ASSESSING QUANTUM EXTREME LEARNING MACHINES FOR SOFTWARE TESTING IN PRACTICE

Asmar Mugeet

Simula Research Laboratory University of Oslo Oslo asmar@simula.no

Hassan Sartaj

Simula Research Laboratory Oslo, Norway hassan@simula.no

Aitor Arrieta

Mondragon University Mondragon, Spain aarrieta@mondragon.edu

Shaukat Ali

Simula Research Laboratory and Oslo Metropolitan University Oslo shaukat@simula.no

Paolo Arcaini

National Institute of Informatics Tokyo arcaini@nii.ac.jp

Maite Arratibel

Orona
San Sebastian, Spain
marratibel@orona-group.com

Julie Marie Gjøby

Welfare Technologies Section,
Oslo Kommune Helseetaten
Oslo, Norway
julie-marie.gjoby@hel.oslo.kommune.no

Narasimha Raghavan Veeraragavan

Cancer Registry of Norway, Norwegian Institute of Public Health, Oslo, Norway nara@kreftregisteret.no

Jan F. Nygård

Cancer Registry of Norway, Oslo, Norway and The Arctic University of Norway Tromsø, Norway jfn@kreftregisteret.no

ABSTRACT

Machine learning has been extensively applied for various classical software testing activities such as test generation, minimization, and prioritization. Along the same lines, recently, there has been interest in applying quantum machine learning to software testing. For example, Quantum Extreme Learning Machines (QELMs) were recently applied for testing classical software of industrial elevators. However, most studies on QELMs, whether in software testing or other areas, used ideal quantum simulators that fail to account for the noise in current quantum computers. While ideal simulations offer insight into QELM's theoretical capabilities, they do not enable studying their performance on current noisy quantum computers. To this end, we study how quantum noise affects QELM in three industrial and real-world classical software testing case studies, providing insights into QELMs' robustness to noise. Such insights assess QELMs potential as a viable solution for industrial software testing problems in today's noisy quantum computing. Our results show that OELMs are significantly affected by quantum noise, with a performance drop of 250% in regression tasks and 50% in classification tasks. Although introducing noise during both ML training and testing phases can improve results, the reduction is insufficient for practical applications. While error mitigation techniques can enhance noise resilience, achieving an average 3.0% performance drop in classification, but their effectiveness varies by context, highlighting the need for QELM-tailored error mitigation strategies.

Keywords Software Testing, Quantum Computing, Machine learning, Quantum Noise

1 Introduction

Machine learning (ML) has enhanced software testing of classical software systems for various activities [1, 2]. Along the same lines, quantum machine learning (QML) [3] is gaining interest in this field [4, 5], aiming to further improve machine learning-assisted software testing with Quantum Computing (QC), which uses quantum-mechanical principles to perform computational tasks [6]. Consequently, it is expected to provide exponential speedups for ML algorithms. Within QML, Quantum Extreme Learning Machines (QELMs) offer an innovative approach to enhance information processing capabilities leading to efficient training of classical linear ML models that can match or even outperform complex ML models [5, 7].

QELMs can potentially address several challenges in machine learning-based software testing, such as high training data cost, test automation complexity, and test environment variability [8]. This is possible due to their ability to map data into higher-dimensional quantum states, which facilitates the development of simpler and more generalizable models [9]. A recent study demonstrated the effectiveness of QELMs in regression testing for industrial elevator software by developing a machine learning model that requires fewer features for predictions compared to the classical machine learning model [5].

However, most studies on QELMs used ideal quantum simulators that do not incorporate quantum noise. While ideal simulations provide valuable insights into the theoretical capabilities of QELMs, they do not reflect the reality since current quantum computers are noisy. Such noise significantly impacts computational accuracy. On the other hand, ideal quantum simulators have high computational costs [10], and simulating large-scale industrial problems with classical computers is often unfeasible [11]. Consequently, the effectiveness of QELMs in real-world applications, especially in the presence of quantum noise, remains largely unexplored.

This paper bridges the gap between ideal simulations and real-world noisy quantum computations by examining the impact of quantum noise on QELM models through the following three industrial and real-world case studies of classical software testing: (1) Industrial Elevator Software: Orona¹–a world leader in building elevators provides this case study. Their dataset is used for machine learning (ML)-based regression testing of industrial elevator software [5]; (2) IoT Application Testing with Medical Device Digital Twins: The second case study is from Oslo City's Health Care department, which is responsible for providing healthcare services to its residents including advanced home care with specialized medical devices. We used a dataset from one particular medical device, i.e., the Karie medicine dispenser [12]. This dataset is used for testing an IoT-based healthcare application with ML-based digital twins of medical devices [13, 14]; (3) Testing Cancer Registration and Support System (CaReSS): The third case study is provided by the Norwegian Cancer Registry's CaReSS software system. The dataset from CaReSS is used for ML-based cost-effective testing [15].

We explore how quantum noise impacts the accuracy and reliability of QELMs under real-world conditions for real-world software testing problems. To cope with quantum noise, several error mitigation methods have been proposed [16, 17, 18]. Therefore, we also assess the feasibility of combining QELMs with noise error mitigation techniques to enhance their applicability on current quantum computers. By focusing on practical applications, we aim to better understand QELMs' resilience to quantum noise and determine their potential as viable solutions for industrial challenges in today's noisy quantum computing era. Our main contributions are as follows: (1) We empirically evaluate the resistance of QELM models to quantum noise through three industrial and real-world software testing case studies from the current practice of one commercial company from Spain and two public sectors from Norway. (2) We assess the performance of QELM models on three real quantum computers from IBM, utilizing their noise models, thereby making it one of the first studies to assess QELMs in noisy conditions for classical software testing. (3) We examine the applicability of quantum noise mitigation techniques to QELMs in the current era of noisy quantum computers.

Our results show that QELMs are impacted by quantum noise despite the claims about their inherent ability to deal with noise. In the Orona dataset, QELM performance dropped to 250% across all noise models during the ML testing phase, highlighting poor results in the regression task. Incorporating noise into both the ML training and testing pipeline improved performance to just above 50%, but the deviation from ideal remained significant. For classification tasks, performance decreased by 50% in the Karie and CaReSS datasets. Noise in the ML pipeline improved CaReSS performance to 30%, but no improvement for the Karie dataset. Furthermore, we observed that, in the context of software testing, ML-based error mitigation methods perform well in classification tasks, but their effectiveness depends on context. ML-based methods performed well in classification, with only a 3.0% deviation from ideal when

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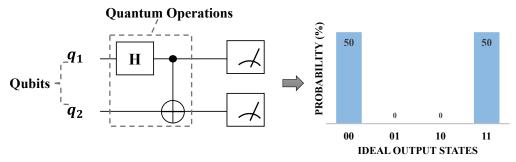


Figure 1: A Two-qubit quantum circuit that creates entanglement between two qubits. The circuit output is an equal probability distribution of two entangled states.

introduced in both the ML training and testing phase, but faced challenges in regression tasks. This underscores that the practical application of QELMs in the current noisy quantum computing era is restricted, encouraging QELM-tailored error mitigation strategies to improve their performance for practical use in software engineering problems and beyond.

2 Background

2.1 Quantum Computing Basics

This section provides an overview of the fundamentals of quantum computing and quantum noise.

Qubits: In classical computing, information is represented using bits, which can only be in one of two states: 0 or 1. In quantum computing (QC), however, the basic unit of information is the quantum bit, or *qubit*, which can exist in a *superposition* of both $|0\rangle$ and $|1\rangle$ states simultaneously, each with a corresponding amplitude (α) . This amplitude is a complex number, characterized by a *magnitude* and a *phase* when represented in polar form. The state of a qubit is expressed using Dirac notation [19] as: $|\psi\rangle = \alpha_0|0\rangle + \alpha_1|1\rangle$, where α_0 and α_1 are the amplitudes associated with the $|0\rangle$ and $|1\rangle$ states, respectively. The likelihood of measuring the qubit in either state is given by the square of the magnitude of its amplitude, with the total probability always summing to 1: $|\alpha_0|^2 + |\alpha_1|^2 = 1$.

Quantum Circuits: Quantum computers are currently programmed using quantum circuits, which consist of a sequence of quantum gates that manipulate the states of qubits. A simple example of a quantum gate is the *NOT* gate, which flips a qubit's state from $|0\rangle$ to $|1\rangle$ or vice versa. In quantum circuits, various quantum gates are applied to create superposition and entanglement between qubits, both of which are essential for processing information. Entanglement is a unique quantum phenomenon where the state of one qubit is directly correlated with the state of another. Figure 1 presents a two-qubit quantum circuit and its corresponding output. This circuit is designed to entangle two qubits. Initially, both qubits $(q_1 \text{ and } q_2)$ are in the state $|0\rangle$. First, a *Hadamard* gate $\mathbb H$ is applied to q_1 , putting it into a superposition of $|0\rangle$ and $|1\rangle$. Then, a *controlled-NOT* gate Φ is used to entangle q_1 with q_2 . After these operations, a measurement operation $\mathbb A$ is performed to collapse the qubits' superposition and entanglement into a definite state of either $|0\rangle$ or $|1\rangle$. The quantum circuit is executed multiple times to generate a probability distribution of the results. This output consists of binary strings, representing the qubits' final states, and their corresponding probabilities indicate how often each outcome occurs over repeated runs.

2.2 Quantum Noise

Current quantum computers are susceptible to quantum noise, which compromises the precision of their computations. Quantum noise arises from various sources. First, environmental factors such as magnetic fields and radiation can impact quantum operations [20]. Interactions between qubits and their environments can lead to disturbances and loss of information in quantum states, a phenomenon known as *decoherence* [21]. Second, unwanted interactions between qubits, even when perfectly isolated from their surroundings, can produce *crosstalk noise* [22], which leads to unintended quantum states. Third, inaccuracies in hardware calibration for quantum gate operations also contribute to noise. Minor calibration errors can result in slight changes in phase or amplitude in qubits. While these changes may not immediately destroy a quantum state, they can lead to undesirable states following a series of gate operations [22]. It is important to note that any qubit in a circuit can be influenced by noise at any stage, resulting in an accumulated effect on the circuit's output. Figure 2 illustrates the difference between the ideal and noisy outputs of the entanglement circuit shown in Figure 1. In the noisy output, states 01 and 10 emerge due to quantum noise, which alters the overall

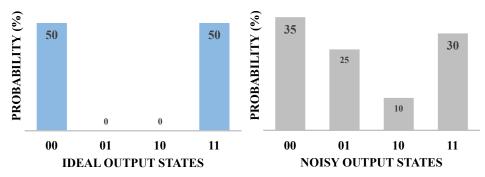


Figure 2: Two-qubit entanglement quantum circuit ideal output and noisy output.

probability distribution of the two entangled qubits compared to the ideal output.

Due to quantum noise in real quantum computers, researchers frequently rely on quantum simulators to run circuits without noise interference [23]. However, ideal quantum simulators are limited by classical computing resources and quickly become impractical, even when using supercomputers, as the number of qubits and operations in a circuit increases [11]. As a result, they are only suitable for circuits with a small number of qubits. In addition to ideal simulators, QC platforms like IBM and Google offer noise models that simulate the noise experienced by their quantum computers. These *noise models* replicate various types of noise, such as decoherence, gate errors, and crosstalk, helping researchers understand how noise impacts quantum computations and enabling error mitigation strategies. Despite their usefulness, noisy simulations also face the same computational limitations as ideal simulators and are only used to approximate real quantum computer behavior for circuits with a small number of qubits.

2.3 Quantum Extreme Learning Machine

Extreme Learning Machine (ELM) is an algorithm proposed to address the limitations of gradient-based backpropagation neural networks [24]. ELM is a single-layer or multi-layer feedforward network where hidden layer weights are randomly assigned and fixed, eliminating the need for iterative tuning of weights via backpropagation. Instead of using gradient descent to minimize an error function, the output of the neural network is used to train a simple linear model for prediction. This approach enables ELM to achieve fast training speeds while maintaining good generalization performance [24]. Quantum Extreme Learning Machine (QELM) is the quantum counterpart of the classical ELM. QELM integrates principles of quantum computing to further enhance the computational power and efficiency of ELMs [25].

Figure 3 compares ELM and QELM, where semantically equivalent components are highlighted with the same color. In classical ELM, the neural network's input layer connects the input data with the hidden layers. It is responsible for transforming the input into a format compatible with the hidden layers (e.g., converting text to numeric representations). In QELM, the equivalent of the input layer is an *Encoder*, which is a quantum circuit responsible for converting classical data into quantum states. Next, in ELM, the randomly initialized hidden layers are responsible for feature extraction and transforming the data into a higher-dimensional feature space, which can be used to train the linear model. In QELM, the equivalent of the hidden layer is the *Reservoir*, a quantum circuit that performs feature extraction and transforms data into a quantum feature space. Finally, in ELM, the output layer extracts the features created by the hidden layer, resulting in a feature vector that is then used to train a linear model for final prediction. In QELM, the measurement operation on the reservoir circuit takes the role of the output layer, returning a classical feature vector after collapsing the superposition and entanglement of qubits.

3 Industrial Context

Classical machine learning has been applied to support classical software testing [2, 1]. In this context, quantum machine learning could replace classical machine learning by leveraging its advantages in computational speed, improved feature extraction, simplified model complexity, and enhanced overall performance [26] to support classical software testing. Along this line, a recent industrial study assessed QELM for regression testing of classical software deployed on industrial elevators [5]. The study highlighted the potential of QELM, where it reduced the number of machine learning features required with QELM compared to the ones required with classical ML models, demonstrating that QELM can outperform classical models in certain situations and has the potential to replace classical ML models for classical software testing. Figure 4 illustrates our application context in which QELM is utilized instead of classical

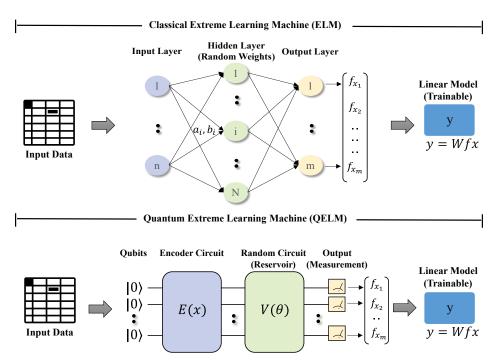


Figure 3: Comparison between classical extreme learning machine and quantum extreme learning machine. The semantically equivalent components in both algorithms are highlighted using the same colors.

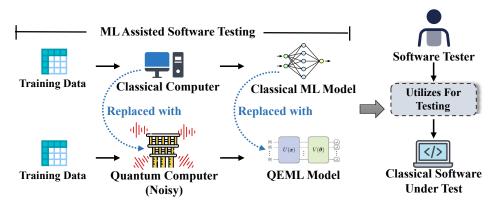


Figure 4: Transition from classical ML-based software testing to QELM-based classical software testing

machine learning to support software testing. In Figure 4, instead of using a classical machine learning model trained on classical data on a classical computer, the software tester employs a QELM model trained on the same classical training data utilizing a current noisy quantum computer. This QELM model can improve performance across various activities, such as regression testing, oracle estimation, and test optimization. Consequently, this setting replaces the classical computer and machine learning model with a quantum computer and QELM model to support the testing activities of the classical system under test.

In this study, we examine three distinct industrial case studies in software testing. Each case study presents a real-world scenario where classical machine learning was applied to support classical software testing. Consequently, classical machine learning can be replaced with QELM to enhance the software testing of the classical software under test. Below, we define the industrial context for each case study.

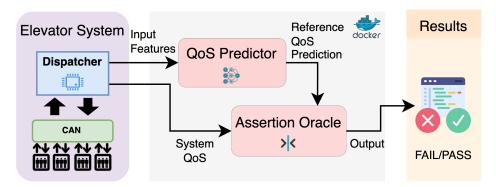


Figure 5: An overview of Orona testing context

3.1 Orona Elevator

3.1.1 Industrial Context

Orona is one of the largest elevator companies worldwide. Elevators aim to safely transport passengers in a building while trying to provide maximum comfort. To measure this comfort, different Quality of Service (QoS) metrics are employed. A well-known QoS metric in this domain is the Average Waiting Time (AWT) of passengers. The waiting time of a passenger refers to the time between the floor call until an elevator attends that call. AWT refers to the average time that a set of passengers need to wait until an elevator serves their call. This metric depends, to a large extent, on the software dispatching algorithm. This algorithm receives as input several data (e.g., the position of each elevator, the weight of each elevator, and their direction), and based on it, its goal is to determine, for each landing call, which is the elevator that should serve it.

3.1.2 ML-based Regression Testing of Industrial Elevator Software

Orona has a suite of elevator dispatching algorithms implemented as software. As with any other software system, these elevator dispatching algorithms evolve over time to handle maintenance (e.g., bug corrections, inclusion of new functionalities, adaption to new hardware demands). Because such systems suffer from the test oracle problem [27], the different versions are usually tested by regression test oracles. Given a set of passengers in a building, the AWTs provided by different dispatching algorithm versions are compared. Ideally, the new version should have better or similar AWT to the old version. These oracles, however, do not scale either when the software needs to be tested at the Hardware-in-the-Loop test levels or when deployed at operation (for run-time monitoring). Therefore, recently, Orona has explored the possibility of using machine learning to predict the QoS (e.g., the AWT) of elevators based on domain-specific inputs (e.g., number of active calls) [28], substituting traditional regression test oracles (as shown in Figure 5). Furthermore, a recent study showed that quantum extreme learning machines can outperform traditional machine-learning techniques in this problem [5]. In the context of this paper, we will study whether the superior performance demonstrated by QELM in Orona's context in [5] still holds under quantum noise.

3.2 Oslo City Healthcare Data

3.2.1 Industrial and Real-World Context

The healthcare department of Oslo City [29] aims to provide efficient and high-quality healthcare services to Oslo residents and extend these services to other counties in Norway. With this aim, Oslo City collaborates with different healthcare companies to develop an IoT-based platform that comprises an interconnected network of smart medical devices, third-party health services, pharmacies, medical professionals, health authorities, caregivers, and patients [30]. In this platform, smart medical devices are essential in providing various health services [31]. These devices are allocated to patients based on their healthcare needs and continuously alert key stakeholders, such as doctors and caregivers, especially in emergencies. For instance, Karie [12] medicine dispenser is one such type of smart medical device, which is developed to deliver timely medications. It retrieves a medication plan from pharmacies, dispenses medicines at the specified time, generates reminder alarms for the patient, and notifies stakeholders about medication adherence. Karie also features a user-friendly interface that can be customized to individual patient preferences, either directly on the device or remotely by caregivers.

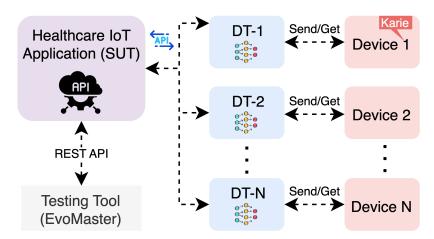


Figure 6: An overview of testing an IoT-based healthcare application with DTs

3.2.2 Testing with ML-based Digital Twins of Medical Devices

System and integration level testing of IoT-based healthcare applications requires incorporating multiple medical devices. However, employing these devices during test execution could potentially result in device damage or service blocking from device servers [13]. Given these challenges, we developed ML-based digital twins (DTs) of medical devices to facilitate automated and thorough testing of IoT-based healthcare applications [30]. Figure 6 shows an overview of test execution infrastructure with medical devices DTs connected to the system under test (SUT). In this setup, a testing tool like EvoMaster [32] generates REST API tests for the SUT. During test execution, the SUT communicates with the DTs that manage all API calls. The DTs then communicate with corresponding physical devices (e.g., Karie) for scenarios such as calibration or synchronization. In this study, we use the Karie device dataset as one of our case studies to assess the potential of QELM in the presence of quantum noise.

3.3 Norway's Cancer Registry Data

3.3.1 Industrial Context

The Cancer Registry of Norway (CRN) collects data about cancer cases across Norway. This data is collected as *cancer messages* sent by various health institutes such as laboratories and hospitals. A cancer message consists of all metadata related to cancer cases, such as diagnosis, treatment history, and follow-up details [15]. More specifically, each cancer message contains detailed information, including the cancer stage, type, topography, morphology, surgical interventions, and medical history. The cancer messages received from various sources are first validated using a well-defined set of rules and guidelines stipulated by international standards, such as ICD-10 and ICD-O-3. Subsequently, CRN analyzes the cancer data and generates statistics to assist policymakers, healthcare authorities, and other relevant stakeholders in decision-making. For this purpose, CRN has developed an automated Cancer Registration Support System (CaReSS) to validate and analyze data and generate statistics [33]. The cancer data and statistics produced with CaReSS are made available for researchers to facilitate cancer research and to improve the quality of the cancer registry system.

3.3.2 ML-based Testing of CaReSS

CaReSS continuously evolves by adding new features, stakeholders, new/revised rules, and enhancements to the rule validation engine, resulting in multiple versions of CaReSS across different environments, such as development and testing. Testing each version across different environments can be both time-intensive and costly. To alleviate the testing cost associated with the evolving CaReSS, we proposed an ML-based approach (namely EvoClass) that predicts and filters whether a test case should be executed on the SUT [15]. As shown in Figure 7, a testing tool like EvoMaster [32] generates an initial set of REST API tests. EvoClass uses a trained ML model to classify tests as likely to lead to success or failure. It discards tests with a high likelihood of producing invalid outputs, possibly due to incorrect input values. The refined set of tests is then executed on evolving versions of CaReSS in a particular environment. In this work, we utilize the CaReSS rule engine dataset as one of our case studies to assess the potential of QELM in the presence of quantum noise.

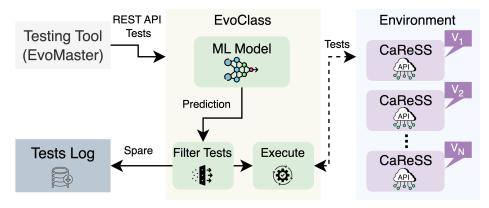


Figure 7: An overview of testing CaReSS

4 Experiment Design

To evaluate the performance and resistance of QELMs to quantum noise, we conducted experiments focusing on two ML tasks, i.e., regression and classification, in the context of three industrial and real-world classical software testing. For each task, we evaluated two distinct scenarios, each reflecting a use case relevant to the practical application of QELM.

4.1 Scenario 1 – Noise Augmentation

We evaluate the QELM's resistance against noise by introducing noise at different stages of a typical ML process. First, noise is added only during the ML testing phase, while the ML training phase is conducted on an ideal simulator. This approach evaluates situations where training can be performed on an ideal simulator, but the computational demands for time and memory are substantial. Such situations arise when the number of qubits (or features in the training data) exceeds the capacity for efficient classical simulation. In these cases, training on an ideal simulator is still feasible, albeit with high computational costs since training is a one-time expense. However, the ML testing or deployment phase may not be conducted under ideal conditions due to high computational demands and the need for quick predictions.

Second, we introduce noise in both the ML training and ML testing phases, evaluating situations where ideal simulation is not an option because the number of qubits exceeds the capacity of current simulators. Here, both training and testing must be performed on real quantum computers, providing insight into QELMs' performance in fully noisy environments.

4.2 Scenario 2 – Integration with Error Mitigation

We explore integrating QELM with quantum error mitigation techniques since noise remains a major challenge when deploying ML models on current quantum computers. Various error mitigation strategies have been proposed to reduce the impact of this noise [16]. This scenario evaluates whether combining QELMs with these techniques can enhance model accuracy and resistance to noise during both the ML training and ML testing phases. Following the same structure as in Scenario 1, we introduce quantum noise and error mitigation methods in two stages: first, only during the ML testing phase, and then during both the ML training and ML testing phases. This approach allows us to assess whether integrating error mitigation techniques can improve the practicality of QELMs for real-world applications in the current era of noisy QC.

4.3 Research Questions

Based on the above two scenarios, we evaluate the noise resistance of QELMs by answering the following research questions (RQs), each considering the training and testing phase in the ML pipeline.

- **RQ1** How resistant is QELM to quantum noise?
- **RQ2** How effective are current practical error mitigation methods for QELMs?

Table 1: Optimal QELM configuration for each case study under ideal simulation, compared with the corresponding classical baselines. The column QELM Configuration shows the best encoder, reservoir, and linear model separated by '-'.

Dataset	QELM Configuration	Metric	Score	Baseline
Orona Karie	HE-Ising-LinearRegression HE-Ising-DecisionTree	MSE Accuracy	11.12 1.0	15.4 0.98
CaReSS	HE-Ising-LogisticRegression	Accuracy	0.92	0.95

4.4 Dataset Characteristics

Orona. The dataset related to the elevator dispatching algorithm used in the experiment contains 12 features, such as the number of upward and downward calls to different floors, the number of calls in the past 5 minutes, and the average travel distance, among others. The same dataset was used in previous studies [28, 5]. The key task of the ML model employed was to predict the average waiting time for a specified period in the future.

Karie. The Karie dataset used for the experiment contains 18 features, including early access to medication, brightness settings, language preference, alarm configurations (e.g., melody, repetitions, and volume), and network connectivity. Note that the dataset with the same features was used to create ML-based DTs in previous work [14]. The primary function of the ML model was to predict the responses (expressed as HTTP status codes) to API requests received from an IoT application to support automated testing.

CaReSS. The CaReSS dataset contains 57 features related to the patient, cancer case, and cancer message. These include key aspects such as patient medical records (e.g., radiation, chemotherapy, hormone treatment), cancer type, tumor behavior, stage, autopsy type, and cancer message validity. The same dataset and features were used in previous work to train a machine learning model for predicting potentially successful or unsuccessful tests [15]. The objective was to execute a minimized set of tests, thereby reducing overall testing costs.

4.5 Benchmarks

QELM Models. As described in Section 2.3, QELM models consist of three primary components. An encoder circuit, which transforms classical data into quantum states. A reservoir circuit, which is responsible for feature extraction and transformation within the quantum system. A linear ML model, which is trained on the quantum features extracted by the reservoir circuit. Several types of encoders and reservoirs have been proposed [7], and the optimal combination of encoder, reservoir, and linear model depends on the specific task. Given the numerous possible combinations of encoder-reservoir circuits and linear models, evaluating all combinations under noisy conditions is impractical. We based our experiment on the encoder-reservoir combination recommended in a software engineering study [5], specifically the *HE-Encoder* circuit for encoding, combined with *Rotation* and *Ising* circuits for the reservoir. For the linear model, we tested three widely used ML algorithms: Linear Regression, Logistic Regression, and Decision Tree Classifier. The performance of these combinations was evaluated on the three industrial datasets, and the results were compared against classical baselines from their respective studies to identify the most effective QELM configuration for each dataset. For all datasets, since the number of features exceeds 10, an ideal simulation becomes computationally expensive. The CaReSS dataset has 57 features; thus, ideal simulation is impractical. Therefore, to establish a baseline for comparison under noisy conditions, we reduce the number of features and select the most important ones that produce results comparable to or better than the classical baseline. The key features are chosen based on the feature importance scores, determined by using the classical baseline models in the respective studies. This leaves us with three features from the Orona dataset, four from the Karie device dataset, and eight from the CaReSS dataset.

Table 1 presents the results of the best QELM configurations for ideal simulations across the three datasets. In all cases, the combination of the HE encoder circuit and Ising reservoir circuit performed the best. For linear models, linear regression was optimal for the Orona dataset, decision tree for the Karie dataset, and logistic regression for the CaReSS dataset. The *score* column indicates the performance of the best QELM configuration. The *baseline* column indicates the performance of the classical baseline of the dataset. For Orona, the classical baseline is an SVM model. For the Karie dataset, the classical baseline is MeDeT. For CaReSS, the classical baseline is EvoClass. While using only the most important features, the QELM model outperformed the classical baseline for the Orona and Karie datasets, for the CaReSS dataset, the QELM model achieved comparable accuracy to the classical baseline that utilized all 57 features. These QELM models, based on the ideal simulation, will serve as the baseline for comparing the results of noise evaluations in our experiments.

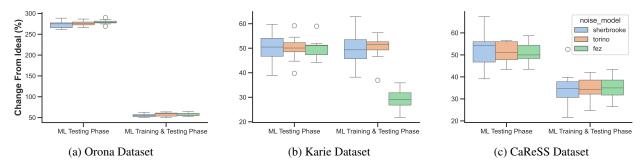


Figure 8: RQ1 – Box plot showing the 10 runs for each dataset on three noise models. The x-axis shows the two phases of noise augmentation and the y-axis shows the percentage change from the ideal values (Score) column from Table 1.

Noise Models. We chose noise models for the noisy simulations based on IBM's real quantum computers. IBM provides the noise models of their quantum computers, which approximate how quantum noise behaves on their actual devices. Specifically, we used the noise models from three IBM quantum systems: IBM Sherbrooke (Eagle r3 processor), IBM Torino (Heron r1 processor), and IBM Fez (Heron r2 processor). Each selected computer represents a different quantum processor provided by IBM, enabling us to evaluate the resistance of QELMs against quantum noise under realistic conditions. All experiments were conducted using IBM's Qiskit framework [34], along with QunaSys's Quri-Paarts library [35], which offers the essential tools for QELM model creation and noise simulation.

Error Mitigation Methods. Various error mitigation methods have been proposed to reduce the impact of quantum noise [16], generally falling into two categories: ML-based error mitigation [17, 18, 36] and non-ML error mitigation [16]. However, each of these methods incurs additional computational costs. For our experiment, we selected one method from each category based on its relevance to the industry. For non-ML error mitigation, the most commonly adopted approach is Zero-Noise Extrapolation (ZNE) [16], which is widely used by companies like IBM. As there is no industry-preferred method for ML-based error mitigation, we chose the Q-LEAR method [17], which is state-of-the-art and has been tested on real quantum computers.

5 Results

5.0.1 RQ1-Resistance to Quantum Noise (Scenario 1)

We executed the best-performing QELM configuration for each dataset in Table 1 10 times, across two phases: noise introduced only during the ML testing phase, and noise present during both ML training and ML testing phase. To evaluate the performance across all datasets, we used the percentage difference from the ideal performance as the metric. Since the Orona dataset involves a regression task, an increase in error indicates worse performance. Thus, for the Orona dataset, we calculated the percentage increase from the ideal as the comparison metric. For the other two datasets (classification tasks), we computed the percentage decrease from the ideal. This approach ensures a consistent metric—percentage change from the ideal—for all three datasets, facilitating cross-comparison. Figure 8 presents the results of 10 runs for each dataset under the three noise models. The x-axis represents the two phases of noise augmentation, while the y-axis shows the percentage change from the ideal values for each dataset.

In Figure 8a, for the Orona dataset, the median percentage change in error exceeds 250% for all three noise models when noise is introduced only during testing, highlighting the extremely poor performance of QELMs on the regression task. When noise is introduced in both the training and testing phases, the median percentage change decreases from over 250% to just above 50%, indicating that the QELM model has some ability to adapt to quantum noise when it is present during both phases. However, the deviation from the ideal performance remains significant, making it challenging to consider the model practical for real-world applications.

For the classification tasks—Karie dataset (Figure 8b) and CaReSS dataset (Figure 8c)—the median percentage change exceeds 50% for all three noise models when noise is introduced only during testing. This indicates poor performance of QELMs on classification tasks, though the impact is not as severe as in the regression task. When noise is introduced during both the training and testing phases, the median percentage change decreases from over 50% to just above 30% for the CaReSS dataset across all three noise models. However, for the Karie dataset, no significant difference is observed for the Sherbrooke and Torino noise models, while the Fez noise model shows an improvement from above 50% to 29%. The fact that Sherbrooke and Torino noise models show improvements in one dataset but not in the other

Table 2: Result of integrating error mitigation methods in both noise augmentation phases. Column T_N shows the result of the integration of error mitigation only on the test time. Column TT_N shows the result of the integration of error mitigation on both train and test time. The row values are the median percentage change from the ideal values. Bold values show the cases where error mitigation provides significant improvement.

a) Integration with ZNE error mitigation

Dataset	Sherbrooke		Torino		Fez	
	T_N	TT_N	T_N	TT_N	T_N	TT_N
Orona	271.8	10.3	271.6	11.4	271.2	1.79
Karie	50.0	50.0	50.0	50.0	50.0	4.0
CaReSS	56.5	34.78	56.5	34.78	56.5	34.78

b) Integration with Q-LEAR error mitigation

Dataset	Sherbrooke		Torino		Fez	
	T_N	TT_N	T_N	TT_N	T_N	TT_N
Orona	307.3	18.7	301.4	22.3	310.0	40.2
Karie	50.0	3.0	50.0	3.0	34.0	3.0
CaReSS	50.0	4.3	56.0	4.3	1.0	0.0

suggests that the ability of QELMs to learn in noisy environments for classification tasks depends on both the dataset and the noise model (the chosen quantum computer). However, even in the case of improvement, the deviation from the ideal is still too large to be practical for real-world applications.

Another observation across all three datasets is that as the number of qubits increases (3 qubits for Orona, 4 qubits for Karie, and 8 qubits for CaReSS), the variance in performance also increases. This suggests that as the number of qubits grows, the model becomes more uncertain, even when noise is present during both training and testing phases. This rising uncertainty implies that QELMs struggle with noise resistance as the model size grows, and their predictions cannot be reliably trusted.

RQ1: QELMs struggle significantly with quantum noise. While noise in both training and testing phases reduces its impact on model performance, the deviation from ideal remains too large for practical use. The variability across datasets and noise models suggests inconsistent noise adaptability, and the uncertainty in prediction increases with the increase in qubits, indicating limited scalability and reliability of QELMs under noisy conditions.

5.0.2 RQ2-Integration with Error Mitigation (Scenario 2)

We executed the best-performing QELM configuration for each dataset in Table 1 10 times, similar to RQ1, focusing on two phases: error mitigation during the ML testing phase only and error mitigation during both ML training and ML testing phases. We applied the same metric—percentage change from ideal—for cross-comparison between the three noise models. Our evaluation revealed that integrating error mitigation in any phase significantly reduces the variance across multiple runs, leading to lower uncertainty in the QELM models. Therefore, we report the median results from the 10 runs for better readability. Table 2 shows the result of integrating error mitigation methods. The column labeled T_N displays the outcomes when error mitigation is applied only during the test phase, while column TT_N shows the results when error mitigation is applied during both the training and testing phases. The values in the rows represent the median percentage change from the ideal values. Table 2-a illustrates the results of integrating ZNE error mitigation, and Table 2-b presents the outcomes for the Q-LEAR error mitigation method.

For both ZNE and Q-LEAR error mitigation methods, the only noticeable improvement over the RQ1 results occurs when error mitigation is applied during both the training and testing phases of the QELM models. The ZNE error mitigation method improved performance under the Fez noise model for the Orona and Karie datasets, with median percentage changes of 1.79% and 4.0%, respectively; however, no improvement was observed for the CaReSS dataset. This indicates that the effectiveness of ZNE depends on both the number of qubits (as the percentage change increases

with qubit size from Orona to CaReSS) and the quantum computer used (with improvements seen only in Fez). For a small number of qubits, such as 3 qubits (Orona dataset), ideal simulation is effective, and considering quantum noise is unnecessary. However, for datasets with 4 to 8 qubits (Karie, CaReSS datasets), ZNE does not improve performance, rendering it impractical for real-world applications.

The Q-LEAR error mitigation method shows significant improvement in classification datasets (Karie, CaReSS) across all noise models. For the Karie dataset, Q-LEAR shows a median percentage change of 3% for all noise models. For the CaReSS dataset, Q-LEAR shows a median percentage change of 4.3% for Sherbrooke and Torino noise models and 0% for the Fez noise model. However, for the regression task, Q-LEAR underperforms compared to the ZNE method. This suggests that, unlike ZNE, Q-LEAR is less dependent on qubit size and the quantum computer used but is more influenced by the type of problem being solved. One reason for Q-LEAR's better performance in classification tasks is due to the nature of the task itself. In classification tasks, machine learning models focus on identifying patterns that correspond to specific classes. As long as distinguishable patterns exist, ML models can learn effectively, even if the specific feature values vary. In contrast, regression tasks rely heavily on the accuracy of the feature values. For ML-based error mitigation methods like Q-LEAR, if the noise-reducing model preserves the patterns necessary for classification, the QELM model can still perform well. This is reflected in Q-LEAR's weaker performance in regression tasks, where it struggles. This suggests that Q-LEAR may alter the feature values when mitigating noise, but it retains the overall patterns for each class, benefiting classification tasks but impairing regression performance, where precise feature values are crucial.

The effectiveness of ZNE and Q-LEAR largely relies on the specific context in which they are used. ZNE's performance is constrained by the size of the qubits and the noise model, whereas Q-LEAR is affected by the characteristics of the task at hand. Neither method is universally applicable to all QELM applications, highlighting the importance of developing error mitigation strategies tailored to benefit QELM models.

RQ2: Integrating error mitigation methods enhances the noise resistance of QELMs, but their effectiveness is context-dependent. Non-ML-based methods like ZNE are constrained by qubit size and noise models, whereas ML-based methods like Q-LEAR excel in classification tasks but struggle with regression. This underscores the necessity for tailored error mitigation strategies to optimize the performance of QELM models for real-world applications.

6 Threats to validity

Construct Validity. A potential threat lies in the metrics used to assess the noise resistance of QELMs. We addressed this by using the percentage change from the ideal QELM model score as the comparison metric, where the ideal score is calculated based on the same metrics used in the original case studies for classical baselines. This allows for a fair comparison of classical baseline ML models with QELM models.

Internal Validity. A potential threat arises from the QELM configuration used across all three datasets. To mitigate this, we selected the best-performing configuration of the encoder-reservoir-linear model for each dataset under ideal conditions (no quantum noise) based on the study [5] and a preliminary experiment. We evaluated this optimal setup under noisy conditions. Real-world applications aim to maximize performance, so evaluating the best configuration helps to understand how well the QELM model performs under noise in practical scenarios.

Conclusion Validity. In the case of QELM models, the introduction of quantum noise adds inherent randomness, which can cause variability in the outcomes. To mitigate this issue and reduce the impact of random bias, we conducted 10 repeated runs for both research questions (RQs) to draw reliable conclusions.

External Validity. One challenge is the selection of case studies. We chose realistic industrial case studies where classical ML models are already in use, demonstrating that QELMs can potentially replace them for improved performance and accuracy. Another threat stems from the noise models used in simulations. To address this, we used noise models from three different real quantum computers provided by IBM, enabling us to evaluate QELMs in realistic, practical scenarios.

7 Discussion and Lesson Learnt

7.1 QELM Applications in Software Engineering

QELMs offer potential advantages in performance and accuracy for tasks where classical machine learning models are typically used for classification and regression. Consequently, this applies to applying classical machine learning techniques for classical software engineering tasks—a widely studied topic in recent years [1, 2]. Software engineering tasks, such as requirements engineering, design and modeling, implementation, testing, and project management, all benefit from classical machine learning models. Specific tasks like requirements tracing, user story detection, automated software modeling, code smell detection, test case generation and optimization, project cost estimation, and performance prediction [1] are prime examples. In all these tasks, QELMs could potentially replace classical machine learning models, delivering improved performance and efficiency. Nonetheless, further investigation is needed.

However, in the current era of noisy quantum computing, QELMs are only practical for small-scale problems. For tasks requiring fewer qubits, such as those involving 1-8 features, QELMs can be simulated on ideal quantum simulators, enabling noise-free execution and better results than classical models. As task complexity increases and the number of qubits grows, ideal simulations become infeasible. Our findings indicate that QELMs are not sufficiently resistant to quantum noise, preventing them from reaching their full potential on real quantum computers. This limitation hinders the scalability of QELMs, making them less viable for large-scale industrial applications in software engineering. To tackle these challenges, a promising approach is to explore methods for breaking complex problems into smaller subproblems, enabling ideal computations that can be managed more effectively with fewer qubits. Numerous techniques from classical computing, such as graph partitioning [37] and hierarchical decomposition [38], can be investigated and adapted for use. Additionally, developing enhanced encoding methods could allow for greater information compression into fewer qubits. This direction aligns with ongoing research in QML [39], and our future work will also focus on these strategies in the context of software testing.

7.2 Practical limitations

For QELM models to be practically applicable to larger problem sizes, using real quantum computers is essential, making error mitigation techniques crucial. However, our study shows that the QELM performance with error mitigation is highly context-dependent, varying with the application and the quantum computer used. Additionally, error mitigation methods introduce significant computational overhead. Both ML-based and non-ML-based methods require multiple quantum circuit executions to calculate their respective features to mitigate noise, which dramatically increases computational costs as problem sizes grow. For instance, the fastest method in our study, ZNE, requires at least three repeated executions per circuit, tripling the computational cost for predicting a single data point. This time cost can negate the advantages of using QELMs, limiting their practical use. In specialized areas, such as medical or safety-critical systems, where either quantum dynamics play an important role or small improvements can yield significant benefits, QELMs with different error mitigation methods to find a working combination on real quantum computers may be worth exploring. However, for more general applications, deploying QELMs with current quantum technology will require customized strategies and task-specific error mitigation techniques.

8 Related Work

QML has emerged as a promising field that harnesses quantum computing to enhance classical ML models, with applications across numerous domains. Researchers have systematically investigated QML's potential to outperform classical methods in various tasks. A recent survey of 94 papers on QML applications [40] identified the most commonly used algorithms as quantum neural networks (QNN), quantum kernel models (QKM), variational quantum eigensolver (VQE), quantum approximate optimization algorithm (QAOA), and quantum annealing. These algorithms show promise in fields such as image processing, natural language processing, software engineering, and physics simulations [40]. Specifically, in software engineering, quantum annealing [41] and QAOA [4] have been applied for test case minimization, and QELM is utilized for regression testing in software systems. Despite the broader exploration of QML, limited studies have focused on its performance in the presence of quantum noise. Previous research [25, 42, 43] has examined the adaptability of QML to quantum noise and compared it to classical ML algorithms. One study [43] found that VQE-based QML models could perform classification tasks under noise in the IoT domain. Other studies [25, 42] concluded that QELMs demonstrate greater resistance to quantum noise than algorithms like VQE and QAOA, which suffer from issues like barren plateaus that hinder their learning capacity.

Most existing research focuses on ideal quantum simulations, with limited studies exploring the effects of noise. The studies that examine the quantum noise effect [25, 43, 42] do not consider practical industrial applications but instead provide insight into the general learning capacity of QML models under noisy conditions. In contrast, in our

study, we conduct experiments to evaluate the real-world applicability of QELMs for software engineering industrial applications in the current era of noisy quantum computers.

9 Conclusion

Quantum Extreme Learning Machines (QELMs) are a novel quantum machine learning approach that enhances information processing through quantum-mechanical principles. Recent research highlights their potential across various fields, including software engineering. This paper evaluated the practical application of QELMs under realistic quantum noise conditions across three industrial case studies in classical software testing in practice. Our results show that QELMs perform well in ideal simulations; however, they are significantly affected by quantum noise, limiting their practical utility on current noisy quantum computers. Although augmenting quantum noise during training and testing improves performance, the impact of noise remains too substantial for effective real-world use. Error mitigation techniques can enhance noise resistance, but their effectiveness varies by context. Non-ML-based methods depend on factors like qubit size and the specific quantum hardware, whereas ML-based methods perform well in classification but struggle with regression tasks. This highlights the need for QELM-specific error mitigation strategies to enhance their applicability in noisy quantum environments.

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References

- [1] S. Wang, L. Huang, A. Gao, J. Ge, T. Zhang, H. Feng, I. Satyarth, M. Li, H. Zhang, and V. Ng, "Machine/deep learning for software engineering: A systematic literature review," *IEEE Transactions on Software Engineering*, vol. 49, no. 3, pp. 1188–1231, 2022.
- [2] Z. Kotti, R. Galanopoulou, and D. Spinellis, "Machine learning for software engineering: A tertiary study," *ACM Comput. Surv.*, vol. 55, no. 12, Mar. 2023. [Online]. Available: https://doi.org/10.1145/3572905
- [3] J. Biamonte, P. Wittek, N. Pancotti, P. Rebentrost, N. Wiebe, and S. Lloyd, "Quantum machine learning," *Nature*, vol. 549, no. 7671, pp. 195–202, 2017.
- [4] X. Wang, S. Ali, T. Yue, and P. Arcaini, "Guess what quantum computing can do for test case optimization," *CoRR*, vol. abs/2312.15547, 2023. [Online]. Available: https://doi.org/10.48550/arXiv.2312.15547
- [5] X. Wang, S. Ali, A. Arrieta, P. Arcaini, and M. Arratibel, "Application of quantum extreme learning machines for qos prediction of elevators' software in an industrial context," in *Companion Proceedings of the 32nd ACM International Conference on the Foundations of Software Engineering*, ser. FSE 2024. New York, NY, USA: Association for Computing Machinery, 2024, pp. 399–410. [Online]. Available: https://doi.org/10.1145/3663529.3663859
- [6] J. Preskill, "Quantum computing in the NISQ era and beyond," Quantum, vol. 2, p. 79, 2018.
- [7] K. Nakajima and I. Fischer, *Reservoir computing*. Springer, 2021.
- [8] Z. Khaliq, S. U. Farooq, and D. A. Khan, "Artificial intelligence in software testing: Impact, problems, challenges and prospect," *CoRR*, vol. abs/2201.05371, 2022. [Online]. Available: https://arxiv.org/abs/2201.05371
- [9] K. Fujii and K. Nakajima, *Quantum Reservoir Computing: A Reservoir Approach Toward Quantum Machine Learning on Near-Term Quantum Devices*. Singapore: Springer Singapore, 2021, pp. 423–450. [Online]. Available: https://doi.org/10.1007/978-981-13-1687-6_18

- [10] E. Younis, K. Sen, K. Yelick, and C. Iancu, "QFAST: Conflating search and numerical optimization for scalable quantum circuit synthesis," in 2021 IEEE International Conference on Quantum Computing and Engineering (QCE), 2021, pp. 232–243.
- [11] Y. Zhou, E. M. Stoudenmire, and X. Waintal, "What Limits the Simulation of Quantum Computers?" *Phys. Rev. X*, vol. 10, p. 041038, Nov 2020. [Online]. Available: https://link.aps.org/doi/10.1103/PhysRevX.10.041038
- [12] Karie Medicine Dispenser, https://kariehealth.com/, [Online; accessed 2-Oct-2024].
- [13] H. Sartaj, S. Ali, T. Yue, and K. Moberg, "Testing Real-World Healthcare IoT Application: Experiences and Lessons Learned," in *Proceedings of the 31st ACM Joint European Software Engineering Conference and Symposium on the Foundations of Software Engineering*, ser. ESEC/FSE 2023. New York, NY, USA: Association for Computing Machinery, 2023, pp. 2044–2049.
- [14] H. Sartaj, S. Ali, and J. M. Gjøby, "MeDeT: Medical Device Digital Twins Creation with Few-shot Meta-learning," 2024. [Online]. Available: https://arxiv.org/abs/2410.03585
- [15] E. Isaku, H. Sartaj, C. Laaber, T. Yue, S. Ali, T. Schwitalla, and J. F. Nygård, "Cost Reduction on Testing Evolving Cancer Registry System," in 2023 IEEE International Conference on Software Maintenance and Evolution (ICSME). IEEE, 2023, pp. 508–518.
- [16] R. LaRose, A. Mari, S. Kaiser, P. J. Karalekas, A. A. Alves, P. Czarnik, M. E. Mandouh, M. H. Gordon, Y. Hindy, A. Robertson, P. Thakre, M. Wahl, D. Samuel, R. Mistri, M. Tremblay, N. Gardner, N. T. Stemen, N. Shammah, and W. J. Zeng, "Mitiq: A software package for error mitigation on noisy quantum computers," *Quantum*, vol. 6, p. 774, Aug 2022. [Online]. Available: https://doi.org/10.22331/q-2022-08-11-774
- [17] A. Muqeet, S. Ali, T. Yue, and P. Arcaini, "A machine learning-based error mitigation approach for reliable software development on IBM's quantum computers," in *Companion Proceedings of the 32nd ACM International Conference on the Foundations of Software Engineering*, ser. FSE 2024. New York, NY, USA: Association for Computing Machinery, 2024, pp. 80–91. [Online]. Available: https://doi.org/10.1145/3663529.3663830
- [18] A. Muqeet, T. Yue, S. Ali, and P. Arcaini, "Mitigating noise in quantum software testing using machine learning," *IEEE Transactions on Software Engineering*, pp. 1–15, 2024.
- [19] P. A. M. Dirac, "A new notation for quantum mechanics," in *Mathematical Proceedings of the Cambridge Philosophical Society*, vol. 35, no. 3. Cambridge University Press, 1939, pp. 416–418.
- [20] S. Resch and U. R. Karpuzcu, "Benchmarking Quantum Computers and the Impact of Quantum Noise," *ACM Comput. Surv.*, vol. 54, no. 7, jul 2021. [Online]. Available: https://doi.org/10.1145/3464420
- [21] R. Alicki, "Decoherence and the Appearance of a Classical World in Quantum Theory," *Journal of Physics A: Mathematical and General*, vol. 37, no. 5, p. 1948, feb 2004. [Online]. Available: https://dx.doi.org/10.1088/0305-4470/37/5/B02
- [22] T. Ayral, F.-M. L. Régent, Z. Saleem, Y. Alexeev, and M. Suchara, "Quantum divide and compute: exploring the effect of different noise sources," *SN Computer Science*, vol. 2, no. 3, p. 132, 2021.
- [23] A. Jamadagni, A. M. Läuchli, and C. Hempel, "Benchmarking quantum computer simulation software packages," *CoRR*, vol. abs/2401.09076, 2024. [Online]. Available: https://doi.org/10.48550/arXiv.2401.09076
- [24] J. Wang, S. Lu, S.-H. Wang, and Y.-D. Zhang, "A review on extreme learning machine," *Multimedia Tools and Applications*, vol. 81, no. 29, pp. 41611–41660, Dec 2022. [Online]. Available: https://doi.org/10.1007/s11042-021-11007-7
- [25] L. Innocenti, S. Lorenzo, I. Palmisano, A. Ferraro, M. Paternostro, and G. M. Palma, "Potential and limitations of quantum extreme learning machines," *Communications Physics*, vol. 6, no. 1, p. 118, May 2023. [Online]. Available: https://doi.org/10.1038/s42005-023-01233-w
- [26] C. Ciliberto, M. Herbster, A. D. Ialongo, M. Pontil, A. Rocchetto, S. Severini, and L. Wossnig, "Quantum machine learning: a classical perspective," *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences*, vol. 474, no. 2209, p. 20170551, 2018.
- [27] J. Ayerdi, S. Segura, A. Arrieta, G. Sagardui, and M. Arratibel, "QoS-aware metamorphic testing: An elevation case study," in 2020 IEEE 31st International Symposium on Software Reliability Engineering (ISSRE), 2020, pp. 104–114.
- [28] A. Gartziandia, A. Arrieta, J. Ayerdi, M. Illarramendi, A. Agirre, G. Sagardui, and M. Arratibel, "Machine learning-based test oracles for performance testing of cyber-physical systems: An industrial case study on elevators dispatching algorithms," *Journal of Software: Evolution and Process*, vol. 34, no. 11, p. e2465, 2022.
- [29] "Norwegian health authority," https://www.oslo.kommune.no/etater-foretak-og-ombud/helseetaten/, [Online; accessed 2-Oct-2024].

- [30] H. Sartaj, S. Ali, T. Yue, and J. M. Gjøby, "HITA: An Architecture for System-level Testing of Healthcare IoT Applications," in *European Conference on Software Architecture*. Cham: Springer, 2024, pp. 451–468.
- [31] H. Sartaj, S. Ali, T. Yue, and K. Moberg, "Model-based digital twins of medicine dispensers for healthcare IoT applications," *Software: Practice and Experience*, vol. 54, no. 6, pp. 1172–1192, 2024.
- [32] A. Arcuri, "EvoMaster: Evolutionary multi-context automated system test generation," in 2018 IEEE 11th International Conference on Software Testing, Verification and Validation (ICST). IEEE, 2018, pp. 394–397.
- [33] C. Laaber, T. Yue, S. Ali, T. Schwitalla, and J. F. Nygård, "Challenges of testing an evolving cancer registration support system in practice," in *Proceedings of the 45th IEEE/ACM International Conference on Software Engineering: Companion Proceedings*, ser. ICSE-Companion 2023. IEEE, 2023, pp. 355–359.
- [34] A. Javadi-Abhari, M. Treinish, K. Krsulich, C. J. Wood, J. Lishman, J. Gacon, S. Martiel, P. D. Nation, L. S. Bishop, A. W. Cross, B. R. Johnson, and J. M. Gambetta, "Quantum computing with Qiskit," *CoRR*, vol. abs/2405.08810, 2024. [Online]. Available: https://doi.org/10.48550/arXiv.2405.08810
- [35] QuanSys, "Quri parts," 2024. [Online]. Available: https://github.com/QunaSys/quri-parts
- [36] T. Patel and D. Tiwari, "Qraft: reverse your quantum circuit and know the correct program output," ser. ASPLOS '21. New York, NY, USA: Association for Computing Machinery, 2021, p. 443–455. [Online]. Available: https://doi.org/10.1145/3445814.3446743
- [37] A. Buluç, H. Meyerhenke, I. Safro, P. Sanders, and C. Schulz, *Recent advances in graph partitioning*. Springer, 2016.
- [38] S. Bansal and M. K. Rana, "An efficient approach of regression testing using hierarchical decomposition slicing." *International Journal of Advanced Research in Computer Science*, vol. 8, no. 7, 2017.
- [39] M. B. Pande, "A comprehensive review of data encoding techniques for quantum machine learning problems," in 2024 Second International Conference on Emerging Trends in Information Technology and Engineering (ICETITE). IEEE, 2024, pp. 1–7.
- [40] D. Peral-García, J. Cruz-Benito, and F. J. García-Peñalvo, "Systematic literature review: Quantum machine learning and its applications," *Computer Science Review*, vol. 51, p. 100619, 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1574013724000030
- [41] X. Wang, A. Muqeet, T. Yue, S. Ali, and P. Arcaini, "Test case minimization with quantum annealers," *ACM Trans. Softw. Eng. Methodol.*, Jul. 2024. [Online]. Available: https://doi.org/10.1145/3680467
- [42] W. Xiong, G. Facelli, M. Sahebi, O. Agnel, T. Chotibut, S. Thanasilp, and Z. Holmes, "On fundamental aspects of quantum extreme learning machines," *CoRR*, vol. abs/2312.15124, 2023. [Online]. Available: https://doi.org/10.48550/arXiv.2312.15124
- [43] S. K. Satpathy, V. Vibhu, B. K. Behera, S. Al-Kuwari, S. Mumtaz, and A. Farouk, "Analysis of quantum machine learning algorithms in noisy channels for classification tasks in the iot extreme environment," *IEEE Internet of Things Journal*, vol. 11, no. 3, pp. 3840–3852, 2024.