**INTERNSHIP REPORT**

**On**

**SOFTWARE QUALITY PREDICTION**

*Submitted by*

**ASMITHA NANDU INDRAPALLY 22J4146693**

*in partial fulfilment of the requirements for the award of the degree of*

# BACHELOR OF TECHNOLOGY

In

# COMPUTER SCIENCE AND ENGINEERING (ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING)

Under the Supervision of

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(Duration: 13th May, 2024 to 25th  May 2024)

# COMPUTER SCIENCE AND ENGINEERING - AIML MALLA REDDY ENGINEERING COLLEGE

(An UGC Autonomous Institution, Approved by AICTE, New Delhi & Affiliated to

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**MAY -2024**

**MALLA REDDY ENGINEERING COLLEGE**

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**BONAFIDE CERTIFICATE**

This is to certify that the “Internship Report” work entitled **“SOFTWARE QUALITY PREDICTION using ML techniques”**, submitted by **I.ASMITHA NANDU(22J41A6693)** to Malla Reddy Engineering College affiliated to JNTUH, Hyderabad in partial fulfilment for the award of **Bachelor of Technology** in **COMPUTER SCIENCE AND ENGINEERING(AIML**) at Skilltimate Technnologies ,Hyderabadis a bonafide record of project work carried out under my supervision during the academic year 2024-2025 and that this work has not been submitted elsewhere for a degree.

|  |  |
| --- | --- |
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**I.ASMITHA NANDU 22J41A6693**

**ABSTRACT**

Software quality estimation is an activity needed at various stages of software development. It may be used for planning the project`s quality assurance practices and for benchmarking. In earlier previous studies, two methods (Multiple Criteria Linear Programming and Multiple Criteria Quadratic Programming) for estimating the quality of software had been used. Also, C5.0, SVM and Neutral network were experimented with for quality estimation. These studies have relatively low accuracies. In this study, we aimed to improve estimation accuracy by using relevant features of a large dataset. We used a feature selection method and correlation matrix for reaching higher accuracies. In addition, we have experimented with recent methods shown to be successful for other prediction tasks. Machine learning algorithms such as Xgboost, Random Forest and Decision Tree are applied to the data to predict the software quality and reveal the relation between the quality and development attributes. The experimental results show that the quality level of software can be well estimated by machine learning algorithms.

**KEY WORDS:** Multiple Criteria Linear Programming(MCLP), Multiple Criteria Quadratic Programming, C5.0, SVM and Neutral network

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**ABOUT THE ORGANIZATION**

**Skilltimate Technologies** was founded in response to the growing demand for new approaches to skill development in a constantly evolving global job market. Recognizing that individuals need to adapt to changing career landscapes, Skilltimate was created to offer a platform where learners can access top-tier training programs and enhance their professional skills. It is driven by the idea that continuous learning is critical for career success and long-term professional growth.

Motivated by the demand to have a new approach regarding raising the skill levels of the constantly changing global workforce, **Skilltimate Technologies** was created to create an ecosystem where individuals could connect themselves to the best training and skills development. Feeling that the job market was constantly in a state of flux, people were therefore being given an opportunity to be equipped with the means to ensure they succeeded in their careers through the birth of **Skilltimate Technologies**.

**Vision and Mission:**

* **Vision**: To be a leading provider of innovative learning and development solutions, empowering individuals and organizations to excel in a dynamic global workforce.
* **Mission**: To create an ecosystem that fosters professional growth through expert-led programs, hands-on learning, and collaboration, ensuring that learners are prepared for current and future career challenges.

**Work Culture:**

* **Expert-Led Programs:** Program designs at Skilltimate Technologies are brought about by industry veterans who bring with them decades of experience and insight into the process of learning. We believe real-world applications are very much important and for that reason every training session we offer has been designed keeping in mind current market demands. It offers training with expert guidance for either career advancement in the current one change or just polishing one's professional skills.
* **Advanced Learning Environment:** According to our belief, a robust stimulating and supportive learning environment is much required to ensure effective education. We at Skilltimate Technologies have been investing in first-class facilities, devised for inspiration of innovation, and to foster creativity. State-of-the-art infrastructure and modern learning tools form the perfect backdrop for the professionals to explore new ideas and hone their skills, making learning really engaging and productive.
* **Innovation and Collaboration Hub:** Beyond being a training provider, Skilltimate Technologies is an innovation hub for ideas and collaboration. Here, participants shall find a unique ecosystem to connect with industry leaders, collaborate on cutting-edge projects, and share ideas with like-minded professionals. More than that, this collaborative learning process opens the door to the creation of new potential opportunities in partnerships and professional networks in this highly interconnected world.
* **Tailored Learning Paths with Hands-On Experience:** At Skilltimate Technologies, we design flexible learning paths for every career stage, from fresh graduates to experienced professionals. Our programs—whether workshops, specialized courses, hackathons, or internships—are crafted to meet specific career goals. By blending theory with hands-on, real-world experience, we ensure that learners can apply their skills effectively, making them job-ready and well-prepared for the workforce.

**OBJECTIVES OF INTERNSHIP**

**Practical Skills Development in Python:** The internship offers hands-on experience with modules from Python, including NumPy, Pandas, Matplotlib, and Scikit-learn. Real projects will be used to improve data manipulation, statistical analysis, and result visualization.

**Develop ability to handle data:** Interns will be able to handle and process a variety of file formats. This is to enable interns to read, clean, and transform the data with the aim of using it for analysis, based on the context of an AI and ML project, while delivering results relevant to the respective lines of business.

**Mastering machine learning techniques:** The internship teaches how to utilize the different available algorithms from Scikit-learn. The course will equip participants with an understanding of model training, model evaluation, and hyperparameter tuning in models to enable drawing pertinent insights from complex datasets.

**General knowledge of CNN:** The attendees of the internship course will be equipped with the required techniques while building and training CNNs for image classification and other applications. In other words, this goal equips interns with the construction of robust models by converting raw data into meaningful features.

**Critical problem-solving skills by AI/ML:** Tasks will encompass data manipulation, visualization, and machine learning. Internees will be able to critically apply problem-solving skills through the methods and techniques of Python in solving any problem methodically.

Statistical Analysis Knowledge During the internship, students will learn basic statistics that underpin much of AI/ML including mean, median, mode, standard deviation, and correlation.

**Adherence to Best Practices on AI/ML:** The internship offers quality data, proper coding standards, and effective usage of data handling. Internees are prompted to render the best practice applicable in each work.

**Promote Independent Learning and Research:** With the internship, students are encouraged to go ahead and explore further into topics outside the formal curriculum. This will be part of their preparation in continuous professional development in AI and ML.

**INTRODUCTION**

In the rapidly evolving landscape of software development, delivering high-quality software products is a critical imperative for organizations. Software quality is not merely a desirable attribute; it significantly impacts customer satisfaction, brand reputation, and overall business success. As software systems become increasingly complex, the need for effective quality assurance practices has intensified, prompting the exploration of innovative methodologies for predicting software quality.

Software quality prediction involves the application of statistical and machine learning techniques to forecast potential defects and assess the overall quality of software products throughout their lifecycle. By analyzing historical data from various stages of software development, organizations can identify patterns and trends that serve as indicators of future quality issues. This proactive approach empowers development teams to address vulnerabilities early in the development process, thus minimizing defects and enhancing product reliability.

The importance of software quality prediction lies in its ability to provide actionable insights that guide decision-making. Traditional quality assurance methods often rely on reactive approaches, where issues are identified only after they have occurred. In contrast, predictive analytics allows teams to anticipate problems before they manifest, facilitating a shift from a reactive to a proactive quality assurance mindset. This transition not only leads to improved product quality but also optimizes resource allocation and reduces overall project costs.

By adopting software quality prediction practices, organizations can achieve several significant outcomes, including reduced defect rates, improved customer satisfaction, enhanced decision-making, and greater alignment of development efforts with business objectives. As the software industry continues to embrace Agile and DevOps methodologies, the integration of predictive analytics into quality assurance processes will play a pivotal role in driving successful software development initiatives.

In conclusion, software quality prediction represents a transformative approach to quality assurance that harnesses the power of data analytics and machine learning. By proactively identifying potential issues and enabling informed decision-making, organizations can deliver high-quality software products that meet the demands of an increasingly competitive market. As this field continues to evolve, the more sophisticated techniques .

# ABOUT THE PROJECT

The **Software Quality Prediction Using Machine Learning Techniques** project aims to leverage machine learning (ML) algorithms to predict software quality, specifically focusing on identifying potential defects and improving the overall reliability of software products. This project is designed to address the challenges faced by software development teams in ensuring high-quality deliverables while adhering to tight deadlines and limited resources.

**Objectives**

1. **Defect Prediction:** Develop models that can accurately predict the likelihood of defects in software modules based on historical data.
2. **Quality Metrics Analysis:** Identify and analyze key metrics that correlate with software quality, providing actionable insights to developers and QA teams.
3. **Resource Optimization:** Facilitate more efficient allocation of testing and development resources by pinpointing high-risk areas in the codebase.
4. **Continuous Improvement:** Create a framework for ongoing model improvement and adaptation to evolving software development practices.

**Project Phases**

1. **Data Collection**
   * **Sources:** Gather historical data from various sources such as:
     + Version control systems (e.g., Git) for commit history and code changes.
     + Static analysis tools (e.g., SonarQube) for code quality metrics.
     + Issue tracking systems (e.g., JIRA) for defect reports and resolution times.
     + Continuous integration/continuous deployment (CI/CD) pipelines for build and test metrics.
   * **Data Types:** Collect quantitative data (e.g., lines of code, defect counts) and qualitative data (e.g., commit messages, defect descriptions).
2. **Data Preprocessing**
   * **Cleaning:** Handle missing values, duplicates, and outliers in the collected data.
   * **Normalization:** Normalize the data to ensure consistency across different metrics.
   * **Feature Selection:** Identify relevant features that contribute to predicting software quality, such as code complexity, code churn, and defect density.
3. **Model Development**
   * **Algorithm Selection:** Choose appropriate machine learning algorithms based on the nature of the data and the prediction goals. Common algorithms include:
     + Decision Trees
     + Random Forests
     + Support Vector Machines (SVM)
     + Neural Networks
     + Gradient Boosting (e.g., XGBoost)
   * **Training and Validation:** Split the dataset into training and testing subsets to develop and validate predictive models. Employ techniques like cross-validation to ensure model robustness.
4. **Model Evaluation**
   * **Performance Metrics:** Assess model performance using metrics such as accuracy, precision, recall, F1 score, and area under the curve (AUC) for classification problems. For regression tasks, metrics like Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) may be used.
   * **Model Selection:** Compare the performance of different models and select the one that best meets the project objectives.
5. **Model Deployment**
   * **Integration:** Integrate the predictive model into the existing development workflow and CI/CD pipeline for real-time predictions.
   * **User Interface:** Develop a user-friendly interface or dashboard for stakeholders to visualize predictions, quality metrics, and trends.
6. **Monitoring and Feedback**
   * **Model Performance Tracking:** Continuously monitor the performance of the deployed model, looking for signs of drift or degradation in accuracy.
   * **Retraining:** Implement a feedback loop for retraining the model with new data to maintain accuracy over time.
7. **Reporting and Visualization**
   * **Dashboards:** Create dashboards for stakeholders that display key quality metrics, defect predictions, and insights derived from the model.
   * **Documentation:** Provide thorough documentation of the project, including methodologies, findings, and recommendations for further improvements.

**Expected Outcomes**

* **Improved Defect Detection:** Enhanced ability to identify high-risk components in the software, allowing for targeted testing and quality assurance efforts.
* **Informed Decision-Making:** Data-driven insights that empower development and QA teams to make informed decisions regarding resource allocation and risk management.
* **Reduced Development Costs:** Decreased post-release defects lead to lower maintenance costs and improved customer satisfaction.
* **Continuous Quality Improvement:** Establish a culture of continuous quality improvement through regular model updates and ongoing analysis of software quality metrics.

# METHODOLOGY

The methodology for implementing software quality prediction using machine learning (ML) techniques involves several structured phases, each critical to the success of the project. Below is a detailed breakdown of the methodology, from problem definition to deployment and monitoring.

**1. Problem Definition and Analysis**

* **Identify Objectives:** Clearly define the goals of the prediction project, such as predicting defect density, predicting the likelihood of specific types of defects, or assessing overall software quality.
* **Stakeholder Involvement:** Engage relevant stakeholders (e.g., developers, QA teams, project managers) to gather insights and align on the objectives..

2. **Data Collection** **Source Identification:** Identify and gather data from various sources, including:

* **Version Control Systems:** Extract commit history, code changes, and contributor information (e.g., Git).
* **Static Code Analysis Tools:** Collect code metrics (e.g., complexity, maintainability) from tools like SonarQube.
* **Issue Tracking Systems:** Gather defect reports, severity, and resolution times from platforms like JIRA.
* **Continuous Integration/Continuous Deployment (CI/CD) Pipelines:** Monitor build and test metrics (e.g., pass/fail rates, test coverage).

**3**. **Data Preprocessing**:

* **Data Cleaning:** Address missing values, outliers, and inconsistencies in the dataset.
* **Feature Engineering:**
* Identify relevant features that impact software quality, such as code complexity, historical defect rates, and testing metrics.
* Create new features if necessary (e.g., calculating code churn from commit history).
* **Normalization and Transformation:** Normalize numerical features to bring them to a common scale, and transform categorical features into numerical representations (e.g., one-hot encoding).

**4.Exploratory Data Analysis (EDA):**

#### Statistical Analysis: Perform statistical analysis to understand data

#### Visualization: Use data visualization techniques (e.g., histograms, scatter plots, heatmaps) to identify patterns and relationships between features and quality metrics.

1. **Model Selection:**

* **Choose Algorithms:** Select appropriate ML algorithms based on the nature of the prediction problem:
* **Classification Problems:** Decision Trees, Random Forests, Support Vector Machines, Gradient Boosting, Neural Networks.
* **Regression Problems:** Linear Regression, Random Forest Regressor, Gradient Boosting Regressor.
* **Hyperparameter Tuning:** Optimize model performance through hyperparameter tuning techniques such as Grid Search or Random Search.

**6. Model Training**

* **Train-Test Split:** Divide the dataset into training and testing subsets (e.g., 70-80% for training, 20-30% for testing) to evaluate model performance.
* **Training:** Train the selected models using the training data, employing cross-validation to assess the robustness of the models.

**7. Model Evaluation**

* **Performance Metrics:** Evaluate the trained models using relevant metrics:
  + For classification tasks: Accuracy, Precision, Recall, F1 Score, ROC-AUC.
  + For regression tasks: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE).
* **Model Comparison:** Compare the performance of different models to select the best-performing one based on evaluation metrics.

**8. Model Deployment**

* **Integration into Development Workflow:** Integrate the predictive model into the existing CI/CD pipeline to provide real-time quality predictions.
* **User Interface Development:** Create a user-friendly dashboard or reporting tool for stakeholders to access predictions and insights.

**9. Monitoring and Maintenance**

* **Continuous Monitoring:** Monitor the model's performance over time to detect any drift or degradation in accuracy.
* **Feedback Loop:** Implement a feedback mechanism to collect user input on model predictions and make necessary adjustments.
* **Retraining:** Periodically retrain the model with new data to ensure it remains relevant and accurate as development practices evolve.

**10. Reporting and Visualization**

* **Dashboard Creation:** Develop dashboards to visualize key metrics, predictions, and trends, enabling stakeholders to make informed decisions.
* **Documentation:** Document the methodologies, findings, and recommendations for continuous improvement of the prediction process.

**11. Continuous Improvement**

* **Iterative Refinement:** Continuously refine the model and methodologies based on feedback and evolving software practices, ensuring alignment with organizational goals.
* **Knowledge Sharing:** Share insights and learnings with the development and QA teams to foster a culture of continuous improvement.

The methodology for software quality prediction using machine learning techniques is a structured and iterative process that emphasizes data-driven decision-making. By leveraging historical data and predictive modeling, organizations can significantly enhance their ability to identify potential quality issues early in the software development lifecycle, leading to improved product quality, reduced costs, and increased customer satisfaction. This methodology not only provides a roadmap for implementing predictive analytics but also fosters a culture of quality and continuous improvement within development teams.

**TECHNICAL OBSERVATIONS & LEARNING FROM INTERNSHIP**

# 1. Code Quality and Best Practices

* **Clean and Maintainable Code:** Emphasizing the importance of writing clean, readable, and maintainable code is crucial for long-term project sustainability. This includes using meaningful variable and function names, proper indentation, and consistent formatting.
* **Adherence to Coding Standards:** Following established coding standards and guidelines (e.g., PEP 8 for Python, Java Code Conventions) helps maintain uniformity across the codebase, making it easier for team members to read and understand each other's work.
* **Version Control Systems:** Utilizing version control systems like Git is essential for effective collaboration management. It allows teams to track changes, revert to previous versions, and manage multiple branches of development seamlessly.

# 2. Debugging and Troubleshooting

* **Identifying and Fixing Bugs:** Familiarity with various debugging techniques, such as rubber duck debugging, code review sessions, and systematic problem-solving approaches, is vital for effectively identifying and resolving issues.
* **Debugging Tools and Logging:** Leveraging debugging tools (e.g., integrated debuggers in IDEs, browser developer tools) and logging frameworks enables developers to trace issues more efficiently. Effective logging practices can provide insights into application behavior and help pinpoint problems.

# 3. Software Development Lifecycle (SDLC)

* **Understanding SDLC Phases:** Familiarity with the various phases of the Software Development Lifecycle—requirement gathering, design, development, testing, deployment, and maintenance—provides a comprehensive view of the software development process.
* **Agile Methodologies:** Knowledge of Agile methodologies (e.g., Scrum, Kanban) and their implementation in real-world projects promotes adaptability and iterative progress, allowing teams to respond to changing requirements effectively.

# 4. Collaboration and Communication

* **Team Collaboration:** Working effectively in a team environment is critical for project success. This includes understanding team roles, sharing responsibilities, and actively participating in discussions.
* **Collaboration Tools:** Utilizing collaboration tools like JIRA, Trello, or Slack facilitates project management and team communication. These tools help track tasks, manage project timelines, and maintain ongoing dialogue.
* **Clear Communication:** The importance of clear and concise communication, both written and verbal, is fundamental in ensuring that all team members are on the same page and that project goals are understood.

**5. Technology Stack**

* **Exposure to Programming Languages and Frameworks:** Gaining exposure to various programming languages, frameworks, and tools enhances versatility as a developer. This includes understanding the strengths and weaknesses of different technologies and their appropriate use cases.

**6. Adaptability to Real-World Challenges**

* **Responding to Changing Conditions:** The project required adapting to fluctuating traffic conditions, enhancing my ability to think critically and adjust strategies based on real-time data
* **Future Improvements and Scalability:** I learned the importance of considering future scalability and enhancements for systems, including the potential integration of machine learning and vehicle-to-infrastructure communication to further optimize traffic management.

# REQUIREMENTS

## REQUIREMENT ANALYSIS

## Requirement analysis is a crucial phase in a software quality prediction project. It involves understanding the needs, constraints, and goals of the project to ensure that the predictive models and associated workflows are aligned with the organization’s objectives. Here’s a comprehensive guide to conducting requirement analysis for software quality prediction:

## REQUIREMENT SPECIFICATION:

**SYSTEM REQUIREMENTS:**

**HARDWARE REQUIREMENTS:**

* System:MINIMUM i3.
* Hard Disk : 40 GB.
* Ram : 4 GB.

**SOFTWARE REQUIREMENTS:**

* **Operating System:** Windows 8
* **Coding Language**: Python 3.7

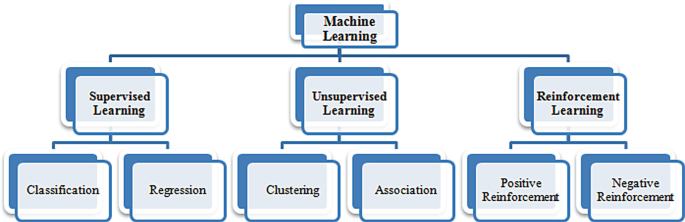
## PYTHON

Python is a high-level, interpreted programming language known for its simplicity and readability. Created by Guido van Rossum and first released in 1991, Python has since gained immense popularity and has become one of the most widely used programming languages worldwide. Here's an overview of Python's key features:

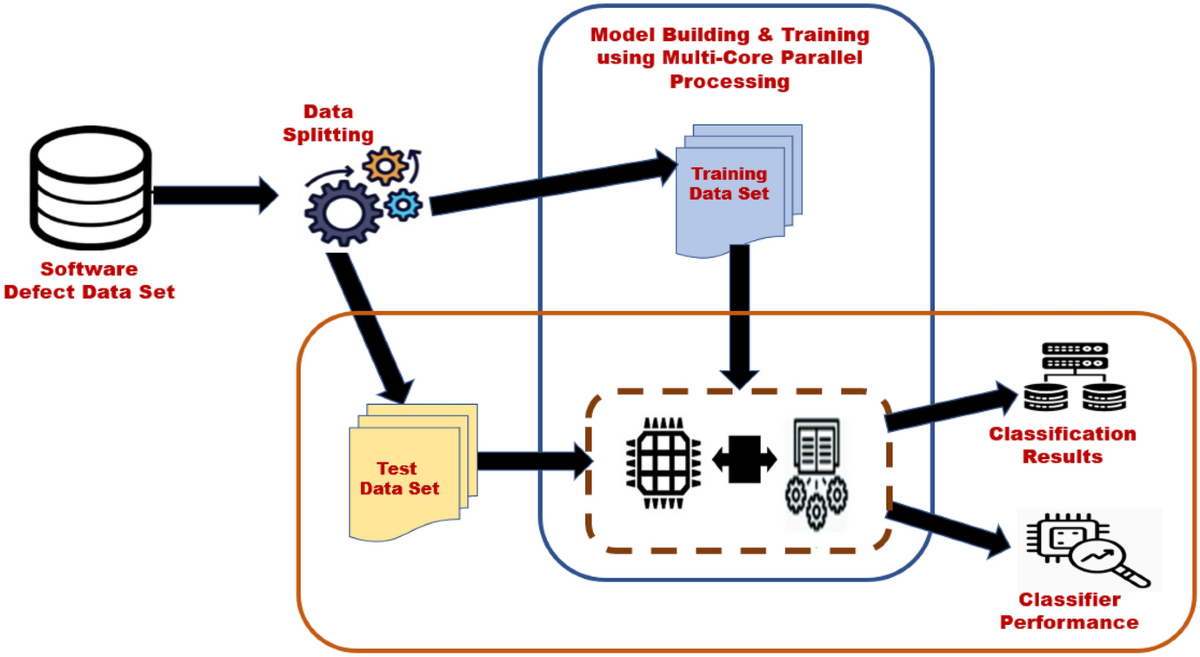
1. **General-Purpose Language:** Python is a versatile, high-level programming language suitable for various applications. It's widely used in web development, data analysis, artificial intelligence, scientific computing, automation, and more. Its readability and simplicity make it an excellent choice for both beginners and experienced developers.
2. **Simple and Readable Syntax:** Python emphasizes readability and simplicity, which is evident in its clean and concise syntax. It uses indentation to define code blocks instead of curly braces, making the code visually appealing and easier to understand. This feature reduces the chances of syntactical errors and encourages maintainability.
3. **Rich Standard Library:** Python comes with a comprehensive standard library that provides modules and packages for a wide range of tasks, from file I/O and networking to mathematical operations and web development. This extensive library reduces the need for third-party dependencies and accelerates development by offering ready-to-use solutions for common programming challenges.
4. **Interpreted and Dynamic:** Python is an interpreted language, meaning that the source code is executed line by line by the Python interpreter. This allows for rapid development and testing cycles without the need for compilation. Python is also dynamically typed, enabling variables to be assigned without declaring their data types explicitly. This flexibility enhances productivity but requires careful attention to variable types during development to avoid runtime errors.
5. **Strong Community and Ecosystem:** Python boasts a vibrant and supportive community of developers worldwide. This community contributes to the language's growth by creating and maintaining libraries, frameworks, and tools. Popular frameworks like Django for web development, NumPy and pandas for data analysis, and TensorFlow for machine learning exemplify the robust ecosystem surrounding Python. The availability of abundant resources, tutorials, and forums makes it easy for developers to learn, collaborate, and solve problems efficiently.

**APPENDICES**

**FLOW CHART**

****

**Activity Diagram**



# CODE OF THE PROJECT

from tkinter import \*

import tkinter

from tkinter import filedialog

import matplotlib.pyplot as plt

from tkinter.filedialog import askopenfilename

import numpy as np

import pandas as pd

import seaborn as sns

from sklearn.preprocessing import LabelEncoder

from sklearn.metrics import accuracy\_score

from sklearn.model\_selection import train\_test\_split

from sklearn.linear\_model import LogisticRegression

from sklearn.decomposition import PCA

from sklearn.preprocessing import normalize

from sklearn.naive\_bayes import BernoulliNB

from sklearn.tree import DecisionTreeClassifier

from sklearn.ensemble import RandomForestClassifier

from sklearn.linear\_model import LogisticRegression

from sklearn.ensemble import GradientBoostingClassifier

from sklearn.ensemble import BaggingClassifier

from sklearn.svm import SVC

from keras.utils.np\_utils import to\_categorical

from keras.models import Sequential

from keras.layers import Dense, Dropout, Activation

from sklearn.metrics import precision\_score

from sklearn.metrics import recall\_score

from sklearn.metrics import f1\_score

main = tkinter.Tk()

main.title("An Experimental Study for Software Quality Prediction with Machine Learning Methods")

main.geometry("1200x1200")

global filename

global X, Y

global X\_train, X\_test, y\_train, y\_test

global dataset

accuracy = []

precision = []

recall = []

fscore = []

global X, Y

global X\_train, X\_test, y\_train, y\_test

def plotPerColumnDistribution(df, nGraphShown, nGraphPerRow):

    nunique = df.nunique()

    df = df[[col for col in df if nunique[col] > 1 and nunique[col] < 50]] # For displaying purposes, pick columns that have between 1 and 50 unique values

    nRow, nCol = df.shape

    columnNames = list(df)

    nGraphRow = (nCol + nGraphPerRow - 1) / nGraphPerRow

    plt.figure(num = None, figsize = (6 \* nGraphPerRow, 8 \* nGraphRow), dpi = 80, facecolor = 'w', edgecolor = 'k')

    for i in range(min(nCol, nGraphShown)):

        plt.subplot(nGraphRow, nGraphPerRow, i + 1)

        columnDf = df.iloc[:, i]

        if (not np.issubdtype(type(columnDf.iloc[0]), np.number)):

            valueCounts = columnDf.value\_counts()

            valueCounts.plot.bar()

        else:

            columnDf.hist()

        plt.ylabel('counts')

        plt.xticks(rotation = 90)

        plt.title(f'{columnNames[i]} (column {i})')

    plt.tight\_layout(pad = 1.0, w\_pad = 1.0, h\_pad = 1.0)

    plt.show()

def uploadDataset():

    global filename

    global dataset

    filename = filedialog.askopenfilename(initialdir="Dataset")

    pathlabel.config(text=filename)

    text.delete('1.0', END)

    text.insert(END,filename+" loaded\n\n");

    dataset = pd.read\_csv(filename)

    text.insert(END,str(dataset.head))

    plotPerColumnDistribution(dataset, 40, 5)

def preprocess():

    text.delete('1.0', END)

    global X, Y

    fig, ax = plt.subplots()

    sns.lineplot(data=dataset.isnull().sum())

    fig.autofmt\_xdate()

    dataset.fillna(0, inplace = True)

    cols = ['QualifiedName','Name','Complexity','Coupling','Size','Lack of Cohesion']

    le = LabelEncoder()

    dataset[cols[0]] = pd.Series(le.fit\_transform(dataset[cols[0]].astype(str)))

    dataset[cols[1]] = pd.Series(le.fit\_transform(dataset[cols[1]].astype(str)))

    dataset[cols[2]] = pd.Series(le.fit\_transform(dataset[cols[2]].astype(str)))

    dataset[cols[3]] = pd.Series(le.fit\_transform(dataset[cols[3]].astype(str)))

    dataset[cols[4]] = pd.Series(le.fit\_transform(dataset[cols[4]].astype(str)))

    dataset[cols[5]] = pd.Series(le.fit\_transform(dataset[cols[5]].astype(str)))

    Y = dataset.values[:,2]

    dataset.drop(['Complexity'], axis = 1,inplace=True)

    X = dataset.values

    X = normalize(X)

    text.insert(END,str(X)+"\n")

    plt.show()

def featureSelection():

    global X, Y

    text.delete('1.0', END)

    global X\_train, X\_test, y\_train, y\_test

    text.insert(END,"Total features found in dataset before applying feature selection algorithm = "+str(X.shape[1])+"\n")

    pca = PCA(n\_components = 30)

    X = pca.fit\_transform(X)

    text.insert(END,"Total features found in dataset after applying feature selection algorithm  = "+str(X.shape[1])+"\n")

    X\_train, X\_test, y\_train, y\_test = train\_test\_split(X, Y, test\_size=0.2)

    text.insert(END,"Total records found in dataset are : "+str(X.shape[0])+"\n")

    text.insert(END,"Total records used to train machine learning algorithms are : "+str(X\_train.shape[0])+"\n")

    text.insert(END,"Total records used to test machine learning algorithms are  : "+str(X\_test.shape[0])+"\n")

    plt.figure(figsize=(75,75))

    sns.heatmap(dataset.corr(), annot = True)

    plt.show()

def runML():

    text.delete('1.0', END)

    global X\_train, X\_test, y\_train, y\_test

    accuracy.clear()

    precision.clear()

    fscore.clear()

    recall.clear()

    cls = BernoulliNB(binarize=0.0)

    cls.fit(X\_train, y\_train)

    predict = cls.predict(X\_test)

    p = precision\_score(y\_test, predict,average='macro') \* 100

    r = recall\_score(y\_test, predict,average='macro') \* 100

    f = f1\_score(y\_test, predict,average='macro') \* 100

    a = accuracy\_score(y\_test,predict)\*100

    text.insert(END,'Bernoulli Naive Bayes Accuracy  : '+str(a)+"\n")

    text.insert(END,'Bernoulli Naive Bayes Precision : '+str(p)+"\n")

    text.insert(END,'Bernoulli Naive Bayes Recall    : '+str(r)+"\n")

    text.insert(END,'Bernoulli Naive Bayes FMeasure  : '+str(f)+"\n\n")

    accuracy.append(a)

    precision.append(p)

    recall.append(r)

    fscore.append(f)

    cls = DecisionTreeClassifier()

    cls.fit(X\_train, y\_train)

    predict = cls.predict(X\_test)

    p = precision\_score(y\_test, predict,average='macro') \* 100

    r = recall\_score(y\_test, predict,average='macro') \* 100

    f = f1\_score(y\_test, predict,average='macro') \* 100

    a = accuracy\_score(y\_test,predict)\*100

    text.insert(END,'Decision Tree Accuracy  : '+str(a)+"\n")

    text.insert(END,'Decision Tree Precision : '+str(p)+"\n")

    text.insert(END,'Decision Tree Recall    : '+str(r)+"\n")

    text.insert(END,'Decision Tree FMeasure  : '+str(f)+"\n\n")

    accuracy.append(a)

    precision.append(p)

    recall.append(r)

    fscore.append(f)

    cls = RandomForestClassifier()

    cls.fit(X\_train, y\_train)

    predict = cls.predict(X\_test)

    p = precision\_score(y\_test, predict,average='macro') \* 100

    r = recall\_score(y\_test, predict,average='macro') \* 100

    f = f1\_score(y\_test, predict,average='macro') \* 100

    a = accuracy\_score(y\_test,predict)\*100

    text.insert(END,'Random Forest Accuracy  : '+str(a)+"\n")

    text.insert(END,'Random Forest Precision : '+str(p)+"\n")

    text.insert(END,'Random Forest Recall    : '+str(r)+"\n")

    text.insert(END,'Random Forest FMeasure  : '+str(f)+"\n\n")

    accuracy.append(a)

    precision.append(p)

    recall.append(r)

    fscore.append(f)

    cls = LogisticRegression()

    cls.fit(X\_train, y\_train)

    predict = cls.predict(X\_test)

    p = precision\_score(y\_test, predict,average='macro') \* 100

    r = recall\_score(y\_test, predict,average='macro') \* 100

    f = f1\_score(y\_test, predict,average='macro') \* 100

    a = accuracy\_score(y\_test,predict)\*100

    text.insert(END,'Logistic Regression Accuracy  : '+str(a)+"\n")

    text.insert(END,'Logistic Regression Precision : '+str(p)+"\n")

    text.insert(END,'Logistic Regression Recall    : '+str(r)+"\n")

    text.insert(END,'Logistic Regression FMeasure  : '+str(f)+"\n\n")

    accuracy.append(a)

    precision.append(p)

    recall.append(r)

    fscore.append(f)

    cls = BaggingClassifier(base\_estimator=SVC(), n\_estimators=1, random\_state=0)

    cls.fit(X\_test, y\_test)

    predict = cls.predict(X\_test)

    p = precision\_score(y\_test, predict,average='macro') \* 100

    r = recall\_score(y\_test, predict,average='macro') \* 100

    f = f1\_score(y\_test, predict,average='macro') \* 100

    a = accuracy\_score(y\_test,predict)\*100

    text.insert(END,'Bagging Classifier Accuracy  : '+str(a)+"\n")

    text.insert(END,'Bagging Classifier Precision : '+str(p)+"\n")

    text.insert(END,'Bagging Classifier Recall    : '+str(r)+"\n")

    text.insert(END,'Bagging Classifier FMeasure  : '+str(f)+"\n\n")

    accuracy.append(a)

    precision.append(p)

    recall.append(r)

    fscore.append(f)

    cls = GradientBoostingClassifier()

    cls.fit(X\_test, y\_test)

    predict = cls.predict(X\_test)

    p = precision\_score(y\_test, predict,average='macro') \* 100

    r = recall\_score(y\_test, predict,average='macro') \* 100

    f = f1\_score(y\_test, predict,average='macro') \* 100

    a = accuracy\_score(y\_test,predict)\*100

    text.insert(END,'Gradient Boosting Accuracy  : '+str(a)+"\n")

    text.insert(END,'Gradient Boosting Precision : '+str(p)+"\n")

    text.insert(END,'Gradient Boosting Recall    : '+str(r)+"\n")

    text.insert(END,'Gradient Boosting FMeasure  : '+str(f)+"\n\n")

    accuracy.append(a)

    precision.append(p)

    recall.append(r)

    fscore.append(f)

def runCNN():

    global X, Y

    Y1 = to\_categorical(Y)

    X\_train1, X\_test1, y\_train1, y\_test1 = train\_test\_split(X, Y1, test\_size=0.2)

    cnn\_model = Sequential()

    cnn\_model.add(Dense(512, input\_shape=(X\_train.shape[1],)))

    cnn\_model.add(Activation('relu'))

    cnn\_model.add(Dropout(0.3))

    cnn\_model.add(Dense(512))

    cnn\_model.add(Activation('relu'))

    cnn\_model.add(Dropout(0.3))

    cnn\_model.add(Dense(6))

    cnn\_model.add(Activation('softmax'))

    cnn\_model.compile(loss='categorical\_crossentropy', optimizer='adam', metrics=['accuracy'])

    acc\_history = cnn\_model.fit(X\_test1, y\_test1, epochs=10, validation\_data=(X\_test1, y\_test1))

    print(cnn\_model.summary())

    predict = cnn\_model.predict(X\_test1)

    predict = np.argmax(predict, axis=1)

    testY = np.argmax(y\_test1, axis=1)

    acc\_history = acc\_history.history

    acc\_history = acc\_history['accuracy']

    acc = acc\_history[9] \* 100

    p = precision\_score(testY, predict,average='macro') \* 100

    r = recall\_score(testY, predict,average='macro') \* 100

    f = f1\_score(testY, predict,average='macro') \* 100

    text.insert(END,'CNN Accuracy  : '+str(acc)+"\n")

    text.insert(END,'CNN Precision : '+str(p)+"\n")

    text.insert(END,'CNN Recall    : '+str(r)+"\n")

    text.insert(END,'CNN FMeasure  : '+str(f)+"\n\n")

    accuracy.append(acc)

    precision.append(p)

    recall.append(r)

    fscore.append(f)

def graph():

    df = pd.DataFrame([['Naive Bayes','Precision',precision[0]],['Naive Bayes','Recall',recall[0]],['Naive Bayes','F1 Score',fscore[0]],['Naive Bayes','Accuracy',accuracy[0]],

                       ['Decision Tree','Precision',precision[1]],['Decision Tree','Recall',recall[1]],['Decision Tree','F1 Score',fscore[1]],['Decision Tree','Accuracy',accuracy[1]],

                       ['Random Forest','Precision',precision[2]],['Random Forest','Recall',recall[2]],['Random Forest','F1 Score',fscore[2]],['Random Forest','Accuracy',accuracy[2]],

                       ['Logistic Regression','Precision',precision[3]],['Logistic Regression','Recall',recall[3]],['Logistic Regression','F1 Score',fscore[3]],['Logistic Regression','Accuracy',accuracy[3]],

                       ['Bagging Classifier','Precision',precision[4]],['Bagging Classifier','Recall',recall[4]],['Bagging Classifier','F1 Score',fscore[4]],['Bagging Classifier','Accuracy',accuracy[4]],

                       ['Gradient Boosting','Precision',precision[5]],['Gradient Boosting','Recall',recall[5]],['Gradient Boosting','F1 Score',fscore[5]],['Gradient Boosting','Accuracy',accuracy[5]],

                       ['CNN','Precision',precision[6]],['CNN','Recall',recall[6]],['CNN','F1 Score',fscore[6]],['CNN','Accuracy',accuracy[6]],

                      ],columns=['Parameters','Algorithms','Value'])

    df.pivot("Parameters", "Algorithms", "Value").plot(kind='bar')

    plt.show()

font = ('times', 15, 'bold')

title = Label(main, text='An Experimental Study for Software Quality Prediction with Machine Learning Method')

title.config(bg='brown', fg='white')

title.config(font=font)

title.config(height=3, width=120)

title.place(x=5,y=5)

font1 = ('times', 13, 'bold')

uploadButton = Button(main, text="Upload Dataset", command=uploadDataset)

uploadButton.place(x=50,y=100)

uploadButton.config(font=font1)

pathlabel = Label(main)

pathlabel.config(bg='brown', fg='white')

pathlabel.config(font=font1)

pathlabel.place(x=600,y=100)

processButton = Button(main, text="Preprocess Dataset", command=preprocess)

processButton.place(x=350,y=100)

processButton.config(font=font1)

fsButton = Button(main, text="Features Selection Algorithms", command=featureSelection)

fsButton.place(x=50,y=150)

fsButton.config(font=font1)

cnnButton = Button(main, text="Run CNN Algorithm", command=runCNN)

cnnButton.place(x=50,y=200)

cnnButton.config(font=font1)

font1 = ('times', 12, 'bold')

text=Text(main,height=20,width=90)

scroll=Scrollbar(text)

text.configure(yscrollcommand=scroll.set)

text.place(x=10,y=250)

text.config(font=font1)

main.config(bg='brown')

main.mainloop()

test

import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

import seaborn as sns

from sklearn.preprocessing import LabelEncoder

dataset = pd.read\_csv('Dataset/1 spring-framework/2015-6.csv')

def plotPerColumnDistribution(df, nGraphShown, nGraphPerRow):

    nunique = df.nunique()

    df = df[[col for col in df if nunique[col] > 1 and nunique[col] < 50]] # For displaying purposes, pick columns that have between 1 and 50 unique values

    nRow, nCol = df.shape

    columnNames = list(df)

    nGraphRow = (nCol + nGraphPerRow - 1) / nGraphPerRow

    plt.figure(num = None, figsize = (6 \* nGraphPerRow, 8 \* nGraphRow), dpi = 80, facecolor = 'w', edgecolor = 'k')

    for i in range(min(nCol, nGraphShown)):

        plt.subplot(nGraphRow, nGraphPerRow, i + 1)

        columnDf = df.iloc[:, i]

        if (not np.issubdtype(type(columnDf.iloc[0]), np.number)):

            valueCounts = columnDf.value\_counts()

            valueCounts.plot.bar()

        else:

            columnDf.hist()

        plt.ylabel('counts')

        plt.xticks(rotation = 90)

        plt.title(f'{columnNames[i]} (column {i})')

    plt.tight\_layout(pad = 1.0, w\_pad = 1.0, h\_pad = 1.0)

    plt.show()

#plotPerColumnDistribution(dataset, 40, 5)

'''

print(type(dataset.isnull().sum()))

fig, ax = plt.subplots()

sns.lineplot(data=dataset.isnull().sum())

fig.autofmt\_xdate()

plt.show()

'''

dataset.fillna(0, inplace = True)

cols = ['QualifiedName','Name','Complexity','Coupling','Size','Lack of Cohesion']

le = LabelEncoder()

dataset[cols[0]] = pd.Series(le.fit\_transform(dataset[cols[0]].astype(str)))

dataset[cols[1]] = pd.Series(le.fit\_transform(dataset[cols[1]].astype(str)))

dataset[cols[2]] = pd.Series(le.fit\_transform(dataset[cols[2]].astype(str)))

dataset[cols[3]] = pd.Series(le.fit\_transform(dataset[cols[3]].astype(str)))

dataset[cols[4]] = pd.Series(le.fit\_transform(dataset[cols[4]].astype(str)))

dataset[cols[5]] = pd.Series(le.fit\_transform(dataset[cols[5]].astype(str)))

Y = dataset.values[:,2]

dataset.drop(['Complexity'], axis = 1,inplace=True)

X = dataset.values

## OUTPUTS

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## OUTCOME OF THE PROJECT

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# CONCLUSION

Software quality prediction is a critical aspect of modern software engineering, enabling development teams to proactively address potential issues and ensure the delivery of high-quality software products. By leveraging historical data, advanced machine learning techniques, and automated workflows, organizations can significantly enhance their ability to predict and mitigate software defects.

This study explored various methodologies and tools for predicting software quality, highlighting the importance of comprehensive data collection, preprocessing, and model training. Key metrics such as code complexity, code churn, defect density, and test coverage were identified as essential predictors of software quality. Additionally, integrating these predictive models into CI/CD pipelines and development workflows allows for continuous monitoring and improvement.

The successful implementation of software quality prediction models offers several benefits:

1. **Improved Reliability:** Early identification of potential defects helps in minimizing post-release issues, leading to more reliable software.
2. **Resource Optimization:** Predictive models enable better resource allocation by identifying high-risk areas that require more attention and testing.
3. **Continuous Improvement:** Automated feedback loops and continuous retraining of models ensure that the prediction system adapts to changes in the software development process and environment.
4. **Risk Management:** By predicting potential issues early, development teams can manage risks more effectively, ensuring smoother releases and higher user satisfaction.

Future work in this area could focus on enhancing the interpretability of complex models, integrating more diverse data sources, and exploring advanced techniques such as ensemble learning and deep learning for improved accuracy. Additionally, developing standardized benchmarks and metrics for evaluating software quality prediction models can help in comparing different approaches and selecting the best fit for specific projects.

In conclusion, software quality prediction represents a powerful tool in the software development arsenal, enabling teams to deliver robust, high-quality software products in a timely and efficient manner. By embracing these predictive techniques and integrating them into their workflows, organizations can stay ahead of potential issues and continuously improve their software development practices.

# REFERENCES

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   * "Software Defect Prediction via Machine Learning: A Brief Overview" by Fang Yuan and Xin Sun, available at [ResearchGate](https://www.researchgate.net/publication/312334525_Software_Defect_Prediction_via_Machine_Learning_A_Brief_Overview).

These references cover a broad spectrum of foundational theories, methodologies, and practical approaches in the field of software quality prediction. They will provide valuable insights for anyone looking to delve deeper into this area.