

2022MT93202- FinalReport1.docx

by 2022mt93202-malliswari Rama Raju ..

Submission date: 30-Apr-2024 11:08AM (UTC+0530)

Submission ID: 2366471044

File name: 2022MT93202-FinalReport1.docx (4.71M)

Word count: 2760

Character count: 16463

REPORT

ON

**APPLICATION OF ARTIFICIAL INTELLIGENCE TECHNIQUES IN SOFTWARE TEST
AUTOMATION**

BY

Name of the Student: MALLISWARI RAMA RAJU

ID No. 2022MT93202

AT

BITS PILANI, WILP DIVISION

OPTUM GLOBAL SOLUTIONS, HYDERABAD, INDIA

BIRLA INSTITUTE OF TECHNOLOGY & SCIENCE, PILANI

WORK INTEGRATED LEARNING PROGRAMMES (WILP) DIVISION

1 SECOND SEMESTER OF ACADEMIC YEAR 2023-2024

APPLICATION OF AI TECHNIQUES IN SOFTWARE TEST AUTOMATION

**Pattern Recognition in production defects to identify similar patterns in new data, aiding
in the recognition of common root causes**

BITS SEZG628T: Dissertation

By

**MALLISWARI RAMA RAJU
2022MT93202**

1 Dissertation Work Carried Out At

Optum Global Solutions, UnitedHealth Group, Hyderabad

Submitted in Partial Fulfilment of M.Tech (Software Engineering) degree programme

Under the Supervision of

PHANI KUMAR DADDANALA

Optum Global Solutions, UnitedHealth Group, Hyderabad



**BIRLA INSTITUTE OF TECHNOLOGY & SCIENCE PILANI
(RAJASTHAN)**

(April, 2024)

ACKNOWLEDGEMENTS:

¹ I would like to express my sincere gratitude to my supervisor, Phani Kumar Daddanala, for his continuous support and guidance throughout the course of this project. His expertise and insights have been instrumental in shaping the direction of my dissertation.

I am also thankful to my BITS mentor, Tanmaya Mahapatra, for their valuable feedback and suggestions at various stages of this dissertation.

Special thanks to my project director, Kapil Agarwal, for his trust and support, throughout this endeavour.

Furthermore, I would like to acknowledge my organization, Optum Global Solutions, for providing the opportunity and funding, without which this dissertation would not have been possible.

I extend my appreciation to my colleagues who provided assistance with data collection and data analysis.

BIRLA INSTITUTE OF TECHNOLOGY & SCIENCE, PILANI
April, 2024

BIRLA INSTITUTE OF TECHNOLOGY & SCIENCE, PILANI
(RAJASTHAN)

WILP DIVISION

Organization: Optum Global Solutions

Location: Hyderabad, India

Duration: 4 Months

Date of start: 1st Jan, 2024

Date of Submission: 30th Apr, 2024

Title of the Project: Application of AI Techniques in Software Test Automation - Pattern Recognition in production defects to identify similar patterns in new data, aiding in the recognition of common root causes

ID No./Name of the Student: 2022MT93202/Malliswari Rama Raju

Name & Designation of Supervisor: Phani Kumar Daddanala, Software Engineering Lead

Name of the Faculty Mentor: Tanmaya Mahapatra

Key Words: *Artificial Intelligence, Test Automation, Production Defect Root Cause Analysis, Machine Learning, XGBoost*

Project Area: AI in Software Test Automation

ABSTRACT:

In the field of software development, software testing is a critical step in the process. Test automation is carried out in a controlled manner in which an application is monitored under specified situations, allowing testers to gauge the threshold and potential dangers associated with the software's deployment. In software testing, artificial intelligence (AI) aids in the prevention of application failovers that might be costly to both the program and the company in the long run [1].

Present study aims at bringing out an innovative approach to software test automation by implementing artificial intelligence (AI) models for Production Defect Root Cause Analysis (RCA). Traditional defect RCA methods often rely on manual inspection or rule-based systems, which can be time-consuming and subjective. In contrast, generative AI models offer the ability to automatically identify patterns in large volumes of production data and generate plausible root causes for defects.

Planned framework implements AI model in the defect RCA process, encompassing Data Collection, Data Pre-Processing, Feature Selection, Model Selection, Training, Evaluation, Deployment, and Maintenance Stages. By leveraging existing machine learning algorithm, the approach enables automated root cause analysis, leading to more efficient quality control processes and product improvements.

Aim is to demonstrate the effectiveness of this approach through experimental validation on real-world production defect datasets. Results are expected to indicate that AI models can achieve high accuracy in identifying defect root causes, outperforming traditional methods. Furthermore, it will discuss the implications of integrating generative AI into defect detection workflows and highlight opportunities for future research and application in software quality assurance domain.

Overall, this dissertation contributes to advancing the field of Defect RCA by leveraging the capabilities of generative AI models to streamline and enhance the defect analysis process, ultimately leading to improved product quality and customer satisfaction.

Signature of the Student

Name: Malliswari Rama Raju

Date: 29th April, 2024

Place: Hyderabad

Signature of the Supervisor

Name: Phani Kumar Daddanala

Date: 29th April, 2024

Place: Hyderabad

Contents:	Page No.
1. Introduction	6
1.1. Background	6
1.2. Research Objective	6
1.3. Scope and Limitations	6
1.3.1. Scope	6
1.3.2. Limitations	7
2. Main Text	7
2.1. Data Collection and Pre-Processing	7
2.1.1. Data Collection	7
2.1.2. Data Pre-Processing	9
2.2. Resolution Prediction Algorithm	10
2.3. Evaluation and Metrics	11
2.4. Conclusions and Recommendations	12
3. Work Plan	12
4. References	13
5. Glossary	14

1. INTRODUCTION:

1.1 Background:

Current application under study “Cirrus” is an Optum proprietary customer installation and member enrolment web application. The application is live in production since 2017, and, it is continuously evolving with new products and different migrations being launched and merged into the system.

Any defects identified in production are logged in CA Rally tool, assigned to appropriate team for analysis and fix, tested, accepted and deployed to production through the established CI/CD pipeline. The accepted defects are then analysed by Quality team to identify the root cause and take appropriate actions during development and testing to prevent similar failures in future.

Root Cause Analysis (RCA) of software defects in production is a systematic process for identifying the underlying causes of the defects. The manual RCA process includes analysing the production defect description, analysing the customer data in database, analysing the codebase and configuration, then identifying the root cause as a Design/Database/Code issue or missed requirement or not a defect. Based on the root cause and finalized defect fix, “Resolution” field in Rally is filled with appropriate resolution of “Design/Code Change”, “Database Change”, “Converted to a User Story”, “Not a Defect” or “Duplicate Defect”.

1.2 Research Objective:

This dissertation aims to provide a comprehensive exploration of pattern recognition techniques in the context of software production defects, offering insights into their effectiveness, practical applications and potential challenges. Through empirical studies and analysis, it seeks to contribute to the advancement of defect analysis methodologies and support the development of more robust and reliable software systems.

1.3 Scope and Limitations:

1.3.1. Scope:

Production defect RCA has been identified as a Classification problem. The primary focus to address the problem is on how AI-based pattern recognition can aid in root cause analysis of software defects and predict their Resolution, based on existing defects, using supervised learning-based classification model.

Current scope of dissertation includes defect data collection, data pre-processing, splitting data into training and test data, implementing supervised learning model for predicting “Resolution” for test data, and measuring accuracy of prediction on test data.

The dissertation has been implemented as a POC (Proof of Concept) in Optum due to database and code integration limitations described below.

1.3.2 Limitations:

- a) Dataset size – Production defects data could be gathered for 2023 and 2024 only, as Rally became the source of truth for prod defects from 2023. This limited the dataset size to less than 1200 records, which posed challenges for training complex predictive AI models.
- b) Data Quality – Prod defects description is not in consistent format and, lacks enough details, as the prod support team is not trained to log defects consistently.
- c) Data and Code Confidentiality – Optum is a US based healthcare insurance organization. Since Cirrus is a member enrolment application, its database consists of member PII (Personal Identifiable Information) and PHI (Protected Health Information), which is confidential and restricted from sharing outside the organization. Cirrus codebase is strictly confidential and cannot be accessed outside, as per company security policies. These limitations do not allow database and code integration with the AI model, reducing the scope and accuracy of the model.

2. MAIN TEXT:

4

2.1 Data Collection & Pre-Processing:

2.1.1 Data Collection:

- a. Gathered historical data on production and non-production defects (starting 1/1/2023), including information such as Defect Name, Description, Severity, Schedule State, Timestamps, Related code changes, and any contextual information.
- b. The dataset is from Cirrus test & prod environments and covers a diverse range of scenarios (Figure 1)

Rank	ID	Name	Project	Creation Date	State	Severity	Environment	Resolution	Defect Reported By	ServiceNow
1	DEB64611	Cirrus - Bill Group Detail Invoice Re-De...	Heimdalls	2024-03-27	Submitted	3-Medium	Production	None	Internally Reported	...
2	DEB63831	Defect: Unable to delete a Contract A...	QIB - Rogue	2024-03-27	Submitted	3-Medium	None	None	Internally Reported	...
3	DEB63221	dropdown is not fetching the list of us...	Thunderstruck (CMT)	2024-03-26	Submitted	3-Minor Problem	None	None	Internally Reported	...
4	DEB62346	Error Message Not Displaying Conditio...	Sandman	2024-03-22	Fixed	4-Cosmetic	None	Design/Code Change	Internally Reported	...
5	DEB61673	SFA records aren't generating in Alpha	QIB - Shazam	2024-03-21	Submitted	3-Medium	Test	None	Internally Reported	...
6	DEB60343	'Family Unit Base with Medicare' and 'F...	QIB - Rogue	2024-03-19	Submitted	3-Medium	None	None	Internally Reported	...
7	DEB60137	(Converted to UserStory) Unable to Cr...	Heimdalls	2024-03-19	Closed	3-Medium	None	Converted	Internally Reported	...
8	DEB60101	Data Remediation for stale Member Gr...	Heimdalls	2024-03-19	Submitted	3-Medium	None	None	Internally Reported	PRB1427787
9	DEB58570	No error for invalid relationshipCode ...	QIB - Rogue	2024-03-15	Open	3-Minor Problem	None	None	Internally Reported	...
10	DEB57788	Add/Update Plans: Dental Vision Expa...	QIB - Shazam	2024-03-14	Submitted	2-Major Problem	None	None	Internally Reported	...
11	DEB57583	Trans id mismatch between Streaming...	Shakti	2024-03-14	Re-Test	2-Major Problem	None	None	Internally Reported	...
12	DEB57582	System error while converting json to ...	Shakti	2024-03-14	Re-Test	2-Major Problem	None	None	Internally Reported	...
13	DEB57322	Duplicate check is failing on Billing Sch...	QIB - Rogue	2024-03-13	Submitted	3-Medium	None	None	Internally Reported	...
14	DEB57034	[INC36084662] [MT Member] member...	incrEdibles	2024-03-13	Submitted	3-Medium	None	None	Internally Reported	...
15	DEB54104	SH SIT: Member logs not visible throug...	QIB - Shazam	2024-03-07	Submitted	3-Medium	None	None	Internally Reported	...
16	DEB53328	CMT: Charlie Issues	Thunderstruck (CMT)	2024-03-06	Submitted	3-Medium	None	None	Internally Reported	...
17	DEB52442	Issue in US943206	Heimdalls	2024-03-04	Submitted	3-Medium	None	None	Internally Reported	...
18	DEB52257	Fixing Unit test BenefitBundleSpec	QIB - Valkyrie	2024-03-04	Submitted	3-Minor Problem	None	None	Internally Reported	...
19	DEB51678	Incorrect Error Message When trying L...	Heimdalls	2024-03-01	Submitted	3-Medium	None	None	Internally Reported	...
20	DEB51646	fix UtilizationandServicePlanRuleServic...	QIB - Valkyrie	2024-03-01	Closed	3-Minor Problem	None	None	Internally Reported	...
21	DEB50769	Fixing BenefitBundleSpec failures	QIB - Rogue	2024-02-29	Submitted	3-Medium	None	Not a Defect	Internally Reported	...
22	DEB50383	ServComp Validation failing due to inv...	QIB - Valkyrie	2024-02-28	Open	3-Minor Problem	None	None	Internally Reported	...
23	DEB50264	Fixing Unit test BenefitBundleSpec	QIB - Valkyrie	2024-02-28	Submitted	3-Minor Problem	None	None	Internally Reported	...

Figure 1 - Cirrus defects logged in Rally tool

- c. Defect details exported from Rally and saved in .csv format (Figure 2):

Formatted ID	Name	Project	Creation Date	State	Severity	Environment	Resolution	Defect Reported By	IncNow_ProblemNow	IncNow_Problem	Owner	R Root Cause	Iteration	Schedule State	Accepted Date
DE64611	Cinrus - Bill Group Detail Invoice Re-Denatation Utility popup	Heimdata	27/03/24	Submitted	3-Medium	Production		Internally Reported						Refining	
DE63631	Defect: Unable to delete a Contract Affiliation after it has been validated	QB - Rogier	27/03/24	Submitted	3-Medium			Internally Reported			Russell Hammond	2024 P46.2	Defined		
DE63271	Engpdown is not fetching the list of vendors through idpapiurl/api	Thunderstroke	26/03/24	Submitted	3-Minor Problem			Internally Reported			Munka Verma	2024 P46.1	In-Progress		
DE62346	Error Message Not Displaying Conditional Value	Sandman	22/03/24	Fixed	4-Cosmetic		Design/Code Change	Internally Reported			Simon Yawin	2024 P46.1	Accepted	25/03/24	
DE61673	SFA records aren't generating in Alpha	QB - Shaaz	21/03/24	Submitted	3-Medium	Test		Internally Reported					Defined		
DE60343	Family Unit Base with Medicines and Family Unit based with Age Gender Search List pagination	QB - Rogier	19/03/24	Submitted	3-Medium			Internally Reported					In-Progress		
DE60137	Converted to UserStory Unable to Create Members in Member Entry in Cinrus Alpha for Q7/78	Heimdata	19/03/24	Closed	3-Medium		Converted	Internally Reported			Samakshi Malhotra	2024 P46.2	Accepted		
DE60101	Data Remediation for state Member Group Action Event	Heimdata	19/03/24	Submitted	3-Medium			Internally Reported	599c-d90903-3c6189446a	Proactive			Refining		
DE59676	No error for multi relationship Code when submitted via API (HPI and CCX)	QB - Rogier	16/03/24	Open	2-Minor Problem			Internally Reported			David Prewett	2024 P46.1	In-Progress		
DE59788	Add/Update Plans: Dental Vision Expense Collapse Navigation Functionality	QB - Shaaz	14/03/24	Submitted	2-Major Problem			Internally Reported			Muhib Adem	US9445989	2024 P46.5	Accepted	20/03/24
DE59763	Trans id mismatch between Streaming & HCP XML for dependents (sourceSystemTransID)	Shakti	14/03/24	Re-Test	2-Major Problem			Internally Reported			Madhavi Mahanthi	2024 P46.1	In-Progress		
DE59762	System error while converting json to XML message (Member Logical delete scenario)	Shakti	14/03/24	Re-Test	2-Major Problem			Internally Reported			Madhavi Mahanthi	2024 P46.1	In-Progress		
DE59752	Duplicate check is failing on Billing Schedule Age Gender Screen	QB - Rogier	13/03/24	Submitted	3-Medium			Internally Reported			Vivekanar Gaddam	2024 P46.1	In-Progress		
DE59704	(INC36084662) [MT Member] memberDemographics API is taking time around 1min for few pay	incrEDibles	13/03/24	Submitted	3-Medium			Internally Reported			JAMES BEISE	2024 P46.2	In-Progress		
DE59404	SH 501 Member logs not visible through CICH JSON	QB - Shaaz	07/03/24	Submitted	3-Medium			Internally Reported					Defined		
DE59338	CHT: Charlie Issues	Thunderstroke	06/03/24	Submitted	3-Medium			Internally Reported			Himanshu Yadav	2024 P46.2	Refining		
DE59442	Issue in US943206	Heimdata	04/03/24	Submitted	3-Medium			Internally Reported			Jay Jordan Ma		Accepted	12/03/24	
DE59297	Fixing Unit test BenefitBundledSpec	QB - Vaidya	04/03/24	Submitted	3-Minor Problem			Internally Reported			Pranav Kumar	2024 P46.5	Accepted	07/03/24	
DE59187	Incorrect Error Message When trying to logically delete group affiliation	Heimdata	01/03/24	Submitted	3-Medium			Internally Reported					Refining		
DE59146	No UtilizationandServicePlanRuleServiceCompositeholder	QB - Vaidya	01/03/24	Closed	3-Minor Problem			Internally Reported			Dushi Vinay	2024 P46.5	Accepted	15/03/24	
DE59769	Fixing BenefitBundledSpec failures	QB - Rogier	29/02/24	Submitted	3-Medium		Not a Defect	Internally Reported			Lugan Fathymath	2024 P46.4	Accepted	01/03/24	
DE59383	DevComp validation failing due to invalid payload	QB - Vaidya	28/02/24	Open	3-Minor Problem			Internally Reported			Dushi Vinay	2024 P46.5	Accepted	14/03/24	
DE59294	Fixing Unit test BenefitBundledSpec	QB - Vaidya	28/02/24	Submitted	3-Minor Problem			Internally Reported			Pranav Kumar	2024 P46.4	Accepted	28/02/24	
DE59027	Getting Exception when trying to add a Member Group Event with Closed status	QB - Rogier	28/02/24	Open	3-Medium	Production	Design/Code Change	Internally Reported					Refining		
DE58874	Update systematic persistence of subAffiliationExternalID / subAffiliationExtIDComOptType	QB - Shaaz	28/02/24	Submitted	2-Major Problem		Design/Code Change	Internally Reported			Keith Black	US6547071	2024 P46.4	Accepted	14/03/24
DE58843	Update error / warning concerning logic	QB - Shaaz	23/02/24	Submitted	2-Major Problem			Internally Reported					Defined		
DE58473	Update "Upload Edit Code and Attributes File" member utility	QB - Shaaz	23/02/24	Submitted	2-Major Problem			Internally Reported			Madhavi Anusha	2024 P46.1	In-Progress		
DE58238	Migration Script Issue - Less than or Equal to Date Update	QB - Shaaz	23/02/24	Submitted	2-Major Problem		Design/Code Change	Internally Reported			Maresh Gurasa	2024 P46.5	Accepted	08/03/24	
DE57137	problem with data persisted in a subAffiliation and ExternalID child table	QB - Shaaz	22/02/24	Submitted	2-Major Problem		Design/Code Change	Internally Reported			Keith Black	US6547073	2024 P46.4	Accepted	26/02/24
DE47126	Regarding [RR2215] MedPCP sent for Dental	incrEDibles	21/02/24	Submitted	3-Medium			Internally Reported					Defined		
DE46683	Contract Option UP - Search Options - Clear button does not set "Show Deleted Records" to	Heimdata	21/02/24	Submitted	3-Minor Problem			Internally Reported					Defined		
DE46645	Handle multiple requests for the same transaction id	Thunderstroke	21/02/24	Submitted	3-Minor Problem			Internally Reported			Khushi Pinar	2024 P46.1	In-Progress		
DE46643	Converted to UserStory Unable to connect against JDBC Connection issue	Thunderstroke	21/02/24	Closed	3-Minor Problem		Converted	Internally Reported			Himanshu Yadav	2024 P46.1	In-Progress		
DE46452	Member Group Action Event - Group Contract Event Not Creating	QB - Rogier	20/02/24	Open	2-Major Problem	Production	Design/Code Change	Internally Reported					Accepted	28/02/24	
DE46385	Update Date and User ID no longer displaying on UI	QB - Shaaz	20/02/24	Submitted	2-Major Problem			Internally Reported			Ane Erit	2024 P46.4	Accepted	22/02/24	
DE44398	NullPointerException on Contract Option In Rule / Contract Opt Pkg In Rule when user press	QB - Rogier	16/02/24	Open	3-Minor Problem			Internally Reported					Accepted	06/03/24	
DE44390	Bill group affiliation to member validation move to UI validation	Sandman	15/02/24	Submitted	3-Minor Problem			Internally Reported			Karna Gurung	2024 P46.4	Accepted	01/03/24	
DE43378	Auto-Close Logic for FWP Benefit Refresh Event	QB - Rogier	14/02/24	Open	3-Medium	Production	Design/Code Change	Internally Reported					Accepted	22/02/24	
DE43475	Not able to fetch Member Record - Cinrus UI Alpha	QB - Shaaz	14/02/24	Submitted	3-Medium			Internally Reported					Defined		
DE43256	CMTO - Upload Source names -> Getting Internal Server Error.	Thunderstroke	14/02/24	Submitted	3-Medium			Internally Reported			Hirekha Sarkar	2024 P46.5	Accepted	19/03/24	
DE42824	Fix BeneCodeNetwork versioning issue	QB - Vaidya	13/02/24	Submitted	3-Minor Problem			Internally Reported			Tyler Amundson	DE704417	2024 P46.4	Accepted	28/02/24
DE42074	Handling Subsidy page with selecting member/subAffiliation	incrEDibles	12/02/24	Submitted	3-Medium			Internally Reported					Accepted	15/02/24	
DE42057	Child Contract Affiliation - No Termination Cancel, No Warning, No Reinstatement	Heimdata	07/02/24	Submitted	3-Medium			Internally Reported					Refining		
DE42045	Child Contract Affiliation - No Termination Cancel Available	Heimdata	07/02/24	Submitted	3-Medium			Internally Reported					Refining		
DE53873	Split Platform Migration - Member Group Contract Option table missing records in Cinrus alpha	Heimdata	06/02/24	Submitted	3-Medium			Internally Reported			Satish Chandrakant	2027 P46.3	Accepted	27/02/24	

Figure 2 - Rally defects exported to .csv

d. Identified relevant features or variables in the data that can contribute to identifying root causes.

e. Raw data from Rally contains the below features:

- Formatted ID (Defect ID)
- Name (Defect Description)
- Project
- Creation Date
- State
- Severity
- Environment
- Resolution
- Build Number
- Defect Reported By
- ServiceNow_Problem
- ServiceNow_Incident
- ServiceNow_Problem Type
- Owner
- RCA Root Cause US
- Iteration
- Schedule State • Accepted Date

f. Features relevant for RCA would be:

- Formatted ID (Defect ID)
- Name
- Description
- Schedule State
- Severity
- Resolution

“Resolution” is the target field whose value needs to be predicted with high accuracy.

2.1.2 Data Pre-processing:

Data Augmentation – Since overall dataset size is limited (~ 1200 records), data augmentation is done to artificially increase the size of dataset by creating modified versions of existing data samples, increasing the record count to > 1600.

Cirrus production defect details are in text format. These are processed and transformed to numeric and binary matrix formats using Label Encoding and One-Hot Encoding techniques. These are the two most used encoding techniques for converting categorical feature to numerical feature [3].

The LabelEncoder class from sklearn.preprocessing module is used to encode the target variable “Resolution” into numerical labels (Figure 3).

```
# Specify columns to drop from features (X)
columns_to_drop = ['Resolution', 'Formatted ID', 'Name', 'Description', 'Severity', 'Schedule State']

# Separate features (X) and target variable (y)
X = data.drop(columns_to_drop, axis=1)
y = data['Resolution'] # Target variable

# Initialize LabelEncoder for target variable
label_encoder = LabelEncoder()

# Encode target variable (y) into numeric labels
y_encoded = label_encoder.fit_transform(y)
```

Figure 3 - Utilising LabelEncoder() as a pre-processing technique

The get_dummies function is used to perform one-hot encoding on input variables of the dataset. OneHotEncoder class from sklearn.preprocessing module is used to convert input array of categorical variables (input features identified above - 'Resolution', 'Formatted ID', 'Name', 'Description', 'Severity', 'Schedule State') into a binary matrix representation, where each category is represented by a binary column (Figure 4).

```
# Specify columns to drop from features (X)
columns_to_drop = ['Resolution', 'Formatted ID', 'Name', 'Description', 'Severity', 'Schedule State']

# Separate features (X) and target variable (y)
X = data.drop(columns_to_drop, axis=1)
y = data['Resolution'] # Target variable

# Initialize LabelEncoder for target variable
label_encoder = LabelEncoder()

# Encode target variable (y) into numeric labels
y_encoded = label_encoder.fit_transform(y)

# One-hot encode categorical features in X
X_encoded = pd.get_dummies(X) # This will one-hot encode all categorical columns
```

Figure 4 - Utilising get_dummies() function for one-hot encoding

2.2 Resolution Prediction Algorithm: Github Link - <https://github.com/msarraj27/Dissertation.git>

- a) First step is to split the dataset into Training and Testing datasets using `train_test_split` function. The train and test sets model is one of the simplest models available where we split the entire dataset into training set and testing set [4].
- b) Using a `test_size` of 0.2, the proportion of dataset to include in test split is defined as 20%, while 80% is used for training. `Random_state` of 42 is used to ensure efficiency of the model as the training and test datasets will remain the same whenever code is run.
- c) Second step is to use machine learning Classification Model XGBoost (Extreme Gradient Boost) to classify and predict the “Resolution” in test dataset (Figure 5).

```
import numpy as np
from sklearn.metrics import accuracy_score, classification_report
from sklearn.preprocessing import StandardScaler
import xgboost as xgb

class SimpleClassifier:
    def __init__(self, n_estimators=100, max_depth=5, learning_rate=0.1):
        self.n_estimators = n_estimators
        self.max_depth = max_depth
        self.learning_rate = learning_rate
        self.scaler = StandardScaler()
        self.model = xgb.XGBClassifier()

    def fit(self, X, y):
        # Scale input features
        X_scaled = self.scaler.fit_transform(X)

        # Fit the XGBoost classifier
        self.model.fit(X_scaled, y)

    def predict(self, X):
        # Scale input features
        X_scaled = self.scaler.transform(X)

        # Make predictions using the XGBoost classifier
        return self.model.predict(X_scaled)

# Example usage:

# Assuming X_train, X_test, y_train, and y_test are defined
# Instantiate the custom XGBoost classifier
model = SimpleClassifier(n_estimators=100, max_depth=5, learning_rate=0.1)

# Train the model
model.fit(X_train, y_train)

# Make predictions on test data
y_pred = model.predict(X_test)

# Evaluate accuracy
accuracy = accuracy_score(y_test, y_pred)
```

Figure 5 - ML algorithm XGBoost for classification and prediction

- 7
- d) XGBoost is an implementation of gradient boosting, a machine learning technique that builds an ensemble of decision trees sequentially, with each tree correcting the errors of its predecessors.
 - e) Self.model variable is to store the initialized XGBClassifier model instance. Storing the model as self.model attribute allows easy access to the model within the class methods and facilitates training and prediction tasks.
 - f) Once the model is initialized, training on training data, evaluating its performance and making predictions on new data is achieved.

2.3 Evaluation and Metrics:

- a) Evaluation of the AI model is done to assess the performance of the algorithm to predict value of target variable “Resolution” in terms of essential metrics such as Accuracy, Precision, Recall, f1-score, Support, Macro Average and Weighted Average (Figure 6).

Accuracy: 0.78				
	precision	recall	f1-score	support
0	0.90	0.56	0.69	16
1	0.50	1.00	0.67	1
2	0.89	0.87	0.88	62
3	0.62	0.44	0.52	18
4	0.68	0.85	0.76	46
6	1.00	1.00	1.00	1
accuracy			0.78	144
macro avg	0.76	0.79	0.75	144
weighted avg	0.79	0.78	0.77	144

Figure 6 - Metrics

- b) Accuracy of **78%** for predicting Resolution of production defects in test dataset is achieved with the implemented AI model.
- c) Precision – It is a measure of the correctness of positive predictions. The precision values range from 0.50 to 1.00, with an **average weighted precision of 0.79**.
- d) Recall – Also known as Sensitivity or True Positive Rate, it is a measure of the model’s ability to correctly identify all positive instances. Recall values range from 0.44 to 1.00, with an **average weighted recall of 0.78**.
- e) F1-Score – It is the harmonic mean of precision and recall, providing a balance between the two metrics. F1-score values range from 0.52 to 1.00, with an **average weighted f1-score of 0.77**.
- f) Support – It indicates the number of actual occurrences of each class in the test set.

2.4 Conclusions and Recommendations:

- a) With the current limitations on dataset and company policy restrictions, accuracy, precision, recall and f1-score values are reasonable. The POC is done to showcase that artificial intelligence is a promising solution to predict RCA of production defects.
- b) With consistent and extensive dataset, and proper database and codebase integration, Generative AI models can be implemented for higher accuracy and prediction of defects based on the customer data.

Future Scope:

Deployment:

- a. Train prod-support team to maintain Rally defects consistently. The business requirement is to create a simple automated RCA approach that will be used for problem avoidance in future [2].
- b. Once extensive dataset is available, enhance the current model to implement Gen AI to predict RCA.
- c. Demo the model to team & MLRB (Machine Learning Review Board) and get their approval.
- d. Upon getting the approval, deploy the model to Rally production defects.

Feedback Loop:

- a. Incorporate feedback from users and domain experts to continuously improve the model's accuracy and effectiveness.

3. WORK PLAN:

Phases	Start Date – End Date	Work to be Done	Status
Submission of Dissertation Outline	13 th Jan – 20 th Jan 2024	<ol style="list-style-type: none">a. Dissertation topic analysis and preparation of Outline reportb. Review and comments by Supervisor	COMPLETED
Design & Development	21 st Jan – 9 th Mar 2024	<ol style="list-style-type: none">a. Identify and design components of AI modelb. Development activity	COMPLETED
Testing	10 th Mar – 31 st Mar 2024	<ol style="list-style-type: none">a. AI model testing, user evaluation, conclusion	COMPLETED
Mid-Term Report Submission	22 nd Mar – 29 th Mar 2024	<ol style="list-style-type: none">a. Prepare & submit mid-term progress report	COMPLETED
Dissertation Review	1 st Apr – 22 nd Apr 2024	<ol style="list-style-type: none">a. Review of Dissertation report and feedback by Supervisor and Examiner, update the report based on feedback	COMPLETED
Final Dissertation Report & Presentation submission	23 rd April – 30 th April 2024	<ol style="list-style-type: none">a. Consolidate the final report and submit in viva portal	COMPLETED

4. REFERENCES:

- [1] Dhaya Sindhu Battina: "Artificial Intelligence in Software Test Automation: A Systematic Literature Review". Published in *Journal of Emerging Technologies and Innovative Research (JETIR)* Volume 6, Issue 12 in December 2019, ISSN-2349-5162.
<https://www.jetir.org/papers/JETIR1912176.pdf>
- [2] Anjali, C., Malar Dhas, J. P., & Amar Pratap Singh, J. (2023). "Automated program and software defect root cause analysis using machine learning techniques". *Automatika*, 64(4), 878–885. <https://doi.org/10.1080/00051144.2023.2225344>
- [3] Suman Biswas, Hridesh Rajan: "Fair Preprocessing: Towards Understanding Compositional Fairness of Data Transformers in Machine Learning Pipeline" *arXiv:2106.06054v5 [cs.LG]* 20 Jul 2021 <https://arxiv.org/pdf/2106.06054>
- [4] Ramraj S, Nishant Uzir, Sunil R, Shatadeep Banerjee "Experimenting XGBoost Algorithm for Prediction and Classification of Different Datasets" 2016 *International Journal of Control Theory and Applications*, SRM University, India, 2016, ISSN : 0974–5572.
https://www.researchgate.net/profile/Shatadeep-Banerjee/publication/318132203_Experimenting_XGBoost_Algorithm_for_Prediction_and_Classification_of_Different_Datasets/links/595b89b0458515117741a571/Experimenting-XGBoost-Algorithm-for-Prediction-and-Classification-of-Different-Datasets.pdf
- [5] Harsh Lal, Gaurav Pahwa: "Root cause analysis of software bugs using machine learning techniques" 2017 7th *International Conference on Cloud Computing, Data Science & Engineering - Confluence (Confluence)*, January 2017.
DOI: [10.1109/CONFLUENCE.2017.7943132](https://doi.org/10.1109/CONFLUENCE.2017.7943132)
- [6] Konstantinos Papageorgiou, Theodosios Theodosiou, Aikaterini Rapti, Elpiniki I. Papageorgiou, Nikolaos Dimitriou, Dimitrios Tzovaras, George Margetis: "A systematic review on machine learning methods for root cause analysis towards zero-defect manufacturing" *Front. Manuf. Technol.*, 28 October 2022, Sec. Sustainable Life Cycle Engineering and Manufacturing, Volume 2 - 2022
| <https://doi.org/10.3389/fmtec.2022.972712>

5. GLOSSARY:

1. RCA [4] – Root Cause Analysis
2. CA Rally [6] – CA Agile Central (Rally) is an Agile Project Management Tool that allow users to gain visibility into the status of features, quality and risks.
3. CI/CD Pipeline [6] – Dev Ops automated process for Continuous Integration/Continuous Deployment
4. POC [6] – Proof of Concept – demonstration that illustrates the feasibility of an idea
5. PII [7] – Personal Identifiable Information – Member information such as First Name, Last Name, SSN, Date of Birth, Address
6. PHI [7] – Protected Health Information – Member health information such as member plan and claims details
7. Defect Resolution [8] – This field indicates the action taken to fix the defect. Valid values in Optum include – Design/Code change, Database Change, Converted, Not a Defect, Duplicate
8. Severity [8] – Shows the impact of defect, classified as Critical, Major, Medium, Low
9. MLRB [12] – Machine Learning Review Board – Board internal to Optum responsible for review and release of AI based software in production. Ensures company standards are met.
10. AI [4] - Artificial Intelligence
11. XGBoost [10] – Extreme Gradient Boosting is a powerful and efficient machine learning algorithm that is used for supervised learning tasks.

ORIGINALITY REPORT

18%

SIMILARITY INDEX

13%

INTERNET SOURCES

4%

PUBLICATIONS

12%

STUDENT PAPERS

PRIMARY SOURCES

1	Submitted to Birla Institute of Technology and Science Pilani Student Paper	4%
2	www.jetir.org Internet Source	3%
3	www.researchgate.net Internet Source	1%
4	www2.mdpi.com Internet Source	1%
5	www.qeios.com Internet Source	1%
6	thesis.univ-biskra.dz Internet Source	1%
7	Submitted to Liverpool John Moores University Student Paper	1%
8	Submitted to University of Wales, Bangor Student Paper	1%

9	Submitted to UOW Malaysia KDU University College Sdn. Bhd Student Paper	1 %
10	www.frontiersin.org Internet Source	1 %
11	hrcak.srce.hr Internet Source	1 %
12	Submitted to CSU, Long Beach Student Paper	1 %
13	ceur-ws.org Internet Source	1 %
14	Submitted to American University in the Emirates Student Paper	<1 %
15	design.cs.iastate.edu Internet Source	<1 %
16	www.coursehero.com Internet Source	<1 %
17	assets.researchsquare.com Internet Source	<1 %
18	dspace.univ-ouargla.dz Internet Source	<1 %
19	www.transperfect.com Internet Source	<1 %

20 "Flexible Automation and Intelligent Manufacturing: Establishing Bridges for More Sustainable Manufacturing Systems", Springer Science and Business Media LLC, 2024
Publication <1 %

21 eprints.hud.ac.uk
Internet Source <1 %

22 Drishti Seth, KPA Dharmanshu Mahajan, Rohit Khanna, Gunjan Chugh. "Chapter 27 Gene Family Classification Using Machine Learning: A Comparative Analysis", Springer Science and Business Media LLC, 2023
Publication <1 %

23 www.semanticscholar.org
Internet Source <1 %

Exclude quotes On

Exclude bibliography On

Exclude assignment template On

Exclude matches < 5 words