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Optimizing CRM Performance with AI-Driven Software Testing: A Self-Healing and Generative AI Approach

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Abstract

In the digital age, optimizing Customer Relationship Management (CRM) system performance is critical for enhancing customer satisfaction and service delivery. However, frequent system updates and evolving business processes introduce challenges, particularly in testing and ensuring software reliability. Traditional manual testing methods are often slow, error-prone, and inefficient. This study proposes an innovative AI-driven approach to software testing, utilizing self-healing and generative AI techniques to automate the testing process and improve system performance. By leveraging AI for dynamic test case creation and automated maintenance of broken test scripts, the approach enhances test coverage, defect detection, and overall CRM system performance. The methodology incorporates various techniques, such as Term Frequency-Inverse Document Frequency (TF-IDF) for sentiment analysis, GPT-3 for AI-powered test case generation, and Computer Vision-based object recognition using Convolutional Neural Networks (CNN) for self-healing test automation. Additionally, anomaly detection using Autoencoders is employed for root cause analysis and defect detection. The results of this study show improved defect detection rates and optimized test execution times, demonstrating the effectiveness of AI in enhancing CRM software testing. The proposed approach not only reduces maintenance overhead but also ensures more reliable CRM system performance, leading to better customer experiences. This research highlights the potential of AI-driven testing methodologies in addressing the challenges of CRM system optimization, providing a scalable solution for future CRM software development.

Keywords: *Customer Relationship Management optimization, AI-driven software testing, self-healing automation, generative AI, defect detection, Convolutional Neural Networks, anomaly detection, test case generation.*

1. Introduction

Optimizing CRM performance is crucial for businesses to enhance customer satisfaction, streamline operations, and improve overall service delivery [1]. In today's fast-paced digital landscape, it is essential to ensure that CRM systems are functioning efficiently and reliably. AI-driven software testing, particularly using self-healing and generative AI, offers a powerful solution for automating testing processes, detecting defects early, and ensuring high-quality software [2]. This approach leverages advanced machine learning and AI models to continuously improve test coverage, accuracy, and system performance [3]. The primary challenges in CRM performance optimization arise from frequent system changes, evolving business processes, and the complexity of integrating various tools and platforms [4]. These factors often lead to inconsistencies in system behaviour, broken test scripts, and unanticipated failures, especially when updates are rolled out or when new features are introduced. Furthermore, the manual testing process can be slow, prone to human error, and inefficient in identifying issues that only emerge under certain conditions [5].

Despite the advancements in automation, traditional testing methods still face significant challenges that affect the scalability and performance of CRM systems [6]. One major issue is the high maintenance overhead; as CRM systems frequently evolve with new features and updates, test scripts need to be continuously revised. This can be time-consuming, prone to human error, and result in inconsistencies in the testing process [7]. Additionally, there is an inefficiency in defect detection, as manual test cases may not cover all possible defect scenarios. Automated tests, while more comprehensive, may still miss critical issues, especially in dynamic environments where system behaviour changes unexpectedly [8]. Moreover, limited flexibility in traditional testing methods, which rely on pre-defined scripts, makes it difficult to adapt to changes in the user interface or business logic [9]. These challenges significantly hinder the ability to efficiently test and optimize CRM systems, ultimately affecting system performance and user experience [10].

To address these issues, I propose an innovative approach using AI-Driven Software Testing: A Self-Healing and Generative AI Approach. This method leverages self-healing test automation to automatically update and correct broken test scripts, reducing maintenance overhead and increasing reliability. Additionally, generative AI is used to create dynamic, context-aware test cases that evolve with the CRM system, improving test coverage and defect detection. This approach will significantly enhance the ability to maintain high-quality CRM systems, reduce downtime, and improve overall customer experience by ensuring consistent and efficient performance testing.

In Section 2, Literature Review Explores existing methods and their limitations. Section 3 Identifies challenges in Customer Relationship Management methods, and secure content verification. Section 4 the Proposed Methodology presents Autoencoder Based AI – Driven Analysis & Root Cause Detection. Section 5, Result and Discussions. While Section 6, Conclusion and Future Works.

2. Literature Review

Azadeh et al. [11] proposed the literature highlights the role of CRM and Resilience Engineering in optimizing IS performance in large corporations. Techniques like DEA and PCA are used for system evaluation, but challenges remain in quantifying factors and balancing CRM and RE, which may limit model effectiveness. Rudarakanchana et al. [12] suggested literature highlights the use of VR simulation for training endovascular teams, enhancing both technical and non-technical skills. Despite challenges like high costs and integration with real-world settings, VR simulation shows promise in improving patient outcomes.

Rodriguez & Honeycutt [13] Utilized literature on CRM adoption in B2B sales highlights its positive impact on sales effectiveness and collaboration. PLS is used to analyse these relationships, particularly with small sample sizes. Limitations include biases in self-reported data, challenges in generalizing results, and the inability to assess long-term effects on sales performance. Amini et al.[14] showed that NC and CRM improve bitumen properties in asphalt mixtures. ANOVA and sensitivity analysis assess their effects, but variability in results based on additive content and type limits generalizability.

Brockman et al. [15] analysed the literature highlights the importance of buyer trust in outsourced CRM suppliers for information sharing and organizational learning, which in turn enhances firm performance. The study uses LISREL 9.2 to assess validity. Limitations include a focus on marketing managers' perspectives, which may not capture the broader organizational view, and variability across industries. Xiao et al. [16] proposed the literature shows that ANN models predict CRM binder viscosity based on factors like asphalt binder source, rubber size, and rubber content, with sensitivity analysis highlighting their impact. Limitations include potential overfitting and fixed input variables.

3. Problem Statement

The integration of Customer Relationship Management (CRM) and Resilience Engineering (RE) techniques to optimize Information Systems (IS) performance in large corporations faces challenges in quantifying the factors involved, leading to difficulties in balancing CRM and RE effectively [17]. These limitations may hinder the full potential of models designed to enhance system performance [18].

Similarly, the use of artificial intelligence (AI), such as ANN models for predicting CRM binder viscosity, presents challenges like potential overfitting and a limited scope due to the fixed nature of input variables [19]. Additionally, biases in data collection methods and variability across industries or applications restrict the generalizability and long-term effectiveness of these models [20].

4. Proposed Framework for AI-Optimized CRM Testing with Self-Healing Automation

The proposed framework enhances CRM software testing using AI techniques. It starts with Data Collection and TF-IDF-based Preprocessing, which convert raw textual data, such as customer feedback, into valuable numerical features that capture the relevance of terms within the data. Performance Evaluation then measures the system's effectiveness by tracking key metrics, including test execution time and defect detection rates, ensuring a high level of test efficiency. Autoencoder-Based AI detects system anomalies by analysing logs and crash reports, pinpointing root causes through pattern recognition in the data is shown in Figure (1),

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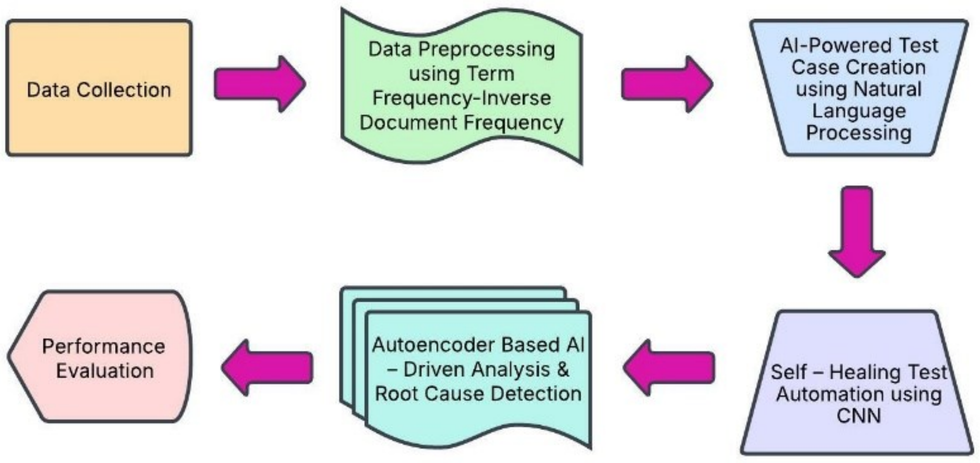
Data Collection
Data Preprocessing using Term Frequency-Inverse Document Frequency
AI-Powered Test Case Creation using Natural Language Processing
Self – Healing Test Automation using CNN
Autoencoder Based AI – Driven Analysis & Root Cause Detection
Performance Evaluation

Figure 1: Block Diagram of AI-Driven CRM Testing and Optimization

AI-Powered Test Case Creation employs NLP models like GPT-3 to generate realistic test scenarios from natural language, enabling more dynamic and context-sensitive testing. Self-Healing Test Automation, using CNNs, enhances the flexibility of test scripts by automatically detecting UI element changes and adapting to new system updates. Generative AI also aids in the dynamic creation of test scripts that evolve with the system, reducing human intervention. Additionally, Anomaly Detection further strengthens the system by identifying previously undetected defects, thus ensuring comprehensive test coverage. This integrated approach provides a dynamic, reliable, and scalable testing solution, reducing maintenance overhead, improving accuracy, and ensuring robust CRM system performance.

4.1 Data Collection

This dataset contains customer sentiments from various sources like social media and reviews, including attributes such as sentiment (positive/negative), text, source, timestamp, user ID, location, and confidence scores. It supports sentiment analysis, text preprocessing, topic modelling, feature engineering, machine learning, and data visualization, offering insights into customer opinions and trends.

Dataset Link: https://www.kaggle.com/datasets/vishweshsalodkar/customer-feedback-dataset

4.2 Data Preprocessing using Term Frequency-Inverse Document Frequency

For Sentiment Analysis on a Customer Feedback Dataset, the best technique is to use Logistic Regression combined with TF-IDF for feature extraction. TF-IDF converts the textual data into numerical vectors, where each word's importance is calculated based on its frequency in a document relative to its frequency across the entire dataset. The TF-IDF value for a term t in a document d is given by in Eq. (1),

$$\mathrm{TF}-\mathrm{IDF}(t,d)=\mathrm{TF}(t,d)\times\mathrm{IDF}(t,D) \tag{1}$$

Where, TF (t, d) is the term frequency, and IDF (t, D) is the inverse document frequency. These features are then fed into a Logistic Regression model, which estimates the probability of a sentiment being positive or negative using the logistic function is defined as Eq. (2),

$$P(y=1\mid x)=\frac{1}{1+e^{-z}} \tag{2}$$

Where, $z=\beta 0+\sum_{i=1}^{n}\beta_i x_i$ is the linear combination of features x_i (TF-IDF values), and β_i are the learned coefficients. This technique effectively classifies customer feedback based on sentiment polarity (positive or negative), providing valuable insights into customer satisfaction.

4.3 AI-Powered Test Case Creation using Natural Language Processing

GPT-3 uses a transformer architecture to generate text, including test cases for CRM systems, by leveraging a powerful self-attention mechanism. This mechanism enables the model to weigh the importance of different words in the sequence when generating output. The core of this mechanism is the scaled dot-product attention, where the attention for a query Q, key K, and value V is calculated as Eq. (3),

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (3)$$

This equation allows GPT-3 to focus on relevant words in the input (e.g., CRM workflows or customer feedback) while generating test cases. After processing the input, GPT-3 predicts the next word in the sequence using its autoregressive approach, meaning it predicts each token based on the previously generated tokens. The model does this by maximizing the probability of the next token y_{i+1} given the previous tokens y_1, y_2, …, y_i using the formula is mentioned as Eq. (4),

$$P(y_{i+1} \mid y_1, y_2, \dots, y_i) = \text{softmax}(W \cdot h_i + b) \quad (4)$$

Where, h_i is the hidden state representing the previous tokens, and W and b are learned parameters. This approach enables GPT-3 to convert CRM business logic or customer feedback into structured test cases, automating the testing process and improving efficiency.

4.4 Self – Healing Test Automation using CNN

For Self-Healing Test Automation, an effective alternative technique is Computer Vision-Based Object Recognition using CNNs. This approach enables automated test scripts to detect and interact with UI elements dynamically, even when their locators change, by analysing visual structures instead of relying on static selectors like XPath. CNNs process UI screenshots by applying convolutional filters to extract features, detect objects, and classify elements such as buttons, text fields, and icons. The fundamental convolution operation in CNNs is expressed as Eq. (5),

$$Y = f(W * X + b) \quad (5)$$

Where, X is the input image (UI screenshot), W is the learned filter (weights), * represents the convolution operation, b is the bias, and f is the activation function (e.g., ReLU). The model generates a feature map that helps recognize UI components and their positions. When test automation encounters a broken locator, CNN-based object recognition can visually map the correct UI element and auto-update the test script. In the context of a customer feedback dataset, CNNs can also analyse sentiment-associated UI elements (e.g., star ratings, feedback forms) and adjust test scripts based on user interactions, enhancing test adaptability and reducing maintenance overhead.

4.5 Autoencoder Based AI – Driven Analysis & Root Cause Detection

For AI-Driven Defect Analysis & Root Cause Detection, an effective technique is Anomaly Detection using Autoencoders, which helps identify software defects by analysing log files, crash reports, and customer feedback. An autoencoder is a neural network trained to reconstruct normal system behaviour by encoding input data X into a compressed representation Z using an encoder function f_θ, and then reconstructing it back as $\hat{X}$ using a decoder function g_ϕ is classified as Eq. (6)

$$Z = f_\theta(X), \hat{X} = g_\phi(Z) \quad (6)$$

During inference, if a defect (anomaly) occurs, the reconstruction error, calculated using Mean Squared Error (MSE), is high is indicated as Eq. (7),

$$MSE = \frac{1}{n}\sum_{i=1}^{n} \left(X_i - \hat{X}_i\right)^2 \quad (7)$$

If this error exceeds a predefined threshold ϵ\epsilonϵ, the system classifies it as an anomaly is identified as Eq. (8),

$$\text{Anomaly if } MSE > \epsilon \quad (8)$$

In the customer feedback dataset, autoencoders can detect abnormal sentiment trends, such as sudden spikes in negative feedback, which could indicate a system issue or defect. By continuously analysing customer responses, this method helps pinpoint the root cause of failures and prioritize defect resolution efficiently.

5. Results and Discussion

The results and discussions section provides an analysis of the performance of AI-driven software testing through two key metrics: Test Execution Time (T_{exec}) and Defect Detection Rate (D_{detect}). The visualizations generated through Matplotlib offer insights into the efficiency and effectiveness of test execution and defect

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detection across multiple test cycles. By examining the execution times and defect detection rates, we can identify areas for optimization in the testing process, highlighting improvements in AI's ability to detect defects and enhance overall test automation efficiency. These results are crucial for refining AI models and further improving CRM software testing performance.

5.1 Analysis and Visualization of Test Execution Times in Software Testing

This Python script simulates and measures Test Execution Time (T_{exec}) for five test cases by recording the start and end times, with random delays added to mimic real-world test execution. Each test case's execution time is calculated by subtracting the start time from the end time, and these times are stored in a list for further analysis. The Matplotlib library is then used to visualize these execution times in a bar chart, where each bar represents the execution time for a specific test case is displayed in Figure (2),

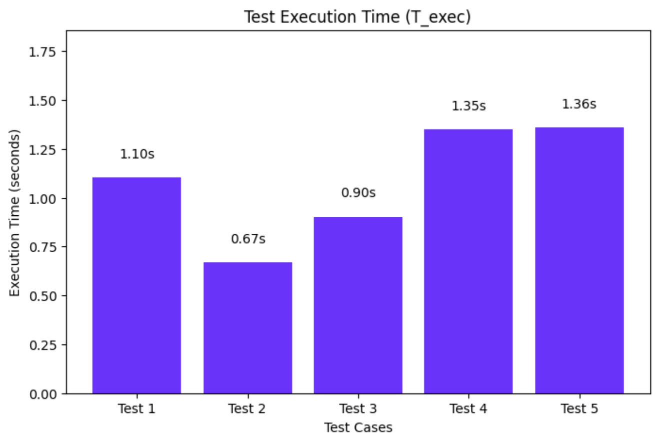

Figure 2: Visualizing Test Execution Time for Optimized Test Automation

The X-axis of the chart corresponds to the test cases (Test 1, Test 2, Test 3, Test 4, Test 5), while the Y-axis represents the execution time in seconds. Each bar is labelled with its exact execution time, and the chart helps easily identify how long each test case takes to run. This visualization aids in pinpointing slow tests, improving test performance, and optimizing overall testing efficiency in AI-driven software testing.

5.2 Analysing AI-Driven Defect Detection Efficiency Across Test Cycles

The bar chart visualizes the Defect Detection Rate (D_{detect}) across five different test cycles. The X-axis represents the test cycles (Cycle 1 to Cycle 5), which correspond to the sequential phases of testing where defects are detected. The Y-axis shows the Defect Detection Rate as a percentage, indicating the proportion of defects identified by AI in comparison to the total defects found during the test cycles. Each bar in the chart represents the Defect Detection Rate for a specific test cycle. The values are displayed on top of each bar for clarity, showing how effectively AI detected the defects during each cycle is shown in Figure (3),

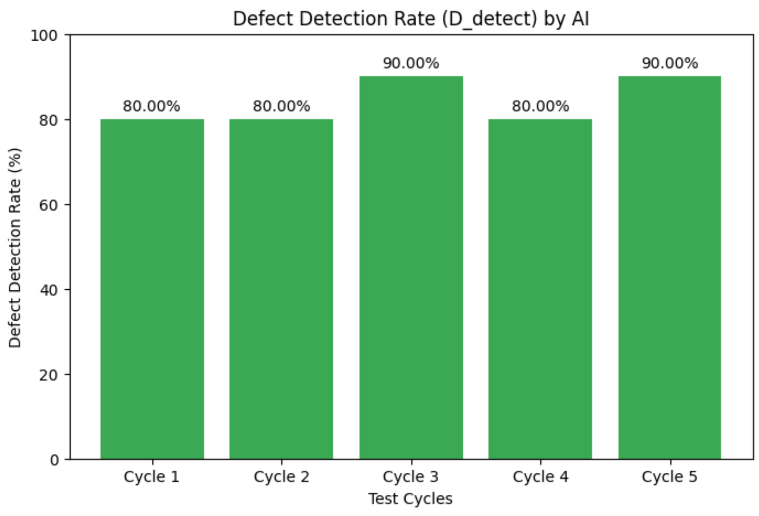

Figure 3: Visualization of Defect Detection Rate in AI-Driven Software Testing

The chart clearly highlights the trend of improvement in defect detection over time, as the AI system continues to detect more defects with increasing accuracy. A higher rate implies that AI is efficiently identifying most of the defects, while a lower rate suggests the AI system might need further optimization. This graph is useful for tracking the performance of AI in defect detection and can be instrumental in improving test automation by enhancing the AI's ability to detect software issues over successive test cycles.

6. Conclusion and Future Works

Introduces an AI-driven software testing approach to optimize CRM system performance, utilizing self-healing automation, generative AI, CNNs, and Autoencoders. The approach improves defect detection, test execution, and overall software reliability by dynamically generating test cases, reducing maintenance overhead, and enhancing test coverage. This framework offers a scalable solution for CRM systems, improving efficiency and customer experience while adapting to frequent updates and complex changes.

Future research could explore the application of the proposed AI-driven testing approach to other types of enterprise software, beyond CRM systems, to assess its broader applicability. Additionally, refining the AI models to handle more complex business logic and user interface changes would improve the adaptability of the system in real-world applications. Further investigation into hybrid AI models combining different machine learning techniques could also lead to more robust defect detection and self-healing capabilities. Another potential direction is integrating real-time monitoring systems to identify issues as they occur, further enhancing the predictive capabilities of the testing framework. Finally, examining the long-term performance and scalability of AI-driven testing in large-scale enterprise environments will provide valuable insights into its effectiveness and potential for broader adoption.

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