An Attempt to Use Machine Learning to Classify Novice and Expert Developers

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Declaration of Originality

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Abstract

This project aims to distinguish novice and expert developers using machine learning. This is important and beneficial in different cases, such as higher education institutions providing computer science courses, companies hiring developers or developers hoping to evaluate their experience level. In the first part of the project, a variety of different models were trained with different data gathered from novice and expert, to identify the best model and data combination for this purpose. The final model is able to achieve a 69.0% accuracy. Features extraction mainly focused on static code analysis. In the later part, two application prototypes were developed using the stated model for two different use case scenarios which require experience classification of developers.

A repository containing all data collected, source code of scripts and applications developed for this project can be found at: https://gabrielchl.dev/2021-thesis-repo

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Chapter 1

Introduction

Code stylometry is a type of stylometry for binary or source code. It is the study of program authorship or related analysis through feature identification in code. This has numerous benefits, such as giving us the ability to identify possible code plagiarism and to identify the source of malicious software. Many research studies have been conducted in this field, with at least 57 publications published between 1957 and 2020 related to this topic (Kalgutkar et al., 2019).

The vast majority of the research mentioned above focuses on attributing the author of a piece of code, very few research studies were done to classify properties of the author of pieces of code, such as the author's level of experience in coding. Thus, the main aim of this project is to explore the approach of using machine learning with code stylometry for such classification problem. While a successful project, that is to be able to obtain a highly accurate model for the problem, is not guaranteed, this project aims to offer valuable insight and data from using the techniques mentioned above.

1.1 Project Importance

The ability to classify developers as novice or expert could bring positive impact in a vast amount of scenarios, as we explore below.

For individual developers, knowing their skill level compared to their peers is a very useful tool in their learning progress. Such self-awareness helps individuals to know where they are standing on the path to being an expert in the computer science field. In Loksa D. et al. (2016)'s study, they studied the impact of several teaching techniques on students learning to code. Results show that the four techniques, one of them being prompting those students to reflect on the problem solving strategies they have used, results in increased productivity, self-efficacy and brings positive impact to the students' growth mindset. Patricia S. (2014)'s article states that without self-awareness, we could not accurately identify our strengths and weaknesses, which is very important in the lifelong learning process.

For higher education institutions, this ability is the key to providing an accurately-tailored educational experience for students with a wide range of skill levels in programming. There has been a lot of research on different education techniques, that all require the classification of stronger and weaker students. Agrawal et al. (2014)'s study shows that grouping strong students with weaker students could maximize the number of students doing better. Lui et al. (2014)'s study shows that using a "Perform" teaching approach would help weak students achieve better performance. Their research targeted weak programmer students in their first programming course, by isolating weak students and "shielding" them from certain "hazards" under the Perform teaching approach, they were more able to write simple programs, achieve higher performance in the examination and improve confidence in programming. These researches highlight the importance of the ability to classify students by their strength. With the model that this project develops, teachers and professors will be able to quickly do so.

For companies hiring programmers, it is proven that companies are very likely to exclude exceptional candidates if students' GPA was used to pre-screen or filter the candidates (Clark et al., 2003). The ability to distinguish experienced developers to novices allows them to gain insight into any candidates quickly and accurately, improving their hiring process. A minor benefit of such ability is to help identify fraudulent applications. According to a survey of 1000 UK citizens, 38% have lied at least once on their CV, with 24% doing so regularly (Job Today, 2017). Employing candidates who exaggerate or falsify certain information on their CV could cost the company both monetary and legally (Babcock, 2003). With the ability to determine if a developer is a novice or expert, this could help companies identify inconsistency between candidates' real experience and what is stated on their job application.

1.2 Project Overview

This project is designed to be separated into two distinct parts, model training and application development, with the model training part given a higher priority.

For the model training part, a mathematical model was developed using data from novice and expert developers. These data were crawled from HackerRank, a competitive programming or programming interview preparation site. Different configurations to fetch such data and features to extract were experimented to optimize the model accuracy. The final model is able to achieve a 68% accuracy.

For the application development part, two applications were developed, one as a website application and the other as a desktop application. These two applications were developed as a prototype, to demonstrate possible uses of the model trained in the first part of the project. The website application was designed for individual developer's use, while the desktop application was designed for corporate or institution's use.

1.3 Project Aims

The overall target of this project is to explore the possibility and if so, to contribute data to establish code author attributes through the use of machine learning models. The project can be broken down into the following list of objectives.

1. Determine if it is possible to classify developers' experience level using features from their code
2. Determine what features would be helpful for the model
3. Determine what model would help achieve better classification accuracy
4. Develop one or more prototype applications to demonstrate possible uses of such model

1.4 Report Overview

The rest of the report is broken down into the following various sections.

In Chapter 2 "Background Research", previous research into code stylometry, machine learning, developers' coding experience and application design and development is introduced and summarized. Useful information that helps this project is highlighted from those research.

In Chapter 3 "Machine Learning Model", the data source, features extracted, the model used and analysis of the final trained model is introduced. Different experiments on these factors, and certain decisions made throughout the process of attempting to obtain a good model as defined in the project aims are discussed.

In Chapter 4 “Prototype Application”, the two developed prototype applications are introduced. Design decisions, detailed implementation methods are discussed, as are the user’s evaluation results and discussion around potential advantages and disadvantages of such applications.

Last but not the least, in Chapter 5 “Discussions and Conclusion”, the list of project aims are reviewed. Limitations of this project, possible future works and final remarks are included.

Chapter 2

Background

2.1 Code Stylometry

Stylometry is the study of the style of a piece of text or art. Where, as a member of the stylometry family, code stylometry focuses on a piece of code. Code stylometry is used for software forensics, which is the determination of if intellectual property rights were infringed, plagiarism detection, authorship attribution, which is the identification of the author and is what most research on code stylometry focuses on, and authorship analysis, which is the analysis of certain properties of the author.

Code stylometry has been applied to a huge range of different code, including different programming languages, both in source code format or binary code. In most cases, to study the style of a piece of code, certain features in the code would be analysed. This is similar to using text features in linguistic stylometry, or linguistic forensics, techniques, such as the number of words, number of different words, vocabulary richness, grammar mistakes, et cetera (Guillen-Nieto et al., 2008). A lot of research has been conducted to explore the application of linguistic features and features specific to programming languages or binary code on code stylometry.

Halstead (1977) proposed a set of metrics to evaluate a piece of code. Instead of using metrics that depend on or could be affected by the machine it is run on, he proposed a set of features, later called Halstead Metrics, that measures the complexity of the code, which is heavily affected by the algorithms used in the code. As one of the earliest sets of metrics proposed to objectively evaluate code, it has been widely used to analyze code for various uses. In one case, it was one of the sets of metrics found to have strong correlations with computer programming courses' students' performance (Castellanos et al., 2017). Halstead's metrics was also found suitable to use for software defect prediction (Mori and Uchihira, 2018).

In one of the earlier papers on code authorship attribution, Oman and Cook (1989) used a set of metrics inspired by the techniques used for English literature authorship analysis. The set of 16 code characteristics used are as below, where the names of the characteristics are directly from Oman and Cook and the grouping of the characteristics is similar to that of their findings after the protocols studies:

- Comments
  - Inline comments on the same line as source code
  - Blocked comments (two or more comments occurring together)
  - Bordered comments (set off by repetitive characters)
  - Keywords followed by comments
- Indentation
  - 1 or 2 space indentation most frequently occurring
  - 3 or 4 space indentation most frequently occurring
  - 5 or greater indentation most frequently occurring
- Letter case
  - Lower case characters only (all source code)
  - Upper case characters only (all source code)
- Identifiers
  - Case used to distinguish between keywords and identifiers
  - Underscore used in identifiers
- Statements
  - BEGIN followed by a statement on the same line
  - THEN followed by a statement on the same line
  - Multiple statements per line
- Blank lines
  - Blank lines in the declaration area
  - Blank lines in the program body

Each of the metrics would give a boolean value. The authors then got 3 PASCAL code snippets, bubble sort, quick sort and tree traversal solutions, from each of the 6 computer science textbooks by different authors. Applying cluster analysis on the metric of code snippet to the 16 boolean values, the authors found 4 of the author's codes showing a perfect or very high connection level. They then repeated the same procedure on 3 companies' code, each split into 6 modules, and found 2 of them clustering together perfectly, while for the third company, the modules shared a lower level of similarity, but 5 of the 6 modules were still clustered correctly.

Criticizing that prior studies, including that by Oman and Cook, were "limited in scope and focus, Spafford and Weeber (1993) discussed the difficulties and approaches to analyzing code left in a computer system by a hacker to establish his or her identity. They proposed a longer list of possible types of features to be analyzed for source code or binary code files, where those feature types focusing on source code analysis includes:

- Language (The programming language used)
- Formatting (Number of statements per line, type and function declarator formatting, et cetera)
- Special features (Such as code specific for certain compilers to read)
- Comments (Consistency, frequency and length)
- Variable names (Variable name formatting, naming styles of local temporary variables)
- Language features (Usage of for loops versus while loops, data types, size of modules, et cetera)
- Scoping (Global versus local identifiers, scope of helper functions)
- Errors
- Other metrics (Halstead metrics, McCabe metrics, et cetera)

Another type of features that were explored were n-grams. Burrows and Tahaghoghi (2007) explored the use of n-grams for code authorship analysis. Firstly, with 10 authors and 16 C code files, they found 6-gram to be the best performer in 1 to 90-grams, having a 77.77% accuracy. Next, they investigated the effect of increasing the code source pool to accuracy. With 1640 files from 100 authors, they maintained a 67.01% accuracy. A more recent study also utilising n-grams by Wisse and Veenman (2015) combined 10 traditional structural, style and layout features with 4 different n-gram metrics to reach a 91.4% accuracy with 10 authors and 85% accuracy with 45 authors. In their study, using JavaScript repositories on GitHub, they also compared the accuracy with the same set of metrics but without the 4 n-grams metrics and results seems to indicate the addition of the n-gram metrics does lead to a distinct improvement, especially when the number of training samples is low.

Bhattathiripad (2012) proposes a different type of metrics, programming blunders, to be used to evaluate code. Pointing out that most explored code features focus on the general coding styles or algorithmic choices of the whole piece of code, Bhattathiripad explores the usage of programming blunders to identify code authorship. Examples of programming blunders include unused variables, unused imported libraries, or a section of code that never gets executed. He then proposes the incorporation of such metrics into the US judiciary official software copyright infringement investigation procedure.

With all the different techniques to extract different information and to use different methods to use such information to establish the code author's identity, there is one flaw, which is the possibility of one imitating another code style to confuse any efforts of code stylometry. Simko et al. (2018) recognizes this issue and observed C and C++ developers obfusticate their own coding styles and the impact on existing machine classifiers and human analysts. Results show that when against machine classifiers, for 80% of the "attacks", the developers successfully confused the classifiers. When against human analysts, the author identification accuracy dropped from 92.7% to 76.2%. Analyzing the changes those programmers made to confuse machine classifiers, the team pointed out that instead of focusing on local implementation details, such as variable naming styles which could be easily changed, focusing on the algorithmic decisions related metrics, such as complex abstract syntax tree features, would help defend against such attacks.

2.2 Code Stylometry with Machine Learning

While about half of the mentioned research studies in Section 2.1 were only discussions and proposals of techniques, mainly on feature extraction, for code stylometry, the other half applied those techniques with machine learning models on different datasets to perform code author attribution or analysis.

2.2.1 Datasets

There are 3 main types of dataset source used in recent papers.

Private code sources from individuals, organizations or companies. This is usually used when the researches require a very specific type of code or developer. Such as in the case of Hayes and Offutt's (2010) study, the team wanted to investigate whether developers are always consistent in their coding styles or if they get more consistent as they grow in experience and competency. For this purpose, they had to collect code from very specific groups of developers, 15 graduate students and 5 experienced developers.

Publicly available code repositories on websites such as SourceForge and GitHub. These sources are mostly suitable when a huge number of data is needed as it takes a lot less time than recruiting participants to write or submit code.

Published pieces of code from websites such as Google Code Jam. Google Code Jam is an annual online coding competition where competitors compete to solve programming tasks. (Google Code Jam, 2021) Similar to code repositories on websites, code from these types of websites are usually shorter. Where code repositories usually contain code written for an entire program, these sites provide relatively short scripts. It is also very commonly used in code stylometry related researches (Caliskan-Islam et al., 2015) (Alsulami et al., 2017) (Simko et al., 2018).

2.2.2 Classifiers

Over all the research, a very wide range of machine learning or classifying techniques have been employed.

As mentioned, Oman and Cook (1989) extracted a matrix of boolean values from the code files. They Used SPSS-X cluster analysis to measure the similarity between files to cluster them together and create groups of similar files, from the same author or company.

Zhang et al. (2017) performed code authorship attribution on a very large scale, in one test, with 8000 Java programs from 8 developers, using the sequential minimal optimization algorithm, originally proposed by Platt (1998), to lower the training time required when using support vector machine models. The sequential minimal optimization algorithm is widely used in the community, given its popularity due to the advantages it offers.

Shevertalov et al. (2009) analyzed 60 Java projects by 20 developers, 3 projects from each developer, but with only 4 features extracted: number of leading spaces, number of leading tabs, number of words on each line and the length of each line. They used the nearest neighbour classification method and achieved a 54.3% and a 75.0% accuracy on identifying the developers of files and projects respectively. Their study focuses on using genetic algorithm to perform data discretization on the features extracted. The team extracted the four features in the form of a histogram, using genetic algorithm, they identified ideal breakpoints for each column in the histogram, which quite significantly improved the accuracy of the nearest neighbour model. Without data discretization, the accuracy was at 46.1% and 65% on the files and projects respectively, around a 10

Krsul and Spafford (1997) performed a comparison between different machine learning models on identifying the authors of 88 C programs by 29 students. The team extracted 49 features including number of lines, average function parameter length, percentage of lines with inline comments, usage of comment highlighting with borders, et cetera. They then evaluated the performance of multilayer perceptron neural network, gaussian classifier, learning vector qualifier (nearest neighbour), histogram and binary tree classifier. The team was able to reach a 98% accuracy with neural network and 100% with Gaussian classifier. This study also revealed the value of normalization with linear discriminant analysis, which helped improve the accuracy by 26% for the neural network model and 25% for the Gaussian classifier model.

2.3 Experience Classification

As different individual developers would have different coding styles, the differences in people with different levels of coding experience were also the subject of research papers. These differences could help identify useful features to classify authors of code as a novice or expert.

Wiedenbeck (1985) studied the differences in novice and expert's programming skills. She measured the accuracy and reaction time of the 2 groups of programmers in two experiments, first when asked to determine if a line of code is syntactically correct or contained an error, and second when asked to determine if a description of a piece of code is accurate. Results from the experiments showed that while the accuracy of novice developers was only 5 - 6% lower than that of the experts, the experts had a much quicker reaction time.

Counsell et al. (2006) investigated the difference in novice and expert developer's definition of software cohesion in object-oriented C++ classes. The results show that, while determining the cohesiveness of classes, novice developers are more affected by the number of methods in a class and expert developers are more affected by how well-documented those classes were. This could hint at a different priority in code evaluation, and possibly in writing code.

Chapter 3

Machine Learning Model

In this chapter, different processes leading to the creation of the final machine learning model will be discussed. Results and decisions made in key experiments during this process will be reviewed as well.

There is one core principle considered when making any decisions in this part, which is to keep things simple. Given the time, experience and resource limitation, it was decided that the target is to create a simple but working, defined as achieving an accuracy higher than 50%, model. An example of such principal affecting decisions is when it was being considered whether developers should be categorized into more than 2 categories, novice and expert. With the principle in mind, it was decided to use binary classification, instead of multiple categories or a regression output, to “keep things simple”.

For this project, it was decided that a machine learning model would be developed to predict whether a developer is a novice or expert by analyzing a piece of the developer's program's source code.

3.1 Data Collection

To train a machine learning model, data collection is one of the most important steps in the process of developing the model. “Garbage in, garbage out”, this concept is also true for machine learning (Jha et al., 2019), thus this part was carefully planned and carried out.

For this project, there are several criteria for the dataset to be used. Firstly, it should contain code samples from two distinguishable types of developers, novice or experts. Secondly, all code samples should have a certain level of differences, to cover more different developer coding styles. Thirdly, for each type of developer, the number of samples should be reasonable for being used for training a machine learning model. Finally, each code sample should be a one-file script, as to keep the project simple, it was decided not to use entire code repositories or multiple-file programs as the unit of an entry.

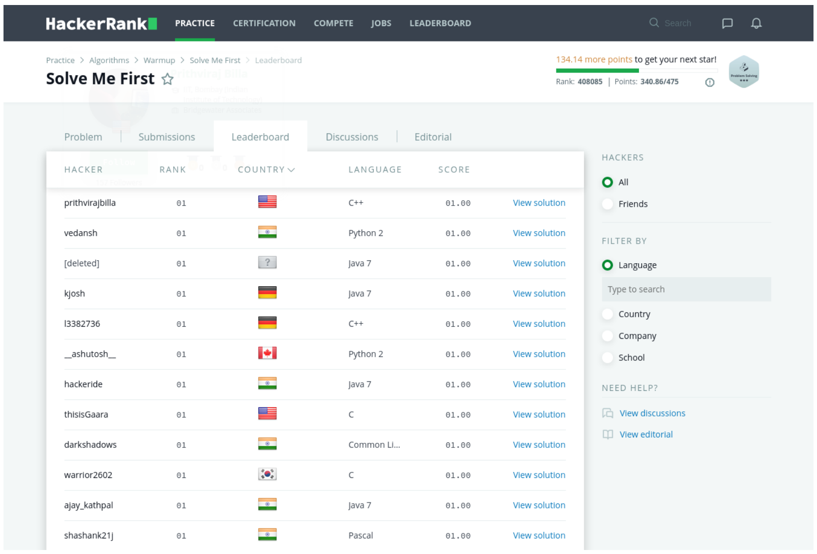
Multiple research studies in the past have constructed a dataset for their machine learning model to train on, some of which published their dataset along with their study results. However, as most of such datasets are not focused on differentiating developer experience, they do not contain such classification data, and therefore could not be used for this project. As a result, it was decided to construct a new set of data for the project.

3.1.1 Source of Data

As mentioned in the background section of this report, there are 3 main types of data source, private code sources, code repositories or published code from coding events or competitions. As the project requires a significant amount of data, with limited time available, the first option, private code sources which require lengthy communication and code collection process from participants, is not viable. Hoping to get single-file scripts instead of entire code repositories, coding events or competitions was chosen as the source of data.

There are multiple coding events or competitions that publish participants' code. While Google Code Jam is a very popular source in related research, it is not suitable to be used in this project as only the username of the participant is available to the public. With the username as the only information from the participant, it is impossible to establish the level of coding experience of that person.

HackerRank is chosen as the data source for this project after evaluations of the website show that its data satisfies the criteria laid and is suitable for this project. HackerRank is a company that provides developer hiring solutions to technology companies by using their coding test systems (HackerRank, 2021). Their website provides coding test practice questions, with over 1 million developers using the website in 2015. The platform has a list of common software engineer interview coding questions, where developers would attempt to solve them and get automated score feedback by running their code and comparing the results to the correct answers. All submitted code is visible to the public, along with the developer's profile, where some would make use of a feature provided by the website to show a link to their LinkedIn profile. Figure 1 shows a screenshot of the leaderboard of a coding question on the site, allowing access to the users' profile, shown in Figure 2, to get their LinkedIn profile. With this feature, it is possible to determine if one is a novice or expert developer using the information found on their LinkedIn profile.



Solve Me First ☆

134.14 more points to get your next star!
Rank: 408085 | Points: 340.86/475

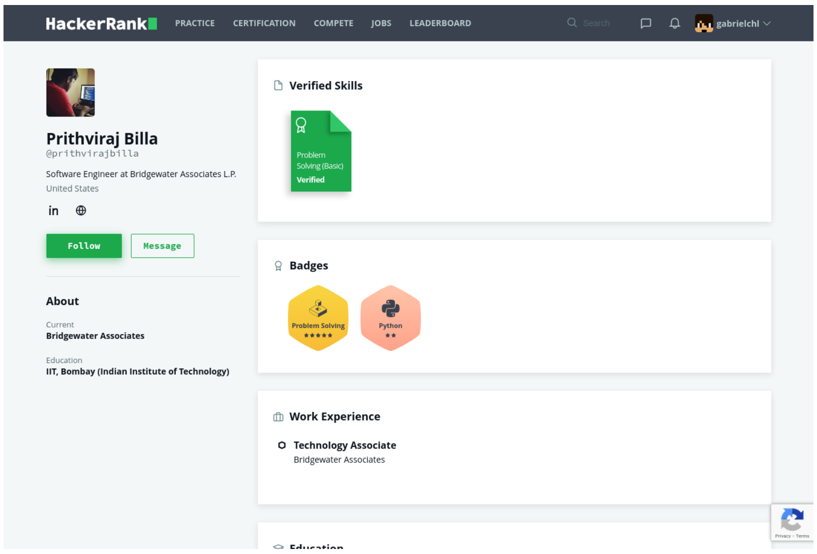
HACKER	RANK	COUNTRY	LANGUAGE	SCORE	
prithvirajbilla	01	🇺🇸	C++	01.00	View solution
vedansh	01	🇮🇳	Python 2	01.00	View solution
[deleted]	01	?	Java 7	01.00	View solution
kjosh	01	🇩🇪	Java 7	01.00	View solution
l3382736	01	🇩🇪	C++	01.00	View solution
__ashutosh__	01	🇨🇦	Python 2	01.00	View solution
hackeride	01	🇮🇳	Java 7	01.00	View solution
thisisGaara	01	🇺🇸	C	01.00	View solution
darkshadows	01	🇮🇳	Common Li...	01.00	View solution
warrior2602	01	🇰🇷	C	01.00	View solution
ajay_kathpal	01	🇮🇳	Java 7	01.00	View solution
shashank21j	01	🇮🇳	Pascal	01.00	View solution

HACKERS
[✓ All] Friends

FILTER BY
[✓ Language] Type to search
Country
Company
School

NEED HELP?
View discussions
View editorial

Figure 3.1: Screenshot of a leaderboard page on HackerRank



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About
Current
Bridgewater Associates
Education
IIT, Bombay (Indian Institute of Technology)

Verified Skills

Badges

Work Experience
Technology Associate
Bridgewater Associates

Education

Figure 3.2: Screenshot of a developer's profile on HackerRank

Internal discussions were made on whether using code repositories or HackerRank would be more suitable for this project. Code repositories tend to include more practical code as used in "real life" scenarios, while HackerRank's code would be more precise and uniform. Using HackerRank's code, the final model would perform better against competitive programming tasks, but not against general code. Eventually, it was decided that instead of having a generalized but less accurate model, it was more desirable to have a more specific and more accurate model. And therefore HackerRank was selected.

3.1.2 Data Extraction

As a lot of different experiments were carried out for this project, the exact method used for data extraction from HackerRank may differ between some experiments. In this section, the general method would be described, while certain special cases would be mentioned in relevant sections.

Firstly, one or more coding questions would be selected, which will be the source of users' solution collection. There are 3 main criteria for choosing a question. Firstly, the question should have a reasonable amount of solution submissions, allowing enough instances for the dataset. Secondly, the solutions should show that the question is solvable using different approaches, this helps increase the variety in the features extracted, improving the model's performance, as proved by Therrien and Doyle (2018). Finally, the question should not be too complicated to be solved by a novice. This is to prevent only collecting experts' solutions, causing insufficient novice data or an imbalance in the data. This criterion is ensured by using the website's question difficulty indicator as a reference. Questions marked as “hard” would not be selected.

The next step is to collect the code solutions. As mentioned, from the question's leaderboard page, it is possible to look up all solutions and their solver. There are a few criteria for the selection of solutions. Firstly, all solutions should be of the same programming language. The site allows submission in a wide range of languages, to produce a simple and precise model, all code samples should be of the same language. For this project, Java was chosen as it is one of the most used languages on the site in terms of the number of submissions using Java. Secondly, all solutions should be using the same code template. When a user starts working on a coding problem, the site would provide a code template, so that the user could focus on the solution instead of the redundant tasks that are the same for each question, such as accepting input from standard input. However, HackerRank occasionally updates those templates, causing fundamental differences in the solutions. For this project, it is decided to filter solutions by only using those with the latest template. Thirdly, only solutions which author's account is linked to his or her LinkedIn account. Fourthly, the solution should appear as a completed solution, instead of a work in progress or test solution. Finally, the information stated in the LinkedIn profile should satisfy requirements for data labelling, which will be discussed in the next section, data labelling.

For the first few experiments, all solutions were inspected, checking that the solution satisfies the above criteria and that for data labelling, and added to the dataset manually. This was done to ensure a better understanding of those code, which led to some changes to the initial list of the criteria set for the code samples. For later experiments, the solution selection part was automated, with human assistance required to determine if the developer's LinkedIn profile satisfies the last criteria stated above.

The solution selection automation part was not simple as HackerRank does not provide any publicly available APIs for such uses. The website also has some measures employed to prevent certain bots to traverse the site. To avoid spending much time to offset those measures, instead of writing a script to act as a browser traversing the site, it was opted to make use of browser userscripts. A browser userscript was written using the Violentmonkey plugin for Mozilla firefox (Violentmonkey, 2021). The script goes through the leaderboard and produces a list of users whose solution satisfies the first 4 criteria for the solutions to be selected. The list is then manually inspected, removing entries that do not satisfy the fifth criterion, producing a final list of users whose solution satisfies all criteria.

3.1.3 Data Labelling

Except for certain experiments where the definition of novice and expert was experimented on, which will be covered at the end of this subsection, all experiments share the same definition. The main principle is that whether one does or does not have work experience in development work defines if he or she is a novice or expert.

Before labelling the data, one final check of the validity of the LinkedIn profile was carried out. Profiles with insufficient information, such as the lack of education history or a number of years not accounted for after graduation from a degree, was removed. This prevents mislabelling data due to a lack of information or profiles being not up to date. Any profiles that the experience level could not be determined with confidence was also removed.

For one to be classified as a novice developer, he or she should not have any work experience, including internships or part-time jobs. The user should be studying towards or have graduated from a programming-related degree. For one to be classified as an expert developer, he or she should have any amount of full-time work experience, working at a programming-related position.

Note that experiment 2 is an exception to the above novice and expert definition. In experiment 2, the definition for an expert is if one has at least 6 months of experience on a full-time job, while that for novice developer is if one wrote the piece of code at least 6 months before his or her first job or internship. At the end of the experiment, it was decided to not use this set of definitions as it does not seem to bring significant advantages to the accuracy of the model but increases the time needed to prepare the dataset.

3.2 Features Extraction

3.2.1 Features

Before discussing the final list of features, certain experiments ran to test different combinations of such features shall be mentioned. The very first list of 12 features, being very similar to the final list, included: 1) number of lines 2) number of empty lines 3) number of line comments 4) number of block comments 5) number of JavaDoc comments 6) number of variables 7) average variable length 8 - 12) number of if, for, do, while and cast statements. Key experiments that impacted the final list of features will be discussed in Section 3.4.

A final set of 14 features, as listed in Table 3.1, were selected to be extracted from the code samples to be used in the final experiment. These features can be divided into 2 groups, algorithmic and styling features. Algorithmic features, such as the number of if statements in the code sample, are features that are affected by the author's approach to the coding question. These features could hint at some of the algorithmic decisions the author made. For example, a developer might prefer to use for loops over while loops, or define many variables instead of calculating the values inline. Styling features, such as whether left curly brackets start at a new line or remain on the same line, are features that are not affected by the author's approach to the coding question. These features are selected being some of the most distinguishable differences in developers' coding style.

Figure 3.3 shows the relationship between the features extracted from the final dataset and their labels, allowing some basic preliminary analysis of the dataset and, possibly, predict the model's performance. According to the figure, it is obvious that most features do not have a very distinguishable correlation with the classification. For features such as the average length of lines and the number of variables, it could be seen that their distribution is very similar for both classifications, and therefore it could be predicted that these features would have minimal impact on the model. Meanwhile, although not very apparent, the opposite could be said about features such as the number of if statements and the ratio of bracket without to with a space before it. These features show visible differences across the 2 classifications and it could be derived that these

Feature	Theoretical Range	Range in Final Dataset	Group	Type
Number of lines	ℤ+	[20; 52]	Algorithmic	Lexical
Number of empty lines	ℤ+	[3; 22]	Styling	Lexical
Average length of lines	ℝ+	[13.976; 29.758]	Styling	Lexical
Number of variables	ℤ+	[1; 11]	Algorithmic	Lexical
Average length of variables	ℝ+	[1; 9.6]	Algorithmic	Lexical
Number of if statements	ℤ+	[0; 3]	Algorithmic	Lexical
Number of for statements	ℤ+	[0; 6]	Algorithmic	Lexical
Number of do statements	ℤ+	[0; 0]	Algorithmic	Lexical
Number of while statements	ℤ+	[0; 2]	Algorithmic	Lexical
Number of switch statements	ℤ+	[0; 0]	Algorithmic	Lexical
Ratio of bracket without to with a space before it	[0; 1]	[0; 1]	Styling	Semantic
Ratio of curly bracket starting in same line to new line	[0; 1]	[0; 1]	Styling	Semantic
Number of spaces (excluding those for indentation)	ℤ+	[17; 205]	Styling	Semantic
Complexity	ℤ+	[1; 9]	Algorithmic	Lexical

Table 3.1: Features used in the final experiment. ℤ+ represents any positive integers and ℝ+ represents any positive real numbers

features might deal a more significant impact on the model.

3.2.2 Features Extraction

The list of features is extracted from the code samples with a script. Over the course of the development of the project, 2 features extractors were developed, the first one in Java and the latter one in Python. Both features extractors would read novice and expert files stored in a local folder and extract a list of features to print in the document

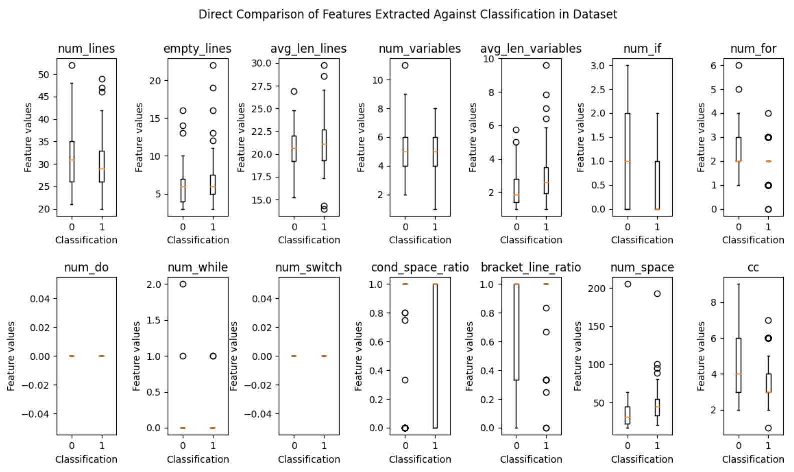


Figure 3.3: Direct comparison of features extracted against classification in the final dataset

or in memory for another component's usage.

The original features extractor, developed in Java with the JavaParser library (JavaParser, 2021), was used in all experiments. JavaParser is a Java code parser and abstract syntax tree (AST) generator. Using JavaParser, the Java code file is broken down into tokens in the AST, allowing filtering of the types of tokens to achieve counting of the number of tokens of a type, fetching a list of token's text of a type, et cetera. The feature extractor starts by reading all files in a folder, then checks each filename against a given list of novice or expert usernames to check if the file was created by a novice or expert for data labelling in the dataset. Then all features would be extracted from the code and the results, along with the data label would be printed in the terminal output in a CSV format. The dataset in CSV file format could then be passed to the training program.

In later stages of the project, a highly similar features extractor was developed, using Python 3 this time. This was due to a decision made to transform the entire project's code to be in the same programming language to make its use for the website application, which is developed in Python as well, simpler. The Python version uses the javalang library (Thunes, 2021), which provides functionalities that are very close to its Java counterpart. For the Python version, instead of printing the result in CSV format in the terminal, it was made as a Python module, which would take in a filename, read its content and return the results as an array, to allow better integration with other components of the system, mainly the training part.

Below are 2 snippets of code demonstrating the extraction of a feature, number of if statements, implemented in both Java and Python feature extractors.

Java:

```
public static void main(String[] args) {
    CompilationUnit cu = StaticJavaParser.parse(file);
    VoidVisitor<?> ifHandler = new IfHandler();
    ifHandler.visit(cu, null);
    System.out.println(((IfHandler) ifHandler).counter);
}

private static class IfHandler extends VoidVisitorAdapter<Void> {
    public int counter = 0;

    @Override
    public void visit(IfStmt n, Void arg) {
        super.visit(n, arg);
        counter++;
    }
}
```

Python:

```
tree = javalang.parse.parse(file)
num_if = len(list(tree.filter(javalang.tree.IfStatement)))
```

3.3 Training

A list of machine learning models, listed in Table 3.2, were selected to be trained and tested for all experiments. The list consists of 10 models from a wide range of different types of models, such as linear models, neural networks and decision trees. This was done to identify the best model in experiments as well as which models generally do better with the dataset.

The model training part is done by a Python script using the scikit-learn library, a set of code developed to assist machine learning operations in Python. Taking the dataset as input, the developed code would train and evaluate the model with 10 splits k-fold cross-validation, where the script would then return the average and standard deviation of the accuracy values obtained from the training of each model.

Initial Used	Full Name	Model Type
LR	Logistic Regression	Linear
LDA	Linear Discriminant Analysis	Discriminant Analysis
KNN	K-neighbours	Neighbours
CART	Decision Tree	Tree
NB	Gaussian Naive Bayes	Naive Bayes
SVM Lin	Support Vector Classification (with linear kernel)	Support Vector Classification
SVM Pol	Support Vector Classification (with polynomial kernel)	Support Vector Classification
SVM / SVM RBF	Support Vector Classification (with radial basis function kernel)	Support Vector Classification
MLP	Multi-layer Perceptron	Neural Network
RF	Random Forest	Ensemble

Table 3.2: Models used in experiments

3.4 Results

In this section, certain important experiments will be discussed, as well as the final model. Model accuracies are calculated as the mean of the results of the 10 split k-fold results unless elsewhere specified.

3.4.1 First Experiment (Experiment 1)

As the first-ever experiment conducted for this project, experiment 1, this experiment was conducted with the aim of setting the basis and expectations for the project. With the 12 initial features, the dataset consists of 27 rows, from 9 authors, where 5 were experts and 4 were novice developers, each contributing 3 files to the dataset. The best model in this experiment, logistic regression, achieved a 70.0% mean-accuracy, while others achieved roughly 60% mean-accuracy. However, it was noticed that the mean-accuracy results sounded positive for the first experiment, the range of accuracies were very wide. The standard deviation of the logistic regression model's accuracies was 0.314, showing huge fluctuations between each run. It was concluded that the size of the dataset was too small, causing unreliable results, prompting the need for larger datasets in future experiments. The resulting model accuracy can be found in Figure 3.4.

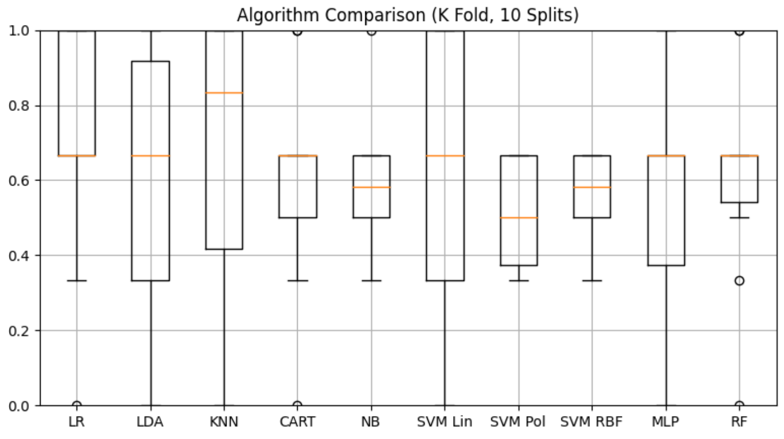


Figure 3.4: Comparison of the accuracy performance of all models in experiment 1

3.4.2 Code Complexity Feature and Removal of General Code (Experiment 16 to 19)

Experiments 16 to 19 experimented on 2 changes, the addition of the complexity feature and removal of general code from the code samples. All 4 experiments were conducted using the same set of 266 code samples, with multiple samples from 26 developers. 115 samples were from novice developers, while 151 were from experts. The differences between the 4 experiments are shown in Table 3.3 while results are included in Table 3.4.

	With Complexity	Without Complexity
With General Code	Experiment 18	Experiment 16
Without General Code	Experiment 19	Experiment 17

Table 3.3: Differences in the settings between experiment 16 to 19

The complexity metric implemented in this set of experiments is a simplified version of the cyclomatic complexity, being the sum of the number of if, for, do, while and switch statements in the file. For the removal of general code, in each code samples, there is a part that is identical in each file, such as the part where it prints the function result out to standard output, these parts are provided by HackerRank in their code template. In experiment 17 and 19, these parts are removed.

Comparing the 4 best models in experiment 18 to 16 and 19 to 17, it could be concluded that the complexity feature did not add value to the model. In experiments 18 and 16, both with general code, the addition of the complexity feature increased the accuracy by 0.22%. While in experiments 19 and 17, both without general code, the feature's

	Experiment Number				
Model	16	17	18	19	Average
LR	0.674675	0.707792	0.684848	0.707792	0.693777
LDA	0.688961	0.683766	0.694156	0.679004	0.686472
KNN	0.534199	0.655411	0.566883	0.674242	0.607684
CART	0.595887	0.616883	0.586580	0.650866	0.612554
NB	0.452814	0.575541	0.457576	0.585065	0.517749
SVM	0.595455	0.669481	0.604545	0.669264	0.634686
MLP	0.693939	0.697835	0.684199	0.697619	0.693398
RF	0.638095	0.707792	0.638312	0.688961	0.668290
Average	0.609253	0.664313	0.614637	0.669102	

Table 3.4: Average model accuracies recorded in experiment 16 to 19

addition decreased the accuracy by 0.85

Similarly, by comparing the 4 best models in experiment 16 to 17 and 18 to 19, conclusions regarding the effect of removing general code could be drawn. In experiments 16 and 17 both without complexity, the removal of general code improved the accuracy by 3.77%. While in experiments 18 and 19, the same measure also improved the accuracy by 2.66%. This shows that removing general code deals a positive impact on the model's performance.

3.4.3 Halstead Metrics (Experiment 20 to 23)

In this set of experiments, the target was to evaluate the effect of the addition of the 6 Halstead metrics on the model's accuracy. This set of experiments are identical to that of experiments 16 to 19, except that for each dataset the 6 new features were added. Table 3.5 shows the full results from all 4 experiments, while Table 3.6 compares the accuracy of the best 4 models in experiments 16 to 19 with experiments 20 to 23.

As discussed in the background section, Halstead metrics is a set of metrics set by Halstead (1977) to evaluate a piece of code. The set of metrics, same as that implemented by this set of experiments, includes program vocabulary, program length, calculated estimated program length, volume, difficulty and effort.

As seen in Table 3.6, in the best 4 models from both sets of experiments, adding Halstead metrics as a feature led to a 4.48% decrease in the accuracy on average. 3 of the models were made less accurate by the new set of features, while the model that benefited from the addition only gained a 0.88% improvement in accuracy. Therefore the conclusion

	Experiment Number				
Model	20	21	22	23	Average
LR	0.660823	0.688528	0.665584	0.683983	0.674730
LDA	0.683983	0.664719	0.674892	0.669481	0.673269
KNN	0.580519	0.534199	0.580519	0.534199	0.557359
CART	0.670130	0.612554	0.660173	0.598268	0.635281
NB	0.655195	0.590693	0.659957	0.600000	0.626461
SVM	0.585065	0.566234	0.585065	0.570779	0.576786
MLP	0.636797	0.627056	0.552381	0.565584	0.595455
RF	0.680519	0.679654	0.670996	0.665584	0.674188
Average	0.644129	0.620455	0.631196	0.610985	

Table 3.5: Average model accuracy values recorded in experiment 20 to 23

Model	16-19 Average	20-23 Average	Difference
LR	0.693777	0.674730	-2.75%
LDA	0.686472	0.673269	-1.92%
MLP	0.693398	0.595455	-14.13%
RF	0.668290	0.674188	0.88%
Average			-4.48%

Table 3.6: Comparison of the difference in model accuracy between experiment 16 to 19 and 20 to 23

was drawn that Halstead metrics should not be included in the final list of features.

3.4.4 JHawk Metrics (Experiment 24 to 25)

This set of experiments were designed to evaluate if the addition of the 32 JHawk metrics would help improve the accuracy of the models. Due to the complexity in extracting JHawk metrics from the code samples, only 157 rows of data were collected, all originally from experiment 19 (with the complexity feature but general code removed). Firstly, to establish a baseline, the same 157 selected entries from experiment 19 were given to the models. For experiment 24, JHawk metrics were extracted from the 157 code samples and directly used as the dataset. For experiment 25, the extracted JHawk metrics were combined with the original set of features used in experiment 19. The results of each experiment and a basic comparison are shown in Table 3.7.

JHawk is a software designed to evaluate Java programs (Virtual Machinery, 2021). The software uses a wide range of metrics to do so. In this set of experiments, code samples were fed to JHawk and the following list of 32 features were extracted using the tool:

number of methods, average cyclomatic complexity, Halstead bugs cumulative value, unweighted class size, CBO, number of comment lines, review factor value, depth of inheritance tree, specialization ratio, cohesion, maximum cyclomatic complexity, number of query methods, number of superclasses, number of subclasses, number of command methods, Halstead length cumulative value, lack of cohesion of methods, number of Java statements, Halstead effort cumulative value, total response for class, maintainability index, number of lines of code, fan in, ReUse ratio, LCOM2, Halstead volume cumulative value, fan out, SIX, total cyclomatic complexity, MPC, number of comments.

	Experiment				
Model	19 (159 rows)	24 JHawk Only	25 Combined	19 vs. 24	19 vs. 25
LR	0.673750	0.485256	0.662821	-27.98%	-1.62%
LDA	0.685833	0.436538	0.564744	-36.35%	-17.66%
KNN	0.595000	0.492949	0.492949	-17.15%	-17.15%
CART	0.565833	0.580769	0.560897	2.64%	-0.87%
NB	0.487500	0.469231	0.509615	-3.75%	4.54%
SVM	0.679583	0.540385	0.540385	-20.48%	-20.48%
MLP	0.628750	0.540385	0.540385	-14.05%	-14.05%
RF	0.597083	0.555128	0.596795	-7.03%	-0.05%
Average				-15.52%	-8.42%

Table 3.7: Average model accuracy values recorded in experiment 24 to 25 with basic comparison statistics

As seen in Table 3.7, in almost all cases, JHawk metrics, no matter if alone or combined with existing features, underperforms the existing set of features quite significantly, with an average of 15.5% and 8.42% decrease in accuracy when comparing the original set of features with JHawk metrics only and combined respectively. The results suggest that JHawk metrics should not be included in the final set of features.

3.4.5 Final Model (Experiment 40)

Experiment 40 was the experiment conducted under this project that set the final model to be used in the entire project. The dataset consisted of 164 rows, from 164 different authors all solving the same coding question, where 91 of them were experts and 73 were novice developers. This experiment used the final list of features as shown in Table 3.1. A comparison of all model's accuracy is shown in Figure 3.5. The coefficients found in the best performing model, logistic regression which achieved a 69.0% accuracy and 0.0936 standard deviation across the results from all 10 splits, for each feature is shown in Figure 3.6.

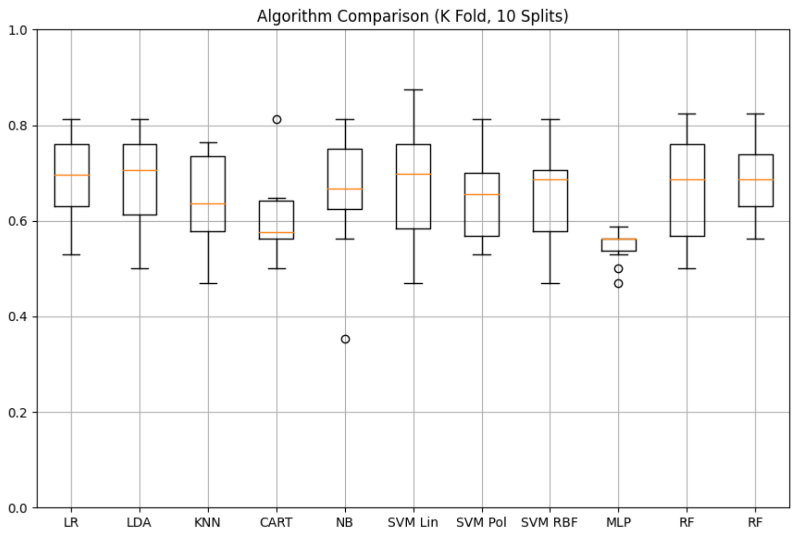


Figure 3.5: Comparison of model accuracy values in experiment 40

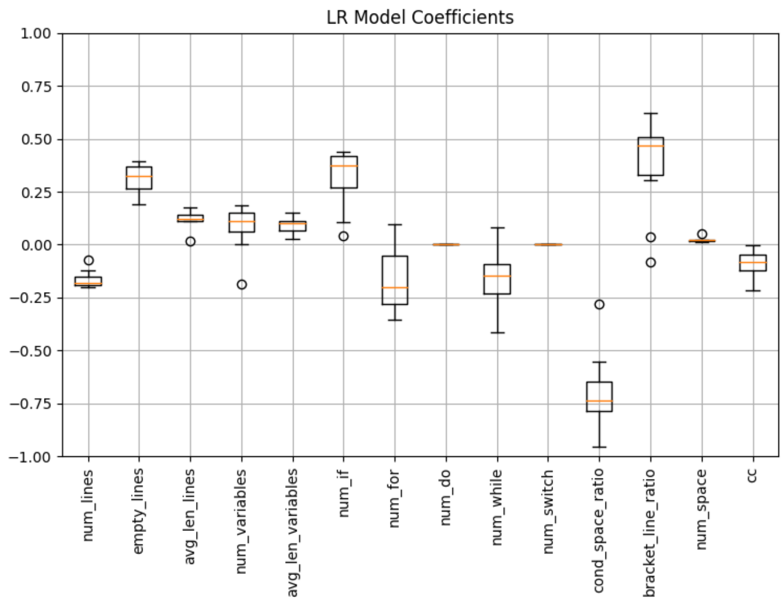


Figure 3.6: Coefficients found in the final logistic regression model

3.4.6 Features Normalization (Experiment 41 and 42)

An additional set of experiments were performed to evaluate the impact of data scaling on the accuracy of the models. 2 additional experiments were made, using the same set of data from experiment 40. In experiment 41, a min-max scaler had been applied to the dataset, mapping all values in each feature to a minimum of 0 and a maximum of 1.

In experiment 42, a standard scaler had been applied to the dataset, mapping all values in each feature to a new range, setting the standard deviation of all values to 1. The results, with comparison data, can be found in Table 3.8, with the name of the best 4 models in experiment 40 highlighted. The conclusion of this set of experiments was that data normalization does not help improve the accuracy of the models.

Model	Experiment				
	40	41 (Min-Max Scaling)	42 (Standard Scaling)	40 vs. 41	40 vs. 42
LR	0.689706	0.683088	0.683456	-0.96%	-0.91%
LDA	0.688971	0.688971	0.688971	0.00%	0.00%
KNN	0.635294	0.603676	0.561765	-4.98%	-11.57%
CART	0.603676	0.597426	0.597426	-1.04%	-1.04%
NB	0.659559	0.659559	0.659559	0.00%	0.00%
SVM Lin	0.684191	0.598162	0.672059	-12.57%	-1.77%
SVM Pol	0.647794	0.641176	0.615441	-1.02%	-4.99%
SVM RBF	0.646324	0.665441	0.616544	2.96%	-4.61%
MLP	0.548897	0.573162	0.615074	4.42%	12.06%
RF	0.670588	0.670588	0.670588	0.00%	0.00%
Average				-1.32%	-1.28%

Table 3.8: Results from experiment 40 to 42, with the best 4 models in experiment 40 highlighted, and results between each experiment compared

3.4.7 Conclusion of the Experiments

Above mentioned, are all key experiments conducted that had a significant impact on decisions made on the training of the final model. As a result of all these experiments, it was decided that the logistic regression model in experiment 40 shall be used as the final model. With 164 pieces of code, each from a different author solving the same coding question, extracting the 14 features as listed in Section 3.2.1, without data normalization, the final model has a 69.0% accuracy when evaluated under 10 split k-fold cross-validation.

Chapter 4

Prototype Application

One of the prototypes developed was a website application, targeting individual users who would like to evaluate their code or just try the model out. The design, implementation and evaluation of the prototype developed will be discussed in the following sections.

4.1 Design

4.1.1 Requirements

For the website application, a list of requirements, both functional and non-functional, were drawn up to assess the final product and guide development.

For functional requirements, the system shall:

- Show the user a coding question
- Take the user's code as input
- Evaluate the code input using the model
- Show the results from the model
- Have instructions on how to proceed on different parts of the website

For non-functional requirements, the system should:

- Be designed to be visually appealing
- Have clear instructions on-screen that users can easily understand
- Be easy to navigate to different parts of the website
- Include a simple description of the project

4.1.2 System Architecture

As a simple website application, the user would interact with the front end component of the system to submit their code and get the result from the model. The server can be split into 3 main components: front end, features extractor and model. The front end component would pass the code submitted to the features extractor after making basic validations to the submission. The features extractor would then parse the code and output an array of the values corresponding to each feature extracted. The array is then passed into the model to get the classification. Finally, the classification is delivered to the user.

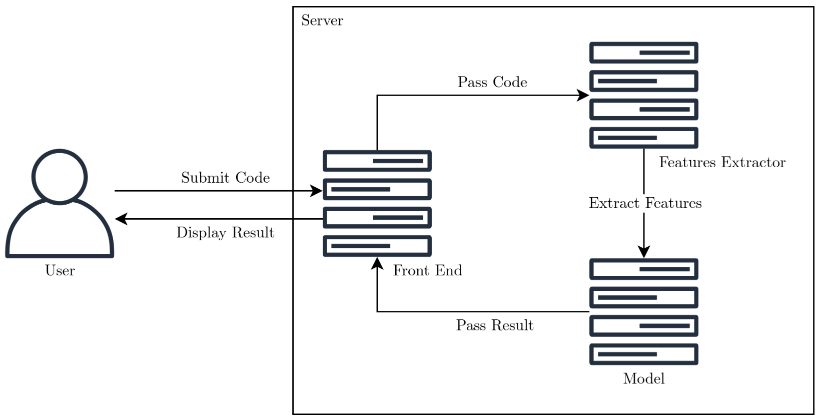


Figure 4.1: The designed components in the system

4.1.3 Use Cases

There is one main use case for the website application, details of the use case is presented in Table 4.1.

Use case: Obtain a developer's experience classification	
Description	An actor uses the website application to evaluate one's development experience
Actors	Individual users who would like to use the developed model to assess the actor's own or other's development experience
Pre-conditions	(none)
Assumptions	The actor is able to perform basic Java programming
Main flow	1. The actor lands at the homepage 2. The actor navigates to the application page 3. The actor downloads the 2 supplied files and completes Solution.java 4. The actor uploads the completed Solution.java 5. The actor submits the form 6. The system extracts features from the uploaded file 7. The system passes those features to the model 8. The system shows the user the classification obtained from the model
Post-conditions	The actor is presented with the classification
Extensions	Step 6) If the file contains a syntax error, the system shows an error and go back to step 4

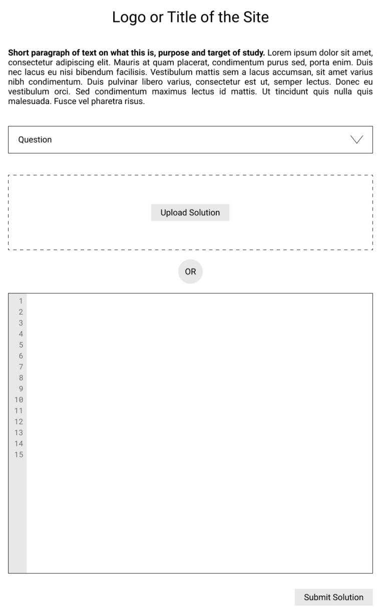
Table 4.1: Use case table for obtaining a developer's experience classification

4.1.4 User Interface Concept

Prior to working on the implementation, a simple wireframe prototype for the key parts of the website was created using Figma, a prototyping tool, allowing some interactions with the wireframe pages. This process provides a preview of how the pages would look and function, to prevent any obvious design mistakes from only being realized at a later stage.

At this stage, there were 2 main pages, including the homepage, which accepts the user's code, and the results page, which shows the classification result from the model. The wireframe for the 2 pages could be seen in Figures 4.2 and 4.3.

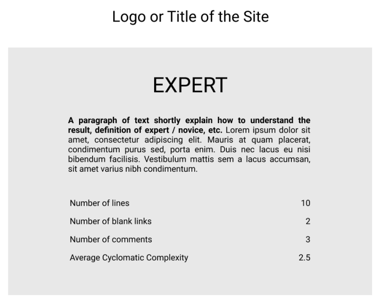
It was considered whether the site should record the user's input and, automatically or



Logo or Title of the Site

Short paragraph of text on what this is, purpose and target of study. Lorem ipsum dolor sit amet, consectetur adipiscing elit. Mauris at quam placerat, condimentum purus sed, porta enim. Duis nec lacus eu nisi bibendum facilisis. Vestibulum mattis sem a lacus accumsan, sit amet varius nibh condimentum. Duis pulvinar libero varius, consectetur est ut, semper lectus. Donec eu vestibulum orci. Sed condimentum maximus lectus id mattis. Ut tincidunt quis nulla quis malesuada. Fusce vel pharetra risus.

Figure 4.2: Mockup of the homepage of the website



Logo or Title of the Site

EXPERT

A paragraph of text shortly explain how to understand the result, definition of expert / novice, etc. Lorem ipsum dolor sit amet, consectetur adipiscing elit. Mauris at quam placerat, condimentum purus sed, porta enim. Duis nec lacus eu nisi bibendum facilisis. Vestibulum mattis sem a lacus accumsan, sit amet varius nibh condimentum.

Number of lines	10
Number of blank links	2
Number of comments	3
Average Cyclomatic Complexity	2.5

Figure 4.3: Mockup of the results page of the website

manually, feed feedback back to the model to further improve it. It was concluded that this should not be done for a number of reasons. Firstly, the model is very fragile, with only 164 rows in the final dataset and a 69.0% accuracy, the model is not mature enough to accept additional data from a similar but different data source, which could have a negative effect on the model. Besides, the site was not designed for this purpose, users were not told extremely clear how novice and expert developers were classified, especially in special and edge cases. Including mislabeled data in a small dataset could easily damage the model. Finally, the website was designed as a prototype, to demonstrate possible uses of the model developed and to experiment with the use of machine learning models in a website for personal uses, a feedback mechanism did not seem very beneficial and crucial to the system. Therefore, it was concluded that it was not appropriate, in this situation, to implement the automatic training feedback feature.

4.2 Implementation

4.2.1 Development Environment

For this website application, Python was selected as the programming language to be used on the server. This is mainly due to the model being developed using Python code as well. By using Python in both the model and server, it is possible to simply export the trained model as a serialized object to the file and import the exact same object onto the server. While it is possible to extract all details of a model, the chosen approach is much simpler and time-efficient.

Atom was used as the code editor, with plugins to support Python code linting according to the PEP8 and Flake8 standards. The code was developed to abide by most of those style guidelines.

The server is developed using Flask, a simple but popular python web server framework. It was chosen over other similar frameworks such as Django based on the amount of personal experience with the framework. The framework handles all browsing sessions, incoming requests, error responses et cetera. Below is a snippet of code, serving a webpage, highlighting the simplicity of using Flask.

```
from flask import Flask, render_template, session

app = Flask(__name__)
app.config['SECRET_KEY'] = '<app secret key>'.encode('utf8')

@app.route('/')
def home():
    return render_template('home.html',
                           mode=session.get('mode'))
```

The render_template function, widely used in this application, is provided by Flask, and renders a web page using the Jinja template engine. Following is a snippet of code showing the usage of the Jinja template syntax to render a link to a web page on the site.

```
<a href="{{ url_for('app_route') }}">[Try It Out]</a>
```

4.2.2 Homepage

During implementation, it was realized that it is better to separate introductory text from the main application part itself to create a better feel of coherence throughout the site. Therefore a separate application page was developed to hold the coding question and to take user input. While the homepage introduces the website.

The functional aim for the homepage is to introduce the website, what it is and how it works. At the top of the page, it shows the name of the site, Coding Expert Detector, and a one-sentence statement, marked "TL;DR", for those who do not prefer reading a lot and would just want to know what the website is about as quickly as possible.

It is then followed by a simple 3 step description, with an illustration diagram, of how the model is trained and used on the site. The diagram, which provides a simple visual explanation of the above, is created in the SVG format using Inkscape, an open-source vector graphic design software, to allow unlimited resizing.

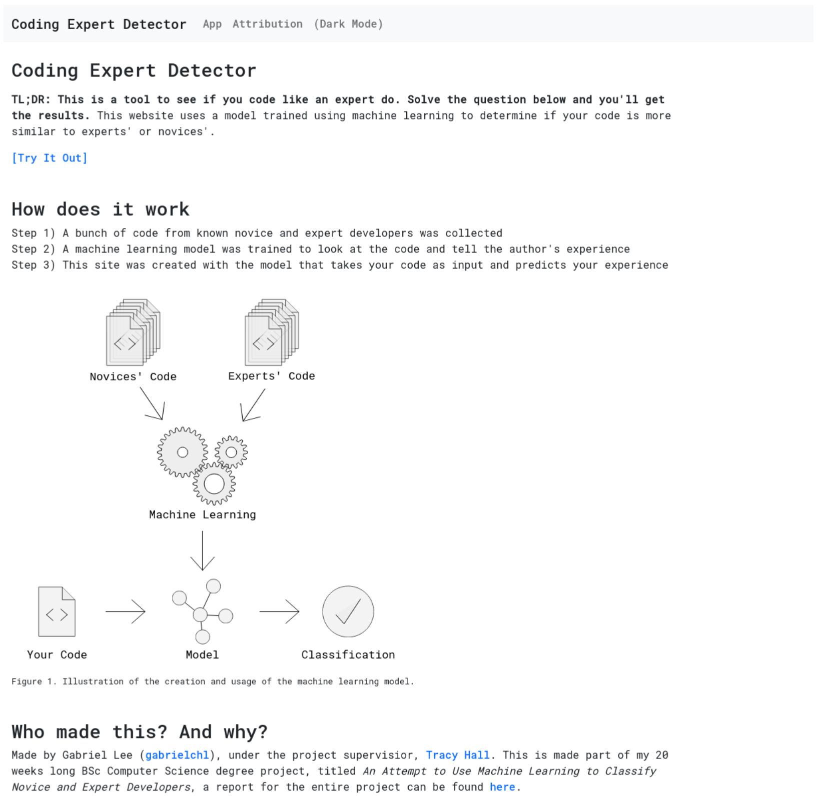
Finally, the page introduces the creator, this project and its supervisor.

4.2.3 Application Page

For the application page, there are only 2 functional aims, display the coding question and take the user's solution code as input. As the page contains quite a lot of content and text, it was split into 4 main steps to assist the user in determining what they were supposed to do at the next step.

The first step was to "read the following question". The question is displayed on the screen, with all mathematical symbols rendered using MathJax, a Javascript library for rendering mathematical scripts elegantly.

The second step was to "download the following files and complete the task". 2 files were provided, Solution.java and Test.java. Solution.java provides the code template for the user to start working on. This template is highly similar to that used in the training dataset to ensure that there are no systematic changes to the data input, causing the model to not be able to identify some features. For Test.java, it provides some test cases for the user to run against their code to confirm that their code works before submitting.



Coding Expert Detector

TL;DR: This is a tool to see if you code like an expert do. Solve the question below and you'll get the results. This website uses a model trained using machine learning to determine if your code is more similar to experts' or novices'.

[Try It Out]

How does it work

Step 1) A bunch of code from known novice and expert developers was collected
Step 2) A machine learning model was trained to look at the code and tell the author's experience
Step 3) This site was created with the model that takes your code as input and predicts your experience

Figure 1. Illustration of the creation and usage of the machine learning model.

Who made this? And why?

Made by Gabriel Lee (gabrielchl), under the project supervisior, Tracy Hall. This is made part of my 20 weeks long BSc Computer Science degree project, titled *An Attempt to Use Machine Learning to Classify Novice and Expert Developers*, a report for the entire project can be found here.

Figure 4.4: Screenshot of the homepage

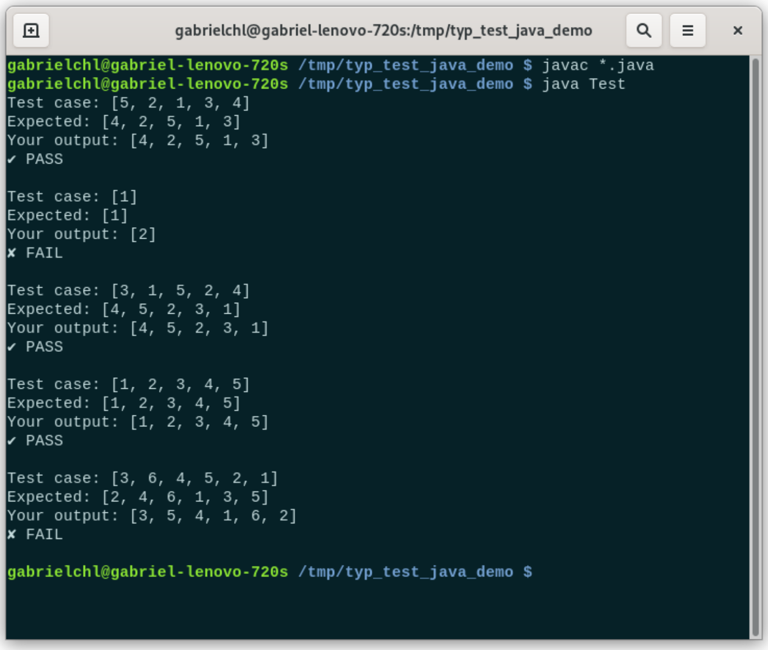
The text on the application page instructs the user to not modify certain parts of the template, as well as suggests how to run those test cases. Figure 4.5 shows the output of the test file with several failed test cases.

The third step was to "upload your solution". The user would upload their Solution.java using a regular file selector button. The code read from the file is then displayed below the file selector button for the user to confirm the file selection. The code viewer is implemented using CodeMirror, an open-source javascript library.

Finally, step 4 includes a very visible submit button, which concludes this page.

4.2.4 Results Page

For the results page, it simply shows the classification calculated by the model with the values of the features extracted. As the classification is the main content to show, it enjoys a significantly large font-size. The values of the features extracted is displayed in a table with the cursor hover highlighting feature. The model is loaded from a file



```
gabrielchl@gabriel-lenovo-720s /tmp/typ_test_java_demo $ javac *.java
gabrielchl@gabriel-lenovo-720s /tmp/typ_test_java_demo $ java Test
Test case: [5, 2, 1, 3, 4]
Expected: [4, 2, 5, 1, 3]
Your output: [4, 2, 5, 1, 3]
✔ PASS

Test case: [1]
Expected: [1]
Your output: [2]
✘ FAIL

Test case: [3, 1, 5, 2, 4]
Expected: [4, 5, 2, 3, 1]
Your output: [4, 5, 2, 3, 1]
✔ PASS

Test case: [1, 2, 3, 4, 5]
Expected: [1, 2, 3, 4, 5]
Your output: [1, 2, 3, 4, 5]
✔ PASS

Test case: [3, 6, 4, 5, 2, 1]
Expected: [2, 4, 6, 1, 3, 5]
Your output: [3, 5, 4, 1, 6, 2]
✘ FAIL

gabrielchl@gabriel-lenovo-720s /tmp/typ_test_java_demo $
```

Figure 4.5: Screenshot of an example output of the test file featuring 2 failed test cases

containing the model as a serialized Python object, as shown in the following code snippet.

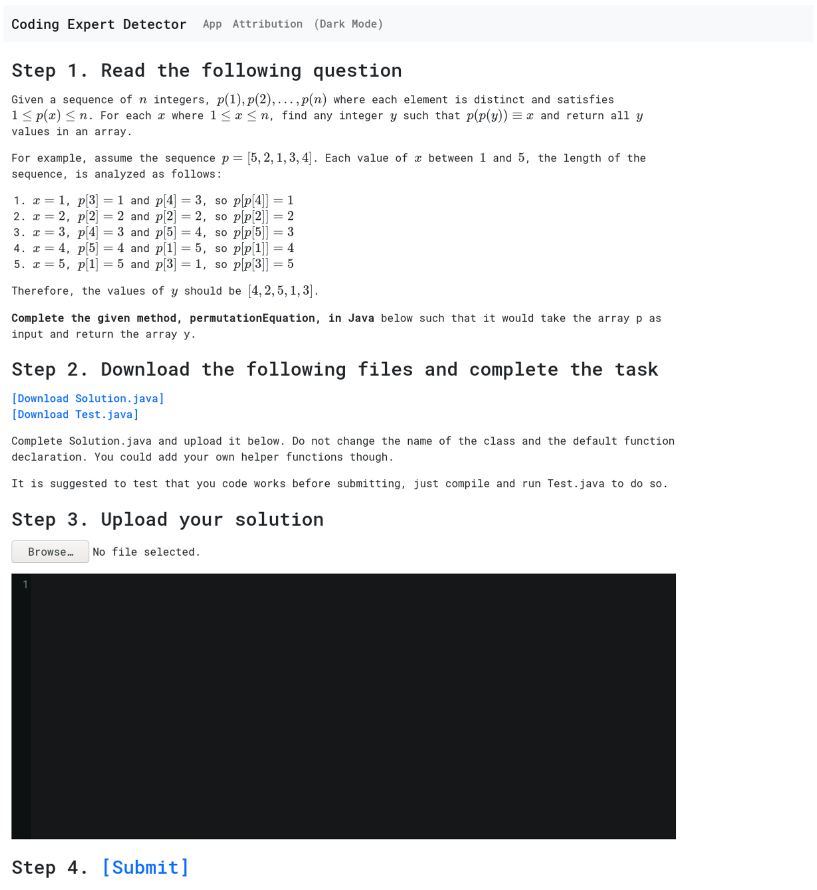
```
model = joblib.load('model.sav')
prediction = model.predict([features])[0]
```

4.2.5 Special Features

Besides the above-mentioned pages, there is 1 feature and another page that is worth mentioning.

The main user group who would use this site is people who would like to know how experienced in programming they are when compared to others or those who would just like to try out the website and see what classification it gives. These people, mostly individual developers, would prefer if the mainly white-coloured user interface has a dark mode feature, similar to that provided in all mainstream code editors. Therefore a dark mode feature is created for the site. The trigger is on the navigation bar of the website, where the user's preference would be stored on the web server along with the user's browsing session so that the colour preference is kept throughout the session.

A page that was not mentioned above is the attribution page, which contains attribution


Coding Expert Detector App Attribution (Dark Mode)

Step 1. Read the following question

Given a sequence of n integers, $p(1), p(2), \ldots, p(n)$ where each element is distinct and satisfies $1 \leq p(x) \leq n$. For each x where $1 \leq x \leq n$, find any integer y such that $p(p(y)) \equiv x$ and return all y values in an array.

For example, assume the sequence $p = [5, 2, 1, 3, 4]$. Each value of x between 1 and 5, the length of the sequence, is analyzed as follows:

1. $x = 1$, $p[3] = 1$ and $p[4] = 3$, so $p[p[4]] = 1$
2. $x = 2$, $p[2] = 2$ and $p[2] = 2$, so $p[p[2]] = 2$
3. $x = 3$, $p[4] = 3$ and $p[5] = 4$, so $p[p[5]] = 3$
4. $x = 4$, $p[5] = 4$ and $p[1] = 5$, so $p[p[1]] = 4$
5. $x = 5$, $p[1] = 5$ and $p[3] = 1$, so $p[p[3]] = 5$

Therefore, the values of y should be $[4, 2, 5, 1, 3]$.

Complete the given method, permutationEquation, in Java below such that it would take the array p as input and return the array y.

Step 2. Download the following files and complete the task

[Download Solution.java]
[Download Test.java]

Complete Solution.java and upload it below. Do not change the name of the class and the default function declaration. You could add your own helper functions though.

It is suggested to test that you code works before submitting, just compile and run Test.java to do so.

Step 3. Upload your solution

Step 4. [Submit]

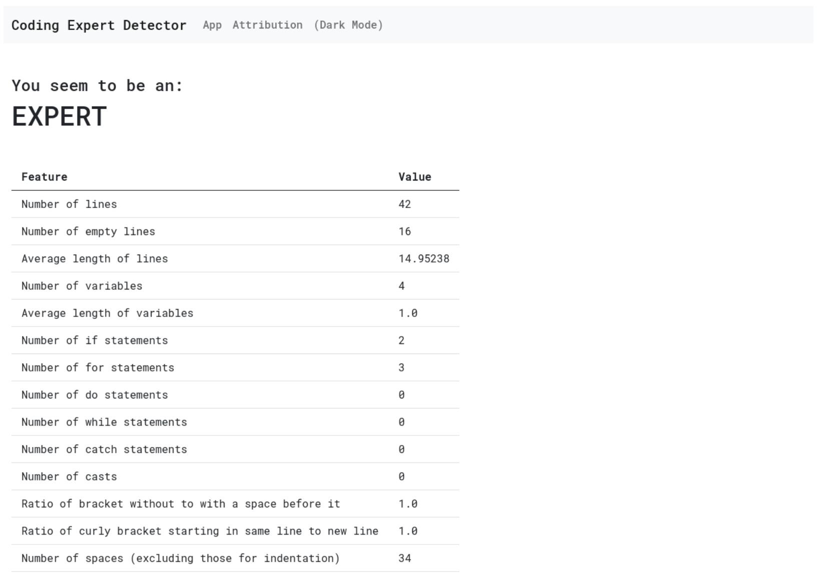
Figure 4.6: Screenshot of the application page

text for this website, and this website only. For this website, the attribution page contains one entry regarding where the idea of the design of the visual elements of the website came from. This will be further discussed in the following section.

4.2.6 Design

Bootstrap, a CSS framework by Twitter, was used for the design of the website. Bootstrap provides a range of basic elements for web developers to quickly build a website. Some elements used include links, navigation bars, tables, et cetera. Using this framework, the basic structure was created.

While Bootstrap does provide a very simple design, its elements' size and colour make the website look just like another generic site. Therefore the design needed to be customized. Using custom CSS rules, in addition to what Bootstrap provides, the colouring for both light and dark mode, text position and font was modified, as well as some other minor

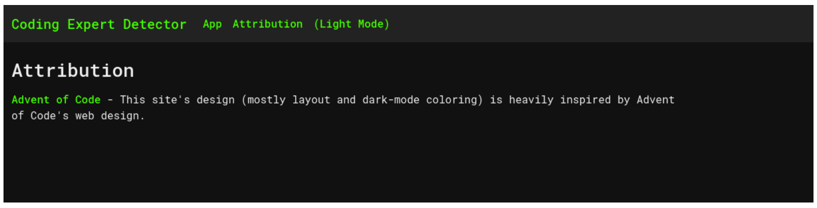

Coding Expert Detector App Attribution (Dark Mode)

You seem to be an:

EXPERT

Feature	Value
Number of lines	42
Number of empty lines	16
Average length of lines	14.95238
Number of variables	4
Average length of variables	1.0
Number of if statements	2
Number of for statements	3
Number of do statements	0
Number of while statements	0
Number of catch statements	0
Number of casts	0
Ratio of bracket without to with a space before it	1.0
Ratio of curly bracket starting in same line to new line	1.0
Number of spaces (excluding those for indentation)	34

Figure 4.7: Screenshot of the results page


Coding Expert Detector App Attribution (Light Mode)

Attribution

Advent of Code - This site's design (mostly layout and dark-mode coloring) is heavily inspired by Advent of Code's web design.

Figure 4.8: Screenshot of the attribution page in dark mode

changes. Parts of the design, including the font and layout, was inspired by the website of Advent of Code, an annual coding competition held in December. Such information was included on the attribution page.

4.3 Evaluation and Testing

4.3.1 Semi-structured Interviews

To evaluate different aspects, including functionality and design, of the website, 2 semi-structured interviews were conducted, one with a novice developer and the other with an expert. The aim of the 2 interviews was to collect user feedback on the website, especially when users tend to be able to give feedback on issues developers themselves could not find or are not aware of. They were introduced to the project and the developed website and asked to use the site, with a minimal amount of instructions given by the interview instructor. A list of questions was prepared prior to the interviews:

1. Can you tell me about your experience with coding, and Java?
2. Can you tell me about your educational credentials? What did you study and when did or will you graduate?
3. Do you think that the instructions were clear?
4. How easy is it to navigate around the site?
5. What do you think about the design of the site? Colouring, font, layout, et cetera.
6. What do you think about the presentation of the question, on a scale from 1 to 10, how hard is it to understand?
7. What do you think about the question itself, on a scale from 1 to 10, how hard is it to solve?
8. What do you think about the results? Do you agree with the classification?
9. Are there any things you would like to add?

Besides the above questions, some followup questions and questions inspired by observing their use of the site were also asked. An example of these questions is "I saw that you spent quite a long time between reading the question and starting with your solution, what were you thinking or doing at the time?". The length of the interviews was around 1 hour for interviewee 1, and 20 minutes for interviewee 2, with both successfully using the site and giving very high-quality feedback. Below is a short introduction to the background of both interviewees.

Interviewee 1 is a male United Kingdom university student, currently enrolled in a Computer Science Bachelor degree, completing his year 3 studies. He does not have any work experience nor commercial software development experience. Interviewee 1 has basic knowledge in the Java programming language, mostly gained in the prior 2 years from the university's lectures.

Interviewee 2 is a male United States university student, currently enrolled in a Computer Engineer Bachelor degree, completing his year 4 studies. He is experienced in software development. Completing his software engineer internship at Google in summer 2020 working on Linux kernel development, he is set to work at Google as a software engineer after graduation in 2021.

Below is a list of feedbacks collected during the interviews:

- Both enjoyed the dark mode toggle ability.
- Both found the question hard to understand. Interviewee 1 spent at least 3.7 minutes reading and understanding the coding task, requiring the interviewer's intervention to explain the question. Interviewee 2 said that "Just say that it is a shuffled array, this is such a complex expression".
- Both agreed that it is easy to navigate around the site. Interviewee 2 suggested adding an additional link to the app at the bottom of the home page.
- Interviewee 1 suggested that the text used to introduce the project on the homepage could be further simplified.
- Interviewee 1 found it slightly hard to solve the question, giving a 6 out of 10, where 10 is that it is very hard to solve.
- Interviewee 2 did not realize that the array provided in the question has its index starting from 1 until 3 minutes into solving the question. The interviewee hated this fact and said that "Please stop using 1-based arrays" and "I have to convert it to 0-base then to 1-base, it's just 2 extra steps".
- Interviewee 2 suggested that the website should provide direct on-site testing, instead of having the user download the test file and run it locally.
- Both agreed that while they're satisfied with the results page design, it would be ideal to include additional information such as what features are more associated with each classification.

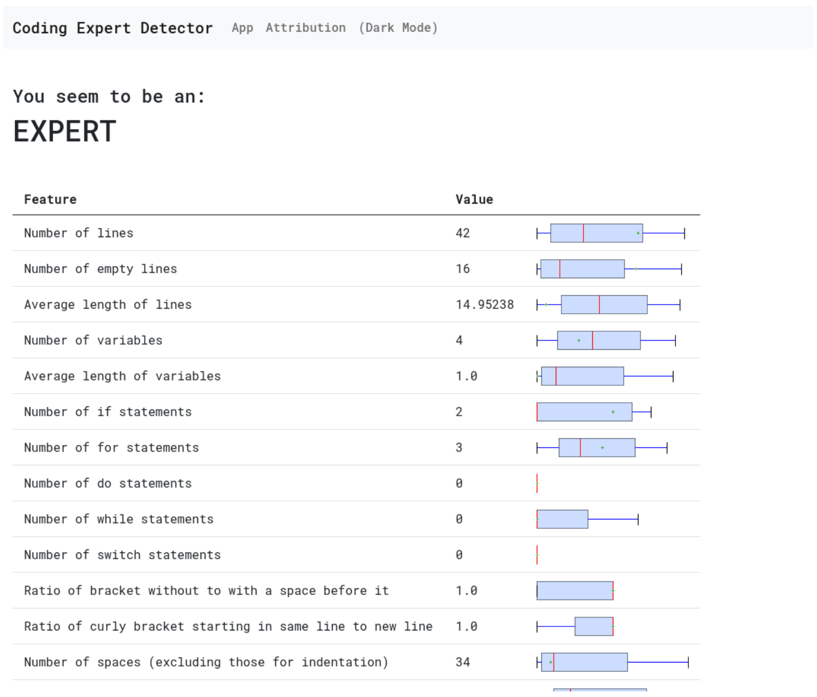
4.3.2 Changes Proposed in the Interviews

In this section, changes proposed by the interviewees or inspired by the 2 interviews will be discussed. Changes implemented post-interviews will be covered. As well as the discussion on certain changes to not be implemented.

The most important change that was suggested by both interviewee was that the question was hard to understand. The following changes were made to simplify parts of the question by introducing the problem from a spoken approach rather than a mathematical approach, while not giving any additional hints to solving the question to keep the input true to the training dataset. The first sentence was modified from "Given a sequence of n integers, p(1), p(2),..., p(n) where each element is distinct and satisfies 1 ¡= x ¡= n." to "p is a shuffled array of n integers, where all integers from 1 to n are in the array.". Additionally, the statement "Note that the array *p* is 1-based." was also added to the end of the question.

A minor change made to the website was to add an additional "try it out" button at the bottom of the home page, as suggested by interviewee 2, that helps people who read the entire homepage easily reach the app page from the bottom of the homepage.

Finally, as both interviewees have agreed, more information was added to the results page. To show more data to help the user interpret the values of the features extracted, a box plot is added next to all values in the results page, showing where their code stands in the dataset, shown in Figure 4.9. Unfortunately, due to time-constraints, certain related improvements could not be completed. This feature would be more complete if the mean or median of the novice's or expert's data could also be shown in the same box plot, potentially showing which category the extracted data tends to be in.



You seem to be an:

EXPERT

Feature	Value
Number of lines	42
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Average length of lines	14.95238
Number of variables	4
Average length of variables	1.0
Number of if statements	2
Number of for statements	3
Number of do statements	0
Number of while statements	0
Number of switch statements	0
Ratio of bracket without to with a space before it	1.0
Ratio of curly bracket starting in same line to new line	1.0
Number of spaces (excluding those for indentation)	34

Figure 4.9: Screenshot of the results page, featuring the box plots next to the feature values

Back to the point where the array p in the question is 1-based. One alternative solution was to change the array to 0-based in the question and the provided test cases. This was not chosen as the solution as the aim was to keep the question as close as possible to that used in the dataset. Ideally, the entire environment should be made identical to that from the original dataset, to minimize any systematic deviation caused in the evaluation. Changing the array to 0-based would affect how developers solve the question, such as requiring or allowing them to remove, or add, a few more lines as a result of the change. This is not desirable and therefore this solution was not implemented.

Another suggestion received was to provide on-site testing. This feature would allow the user to directly code using the code editor on the webpage and have their code run against test cases through the web interface, removing the need for a user to download and run files locally. This was not implemented due to time constraints. However, it was determined that it would be beneficial to the user experience and if such a site is to be used, this feature would be valuable.

4.3.3 Testing

During the development process, a list of tests has been conducted to ensure the completeness and readiness of the website application. Table 4.2 shows the list, grouped by the type of test conducted, along with the final status of each test.

Test	Results
Functional Tests	
Links in the navigation bar on all pages directs the user to respective pages	Success
Both links to the application page at the homepage directs the user to the application page	Success
Dark and light mode switch toggles the colour scheme to the respective mode on all pages	Success
Both Solution.java and Test.java files can be downloaded through the link on the application page	Success
User can select one, and only one, file in the application through the file selector	Success
The code viewer shows the content of the file selected upon selection	Success
The system rejects submission without a file being selected, showing an error message	Success
The system shows a custom error page for errors triggered, such as by a syntax error in the file submitted	Success
For syntax errors, the system shows debug text of the error	Success
The result page shows a classification of either novice or expert	Success
Usability Tests	
Content on all pages are free of grammar and spelling mistakes	Success

Test	Results
Links on all pages share the same style and is outstanding from other text	Success
Consistent navigation bar visible on all pages	Success
The site satisfies Web Content Accessibility Guideline requirements, tested by WAVE Web Accessibility Evaluation Tool, made by Utah State University	Success, with no regular errors and text contrast errors
Pass all accessibility tests in Lighthouse by Google	Success, with a 100/100 score
Compatibility Tests	
All pages display and function properly in IE11, Google Chrome 50, 60, 70, 86, Firefox 60, 70, 82, Opera 50, 60, 71	Success
All pages display and function properly in any display dimension wider than 300 pixels and taller than 200 pixels	Success
Performance Tests	
Obtain a score higher than 80/100 in PageSpeed Insights by Google on both mobile and desktop tests	Success, with 87/100 and 98/100 for mobile and desktop tests respectively
Obtain an A grade in GTmetrix's performance test	Success, obtaining an A grade with 100% in performance and 95% in structure tests

Table 4.2: List of tests conducted against the website application, grouped into categories, along with the test results

4.4 Desktop Application

4.4.1 Design and Implementation

Another minor prototype created was a desktop application, allowing developer experience classification against multiple files at a time. This application targets group or corporate users. This is a very rough prototype, created with the sole purpose of demonstrating a possible use of the model for group or corporate users.

Implemented with Java using JavaFX, the application only has 2 screens. The first, as shown in Figure 4.10 is one that shows a file selection button, allowing the user to select one or more files to be analyzed. The second, as shown in Figure 4.11, shows the received file's names, their author experience classification, as well as the features extracted as a table.

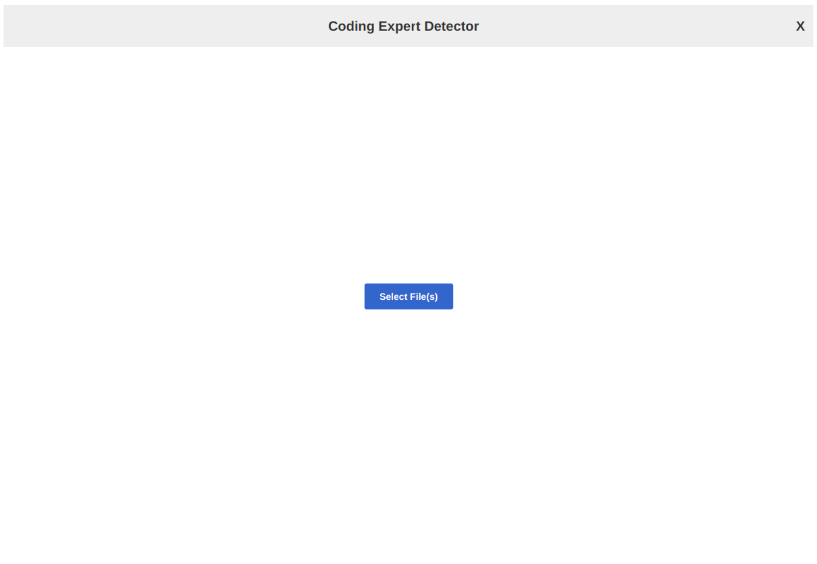
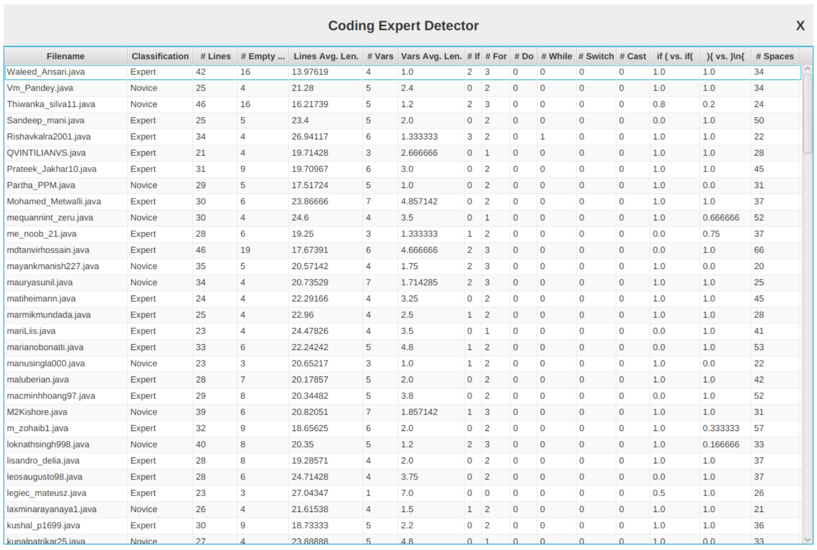


Figure 4.10: Screenshot of the home screen of the desktop application prototype



Filename	Classification	# Lines	# Empty ...	Lines Avg. Len.	# Vars	Vars Avg. Len.	# If	# For	# Do	# While	# Switch	# Cast	if (vs. if(	){ vs.)\n{	# Spaces
Waleed_Ansari.java	Expert	42	16	13.97619	4	1.0	2	3	0	0	0	0	1.0	1.0	34
Vm_Pandey.java	Novice	25	4	21.28	5	2.4	0	2	0	0	0	0	1.0	1.0	34
Thiwanka_silva11.java	Novice	46	16	16.21739	5	1.2	2	3	0	0	0	0	0.8	0.2	24
Sandeep_mani.java	Expert	25	5	23.4	5	2.0	0	2	0	0	0	0	0.0	1.0	50
Rishavkalra2001.java	Expert	34	4	26.94117	6	1.333333	3	2	0	1	0	0	1.0	1.0	22
QVINTILIANVS.java	Expert	21	4	19.71428	3	2.666666	0	1	0	0	0	0	1.0	1.0	28
Prateek_Jakhar10.java	Expert	31	9	19.70967	6	3.0	0	2	0	0	0	0	1.0	1.0	45
Partha_PPM.java	Novice	29	5	17.51724	5	1.0	0	2	0	0	0	0	1.0	0.0	31
Mohamed_Metwalli.java	Expert	30	6	23.86666	7	4.857142	0	2	0	0	0	0	1.0	1.0	37
mequannint_zeru.java	Novice	30	4	24.6	4	3.5	0	1	0	0	0	0	1.0	0.666666	52
me_noob_21.java	Expert	28	6	19.25	3	1.333333	1	2	0	0	0	0	0.0	0.75	37
mdtanvirhossain.java	Expert	46	19	17.67391	6	4.666666	2	3	0	0	0	0	0.0	1.0	66
mayankmanish227.java	Novice	35	5	20.57142	4	1.75	2	3	0	0	0	0	1.0	0.0	20
mauryasunil.java	Novice	34	4	20.73529	7	1.714285	2	3	0	0	0	0	1.0	1.0	25
matiheimann.java	Expert	24	4	22.29166	4	3.25	0	2	0	0	0	0	1.0	1.0	45
marmikmundada.java	Expert	25	4	22.96	4	2.5	1	2	0	0	0	0	1.0	1.0	28
mariLiis.java	Expert	23	4	24.47826	4	3.5	0	1	0	0	0	0	0.0	1.0	41
marianobonatti.java	Expert	33	6	22.24242	5	4.8	1	2	0	0	0	0	0.0	1.0	53
manusingla000.java	Novice	23	3	20.65217	3	1.0	1	2	0	0	0	0	1.0	0.0	22
maluberian.java	Expert	28	7	20.17857	5	2.0	0	2	0	0	0	0	1.0	1.0	42
macminhhoang97.java	Expert	29	8	20.34482	5	3.8	0	2	0	0	0	0	0.0	1.0	52
M2Kishore.java	Novice	39	6	20.82051	7	1.857142	1	3	0	0	0	0	1.0	1.0	31
m_zohaib1.java	Expert	32	9	18.65625	6	2.0	0	2	0	0	0	0	1.0	0.333333	57
loknathsingh998.java	Novice	40	8	20.35	5	1.2	2	3	0	0	0	0	1.0	0.166666	33
lisandro_delia.java	Expert	28	8	19.28571	4	2.0	0	2	0	0	0	0	1.0	1.0	37
leosaugusto98.java	Expert	28	6	24.71428	4	3.75	0	2	0	0	0	0	0.0	1.0	37
legiec_mateusz.java	Expert	23	3	27.04347	1	7.0	0	0	0	0	0	0	0.5	1.0	26
laxminarayanaya1.java	Novice	26	4	21.61538	4	1.5	1	2	0	0	0	0	1.0	1.0	21
kushal_p1699.java	Expert	30	9	18.73333	5	2.2	0	2	0	0	0	0	1.0	1.0	36
kunalpatrikar25.java	Novice	27	4	23.88888	5	4.8	0	1	0	0	0	0	1.0	0.0	33

Figure 4.11: Screenshot of the results screen of the desktop application prototype

The model itself is not stored in the application. The application was implemented to make a request to the website application's server to fetch the features extracted and classification results. While this method is not ideal, as it requires an internet connection to connect with the website application's server and lowers the efficiency of the application as it has to send the request and wait for a reply, it was implemented by exporting a Python model to be used in a Java application could induce unforeseen complications. It should be noted here that with enough study in place for such a solution, it would be more preferable to the current solution.

4.4.2 Ethical Concerns

Given that the application is designed to give corporations the ability to determine one's programming experience by analyzing their code, ethical concerns may arise regarding related issues.

The preselection of job application candidates would be the biggest concern of all concerns. While it is understood that such pre-selection methods are not always accurate and causes the loss of talents or results in hiring candidates who are not suitable for the job, it could be arguable that these methods help save time for both the company and the candidates, making the entire application process more efficient.

The true concern is if the pre-selection method is fair. As the model was trained using a dataset, biases could be existing in the dataset and be carried over to the final model during the training model. These biases could be due to the bias in the data source itself, or by human-induced, or systematic bias during the collection of data. These biases could damage the reliability of the model, as well as its fairness as it could give an advantage or disadvantage to a group of people whose code exhibits features picked up by the model but non-related to their development experience.

The model developed in this project is not ready for real-life deployment. Not only does it have low accuracy, but it was not thoroughly studied as well, such as to establish the fact that whether there are biases in the model. Before these concerns are investigated and addressed, such a system should not be deployed.

Chapter 5

Discussions and Conclusion

5.1 Review of Project Aims

As listed in Section 1.3, a list of 4 aims were set at the beginning of the project. In this section, the completion status of each of those aims, along with discussions regarding the work done will be covered.

5.1.1 "Determine if it is possible to classify developers' experience level using features from their code"

The first part of this chapter, mainly described in Chapter 3 provides an overview of work done on training a model to classify developers' experience level using features from their code. The data source, steps for feature extraction, the method for model evaluation, models to train, et cetera were experimented with and discussed. With a 69.0% accuracy in the final model produced in this project, trained using an extremely focused and limited dataset, it set a baseline for future research into similar topics.

5.1.2 "Determine what features would be helpful for the model"

With the several experiments conducted, along with the analysis of the final model, it was concluded that certain features are more positively linked to novice developers' behaviours and vice versa. These experiments also helped identify features that affect the model's accuracy, positively or negatively. These findings were shown in Section

3.4.5

5.1.3 "Determine what model would help achieve better classification accuracy"

Throughout all experiments, a wide set of models were tested and evaluated using their accuracy, as listed in Section 3.3. This helped identify the best performing model, logistic regression, for the dataset.

While there was much work that could be done to further improve different aspects in the whole machine learning model training process, as to be discussed in Section 5.3 Future Work, it could be said that the aims set out related to the model is fulfilled.

5.1.4 "Develop one or more prototype applications to demonstrate possible uses of such model"

As the main focus of Chapter 4, 2 applications were developed. One developed as a website application utilizing the trained model, completed with full user interface design, testing and feedback evaluation, and another application developed as a desktop application prototype, mostly for demonstration purposes.

The aim set is completed, with the website application fully developed. However, it would have been a bigger success if similar could be said about the desktop application. Further work that could be done regarding the applications will be discussed in Section 5.3.

5.2 Limitations

There were two main limitations restricting the progress of the project, namely time constraints and the lack of knowledge, as discussed below. These limitations gave the project much space for future improvements.

Time-wise, this project has very limited time, 20 weeks, for its completion, including the planning and report-writing processes. Many decisions made, such as not to do further experiments on the development of the model, or not complete the desktop application development, were hugely affected by the time constraint.

Knowledge-wise, having a little more than 2 years of background studying in a computer science bachelor degree, also restricted some possibilities of the project, together with the time limitations. Not having any rich knowledge or industry experience in topics such as code stylometry and machine learning, quite a lot of time had to be spent on research. Besides, this inevitably also affects the quality of the work, by not using industry or academic standard methods to conduct certain tasks, such as to measure the accuracy of the models. Although doing all the background research as mentioned in Chapter 2 did provide certain vital information and techniques for this project, many things had to be discovered and learnt in practice.

5.3 Future Work

With the limitations mentioned in the previous section, there are many things in the project that could be improved or further worked on, which will be discussed in this section.

5.3.1 A More General and Larger Dataset

The current dataset is very specific, all short Java solutions to the same coding question. The specificity was desirable for this project as it helps narrow the scope of the project, possibly saving time. However, to make a bigger impact in the field, the dataset must not be so limited and should be generalized, such that more types of code could be analyzed. Besides, the size of the dataset used in this project was rather small. A larger dataset could benefit the model's accuracy.

5.3.2 Experiments on Features

In this project, several experiments were carried on testing different features to be extracted from the code samples to evaluate their effectiveness in improving the accuracy of the models being trained. However, most of those features were more simple ones, such that they are easily extracted and the values are mostly directly used in the dataset without any organization or preprocessing. More experiments could be carried on more complex features, such as n-grams and more abstract syntax tree features, as well as to test different combinations of those features against the accuracy of the models.

5.3.3 Experiments on Models

Besides features extraction, another important part of this project is the set of models to be trained. While the set of models selected for this project is rather diverse, representing a wide range of types of model, there were no adjustments or configurations made on those models. Further work could be done to experiment with different configurations of those models, or to test new models of the same type as the best models from the existing group, in an attempt to reach better results.

5.3.4 Study on Models

More work could also be done on the final model, where the correlation found between features and the classification could be further studied, as well as to test the model in extreme cases and against possible biases cases.

5.3.5 Further Application Development

For the website application, a larger user test and evaluation could be beneficial to collect more ideas for improving the site. It is also worth holding ethical discussions before publishing the site for individual uses, once a good model is ready for it.

For the desktop application, future works could complete the existing prototype or take the existing prototype as an example to develop a program with similar features for the same target user group, which in this case is for group or corporate users.

5.3.6 Publish Research

Last but not the least, is to publish the findings of this project, mainly the machine learning model part, and best with the addition of possible future works done. While there were no new trivial approaches to training a model or new method for dataset construction, it is believed that the value of this project is that it explores the possibility of using the machine learning approach to categorize developers according to their development experience, which is undone, and provides a base for any futures studies in this field, which could possible bring a huge impact to the internet technology industry.

5.4 Personal Remarks

In this section, personal remarks will be covered, in a less formal format than other chapters.

To conclude this project, I would say that it was a success, at least technically a success, as all the aims we set at the beginning of the project were fully completed. Looking at the final products, a 69.0% accurate model, a fully developed web application and a desktop application prototype, many things could have been done better, such as those discussed in Section 5.3 Future Work, to achieve better results. However, regrettably, this was not possible given the time constraint. While a 69.0% accuracy is not bad at all, especially for a bachelor student in a 20-week project, I believe it could be much better with more time and resources spent in the research. I would not say that the project was a great success, but I am still very thankful for the completion of this amazing project, which I truly believe does possibly have great value.

Most techniques or processes used in this project are self-learnt, if one would like to know how much I've learnt in this project. Although I view this project as an amateur academic research, I do understand that the School of Computing and Communications view this as a student project and therefore would like students to state how much they have learnt, which therefore is listed below:

- Machine learning dataset collection and construction techniques
- Machine learning model training and analysis techniques
- Machine learning results handling and presentation techniques
- Application development process

The biggest thing that I've got out of these 20 weeks, in my opinion, is not any of the above knowledge, but rather the experience of conducting a study in the computer science field. I have had experience with biotechnology research studies but never a computer science research. This project gave me the rare experience of conducting research independently with a supervisor from the planning process, to execution. Throughout the process, I have learnt to appreciate certain practices academics use, such as their data presentation techniques, as well as the importance of citing in writings, et cetera.

I would like to once again thank this project's supervisor, Professor Tracy Hall for her guidance, support and feedback along the way.

Finally, although there are certain regrets regarding some limitations of the project, I would say that this was a good project, achieving great results overall and I enjoyed it a lot. I am hopeful that more studies would be conducted into this field as I believe it will bring a positive impact on the technology industry.

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Appendix

Original Project Proposal

An Attempt to Use Machine Learning to Classify Novice and Experienced Developers

Student: Chi Hong, Lee   Supervisor: Tracy, Hall

Abstract

This proposed project aims to distinguish novice and experienced developers using machine learning. This is important and beneficial for higher education institutions providing computer science course or companies hiring developers. This project is split into 2 parts, training a model to classify novice and experienced developers and making an Atom package that analysis code in the code editor and predict if the writer is a novice or experienced developer using the model developed.

Introduction

Between the school-year 2008/09 and 2018/19, the number of undergraduate computer science students jumped from 56030 to 116045. [1][2] With a constantly increasing number of students studying computer science, there is a need for higher education institutions and companies to be able to classify novice and experienced developers.

For higher education institutions, this ability is the key to providing an accurately-tailored educational experience for students with a wide range of skill levels in programming. There has been a lot of research on different education techniques, that all require the classification of stronger and weaker students. Agrawal R. et al. (2014)'s [3] study shows that grouping strong students with weaker students could maximize the number of students doing better. Lui A. K. et al. (2014)'s [4] study shows that using a "Perform" teaching approach would help weak students achieve better performance. Their research targeted weak programmer students in their first programming course, by isolating weak students and "shielding" them from certain "hazards" under the Perform teaching approach, they were more able to write simple programs, achieve higher performance in the examination and improve confidence in programming. These researches highlight the importance of the ability to classify students by their strength. With the model that this project develops, teachers and professors will be able to quickly do so.

For companies hiring programmers, it is proven that companies are very likely to exclude exceptional candidates if students' GPA was used to pre-screen or filter the candidates. [5] The ability to distinguish experienced developers to novices allows them to gain insight into any candidates quickly and accurately, improving their hiring process.

This proposed project is split into two stages. Firstly, a mathematical model will be developed using machine learning to classify developers as a novice or experienced one using samples of their code The second stage would be to develop a package for the code editor Atom that will analyse the user's code and display a score out of 100 on the screen, representing how similar their code is to that from an experienced developer using the model developed in the first stage of the project.

The remaining part of this proposal document includes the following sections: Related work: Related research that could possibly provide additional information, insight, or assistance for this project will be discussed; Methods: This project will be split into several parts and the method for carrying out each part will be discussed; Potential challenge: Any potential challenges that might have to be faced while conducting the project will be discussed, as to methods to avoid such challenges or possible solutions. Provisional Timetable: Time usage will be estimated for each stage of this project in this section.

Related Work

Rehman et al. (2020)'s study [6] shows that there are certain activities that novice developers perform on GitHub, this data will assist the data labelling process. By comparing the findings in this paper to data subjects, the accuracy for labels could be increased.

Methods

This project is split into two stages, developing a model and making an Atom package.

For the first stage, developing a model, there will be several steps.

Firstly, to identify a publicly-available code repository or other source code as the data source. Given the time and resource limitations, only one repository or source code will be selected to get a model that has a high accuracy for the same organization of the selected repository or source code and same programming language. However, this will possibly lower the accuracy of the model when tested against code from another repository or source code, especially from another organization, more discussion on this issue can be found in the following section. The selection process of the code repository or source code will be based on the criteria named in the following table.

Criteria	Description
Must have at least 25 novice and 25 experienced authors	To ensure diversity in the dataset, enough data for each classification is needed
Must have at least 30 lines of code from each author	For most of the time, more data in the dataset would result in a more accurate model
Must use only 1 programing language for all lines of code selected in the data source	As this project is aiming for accuracy, it is best to tighten control over variables that might affect the classification other than the source code features itself

After the data source is determined, the approach suggested by McQueen et al. (1995) [7] will be used to extract and refine the data to train the model. There is no current research that could identify absolutely the best model for reading code. Therefore, as suggested by Chicco (2017) [8], multiple models will be used to find the most appropriate one for our data, starting from the simplest models.

Following is a list of possible features to be extracted from the data source according to different pieces of literature:

Features	Description
Syntax errors	Wiedenbeck, S. (1985)'s study [7] shows that novice developers are less able to highlight syntax error in a piece of code when compared to expert developers. It could be deduced that there would be more syntax errors in novice developers' code, given their lower ability to realize such errors.
Code complication	Wiedenbeck, S. (1985)'s study [7] shows that when shown a piece of code and a correct or incorrect description of the code, novice developers are less likely to be able to determine correctly if the description matches the code when compared to expert developers. It could be deduced that novice's code would be less

	complicated or elegant, as they are less able to understand complicated pieces of code.
Features that will show the difference between novice and experienced developers' code, according to studies. Methods to extract and prepare such features have to be further discussed and determined.	
Code style consistency	Kramer, M. et al. (2017)'s study [9] shows that novice developers memorize pieces of code line by line, rather than by its structure as what expert developers do. Thus resulting in expert developers being more able to memorize pieces of code. There is a chance that this will affect one's code style consistency, as a higher ability to memorize code could result in more code reuses.
Empty catch or finally block for error handling	Asaduzzaman, M. et al. (2016)'s study [10] shows that novice developers are more likely to ignore exceptions, by leaving catch or finally blocks empty.
Usage of generic or specific exception handlers	Asaduzzaman, M. et al. (2016)'s study [10] shows that novice developers are more likely to use generic exception handler by using a single catch block for all exceptions, rather than specific exception handlers.
Features that can be extracted from the dataset, where investigation have to be done to evaluate if such features can be used to classify novice and experienced developers. The following features are mainly structural details of the piece of code, some of them will most likely be divided by the number of characters or words in the file during the data preparation process.	
Lexical metrics, including: - Number of comments - Number of functions - Nesting depth of loops and if statements - Number of words - Line length - Number of empty lines - Number of tabs	Extracted from Caliskan-Islam A. et al. (2015)'s [11] study. Their study successfully produced a model, which was trained using a similar set of features, that could de-anonymize a developer using their code with very high accuracy.
Tab-indent to space-indent ratio	
Variable name average length	
n-gram analysis	Gorshkov S. et al. (2019)'s [12] study shows that when training a model to recognize code authors in a small pool of developers, 30, the model could reach a 97% accuracy when only trained using n-gram data from the code.

Of all the possible features listed above, different combinations between them will be tested while training the model in an attempt to achieve a higher model accuracy.

For the second stage of this project, making an Atom package, there will also be multiple steps.

Before coding begins, research on other Atom packages, specifically linters and code performance displayers, will be conducted to assist in designing the user interface of the package.

Next, the package will be developed. The package will have a simple, intuitive user interface showing a score out of 100 on the screen, representing how similar their code is to that from an experienced developer using the model developed in the first stage of the project, and also possibly hints on issues in the code preventing the score from reaching 100.

The model may be included in the Atom package itself or placed on a server, where the Atom package will send the code to the server, encrypted, and the server would return the score to the user.

The package will only analyze the code in the active tab when the package is opened. No sensitive user data will be retrieved and no data will be stored by the package.

Details and Usage of the Final Product(s)

There are 2 sub-sections, one for each final product in this section. We will discuss the details of each final product and how could it be used.

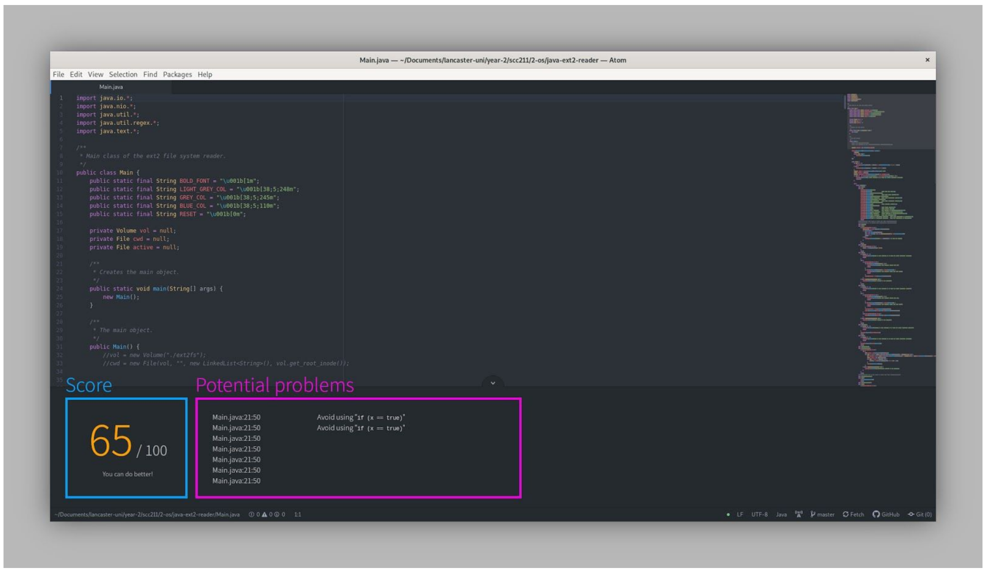
The Model

The final model would take a number of inputs, which would be features extracted from the code, and output the classification result. The result could be as one number, for example, it could be a number between 0 to 1 where 0 represents the code is likely coded by a novice developer and 1 represents it is by an experienced developer. It could also be two numbers, as a confidence score for each type of developer. This depends on which model is used.

One example usage of the model is that companies could use it to filter job application candidates. Usually, applicants would attach a link to their previous coding projects or GitHub profile, which would include code developed by themselves. To reduce human resources usage, a company could use the model to quickly identify novice or experienced developers according to their code.

The Atom Package

Atom is an open-source code editor and one of the most popular. For this part of the project, a plugin for Atom, which is called a package, will be developed. The package will provide a graphical interface showing two things. Firstly, a score out of 100, showing how similar the developer’s code is to what a piece of code by an expert would be like. The score will be calculated using the output of the model mentioned above. The second part is a list of problems found in the user’s code that might have lowered the score. The following image shows a draft of how the graphical user interface might look like.


Main.java — ~/Documents/lancaster-uni/year-2/scc211/2-os/java-ext2-reader — Atom
File Edit View Selection Find Packages Help
Main.java

```java
import java.io.*;
import java.nio.*;
import java.util.*;
import java.util.regex.*;
import java.text.*;

/**
 * Main class of the ext2 file system reader.
 */
public class Main {
    public static final String BOLD_FONT = "\u001b[1m";
    public static final String LIGHT_GREY_COL = "\u001b[38;5;248m";
    public static final String GREY_COL = "\u001b[38;5;245m";
    public static final String BLUE_COL = "\u001b[38;5;110m";
    public static final String RESET = "\u001b[0m";

    private Volume vol = null;
    private File cwd = null;
    private File active = null;

    /**
     * Creates the main object.
     */
    public static void main(String[] args) {
        new Main();
    }

    /**
     * The main object.
     */
    public Main() {
        //vol = new Volume("./ext2fs");
        //cwd = new File(vol, "", new LinkedList<String>(), vol.get_root_inode());
```

```
Main.java:21:50        Avoid using "if (x == true)"
Main.java:21:50        Avoid using "if (x == true)"
Main.java:21:50
Main.java:21:50
Main.java:21:50
Main.java:21:50
Main.java:21:50
```

~/Documents/lancaster-uni/year-2/scc211/2-os/java-ext2-reader/Main.java 0 0 0 1:1
LF UTF-8 Java master Fetch GitHub Git (0)

A developer could use such information provided by the package in different ways. Developers could use it to keep track of their code style changes over a long period of time. For example, a computer science student might record his/her score at the beginning and the end of the course and measure the improvement in his code, represented by the score. For one-time uses, one could use the tool to highlight potential problems that might not be highlighted by other linters or code stylers.

Potential Challenge

Unable to Find a Single Data Source with Enough Data on Both Novice and Experienced Developers

In such a case, the requirement that data should only be collected from a single data source will be lifted. An attempt will be made to look for 2 highly similar data source, hopefully, one mainly developed by novice developers and the other by experienced developers.

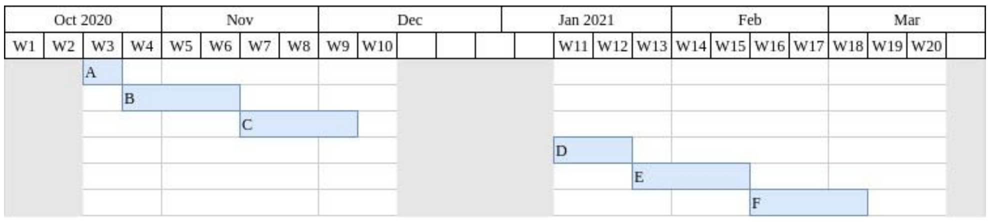
Developed Model Underfitting or Overfitting

It is possible that the developed model will underfit or overfit, especially with the small number of training data. Any model's accuracy on the test data will be closely monitored. If needed, additional test data will be brought in to test the model for overfitting.

Provisional Timetable

This project's implementation part will begin mid-October 2020 to mid-March 2021, the table below shows each part of the project as well as the time estimated to complete them. The project will be carried out similarly to a waterfall development model. Note that buffers are included, which can be seen in the task flow timeline.

Content	Estimated time usage
A. Identification of the source of data The data source will be identified, according to the criteria mentioned above. Information of the data source and its owner will be collected, including how does the organization handles error report, how do new developers get on board, etc. This information will help the next step, data extraction.	1 week
B. Data extraction The data will be organized. The initial set of data points to collect from the data will be decided and executed at this point. Data labelling for the training and test part of the machine learning model will also be completed in this stage.	3 weeks
C. Model training and refining	3 weeks
D. Model analysis An effort will be made attempting to understand the model and potentially highlight variables that affect the output of the model heavily.	2 weeks
E. Atom package development Atom package development, testing and deployment will be done in this stage. The package itself will be coded using Javascript.	3 weeks
F. Writing the final project report	3 weeks



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List of Significant Experiments

Experiment ID	Week #	Meeting #	# of Rows	Details
1	4	6	27	Any work experience = experienced
2	4	6	106	6 months after first job = experienced; 6 months before first job/intern = novice, new data used because of new work experience definition and slight difference in data collection process
3	4	6	174	2 with more new data
16	6	8	266	Without complexity, With general code
17	6	8	266	Without complexity, Without general code
18	6	8	266	With complexity, With general code
19	6	8	266	With complexity, Without general code
20	7	9	266	16 with Halstead metrics
21	7	9	266	17 with Halstead metrics
22	7	9	266	18 with Halstead metrics
23	7	9	266	19 with Halstead metrics
24	7	9	157	19 with only JHawk metrics
25	7	9	157	19 combined with JHawk metrics
26	6	8	196	Regression Test
27	8	10	Variable	19 dataset split by questions
28	8	10	83	Based on 19, with more solutions for the question: Kangaroo (50 -¿ 83)
29	8	10	51	Based on 19, with more solutions for the question: Grading (27 -¿ 51)
31	9	11	55	Question: Circular Array Rotation, 55 rows (new), original
32	9	11	55	Question: Circular Array Rotation, 55 rows (new), no general
33	9	11	79	Question: Circular Array Rotation, 79 rows (new + old 55), original
34	9	11	79	Question: Circular Array Rotation, 79 rows (new + old 55), no general
35	11	13	69	Question: Sequence Equation, 69 rows, original
36	11	13	69	Question: Sequence Equation, 69 rows, original, no general

Experiment ID	Week #	Meeting #	# of Rows	Details
37	11	13	90	Question: Sequence Equation, 90 rows (inc'l old 69), original
38	11	13	90	Question: Sequence Equation, 90 rows (inc'l old 69), original, no general
39	11	13	164	Question: Sequence Equation, all new users parsed using script, original
40	11	13	164	Question: Sequence Equation, all new users parsed using script, no general
41	19	20	164	Set 40, with min max scaler
42	19	20	164	Set 40, with standard scaler

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