

# International Journal of INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

ISSN:2147-6799 www.ijisae.org Original Research Paper

### Controlling Runtime-Anomaly of A Web Application Using Advanced Machine Learning

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**Submitted:** 15/01/2024 **Revised:** 25/02/2024 **Accepted:** 05/03/2024

**Abstract: INTRODUCTION:** Controlling run-time anomalies using machine learning in software will help us to increase product efficiency and reliability. In this field, we are still in a very early stage. In our case, for a Web-Application the anomaly detection and correction at run time is yet to be developed.

**OBJECTIVES**: The goal of this study is to provide a method to Detect and Classify an anomaly and Fix that on run time using Machine Learning.

**METHODS**: A systematic step-by-step approach is launched with the study of 57 papers on anomaly detection algorithms and Runtime error detection and correction methodologies

**RESULTS**: The major number of papers are related to network anomaly detection algorithms (42%) and another real-time system (like flight/train, etc.) error detection and corrections techniques (18%). Papers related to software error detection are 30%, and papers our research focused on are 10%.

**CONCLUSION**: To detect an anomaly in the application log, we would be using the Pattern search and Local Outlier Factor to detect and classify the errors. Then finally, using the Generative AI, we will fix the detected errors.

Keywords: Runtime anomaly, Machine learning, Web Application Monitoring, Autoencoders, Security

#### 1. Introduction

The product industry gives support only when there is an issue reported. Always relying on the customer's feedback or report. Nowadays, a very small number of software industries monitor and track the errors in run We can never assure a 100% error-free environment. Still, by implementing such technology into our current infrastructure, we could significantly reduce product failure rates while also providing reliable results with greater accuracy than before - ultimately leading to happier customers who trust their products more than ever. time/production. The encountered issue will only be reported/fixed if the user understands that there is a bug! This may take another few weeks/months

QVM (Quality Virtual Machine) and watchdogs like Comprehensive and efficient runtime checking in system software are a few of them. But they are related to saving that environment (in that specific time) properties so that the scenario can be recreated to fix. To address this issue, researchers are exploring ways to develop plug-and-play error/failure detection systems that utilize machine learning (ML) algorithms for learning from past errors/failures/bugs encountered by similar systems. Once detected using ML techniques, AI-based solutions will try fixing them automatically or prompt notification to the manufacturer so they can provide an appropriate hotfix release.

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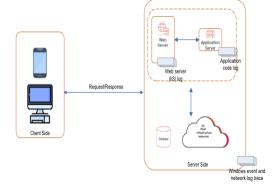


Fig 1. The error will be traced and classified using the logs.

Some of the research has already been done in this scope.

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An interactive computer program that has two primary layers - Client and servers. Client-built with web technologies such as HTML, C SS, and JavaScript. The Server is built with Java, C#, Python, and other serverside programming languages. Based on the requirements, the

server layer may interact with the Database, Cloud, Operating System resources, or other service APIs, etc.

In this Era, Automation is the only way to do business. Web Application is widely used in such scenarios.

|  | Free University of BozenBolzano, BozenBolzano Italy     Università degli Studi dell'Insubri a, Varese, Italy      | monitor issue. Once the regression to be run root can continue smell in recommendation and their                                    | ting server to rate developer fixton testing is donnot not identify the buse of the exposition to induce the exception and the exception of th | cception. Finally the cool checks if any code tion report the same as commend ation system al using the code smells | medium sized enterprises and a set of prediction techniques such as regression and machine learning. They provided a tailored SQA model to the identified companies to gather the bug/issue's history.   | using an issue tracking tool, say Jira. Here, they did not try to learn the error occurred in end user's site, using the machine learning and no analysis for further action for automatic fixing. |
|--|---|---|--|---|--|--|
| Ruchik a<br>Malhot<br>ra<br>Nov<br>2014<br>[2] | A systematic review of machine learning techniques for software fault prediction  Delhi Technologic al University | mechan<br>them ea<br>Using<br>Softwar<br>Fault<br>Predicti<br>(SFT) the<br>models<br>fault pro-<br>professi<br>(fault pro-<br>SDLC. | ism to detect<br>orly.  The constant of the classification as one are not. So to   | hat the fy the testing resources y phase of   | Using ML techniques for SFP models. Secondly, to construct the SFP model consider the performanc e accuracy along with the capabilities of the ML model. Identify the difference between the statistical and the ML techniques. Compare the performanc es on accuracy among the ML techniques. | research had been done for the early prediction of the errors/bu gs while in developm ent stage to improve the quality using the ML concept named - SFP (Software Fault                            |
| Author<br>/ Date                               | Topic / Focus /<br>Question   |   | Concept<br>Theoretical<br>Model  | Paradigm Method   | Research gaps /<br>Findings  |  |
| Valenti na Lenard uzzi Et al. [1] Sept. 2017   | A Dynamical Quality Model to Continuousl y Monitor S Maintenanc e   | Software  | When an stake holder encounter an error, the error would be listen by the "exception listener" on the JVM and  | They identified set of software quality assurance those are being practiced in small and                            | The research was done for to track the exception s and notify the exception to the   |  |

#### 2. Literature Review

Software failure at run time, studied in different research. Some of them are Comprehensive and efficient runtime checking in the system, QVM - QVM-quality virtual Machine, and A Dynamical Quality Model to

Continuously Monitor Software Maintenance. In almost all the research the researcher focused on saving the failure configuration so that the scenario can be recreated by the developer and fix them. Some research related to the study related to failure due to resource leaks. And so on.

Different researchers tried to provide models or approaches to predict errors or failures when the software is under development, in other words, early detection of errors. And found some of the research works related to run time software failure detection where the failure may be a memory leak or a resource failure so that the system condition of that specific time can be captured and can be used to recreate the scenario by the developer to fix the issue.

The wide area of our research would be related to Machine Learning and Artificial Intelligence, which covers the following areas:

- Detect the error/failure that occurred in the system that failed the software using soft computing by using the ML algorithm.
- Classify the error type using the Classification algorithm.
- Analysis and learning of different types of run time failures or errors using ML algorithm.
- Check and apply the automated fix (available) based on the analysis using soft computing. If no fix is available, notify us to prepare a fix.

Table 1. The tabular form of Literature Review

| quality test  | By            |  |
|---------------|---------------|--|
| even with the | summarizin    |  |
| less          | g the         |  |
| resources.    | strength and  |  |
|               | weakness of   |  |
|               | ML            |  |
|               | techniques    |  |
|               | identify the  |  |
|               | application   |  |
|               | of the ML     |  |
|               | techniques in |  |
|               | SFP.          |  |

|                                  |   |  |            | ent and<br>analyse to<br>fix them<br>using AI<br>or initiate<br>fix to the |
|----------------------------------|---|--|------------|--|
| Syahan<br>a Nur Et<br>al.<br>[5] | Machine<br>Learning<br>Techniques<br>for Software | The research is used to identify the similar | Literature | This research is about   |

| Awni   | Software   | Software                   | Prediction of       | The                  |   | Sep    | Bug              |
|--------|------------|----------------------------|---------------------|----------------------|---|--------|------------------|
| Hamm   | U          | Bug                        | future              | research             |   | 2020   | Predict          |
| ouri   | Prediction | Prediction                 | software            | was done             |   |        | A                |
| Et al. | using      | SBP is based               |                     |                      |   |        | System           |
| [3]    | Machine    | on three                   | by using            |                      |   |        | Review           |
| 2018   | Learning   | supervised<br>machine      | three<br>ML         | software             |   |        | Univer           |
| 2018   | Approach   | learning                   | algorithms.         | bugs to fix them     |   |        | Putra            |
|        |            | algorithms.                | Naïve               | before               |   |        | Malays           |
|        |            | Prediction of              |                     | productio            |   |        | iviaiays         |
|        |            | future                     | (NB),               | n release.           |   |        |                  |
|        |            | software                   | Decision            | The                  |   |        |                  |
|        |            | faults is done             | Tree (DT)           | research             |   |        |                  |
|        |            | based on the               | and                 | talks about          |   |        |                  |
|        |            | historical                 | Artificial          | the                  |   |        |                  |
|        |            | data.                      | Neural              | future               |   |        |                  |
|        |            |                            | Networks            | work                 |   |        |                  |
|        |            | talks about                |                     |                      |   |        |                  |
|        |            | the                        | research            | compare              |   |        |                  |
|        |            | increasing<br>the software | used the historical | more ML algorithm    |   |        |                  |
|        |            | quality,                   | fault data,         | to                   |   |        |                  |
|        |            | reliability                | required            | improve              |   |        |                  |
|        |            | and reducing               | •                   | _                    |   |        |                  |
|        |            | the                        | computing           | efficienc y          |   |        |                  |
|        |            | maintenance                | techniques.         | of the               |   |        |                  |
|        |            | cost.                      | By                  | model.               |   |        |                  |
|        |            |                            | comparing           | Whereas,             |   |        |                  |
|        |            |                            | these               | our                  |   |        |                  |
|        |            |                            | algorithm           | proposal is          |   |        |                  |
|        |            |                            |                     | to track             |   |        |                  |
|        |            |                            |                     | and learn<br>the bug |   |        |                  |
|        |            |                            |                     | using ML,            |   |        |                  |
|        |            |                            |                     | that are             |   |        |                  |
|        |            |                            |                     | occurring            |   |        |                  |
|        |            |                            |                     | at                   |   |        |                  |
|        |            |                            |                     | live/prod            |   |        |                  |
|        |            |                            |                     | uction               |   | Matthe | QVM:             |
|        |            |                            |                     | software             |   | W      | efficier         |
|        |            |                            |                     | environm             |   | Arnold | runtime          |
|        |            |                            |                     | ent                  |   | Et al. | detection        |
|        |            |                            |                     | (custome r site).    |   | [4]    | defects          |
|        |            |                            |                     | It means             |   | Oct    | deploy<br>system |
|        |            |                            |                     | our                  |   | 2008   | System           |
|        |            |                            |                     | research             |   | 2000   |                  |
|        |            |                            |                     | will                 |   |        |                  |
|        |            |                            |                     | provide a            |   |        |                  |
|        |            |                            |                     | model to             |   |        |                  |
|        |            |                            |                     | learn the            |   |        |                  |
|        |            |                            |                     | errors               |   |        |                  |
|        |            |                            |                     | using ML,            |   |        |                  |
|        |            |                            |                     | that occurs          |   |        |                  |
|        |            |                            |                     | at client<br>end     |   |        |                  |
|        |            |                            |                     | at runtime           |   |        |                  |
|        |            |                            |                     | / productio          |   |        |                  |
|        |            |                            |                     | n                    |   |        |                  |
|        |            |                            |                     | environm             |   |        |                  |
|        | 1          | 1                          |                     |                      | L |        | l                |

| Sep<br>2020                         | Bug<br>Prediction:<br>A<br>Systematic<br>Review<br>Universiti<br>Putra<br>Malaysia | models those are available to predict the bugs of a software before the testing starts. The researchers narrowed down to 31 main studies on this research. This research was to check, by using machine learning till what extent the bug prediction is possible of a software. | Multiple of (31) Model study was considered for this. Six machine learning algorithm had been identified. Area Under Curve (AUC) or F-Measure are bused to evaluate the | g the different methods and their accuracy with the methods used to predict the software  |
|-------------------------------------|--|---|---|---|
| Matthe w Arnold Et al. [4] Oct 2008 | QVM: an efficient runtime for detecting defects in deployed systems                | configuration   |   | The research is to track the run time software failure and trace the configura tion propertie s, for what the failure occurred like resource leak. This research does not cover the |

| Chang<br>Lou | Comprehen | To detect any anomalies | Exploration type of | The researche r |  |                 |                |              |
|--------------|-----------|-------------------------|---------------------|-----------------|--|-----------------|----------------|--------------|
| CI           | G 1       |                         | P 1                 | TEI             |  |                 |                |              |
|              |           | applications.           |                     |                 |  |                 | errors.        |              |
|              |           | issues in several live  |                     |                 |  |                 | and detects    |              |
|              |           | multiple                |                     |                 |  |                 | mimics them    |              |
|              |           | and fix                 |                     |                 |  |                 | program,       |              |
|              |           | could detect            |                     |                 |  |                 | main           |              |
|              |           | researcher              |                     |                 |  |                 | from the       |              |
|              |           | JVM the                 |                     |                 |  |                 | operations     |              |
|              |           | IBM J9                  |                     |                 |  |                 | important      |              |
|              |           | the QVM on              |                     |                 |  |                 | selects        |              |
|              |           | implementin g           |                     |                 |  |                 | 3. Checker     |              |
|              |           | By                      |                     |                 |  |                 | one.           |              |
|              |           | properties etc.         |                     |                 |  |                 | monitor each   |              |
|              |           | heap                    |                     |                 |  |                 | checker to     |              |
|              |           | assertion,              |                     |                 |  |                 | write a        |              |
|              |           | such as, Java           |                     |                 |  |                 | and then       |              |
|              |           | of properties           |                     |                 |  |                 | indicators     |              |
|              |           | correctness             |                     | fix that.       |  |                 | health         |              |
|              |           | specified               |                     | possible        |  |                 | some system    |              |
|              |           | the user                |                     | and if          |  |                 | 2. Define      |              |
|              |           | and validate            |                     | analyse         |  |                 | input.         |              |
|              |           | application             |                     | ML then         |  |                 | presupplied    |              |
|              |           | production              |                     | ent using       |  |                 | with           |              |
|              |           | the                     |                     | environm        |  |                 | public APIs    |              |
|              |           | monitoring              |                     | n               |  |                 | software's     |              |
|              |           | continuously            |                     | productio       |  | watchdogs.      | invokes the    |              |
|              |           | defects by              |                     | in              |  | intrinsic       | client and     |              |
|              |           | detects the             |                     | run time        |  | this as         | like a special |              |
|              |           | which                   |                     | rror at the     |  | They named      | that works     |              |
|              |           | Machine",               |                     | failures/e      |  | recovery.       | Probebased     |              |
|              |           | Virtual                 |                     | learn the       |  | expedite        | 1.             |              |
|              |           | "Quality                |                     | model is to     |  | for             | approaches:    |              |
|              |           | named                   |                     | research        |  | failure to help | general        |              |
|              |           | app roch                |                     | proposed        |  | production      | has three      | 301115 / 11. |
|              |           | proposed an             |                     | Our             |  | reproduce the   | constructio n  | using AI.    |
|              |           | research                |                     | failure.        |  | saved to        | Checker        | analysis     |
|              |           | this the                |                     | tion            |  | information is  | checkers.      | after        |
|              |           | To overcome             |                     | configura       |  | fault           | watchdog       | action       |
|              |           | task.                   |                     | the             |  | Then precise    | write the      | •            |
|              |           | consuming               |                     | failure and     |  | granularity.    | - How to       | algorithm    |
|              |           | time                    |                     | network         |  | with finer      | mail program   | ML           |
|              |           | affordable and          |                     | failure,        |  | anomalies       | mimics the     |              |
|              |           | challenging,            |                     | s,<br>hardware  |  | detectors that  | one that       |              |
|              |           | is a                    |                     | s,              |  | detectors that  | watchdog is    |              |
|              |           | environment             |                     | exception       |  | failure         | type of        | the          |
|              |           | testing                 |                     | time code       |  | intrinsic       | An effective   |              |
|              |           | the issue in            |                     | like run        |  | which is a      | watchdog. 3.   | we are       |
|              |           | recreation of           |                     | failures        |  | software        | good           | Whereas      |
|              |           | such case               |                     | for other       |  | regarding a     | what makes a   |              |
|              |           | them. In                |                     | exception       |  | research is     | for coding -   | occur a      |
|              |           | issue to fix            |                     | runtime         |  | task. So the    | principles     | issues       |

| Et al. | sive and    | occurs in a     | methodolog y   | filled the  |
|--------|-------------|-----------------|----------------|-------------|
| [6]    | efficient   | system can be   | has been       | gap they    |
|        | runtime     | tracked         | used           | find by     |
| May    | checking in | from outside    | initially for  | impleme     |
| 2019   | system      | by using a      | this intrinsic | nting the   |
|        | software    | thin module     | failure        | mimic       |
|        | through     | with a simple   | detector.      | type        |
|        | watchdogs   | independent     | Some           | watchdog    |
|        |             | underlaid       | points were    | automatic   |
|        |             | code is         | considered     | ally by     |
|        |             | enough to       | here are:      | using the   |
|        |             | monitor the     | 1. Define the  | main        |
|        |             | failure. But    | characteristi  | program     |
|        |             | tracking the    | c of good      | source      |
|        |             | intrinsic       | watchdog -     | code. The   |
|        |             | failures, occur | watchdog       | research is |
|        |             | in system       | Abstraction.   | only for    |
|        |             | software is     | 2. Define the  | the         |
|        |             | not a easy      | design         | intrinsic   |
|        |             | Ĭ               | Č              |             |

| Dr. K. P. | Implementa    | This research  | According to   | The          |
|-----------|---------------|----------------|----------------|--------------|
| Parades   | tion of Fault | talks about    | research,      | research     |
| hi Et al. | Detection     | the fault      | fault can      | was about    |
| [36]      | Framework     | detection      | occur in three | the          |
| Sep       | For           | monitoring     | ways.          | utilizatio n |
| 2022      | Healthcare    | framework      | Device         | of IoT and   |
|           | Monitoring    | for IoT        | failure,       | wireless     |
|           | System        | sensors and    | Software       | networks     |
|           | Using IoT,    | wireless       | issue and      | for patient  |
|           | Sensors In    | environment    | Communica      | health to    |
|           | Wireless      | in healthcare. | tion failure.  | analyse      |
|           | Environmen    | This           | Failures can   | and detect   |
|           | t             | framework of   | be detected:   | the          |
|           |               | fault          | Detect the     | fault in     |
|           |               | detection      | damaged        | monitorin    |
|           |               | identifies the | sensor nodes   | g devices.   |
|           |               | flaws in the   | and select the | This         |
|           |               | system and     | alternate set  |              |
|           |               | isolates the   | of nodes to    |              |
|           |               | complex        |                |              |

|  | •              |                      |             |
|--|----------------|----------------------|-------------|
|  | process or     | continue the data    | research    |
|  | variables so   | transmissio n. The   | shows       |
|  | that we can    | faulty nodes will be | 80%         |
|  | save extra     | barred from          | accuracy    |
|  | relevant       | participatin g until | in fault    |
|  | information    | they are repaired or | detection.  |
|  | about the      | replaced. Sensor     | If we learn |
|  | problem.       | network should be    | the         |
|  | This fault     | tiny and human       | hardware    |
|  | detection      | influence should be  | ,           |
|  | framework      | minimum on           | software,   |
|  | provides an    | installation install | configura   |
|  | effective      | in                   | tion and    |
|  | impact in an   | any sort of          | network     |
|  | IoT sensors    | environmen           | failures    |
|  | and wireless   | t.                   | using the   |
|  | environment    | To validate the      | machine     |
|  | in healthcare. | findings             | learning    |
|  |                | the MSVM model       | and try to  |
|  |                | was implemente d     | fix them    |
|  |                | and to classify the  | using the   |
|  |                | classes in           | AI may      |
|  |                | the dataset the SVM  | create an   |
|  |                | model was used.      | impact in   |
|  |                |                      | quality of  |
|  |                |                      | the IoT     |
|  |                |                      | devices     |
|  |                |                      | and         |
|  |                |                      | wireless    |
|  |                |                      | networks.   |
|  |                |                      | In our      |
|  |                |                      | research    |
|  |                |                      | we are      |
|  |                |                      | trying to   |
|  |                |                      | fill this   |
|  |                |                      | gap by      |
|  |                |                      | working     |
|  |                |                      | with an     |
|  |                |                      |             |
|  | ı              | '                    | ı           |

| Conce the fault is detected, the fault diagnosis is performed at a central node, they are called a network server, to reduce the computatio nal load on the sensor.  L. A machine Seabra learning focusing on approach to error detection and Aug recovery in 1995 assembly assembly system in a manufacturin g system.  The research is are divided into in 3 about a layers. 1. manufact wring assembly 2. The system gassembly assembly 2. The system of the sensor wring assembly and the sensor.  A machine The research is focusing on are divided into in 3 about a layers. 1. manufact wring assembly 2. The system error detection and manufacturin Domain detection and manufacturin g system.  Knowledge and recovery using the Functions 4. Training and Learning research is 5. about Experiment al Setup 6.   |         |               |                 | C1/          | 1           |
|--|---------|---------------|-----------------|--------------|-------------|
| fault is detected, the fault diagnosis is performed at a central node, they are called a network server, to reduce the computatio nal load on the sensor.  L. A machine The research is seabra learning focusing on Lopes approach to error detection and recovery in robotized assembly assembly assembly assembly 2. The system in a manufacturin g system.  The proposal This are divided research is into in 3 about a layers. 1. manufact Planning uring Strategy assembly 2. The system in a manufacturin g system.  Knowledge and 3. recovery using the Functions 4. ML. But Training and Learning research is about Experiment al Setup 6. error   |         |               |                 | or faulty.   |             |
| detected, the fault diagnosis is performed at a central node, they are called a network server, to reduce the computatio nal load on the sensor.  L. A machine The research is focusing on Lopes approach to error detection and recovery in Aug recovery in robotized assembly assembly system in a manufacturin g system.  The proposal This research is into in 3 about a layers. 1. manufact Planning uring Strategy assembly 2. The system system in a manufacturin g system.  Knowledge and 3. recovery using the Functions 4. Training and Learning research is software al Setup 6.  |         |               |                 |              |             |
| fault diagnosis is performed at a central node, they are called a network server, to reduce the computatio nal load on the sensor.  L. A machine The research is learning focusing on approach to error detection and [8] detection and recovery in Aug recovery in robotized assembly 1995 assembly assembly 1995 assembly 1995 assembly 1996 assembly 1997 assembly 1996 assembly 1997 assembly 1998 assembly 1999 assembly 1999 assembly 1999 assembly 1990 assembly 1990 assembly 1990 assembly 1991 assembly 1995 assembly 1995 assembly 1996 assembly 1997 assembly 1998 assembly 1999 assembly 1999 assembly 1990 assembly 2. The 1990 assembly 2. The 200 assembly 200 |         |               |                 |              |             |
| diagnosis is performed at a central node, they are called a network server, to reduce the computatio nal load on the sensor.  L. A machine Seabra learning focusing on Lopes approach to Et. Al. error detection and Aug recovery in robotized assembly assembly assembly 2. The system in a manufacturin g system.  Seabra learning focusing on error detection and layers. 1. manufact research is into in 3 about a layers. 1. manufact Planning uring assembly 2. The system of the system in a manufacturin g system.  Knowledge and 3. recovery supervision using the Functions 4. ML. But Training and the Training and the Experiment al Setup 6. error  |         |               |                 |              |             |
| Description   Description  |         |               |                 |              |             |
| at a central node, they are called a network server, to reduce the computatio nal load on the sensor.  L. A machine The research is focusing on are divided research is into in 3 about a layers. 1. manufact wring assembly assembly assembly 2. The system in a manufacturin g system.  Aug recovery in robotized assembly 2. The system and manufacturin g system.  Assembly assembly assembly and telection and manufacturin g system.  Knowledge and 3. recovery using the Functions 4. Training and Learning research is 5. about Experiment al Setup 6.   |         |               |                 |              |             |
| L.   A machine   The research is research is   Into in 3   about a   about a   about a   assembly   and   and   and   and   assembly   assembly   and     |         |               |                 | performed    |             |
| are called a network server, to reduce the computatio nal load on the sensor.  L. A machine Seabra learning focusing on Lopes approach to Et. Al. error detection and Aug recovery in 1995 assembly assembly assembly 2. The system in a manufacturin g system.  Basembly assembly assembl |         |               |                 |              |             |
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| Sana<br>Ullah<br>J an a<br>Et. al.<br>[7]<br>Aug<br>2019                         | A distributed sensor-fault detection and diagnosis framework using machine learning | The research is about a distributed sensor-fault detection to diagnose a system based on machine learning algorithms. | detection block implemente d in the sensor order to achie output immediate y after da collection. Th block is made with autoencoder transform the inpu signal into lowerdimensional feature vector which is th provided to Support Vector Machine (SVM) for | sensors fault detection and diagnosis an in IoTs. In to our research we are proposin g   |
| Laksh<br>mi<br>Geetha<br>njali<br>Manda<br>gondi<br>Et. A<br>[31]<br>Feb<br>2021 | Using Machine Learning  | to use machine learning techniques to "learn" hov to distinguish  | anomaly query classificatio n can be done to specific attack type.  Here the researcher used multiple algorithms Local Outlier Factor, Random Forest and Term Frequency Inverse Document Frequency. To decide which one has the more efficiency to          | run time failure os a software and try to fix using AIML.  In this research the work is only focused on the Anomaly detection algorithm s and their performa nce. But our research is about anomaly detection, classifica tion and fixetion. |

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| Et. Al.             | Attack                            | detection of  | model to   | uses ML process to   |
| Et. Al. [35]        | Attack<br>Detection               | detection of web attacks,                                 | model to<br>learn the  | uses ML<br>process to<br>detection   |
| Et. Al. [35]<br>Nov | Attack<br>Detection<br>using Deep | detection of<br>web attacks,<br>done through              | model to<br>learn the<br>sequences of  | uses ML<br>process to<br>detection<br>of web   |
| Et. Al. [35]<br>Nov | Attack<br>Detection<br>using Deep | detection of<br>web attacks,<br>done through<br>HTTP/HTTP | model to<br>learn the<br>sequences of<br>word and  | uses ML<br>process to<br>detection<br>of web   |
| Et. Al. [35]<br>Nov | Attack<br>Detection<br>using Deep | detection of<br>web attacks,<br>done through<br>HTTP/HTTP | model to<br>learn the<br>sequences of<br>word and<br>wight each  | uses ML<br>process to<br>detection<br>of web<br>attacks  |
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#### 3. Problem Identification

#### 3.1. Errors and Anomalies

Mistakes made during development, which can be more conceptual or logical, are the errors in software. Bugs are incorrect behavior or the exposure of these errors at the time of functioning of the software. Sometimes, the failure of software may happen due to configuration, improper data read, and locking of a resource for infinite time, network, and other hardware resources. There may be a chance of having 15 to 50 bugs in each 1000 lines of code. The more the requirements, the more the code, and the more the code the more the code the more the errors. Not only the codes but the more the requirements of automation increase, the more the complexity of configurations and infrastructures increase. Doing early detection of errors, rigorous testing is being done as a part of the SDLC process.

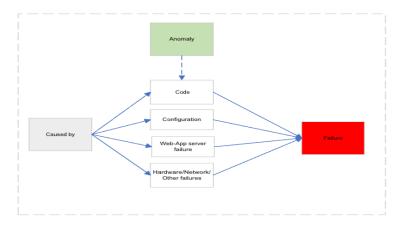


Fig 2. Anomalies that can appear in a web application at run time

#### 3.2. Traditional Approach to Report Production **Anomaly**

Product industries have relied on customer feedback or reports to identify issues with their products. This means that if a user does not report an issue promptly or accurately enough, it may take weeks or months before the problem is identified and fixed by the company.

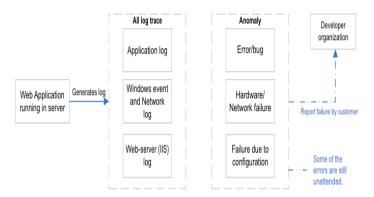


Fig 3. Traditional error/failure reported by customers/users

#### 4. Proposed System

However, what if we have a system that is efficient enough to learn (Detect and Classify) from the errors/bugs/failures that occur in the production web application and Fix/notify company immediately? Increasing reliability, consistency, and customer satisfaction will directly impact the quality.

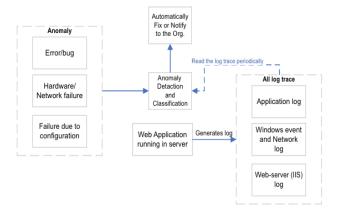


Fig 4. Flow Diagram of the proposed approach4

Overall, having such self-learning and self-correcting systems in place within the train/bus/plane automation industry can help increase safety, reduce downtime, and improve the overall reliability of the product.

Our research aims to develop a framework that can Detect, Classify, and Fix anomalies occurring in web application software (Web/App), which may arise from code, configuration, hardware, or network. We will use a machine learning algorithm to detect-classify and learn from the errors and fix them using an AI algorithm module on the fly. If the errors cannot be fixed, we will notify the developer company to address the problem. This will help to bridge the gap to error detection using ML and correction at run time for web applications.

In conclusion, with the increasing reliance on softwaredriven solutions across industries and sectors worldwide, ensuring high accuracy and reliability has become more important than ever before. By leveraging API-based monitoring tools & techniques along with other best practices like continuous testing & deployment methodologies, businesses can deliver top-notch quality services/products while minimizing risks associated with bugs/errors encountered during the development/deployment phases thereof.

#### 5. Methodology

The goal of the study is to Design and implement a model that provides a framework to increase the productivity and reliability of an app/web application.

**H1:** Detection and Classification of anomalies occurring in the web applications will increase the efficiency of that web application (used by the customer).

Design a client and API and develop an algorithm to detect the error and other environmental factors that can learn the error/failure occurs with the cause of arising of issues at the run time of the web application. And other environmental variables at that point in time. Such as virtual memory, Network delay or timeout, File not found, deadlock in the Read-write of a file, etc.

Detect Anomaly Using Pattern Search (DAUPS) - Soft computing Machine Learning algorithms are to be used along with LOF to detect and classify the errors that occurred in the system:

- Detect Anomaly Using Pattern Search (DAUPS).
- KNN-Local Outlier Factor (LOF)

**H2:** The efficiency of the web application will be enhanced when a detected anomaly in a web application is fixed.

Automate and develop an algorithm to analyze the learned anomaly by using Generative AI techniques and define the probable fixes to fix the anomaly automatically at the product level.

While analyzing the learned data, the optimization and decision-making would be done using the following algorithms:

#### • Generative AI.

Then either the anomaly will be fixed and notified, or notify the anomaly to the developer organization to provide the fix.

#### 5.1. Modules of the proposed system

**5.1.1. The Anomaly Learning System (ALS)** The anomalies (Error/Bug/Failure) that occur in the production web application server would be Detected and Classified by the Anomaly Learning System using ML.

The module would be trained with a supervised and semisupervised algorithm. So that the Anomaly Learning System (ALS) can classify the issue that appeared in the system if required, learn as a new record, and synchronize with the cloud centrally.

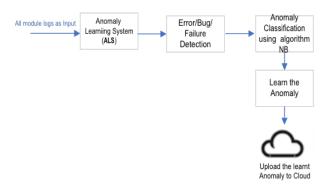


Fig 5. Anomaly Learning System (ALS)

5.1.2. Fix or Notify to organization with AI (FN) The responsibility of this module is to check for the best match of the solution and apply that. If no fix is found, then notify the development organization to fix that manually and update the knowledge base. The following process may be observed.

- If the FN cannot fix the issue using AI, then the Notify system will immediately raise concerns to the Owner company.
- If fixed, then update the AI knowledge base with the fix and notify the development organization. So that the fix can be used across the board for all web application servers.



Fig 6. Fix/Notify to Organization (FN)

#### 5.2. Characterizing the error/failure/anomaly

For the detection of anomalies in web applications, generally, the volume of logs generated by the usage of the application is taken into consideration. More usage of the application generates more logs. The more usage of the application, the more chances of increasing errors or anomalies. The modules involved in running a web application are:

- Web/App Application
- Web server (hosts the web application)
- Windows event log (manages hardware and network resources) The Anomaly includes:
- Code error an error occurs in web application code.
- Server error error/bug occurs in the web server while handling the request and response or any configuration error.
- Hardware/Network failure failure occurs in server hardware, network, or in communication with the cloud resources.

#### 5.3. Research Methodology:

The characteristics of both methods, Qualitative and Quantitative, i.e., the Mixed method, would be used here to validate the research. Exploratory research type, where we need to know elaborately how the components of the proposed system work:

- · A client component would be deployed in the webserver to detect and classify the anomaly that occurs in the web application and server.
- · An API will talk to the above client and update the central knowledgebase with the anomaly that is learned in the above step. Along with the learning a new event would be triggered to identify a fix and initiate that.
- Once an anomaly is detected that is not learned before, update the knowledge base. Initiate the process to match the fix for that anomaly. If found, trigger that to fix the anomaly. If that is resolved, map the fix with the anomaly. Else raise concern to the development organization.
- If the anomaly is already in the knowledgebase and the fix is mapped, then trigger that to fix the anomaly.

It is planned to split the activity into phases with the proper guidance which will cover all the following, that will take care of all anomalous events in depth.

The project will work in the following pattern:

- Gather logs.
- Detection of anomalous events from the log using soft computing ML algorithms.

- Classify the detected anomalies using soft computing ML algorithms.
- Learn the anomaly in a centralized knowledge base.
- Map, Apply, and Notify the fix using Generative AI. If not fix is not available, notify the development Organization.

#### 5.3.1. Data Collection

ORACLE Ind. has multiple internal web applications hosted on its internal servers. We have chosen one of the web applications to collect our required logs. For the web application, there are different log streams, such as Application code logs, IIS logs, and Windows event logs. The application is developed on the .Net framework using C#, Python, and PowerShell for logging. Log4Net is used in code. The logs are being collected periodically (once every 5 days).

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Fig 7. Application log trace

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Fig 8. IIS HTTPERR log trace – web server

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## Channels | List |
## Channels | List | Channels | Chan
```

Fig 9. Inetpub log trace – web server

Making an effort to reproduce an error in production or chasing IIS logs or error logs is not so easy. The hidden point is, there are probably several errors going on that we aren't even aware of. The easy way to see an error is when a customer raises a concern by saying, the production site is throwing errors!

Collection information from the different log traces of the web application and the web servers (like IIS) is the most important point to detect the runtime error.

By browsing the internet, we can get the knowledge of how to identify the type of exceptions/errors and segregate them into groups. We may not encounter all types of exceptions or errors in a sample web application, and we can get more from the internet.

#### **5.3.2. Process** the gathered information and consolidate them

Information would be compiled and consolidated into volumes that are collected through the different sources. These volumes would be used at the time of doing experiments, formalization of statistical models, and the preparation of a thesis or dissertation.

An earlier collection of the immense volume of information would be an asset to the research work.

#### 5.3.3. Search and collect the software packages and, if required, develop

No availability of such software packages has a direct impact on this line of research. Only one left-out point we need to implement a prototype (collection of several scripts) to detect, classify, and fix such runtime errors.

#### 5.3.4. Verifying the test results, identifying the findings of experiments, and confirming the research

Several verifications would be subjected to the generated outputs that would be traced from a web application. The difference in types would be noted down for further classification and fixing.

#### 6. Dataset and Algorithms Discussed

#### 6.1. Dataset

The real-time logs of a web application, web server, and Windows event are collected from a web application that communicates with the OCI cloud that is internal to ORACLE.

#### 6.1.1. Application Architecture

The real-time application from which we have collected the log is split into three layers:

- Client side.
- Web server.
- Cloud resources.

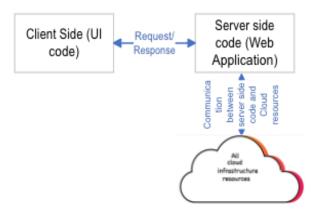


Fig 10. The architecture of Real-time Web-Application from where the log was collected

#### 6.2. Algorithmic Concepts

#### **Machine Learning:**

Learnings that are done by a machine means the skill in the form of artificial intelligence that enables the computer to learn specific tasks without being programmed specifically. A piece of software program that uses multiple algorithms to learn about a targeted object.

#### **Supervised Learning:**

Based on past knowledge, Supervised learning requires labeled data. To identify, it applies the past knowledge to the new data.

#### **Unsupervised learning:**

Whereas the unsupervised draws the conclusion from the datasets directly. The unlabelled data are used in this learning.

#### Logs as Input:

Web applications or any software applications generate large data system logs. They are typically unstructured text written line by line in a file by maintaining the time sequence. While the log line is being written by a code statement it contains a Constant and a Variable part. The constant part is directly Written by the coder, but the variable part is written by the system with that specific time value. It may be data or maybe an error exception. The log format depends on the developer, where the logger may be in-house or logger utilities software available in the market. For example, Log4Net is for the .Net platform, and Log4J is for Java platform development.

Fig 11. Sample of a log which is taken as an input

#### Anomaly:

#### 6.3. Detect Anomaly Using Pattern Search (DAUPS):

Something that is not normal surrounding it, i.e., the thing that is unusual or irrelevant or unacceptable called an anomaly. This came from the Greek word "anomolia".

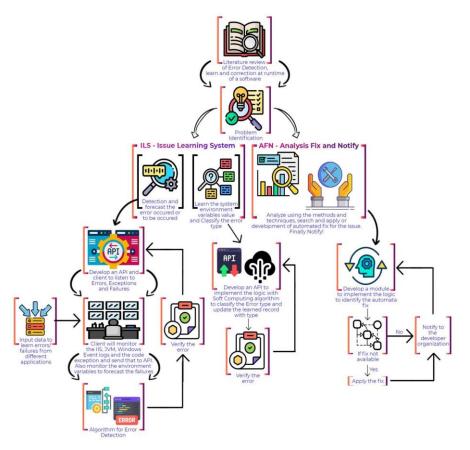


Fig 12. Flowchart of the overall Research Outline

This approach to detecting anomalies in a log file is based on the given pattern initially. Once the pattern is identified in the log string, then read the whole string or context of the log stream. Check the occurrence of the exception/error with the knowledgebase. If this is already in the knowledgebase, then increase the occurrence against that log stream; if it does not exist in the knowledgebase, then enter this with the frequency of occurrence.

#### 6.4. KNN-Local Outlier Factor (LOF)

A data point that is far from the rest of the data points is called an Outlier. A point is treated as an outlier based on its local neighbors called a local outlier.

The algorithm's local outlier factor works based on the local density. Internally, this uses the KNN (K-Nearest Neighbours) algorithm, where K is the number of data points to be referenced.

- Calculate the Reachability Distance
- Calculate the local reachability Density of all K neighbors.

The value with the high density is the local outlier.

#### 7. Results and Discussions

7.1. Error Detection that occurred in Module 1

#### 7.1.1. Introduction & the EDO system

The error detection system is such type of system where that tries to read the exception/error that occurred in the application, webserver, and Windows logs.

- This module will take error inputs from several log sources (Application log, IIS server log, IIS client log, Windows system log, etc.)
- Building a keyword patterns library of exception/error/failure/warning will help us to detect/forecast the error.

- The responsibility of this module is to filter out the exceptions/errors/failures/warnings from the log traces.
- The initial detection of the errors will be treated as supervised learning.

**7.1.2.** Learn the system environment variable values and classify the error types We have the following error types:

- Configuration error
- Resource error
- Other failures (Hardware, Network, etc.)

## 7.1.3. The proposed detection and classification algorithm DAUSP:

- This is a supervised ML model to detect the errors that occur in the logs.
- Let 'P' be the set of predefined pattern key word or data to identify the error and exceptions in log-trace. P = (p1, p2, ..., pn).
- If we have a 'T' number of tuples (log traces), where 'T'=(t1, t2, ..., tn). For each pattern, 'p' would be checked for the match with each tuple

't'.

• Now, all matched tuples are kept in a list 'L' and will be used as a 'T' in LOF to classify them.

Note: We would be using the list of negative adjectives (how the sentence sounds positive/negative) pattern to identify and learn the errors.

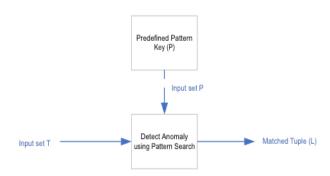


Fig 13. Detect Anomaly using Pattern Search.

#### KNN-LOF:

KNN (K-Nearest Neighbours)

LOF is an unsupervised Anomaly detection algorithm that internally uses the KNN algorithm to detect the distance of the selected data points with K-th data points.

And in LOF the calculated distance in KNN is being used to calculate the density.

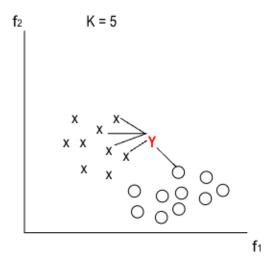


Fig 14. Classified the datapoint (f1 and f2 are the two categories here) Y based on the distance between the new data points using K = 5.

**K-Value** is a hyper parameter that gives us the count by using which we check the K (number of) nearest data points.

Euclidian distance for classification: Between the two data points (x1,y1) and (x2,y2), we can find the distance

by using the formula:  $\sqrt{(x^2-x^1)^2+(y^2-y^1)^2}$ . Here, based on the K value, we can identify the new data point, which means we can classify the error that is detected in an earlier stage.

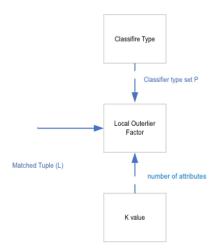


Fig 15. KNN with the input from earlier stages and Classifier type

Suppose we have a classifier type:

- File not found may have attributes File Location, File Name, Failed action, etc.
- Resource Locked by another process may have attributes File Location, File Name, Failed action, Locked by, etc..

For now we are not directly applying the Local Outer Factor (LOF) in classifying the errors. If the model fails to classify the errors using KNN, then LOF will be implemented.

#### 7.2. Error Correction that occurred in Module 2

#### 7.2.1. Analysis and Notify

A model to analyze and fix it comes into the picture once the error is detected and classified.

This model has three sections:

• The different types of anomaly are to be fixed in different timeframes and environments.

- o Run-Time Code error is to be fixed in a parallel environment as triage of fixing the code may create downtime in a production environment.
- o Run-time configuration errors can be fixed directly in a production environment by keeping a backup of the original configuration.
- Web-Server error can be fixed at the run time in a production environment.
- Hardware/resource / Networking error can be fixed at run time in a production environment.
- Identify the suitable fix available from knowledgebase.
- For different types of anomaly, the way of applying a fix would be different.

The Generative-AI model would be used to apply the fix. In our case, we will be using the text-to-text model to fix the anomalies.

#### Conclusion

The studies on proactively addressing runtime anomalies in web applications discovered that applying sophisticated machine learning approaches has much potential to improve the overall quality, efficiency, and security of Internet-based services. Through its accurate use of complex models such as deep learning, anomaly detection algorithms, and reinforcement learning, it is possible to detect and curb misbehavior and system instability before they become problematic. The approach is also useful in the real-time identification of anomalies and is simultaneously used in predictive maintenance since it can predict possible defects that may affect users. Further, when the machine learning models are integrated with the current monitoring tools, it offers the ability to have an end-to-end check using a systematic approach for managing irritations. In general, the use of modern machine learning technologies in this field can be considered as the shift to a new level of Web applications development, which will be more intelligent, adaptive, and robust in terms of protection and management, and the perspective for further developments in the field of automated control and security systems.

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