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SOURCE CODE VULNERABILITY DETECTION USING AI

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MSc Final Project Declaration

This report is submitted in partial fulfilment of the requirement for the degree of Master of Science in 7COM1039-0509-2022 - Advanced Computer Science Masters Project at the University of Hertfordshire (UH).

It is my own work except where indicated in the report.

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**Abstract**

Within the dynamic realm of cybersecurity, the identification of weaknesses present in source code continues to be a matter of utmost importance. Conventional machine learning-based scanners have demonstrated certain limits in the areas of feature engineering, data scarcity for developing vulnerabilities, and the ability to generalise to novel threats, notwithstanding their effectiveness. This dissertation explores the potential of Convolutional Neural Networks (CNNs) as a potential solution to the aforementioned difficulties. The primary focus of this research lies in the automation of the feature engineering process, the capacity of Convolutional Neural Networks (CNNs) to acquire knowledge from little labelled data, and their effectiveness in mitigating false negatives and positives. The results of the study highlight the considerable potential of Convolutional Neural Networks (CNNs) in the field of cybersecurity. The model that was constructed demonstrated an accuracy rate approaching 97% and a loss value of 0.0778. Although the findings show promise, the precision metric reveals possible areas for improvement. The research not only provides a comprehensive model for the subject of cyber security, but also establishes a foundation for future studies aimed at enhancing and implementing CNN-based vulnerability detection systems in practical settings.

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# Chapter 1: Introduction

## 1.1 Background

The need for software applications is skyrocketed in the twenty-first century. These applications pervade every facet of our lives, from personal tasks to professional operations. Software automates our daily chores, powers the business world, drives scientific research, facilitates global communications, enhances healthcare, and even entertains us. Mobile apps, desktop software, web applications, and complex systems powering industries and governments have become fundamental components of our societal fabric. The comfort, efficiency, and innovation provided by these applications have drastically transformed our lives, making the world more interconnected and information more accessible.

However, the widespread use of software programmes has also resulted in a remarkable rise in cyberattacks. Cybersecurity threats and breaches are more frequent and highly sophisticated. Every day, risks to organisations, governments, and people include espionage, sabotage, and ransomware assaults. The cost of cybercrime is predicted to increase from $3 trillion in 2015 to $10.5 trillion annually by 2025, according to a report by Cybersecurity Ventures (Ene, 2023). This quick rise emphasises how difficult it is for businesses and people to safeguard their digital assets.

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Figure 1 : Estimated cost of cybercrime worldwide (Fleck , 2022)

The vulnerabilities found in the source code of software programmes are the primary cause of many of these cyberattacks. A weakness or defect in the system, which might be used to overcome security measures or issue malicious instructions, is referred to as a vulnerability in this context. Numerous factors, including faulty programming, insufficient testing, the usage of unsecured third-party libraries, or out-of-date components, may lead to the introduction of vulnerabilities. Such vulnerabilities have a higher chance of occurring due to the complexity and size of software programmes increasing. If these flaws are not found and fixed in a timely manner, they might serve as a point of entry for attackers, potentially resulting in data loss, system damage, and dire financial and reputational repercussions (Yang et al., 2022).

The consequences of source code vulnerabilities have been shown throughout time by serious cyberattacks. By taking advantage of a defect in the widely used OpenSSL library, the Heartbleed bug in 2014 jeopardised internet security. This flaw made it possible for unauthorised people to access private data, including passwords and secret codes (Bojanova et al, 2023). A vulnerability in the web development framework Apache Struts caused a data breach at Equifax in 2017 that exposed the personal information of almost 147 million customers. According to Erickson et al. (2023) one significant cause was Equifax's refusal to address the known vulnerability. These occurrences highlight the need for more sophisticated tools that make use of Artificial Intelligence (AI) approaches to find software source code vulnerabilities.

## 1.2 Problem Statement

To provide effective cybersecurity measures, source code vulnerabilities must be found. Existing source code vulnerability scanners based on machine learning have showed promise in spotting possible flaws. These scanners, however, have a number of drawbacks and restrictions. This research project seeks to investigate the application of deep learning approaches for source code vulnerability identification in order to address the limitations of the traditon solution. Deep learning can automate the feature engineering process, allowing models to derive their learning directly from representations of the original source code. This study intends to enhance overall cybersecurity measures by increasing the precision, efficacy, and generalizability of source code vulnerability identification using deep learning methods.

## 1.3 Research Questions

1. How can CNNs improve detection accuracy by automating the feature engineering process in source code vulnerability detection, which would otherwise need human feature engineering?
2. How can a CNN-based model be created to automate feature engineering for the detection of source code vulnerabilities?
3. How can CNN models' architecture and hyperparameters be optimised for best results in detecting source code vulnerabilities?
4. What metrics should be used to evaluate the efficacy of a CNN-based vulnerability detection system for source code?

## 1.4 Aim & objective

The aim of this research work is to investigate and develop an effective source code vulnerability detection system using convolutional neural networks (CNNs), addressing the limitations of traditional machine learning-based scanners.

**Objectives**

1. To review and assess existing research on the use of CNNs in other fields and the detection of source code vulnerabilities in order to gain knowledge and pinpoint best practises.
2. Creating and implementing a CNN-based source code vulnerability detection model that automates feature engineering, eliminates the need for manual feature engineering, and boosts detection precision.
3. To Evaluate the performance of the CNN-based source code vulnerability detection system against conventional machine learning-based scanners and other cutting-edge techniques.
4. To conclude the work , with a focus on highlighting the merits of the CNN-based model in comparison to conventional approaches, and to propose suggestions for further investigation.

## 1.5 Paper Outline

### 1.5.1 Introduction

This section highlights the importance of detecting source code vulnerabilities and the limitations of traditional machine learning scanners as well as aim and objective of the research work.

### 1.5.2 Literature Review

This section delves into literature reviews of current vulnerability detection methodologies, weighing the strengths and weaknesses of traditional scanners. It also identified the gap of the current work.

### 1.5.3 Methodology

Here, the research approach is detailed, from data acquisition to its CNN-specific representation.

### 1.5.4 Implementation

The section discusses the intricacies of CNN model development, its implementation, and evaluation metrics, with a focus on training techniques for limited data.

### 1.5.5 Results

Findings from the CNN-based system are analysed, benchmarked against traditional methods.

### 1.5.6 Conclusion

The study's contributions are summarized, emphasizing the benefits of CNNs for vulnerability detection, and suggesting avenues for future research in this domain.

# Chapter 2: Literature Review

## 2.1 Related Works

Fang et al.'s (2020) study focused on the topic of growing computer system vulnerabilities and the significance of knowing which ones are most likely to be used by attackers. They sought to quickly sort out the non-exploitable vulnerabilities and focus patching efforts on those who were most at risk since they understood that only a tiny percentage of vulnerabilities are actually exploited. By suggesting a novel exploit prediction model, fastEmbed, which combines the fastText and LightGBM algorithms, they distinguished their approach from earlier ones. This approach captures the context and meaning of language connected to vulnerabilities, unlike conventional systems that just take into account static statistical data, which is essential for anticipating exploits.

The fastEmbed model was evaluated against the most recent exploit prediction best practices. Without any time-mixing bias, it showed improved performance in both generalisation and prediction. On average, it outperformed the benchmark models by 6.283%. Specifically, the model outperformed techniques employing characteristics from the darkweb/deepweb by 33.577%, with an F1 score of 0.586 for the minority class, in predicting exploits "in the wild". The researchers reported that compared to current datasets on a platform called SecurityFocus, their model could forecast exploitability and exploitation in the wild up to 5 days in advance. Additionally, it foresaw the day-ahead distribution of Proof of Concepts (PoCs). This approach may be used with other sources of threat information, such as security blogs.

The researchers did admit that more effort is needed to increase the precision and calibre of exploits labelling and evidence of exploits in the wild. They recommended looking into more time- and coverage-efficient data sources, concentrating in particular on those exploited by hackers, such as the deep and black web. In conclusion, this work represents a significant advancement in exploit prediction by providing a more detailed strategy for selecting the most crucial fixes for system vulnerabilities.

The study by Fang et al. (2020) showed numerous improvements in exploit prediction models, but it also included a number of flaws and opportunities for development.  First of all, the study concentrated on very uneven data sets, which may not provide a precise or thorough depiction of actual circumstances. Highly skewed datasets may result in models that succeed on classes that are overrepresented but fall short on classes that are underrepresented. Given the crucial significance of vulnerability exploitation, it might be disastrous to misclassify a major but uncommon occurrence.

Second, the presence of a proof of concept (PoC) in the Exploit-DB database was noted in the study. As a result, the model's accuracy might be impacted. The training data could not accurately represent the complete range of vulnerabilities. The quality of the training data determines how well a model performs, and apparent bias and incompleteness may reduce the resilience and generalizability of the model. Additionally, their model heavily relied on the crucial components of the text that dealt with vulnerabilities, which was seen to be its most crucial component. Although this method was successful in capturing the context and meaning of the text's words, it may not be adequate or thorough enough to handle complicated vulnerability prediction situations. Analysis of many technological, environmental, and human aspects is often required for vulnerability assessment; however, text alone may not adequately reflect these elements.

Additionally, Fang et al. (2020) discovered that although their model outperformed others when used with vulnerability knowledge from sources like SecurityFocus, it underperformed when used with the National Vulnerability Database (NVD). Due to its inconsistent performance, the model may not be consistently applicable across various intelligence sources, which would restrict its adaptability. Last but not least, in real-world scenarios, the model's capacity to forecast an exploitability and exploitation in the wild of a vulnerability on SecurityFocus five days earlier than current data sets may not be sufficient. A five-day forecast window would not be sufficient for the implementation of preventative measures in the case of cybersecurity attacks, which often demand urgent action and prediction.

The limits of Fang et al.'s study indicate areas that need more investigation, despite the fact that their work has improved the state-of-the-art in vulnerability exploit prediction. There is a need for more balanced datasets, better PoC data quality, thorough feature extraction, broader application across various intelligence sources, and quicker vulnerability prediction.

Gupta et al. (2020) investigated how machine learning may be used to enhance bug identification in the early phases of the Software Development Lifecycle (SDLC). The goal of the study was to lessen the time and effort required for system and bug maintenance and to avert runtime emergencies. The researchers used the NASA-KC2, PC3, JM1, and CM1 datasets to evaluate five machine learning models. The models were AdaBoost, XGBoost, Random Forest, Decision Tree, and Logistic Regression. Although Logistic Regression and Decision Tree fared rather well, Random Forest and AdaBoost stood out as the top performers. The greatest outcomes, nevertheless, were from the XGBoost model.

The group then made the decision to improve the already-existing XGBoost model by modifying N\_estimator, learning rate, max depth, and subsample, which they dubbed Tuned XGBoost. The study's findings showed that the Tuned XGBoost model performed better than any other model they tested. Particularly, across several datasets, the Tuned XGBoost model showed good levels of accuracy, precision, recall, and AUC. It obtained accuracy of 97%, precision of 95%, recall of 98%, and AUC of 96% on the PC3 dataset. The model achieved 94% accuracy, 95% precision, 90% recall, and 94% AUC on the JM1 dataset. It demonstrated 95% accuracy, 97% precision, 95% recall, and 96% AUC when evaluated on the CM1 dataset. Finally, it demonstrated 94% accuracy, 93.3% precision, 95% recall, and 96% AUC on the KC2 dataset.

The study by Gupta et al. (2020) did provide outstanding outcomes for bug discovery using machine learning algorithms. There are a few issues to be aware of, however, as with any research.

First off, although the Tuned XGBoost model they suggested fared better than the other models in the majority of areas, it is far from perfect. Overfitting could result from adjusting the XGBoost model's N\_estimator, learning rate, max depth, and subsample parameters. When a model gets extremely complicated and excels on training data but fails to generalise to fresh, untried data, it is said to be overfit. Although Gupta and his colleagues claimed better results, it's not obvious whether the model can continue to perform at this high level with other datasets or in practical applications.

Second, to solve the class imbalance problem in the datasets, the study largely depends on the Synthetic Minority Over-sampling Technique (SMOTE). SMOTE may enhance model performance, but it also generates synthetic data that might not always accurately represent actual circumstances. This suggests that the models' excellent performance may not totally apply to real-world circumstances and may be partially explained by these synthetic findings.

The researchers' method for feature scaling at the data preprocessing stage could possibly have drawbacks. A method for standardising the range of independent variables or features in data is called feature scaling. The assumption that all characteristics are equally relevant is not necessarily true, despite the fact that this is a prevalent practise in machine learning to improve models' performance. In fact, certain characteristics could be more important than others for forecasting software defects. Their approach doesn't seem to account for this possible variance.

As a result, even if Gupta et al.'s (2020) study shows a positive development in early bug discovery, there are important limits to take into account, especially in the area of source code vulnerability detection. Although their Tuned XGBoost model performed well in trials, there is a chance that overfitting may cause it to perform poorly in practical applications. Additionally, the model's strong reliance on the SMOTE approach can cause an imbalance between artificial observations and real-world data, which might result in false positives or false negatives when detecting vulnerabilities. Their research's widespread use of feature scaling might obscure critical vulnerability indications and risk missing vital elements of bug discovery.

A machine learning model was created by Pinnamaneni et al. (2022) study to discover insecure Python libraries in Docker container images after they analysed the security vulnerabilities in these images. Due to their characteristics, Docker container images are favoured over virtual machines since they include everything required to operate an application. The researchers chose to concentrate on static code analysis since they may potentially pose security problems.

To classify the code as either susceptible or not, the team employed a variety of supervised classification machine learning methods, including Linear Regression, Decision Trees, Naive Bayes, K-Nearest Neighbours (KNN), Support Vector Machine (SVM), Random Forest, Gradient Boost, and XGBoost. According to the research, the algorithms for Decision Tree, Random Forest, Gradient Boost, and XGBoost all obtained 100% accuracy and precision.

They employed soft voting between the Decision Tree, Random Forest, and Gradient Boost algorithms to build a model that can manage any size database. They next used Streamlit to design a user interface that leverages the developed model to determine if new code is susceptible. This interface recognises the programming language of the code, and if Python is used, it determines if the code is susceptible and names the libraries that are responsible.

Their study has helped develop a useful technique for scanning and locating Python code vulnerabilities in Docker container images. The database should be expanded to include other programming languages, such as C, C++, Java, and Go, and further vulnerabilities should also be added, they suggest.

The study of Pinnamaneni et al. (2022) is a significant step towards securing Docker container images, although it does have certain limitations, especially in terms of how it approaches source code vulnerability identification. First off, their model lacks adaptability since it was trained just to find vulnerabilities in Python libraries. As a result, when used on code created in other languages, its effectiveness drastically drops. As a result of its Python focus, it cannot be used to scan the source code of programmes written in other well-known programming languages, such as C, C++, Java, or Go.

Second, while reaching purportedly 100 percent accuracy and precision, the machine learning algorithms utilised may be at danger of overfitting, which might result in a high percentage of false positives or negatives when applied to fresh, untested data. When the model is exposed to data including new kinds of vulnerabilities or libraries that weren't included in the training data, overfitting may also make the model perform badly. The report also ignores additional dangers including DOS attacks, cross-site scripting, memory corruption, and overflow vulnerabilities since it only focuses on keylogging vulnerabilities. Users may be exposed to a broad variety of possible threats as a result of this tool's lack of comprehensiveness.

Last but not least, the model's dependence on libraries to assess vulnerability may leave out other crucial aspects of the code, which may result in vulnerabilities that do not directly touch these libraries. As a result, it can fail to notice certain vulnerabilities.

To sum up, there are certain drawbacks to the study (Pinnamaneni et al. 2022) on the security of Docker container images and the identification of Python library vulnerabilities. The method's ability to scan code written in other languages is limited by its Python-specific nature. Despite claiming great accuracy, the used machine learning models may overfit the data and result in incorrect classifications on previously unknown data. Additionally, while keylogging vulnerabilities are the emphasis, other attacks may go unnoticed, possibly putting users at danger. Last but not least, by depending entirely on libraries to forecast vulnerability, the model may miss other important components of code vulnerabilities unrelated to these libraries.

In their study, Letychevskyi et al. (2020) used machine learning (ML) to improve the identification of flaws in low-level code. To find possible weaknesses, they employed symbolic modelling to depict computer programmes as a directed graph. By fusing symbolic modelling and machine learning, the attainable route generating process was intended to be improved. The group created a particular method for producing training data via their trials. They made use of numerous node-embedding techniques, including LLE, SPE, node2vec, DeepWalk, and artificial neural networks (ANN) and support vector machines (SVM) for classification.

The results showed that an accuracy rate of 86% was attained using the ANN approach in conjunction with node2vec node embedding. Tests utilising node-embedding techniques based on matrix factorization produced less favourable results, which may be related to the sparse nature of control flow graphs (each node may have up to two successors).

The researchers came to the conclusion that symbolic modelling methods might be greatly complemented by an ML-based strategy for determining the shortest route. They emphasised that the precision attained demonstrated the potential of their original strategy. In addition, they suggested expanding the set's size and variety, refining the node-embedding algorithm's hyperparameters, and developing a specific classifier to assess nodes' connectivity because their previous work assumed that connections between nodes always existed even though this may not always be the case.

Despite the study's positive results, there are a number of possible drawbacks.  First off, although control flow graphs are often sparse networks, the research relied on a node-embedding approach that may not perform well for such graphs. Its wide application may be constrained by the research's inferior performance with matrix factorization-based node-embedding techniques.  In real-world applications, the link between nodes doesn't always exist, according to the methodology's second assumption. This can result in mistakes or omissions during the vulnerability identification procedure.

A variety of ML classification techniques were also tried in the research, and it was discovered that the Artificial Neural Network (ANN) approach using node2vec node embedding obtained 86% accuracy, which, although excellent, also highlighted possible drawbacks. The success of the ANN in this situation demonstrates its potential for source code vulnerability scanning.

Artificial neural networks are promise for identifying vulnerabilities because of a number of benefits. The capacity to learn and model non-linear and complicated connections, which is highly helpful for comprehending the interactions inside source code, makes them outstanding at capturing complex relationships in data and coping with large dimensionality. Additionally, ANNs are very tolerant to noisy input, which is a characteristic of big code bases often.

In conclusion, although showing that machine learning may be used to discover code vulnerabilities, the Letychevskyi et al. (2020) research has certain drawbacks. The complexity of actual software systems may not be accurately captured by the assumptions and methodologies utilised, and it is possible that certain vulnerabilities may go unnoticed. Nevertheless, the study's performance of the artificial neural network points to a potential direction for source code vulnerability scanning research and development in the future. Future research should look at enlarging and diversifying the data set, enhancing the hyperparameter optimisation of the node-embedding method, and creating specific classifiers to evaluate node connectedness.

Santithanmanan et al. (2022) conducted a research study that concentrated on Cross-Site Scripting (XSS) assaults, a widespread issue in online applications, and especially targeted Cisco Enterprise's Network Function Virtualization Infrastructure Software (NFVIS). In these XSS attacks, malicious code (typically JavaScript) is injected and then distributed to other users through a URL. Due to the possibility of sensitive user data being stolen, the hazard is very serious.

The researchers employed machine learning methods to pinpoint the URLs that could be responsible for these assaults. The k-Nearest Neighbours (k-NN), Decision Tree, Support Vector Machine (SVM), and Gaussian Naive Bayes machine learning techniques were used. On a dataset that was divided between training and testing portions in a ratio of 70:30, these models were trained and assessed. The k-NN model was the most accurate of the four evaluated approaches, according to the study's findings. In only 0.1633 seconds, it was able to determine if a URL was hazardous or benign, achieving an extremely high accuracy rate of 99.6%. It is a promising tool for quick identification and defence against XSS assaults because of its precision and speed. As with every study, there are, nevertheless, certain gaps or opportunities for improvement.

The study's chosen machine learning models, such as k-NN, Decision Tree, SVM, and Gaussian Naive Bayes, all have inherent drawbacks. Although the k-NN model's excellent accuracy of 99.6% was obtained, it may not perform as well when dealing with big data sets or when the input dimensions are high. Additionally, it presumes that all traits are equally important, which may not always be the case.  Furthermore, the use of a 70:30 split to divide the dataset into training and testing sets might result in overfitting. A typical issue in machine learning is overfitting, when a model performs well on training data but struggles to generalise to new data. This might imply that the models would perform less well in a practical application than they would in a lab setting.

Additionally, even if the research advances the automated classification of XSS assaults, it only pays attention to two properties: URL and JavaScript. As XSS attacks may be implemented through various techniques, this may create detection system gaps.  Additionally, the paper avoids addressing the possibility of false positives or negatives, which might pose serious problems for machine learning-based vulnerability identification. While a high false negative rate might imply overlooking important vulnerabilities, a high false positive rate could result in actions being made that are unnecessary.

In conclusion, although making important advancements in XSS vulnerability identification, Santithanmanan et al.'s study (2022) has certain drawbacks. The 70:30 dataset split runs the danger of overfitting since the machine learning algorithms utilised, especially the k-NN model, have intrinsic limits when handling huge data sets or high input dimensions. The research may have overlooked other possible attack paths due to its emphasis on URL and JavaScript as the only criteria for identifying XSS assaults. Furthermore, a crucial issue in machine learning-based vulnerability identification, the likelihood of false positives or negatives, was not addressed in the study. Due to these drawbacks, it is possible that more thorough methods including more features and various machine learning algorithms would be required for more accurate and reliable vulnerability identification, even though the work makes a vital contribution.

### 2.1.1 Conclusion

It is clear from the thorough literature study that a variety of machine learning models have been effectively used in this area, each providing a distinctive viewpoint and solution. Nevertheless, it is evident that these studies have inherent drawbacks, including overfitting, data imbalance, a limited scope, and false positive and negative concerns.

Nevertheless, these difficulties provide a strong justification for the use of deep learning, and more particularly, Convolutional Neural Network (CNN) algorithms, in the identification of source code vulnerabilities. Because deep learning can learn from vast, varied data sets and has inherent robustness against overfitting, it has shown promise in tackling issues like overfitting and data imbalance. It is more likely to find vulnerabilities that are not simply limited to certain code qualities because CNNs' high dimensionality processing capacity enables them to discover complicated patterns in source code that other models may overlook.

Additionally, the inbuilt capability of CNNs to maintain the spatial hierarchy in data may eventually result in a more comprehensive approach to vulnerability identification, resolving the problem of the research' restricted emphasis. Last but not least, CNNs may successfully reduce the percentage of false positives and negatives, hence improving the dependability of vulnerability detection systems. The adoption of deep learning, specifically CNN algorithms, in source code vulnerability detection presents a promising avenue to overcome current limitations and enhance the reliability and robustness of vulnerability detection systems, even though previous research has made significant advances in the field.

# Chapter 3: Methodology

## 3.1 Quantitative Research Approach

Quantitative research is a methodological approach that emphasises the structured collection and analysis of numerical data (Bryman, 2012). This approach, which is rooted in the positivist tradition, holds that reality can be captured and comprehended through objective and scientific methods. Multiple significant factors influenced our decision to adopt a quantitative methodology for this investigation. First, the complexities of vulnerability detection necessitate the highest degree of accuracy. According to Creswell (2013), by employing a quantitative methodology, we can objectively evaluate the performance of our CNN model, including metrics such as accuracy and precision. The second advantage of quantitative study results is their applicability to a variety of contexts. This implies that the insights we acquire regarding CNN's efficacy in identifying vulnerabilities can be applied to a vast array of software scenarios. Moreover, the profundity of statistical analysis made possible by the quantitative method is invaluable. According to Field (2009).

## 3.2 The Dataset & Coding

The primary focus of the Draper VDISC Dataset is on the identification and assessment of vulnerabilities inside source code. The dataset comprises the source code of 1.27 million functions obtained from open source software. Each function has been annotated to identify possible vulnerabilities using static analysis techniques. The dataset has been divided into three segments, namely train, validate, and test, following an 80:10:10 split. These segments are stored in three HDF5 files, together using around 1 GB of storage space. The source code of each function is represented as a variable-length UTF-8 string, beginning with its name. The dataset provides five binary labels denoting 'vulnerability' for each function, representing the four most popular Common Weakness Enumerations (CWEs) as well as an extra category for other CWEs. It is worth noting that individual functions have the potential to be linked with several Common Weakness Enumerations (CWEs).

The selection of Python as the programming language for this study was based on its wide range of libraries and frameworks specifically designed for deep learning, including TensorFlow and Keras. The adaptability of this system guarantees a smooth workflow that encompasses all stages, starting with data pre-treatment and extending through model building. Moreover, the extensive community support around Python means that any issues encountered throughout the research process may be promptly resolved. Although R and Java possess their own unique capabilities, they do not provide the same level of comprehensive deep learning environment as Python. Additionally, these languages sometimes need more complex coding techniques to accomplish identical tasks.

The selection of Google Colab as the development platform was based on its user-friendly nature and browser-based interface, which eliminates the need for any setup process. The availability of free GPU access provided by this platform is of great value for the computationally demanding training procedures connected with deep learning models. The platform's interface with Google Drive and its support for interactive visualisations enhance the efficiency of the research process, making it an ideal setting for achieving the study's goals.

## 3.3 Methodology Flowchart for Deep Learning Model Development

The flowchart provides a logical overview of the methodology used to construct a deep learning model. It begins with environment preparation, followed by data collection and pre-processing. Next, the model is configured, trained, and assessed. Visualising and analysing the training and validation metrics is the final phase. Each major phase is broken down into specific duties to ensure a thorough comprehension of the entire procedure.

A diagram of a model

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Figure 2 : Methodology Flowchart

## 3.4 Setting Up the Environment

In the initial phase of the research, it was crucial to create an environment suitable for the execution of the deep learning model. This entailed establishing the required software libraries and tools that would aid in data processing, model training, and evaluation.

### 3.4.1 Installation of Required Libraries

Before delving into the data analysis and model development, specific Python libraries were installed to guarantee the code's execution. The libraries were selected based on their applicability to the current duties and their popularity within the deep learning community. Using the 'pip' package manager, the libraries were installed.

### 3.4.2 Importing Necessary Libraries and Modules

After installing essential libraries, they were integrated into the Python environment to support various research stages. Libraries like h5py facilitate the handling of large datasets, while pandas aids in data manipulation and analysis. TensorFlow, developed by Google, underpins the design and training of the CNN model, while numpy streamlines numerical computations. Visualization needs are addressed by matplotlib, and post-training model evaluation is conducted using sklearn metrics from the scikit-learn library. The pickle module assists in serializing Python objects, preserving datasets and model states. The os module manages OS interactions, and keras.callbacks.ModelCheckpoint from Keras monitors and saves model performance improvements.

## 3.5 Data Acquisition and Pre-processing

The integrity and preparation of the data form the foundation of any machine learning or data-driven research. This section explains the actions taken to obtain, import, investigate, transform, and tokenize the crucial datasets for this study.

### 3.5.1 Loading the Datasets (Train, Validate, Test)

Datasets in research are typically divided into three primary sets:

1. Training Set: Used to train the model. It provides the raw material from which the initial model is crafted.
2. Validation Set: Assists in tuning the model parameters and preventing overfitting. It acts as a checkpoint to ensure the model is learning correctly.
3. Testing Set: Used to evaluate the model's performance. It offers an unbiased evaluation of a final model fit on the training dataset.

The HDF5 format was used to store the datasets for this study. HDF5 stands for Hierarchical Data Format version 5, a popular format for storing large datasets because of its scalability and performance (Collette, 2013). These datasets were loaded with the aid of the 'h5py' library, a Pythonic interface to the HDF5 binary data format.

### 3.5.2 Exploring the Dataset Structure

Before beginning data pre-processing, it is essential to comprehend the structure of the dataset. This requires identifying the numerous features, identifiers, and data types associated with them. By examining the primary components or keys of the datasets, one can gain insight into the nature of the data being processed, which in turn informs subsequent pre-processing steps.

### 3.5.3 Data Transformation and Decoding

The process of converting data from one structure or format to another is known as data transformation. Given that the datasets were stored in HDF5, a transformation was required to assure compatibility with the research tools and libraries.  When coping with data that may be stored as bytes, decoding is essential. Textual data within the datasets, for instance, required decoding from bytes to strings using UTF-8 encoding. UTF-8 is a character encoding that is capable of encoding all conceivable Unicode code points, making it suitable for decoding diverse datasets (Yergeau, 2003).

### 3.5.4 Data Tokenization and Conversion

Tokenization is an essential process, particularly when dealing with textual data. It entails dividing text into tiny units known as tokens. These identifiers can be as small as single words or as vast as complete sentences. In the context of machine learning, tokenization helps convert human-readable text into a format that can be understood by a machine learning model. For tokenization, the 'Tokenizer' class from the 'keras.preprocessing.text' module was used. It not only converts texts into tokens, but also tokens into sequences of integers. This conversion is essential because machine learning models, particularly deep learning models, operate on numerical data.

## 3.6 Model Configuration

Configuring the machine learning model is a crucial component of the research procedure. It determines how the model will process the data, the architecture it will adhere to, and how its efficacy will be optimised. This section delves into the configuration details of the model based on the provided source code.

### 3.6.1 Setting Global Parameters

Before initializing the model, it was essential to define some global parameters that would dictate the model's behavior and structure. These parameters included:

1. Batch Size: Determines the number of training examples utilized in one iteration. A smaller batch size often provides a regularizing effect and lower generalization error (Goodfellow et al., 2016).
2. Epochs: Represents the number of times the learning algorithm will work through the entire training dataset. Training a model for too many epochs can lead to overfitting (Smith, 2017).
3. Embedding Dimensions: Specifies the size of the embedding vectors. Embedding is a technique used to convert categorical data, like words, into a form that can be provided to machine learning algorithms (Mikolov et al., 2013).

#### 3.6.2 Model Architecture

#### 3.6.2.1 Embedding Layer

The embedding layer was created using the Keras library's 'Embedding' class. This layer functions as the model's initial layer, transforming integer indices into dense, fixed-size vectors. It is essential for managing textual data because it provides a method to reduce dimensionality and efficiently manage the extensive vocabulary space.

#### 3.6.2.2 Convolutional Layer

Keras' 'Conv1D' class was utilised to implement the convolutional layer. Processing data with a grid-like topology, such as time-series data or image data, requires convolutional layers. Each neuron processes data only for its receptive field (LeCun et al., 1998), allowing them to recognise spatial patterns.

#### 3.6.2.3 Pooling Layer

The 'MaxPooling1D' class was selected for the layer's pooling. Its primary function is to gradually reduce the spatial dimension of the representation, thereby decreasing the number of network parameters and computations. This layer prevents overfitting by supplying an abstract representation of the data.

#### 3.6.2.4 Dropout and Flatten Layers

The 'Dropout' class was utilised to introduce dropout as a technique for regularisation. (Srivastava et al., 2014) Dropout arbitrarily selects neurons to disregard during training, reducing the likelihood of overfitting. The 'Flatten' class was used to convert multidimensional input into a 1D array by flattening the input.

#### 3.6.2.5 Dense Layers

The Keras 'Dense' class was used to construct layers with complete connectivity. Using their learned weights, these layers classify the features extracted by the previous layers.

### 3.6.3 Model Compilation

#### 3.6.3.1 Custom Optimizers

The 'Adam' optimizer from Keras was selected due to its effectiveness and minimal memory requirement. Optimizers modify the neural network's attributes, such as weights and learning rate, to minimise losses.

#### 3.6.3.2 Loss and Metrics

The 'categorical\_crossentropy' loss function was utilised to evaluate the efficacy of the model. During training, the objective of the model is to minimise this function. To evaluate the efficacy of the model, 'accuracy' was chosen as a metric.

## 3.7 Training the Model

Training is a crucial component of the machine learning pipeline. It involves feeding data into the model, modifying the weights, and optimising the algorithm to make accurate predictions. This section details the training of the model, including the configuration of responses, the selection of data subsets, and the actual training procedure.

### 3.7.1 Callbacks Configuration

Callbacks are an indispensable component of deep learning models, particularly when utilising frameworks such as TensorFlow. They enable the execution of specific sets of actions at various phases of training, which can be useful for monitoring the model's performance, storing the optimal model weights, and even modifying the learning rate dynamically.

#### 3.7.1.1 TensorBoard Callback

TensorBoard is an included visualisation utility with TensorFlow. It enables researchers to monitor the model's metrics, visualise the model's architecture, and even observe the evolution of weights. TensorBoard was configured for this study to log data at each epoch. This continuous logging enabled real-time performance monitoring and facilitated the identification and correction of any anomalies in the training process (TensorFlow, 2020).

#### 3.7.1.2 Model Checkpoint Callback

It is crucial to ensure that the finest version of the model is preserved. This functionality is provided by the Model Checkpoint callback in TensorFlow, which continuously saves the model weights after each epoch, but only if the model's performance (on a specified metric, such as validation accuracy) improves from the prior best. This method ensures that the optimal model is retained even if the training process is interrupted or if the model begins to overfit and its performance degrades (Chollet et al., 2015).

### 3.7.2 Data Subset Selection for Training

Due to the abundance of available data, it was necessary to select a representative subset for training. This subset was selected using stratified sampling to ensure that all classes in the dataset are represented proportionally. This method ensures that the model is not biassed towards a specific class and can generalise well to unseen data (Bishop, 2006).

### 3.7.3 Model Training Process

After setting up the environment and selecting the data subset, model training started. The model was trained using the Adam optimizer, a well-known optimisation algorithm that incorporates the most advantageous characteristics of the AdaGrad and RMSProp algorithms (Kingma & Ba, 2014). The utilised loss function was categorical crossentropy, which is appropriate for multiclass classification issues.

The training procedure involved providing packets of data to the model, forward propagating the input through the network, calculating the loss, and then backpropagating the error to modify the model weights. This process was repeated multiple times until the model's performance on the validation set stopped improving, indicating that it had likely attained its optimal state.

## 3.8 Model Evaluation and Prediction

Evaluation of a machine learning model's efficacy is a crucial aspect of any research. It reveals the model's ability to generalise to unobserved data and its overall accuracy. This section explores the processes and methodologies used to evaluate the model developed for this study.

### 3.8.1 Model Loading

Once the model had been trained, it was stored to memory in order to prevent retraining and ensure reproducibility. Using the 'h5py' module, the model was saved in Hierarchical Data Format (HDF5), a versatile format for holding large datasets and models (Collette, 2013).  To evaluate the efficacy of the model, it was reloaded into the Python environment. For this purpose, the 'load\_model' function from the 'keras.models' module was used. This loading method assured that all weights, biases, and hyperparameters were accurately restored, allowing for a seamless transition from training to evaluation.

### 3.8.2 Performance Metrics Calculation for Training Data

After populating the model with training data, its performance was evaluated. This stage is essential for evaluating the model's performance during the training phase.  Several metrics, including accuracy, precision, recall, and the F1-score, were computed. These metrics provide a comprehensive perspective on the performance of the model. Pedregosa et al. (2011) define accuracy as an overall measure of correct predictions, whereas precision and recall concentrate on the model's performance regarding positive class predictions. In contrast, the F1-score provides a balance between precision and recall. Given its extensive functionality and usability for evaluation tasks, the'sklearn.metrics' module was utilised to compute these metrics.

### 3.8.3 Batch Prediction

Batch prediction was utilised to ensure accurate and rapid predictions, particularly when dealing with large datasets. Instead of predicting the output for each individual data point, the data were organised into blocks and predictions were made for each batch. This strategy exploits the parallel processing capabilities of modern GPUs, resulting in substantial speedups (Abadi et al., 2016).

### 3.8.4 Performance Metrics Calculation for Test Data

After evaluating the efficacy of the model on the training data, it was evaluated on the test data. This phase is crucial because it reveals the model's ability to generalise to new data. Similar to the training data evaluation, accuracy, precision, recall, and the F1-score were calculated for the test data. The results of this evaluation provided a clear picture of the model's applicability in the real world and its potential flaws.

# Chapter 4: Implementation

## 4.1 Importing libraries

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Figure 3: importing libraries

During the first phases of the research project, a number of crucial libraries and modules were integrated. The `h5py` library was used for the purpose of managing HDF5 files, whilst `pandas` was applied for doing data analysis. The `tensorflow` framework was selected as the preferred choice for conducting machine learning tasks, while `numpy` was used to streamline numerical processes. The use of the `matplotlib` library facilitated the implementation of data visualisation, while the `sklearn.metrics` package furnished tools for the assessment of performance. The process of serialising Python objects was accomplished via the use of the `pickle` module, while the management of operating system-dependent operations was facilitated by the `os` module. In order to guarantee frequent model saving during training, the `ModelCheckpoint` from `keras.callbacks` was used. The aforementioned imports jointly established the foundation for the deployment of the system.

## 4.2 Creating data frame

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Figure 4: creating data frame

The code snippet allows for the retrieval of data from an object resembling a dictionary, referred to as `data`, by using the key `'functionSource'`. The data that has been obtained is then transformed into a numpy array by using the `[:]` slicing notation. Following this, the array undergoes a transformation and is converted into a pandas DataFrame, which is assigned the name `mydf`. In essence, the code is retrieving the data from the 'functionSource' and transforming it into a structured table format to facilitate its modification and analysis.

## 4.3 Importing processed dataset

A screen shot of a computer code

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Figure 6: Importing processed dataset

The code segment given is concerned with the loading and preparation of datasets for the purpose of a deep learning job. The `pd.read\_pickle` method is used to import three datasets, namely 'train', 'validate', and 'test', from pickle files. It is probable that these datasets pertain to the detection of vulnerabilities. After being initialised, nested loops are used to iterate over designated columns inside the datasets. This process involves the conversion of boolean values (True and False) into their corresponding integer representations (1 and 0) using the `map` function. This conversion is considered essential for algorithms that need numerical input. Finally, the 'functionSource' column is taken from the 'train' dataset and stored in the variable `x\_all`. Each element in `x\_all` is decoded from byte format to 'utf-8' string format, in order to facilitate further text processing or tokenization.

## 4.4 One-Hot-Enconding (OHE) on the datasets

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Figure 9: One-Hot-ecncoding on the dataset

The provided code sample does one-hot encoding on designated columns inside the 'train', 'test', and 'validate' datasets. Three lists, namely `y\_train`, `y\_test`, and `y\_validate`, are initialised to hold the one-hot encoded data. The process of one-hot encoding involves the conversion of categorical data into a machine learning-compatible format. This is achieved by translating a column containing 'n' categories into 'n' binary columns. The provided code employs a loop to cycle over columns 1 to 5, whereby the `tf.keras.utils.to\_categorical` function is used for the purpose of encoding. The function necessitates the input of data and the number of classes, denoted as `NUM\_CLASSES`. Following the encoding process, the data undergoes conversion into the integer data type in order to ensure compatibility with certain deep learning methodologies. The encoded data obtained from each dataset is thereafter added to their corresponding lists.

## 4.5 Model Definition

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Figure 10: Model definition for CNN

The code shown implements a convolutional neural network (CNN) for the purpose of text processing, using the Keras API inside the TensorFlow framework. To begin, a matrix of weights, denoted as `random\_weights`, is constructed using a Gaussian distribution, where the values are modest and centred around zero. The Convolutional Neural Network (CNN) architecture commences with an initial layer known as the "Embedding" layer, which plays a vital role in transforming language stored as integers into dense vectors. Subsequently, a `Convolution1D` layer is used, consisting of 512 filters and using a rectified linear unit (ReLU) activation function. This is then followed by a `MaxPool1D` layer, which serves the purpose of reducing the dimensionality. In order to mitigate the issue of overfitting, a dropout layer is included into the model architecture, thereby deactivating half of the input units during training. The input is then transformed into a flattened format and propagated through a sequence of three `Dense` layers. The last layer employs a sigmoid activation function to facilitate binary classification. The optimisation of the model is performed using the Adam optimizer, which is configured with certain hyperparameters. The loss function used is binary cross-entropy, and the measure used to evaluate the model's performance is accuracy. The architecture of the model may be visualised by using the `model.summary()` function.

# Chapter 5: Results

## 5.1 Analysis of the Created CNN Model

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Figure 13: Created CNN Model for Vulnerability Detection

The Convolutional Neural Network (CNN) model developed for this dissertation represents a significant paradigm change in the realm of vulnerability identification in the field of cybersecurity. In contrast to conventional machine learning models, this Convolutional Neural Network (CNN) has been painstakingly engineered to demonstrate exceptional performance in identifying system vulnerabilities. The architecture of the system is carefully designed, beginning with the embedding layer that exhibits an output shape of (None, 500, 13) and a total of 130,000 parameters. This particular layer is designed to maintain a balance in the dimensionality of data, so guaranteeing that crucial information is preserved while minimising the computational expenses associated with excessive processing. According to Goodfellow et al. (2016), these 13 dimensions effectively represent the essential characteristics of the input data. Next in the sequence is the Conv1D layer, which is augmented with 512 filters to increase the model's ability to detect complex patterns. This design decision is substantiated by the research conducted by LeCun et al. (2015).

The subsequent addition to the model is the MaxPooling1D layer, which serves the purpose of decreasing spatial dimensions. This aids in addressing issues related to overfitting and computational complexity. The inclusion of a dropout layer in the model serves to enhance its resistance to overfitting, as emphasised by Srivastava et al. (2014). The thick layers, which are integral components of the model, provide significant computing capabilities. The first dense layer, consisting of 64 units, serves as a bottleneck, effectively decreasing the dimensionality of the input while retaining its fundamental characteristics. The aforementioned thick layers, which have been fine-tuned and configured with 16 and 1 units respectively, efficiently channel the identified characteristics to the final output, hence ensuring accurate detection of vulnerabilities.

## 5.2 Analysis of the Training Process for the CNN Model

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Figure 14: Training and validation loss over selected epoch

The vulnerability detection CNN model underwent training using a significant dataset of 1,019,471 samples. Additionally, the model was verified using 127,476 samples. The comprehensive training regimen used assures the model's resilience and capacity to effectively navigate a wide range of situations, as underscored by Bengio et al. (2012). The training process of the model spanned a total of 40 epochs, which was carefully chosen to achieve a trade-off between computing efficiency and performance. It is worth mentioning that there was a considerable improvement in the validation loss from the first epoch to the 36th epoch, which demonstrates the model's successful learning process and the appropriateness of the selected hyperparameters, as shown by Goodfellow et al. (2016). The accuracy metrics of the model provide further evidence of its effectiveness, starting at 98.05% and consistently demonstrating remarkable performance throughout the training phase. The evaluation criteria for loss and the observed pattern of validation loss provide supporting evidence for the efficacy of the model and its capacity to mitigate overfitting.

During the training procedure, an observation was made about the speed of the `on\_train\_batch\_end` function, however it did not seem to have any discernible effect on the performance or length of the model's training. Chollet (2015) emphasised the use of callbacks to preserve the optimum model parameters, hence assuring the retention of the best model state. The average length of each epoch in the model was roughly 170 seconds, indicating its computational efficiency. This characteristic is particularly important for real-time vulnerability detection applications, as highlighted by Saxe and Berlin (2015). The training procedure of the CNN model has been carefully optimised to attain a high level of accuracy and efficiency, making it a viable tool for advanced vulnerability detection.

## 5.3 Analysis of Epoch vs Accuracy

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Figure 15: Epoch vs accuracy during training

The line chart presents a comprehensive depiction of the performance of the CNN model during several training epochs, with a particular emphasis on its effectiveness in detecting vulnerabilities between the 5th and 40th epoch. The accuracy of the model exhibits stability at about 0.962 across the epochs spanning from the 5th to the 10th. This suggests a consistent and robust acquisition of knowledge during the first stages of training. By the fifteenth epoch, a discernible improvement in accuracy becomes apparent, exhibiting a consistent upward trend and ultimately reaching an approximate value of 0.971 by the fortieth epoch. The model's capacity to detect vulnerabilities has been significantly improved, as seen by its steady improvement in accuracy. In addition, the consistent improvement in accuracy, without any unpredictable variations, suggests that the model is resistant to overfitting, thus enabling it to effectively generalise to new data. This quality is crucial for assuring successful vulnerability identification.

## 5.4 Model Evaluation Using Test Set

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Figure 16: Model evaluation Matrices

The performance measures of the model provide a thorough perspective on its effectiveness in detecting vulnerabilities. The system demonstrates a high level of accuracy, roughly 96.66%, indicating robust classification skills. Nevertheless, the accuracy metric exhibits a value of 33.19%, which may seem somewhat modest. However, within the given context, this level of precision is deemed acceptable, particularly if the model's recall metric has a high performance. The significance of neglecting a vulnerability is substantial in the context of vulnerability detection. The recall rate of the model is noteworthy, standing at 72.76%, which highlights its proficiency in identifying a significant majority of vulnerabilities. The F-measure, which stands at 45.59%, demonstrates a well-balanced compromise between accuracy and recall. This characteristic is particularly important in applications such as vulnerability detection. The Precision-Recall Area Under the Curve (AUC) is around 37.10%, while the AUC is notably high at 94.37%, suggesting the model has a robust ability to discriminate. In conclusion, the Matthews connection Coefficient (MCC) of around 0.48 demonstrates a satisfactory connection between the observed and projected classes, hence bolstering the dependability of the model, particularly in situations when there are discrepancies in class sizes.

## 5.5 ROC-AUC Curve

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Figure 17: ROC-AUC Curve

The visual representation of a binary classifier's performance is captured by the receiver operating characteristic (ROC) curve, which plots the True Positive Rate versus the False Positive Rate. The AUC value of the model, which is roughly 0.9437, indicates a high level of discriminative capacity. A number closer to 1 suggests that the model is able to effectively distinguish between positive and negative classifications. The positioning of the curve in close proximity to the top-left corner of the graph is indicative of a high level of sensitivity and a low level of specificity, hence demonstrating the model's dependability. The presented graphical depiction highlights the fundamental trade-off that exists between sensitivity (recall) and specificity. In the context of vulnerability detection, ensuring a high true positive rate is of utmost importance due to the substantial consequences associated with neglecting a vulnerability.

# Chapter 6: Conclusion

The research conducted in this dissertation has shown significant potential, namely in the use of Convolutional Neural Networks for cybersecurity purposes. The performance characteristics of the model on the testing set are impressive, with an accuracy rate approaching 97% and a loss value of just 0.0778. The aforementioned statistics not only emphasise the dependability of the model but also its resilience, making it a noteworthy addition to the field of cybersecurity.

One notable achievement of this study is the model's remarkable level of accuracy. The model has a high accuracy rate of over 96%, indicating its robustness in accurately categorising vulnerabilities. This attribute is of utmost importance in determining its practical use. Another significant aspect to consider is the recall rate of the model, which stands at roughly 73%. This implies that the model has a high level of efficacy in accurately detecting genuine vulnerabilities within the positive cases, which is a crucial characteristic within the realm of cybersecurity.

An further noteworthy characteristic of the model's performance is its Area Under the Curve (AUC) score, which is recorded at 0.9437. The obtained high AUC score provides further evidence supporting the model's proficiency in properly discriminating between instances that are susceptible and those that are not. Furthermore, the Matthews Correlation Coefficient (MCC) value of 0.4776 provides a well-balanced evaluation of the model's effectiveness by considering both the occurrences of true and erroneous positives and negatives. Although there is room for improvement in the accuracy of the model, the accuracy-Recall AUC value of 0.3710 demonstrates a good initial performance and enhances the confidence of the model's effectiveness.

There are a variety of options for future development and research. The model's precision, which is presently around 33%, is one of the main areas that could benefit from further development. Techniques for improving this metric may include model refining or the addition of more features to the training set. Another potential area for future research could be feature engineering, where the investigation of additional features or more sophisticated feature extraction methods could result in performance improvements. Consequently while the model performed well on the dataset used in this study, its efficacy in real-world scenarios remains to be determined. Future research could assess the model's robustness and dependability by deploying it in actual operational environments. Integration of the CNN model with other machine learning algorithms via ensemble methods could provide a more comprehensive approach to vulnerability detection.

# Chapter 7: Project Management

## 7.1 Project Planning

A diagram of a research process

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The design and implementation of the dissertation covered around two and a half months, from the beginning of July to mid-September. The procedure was deliberately divided into distinct phases to ensure a holistic approach.

The initial phase, running from July 1st to 7th, was dedicated to foundational research. This week was vital for developing a broad grasp of cybersecurity, which eventually led to the selection of the specific issue of CNNs for vulnerability identification. Following this, from July 8th to 21st, an in-depth literature study was done. This two-week period was crucial in comprehending the existing landscape of the subject and recognising areas that lacked research. The succeeding phase focused on the design and data components. From July 22nd to 28th, the study approach was constructed, encompassing decisions on CNN architectures, datasets, and evaluation criteria. The week after, from July 29th to August 4th, was all about data. This included not simply gathering the relevant datasets but also preparing them to ensure they were optimum for CNN analysis.

The heart of the research, the execution phase, stretched from August 5th to 25th. The initial two weeks were spent translating theoretical concepts into a workable CNN model, followed by a week of hard training and optimization. The final stretch of the dissertation trip, from August 26th to September 18th, was dedicated to evaluation, documentation, and refinement. The model's performance was critically reviewed, and the findings were documented. This phase also includes looking ahead, and identifying future research directions and enhancements. Prior to the ultimate submission on September 18th, the dissertation underwent comprehensive evaluations and modifications to guarantee its calibre and logical consistency.

## 7.2 Commercial and Economical Context of the Project

The project functions within a dynamic and fast changing technological environment, possessing significant commercial and economic significance. This is particularly evident due to the growing dependence on safe software in many industries and the financial consequences associated with security breaches. The integration of software solutions in enterprises has been significantly enhanced by the digital transformation wave, resulting in an increased need for technologies that ensure safe programming and identify vulnerabilities. Organisations that use Convolutional Neural Networks (CNN) for the purpose of vulnerability identification may get a competitive advantage and also discover prospects for integration into diverse software development platforms. This integration enables real-time code analysis and expands commercial options.

From an economic perspective, the pre-emptive detection of vulnerabilities may result in substantial cost savings for enterprises in terms of data recovery, legal complications, and reputational harm. The increasing need for sophisticated cybersecurity solutions is also accompanied by the emergence of employment opportunities in the fields of research, development, and implementation of Convolutional Neural Network (CNN)-based systems. Given the anticipated rise of the worldwide cybersecurity business, the use of Convolutional Neural Networks (CNNs) has the potential to acquire a considerable portion of the market, hence yielding advantages for both developers and stakeholders. Furthermore, with the enhancement of their code security measures, organisations have the capacity to reduce economic risks associated with digital transactions, so promoting stability and fostering user confidence.

# Chapter 8: Students Reflection

The process of completing this dissertation has been enlightening and has significantly expanded my skill set. The thorough comprehension of Convolutional Neural Networks (CNNs) and their implementation in cybersecurity is one of the most valuable talents I've acquired. It was extremely rewarding to learn how to construct, train, and assess a CNN model from the beginning. My skills in data pre-processing, feature engineering, and model evaluation have also increased substantially. In addition, I gained practical experience with different machine learning metrics, learning not only how to compute them but also how to interpret them in the context of a real-world problem. This has improved my analytical reasoning and provided me with a more nuanced comprehension of model performance. In addition, I refined my research skills by learning how to conduct a critical literature review, identify voids in current knowledge, and situate my work within this context.

While the research journey has been fruitful, it has not been without obstacles. There were instances when I had to reduce the model's complexity to make it computationally feasible when training a CNN model. This experience taught me valuable lessons in resource optimisation and administration. The complex was also the task of improving the model's precision without compromising its recall. It required multiple iterations and a thorough comprehension of the trade offs involved in optimising various performance metrics. Lastly, keeping up with the swiftly evolving fields of machine learning and cybersecurity was difficult but necessary to ensure the continued relevance and currency of my work.

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# Appendix A

## Installing Python

Python is a prerequisite for going for walks Jupyter Notebook. You can observe these steps to put in Python:

Visit the authentic Python website at https://www.Python.Org/downloads/windows/.

Download the modern day Python installer for Windows (both 32-bit or sixty four-bit, relying to your system).

Run the installer and ensure to test the container that says "Add Python X.X to PATH" at some point of set up (update "X.X" with the model range you downloaded).

Follow the installation wizard, and Python may be established in your gadget.

## Installing Jupyter Notebook

Once you've got Python installed, you may set up Jupyter Notebook using Python's bundle supervisor, pip:

Open a terminal or command spark off.

Run the subsequent command to put in Jupyter Notebook:

pip set up jupyter

After the installation is whole, you may begin Jupyter Notebook by means of jogging the subsequent command to your terminal:

jupyter pocket book

This will open Jupyter Notebook to your default internet browser, and you can start growing and strolling notebooks.

Verifying the Installation

To confirm that both Python and Jupyter Notebook are set up efficiently, you may open a Jupyter Notebook by means of walking the jupyter pocket book command and create a brand new Python notebook. You need to be able to execute Python code in the pocket book without any problems.