In addition to this, it can be used alongside other libraries specific to Python such as Numpy and Pandas, which will make preparing and working with the dataset much easier.

Flask will be the chosen tool to create the application for deploying the model. Flask is a Python library used to help design and create web applications. Flask is a lightweight framework designed with ease of use in mind and is therefore better suited to small, lightweight applications (Deery, 2022). When testing the performance ASP.NET Core, Express.JS, and Flask, Jonsson (2022) found that ASP.NET Core used the least amount of CPU, and memory usage while also performing the fastest. Flask however used the most CPU and memory usage, while also performing the slowest. Despite the slower performance, Flask will be suitable for this type of application due to its smaller scale, meaning it will not need as many resources.

# CRISP-DM Implementation

## Data Understanding

The selected dataset for this machine learning prediction program is the ‘wine’ dataset. This dataset includes various statistics about different types of wine. The objective of the created models is to accurately predict the ‘type’ of wine as displayed in the last column of the dataset.

The built in pandas functions ‘head’ and ‘info’ being used on the dataset to provide basic information about its features and structure, as is shown in Appendix A, Figure 1.

A chart of red and blue squares

Description automatically generated

Figure ii

Figure ii shows a created to show the correlation between the different characteristics of red wine. The code to create this graph can be found in Appendix A, Figure 2.

A screenshot of a chart

Description automatically generated

Figure iii

Figure iii shows a created to show the correlation between the different characteristics of white wine. The code to create this graph can be found in Appendix A, Figure 2.

A screenshot of a graph

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Figure iv

Figure iv show a pair plot created to show the correlation between different variables for both wine types. The code used to create this can be found in. The code used to create this graph can be found in Appendix A, Figure 3.

## Data Preparation

As shown in Appendix B, Figure 1, The data set has been cleaned by removing all any duplicated entries and removing any rows that contain null values. This will improve the accuracy and performance of the models by ensuring they are only using reliable and correct data.

Appendix B, Figure 2 displays code used to Prepare the data for the modelling process. This code separates the features and target variable, then splits them again into training and testing data, finally it normalises the data using a standard scalar.

## Data Modelling

For determining the type of wine using new data, three different types of classification models were developed and evaluated against each other. The chosen classification models are a k-nearest neighbors (KNN) model with the number of neighbors being set to 5, a logistic regression (LR) model, and a support vector machine (SVM) model.

The code used to create these models can be found in:

* Appendix C, Figure 1
* Appendix C, Figure 2
* Appendix C, Figure 3

## Data Evaluation

Evaluating the results of the KNN model as shown in Appendix D, Figure 1 reveals that the model has an accuracy rating of 99.25%. This can be seen in the confusion matrix which reveals that ‘red’ was correctly classified 288 with only 1 false negative, and white being correctly classified 768 times with only 7 false positives. The classification report reveals that the average F1-score for both ‘red’ and ‘white’ classes is 99%.

Evaluating the results of the LR classification model as shown in Appendix D, Figure 2 shows the model received a slightly higher accuracy rating of 99.53%. This model had one more false negative on the confusion matrix with 287 true positives and 2 false positives, however white was correctly classified more than KNN classification with it being correctly identified 772 times with only 3 false positives. The F1 score results for LR classification were 99% for red wine and 100% for white wine.

The SVM classification evaluation provided the overall best results out of all three models used. This model has an accuracy of 99.62%. The confusion matrix results listed only 2 false positive and 2 false negatives. The F1 score results listed were the same as the LR classification results with a 99% score for red wine and a 100% score for white wine. The results can be found in Appendix D, Figure 3.

Comparing the results of all three models revelals that the SVM model had the highest overall accuracy and F1-score. In addition to this, the confusion matrix revealed it had the lowest number of false negatives, and had only 1 false negative more than the KNN model, which had the lowest number of false negatives. As a result of these scores SVM will be the chosen model to be used in the Flask application.

## Deployment

A screenshot of a computer

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*Figure i*

Deployment was achieved through using two python libraries: Pickle and Flask. Pickle was used to export the selected model as a PKL file, which can then be used to make predictions with new data. A flask application was then created which will provide a form to the user which can be used to enter in new data. When clicking the submit button, the Flask application will use the exported model file to predict the type of wine using the data the user has entered, as shown in Figure i.

Code can be found in:

* Appendix E, Figure 1
* Appendix E, Figure 2
* Appendix E, Figure 3

# Tools and Techniques Evaluation

Python has a variety of advantages that make it suitable for machine learning. Python features many different libraries that make handling, transforming, and predicting data easy such as Scikit-learn, Pandas, Numpy, and more. Ryabtsev (2024) states that Python is a very flexible option for coding, with it being completely platform independent and allowing for developers to quickly create and run code without the need for it to be recompiled due to it being an interpreted language. Contrasting this, Limón (2022) states that Interpreted languages like Python typically have slower execution speeds when compared to other compiled languages, since they need to translate the source code at run time each time every time the code is executed.

Sci-kit Learn was used to perform the data modelling since there are many different advantages to using it. Sci-kit Learn has a wide array of supported model types for classification, regression, dimension reduction, and more, with extensive support and documentation for each of its supported models (Data Basecamp, 2022). In addition to this it is very easy to use and does not require much code in order to properly set up and create models.

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# CRISP-DM Evaluation

CRISP-DM is a tiered, industry standard, iterative model used for data mining and data analytics (Hotz, 2023). As a result of being iterative, the model will allow for continuous development, to ensure the final product meets all requirements and is ready to be deployed. CRISP-DM has a wide variety of benefits when used for machine learning projects such as its naturally easy to follow and implement design. Saltz (2021) states that due to the simple design of the model, data scientists will naturally tend to follow a process similar to CRISP-DM if not provided with management directions, making it easy to follow and implement into projects. Mithun (2021) contrasts this by stating that due to the model’s simplicity, it is missing key features that should be included with larger projects, such as including hypothesis farming between the modelling and data preparation phases in order to evaluate any ideas put forward by the client. Another benefit to using the CRISP-DM model is that it allows for a focus to be place on setting and understanding a clear set of business requirements which can improve the project outcomes, reduce risk and improve communication between stakeholders (Stefanovskyi, 2023). This will help the projects goals stay focused and on track as business is the first step taken on each iteration. Overall, CRISP-DM is a dependable model suitable for most machine learning projects due to its easy to follow, iterative nature.

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# Appendices

## Appendix A

### Figure 1

A screenshot of a computer

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### Figure 2

A screen shot of a computer program

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### Figure 3

A screen shot of a computer code

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### Figure 4

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## Appendix B

### Figure 1

A screen shot of a computer code

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### Figure 2

A computer screen shot of a program code

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## Appendix C

### Figure 1

A screenshot of a computer program

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### Figure 2

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### Figure 3

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## Appendix D

### Figure 1

A screenshot of a computer program

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### Figure 2

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### Figure 3

A screenshot of a computer program

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## Appendix E

### Figure 1

A black background with colorful text

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### Figure 2

A screen shot of a computer program

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### Figure 3

A screen shot of a computer program

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