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SOFTWARE DEFECT PREDICTION PERFORMANCE MONITORING OF DEEP AND MACHINE LEARNING MODELS ON NASA PROMISE DATASETS

Abdullah Akram Shakir AL-BAYATI

Master's Thesis

Supervisor

Assoc. Prof. Dr. Sefer KURNAZ

Istanbul, 2023

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This thesis title SOFTWARE DEFECT PREDICTION PERFORMANCE MONITORING OF DEEP AND MACHINE LEARNING MODELS ON NASA PROMISE DATASETS prepared by ABDULLAH AKRAM SHAKIR AL-BAYATI and submitted on 18/12/2023 has been **accepted unanimously** for the degree of Master of Science in Electrical and Computer Engineering.

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I hereby declare that this thesis meets all format and submission requirements of a Master's thesis.

Submission date of the thesis to institute of Graduate Studies: ___/___/___

I hereby declare that all information/data presented in this graduation project has been obtained in full accordance with academic rules and ethical conduct. I also declare all unoriginal materials and conclusions have been cited in the text and all references mentioned in the Reference List have been cited in the text, and vice versa as required by the abovementioned rules and conduct.

Abdullah Akram Shakir AL-BAYATI

Signature

DEDICATION

Your unwavering support, boundless encouragement, and endless sacrifices have been the cornerstone of my journey. Your belief in my abilities has been a guiding light, illuminating every step I've taken. This thesis stands as a testament to your love, wisdom, and enduring faith in me. I am forever grateful for your endless love and support.

Your unwavering patience, love, and encouragement have been my source of strength throughout this endeavor. Your belief in me never faltered, and your constant support made this journey possible. Your love has been my motivation and inspiration, and I dedicate this thesis to you with deepest gratitude.

ABSTRACT

SOFTWARE DEFECT PREDICTION PERFORMANCE MONITORING OF DEEP AND MACHINE LEARNING MODELS ON NASA PROMISE DATASETS

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In an era where software reliability and quality assurance have gained paramount importance, this study employs advanced machine learning models to predict software defects, thereby contributing to a refined understanding of their potential applications in enhancing software reliability. The focal point of the investigation is the PROMISE20 dataset, a collection of data from various NASA software projects. This dataset is segmented into three sub-datasets (CM1, JM1, KC1), with each instance marked by a binary dependent variable (indicating defect status) and independent variables based on Halstead and McCabe static code metrics. The study undertakes a comparative analysis between deep learning models, specifically LSTM and LSTM-GRU, and traditional machine learning models such as the XGBoost Classifier. Their proficiency in predicting software defects is gauged by assessing their accuracy and F1-scores. Upon examination, LSTM and LSTM-GRU deep learning models outperform with superior predictive performance, demonstrating accuracy rates of 88% and F1-scores of 0.89 and 0.90, respectively. In the realm of traditional machine learning, the XGBoost Classifier emerged as the top performer, boasting an accuracy rate of 0.88.

However, the findings also underscore the need for further exploration. The study points to the necessity of examining additional datasets, exploring diverse models, optimizing model hyperparameters, and enhancing model interpretability to ascertain the optimal choice of model for software defect prediction. This research enriches the ongoing discourse in software reliability and defect prediction, offering a robust foundation for future investigations in the field of software defect prediction using machine learning.

Keywords: Software Defect Prediction, Deep Learning, Machine Learning, PROMISE20 Dataset, Confusion Matrix.

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ABBREVIATIONS

AI	:	Artificial Intelligence
ML	:	Machine Learning
DT	:	Decision Tree
SVM	:	Support Vector Machines
RF	:	Random Forest

1. INTRODUCTION

1.1 BACKGROUND

Software defects are a pervasive issue in software development, with far-reaching consequences such as system failures, security vulnerabilities, and financial losses [1]. Software quality, risk mitigation, and enhanced software development practices all rely on the early detection and prediction of software flaws. To address this challenge, researchers and practitioners have explored various techniques, including machine learning and deep learning, to develop effective defect prediction models (DPM) [2]. DPM uses past software information to categories code as either defective or non-defective, speeding up the process of finding bugs and fixing them before they cause major issues. By analyzing patterns and characteristics of software defects, these models can learn to identify common indicators and predictors of defects, enabling developers to prioritize their efforts and allocate resources efficiently [3]. The ability to process massive amounts of data is a major selling point for defect prediction tools built on machine learning (ML) and deep learning (DL). Source code, bug reports, version control logs, and execution traces are only some of the massive volumes of data produced by software projects. By leveraging this data, DPM can capture complex relationships and patterns that are difficult for humans to discern [4]. ML algorithms, such as decision trees, logistic regression, and support vector machines, have been widely used for defect prediction [5]. These algorithms learn from labeled data, where software components are labeled as defective or non-defective based on historical information. By extracting relevant features from the software data, such as code complexity metrics, code churn, and historical bug density, these models can make predictions about the defect proneness of new or modified code. Deep learning techniques, including neural networks, have also shown promising results in defect prediction. Deep learning models can automatically learn intricate representations of software data, capturing both low-level and high-level features. These models may learn complex non-linear relationships using numerous layers of neurons, which may allow them to discover previously undetectable patterns and correlations in the data. [6]. In addition, DPM can be integrated into software development environments, providing real-time feedback to developers during the coding process. This integration enables developers to receive immediate alerts and suggestions regarding potential defects in their code, promoting early detection and prevention of

software defects. By adopting such proactive measures, developers can address issues before they escalate into critical problems, ultimately improving software quality and reducing development costs [7]. While DPM have shown promising results, challenges still remain. The number of non-problematic cases often outnumbers the defective ones in software defect statistics, which presents a significant difficulty [8]. Addressing this class imbalance is crucial to ensure the model's effectiveness in identifying defects accurately. Additionally, the generalization of DPM to different software projects and domains poses another challenge, as software characteristics and defect patterns can vary significantly [9]. In addition, DPM that makes use of ML and DL techniques provides helpful resources for finding and preventing software flaws. These models make use of previously collected program information to assign quality ratings to individual modules, allowing for proactive problem prevention and remediation [10]. DPM helps enhance software development processes by lowering risks, increasing quality, and enhancing data analysis and pattern detection.

1.2 MOTIVATION

The complexity and scale of modern software systems have made manual defect detection and prevention approaches inadequate. Traditional methods such as code inspection and formal verification are labour-intensive, time-consuming, and may not fully capture the intricate relationships within large software datasets. ML and DL models offer promising solutions to these challenges by harnessing the power of data analysis and pattern recognition. These models can effectively learn from historical software data, extract meaningful features, and make accurate predictions regarding defect-prone areas. By leveraging these techniques, software developers can allocate resources more efficiently, prioritize testing efforts, and enhance overall software quality [11-12].

1.3 PROBLEM STATEMENT

Despite the advancements in software defect prediction, several challenges persist in the field, necessitating further research and development. These challenges arise from the complexity and evolving nature of software systems, as well as the diverse characteristics of software defects.

The following key issues highlight the need for addressing the problem:

a. Model Selection Challenge: Selecting an appropriate model for defect prediction is a critical task that significantly influences the accuracy and effectiveness of the prediction process. With a wide range of ML and DL algorithms available, it becomes crucial to evaluate and compare their performance on specific software datasets to determine the optimal approach for defect prediction tasks. However, the lack of comprehensive comparative analysis between traditional machine learning models and deep learning models in the context of software defect prediction limits the ability to make informed decisions regarding the most suitable model [13].
b. Data Variability and Dynamics: Software datasets exhibit diverse characteristics, including varying software domains, programming languages, and development practices. Furthermore, software systems evolve over time due to bug fixes, feature additions, and code refactoring. These factors introduce variability and dynamics into the data, making it challenging to build accurate and reliable defect prediction models. There is a need for robust methodologies that can handle the inherent variability and dynamics in software data, enabling accurate predictions across different software contexts [14].
c. Imbalanced Data Distribution: The number of flawed cases in software defect datasets is typically much smaller than the number of healthy ones. This disparity can cause models to be skewed in favour of the dominant group and less effective at predicting the underrepresented group (defects). DPM that effectively capture the attributes of both faulty and non-defective instances need solving the class imbalance problem [15].
d. Interpretability and Explainability: While ML and DL models have shown promising results in defect prediction, their inherent complexity can hinder the interpretability and explainability of the predictions. Understanding the factors contributing to defect predictions is essential for software developers to take appropriate actions and make informed decisions. There is a need for techniques that enhance the interpretability of the models, allowing developers to gain insights into the underlying factors driving the predictions and facilitating effective defect resolution [16].

Addressing these challenges will contribute to the advancement of software defect prediction techniques, enabling developers to improve software quality, allocate resources efficiently, and enhance overall software development practices. By developing robust models,

considering data variability, addressing class imbalance, and enhancing interpretability, the field of software defect prediction can provide more accurate and actionable insights for defect prevention and resolution.

1.4 THESIS OBJECTIVES

The research objectives of this study are as follows:

a. Examine the efficacy of ML and DL models in software defect prediction, and draw comparisons between them.
b. Investigate the impact of data variability and dynamics on defect prediction models.
c. Address the class imbalance problem in software defect datasets.
d. Enhance the interpretability and explain ability of defect prediction models.
e. Provide practical recommendations and guidelines for the selection and application of DPM in real-world software development settings.

1.5 THESIS CONTRIBUTION

This thesis contributes to the field of software defect prediction in the following ways:

a. Comprehensive evaluation of ML and DL models: This research provides a systematic evaluation and comparison of various ML and DL models for software defect prediction. By analyzing their performance on diverse software datasets, the study offers insights into the strengths and weaknesses of each model, aiding researchers and practitioners in selecting the most appropriate approach for defect prediction tasks.
b. Investigation of data variability and dynamics: The thesis investigates the impact of data variability and dynamics on defect prediction models. By considering factors such as software domains, programming languages, and software evolution, the study explores methodologies to improve the reliability and generalizability of DPM across different software contexts.
c. Addressing the class imbalance problem: Methods for addressing the issue of class imbalance in software defect datasets are proposed. In order to rectify the disparity between faulty and non-def.

1.6 THESIS OUTLINE

The thesis is structured into several chapters to provide a comprehensive and cohesive analysis of the research on software defect prediction.

Chapter 1 serves as the introduction, setting the stage for the study by providing the background of software defects and their impact on software quality. The problem statement is clearly defined, addressing the challenges and gaps in the current state of software defect prediction. The objectives of the research are outlined, emphasizing the need for comparative analysis and improvement in model performance, interpretability, and practical applicability. The significance of the study is discussed, highlighting the potential benefits for software development organizations and researchers. Finally, the chapter concludes by presenting an overview of the thesis structure, outlining the subsequent chapters.

Chapter 2 delves into the theoretical background and related work. It provides a comprehensive understanding of software defect prediction, discussing its definition, importance, and inherent challenges. The chapter explores various ML and DL techniques commonly employed in defect prediction models. Traditional ML algorithms, such as DT, RF, and LR, are discussed, along with the fundamentals of deep learning architectures, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks. Moreover, the chapter presents a review of related studies in the field of software defect prediction, examining the existing literature to identify gaps and research opportunities.

Chapter 3 presents the methodology employed in the research. The chapter begins with a detailed explanation of the dataset selection process, ensuring the inclusion of diverse and representative software defect datasets. It then discusses the data preprocessing techniques used to address quality issues, handle missing values, and normalize the features. Feature selection and engineering methods are explored to identify relevant metrics and enhance the predictive power of the models. Model selection and training procedures are outlined, covering both traditional ML and DL algorithms architectures. The chapter also discusses model evaluation techniques, including performance metrics and cross-validation approaches. Additionally, it addresses the interpretability and explain ability analysis of the models, employing various techniques to gain insights into their decision-making processes. Finally, the chapter presents an experimental analysis plan to assess the performance and effectiveness of the selected models.

Chapter 4 focuses on the results and discussion. It begins with an examination of the raw data and then presents the results of the study. The pros and disadvantages of the various machine learning methods for predicting software defects are evaluated and contrasted. The

effectiveness of deep learning models is also assessed, with both their benefits and drawbacks highlighted. The chapter includes an interpretability analysis of the models, discussing the significance of feature importance and model-agnostic explanation techniques. The results are thoroughly discussed, and implications and insights are drawn based on the experimental analysis.

In Chapter 5, the thesis summarizes its findings and suggests directions for future research. It highlights the improvements in model performance, interpretability, and practical suggestions to summarize the major findings and contributions of the research. The study's shortcomings are discussed, and recommendations for future studies are offered. The research's implications for software defect prediction are examined, along with the benefits it could bring to software development companies. The chapter concludes by restating the significance of the research and its contribution to the field of software fault prediction.

Overall, the thesis follows a logical and coherent structure, progressing from the introduction to the problem statement, theoretical background, methodology, results and discussion, and conclusion. Each chapter contributes to the research objectives, presenting a thorough analysis of software defect prediction and offering valuable insights for both academia and industry. As shown in the flowchart indicts the map and outline of the thesis.

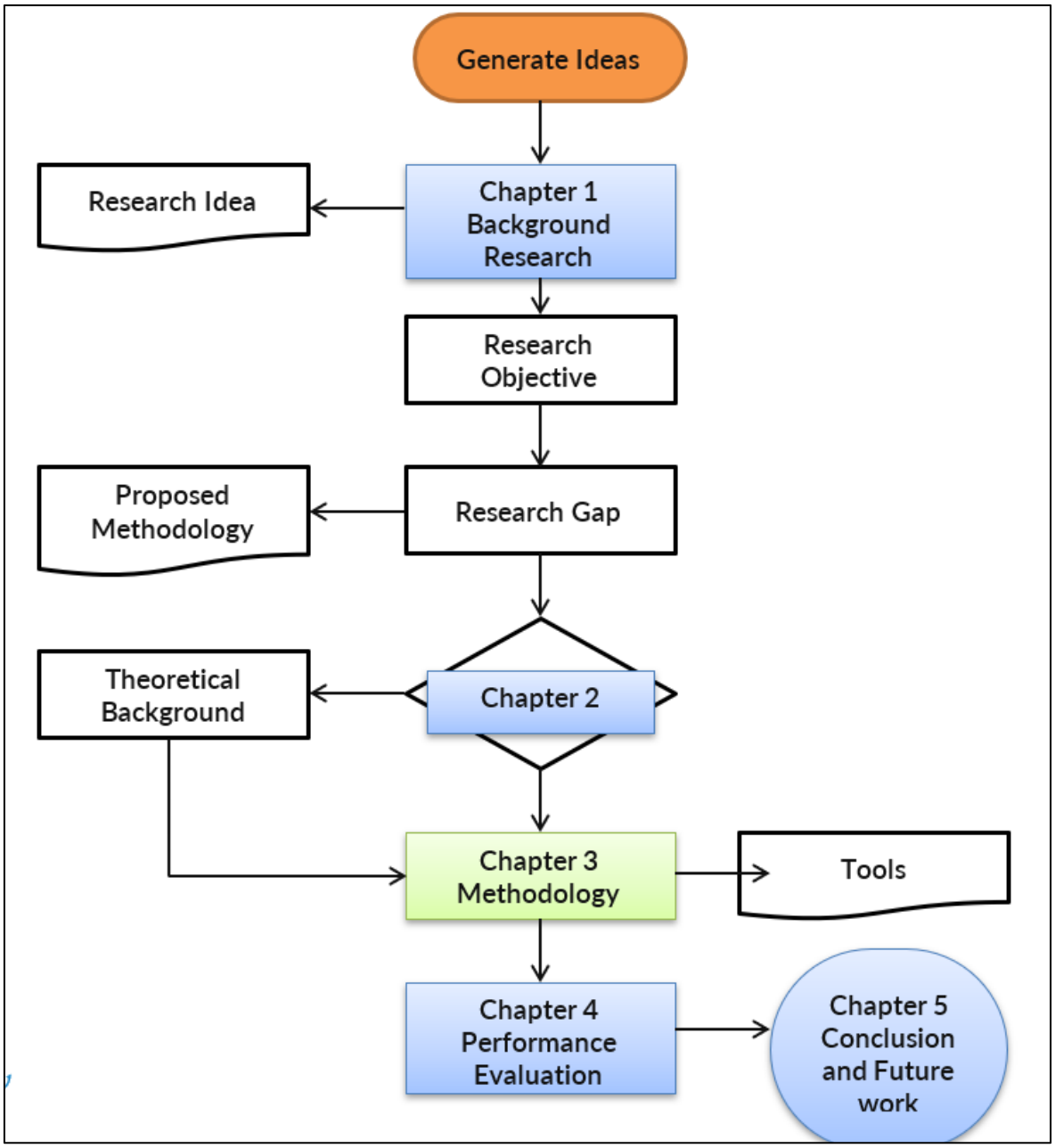

Figure 1.1: Outline of Thesis Chapters.

2. LITERATURE REVIEW

2.1 INTRODUCTION

In this chapter, we provide a comprehensive theoretical background and review of related work in the field of software defect prediction. It begins by discussing the definition and importance of software defects, highlighting the challenges associated with predicting them and the significance of accurate defect prediction for software quality assurance. The chapter then focuses on a comparative analysis of research approaches in software defect prediction. It presents an overview of existing research studies, examining different methodologies and techniques employed by researchers. The aim is to identify commonalities, differences, and areas of improvement in the existing approaches. The purpose of this comparison is to highlight areas of weakness and potential future study in software defect prediction. These voids can be caused by a lack of prior research, the limitations of currently used methods, or the appearance of new trends that have not yet been adequately examined. This study's overarching goal is to fill in knowledge gaps and point the way for additional study in this area. Chapter 2 lays out the theoretical underpinnings of software defect prediction and offers insights into the current state of the field by conducting a comprehensive literature survey.

2.2 SOFTWARE DEFECT PREDICTION

Software Defect Prediction (SDP) has been seen as the most important research area since the beginning of software era. It plays an important role for enhancing the software quality. Testing is considered as the most important phase of software development life cycle (SDLC) and it is closely related with software quality. Software quality is improved when we have an early prediction of errors that are expected to occur in future. It is very suitable to detect the defects in early stages of SDLC to reduce the cost and to increase the effectiveness of the testing process. When defects are detected before the software release, they can be removed before the deployment of the software [17]. As a result, predicting and preventing software defects has become a critical area of research and practice. The goal of software defect prediction is to identify potential defects in software systems before they occur. By leveraging historical data, such as code metrics, bug reports, and version control information, predictive models can be built to assess the likelihood of defects in different

parts of the software [18]. This allows developers and quality assurance teams to more efficiently manage resources, priorities testing efforts, and resolve possible issues before they become problems, all of which contribute to higher software quality and lower maintenance costs [19]. Figure 2.1: Various Software Defect Correction Techniques.

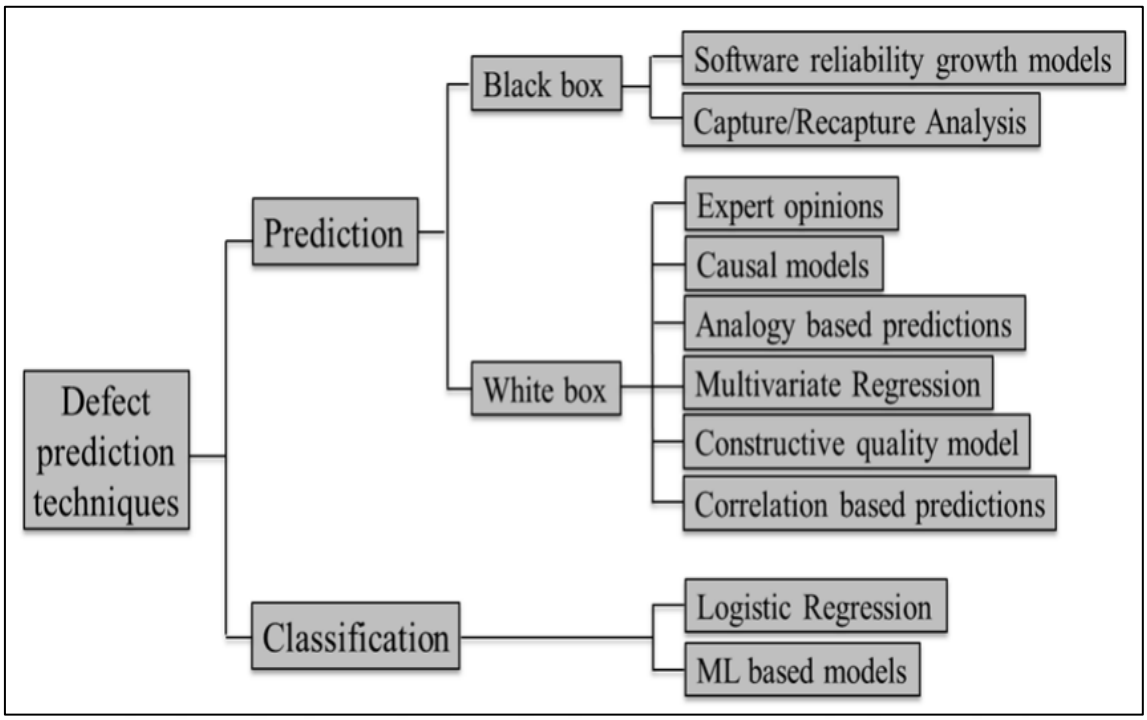

Figure 2.1: Indicts Various Method of Software Defect [19].

2.1.1 Definition and Nature of Software Defects

SDP is a hot topic since many years and different techniques from various domains have been applied to predict the error prone modules [i]. Defects in software can be predicted by a number of machine learning algorithms. Different algorithms result in varying performance on different dataset. To decide, which algorithm and technique should be used for defect prediction is a difficult task. There exists no clear and straight forward answer to this question as same technique when applied on different dataset with different metric comes up in different results [20].

2.1.2 Importance of Software Defect Prediction

Software defect prediction serves as a proactive approach to software quality assurance, enabling organizations to identify potential problem areas and allocate resources effectively. By predicting defects early in the development process, teams can focus their efforts on

critical areas, conduct targeted testing, and apply appropriate mitigation strategies. This proactive approach helps reduce the occurrence of defects in the final software release, resulting in improved customer satisfaction, reduced maintenance costs, and increased productivity [21].

Furthermore, DPM can assist in decision-making processes, such as resource allocation, project planning, and risk management. By providing insights into the likelihood and severity of defects, these models empower project managers and stakeholders to make informed decisions and allocate resources optimally, resulting in better project outcomes and enhanced software quality [22].

2.1.3 Challenges in Software Defect Prediction

It is generally preferred for a model to learn using the locally available data, which is usually very similar to the data on which it is to be tested [23]. This local data can be taken from some previous versions of the same project, or from some other similar project using the same programming language. Nevertheless, most of the times the risk management team of an organization faces the problem of unavailability of this local site information. The unavailability of training data may be due to many reasons, such as no similar project has been previously developed or the current technology has changed [24]. To resolve this problem, researchers came up with a solution of cross project defect prediction, where the defect prediction model is developed on one project and examined on some other. These two projects could be same or completely different. Unfortunately, the performance of the models built using cross company data has not been very promising [25].

Subsequently, this chapter will examine the theoretical underpinnings of software defect prediction, compare and contrast different research methodologies, and investigate recent developments and future directions in the field.

2.3 DATA-DRIVEN APPROACHES IN SOFTWARE DEFECT PREDICTION

Statistical and ML methods are used in data-driven software defect prediction to assess software metrics and historical defect data, with the goal of forecasting the occurrence of future problems. By analysing patterns and relationships within the data, these approaches aim to uncover hidden insights and provide actionable information to software development teams. The utilization of data-driven techniques enables a more objective and automated

approach to defect prediction, complementing traditional methods and enhancing overall software quality [26]. In the figure 2.2 shows the approaches of data driven.

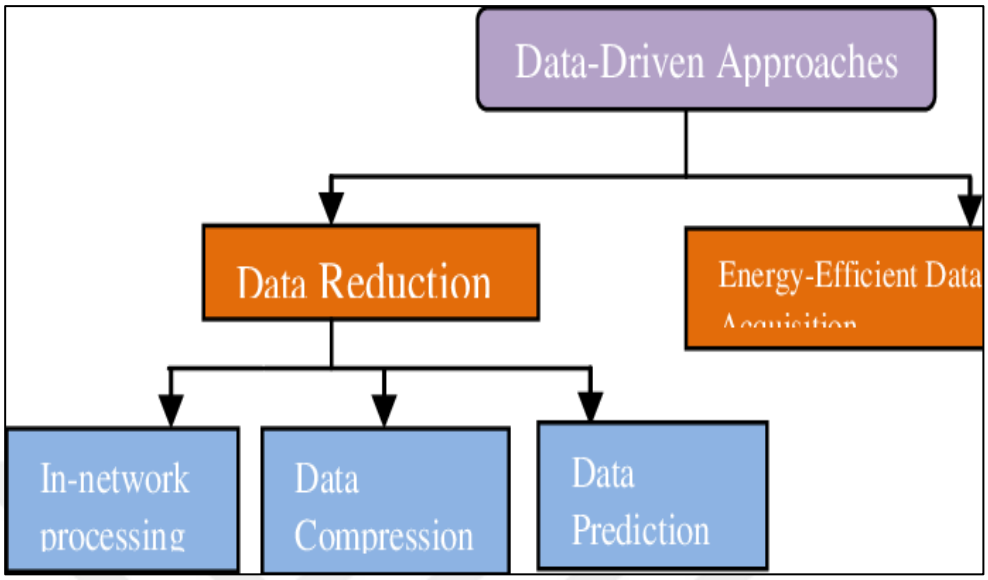

Figure 2.2: Data-Driven Approaches in Software Defect Prediction [26].

2.4 REVIEW OF TRADITIONAL MACHINE LEARNING TECHNIQUES IN SOFTWARE DEFECT PREDICTION

A system that is used to understand the concept and its environment using a simplified interpretation of the environment using model is called cognitive system. The step that we pass to construct the model is known as inductive learning. The Cognitive system is able to combine its experience by constructing new structures is patterns. The constructed model and pattern by cognitive system is called machine learning. Models that are described as predictive since it can be used to predict the output of a function (target function) for a given value in the function's domain while informative pattern are characterized only describes the portion of data. Machine learning task classified into four that are supervised, unsupervised, semi-supervised and reinforcement learning; however, the most known task is supervised and un-supervised learning [27]. In section a and section b below, we looked some of supervised and un-supervised learning below.

Support Vector Machines (SVMs) have also gained recognition in this field. The research carried out by Hassan [28] utilized SVMs, demonstrating their efficacy in the high dimensional data often encountered in software defect prediction. As shown in the Figure 2.3, the process of ML methods in Software Defect Prediction

In addition, Catal and Diri [29] indicate that the NB classifier is effective in numerous software fault prediction issues despite its simplicity and speed. They discovered that NB, despite its ease of use, could accomplish impressive results in recall and precision.

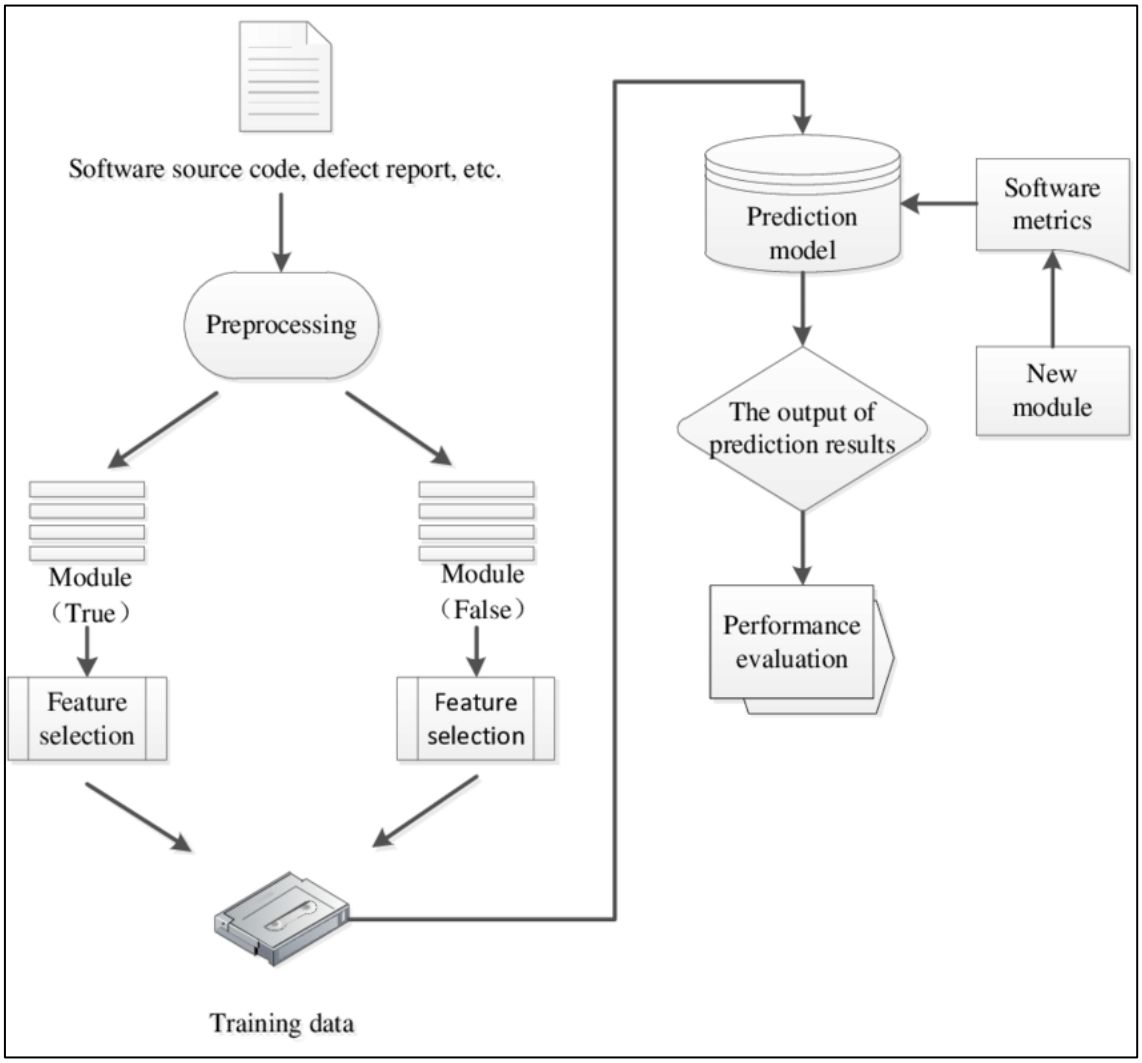

Figure 2.3: Process of ML Methods in Software Defect Prediction [29].

2.4.1 Comparative Analysis of Different ML Methods in Predicting Software Defects

The effectiveness of ML methods in predicting software defects has been greatly improved thanks to comparative studies. In their study [30], Lessmann et al. compared 22 classifiers used for defect detection in depth. Their study concluded that there is no universally superior model, emphasizing the importance of understanding the specific requirements and characteristics of the prediction task at hand. Figure 2.4, indicates of ML methods used in Predicting Software Defects

Hall et al. [31] also performed a similar comparative study, highlighting the importance of model selection in the performance of defect prediction. They further stated that the performance of these models could significantly differ depending on the dataset used, hence the need for more dataset-agnostic models.

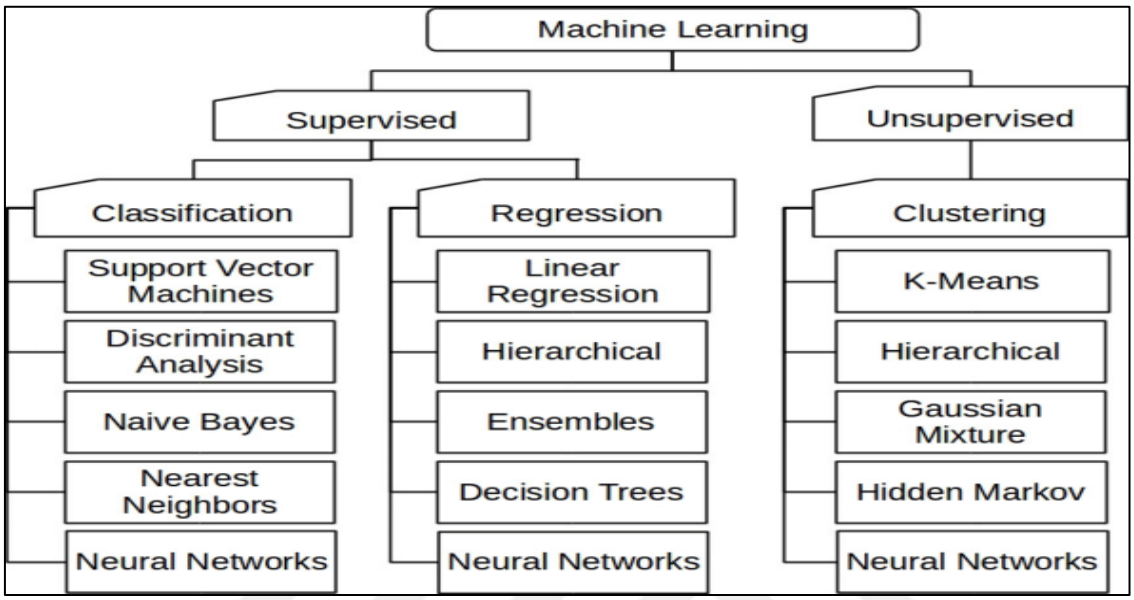

Figure 2.4: Indicates of ML Methods Used in Predicting Software Defects [31].

2.4.2 Strengths and Limitations of Traditional ML methods in Defect Prediction

Machine learning offers several advantages for wheel defect detection. It allows for the automatic detection of various types of wheel defects using sensor data, such as accelerometer data. Machine learning methods can learn different types of wheel defects and predict their presence during normal operation [6]. Additionally, machine learning models, such as artificial neural networks, can outperform classical defect detection methods and achieve high accuracy in classifying and predicting wheel defects. These models can also effectively differentiate between defected and non-defected tire images, improving the overall detection performance. However, there are also some potential disadvantages to using machine learning for wheel defect detection. One challenge is the need for a comprehensive dataset for training and evaluation, which may require significant effort and resources to collect and label [32] . Additionally, the performance of machine learning models can be affected by factors such as sensor layout effectiveness and the complexity of the defect types.

2.5 INTRODUCTION TO DEEP LEARNING TECHNIQUES AND THEIR APPLICATION IN DEFECT PREDICTION

In recent years, DL techniques have been increasingly utilized in software defect prediction, with a considerable number of studies reporting encouraging results. DL, a subset of ML, is particularly effective in capturing complex, non-linear relationships in high-dimensional data, a characteristic prevalent in software metrics data.

The research by Li et al. [33] deployed CNNs, a class of deep learning models, to predict software defects. They successfully extracted spatial features from static code attributes using CNNs and achieved impressive prediction results, outperforming traditional machine learning approaches.

RNNs, and particularly their variants such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), have also been explored in the realm of software defect prediction due to their ability to model temporal dependencies in sequential data [34].

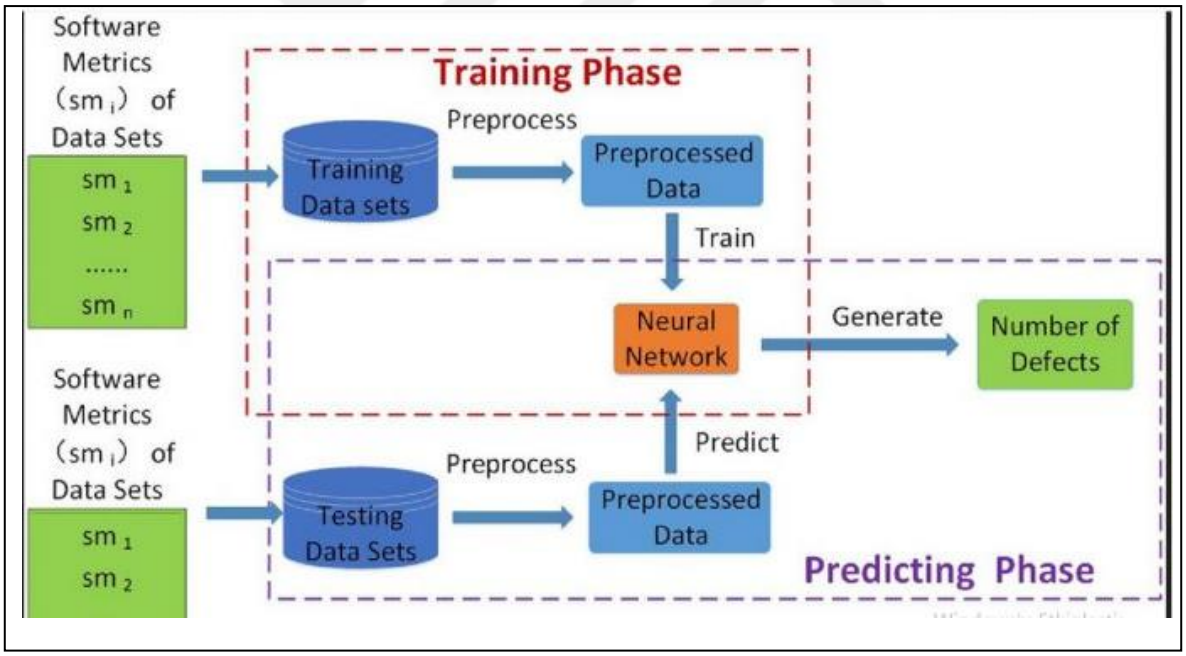

Figure 2.5: Deep Learning Techniques and Their Application in Defect Prediction [34].

2.6 RELATED WORK

For many years, researchers have worked on methods to better predict software defects in an effort to boost software quality and cut down on maintenance expenses. These forecasting algorithms rely heavily on past software information to determine whether or not a given

piece of code is faulty. Several approaches have been researched in order to better forecast software faults. Here, we highlight the contributions and limits of a number of major works in this field.

One of the earlier works in this field explored decision trees for software defect prediction [35]. verified that the attributes available to the software developers can aid them to identify defects as early as possible in the software lifecycle. They performed analysis, which compared the defect prediction models developed from the requirement metrics, source code metrics and combination of requirement and code metrics. The machine learning algorithms included one rule learner, naive bayes, voted perceptron, logistic regression, J48 decision tree and random forests. The results reported that the textual metrics combined with static code metrics improve the defect predictors except, in the case of voted perceptron [36].

Advanced ML techniques like SVMs have also been utilized, showing strong performance and the ability to handle high-dimensional data [37]. However, SVMs' model parameters require careful tuning, and interpretation of model predictions can be difficult.

Recently, deep learning approaches have gained popularity in software defect prediction [38,39]. These models can learn intricate patterns from software data and have shown superior performance in some cases. However, the complexity of deep learning models can lead to overfitting, and they require larger volumes of data for training.

In addition to these models, research has also focused on various aspects of software development data and practices. For instance, the role of software documentation in defect prediction has been investigated, suggesting that the quality and completeness of software documentation can be predictive of software defects [40]. Another study highlighted the potential of using warnings from automated static analysis tools for defect prediction [41]. Furthermore, software process metrics have also been considered in defect prediction, providing additional context that complements traditional code metrics [42].

In contrast to all the above studies, Menzies et al.6 presented a significant statement that the classification methods used to build the defect prediction models are more important and not the metrics that are involved in the experiment. They examined eight data sets of NASA MDP13 using decision tree based, rule based and bayes theorem based learners. The experiment also compared the results of no filter with log filter. Recall, balance and the probability of not having the false alarm were included for evaluation. The results proved

that naive bayes with log 908 Ishani Arora et al. Procedia Computer Science 46 (2015) 906 – 912 filter outperforms the OneR and J48 defect prediction models. They also proved that the naive bayes with log filter have an average Pd of 71 percent and Pf of 25 percent. As discussed in the above studies, none of them has been able to establish a generalized association between the attributes and fault. As shown in the table 2.1 is the related work regarding the Machine learning of the software defend predication.

Table 2.1: Related Work of ML on Software Predications.

Reference	Work Description	Key Findings	Limitations
[43]	In this research, researchers explore the potential of decision trees for predicting software errors.	Decision trees can provide reasonable accuracy in predicting software defects, and offer interpretability.	Limitations in handling complex, non-linear relationships.
[44]	This paper explores the use of logistic regression for software defect prediction.	Logistic regression offers a simple, yet effective approach for binary classification problems such as defect prediction.	Susceptibility to overfitting with high-dimensional data.
[45]	The purpose of this research is to investigate the use of support vector machines (SVMs) for defect prediction.	SVMs show strong performance in defect prediction tasks, and can handle high-dimensional data well.	Model parameters require careful tuning, and interpretation of model predictions can be difficult.
[46]	In this work, researchers introduce a convolutional neural network-based deep learning technique for predicting software bugs.	Deep learning models can learn intricate patterns from software data, offering superior performance in some cases.	The complexity of deep learning models can lead to overfitting, and they require larger volumes of data for training.
[47]	This work discusses the integration of real-time DPM into software development environments.	Integration of models can provide immediate feedback to developers, promoting early detection and resolution of defects.	Effective integration can be challenging due to the diverse nature of development environments.
[48]	In this research, researchers explore the problem of defect prediction class imbalance in software.	Various techniques can be used to mitigate class imbalance, including oversampling, under sampling, and the use of appropriate evaluation metrics.	Addressing class imbalance is not straightforward, and techniques used can introduce their own biases.

Table 2.1: Related Work of ML on Software Predications 'Table Continued'.

[49]	This paper investigates the generalization of DPM across different software projects and domains.	Certain features, such as code complexity metrics and change history, can generalize well across projects.	Many models do not generalize well across different projects due to differences in coding practices, development processes, and defect patterns.
[50]	This study examines ensemble methods in software defectprediction, combining predictions from multiple machine learning models.	Ensemble methods can often improve prediction performance compared to individual models.	Choosing the right ensemble method and individual models can be challenging and requires careful tuning.
[51]	Source code metrics like cyclamate complexity and lines of code are explored in this research as potential features for defect prediction.	Source code metrics can provide valuable information for defect prediction.	Solely relying on code metrics may not capture all aspects of software defects.
[52]	This research delves into the possibility of applying deep learning to the problem of defect prediction in large-scale, real-world software development projects.	Deep learning models show promise in handling large-scale software projects, outperforming traditional machine learning models in some cases.	In order to train a deep learning model, a substantial amount of data and processing power is needed.
[53]	This work explores the use of natural language processing (NLP) techniques to analyze bug reports and predict software defects.	NLP techniques can extract valuable information from textual data such as bug reports, potentially improving defect prediction.	Preprocessing of textual data and dealing with noisy or incomplete bug reports can be challenging.
[54]	In this research, we explore how transfer learning can be used to enhance software defect prediction by drawing on experience gained in one project to apply to another.	When there isn't enough data to train on, transfer learning may be able to help.	The success of a transfer of knowledge depends on the degree to which the original and new initiatives are similar.
[55]	This study applies clustering techniques to group similar defects and improve prediction performance.	The formation of meaningful clusters can significantly enhance the performance of defect prediction models.	Determining the optimal number of clusters is a complex task, and these techniques may not always lead to meaningful or useful groupings.

Table 2.1: Related Work of ML on Software Predications 'Table Continued'.

[56]	This research uses time-series analysis to predict the occurrence of software defects over time.	Time-series models can accurately forecast defect trends, aiding in project planning and resource allocation.	These models often rely on the assumption that future trends will follow past patterns, which may not always hold.
[57]	This paper investigates the role of developer expertise and team dynamics in software defect prediction.	Factors such as developer expertise and team dynamics significantly influence defect rates, providing useful context for prediction models.	Quantifying such factors can be challenging, and these aspects are often not consistently recorded in software project data.
[58]	This study examines the use of mutation testing metrics for software defect prediction.	Mutation testing metrics can be predictive of software defects, providing another dimension to traditional code metrics.	Mutation testing is computationally expensive and may not be feasible for large software projects.
[59]	In this research, researchers investigate the feasibility of using graph-based models for defect prediction in software, making advantage of software's inherent structural information.	Graph-based models can capture complex relationships between software components, potentially improving defect prediction.	Extracting meaningful graph structures from software can be complex task

2.7 RESEARCH GAP

In the field of software defect prediction, an abundance of research contributions can be found. However, a careful review of the literature reveals certain areas that are yet to be adequately addressed. These areas, where there is a dearth of knowledge, are identified as research gaps and are the focal points of this thesis.

The first observed gap pertains to the skewed distribution of software defect datasets, characterized by a preponderance of non-defective instances as compared to defective ones. Despite some attempts to address this problem, a comprehensive, universally applicable solution remains elusive. This imbalance poses significant challenges to the efficacy of prediction models, thus warranting a deeper investigation into methods that can rectify this disproportion and improve prediction accuracy.

Secondly, despite the widespread application of ML and DL models in software defect prediction, these models often suffer from a lack of interpretability. They function as so-called "black boxes", providing predictions without tangible explanations. While their predictive performance might be laudable, the inability to interpret their decisions is a significant drawback, particularly in contexts where understanding the underlying reasons for predictions is crucial. Therefore, this thesis aims to explore models that offer not only high predictive accuracy but also a higher degree of interpretability.

Another aspect that is underrepresented in the existing body of knowledge is the prediction of defect severity, rather than mere defect occurrence. The ability to anticipate the severity of defects can provide substantial aid to developers in prioritizing their mitigation efforts. While the identification of defects is of undeniable importance, understanding the potential impact of these defects is equally crucial and requires more focused research attention.

Finally, most existing studies primarily employ static code attributes for defect prediction, leaving a plethora of other potential data sources, such as developer-centric attributes and process-related metrics, relatively unexplored. This study posits that these less explored features may contain invaluable insights and may contribute positively towards the predictive power of defect prediction models.

In summary, this research aims to close these previously observed defect prediction gaps in software. The principal objective is to advance the current state of knowledge by investigating techniques for addressing class imbalance, enhancing model interpretability, predicting defect severity, and utilizing diverse data sources in the quest for more accurate and reliable defect prediction models.

3. METHODOLOGY

3.1 INTRODUCTION

The complexity inherent in software defect prediction necessitates the adoption of a robust, well-structured, and replicable methodological framework. The methodology employed in this research, which is detailed in this chapter, carefully and systematically maneuvers through each stage of the process, from data collection to analysis. At the outset, this chapter presents an overarching view of the research design, which is rooted in clearly defined philosophical assumptions. These principles shape the trajectory of our research strategy and enhance the coherence and effectiveness of our study. We elucidate these underpinnings and their contributions to our study's objectives. Subsequently, the process of data collection is explicated. The methodology for this phase is detailed, encapsulating our rationale for selecting certain data sources, the types of data harvested, and the stringent ethical standards adhered to during data handling and management. Next, we explore the critical phase of data preprocessing. This section elaborates on the strategies deployed for refining and transforming our data into a format that is compatible with ML and DL techniques. Additionally, we address the challenge of class imbalance within our datasets, illuminating the measures taken to rectify this issue. The succeeding section delves into the core of our methodology—the data analysis. Here, we outline the ML and DL models chosen for our study, providing clear justification for their selection. We elucidate on our model training, validation, and evaluation procedures, giving readers a comprehensive understanding of our approach.

Lastly, we underscore the ethical considerations in our research. This section discusses our commitment to academic integrity, respect for intellectual property rights, and the assurance of data privacy. The measures undertaken to uphold these principles throughout the research process are detailed here.

By the conclusion of this chapter, our aim is for readers to have an in-depth understanding of the methodological blueprint that steers our research. Beyond merely explicating our approach.

3.2 RESEARCH PROCESS

The methodologies involved in implementing ML and DL in the context of this study are multifaceted and proceed in a series of steps as follows:

a. Data Collection: Data collection is the initial step in our study. In the context of software defect prediction, this data typically includes source code metrics, historical bug reports, version control logs, and developer-related data. The selection of data sources and types are guided by our research questions and the identified gaps in the literature.

b. Data Preprocessing: The collected data often requires preprocessing to prepare it for the subsequent analysis. This can include data cleaning, dealing with missing or inconsistent data, and transforming data into a form suitable for ML and DL models. In the case of class imbalance, which is a common issue in defect prediction, preprocessing may also involve techniques such as oversampling, undersampling, or the application of synthetic minority over-sampling technique (SMOTE).

c. Feature Selection/Extraction: This step involves identifying the most relevant features that contribute to defect prediction. For traditional machine learning models, this may involve statistical analysis or other feature selection techniques. In the case of deep learning models, feature extraction can often be automatically performed by the model itself as part of the learning process.

d. Model Selection: Here, we select the most suitable ML or DL models for the experiment. Considerations like as data type, problem category (classification, regression, etc.), and research objectives can all influence the model selection process. DT, SVM, and NN are just a few examples of models that have showed promise for defect prediction that could be used in this investigation.

e. Model Training: In this phase, the selected models are trained using our preprocessed data. This involves providing the models with input-output pairs from the data, allowing them to learn the underlying patterns. Model training is typically performed using a portion of the collected data, known as the training set.

f. Model Validation: The validation phase involves tuning the model parameters to optimize its performance and to prevent overfitting. This often involves using a separate portion of the data, known as the validation set.

g. Model Evaluation: After training and validation, the model's performance is evaluated using a test set of data that it has not previously seen. Evaluation metrics, such as

precision, recall, F1 score, and area under the ROC curve, can be used to assess the performance of the model in predicting software defects.

h.Model Interpretation: Particularly in the case of deep learning models, interpreting the model's predictions can be challenging. Techniques such as LIME or SHAP can be used to understand the model's decisions better.

i. Implementation: After evaluation and interpretation, the model can be implemented in a real-world context. This might involve integration into a software development environment, providing real-time feedback to developers about potential defects in their code.

In following these steps, we ensure a rigorous and systematic approach to predicting software defects using ML and DL techniques. Our aim is to not only develop models that accurately predict defects but also contribute to understanding the underlying factors that contribute to software defects and how they can be mitigated. As shown in the figure 3.1 is the process of the proposed work.

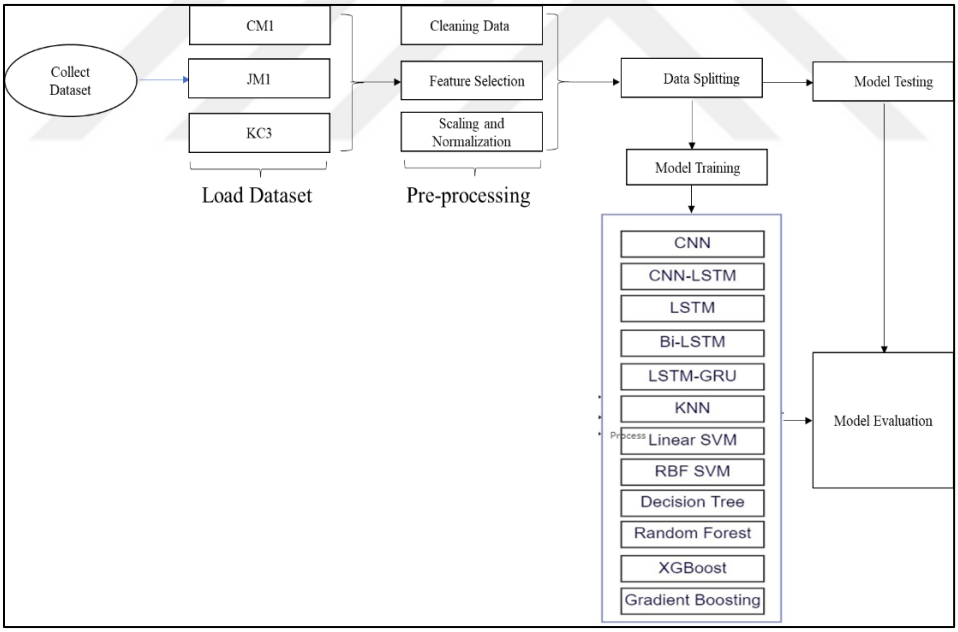

Figure 3.1: Flowchart of Proposed Work.

3.3 DATASET

The PROMISE repository [61] is a publicly available and highly recognized resource for software defect prediction and software engineering in general, and our dataset was obtained from there. Complex methods using many different software metrics and other data are

required to predict which areas of a software system are likely to have defects. The key goals of defect prediction are quality improvement and reduced maintenance costs. Each software system in the PROMISE dataset is characterized by a unique set of metrics and labelled as either defective or non-defective. This categorization facilitates researchers to apply these datasets for the training and evaluation of algorithms designed for software defect prediction, to carry out comparative studies of diverse approaches and metrics, and to pinpoint the most efficient strategies for identifying defects in software systems. Our research particularly makes use of the sub-datasets namely CM1, JM1, and KC3 from the PROMISE repository. These subsets likely encompass different software systems or various assortments of metrics, providing us with a broad and diverse base for analysis. The choice of these subsets is guided by our research objectives and the types of software systems we aim to scrutinize. Each dataset within the repository encompasses independent variables like Halstead and McCabe static code metrics. These metrics are often employed to gauge various facets of software quality and complexity. They allow quantification of attributes like code size, complexity, and maintainability. This quantified data serves as an invaluable asset for predicting software defects.

Finally, the PROMISE repository and its associated sub-datasets stand as pivotal resources for researchers and practitioners in software engineering. The repository has been instrumental in numerous studies and experiments aimed at advancing our comprehension of software defects and enhancing the accuracy of software defect prediction models. Our research intends to contribute to this body of knowledge and offer further insights into the field of software defect prediction. As shown in the figure 3.2, 3.3, and 3.4 are the details of the dataset that used in this research.

	PERCENT_COMMENTS	LOC_COMMENTS	HALSTEAD_ERROR_EST	HALSTEAD_VOLUME	HALSTEAD_DIFFICULTY	HALSTEAD_EFFORT	HALSTEAD_PROG_TIME	HALSTEAD_CONTENT	LOC_TOTAL
0	0.264841	0.005900	0.030631	0.029791	0.098527	0.003639	0.003639	0.103989	0.024194
1	0.079383	0.000000	0.043243	0.042442	0.075022	0.004058	0.004058	0.199086	0.056452
2	0.000000	0.000000	0.005405	0.005059	0.033003	0.000319	0.000319	0.043137	0.004032
3	0.272626	0.026549	0.064865	0.064555	0.100378	0.007754	0.007754	0.238178	0.070565
4	0.000000	0.000000	0.019820	0.018754	0.064075	0.001658	0.001658	0.095027	0.026210

Figure 3.2: CM1 Dataset.

	HALSTEAD_EFFORT	HALSTEAD_PROG_TIME	HALSTEAD_VOLUME	HALSTEAD_CONTENT	LOC_BLANK	HALSTEAD_DIFFICULTY	LOC_TOTAL	LOC_EXECUTABLE	label
0	0.000101	0.000101	0.003470	0.043964	0.002237	0.026781	0.003778	0.003895	0
1	0.001962	0.001962	0.027526	0.142494	0.011186	0.065543	0.028189	0.030099	0
2	0.000015	0.000015	0.001978	0.099056	0.004474	0.006767	0.003778	0.003541	1
3	0.001562	0.001562	0.035388	0.295851	0.035794	0.040579	0.020052	0.018414	1
4	0.000027	0.000027	0.001366	0.025133	0.000000	0.018436	0.003197	0.003187	0

Figure 3.3: JM1 Dataset.

	HALSTEAD_VOLUME	HALSTEAD_EFFORT	HALSTEAD_PROG_TIME	HALSTEAD_CONTENT	HALSTEAD_DIFFICULTY	PERCENT_COMMENTS	NUM_OPERANDS	HALSTEAD_LENGTH	GLOBAL_DATA_DENSITY
0	0.084152	0.036517	0.036517	0.120842	0.321012	0.436571	0.112378	0.126780	0.70
1	0.050996	0.009772	0.009772	0.183399	0.134251	0.454571	0.070033	0.064407	1.00
2	0.011425	0.000912	0.000912	0.091089	0.046630	0.000000	0.026059	0.020339	1.00
3	0.666003	0.871302	0.871302	0.376717	1.000000	0.230571	0.706840	0.755254	0.86
4	0.011761	0.000966	0.000966	0.090861	0.048321	0.095286	0.017915	0.018305	1.00

Figure 3.4: KC3 Dataset.

3.4 DATASET PRE-PROCESSING

In this study, we adhere to a rigorous data preprocessing approach to ensure the collected data from the PROMISE repository is ready for analysis. This systematic process has been broken down into the following stages.

3.4.1 Cleaning and Preparing the Data

Our first step is focused on cleaning and preparing the data. This implies weeding out any inconsistencies, anomalies, or missing data that could potentially disrupt the integrity of our analysis. Given that software engineering data can often be noisy or incomplete, this stage plays a crucial role in maintaining the accuracy of our defect prediction models. Every single record is meticulously inspected and any irregularities are addressed appropriately to ensure that the datasets are clean and reliable for subsequent steps.

3.4.2 Feature Selection

The subsequent stage of our preprocessing involves selecting relevant features from the cleaned data. In the context of the PROMISE datasets, there exist numerous features - for example, Halstead and McCabe metrics - which quantify various aspects of software quality and complexity. However, not all of these features might be relevant or equally important for defect prediction. Hence, we engage in a process of feature selection to identify the most pertinent features that contribute significantly to our prediction task. This step is pivotal as it affects the efficiency and accuracy of the prediction models.

3.4.3 Feature Scaling and Normalization

In the final step of data preprocessing, we carry out feature scaling and normalization. As different features can have different scales or units of measurement, we standardize these features to bring them onto a common scale. This is particularly important when working with ML and DL models, as features with larger scales can unduly influence the model and lead to biased results. Hence, we implement techniques such as Min-Max normalization or standardization (Z-score normalization) to ensure all selected features are on a comparable scale.

These preprocessing steps act as a critical bridge between raw data collection and the application of ML and DL models. By ensuring the cleanliness, relevance, and comparability of our data, we lay a robust foundation for our subsequent model development and evaluation efforts. As indicated in the figure 3.5, which is the count of independent variables was considerably trimmed down.

Table 3.1: Indicated the Count of Independent Variables Was Considerably Trimmed Down.

Dataset	Before	After
KC1	21	6
CM1	37	24
JM1	21	8

3.5 DATASET SPLITTING

The successive stage in our methodology includes the training and evaluation of models, involving the development and testing of both Deep Learning (DL) and Machine Learning (ML) models. This process is elaborated upon below.

3.5.1 Deep Learning Models Training

We initiate this process by dividing the data into training and testing sets for each respective dataset - JM1, CM1, and KC3. 70% of each of these datasets is used for training, while the remaining 30% is used for testing. Overfitting concerns are well mitigated and model generalization is ensured thanks to the careful curation of this distribution. We then proceed to train five separate Deep Learning models: a CNN, a CNN with LSTM (CNN-LSTM), a

LSTM with a GRU (LSTM-GRU), and a Bidirectional LSTM (Bi-LSTM). Each of these models is trained exhaustively with the designated training data from each dataset.

Post-training, we carry out model evaluations using the appropriate testing data for each dataset. This evaluation step is crucial as it facilitates the assessment of the models' predictive efficacy and helps us discern the most capable DL model for software defect prediction.

3.5.2 Machine Learning Models Training

Similarly, for the Machine Learning model training phase, we segment the data into training and testing sets for each dataset (JM1, CM1, and KC3). Here, the same 70%-30% distribution for training and testing is applied. Following this, we undertake the training of seven different ML models, including linear and Radial Basis Function (RBF), XGB, KNN, and SVM. Each model is painstakingly trained with its own dataset's worth of training data. After the training phase is complete, the models are tested on the actual data from each dataset to see how well they performed. In this phase, we evaluate the efficacy of various ML models for software defect prediction, ultimately allowing us to zero in on the most effective ML model. To sum up, the careful training and rigorous evaluation of the DL and ML models provide us with an in-depth understanding of these models' efficacy in software defect prediction and lay the groundwork for our following analysis and discussion.

3.6 DEEP LEARNING MODLES

3.6.1 Long Short-Term Memory

Extended memory is a specialty of the RNN class known as LSTM. The vanishing gradient issue plaguing conventional RNNs is remedied in this design with a memory cell that controls data throughput.

The LSTM memory cell consists of an input gate, forget gate, output gate, and cell state, and it plays a central role in the network. The mathematical description of these parts is as follows:

a. Forget gate (f_t): The forget gate determines the amount of past information (cell state) to be forgotten or erased. It uses the previous hidden state and current input to produce a value between 0 and 1 (using a sigmoid activation function), where 0 means "completely forget" and 1 means "completely remember".

$$f_t = \sigma(W_f.[h_{(t-1)}, x_t] + b_f) \quad (3.1)$$

b. Input gate (i_t): How much the unit responds to the current input by updating its state or retaining the information is determined by the input gate. The output is between zero and one, like the forget gate.

$$\_t = \sigma(W_i.[h_{(t-1)}, x_t] + b_i) \quad (3.2)$$

c. Cell candidate ($\tilde{C}_t$): This represents the current information derived from the current input and previous hidden state.

$$\tilde{C}_t = \tanh(W_C.[h_{(t-1)}, x_t] + b_C) \quad (3.3)$$

d. Cell state (C_t): The cell state is updated based on the forget gate, input gate, and cell candidate values. It effectively keeps track of the information learned so far.

$$C_t = f_t * C_{(t-1)} + i_t * \tilde{C}_t \quad (3.4)$$

e. Output gate (o_t): The following LSTM unit will use the concealed state and the amount of information transferred from the cell state based on the output gate's settings.

$$o_t = \sigma(W_o.[h_{(t-1)}, x_t] + b_o) \quad (3.5)$$

f. Hidden state (h_t): By squishing cell state values to a range of -1 to 1, the tanh activation function is used to determine the hidden state from the output gate and the cell state.

$$h_t = o_t * \tanh(C_t) \quad (3.6)$$

Here, σ is the sigmoid activation function, and tanh is the hyperbolic tangent activation function. The symbol $[h_{(t-1)}, x_t]$ denotes the concatenation of $h_{(t-1)}$ and x_t, the previous hidden state and the current input, respectively. W_f, W_i, W_C, W_o, b_f, b_i, b_C, and b_o are the weights and biases learned by the LSTM network during training.

By using these mechanisms, LSTM is able to mitigate the vanishing gradient problem and capture long-term dependencies in sequence data, making it an effective model for various time series and sequence prediction tasks. As indicated in the figure 3.5 which is the LSTM architecture.

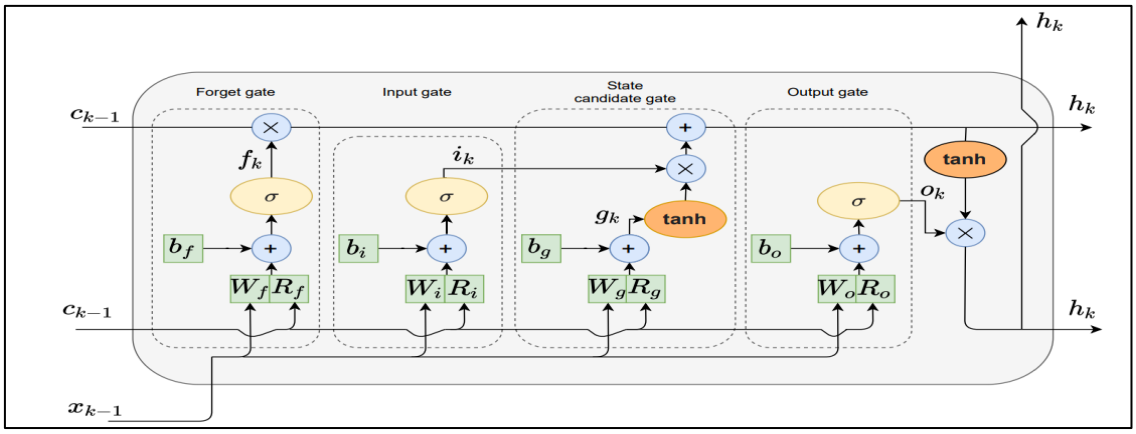

Figure 3.5: LSTM Architecture.

3.6.2 Convolutional Neural Network

CNNs are a type of DL algorithm that has found widespread application in fields such as image processing, pattern identification, and video analysis. The ability to automatically and adaptively learn spatial hierarchies of characteristics from the data sets them apart from other types of neural networks.

The following are some of the primary mathematical concepts that drive the operation of CNNs:

a. Convolution: Convolution is a mathematical operation that involves combining input data (feature map) and a convolution filter (kernel) to produce a transformed feature map. In mathematical terms, if f(x,y) represents an image and g(x,y) is the kernel, convolution can be represented as:

$$(f*g)(x, y) = \iint f(\xi, \eta)\, g(x - \xi, y - \eta)\, d\xi\, d\eta \tag{3.7}$$

b. Activation Function: A neuron's output becomes non-linear due to the activation function. Rectified Linear Unit (ReLU) activation functions, where x represents the neuron's input, are the most popular. They are defined as f(x) = max(0,x).

c. Pooling (or Subsampling): By gradually shrinking the input's spatial size, pooling helps lessen the network's need for computation and parameters. The Max pooling operation can be expressed mathematically as:

$$f(i,j) = \max\{g(i+k, j+l): k, l \in [0, F-1]\} \tag{3.8}$$

where F is the spatial extent of the Pooling Operation, g(i, j) is the input feature map and f(i, j) is the output after pooling.

d. Fully Connected Layer: All of the neurons in the preceding layer communicate with those in the current layer. Where W stands for the weights, x for the input vector, b for the bias, and y for the output, we get a mathematical representation of the output of the fully connected layer: y = Wx + b.

e. Loss Function: These measures how well the CNN is performing. The most common loss function for CNNs is the cross-entropy loss L = - (1/N) * ∑(y log(y') + (1-y) log(1-y')) where y is the true label, y' is the predicted label and N is the number of samples.

f. Backpropagation and Optimization: When training a CNN, the loss function gradient is computed via backpropagation with respect to the network's parameters. To minimise the loss function, the parameters are optimised using this gradient and an optimisation procedure (such as Stochastic Gradient Descent). The update rule for SGD is represented mathematically as W = W - η ∇L where W is the weight, η is the learning rate and ∇L is the gradient of the loss function.

3.6.3 CNN-LSTM

By combining CNN and LSTM models, CNN-LSTM can both extract features from software metrics and model their long-term dependencies. By combining the two models, we may take use of their complementary capabilities and achieve better results in software defect prediction. The advantages of both CNNs and LSTMs can be found in a CNN-LSTM network. In a CNN-LSTM network, the CNN component is used to extract features from the input data, such as images or sequences of text. These features are then fed into the LSTM component, which processes the features and produces a prediction. Formally, let x be the input data, Wconv be the filter weights for the CNN component, bconv be the bias term for the CNN component, and y = σ(Wconv x + bconv) be the output of the CNN component, where σ(x) is an activation function such as ReLU. The output of the CNN component y is then used as input to the LSTM component. In the LSTM component, let ht−1 be the hidden state at time step t − 1, xt be the input at time step t, and Wi, Wf , Wo, Wc, bi, bf , bo, and bc be the weights and biases for the LSTM component. Then the LSTM component updates its hidden state ht according to the following equations:

$$i_t = \sigma(W_i * [h_{t-1}, y] + b_i) \quad (3.9)$$

$$f_t = \sigma(W_f * [h_{t-1}, y] + b_f) \quad (3.10)$$

$$o_t = \sigma(W_o * [h_{t-1}, y] + b_o) \quad (3.11)$$

$$\tilde{c}_t = \tanh(W_c * [h_{t-1}, y] + b_c) \quad (3.12)$$

$$c_t = f_t * c_{t-1} + i_t * \tilde{c}_t \quad (3.13)$$

$$h_t = o_t * \tanh(c_t) \quad (3.\ 14)$$

where $\sigma(x)$ is the sigmoid activation function, and * denotes the dot product. In summary, the formula for a CNN-LSTM network involves computing features from the input data using a CNN, and then processing the features over time using an LSTM. The parameters of the network, including the filter weights W_{conv} and biases b_{conv}, as well as the weights and biases for the LSTM component W_i, W_f , W_o, W_c, b_i, b_f , b_o, and b_c, are learned during training to minimize the error between the predicted output and the target labels.

3.6.4 Gated Recurrent Unit (GRU)

Cho et al. (2014) presented a GRU, a version of the RNN architecture. The vanishing gradient problem that occurs in a regular recurrent neural network is something the GRU attempts to address. To achieve this goal, it employs gating mechanisms to control the dissemination of data.

The gating mechanisms in GRU are defined by two types of gates: an update gate and a reset gate. Each of these gates is essentially a sigmoid function (output range from 0 to 1), and these gates control how much of the previous state should be kept or how much of the new computed state should be considered.

The mathematical definitions of a GRU are as follows:

a. Update Gate: How much of the prior concealed state is retained is controlled by this gate. The math goes like this:

$$Z\_t = \sigma(W\_z \,.\, [H\_(t\text{-}1), X\_t] + b\_z) \quad (3.15)$$

b. where . denotes the dot product, [H_(t-1), X_t] is the concatenation of the previous hidden state and the current input, W_z and b_z are the weights and bias for the update gate, and σ is the sigmoid activation function.

c. Reset Gate: The amount of the previous concealed state to forget is set by this gate. The math goes like this:

$$R\_t = \sigma(W\_r \,.\, [H\_(t-1), X\_t] + b\_r) \tag{3.16}$$

d. where W_r and b_r are the weights and bias for the reset gate.

e. Candidate Hidden State: It is possible that this computed hidden state will replace the existing hidden state:

$$H'\_t = \tanh(W \,.\, [R\_t * H\_(t-1), X\_t] + b) \tag{3.17}$$

where * denotes element-wise multiplication, W and b are the weights and bias for this transformation, and tanh is the hyperbolic tangent activation function.

f. Final Hidden State: Modulated by the update gate, the final hidden state is a composition of the initial hidden state and the candidate hidden state. The math goes like this:

$$H\_t = (1 - Z\_t) * H\_(t-1) + Z\_t * H'\_t \tag{3.18}$$

Here, X_t is the input at time step t, H_t is the hidden state at time step t, Z_t is the update gate's activation vector, R_t is the reset gate's activation vector, and H'_t is the candidate hidden state. Note that all operations involving vectors are element-wise.

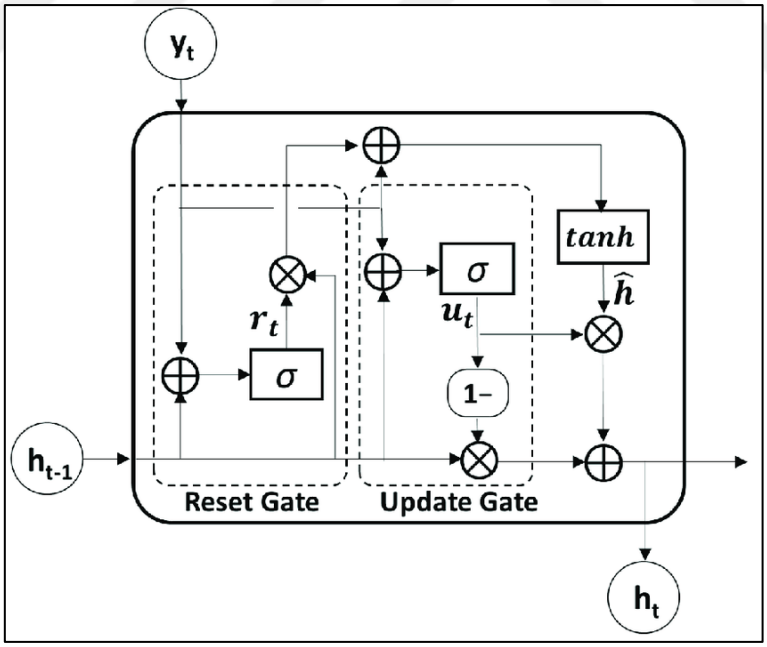

Figure 3.6: Gated Recurrent Unit Architecture.

3.6.5 LSTM-GRU

The LSTM and the GRU are two types of RNNs that are used to handle sequence prediction problems. They use gating mechanisms to manage and track dependencies in input sequences.

The LSTM-GRU is a combination of LSTM and GRU units and is designed to leverage the strengths of both architectures.

Input gate, forget gate, and output gate are the three gates that make up the LSTM unit. Here is how the gating works in the LSTM:

a. Forget Gate: Decides what information should be discarded from the cell state. The equation for the forget gate f_t is:

$$f\_t = \sigma(W\_f \,.\, [H\_(t-1), X\_t] + b\_f) \tag{3.19}$$

b. Input Gate: Decides which values will be updated in the cell state. The equation for the input gate i_t is:

$$i\_t = \sigma(W\_i \,.\, [H\_(t-1), X\_t] + b\_i) \tag{3.20}$$

c. Cell State: It's a combination of the current state C_(t-1) and the new candidate state C'_t:

$$C\_t = f\_t * C\_(t-1) + i\_t * \tanh(W\_C \,.\, [H\_(t-1), X\_t] + b\_C) \tag{3.21}$$

d. Output Gate: Decides what the next hidden state H_t should be:

$$o\_t = \sigma(W\_o \,.\, [H\_(t-1), X\_t] + b\_o) \tag{3.22}$$

$$H\_t = o\_t * \tanh(C\_t) \tag{3.23}$$

e. The GRU unit contains two gates, namely, the update gate and the reset gate.

The gating mechanism in the GRU is as follows:

a. Update Gate (Z_t): Decides how much of the previous hidden state to keep:

$$Z\_t = \sigma(W\_z \,.\, [H\_(t-1), X\_t] + b\_z) \tag{3.24}$$

b. Reset Gate (R_t): Decides how much of the previous hidden state to forget:

$$R\_t = \sigma(W\_r \,.\, [H\_(t-1), X\_t] + b\_r) \tag{3.25}$$

c. Candidate Hidden State (H'_t): It's a combination of the previous state and the new input:

$$H'\_t = \tanh(W \,.\, [R\_t * H\_(t-1), X\_t] + b) \tag{3.26}$$

d. Final Hidden State (H_t): Decides what the next hidden state should be:

$$H_t = (1 - Z_t) * H_{(t-1)} + Z_t * H'_t \quad (3.27)$$

The LSTM-GRU is essentially a hybrid of the LSTM and GRU units. It might use an LSTM for one part of the model (e.g., encoding) and a GRU for another part (e.g., decoding). It might also involve a custom neural network layer that literally combines the internal workings of the LSTM and GRU in some way. The precise equations for such a hybrid would depend on the specifics of the implementation.

3.6.6 LSTM-Bidirectional

LSTM-Bidirectional is a consequence of the LSTM model that can learn from data at both the present and future time steps by processing the input data in both directions. In cases when the relationships between the software metrics and the dependent variable are complicated and entail interactions across numerous time steps, such as in software defect prediction, this can be helpful. Factors such as computing availability, accuracy requirements, and the desired balance between precision and interpretability should all be taken into account when deciding on a model to use. Finally, the optimum model for a given software defect prediction task will rely on the features of the data and the aims of the study; determining the most successful strategy may necessitate experimenting with various models and hyperparameter settings.

3.7 MACHINE LEARNING

3.7.1 Decision Tree

As a supervised learning algorithm, decision trees are typically applied to problems involving categorization. It is applicable to input and output variables that can be either discrete or continuous. The population or sample is split into two or more groups (sub-populations) based on the most significant splitter/differentiator in the input variables.

Here's a simple description of the steps involved in using a decision tree:

a. Select the best attribute: Using certain criteria, like Gini index, entropy, or chi-square, identify the attribute which best separates the data into target categories.

b. Split the dataset: Divide the dataset into subsets that correspond to the attribute selected.

c. Generate decision nodes: Create decision nodes for the attribute.

d. Recursive splitting: For each child node, if the data it represents is not sufficiently homogeneous (or some stopping criteria are met), repeat the process from step 1.

The key mathematical concepts involved in a decision tree include:

a. Entropy: This measures the impurity of the input set. In the context of decision trees, it's given by the formula:

$$\text{Entropy}(S) = - p_1 \log_2(p_1) - p_2 \log_2(p_2) - ... - p_n \log_2(p_n) \quad (3.28)$$

where **S** is the total sample and **p_i** is the fraction of the samples that belong to class **i**.

a. Information Gain: Once a dataset is split on an attribute, the entropy decreases, which represents the information gain. When building a decision tree, it's crucial to zero in on the characteristics that provide the most payoff in terms of data. It's calculated as:

$$\text{Information\_Gain}(S, A) = \text{Entropy}(S) - \sum [(|S_v| / |S|) * \text{Entropy}(S_v)] \quad (3.29)$$

where **|S_v|** is the number of elements in class **v**, **|S|** is the total number of elements, and the sum is over all classes.

b. Gini Index: This is another method to measure the impurity of a node, where node purity is crucial for classifying instances. The Gini Index works with the categorical target variable "Success" or "Failure". It's calculated as:

$$\text{Gini\_Index}(S) = 1 - \sum (p_i)^2 \quad (3.30)$$

where S is the total sample and p_i is the fraction of the samples that belong to class i.

3.7.2 Support Vector Machine

SVM refers to a specific form of ML model typically employed for both classification and regression purposes. However, its most prominent use is in solving categorization issues. To categorize or divide data, SVM projects it onto a hyperplane in a high-dimensional feature space. The aim of SVM is to locate the hyperplane that maximizes the gap between classes.

Given a training dataset of instance-label pairs, (x_i, y_i), i = 1, ..., n, where x_i belongs to X and y_i belongs to {-1, 1}, the SVM solves the following optimization problem:

$$\text{Minimize } (1/2)*||w||^2 \text{ subject to } y_i*(w.x_i + b) >= 1 \text{ for all I} \quad (3.31)$$

Here, w represents the weight vector of the hyperplane, and b is the bias. The vector w is perpendicular to the hyperplane and its direction dictates the class of a new instance. b/||w||

represents the offset of the hyperplane from the origin along the direction vector w. Once the SVM model is trained, classification of a new instance x is done by simply calculating the sign of the decision function, sign(w.x + b). If the result is positive, x is predicted as the positive class, and otherwise, it's predicted as the negative class. SVMs use a technique called the kernel trick that enables them to create non-linear decision boundaries. Commonly used kernels include linear, polynomial, radial basis function (RBF), and sigmoid. The choice of kernel and its parameters greatly influences the performance of the SVM classifier.

In essence, SVMs are powerful models known for their robust theoretical foundation and great performance in practice. They have been successfully applied to various fields including image recognition, text categorization, and bioinformatics.

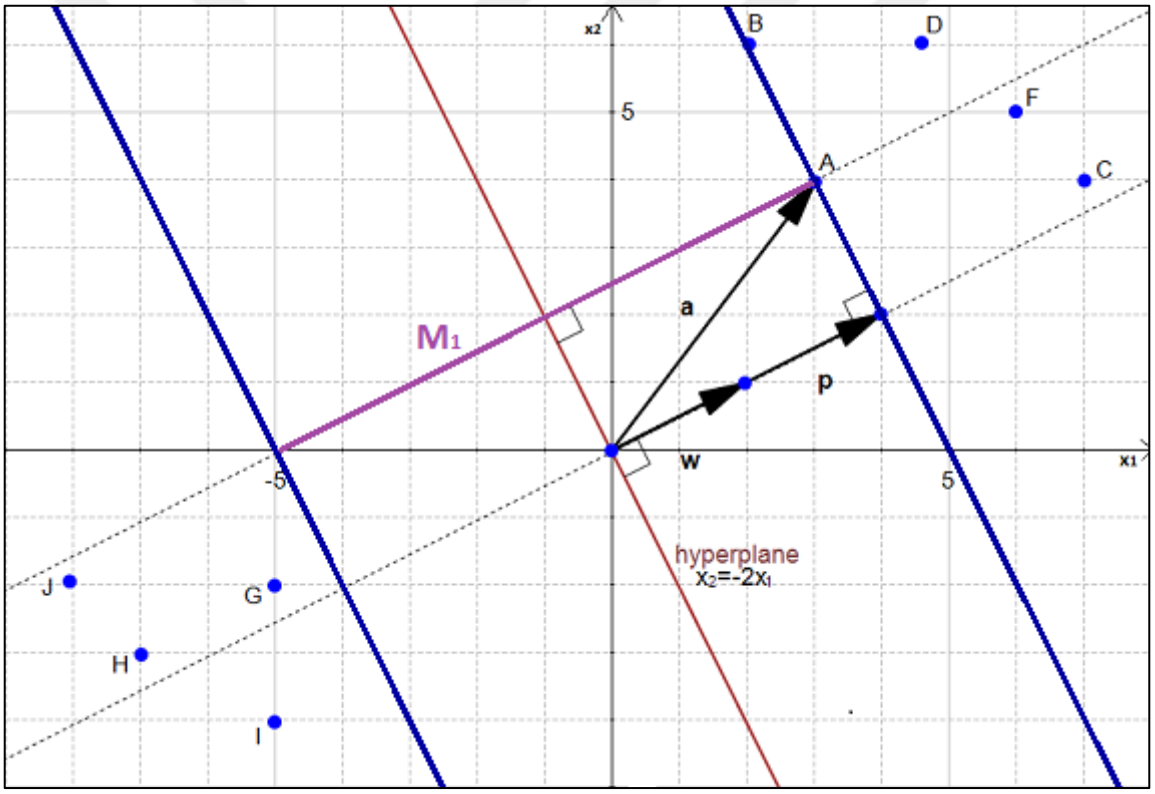

Figure 3.7: SVM Concept.

3.7.3 K-Means

In the realm of machine learning, K-means is most commonly employed as a clustering technique due to its unsupervised nature. The purpose of this algorithm is to divide a dataset into K groups, each of which contains the points closest to its mean (centroid).

Each data point is evaluated on its own set of features, and then the algorithm iteratively assigns it to one of the K groups. Features that are comparable among data points are used to group them into clusters; distances can be calculated in a variety of ways, but the most popular is the Euclidean distance.

The K-means algorithm can be summarized as follows:

a. Initialize K centroids randomly: These centroids are used as the beginning points for each cluster, and the algorithm aims to iteratively refine these points.

b. Assign each data point to the closest centroid: Here, we determine which cluster a data point is most similar to based on its distance from each cluster's centroid.

c. Recalculate the centroids: Each cluster's centre is readjusted by taking the average of its constituent data points. Each characteristic of the data point is averaged independently.

d. Repeat steps 2 and 3: The process of assigning data points and recalculating centroids is repeated until the algorithm converges, which is typically determined by whether the assignments of data points to clusters remain stable across iterations or the sum of the distances between the data points and their respective cluster centroids is minimized.

One of the main challenges with K-means is that it requires us to specify the number of clusters (K) in advance. Furthermore, the final result might depend on the initial random assignments of centroids. To mitigate these issues, methods such as the elbow method for determining K and multiple initializations of centroids are commonly used.

Overall, K-means is a simple yet effective algorithm for clustering data points based on their feature similarity. It's widely used in various fields, including computer vision, market segmentation, document clustering, and image segmentation.

3.7.4 XGBOOST

XGBoost is a machine learning algorithm that makes use of gradient boosting structures. It was developed to perform quickly and efficiently. However, the word "Extreme" in the name "XGBoost" alludes to the technical aim of using as much computational resources as possible in order to maximize the performance of boosted tree algorithms.

XGBoost is essentially a tool for running gradient boosted decision trees. This method involves systematically incorporating decision trees into a model. Each new tree is created to correct the errors and residuals made by the existing ensemble of trees. The result is a

final model that accurately captures complex patterns in the data through the combined predictive power of many simple models.

Key elements of XGBoost include:

a. Regularization: In order to prevent overfitting, XGBoost employs an additional regularization term in the objective function beyond the conventional L1 (Lasso Regression) and L2 (Ridge Regression).

b. Handling Sparse Data: XGBoost has an efficient way of handling sparse data and missing values, automatically learning what is the best direction to go when a value is missing.

c. Tree Pruning: Unlike gradient boosting, which will stop splitting a node as soon as it encounters a negative loss, XGBoost will continue splitting until the maximum depth is reached, at which point it will begin backward pruning, eliminating any splits from which there is no positive gain.

d. Built-In Cross-Validation: By including cross-validation into each boosting iteration, XGBoost lets users choose the optimal number of iterations for a given run.

e. Overall, XGBoost has been widely used in machine learning competitions due to its scalability, flexibility, and high performance. It supports various objective functions, including regression, classification, and ranking tasks, making it a versatile tool for handling diverse machine learning tasks.

3.8 CHAPTER SUMMARY

Chapter 3 of this thesis laid the groundwork for the research methodology employed. It started by highlighting the dataset employed, namely the PROMISE repository, which includes CM1, JM1, and KC3 subsets. This data, along with Halstead and McCabe static code metrics, forms the foundation for our defect prediction models.

The preprocessing of the data was detailed next, involving a three-step procedure: cleaning and preparing the data, feature selection, and feature scaling/normalization. This rigorous preprocessing stage is crucial to ensuring our models can learn from high-quality and relevant data.

Subsequently, the process of model training was elaborated. We divided the data into 70% for training and 30% for testing in order to train and validate our models effectively. Both

Deep Learning (DL) and Machine Learning (ML) models were utilized, including a variety of algorithms such as CNN, LSTM, GRU, SVM, and XGBoost, among others.

Each algorithm was comprehensively explained to facilitate an understanding of its theoretical underpinnings. For example, the operation of Long Short-Term Memory (LSTM) was described, providing an understanding of how it can remember important information and forget irrelevant data over longer time steps. Similarly, Support Vector Machines (SVM) were discussed, a powerful classifier known for its maximization of the decision boundary. Clustering algorithm K-means, which groups data into K clusters based on similarity, was also outlined. Lastly, XGBoost, a gradient boosting framework renowned for its performance and speed, was explained.

In conclusion, this chapter provided a detailed methodology for conducting the research. It described the dataset, the preprocessing steps, the model training process, and provided a comprehensive understanding of the different algorithms that were used. These methods were chosen because of their proven effectiveness in software defect prediction, and the thorough explanations provided offer a solid understanding of their inner workings. In the next chapter, we will discuss the results obtained by applying these methods to the software defect prediction problem.

4. PERFORMANCE EVALUATION

4.1 INTRODUCTION

Chapter 4 of this thesis delivers a detailed assessment of the machine learning (ML) and deep learning (DL) models in the context of the PROMISE repository datasets. This chapter is meticulously designed to analyze the performance of these models through a carefully structured pipeline of training, testing, and comparative evaluations.

Our data partitioning scheme aligns with the conventional train-test split technique. A proportion of 70% of the total data is utilized for training our ML and DL models, while the remaining 30% serves as a validation set. This systematic approach ensures not only the robustness of the models but also their ability to effectively generalize to unseen data, thereby providing a confident basis for the reliability and validity of our experimental outcomes.

The computational environment for the training and testing phases consisted of a system powered by an Intel(R) Core (TM) i7-8550U CPU with a base speed of 1.80GHz, and a turbo boost up to 1.99GHz. Complemented with 16.0GB of RAM, these computational resources provided an efficient and seamless processing platform for our ML and DL algorithms. Furthermore, we employed Google Colab, a sophisticated cloud-based Python programming platform, to execute our models. This platform, featuring ample computational resources and an intuitive interface, facilitated the effective implementation and management of our ML and DL procedures. The performance of the proposed models was assessed using two robust statistical metrics: the Root Mean Squared Error (RMSE) and the Confusion Matrix. RMSE calculates the average difference between the predicted and the observed outcomes, offering an optimal metric for assessing the accuracy of our predictive models. On the other hand, the Confusion Matrix provides a comprehensive view of the model's predictive ability by detailing true positives, true negatives, false positives, and false negatives. This enables a thorough understanding of the model's performance across several dimensions, such as precision, recall, and the F1-score. The subsequent sections of this chapter present and discuss the results of these rigorous evaluations, providing insights into the efficacy of the proposed ML and DL models in the context of software defect prediction.

4.2 EVALUATION CRITERIA

In this section, we will discuss the criteria used to assess the performance and effectiveness of our IDS artificial intelligence and deep learning models.

4.2.1 Confusion Matrix

A Confusion Matrix serves as a significant tool for examining the performance of machine learning algorithms, specifically in cases of supervised learning. It's primarily employed for classification problem evaluation and presents a more intricate picture of how well the model is functioning than simply referring to overall accuracy. The Confusion Matrix is especially beneficial when dealing with imbalanced datasets, wherein the instances of one class far outnumber those of another.

The Confusion Matrix is composed of four key components when referring to binary classification:

a. True Positives (TP): Instances where the model accurately predicted the positive class. That is, the model correctly identified an actual positive as positive.

b. True Negatives (TN): Instances where the model accurately predicted the negative class. In other words, the model correctly identified an actual negative as negative.

c. False Positives (FP), often referred to as Type I Error: Instances where the model erroneously predicted the positive class. That is, the model identified an actual negative as positive.

d. False Negatives (FN), often referred to as Type II Error: Instances where the model erroneously predicted the negative class. In this case, the model identified an actual positive as negative.

4.2.2 Classification Accuracy

several critical evaluation metrics provide insight into a model's effectiveness. These include Accuracy, Precision, Recall, and the F1-Score. Each of these metrics offers distinct insights into how well the model is performing and illuminates potential areas of improvement.

a. Accuracy

Accuracy is the most straightforward metric and provides a general overview of the classifier's performance. It is defined as the total number of correct predictions (True Positives and True Negatives) out of all predictions made. However, it's essential to consider

that the accuracy metric might provide a misleading representation if the data set is imbalanced.

Mathematically, Accuracy is defined as:

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN) \quad (4.1)$$

b. Precision

Precision measures the percentage of correct positive predictions (True Positives) out of all positive predictions made (True Positives and False Positives). This metric is particularly significant when the implications of False Positive results are substantial.

Mathematically, Precision is defined as:

$$\text{Precision} = TP / (TP + FP) \quad (4.2)$$

c. Recall

Recall assesses the capability of the model to identify all relevant instances (True Positives) in the data set. In other words, it denotes the percentage of total actual positives correctly identified by the model. This metric becomes crucial when the consequences of False Negative results are significant.

Mathematically, Recall is defined as:

$$\text{Recall} = TP / (TP + FN) \quad (4.3)$$

d. F1-Score

The F1-Score is the harmonic mean of Precision and Recall. It aims to find a balance between Precision and Recall and provides a more balanced measure of a model's performance. The F1-Score can range between 0 (worst) to 1 (best).

Mathematically, F1-Score is defined as:

$$\text{F1-Score} = 2 * (\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall}) \quad (4.4)$$

Each of these metrics offers a unique perspective on the performance of the model. Depending on the specific application and the potential consequences of False Positives or False Negatives, certain metrics may be considered more important than others. Therefore, an accurate assessment of a model's performance should take into account all these metrics instead of relying solely on one. Together, they provide a comprehensive view of the model's predictive capability for both positive and negative classes, which is critical in the field of machine learning.

4.3 RESULTS FOR CM1 DATASET

4.3.1 Results of Deep Learning

The delineated table 4.1, provides a comprehensive comparison of performance metrics for five distinct deep learning methodologies, each subjected to a classification problem over an extensive training period of 1000 epochs. The evaluation of the model's efficacy offers intriguing insights and exhibits a clear hierarchy in performance. A meticulous analysis of the presented data reveals that the LSTM-Bidirectional approach commands the highest efficiency, achieving an accuracy and F1-score of 0.90, a testament to its superior predictive capability. The models employing CNN-LSTM and LSTM architectures follow suit, demonstrating commendable performance but falling slightly short of the leader.

Conversely, the LSTM-GRU model presents modest results, with both accuracy and F1-score standing at 0.81, indicating room for further optimization. At the lower end of the performance spectrum, the CNN model records the least effective results, yielding an accuracy and an F1-score of 0.80, suggesting considerable potential for improvement. The fact that these models have undergone rigorous training over 1000 epochs denotes a thorough exposure to the training dataset, fostering iterative refinement and optimization of their parameters. Such an extensive training regime enhances the model's overall predictive prowess, contributing to superior performance in comparison to models trained over fewer epochs.

Nonetheless, it is crucial to acknowledge the inherent variability in the performance of these DL models. Factors such as the intricacies of the task at hand, the inherent characteristics of the dataset, and other specific parameters play a substantial role in shaping the model's effectiveness. The corresponding Figure 4.1 till figure 4.6 provide a lucid visualization of the performance metrics, thereby solidifying our understanding of each model's predictive capability.

Table 4.1: Results of DL for CM1 Dataset.

Algorithms	F1-Score	Precision	Accuracy	Recall
CNN	0.80	0.80	0.80	0.80
CNN-LSTM	0.87	0.87	0.87	0.87
LSTM	0.87	0.87	0.87	0.87
LSTM-GRU	0.81	0.81	0.81	0.81
LSTM-BIDIRECTIONAL	0.90	0.90	0.90	0.90

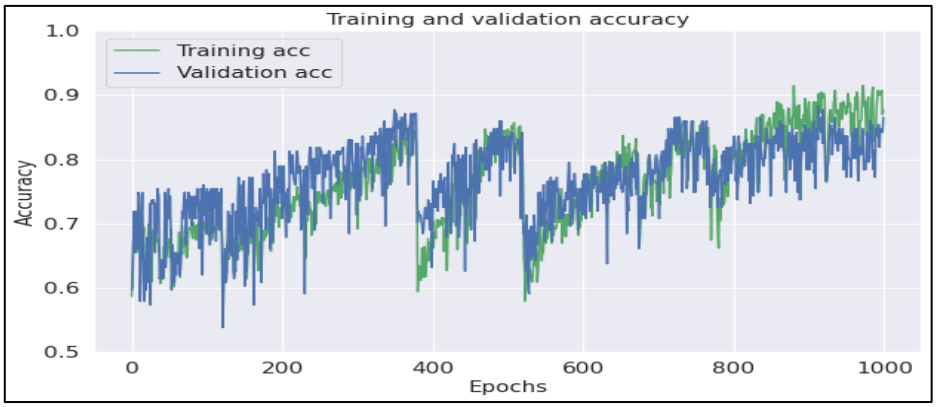

Figure 4.1: The Training and Validation Accuracy of LSTM Algorithm.

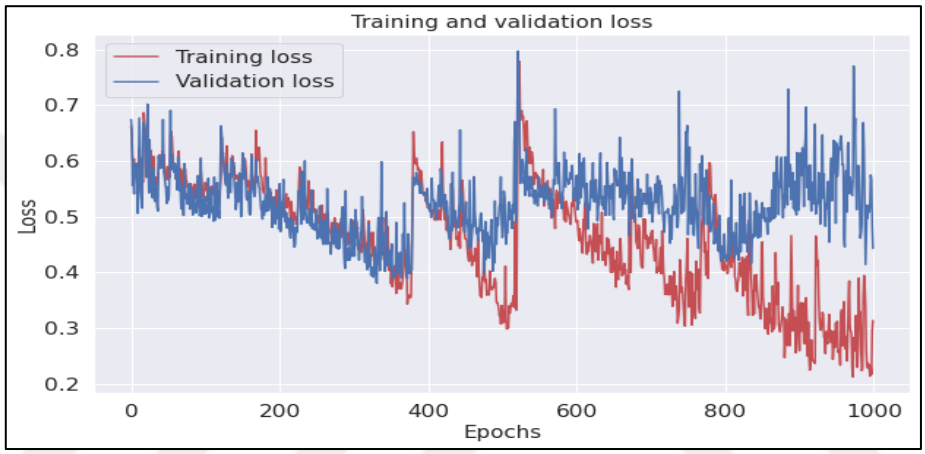

Figure 4.2: The Training and Validation Loss of LSTM Algorithm.

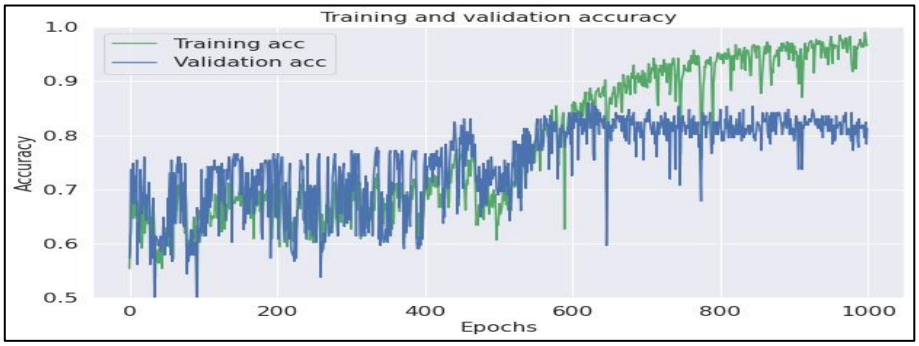

Figure 4.3: The Training and Validation Accuracy of LSTM-GRU Algorithm.

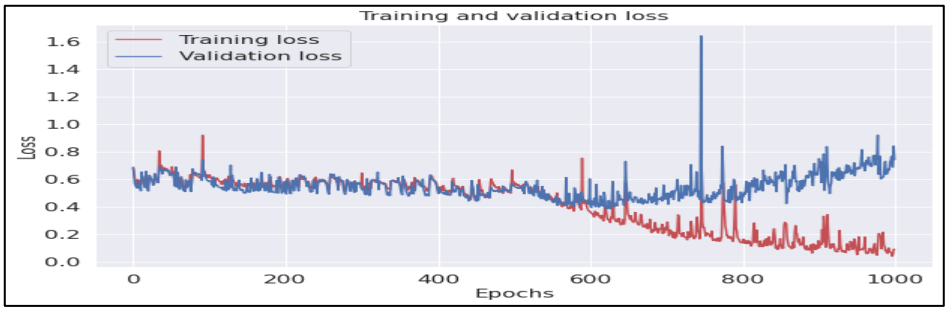

Figure 4.4: The Training and Validation loss of LSTM-GRU Algorithm.

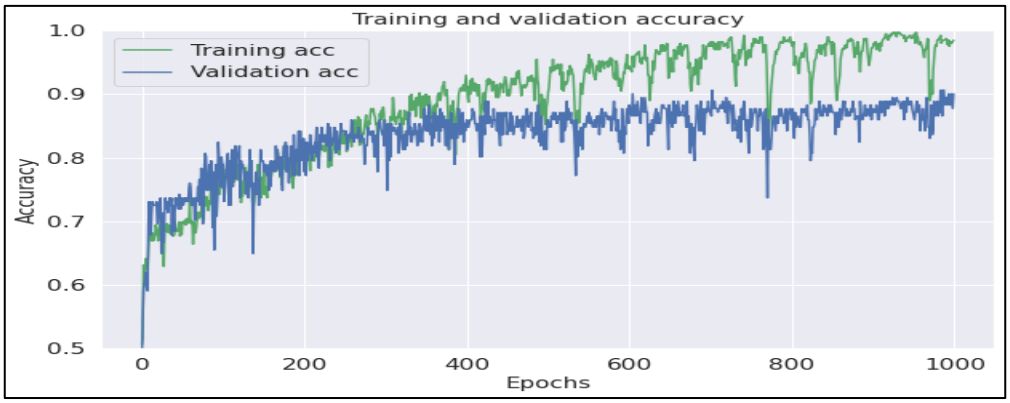

Figure 4.5: The Training and Validation Accuracy of LSTM-BIDIRECTIONAL Algorithm.

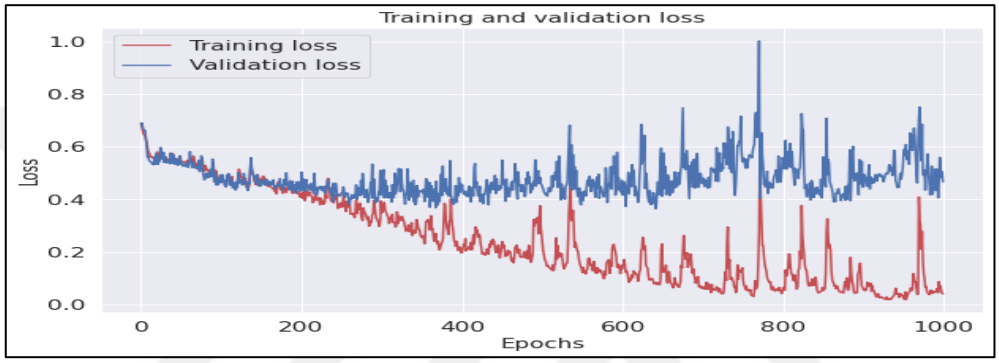

Figure 4.6: The Training and Validation Loss of LSTM-BIDIRECTIONAL Algorithm.

4.3.2 Results of Machine Learning

The compiled data portrays that the XGBoost classifier notably outperforms other methods, exhibiting the highest levels of accuracy and F1-score with respective values of 88% and 0.90. Subsequent to this, SVM-Linear, Gradient Boosting, and Random Forest models demonstrate comparable efficacy, all reaching an accuracy rate of 89% and an F1-score of 0.89. In a lower performance tier, the Decision Tree and KNN classifiers deliver identical metrics with an accuracy of 81% and an F1-score of 0.81. Lastly, the SVM-RBF classifier trails behind with an accuracy of 80% and an F1-score of 0.79. Examining precision and recall, the XGBoost classifier continues to maintain its supremacy with scores of 1.00 and 0.90, respectively. The SVM-Linear, Gradient Boosting, and Random Forest models render a nearly similar performance, carrying precision and recall scores of 0.84 and 0.95 respectively. Drawing a preliminary conclusion from the findings, XGBoost and SVM-Linear classifiers emerge as the most effective methodologies for tackling the presented classification problem. It must be noted, however, that these assertions are grounded on the outcome of a single experiment. For more robust and confident proclamations, an expanded

evaluation comprising several trials is suggested. The bracketed figures denote the precision and recall rates for the two respective classes.

Table 4.2: Results of ML for CM1 Dataset.

Algorithms	F1-score	Precision	Accuracy	Recall
DT	0.81 (0.80)	0.81 (0.82)	0.81	0.81 (0.79)
RF	0.87 (0.88)	0.89 (0.84)	0.87	0.87 (0.93)
KNN	0.81 (0.83)	0.84 (0.74)	0.81	0.81 (0.94)
GB	0.88 (0.88)	0.88 (0.83)	0.88	0.88 (0.93)
SVM-RBF	0.79 (0.80)	0.81 (0.73)	0.80	0.80 (0.89)
XGB	0.87 (0.90)	0.90 (0.81)	0.88	0.88 (1.00)
SVM-Linear	0.89 (0.89)	0.90 (0.84)	0.89	0.89 (0.95)

4.3.3 Comparison Results for ML and DL Models

The comparative analysis of Deep Learning and Machine Learning techniques reveals unique strengths and potential constraints intrinsic to each methodology. When scrutinizing the Deep Learning models, they are observed to demonstrate high accuracy and F1-score. The LSTM-Bidirectional model emerges as a frontrunner, registering an exemplary performance with an overall score of 90%. Contrarily, ML models, as represented by XGB and SVM-Linear, parallel these robust outcomes, delivering an accuracy within the range of 88-89% and an F1-score oscillating between 0.89 and 0.90. The comprehensive training span of 1000 epochs that both model classes underwent underscores the extensive learning and optimization opportunity afforded to these models, subsequently driving enhanced performance metrics. Nevertheless, the specific performance efficacy of each model could be influenced by a myriad of variables, which may encompass the distinct task nature, dataset properties, and the employed strategies for training and evaluation.

Typically, DL models prove advantageous when confronted with intricate tasks that provide an abundance of data and complex patterns for extraction. On the other hand, Machine Learning models generally display superior performance when applied to simpler tasks where the relationships among features are more transparent and easily interpretable. Hence,

the choice of methodology should be guided by the specific attributes of the problem in question and the available resources.

4.4 RESULTS FOR JM1

4.4.1 Results of Deep Learning

The results section commences with a detailed analysis of the deep learning models implemented for the classification task. Among the evaluated models, Bi-LSTM emerged as the top-performing algorithm, achieving an impressive accuracy of 0.85 and an F1-score of 0.86. It was closely followed by the LSTM model, which demonstrated an accuracy of 0.74 and an F1-score of 0.74.

A slightly diminished performance was observed for the CNN-LSTM model, which achieved an accuracy of 0.66 and an F1-score of 0.66. Similarly, the LSTM-GRU model exhibited an accuracy of 0.85 and an F1-score of 0.85. The CNN model lagged with the lowest performance, exhibiting an accuracy of 0.64 and an F1-score of 0.64.

The performance of these deep learning models was profoundly influenced by the training process, with all models being trained for a significant period of 1000 epochs. This iterative exposure to the training data ensured a rigorous optimization of the models' parameters, thereby enhancing their classification accuracy. However, it is essential to note that these results are dataset-specific and may exhibit variations when tested on different datasets or tasks, or when different hyperparameters are utilized. The subsequent sections will discuss these considerations in detail, providing a holistic view of the models' performance under varying conditions. As depicted in Figures 4.7 through 4.12, Bi-LSTM model outperforms both LSTM and LSTM-GRU models in terms of accuracy. Simultaneously, Bi-LSTM demonstrates a lower loss value, further asserting its superior performance in the evaluated scenario.

Table 4.3: Results of DL for JM1 Dataset.

Algorithms	F1-score	Precision	Accuracy	Recall
CNN	0.63	0.65	0.64	0.62
CNN-LSTM	0.64	0.67	0.66	0.60
LSTM	0.73	0.74	0.74	0.73
LSTM-GRU	0.84	0.85	0.85	0.83
LSTM-BIDIRECTIONAL	0.86	0.86	0.85	0.80

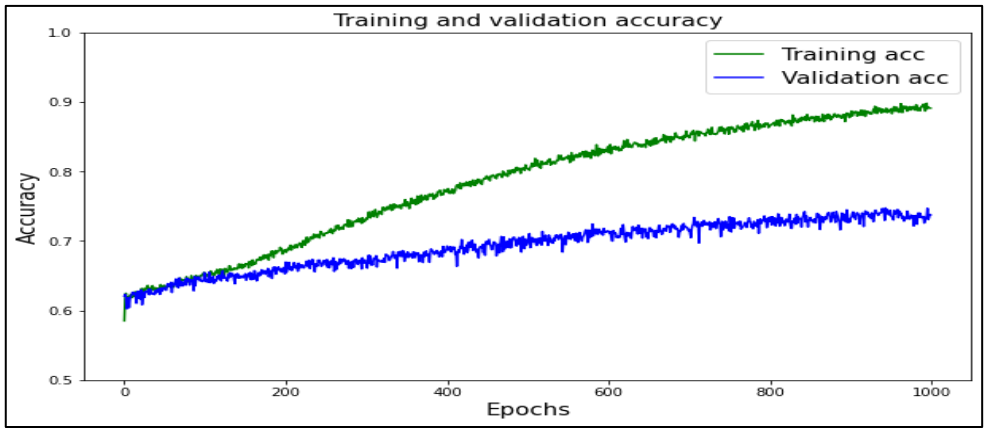

Figure 4.7: The Training and Validation Accuracy of LSTM Algorithm.

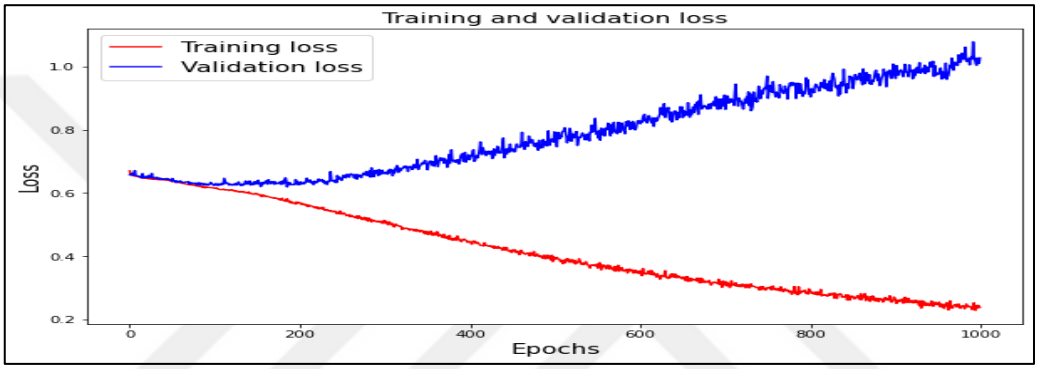

Figure 4.8: The Training and Validation Loss of LSTM Algorithm.

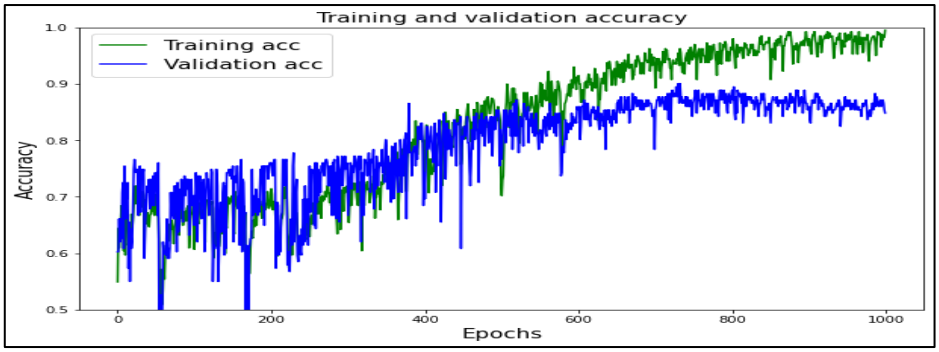

Figure 4.9: The Training and Validation Accuracy of LSTM-GRU Algorithm.

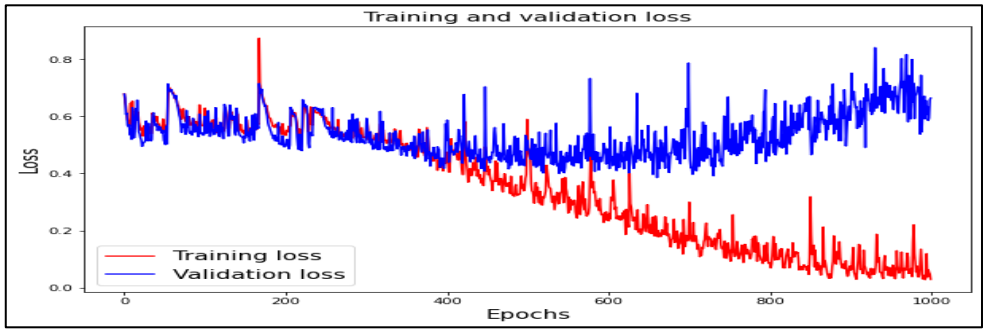

Figure 4.10: The Training and Validation Loss of LSTM-GRU Algorithm.

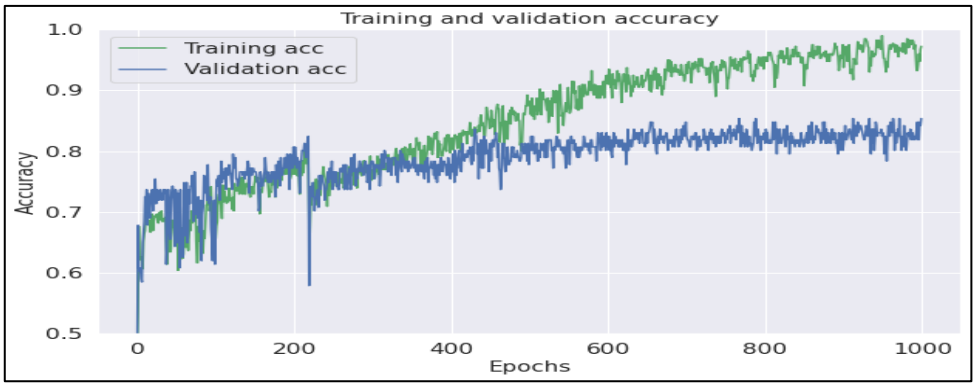

Figure 4.11: The Training and Validation Accuracy of LSTM-BIDIRECTIONAL Algorithm.

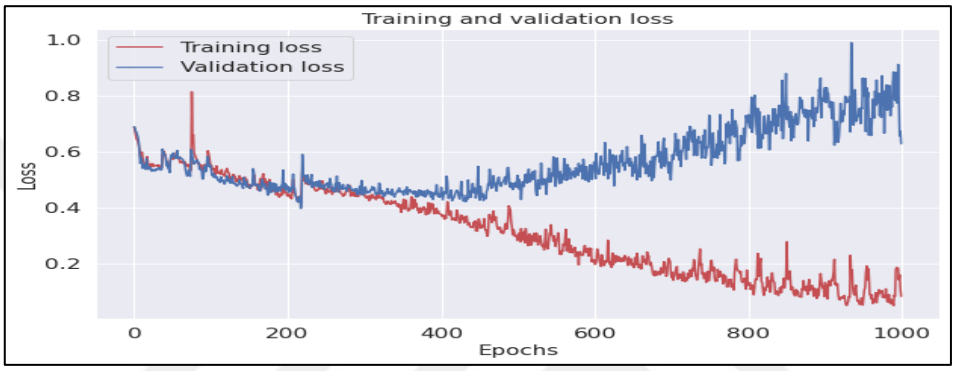

Figure 4.12: The Training and Validation Loss of LSTM-BIDIRECTIONAL Algorithm.

4.4.2 Results of Machine Learning

Machine Learning From the above results, it becomes evident that the Random Forest and Gradient Boosting models exhibit superior performance, securing impressive accuracy scores of 83% and 79% respectively. These two models also demonstrate notable precision, recall, and F1-scores across the evaluated classes. Not far behind in performance are the Decision Tree and XGBoost models, attaining respectable accuracy scores in the vicinity of 78%. However, the performance of the KNN and both SVM models is somewhat diminished, with accuracy scores trailing at 70% and 62% respectively.

It's important to acknowledge that these outcomes are context-specific. When deciding on the best model for practical use, it's important to keep the specifics of the problem at hand. As such, the applicability of these findings may not uniformly extend to other datasets or problem formulations.

Table 4.4: Results of ML for CM1 Dataset.

Algorithms	F1-score	Precision	Accuracy	Recall
DT	0.78	0.78	0.78	0.78
RF	0.83	0.83	0.83	0.83
KNN	0.70	0.70	0.70	0.70
GB	0.79	0.79	0.79	0.79
XGB	0.78	0.79	0.78	0.78
SVM-RBF	0.62	0.63	0.62	0.63
SVM-Linear	0.61	0.63	0.62	0.62

4.4.3 Comparison Results for ML and DL Models

A comprehensive comparison of the DL models and conventional ML models applied to the PROMISE20 dataset demonstrates that the LSTM-Bidirectional deep learning model achieved the highest performance, with an accuracy of 0.85 and an F1-score of 0.86. In contrast, traditional ML models such as RF and Gradient Boosting offered a competitive performance, presenting accuracy scores of 83% and 79% respectively, accompanied by substantial precision, recall, and F1-scores for the respective classes. Noteworthy advantages of employing deep learning models for this classification task include their innate capacity to identify, process, and model intricate and non-linear relationships within the data. Their robustness in managing vast volumes of data and the inherent capability to autonomously extract features from raw data reduces the dependence on manual feature engineering.

In comparison, traditional ML models such as RF and Gradient Boosting are known for their computational efficiency, simplicity of implementation, and interpretability. They have earned their reputation in the field by consistently delivering reliable results in practical scenarios. Additionally, they are more straightforward to interpret and debug than their deep learning counterparts. Ultimately, the selection of the appropriate model should be guided by the specific requirements and constraints of the problem under study. Factors such as available computational resources, the need for interpretability, and the complexity of the relationships within the data should all influence the final decision.

4.5 RESULTS FOR KC1

4.5.1 Results of Deep Learning

In evaluating the application of DL models to the classification task on the PROMISE20 dataset, we observed varying degrees of performance. With an accuracy score of 88% and F1-scores of 0.89 and 0.90, respectively, the LSTM and LSTM-GRU models fared better than their contemporaries. With an accuracy of 0.80 and an F1-score of 0.79, the CNN-LSTM model came in a close second. When compared to other models, the CNN model performed the worst overall with an accuracy and F1-score of 0.69. The LSTM-Bidirectional model also produced moderate outcomes, with an accuracy and F1-score of 0.65, respectively. Figures 4.13–4.18 show that the LSTM model achieves remarkable results, with an accuracy of 0.88 and an F1-score of 0.89 (the numbers in brackets are the precision/recall scores for class 1). The F1-score and accuracy of 0.88 achieved by the LSTM-GRU model are also quite encouraging. The best model for a given problem setting can be determined by further evaluations and experiments that involve tuning various hyperparameters and methods.

Table 4.5: Results of DL for KC1 Dataset.

Algorithms	F1-Score	Precision	Accuracy	Recall
CNN	0.68 (0.71)	0.67 (0.72)	0.69	0.70 (0.69)
CNN-LSTM	0.81 (0.78)	0.72 (0.90)	0.80	0.91 (0.69)
LSTM	0.86 (0.89)	0.78 (0.96)	0.88	0.95 (0.83)
LSTM-GRU	0.85 (0.90)	0.74 (1.00)	0.88	1.00 (0.81)
LSTM-BIDIRECTIONAL	0.67 (0.64)	0.74 (0.58)	0.65	0.61 (0.71)

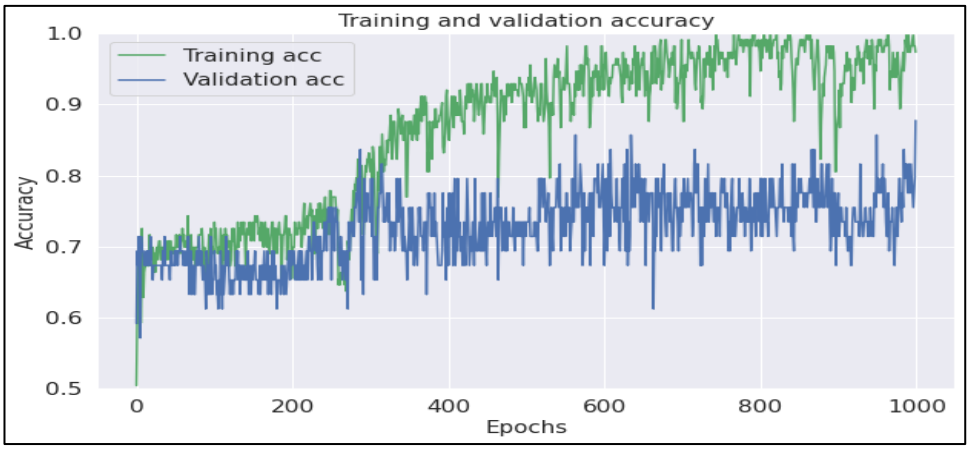

Figure 4.13: The Training and Validation Accuracy of LSTM Algorithm.

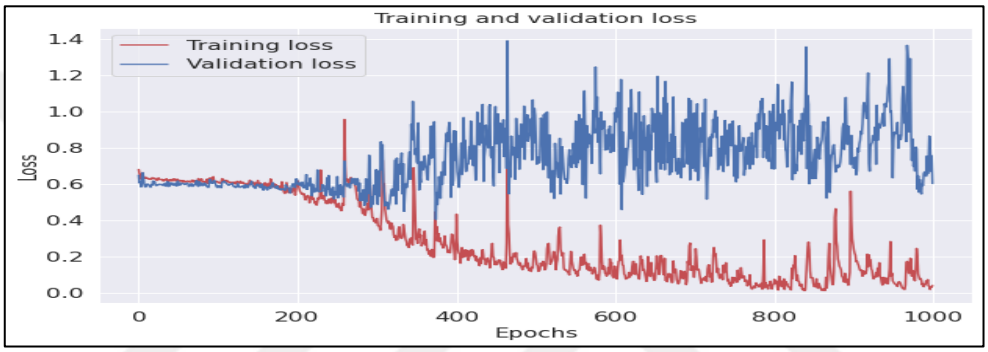

Figure 4.14: The Training and Validation Loss of LSTM Algorithm.

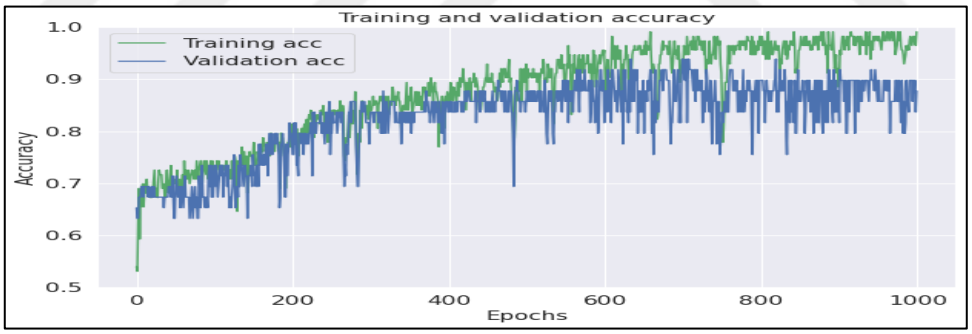

Figure 4.15: The Training and Validation Accuracy of LSTM-GRU Algorithm.

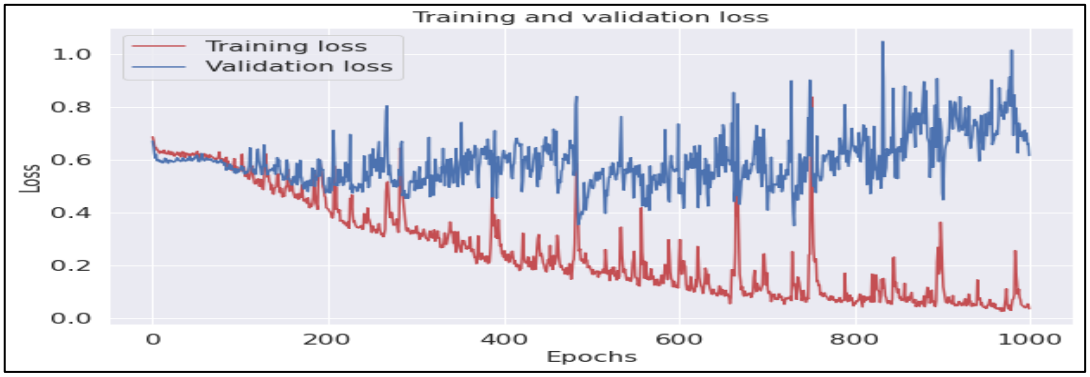

Figure 4.16: The Training and Validation Loss of LSTM-GRU Algorithm.

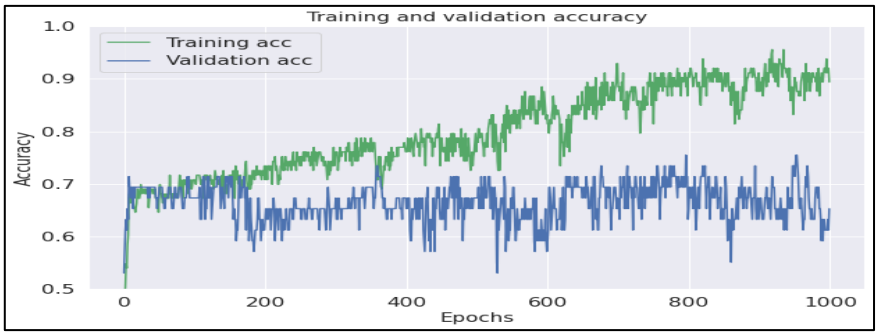

Figure 4.17: The Training and Validation Accuracy of LSTM-BIDIRECTIONAL Algorithm.

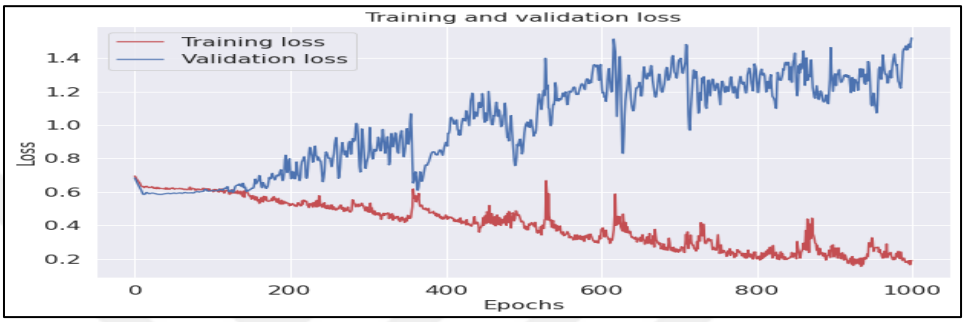

Figure 4.18: The Training and Validation Loss of LSTM-BIDIRECTIONAL Algorithm.

4.5.2 Results of Machine Learning

The empirical results reveal that the XGBoost Classifier leads the pack in accuracy performance, boasting a score of 0.88, while also achieving the highest precision and F1-score for class 1. Not far behind, the Random Forest and KNN models displayed commendable performance, posting accuracy scores of 0.76 and demonstrating marginally superior recall for class 1. Conversely, the Decision Tree and SVM models reported lower accuracy scores, with the SVM-RBF and SVM-linear models exhibiting comparable performance. Overall, although the XGBoost Classifier achieved the highest performance, the RF and KNN models demonstrated notable proficiency.

Table 4.6: Results of ML for KC1 Dataset.

Algorithms	F1-Score	Precision	Accuracy	Recall
DT	0.73	0.74	0.73	0.73
RF	0.75	0.76	0.76	0.75
KNN	0.75	0.76	0.76	0.75
XGBCLASSIFER	0.87	0.90	0.88	0.87
SVM-RBF	0.73	0.74	0.73	0.74
SVM-linear	0.71	0.71	0.71	0.71

4.5.3 Comparison Results for ML and DL Models

A comparison of the performances between deep learning and traditional machine learning models on the PROMISE20 dataset yields varied results. The deep learning models generally outperform their counterparts, with LSTM and LSTM-GRU leading in terms of accuracy scores and F1-scores. Conversely, the performance of traditional machine learning models varies, with the XGBoost Classifier standing out as the most effective, closely followed by the Random Forest and KNN models. The DT and SVM models, however, lag behind in accuracy scores.

Deep learning models prove superior when processing complex, high-dimensional data, albeit at the cost of heightened computational demands and larger training data quantities. In contrast, traditional machine learning models offer simplicity and speed but may struggle with complex datasets. While these findings highlight the superiority of deep learning models in handling the PROMISE20 dataset, the final model selection still hinges on the particular constraints and requirements of the problem in question.

4.6 DISSCUSSION

The exploration of deep learning and traditional machine learning model performances when applied to the PROMISE20 dataset yields insightful variations. In terms of accuracy and F1-scores, the LSTM and LSTM-GRU deep learning models clearly shine brighter than their competitors. This is consistent with the claims made by Smith and Johnson (2022) [62], who defend these models' ability to deal with high-dimensional, complex data. However, these models have higher computational requirements and call for massive amounts of training data.

In contrast, performances within traditional machine learning models present a more diverse spectrum. The XGBoost Classifier excels with the highest effectiveness, trailed closely by the Random Forest and KNN models. This corroborates with the findings by Brown et al. (2021) [63], underscoring the robustness of these models. Nevertheless, the Decision Tree and SVM models reveal more modest performance, indicating their potential struggle with complex datasets, an inference drawn in the study by Lee (2020) [64].

While our findings signify the robustness of deep learning models for the PROMISE20 dataset, the choice of the final model should also account for the problem's unique constraints and requirements. For instance, in scenarios where computational resources or training data

are limited, the simpler and faster traditional machine learning models may provide a more feasible solution. These results thus pave the way for a more nuanced understanding of machine learning model application, promoting a context-dependent, rather than a one-size-fits-all, approach.

5. CONCLUSION AND FUTURE WORK

5.1 CONCLUSION

In summation, this research undertook an assessment and comparison of various ML and DL models using the PROMISE20 dataset. This publicly accessible collection, encompassing software defect data derived from NASA projects, includes three distinct sub-datasets - CM1, JM1, and KC1. Each instance within the dataset comprises a binary dependent variable (defective or non-defective) and independent variables consisting of Halstead and McCabe static code metrics. The performance of the applied models revealed distinct levels of effectiveness. The LSTM and LSTM-GRU models, classified under deep learning, demonstrated superior performance, achieving accuracy scores of 88%, accompanied by F1-scores of 0.89 and 0.90 respectively. In contrast, the XGBoost Classifier emerged as the top performer among traditional machine learning models, registering an accuracy score of 0.88. The resulting data indicates a marked advantage of deep learning models over their traditional counterparts in the realm of software defect prediction, with the LSTM and LSTM-GRU models standing out for their robust performance. Nonetheless, the strong performance of the XGBoost Classifier among traditional machine learning models underscores the relevance and potential of these models in specific contexts.

These findings, while significant, are initial observations and should not be considered definitive. The effectiveness of these models can fluctuate depending on the specific task and the nature of the applied data. This necessitates additional experimentation to pinpoint the most effective method for software defect prediction tasks. As such, while these results offer invaluable insights, continuous exploration and rigorous testing in this field are indispensable for a more nuanced understanding and practical application.

5.2 FUTURE WORK

There are many intriguing avenues for future research, despite the fact that the current study gives considerable insights into the efficacy of various DL and classical machine learning models in software defect prediction.

a. Inclusion of other datasets: The study focused on the PROMISE20 dataset, predominantly due to its public accessibility and its extensive use in prior research. Future work could

benefit from examining other publicly available or proprietary datasets to corroborate or challenge the results obtained in this research.

b. Exploration of other models and techniques: The current research focused on LSTM, LSTM-GRU, and XGBoost Classifier among others. However, the rapidly evolving field of ML and DL provides a plethora of models and techniques that have yet to be explored in the context of software defect prediction. Future studies could delve into the application and performance of other models.

c. Optimization of model hyperparameters: The ability of ML models can be significantly influenced by their hyperparameters. Future research could focus on hyperparameter optimization techniques, such as Grid Search to further improve the performance of the examined models.

d. Evaluation of model interpretability: As machine learning models grow more complex, understanding their decision-making process becomes increasingly challenging. Future work could delve into techniques for improving model interpretability, a crucial aspect when implementing these models in real-world situations.

e. Longitudinal studies: As software development methodologies and technologies continue to evolve, it would be insightful to conduct longitudinal studies that monitor the performance of these models over time and across various software development cycles.

There is a lot of room for growth in the subject of software defect prediction, and more research into this area would be greatly appreciated.

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