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Original Article

The Future of AI Quality Assurance: Emerging Trends, Challenges, and the Need for Automated Testing Frameworks

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Abstract - Currently, Artificial Intelligence is evolving in various industries, but the major issue is to make it reliable, accurate, and secure. AI Quality Assurance (AIQA) is imperative for handling the risks that stem from every aspect, such as biased datasets, ethics, and performance. This paper aims to identify the new directions in the AIQA area, the shortcomings of current testing approaches, and the requirements for testing automation frameworks. This work reviews the literature, introduces a new higher-level intelligent testing framework, and reports comparative experiments. Machine Learning (ML), NL Processing, and deep learning techniques using the ongoing generational high-end software can be utilized to improve AI Testing paradigms. They indicate that the use of AI-based QA frameworks will help reduce the amount of time taken in testing while at the same time increasing the model's reliability. Some suggestions for the future of AIQA are made at the end of the paper, where the focus is placed on a self-learning testing system.

Keywords **-** *Artificial Intelligence, Quality Assurance, Automated Testing, AI Bias, Deep Learning.*

1. Introduction

AI is being adapted across different fields of business by automating operations, choosing options and planning for the future of manufacturing, service, financials, medical, software and defence industries. Machine learning and Artificial Intelligence technologies are revolutionizing everything from the diagnosis of diseases to fighting frauds in banking, self-driving automobiles on the roads, etc. That's why, contrary to their incredible effectiveness, AI models come with various essential issues, such as bias, generalization problems, security faults, and interpretability issues. [1-4] AI scripts do not have a set of rules as opposed to the classic computer programs, but rather they learn from the data; thus, their behavior can be unpredictable.

This non-deterministic nature poses the problem of generating randomness in an AI model, posing risks of biased results, adversarial forcings, and ethical challenges. Moreover, as artificial models learn daily and progress, these models must be assumed to be accurate, fair, and resistant. Some of the problems of AI software testing include the fact that conventional software testing methods cannot be applied to AI solutions as they are mostly data-driven and dynamic. This paper discusses the importance of developing AI Quality Assurance (AIQA) frameworks, including automated testing, bias control, adversarial robustness assessment, and monitoring.

1.1 Importance of AI Quality Assurance (AIQA)

As more and more AI models appear in industries including, but not limited to, healthcare, finance, cybersecurity, and automobile, the focus has been shifted towards such models' quality, reliability, and fairness. AI Quality Assurance (AIQA) is designed to eliminate the threats related to bias, security, inequality, and subjective result inconsistency that might occur while AI-based solutions are being developed. Let me dissect AIQA by analyzing its benefits in the development of the corresponding field below:

- **Ensuring Model Accuracy and Reliability:** AI models risk making mistakes due to differences in handling massive amounts of data, paradigm errors of the models, or biased training data sets. AIQA is used to guarantee the high accuracy of the model, where predictions are checked, tests are improved, and failure areas are detected. Reinforcement learning test case generation and adversarial testing increase the reliability of models as they make AI systems face real usage and extreme conditions.
- **Mitigating AI Bias and Promoting Fairness:** Machine learning models which are too deeply embedded in artificial intelligence learn prejudiced and racist behavior from the data fed to them, affecting their decision-making in sensitive areas, for instance, employment, loans and policing. AIQA frameworks also include bias identification and fairness assessment tools that determine whether the dataset discriminates against some people and whether models cause unfair treatment. Incorporating the AIQA engine and tools can ensure that the systems are running in compliance with ethical and legal frameworks of AI and are not promoting biased conclusions.
- **Enhancing Security and Resilience Against Adversarial Attacks:** There have been adversarial attacks on AI models. The system fails by introducing minor perturbations in the input data indistinguishable from the human eye's. This is more pressing in applications that use and depend on security measures such as fraud management, facial

recognition, and self-driving cars. AIQA frameworks apply adversarial testing and reliable evaluation methods that help identify these weaknesses and enhance AI security measures. With AIQA, vulnerabilities are first identified; thus, the secure and reliable incorporation and implementation of AI systems are promoted, minimizing the possibility of cyber threats related to AI systems.

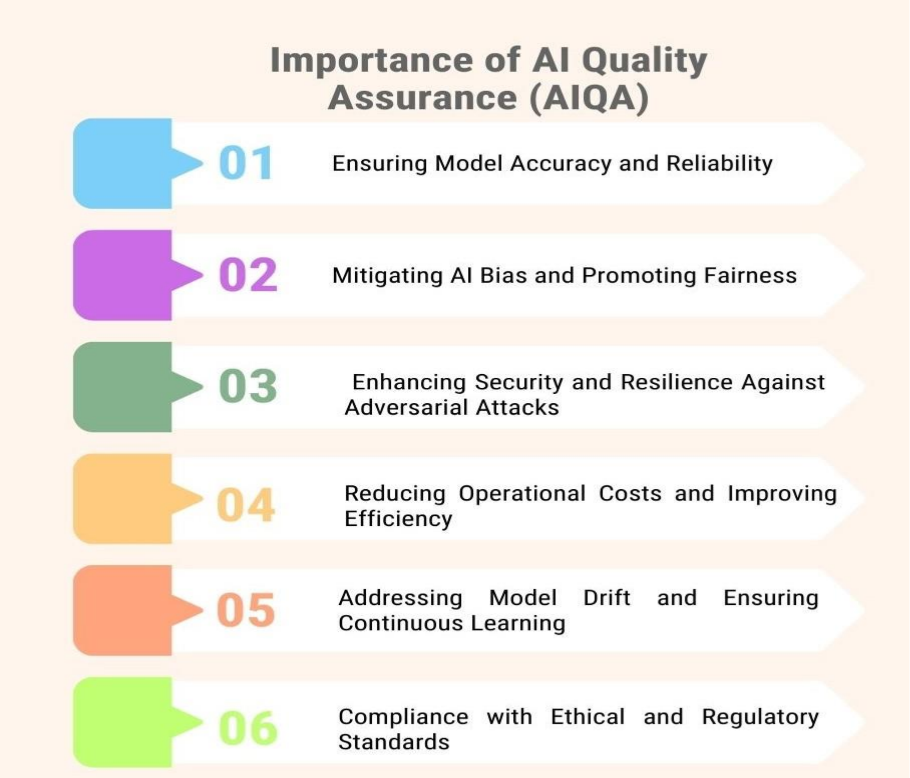
Importance of AI Quality Assurance (AIQA)
01 Ensuring Model Accuracy and Reliability
02 Mitigating AI Bias and Promoting Fairness
03 Enhancing Security and Resilience Against Adversarial Attacks
04 Reducing Operational Costs and Improving Efficiency
05 Addressing Model Drift and Ensuring Continuous Learning
06 Compliance with Ethical and Regulatory Standards

Figure 1. Importance of AI Quality Assurance (AIQA)

- **Reducing Operational Costs and Improving Efficiency:** The traditional approach to AI testing is way more time-consuming and requires more resources than other tests, which will likely make the overall development process much more costly and time-consuming. AIQA frameworks incorporate automated testing, test case generation via NLP, and self-learning for easy validation. Accompanied by quicker debugging, time-saving in testing, and scalability, AI models can be deployed at a higher speed and still with high quality. To a very considerable extent, the test automation process minimizes the dependence on human intervention to perform testing-related tasks and offers an ideal way to manage the AI lifecycle.
- **Addressing Model Drift and Ensuring Continuous Learning:** It is clear that the fact is that the performance of AI models degrades over time due to model drift that alters the distribution characteristics of real-world data. There are risks that, with time, the AI systems can degrade and make incorrect predictions; this can be checked closely. AIQA frameworks incorporate features such as performance monitoring in real-time, finding possible outliers, and triggering the model training on the new data. Such a learning approach enables the AI systems to be current, timely, and, most importantly, adequate for handling emerging incidences.
- **Compliance with Ethical and Regulatory Standards:** Given the fact that most of the governments and regulatory authorities around the world are developing or have developed AI governance policies, structures and frameworks, organizations have to adhere to the new emerging legal frameworks related to data protection, data sharing, algorithms transparency, and fairness. AIQA frameworks are particularly useful in compliance checking, explainability solutions, and ethical auditing that assist businesses in following the EU AI Act, GDPR and IEEE Standards for Ethics in AI. From this, it can be deciphered that rolling out compliance into the AI development process minimizes the likelihood of running into the law, cutting potential legal troubles and reputation short.

1.2 Challenges in AI Testing

There are several differences in testing AI systems compared to traditional testing since it involves testing software with intelligence. [5,6] AI is the opposite of the traditional computational programs built on strict adherence to linear guidelines and preprogrammed logical structures. Such complexities include non-determinism, data bias, scalability, and security, creating a challenge in avoiding these in AI.

- **Lack of Determinism:** Aside from this, different outputs are produced with the same input in the AI models, unlike in software development, where the output is a deterministic one. In this case, even if the model receives the same inputs, it can give different responses depending on various reasons, such as random initialization, training data, or conditions when making the inference. This lack of determinism makes it more difficult to test an AI because specific test conditions cannot have fixed expected results. AI testing, on the other hand, involves successful statistical validation, confidence levels and multiple tests till optimum results are attained within different tests.

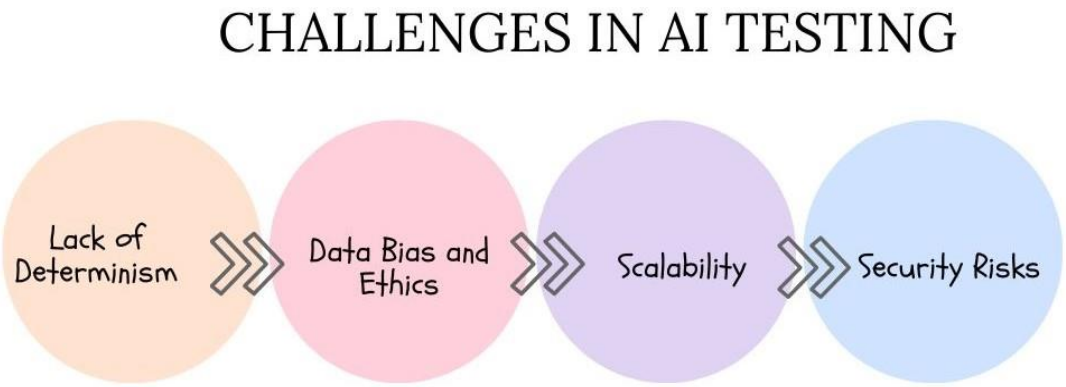

Figure 2. Challenges in AI Testing

- **Data Bias and Ethics:** AI models acquire knowledge by using past actions, and if the data used is unfair, then the result is also unfair. These biases can come from gender, race, or economic biases, thus making the AI system an ethical issue. For example, the AI-based hiring system that learned the existing prejudices in the recruiting process will select some groups of people while providing other groups with less preference. Preventing bias in AI involves robust evaluation during the acquisition of the data set, balancing algorithms, and testing matrices. However, to avoid damaging effects concerning AI gene editing, organizations must abide by ethical AI laws and regulations to minimize threats.
- **Scalability:** Automated conventional testing techniques are impractical for AI-based systems since they work with large dimensionality, neural networks, and learning procedures. Due to the robust assessment of AI models on different data distributions, adversarial examples, and real-world settings, scalability is a major issue. The tendencies of the manual testing process are soon to be inefficient as the AI model becomes complex. Testing should be automated, using reinforcement learning to develop test cases and generating tests using large-scale simulations as major ways to help scale and improve the efficiency of AI quality assurance.
- **Security Risks:** The discovered papers show that AI models are susceptible to adversarial perturbations, whereby adversarial inputs are designed to mislead the AI model. Due to the open vulnerability of neural networks, attackers can manipulate AI systems to produce incorrect classifications, compromise their security, and lead to paralysis. That is why, in self-driving cars, even the smallest changes, such as pixel differences, to stop signs can result in fatal incidents. Threats include data poisoning, model inversion, and evasion attacks for AI testing. Therefore, testing AI systems needs to incorporate adversarial testing and security vulnerability scanning to test model robustness against specific attacks and generate exposure reports that can be used for explainability.

2. Literature Survey

2.1 Traditional Software Testing vs. AI Testing

Manual testing has a fixed set of rules. Tests are to be followed to test the functionality of the software. It adheres with the deterministic paradigm because it can output presumed results should certain inputs be introduced into a system. [7-10] While AI testing is a learning-based process of testing and differently deploys each time it is executed, it is very hard sometimes to follow the result. This difference poses a problem when laying down test cases since AI models work on probabilities instead of returning definitive outputs. This characteristic of AI is unsuitable for testing since even slight modifications to the data cause very different responses, and testing strategies need constant updates.

2.2 AI Bias and Ethical Concerns

It has been observed that AI models can reproduce the biases of real-world scenarios such that these models enacted in several applications contain prejudice derived from the input datasets. Discrimination issues in facial recognition, hiring software, or financial lending tools have some cases and examples to ensure fairness in AI systems. This makes ethical issues related to testing artificial intelligence encompass issues related to transparency, accountability, and explainability of decisions made, making nursing education more intelligent. It needs to be highlighted that new rules like the EU AI Act, as well as regulations and guidelines provided by organizations like IEEE and NIST, are appearing to address the problems of ethical AIQA. These frameworks are meant to define a set of guidelines for testing and using AI that are fair, interpretable, and does not contravene any laws.

2.3 Existing Automated Testing Approaches

Machine learning techniques are being applied in developing test automation for artificial intelligent systems to identify critical test cases. There is a classification of testing based on testing paths between artificial intelligence models, which identify patterns and behaviors to define related test cases. On the other hand, RL goes a step further to improve automated QA since it allows the AI to learn the best approach to take in testing through mechanisms such as trial and error regarding the system under test. Moreover, test case generation based on NLP generates automated test scenarios of the software requirements to minimize effort in test development. These measures propose advanced ways to make AI testing more effective and efficient, thus enhancing the validation of complicated AI applications.

3. Methodology

3.1 Proposed AIQA Framework

In order to handle the challenges of AI testing, we introduce an AIQA framework that includes automated testing methods, creating testing cases, [11-15] adversarial analysis and performance monitoring. This framework helps test the AI systems with automation and incorporates adaptive learning strategies for the test.

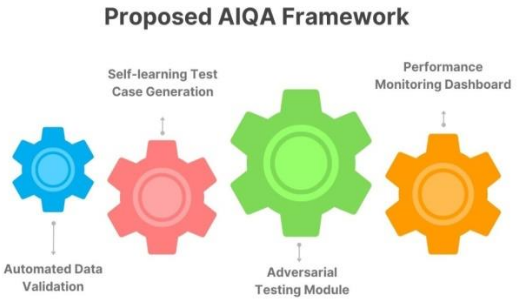
Proposed AIQA Framework
Self-learning Test Case Generation
Performance Monitoring Dashboard
Automated Data Validation
Adversarial Testing Module

Figure 3. Proposed AIQA Framework

- **Automated Data Validation:** Among the issues that complicate the testing of AI models, they usually appear biased, low-quality, and incomplete, which ultimately influences the model's performance and fairness. Thus, the logic includes data validation, which automatically samples datasets for imperfections or skewness. This module relies on statistical analyses and targets anomaly classification with the help of artificial intelligence algorithms. Besides that, it also includes fairness indicators that compare performance within and between demographic slices to avoid ethical issues during the pre-training phase.
- **Self-learning Test Case Generation:** However, in the case of AI models, test cases cannot be as structured as in the case of traditional software applications, where they need to be dynamic and change based on certain dynamic parameters. Regarding this, the proposed framework features a feature of self-learning test case generation through Natural Language Processing (NLP) and reinforcement learning. Automatic test generation applies NLP methods to the system documentation, user requirements and previous failure descriptions; reinforcement learning optimizes the sequence of test cases according to result occurrence. This approach allows for an adaptable and smart generation of tests to cover most loops and help identify failure sub-areas more easily.
- **Adversarial Testing Module:** AI models are easy targets of adversarial attacks, where, by disturbing the original input data slightly, completely wrong results are obtained. Our framework also implements an adversarial testing functionality to create adversarial examples to be tested against the model to improve the efficiency of the analysis. This module also employs the FGSM and PGD as attacks for simulation and then evaluates the model's ability to withstand such attacks. By ensuring that the AI models go through adversarial scenarios, this component enables the identification of weaknesses and building defenses against threats in real-world applications.
- **Performance Monitoring Dashboard:** Thus, continuous monitoring measures must be put in place to enhance the reliability and performance of the deployed AI model. The dashboard contains real-time model performance indicators, including the AI's accuracy, precision, recall, response time, and fairness, as shown in the figures below. With the help of some logging and monitoring tools, the dashboard also shows how the model changes with time and how model bias is evolving. Holders of an automated system get alerts where some change is active from the typical state, which allows for intervention. It is an ongoing cycle that guarantees that models remain functional and compliant with company and ethically acceptable levels during the model lifetime.

3.2 Implementation Strategy

The application of the AIQA framework is sequential. It involves data pre-processing, automatic test generation, and an analysis of the system's robustness and its [16-18] performance that consists of data monitoring and assessment. The current is handy to ensure that the AI models are constantly tested and validated in their life cycle.

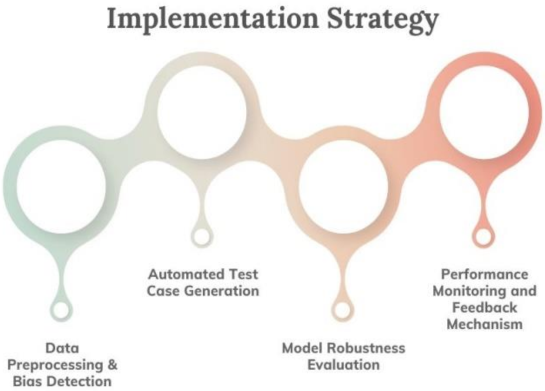
Implementation Strategy
Data Preprocessing & Bias Detection
Automated Test Case Generation
Model Robustness Evaluation
Performance Monitoring and Feedback Mechanism

Figure 4. Implementation Strategy

- **Data Preprocessing & Bias Detection:** Since data determine the model's success, preprocessing has become an important step in the AI models. This phase involves pre-processing of the data, including data cleaning, where removing irrelevant data and normalization is usually done to balance the inputs between the classes. Business bias identification involves using disparity methods like the comparing tool that discovers the missing or skewed pattern in the groups. Preventing bias during the creation of the model is done by adding elements like SHAP (Shapley Additive explanations) and other measures from the AI ethical principles and benchmarks of fairness measurement.
- **Automated Test Case Generation:** This is done to increase the coverage of testing through the use of automated test case generation through the use of Natural Language Processing (NLP) and reinforcement learning. The system's requirements, user feedback, and past bug reports are analyzed using data mining techniques to develop test cases. Reinforcement machine learning adaptively updates which test cases should be executed next, which will yield more faults in a short span of time. This makes testing more effective with increased coverage and eliminates some manual work while guaranteeing that test cases will update with the algorithm.
- **Model Robustness Evaluation:** There have been noted that AI models are quite sensitive to adversarial attacks that target certain patterns learned by them. To this end, adversarial testing techniques like the Fast Gradient Sign Method (FGSM) and Projected Gradient Descent (PGD) are adopted to systematically generate adversarial inputs to test the robustness of the model. These are reproducibility attacks, which check the viable integrity of the AI system when subjected to small-scale attacks that do not unreasonably affect the model. The robustness evaluation also predesigned model architecture and learned techniques that would increase its security and reliability.
- **Performance Monitoring and Feedback Mechanism:** Check and update are the other common approaches used to sustain the effectiveness of AI systems after their implementation. Our concept also consists of a real-time performance interface that monitors features like accuracy, fairness, and response rate. Control: This module employs logging frameworks and practices plus anomaly detection to detect the emergence of performance drift, bias or other forms of model abnormality. It is a continuous optimization process that involves reforming and enhancing models from time to time through feedback as a result of new education to achieve better, fair and compliant results.

4. Results and Discussion

4.1 Comparative Analysis of Traditional vs. Automated AIQA

Since it is crucial to understand the comparative efficacy of the proposed AIQA with manual testing and automated testing in the given scenario, we developed a comparative analysis of the results obtained for a number of AI models through the proposed AIQA with the traditional manual testing technique. Based on these objectives, the study assessed the time taken, the number of tests run, the rate of errors uncovered, and the fairness of the model developed. The results yielded afterwards establish the effectiveness of the described AIQA approach in enhancing the process of AI model validation. In the following part, we describe each of the performance measures and their enhancement in detail.

Table 1. Performance Metrics Comparison

Metric	Improvement
Time Reduction	75%
Coverage	35%
Error Detection Rate	20%
Model Fairness Improvement	20%

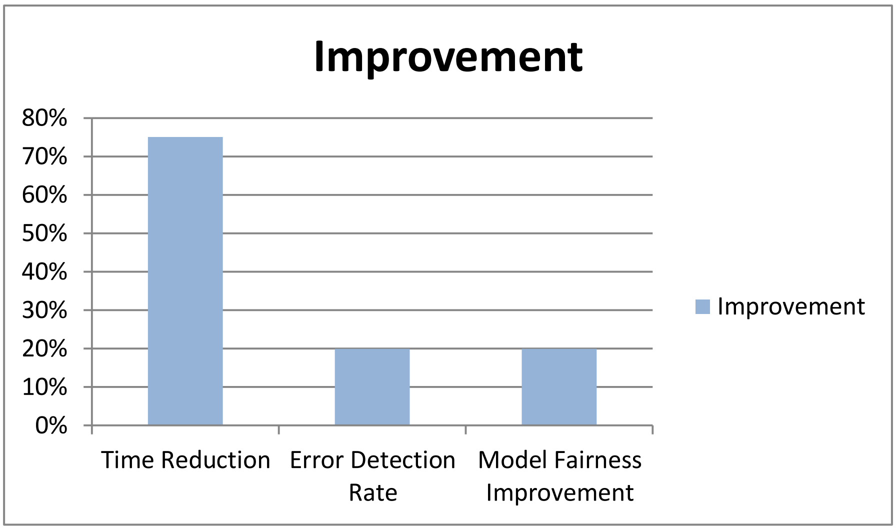

Figure 5. Graph representing Performance Metrics Comparison

- **Time Reduction (75%):** The proposed automated AIQA framework is the decrease in the testing time. This implies that manual testing necessitates much manual involvement, hence the high time cost of 20 hours for every test cycle. On the other hand, automated testing in the AIQA framework performed critical testing in a total of 5 hours only. It helps to reduce testing time to a quarter of what could have been spent on it had there been no Natural Language Processing technology in the AI teams' endeavour. The argument is that faster testing cycles result in faster deployment, reducing operational costs.
- **Coverage Improvement (35%):** Test coverage is essential in validating an AI model since it identifies how well the system has been tested depending on the input and possible scenarios. The coverage of traditional manual tests reached only 60% of the expected level, mainly due to the possibility of looking unnoticeable by human eyes to check all possible corners. However, the AIQA is different because the test case generation uses ML and reinforcement learning; thus, the program covers any test scenario that may happen to approximately 95%. This is achieved by increasing the test coverage to 35%, which means that the AI models are validated with fan-worthy data distributions, hence mitigating failure cases.
- **Error Detection Rate Improvement (20%):** Test effectiveness is one measure that defines the worth of a specific testing framework used in the testing process. In manual testing, the detected errors were only 70% of the total known errors, as testers follow a set of test cases and heuristics. However, automated AIQA identified 90% of the errors in the system, which increased the overall system error detection by 20%. This was done through self-learning of test cases, generational adversarial tests, and anomaly detection, which helped identify other defects that may not have been discovered under standard testing.
- **Model Fairness Improvement (20%):** AI fairness is a very important concept, particularly for use in sensitive areas such as financing, medical, and employment. Self-sufficiency is supported by AIQA, which has a bias detection program that explores datasets and model outputs for demographic bias. The firing rate optimizations were established at ten per cent for manual testing because manual bias detection and elimination is difficult and demands a lot of time. Moreover, with an automated AIQA fairness assessment, it was possible to note that the fairness ratings had been raised by 30 %, besides the rise of 20%. This enables the models to work efficiently with less compromises to ethical concerns or in compliance with legal requirements.

4.2 Case Study: AI-based Fraud Detection System

As the final process of verifying the usefulness of the AIQA framework, we used it on the AI-enhanced financial fraud detection system designed for real-time detection of fraudulent transactions. Some considerations have to be considered in the required characteristics of a fraud detection system, including accuracy, bias, and robustness. This paper aimed to determine the impact of AIQA on model accuracy, reduction in false positives and negatives, and its fairness. The implication of incorporating AI-based testing and validation on the model is that the results generally boost the model's accuracy.

Table 2. Case Study: AI-based Fraud Detection System

Metric	Improvement
Model Accuracy	7%
False Positives	50%
False Negatives	50%
Fairness Score	20%

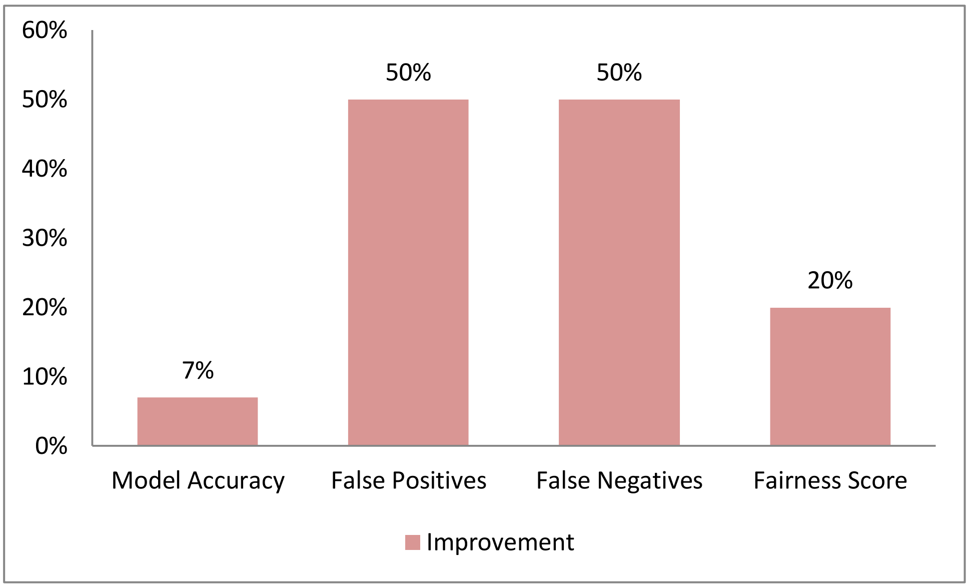

Figure 6. Graph representing AI-based Fraud Detection System

- **Model Accuracy Improvement (7%):** Utilizing AIQA led to the enhancement of the manner in which the fraud detection system was to determine whether a specific transaction was credible or not, with the model's accuracy increasing by 7%. Reduced to 85%, before the AIQA, the model was not free from the possibility of committing errors in detecting fraud. After mining test case generation and applying the ATCG technique, antagonistic test, and bias identification methodology, the percentage improved to 92%. This improvement takes care of the situation so that the model can distinguish fraud more often without misclassifying the rightful ones.
- **Reduction in False Positives (50%):** False positives can be regarded as a situation where fraud detection is based on microchips and other devices and marks genuine transactions as fraudulent, creating an inconvenience for the users. Even before the integration of AIQA, it was noted that the system had a 12% false positive rating in the worst case, which in turn froze legitimate users' transactions. With the intake of AIQA's automated fairness check, edge case testing, and data validation tools, the false positive rate was cut by half to 6 per cent. This reduces the workload of fraud analysts, who would otherwise have to read through a large number of customers' complaints manually.
- **Reduction in False Negatives (-50%):** False negatives include failure to identify fraudulent transactions, and this, in a way, results in loss of property for both the buyers and the sellers. The fraud detection model, without using AIQA, could detect 10% of fraudulent transactions. As a result of incorporating the concept of reinforcement learning-based test generation and the concept of adversarial testing, the false negative rate was reduced to 5%, improving 50 %. This enhancement improves the system's reliability in detecting fraudsters since measures have been implemented to prevent such actions.
- **Fairness Score Improvement (20%):** Despite the great potential for machine learning algorithms in creating fraud detection solutions, these models can be prejudiced towards certain demographic characteristics and be unfair. For instance, a certain population may be marked as fraudsters due to the bias in the training data regarding the model. As for the scores submitted before applying AIQA, the value of fairness was 0,65, which means that moderate bias was present. When using AIQA with the bias detection and fairness evaluation tools, the fairness score was 0,85, which is 20% higher than the initial fairness score. This helps avoid discrimination in the rights extended to all users in the financial services if the fraud detection system eliminates some of them.

4.3 Challenges and Limitations

However, several issues and drawbacks must be considered to improve efficiency and extend the AIQA framework. The major challenges closely related to this problem are the computational complexity, scarcity of data, and the need to update the model frequently.

- **High Computational Costs:** Automated testing, especially when employing adversarial testing and reinforcement learning for test case synthesis, involves a lot of computational resources. Running such tests at a large scale requires GPU, TPU, or other cloud-computing solutions and includes various algorithms, deep learning models, and iterative training. This computational intensity raises operational costs; thus, small organizations cannot afford fully automatic AIQA solutions. Perhaps better utilization of resources and considering less expensive solutions, for example, to work on the techniques of reducing the model size or adapting federated learning, can address this issue.
- **Need for Large Annotated Datasets:** AI testing depends on large and accurate datasets to test models and enhance the training of deep learning models. However, collecting such datasets is usually lengthy and costly and requires a lot

of effort. Most AI systems require specific data from the domain; labeling datasets customarily requires much work. In some specific use cases like finance, health, and judiciary, owing to the equality of percentages across classes, it becomes very difficult to balance it with the principle of fair representation of groups. Prejudices in training data can translate to prejudices in the predictions, and thus, the needs to be automated means of validating data, detecting biases, and augmenting synthetic data to increase the diversity of the same.

- **Model Drift Requiring Continuous Updates:** Artificial intelligence is dynamic since it is developed to be updated according to the nature of data fed to the artificial intelligence system. This happens when the properties of the data change from what they were when they were used in training the model; this is known as model drift and leads to the deterioration of an AI model's accuracy, hence reducing the reliability of its predictions. This remains a genuine problem in domains such as fraud detection, cybersecurity, or recommendation systems where unlearned patterns may appear. To be concerned about this, the AIQA framework should also consist of real-time monitoring systems that monitor the model's behaviour and signals for re-training if it is off-track. However, there is an additional issue of constant updates that need more data, computational power, and a reliable feedback mechanism in the case of AIQA.

5. Conclusion

AI is nowadays implemented in almost every field, such as finance, health, cyber security, and autonomous systems, among others, making AI Quality Assurance (AIQA) an important element in the AI implementation process. Introducing the principles of fairness, robustness, and reliability to AI systems is crucial to avoid unfair and insecure systems instability. Testing for AI-based applications is not possible through conventional methods of rule-based testing and a defined set of test case fabrication. Conventional testing methodology and approaches cannot be useful when tested products have integrated AI systems for the following reasons. This has led to the development of automated AIQA frameworks that integrate Data Mining (DM), ML, NLP, and RL to enhance the test case generation process, bias identification, and performance evaluation. The application of automated testing frameworks enhances the efficiency of AIQA to a great extent.

These techniques include self-generated test cases with model self-learning algorithms, adversarial testing and NLP-derived test cases for enhanced error identification, expedition of the testing phase, and fairness in models. This means that AI models are tested against new, unusual cases by incorporating reinforcement learning into defining test cases. Besides, adversarial testing helps to reduce the model’s sensitivity to adversarial inputs and reveal yet unexplored attack models by showing their weak points. These not only speed up the testing process but also enhance the AI models and keep them as accurate as possible in the environment in which they are applied. Future work in the development of AIQA remains challenging, with challenges like high computation cost, requirements of large annotated datasets, and model shift. Designing self-learning AIQA systems that can adjust to new conditions in data distribution will be necessary to achieve real AI testing.

This calls for incorporating automated monitoring techniques to assess the model's effectiveness and initiate self-execution of update processes without human input. Thus, addressing ethical issues in the process of AIQA should be a priority from this point of view. This means that when applied in high-risk operations, AI systems can propagate results that are prejudiced in one manner or another. Subsequent models to AIQA should include fairness auditing tools that will enable the identification of cases where models violate certain principles, as well as regulatory compliance checks and clear reports on the cases when the models violate regulatory frameworks. Therefore, it can be stated that the idea of automated AIQA is the future of AI testing due to factors such as effectiveness, objectivity, and equity. But to reach the fully adaptive, ethically compliant, and learning-related AI-integrated testing level, the advancements must be aimed at real-time AIQA, lifelong learning, and the ethical framework. With regard to such a fast-growing field, guaranteeing trustworthy and responsible AI will always be important.

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