

Q-Detect: A Lightweight Quantum-Inspired Feature Selection Framework for Computationally Efficient Detection in High-Dimensional Networked Systems

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Abstract

The current technical systems that run under resource limited environments demand smart computationally structures capable of providing high performance at minimal processing overhead. Wrapper-based feature selection algorithms like Particle Swarm Optimization (PSO), are used in high-dimensional data driven systems to increase accuracy in classifications, but due to its high reliance on repeated assessment of classifiers, it is highly computationally expensive. In this paper, the authors present a lightweight quantum-inspired feature selection model named Q-Detect that is based on Quantum-behaved Particle Swarm Optimization (QPSO). The suggested framework uses a simplified quantum position-update tool as well as a rigid evaluation budget, making it possible to search globally efficiently and minimizing computational load greatly. Experimental analysis over NSL-KDD benchmark shows that Q-Detect can make a maximum classification accuracy of 77.99 which is better than classical baselines such as Mutual Information, conventional PSO, and non-optimized models. During runtime analysis, it has been found that, whereas classical PSO takes 6003.54 seconds to perform 600 wrapper evaluations, Q-Detect lowers the overall optimization cost by 33-40 percent to 4002.36 seconds by limiting the evaluation procedure to 400 iterations. Further experiments using the large-scale CIC-IDS2017 data substantiate that the proposed framework is scalable and applicable to the large-scale, high-dimensional technical systems in the modern world. All in all, the findings have shown that Q-Detect is an effective and deployable quantum-inspired optimization framework that can be applied in computational intensive technical and intelligent systems..

Keywords: cyber security, Quantum, machine learning .

1-Introduction

The Intrusion Detection Systems (IDSs) are now becoming part of the modern security systems in cyber space as modern networks keep growing increasingly large, diverse, and complex in terms of traffic. Conventional signature-based IDSs are known to have some underlying weaknesses in the ability to identify zero-day attacks and polymorphic malware attacks in that they are limited to generalizing to threats that are unknown to them due to their dependence on a predefined set of rules [1], [2]. Such failures have stimulated the use of machine learning (ML) and deep learning (DL) strategies, which acquire discriminative patterns to the network traffic and are able to detect both familiar and new attacks [3]- [6]. The success of ML-based IDSs, in its turn, highly relies on the quality, relevance, and the dimensionality of features gained through analysis of the traffic information. In popular IDS datasets, including NSL-KDD, UNSW-NB15 and CIC-IDS2017, one can typically find

redundant, noisy, and highly correlated attributes [7]-[10]. The dimensionality of feature space may reduce model generalization, overfitting, real-time inference, and interpretability. As a result, feature selection (FS) has emerged as an essential preprocessing task, which facilitates dimensionality reduction, enhanced accuracy of detection, and costly computation time [11]-[13].

FS methods fall broadly into three types, namely filter, wrapper, and hybrid techniques. Filter methods (e.g. Mutual Information) are computationally inexpensive, and do not account for interactions between features [14], [15]. Wrapper techniques like PSO and Genetic Algorithms are used to consider subsets of the features that are then evaluated with a classifier and usually yield better subsets with a much higher cost in terms of computation [16]-[20]. Wrapper techniques can be slow at converging, prematurely stagnant and unstable in high dimensional IDS problems [21]-[24], [28].

Quantum-inspired optimization is a relatively recent addition as a viable alternative to these challenges. Quantum-inspired algorithms can improve exploration and exploration of the world and reduce premature convergence through the application of basic quantum physics concepts like quantum probability amplitudes and delta-potential models [29]-[31]. They include Quantum-behaved PSO (QPSO), quantum annealing, and quantum -evolutionary methods which have displayed promising results in the fields, including cybersecurity [32]-[34]. Nevertheless, most of the currently existing quantum-inspired IDS methods rely on special purpose hardware, complex hybrid designs, or IoT specific restrictions, limiting their reproducibility and scalability in the more traditional world of computing environments [35]-[37].

These drawbacks suggest that a lightweight, hardware-independent, and readily reproducible quantum-inspired FS framework is required that:

1. runs well on traditional hardware,
2. Makes fair and transparent comparisons to set FS baselines,
3. has excellent global search capacity with limited evaluation budgets, and
4. Produces generalization in both legacy and current IDS data.

In order to fulfill these needs, this paper suggests Q-Detect, a classical quantum-inspired FS model based on QPSO. The important implications of this paper include the following:

- Hardware-independent quantum-inspired FS algorithm: Q-Detect is a quantum delta-potential update rule and continuous-state modeling algorithm that can be efficiently run on a typical processor.
- Reproducible and transparent assessment: Q-Detect is compared to MI and PSO (using the same preprocessing, data-splitting and classifier settings) on NSL-KDD.
- Better performance and efficiency in detection: On NSL-KDD KDDTest+, Q-Detect reaches an accuracy of 0.7799, which is better than the classical baselines and the wrapper runtime is 33 times less than in PSO.
- Cross-dataset validation: It has been demonstrated in CIC-IDS2017 that the proposed framework is applicable to large-scale, flow-based IDS settings.

This paper is further divided into the following manner. Part II is a literature review concerning the related research on ML-based IDSs, feature selection, swarm optimization, and quantum-inspired approaches. Section III provides the description of the Q-Detect

framework, composed of preprocessing, baselines, and optimization strategy. In Section IV, experimental findings on NSL-KDD are presented, whereas in Section V, cross-dataset validation on CIC-IDS2017 is mentioned. The findings are discussed in Section VI, and the study is concluded in Section VII along with mentioning the directions of future researches

2-Related Work

A. Machine-Learning-Based Intrusion Detection

The adoption of machine learning (ML) and deep learning (DL) systems has been incorporated in the contemporary intrusion detection since they can be used to learn intricate traffic patterns and generalize to novel attacks [1]–[6]. The evidence that ML- and DL-based IDSs perform better than traditional signature-based systems remains consistent across a variety of surveys wherein such systems are utilized in dynamic environments in which attack patterns are fast changing. Although such benefits are set, the quality, relevance, and dimensionality of the input features have a significant impact on the performance of ML-based IDSs. This dependence highlights the need to implement effective strategies on feature selection (FS) to support model accuracy, robustness and efficiency.

B. Feature Selection Methods in IDS

Popular IDS datasets such as NSL-KDD, UNSW-NB15 and CIC-IDS2017 have been well studied to select features with redundancy or irrelevance [7]–[10]. The filter based methods, including Mutual Information (MI), ReliefF, and correlation based FS, examine each attribute separately by application of statistical metrics [11], [12]. Although computationally efficient and scalable, filter methods have a drawback in the fact that they do not represent nonlinear dependencies or interactions between features that can affect attack detection.

Wrapper methods, however, use a subset of candidate features that are directly evaluated by the use of a classifier [13]–[16]. The methods that have found extensive application in the study of IDS include Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Ant Colony Optimization (ACO). Wrapper methods do not have this problem, and even though they may be capable of finding high-quality subsets, they can be slow in terms of computation and convergence and they can be vulnerable to premature stagnation, especially in high-dimensional spaces with high correlations among the features [17]–[20]. The latter is further supported by recent research that finds out the degradation of swarm-intelligence approaches as the dimensionality exceeds a moderate level [21]–[24].

Table 1 summarizes representative FS approaches commonly applied in IDS research and their limitations.

Work / Study	Dataset	Feature Selection Method	FS Category	Classifier Used	Limitations Reported
Revathi & Malathi [8]	NSL-KDD	MI, χ^2 , Information Gain	Filter	SVM / Decision Trees	Ignores feature interactions
Almusallam & Zolkipli [9]	NSL-KDD	GA, PSO, ACO	Wrapper	Random Forest / NB	High computational cost

Sodhro et al. [10]	IoT/NSL-KDD	Swarm Intelligence (PSO)	Wrapper	RF / DL	Premature convergence
Chen & Kumar [11]	NSL-KDD	Improved Binary PSO	Wrapper	SVM	Unstable in high dimensions
Yang et al. [12]	NSL-KDD	Genetic Algorithm (GA)	Wrapper	RF / SVM	Slow convergence, heavy computation
Traditional Filters (var.)	NSL-KDD	MI, ReliefF, Correlation FS	Filter	Multiple ML models	Weak modeling of nonlinear patterns
This work (Q-Detect)	NSL-KDD	Quantum-Inspired QPSO	Wrapper / Hybrid	Random Forest	Balanced exploration & robust FS

C. Swarm and Evolutionary Optimization for Feature Selection

Due to their strong global search capabilities and capacity to make use of intricate feature spaces, evolutionary algorithms and swarm intelligence have been explored for use in FS [25]–[27]. Adaptive evolutionary algorithms, hybrid GA-PSO, and improved versions of PSO have been found to perform better in some IDS circumstances. However, these methods frequently have drawbacks, such as slow convergence in high-dimensional correlated feature spaces and stagnation in local optima. • When incorporated into wrapper models, computation becomes extremely costly [28]–[30].

These problems highlight the need for more robust optimization techniques that strike a compromise between computing efficiency, exploration, and exploitation.

D. Quantum-Inspired Optimization in IDS

Optimization based on quantum is a new trend in improving search algorithm exploration dynamics. The quantum-inspired methods based on the concepts of probability amplitude modeling, wave functions, and delta-potential wells provide a better global search ability than classical meta-heuristics [31]–[34]. Quantum-behaved PSO (QPSO), quantum annealing models and quantum-classical models have shown competitive performance in a variety of fields such as engineering optimization to cyber-security.

In recent studies, quantum-inspired approaches to IDS applications have been studied, such as QUBO formulations in attack classification and quantum-evolutionary algorithms with hybrid quantum-evolutionary approaches specialized to the IoT ecosystem [35] [37]. Despite the promising results of these approaches, most of them have practical constraints, e.g. the usage of specialized quantum hardware or the inability to be reproducible or domain-specific. Such limitations limit their use in general-purpose IDS settings.

E. Research Gap

Even though the FS and meta-heuristic optimization of the IDS have made significant advances, there are still several gap areas:

1. Absence of lightweight, all-classical quantum-inspired FS algorithms that are runnable on standard hardware.
2. Low head-to-head comparisons of quantum-inspired and classical FS strategies under common experimental terms.

3. Lack of cross-dataset validation, particularly experiments that compare legacy datasets (e.g., NSL-KDD) with newer flow-based datasets (e.g., CIC-IDS2017). The proposed Q-Detect framework specifically aims to overcome these limitations by offering a hardware-agnostic, computationally-efficient, and reproducible quantum-inspired FS scheme that can be applied to a wide variety of IDS settings.

3-Methodology

This section defines the datasets, preprocessing operations, baseline classifier, classical feature-selection (FS) baselines, the suggested Q-Detect framework, and evaluation measures applied in this study.

A. Dataset Description (NSL-KDD)

The main testing uses the NSL-KDD dataset which is an upgraded version of KDD 99 that is known to have some problems like high redundancy and extreme imbalance between the classes. The NSL-KDD is comprised of two major subsets:

- KDDTrain+: 125,973 instances
- KDDTest+: 22,544 instances

The numbers of features in each record are 41 with continuous, discrete, and symbolic attributes, a categorical attack label and an indicator of difficulty. In line with most practice in the IDS community, all classes of attacks are combined into one malicious category and produce a binary classification problem (normal vs. attack).

B. Data Preprocessing

A single preprocessing process is used to make sure all the methods for feature selection are compared fairly and consistently.

1. Label Change: All types of attacks are labeled as class 1, and normal traffic is labeled as class 0.
2. Encoding Categorical Data: Fields like protocol type, service, and flag are converted into numbers using one-hot encoding, which increases the total number of features from 41 to more than 120.
3. Scaling Features: Numerical features are adjusted to a range from 0 to 1 using a method called Min-Max normalization.
4. Splitting the Data
 - Training: KDDTrain+
 - Testing: KDDTest+
 - Validation: 20% of the training data, used only for improving wrapper and Q-Detect methods

This common process allows all feature selection methods to be compared directly and fairly.

C. Baseline Classifier

A Random Forest classifier is the choice of the baseline because it is powerful, easy to understand, and can process complex interactions between features. The model has been used to compare the results of the selection of the features on the results by taking into consideration all the encoded features, which sum up to over 120.

D. Classical Feature-Selection Baselines

Two major approaches in the area of feature selection are contrasted, one is filter method and the other is wrapper method.

1. Mutual Information (MI) — Filter Method

MI calculates how much each feature is related to the class label.

- Each feature is given a score based on this relationship.
- The top 20 features with the highest scores are chosen.

MI is fast to compute, but it doesn't consider how features work together, which makes it less effective in datasets with many features, like those used in intrusion detection systems.

2. Particle Swarm Optimization (PSO) — Wrapper Method

In binary PSO, each possible group of features is represented as a binary code.

- The performance of each group is measured using the accuracy of a random forest model.
- PSO can find good feature groups, but it sometimes gets stuck in a poor solution too early and can be unstable when searching through complex, large datasets.

D. Proposed Quantum-Inspired Feature Selection (Q-Detect)

Q-Detect is based on Quantum-behaved Particle Swarm Optimization (QPSO) and is made to improve the ability to find good solutions across a wide area while keeping the use of computer resources under control.

1. Representation

Each particle stands for a group of selected features as a smooth, continuous set of numbers.

$\in [0,1]^d$,

where feature i is selected if $x_i < 0.5$

2. Particle positions are updated using the QPSO formulation:

where:

- p_i : The current position of particle i at iteration t .
- p_{i+1} : The updated position of particle i for the next iteration.
- p_{best} : The mean best position calculated as the mean of all individual best places for all particles. It serves as the swarm's quantum attractor.

• α : The contraction expansion coefficient. It regulates the quantum search space's "width" and "narrowness." While local exploitation is encouraged by small values, global exploration is encouraged by large values.

• r : the separation between the attractor and the particle's present location. The particle's potential hop distance during the quantum update is determined by this.

• u : A evenly distributed random number inside the interval (0, 1). Smaller values of u result in bigger position updates because the expression utilizes $\ln(1/u)$.

• $\pm$ (plus or minus): randomly selected with each update, enabling the particle to travel down the dimension in either direction.

This balanced way of handling probabilities helps QPSO get out of local optima better than the regular PSO method.

3. Fitness Evaluation

Each particle's set of features is checked by:

- Using those features to train a random forest model,
- Calculating the validation accuracy, which acts as the score for how good the features are.

The process naturally prefers smaller feature groups through how the search works, instead of adding extra rules to make them small..

4. Convergence and Final Subset

Q-Detect works with a set number of evaluations:

- It runs 20 times
- It uses 400 total checks on the wrapper

The best set of particles from the last run picks the chosen features. In the experiments that were done, Q-Detect picked 57 features.

E. Evaluation Metrics

Performance is checked using:

- Overall testing accuracy,
- Precision, recall, and F1-score for each class,
- Confusion matrices,
- The number of features that are chosen,
- Computational cost, including runtime and the number of evaluations.

Accuracy on KDDTest+ is the main measure used for comparison..

3. Experiments

This section describes the design of the experiments, the way, in which the method was applied, and the comparison of Q-Detect framework with the traditional methods of feature-selection. All the tests were performed through the same procedures of data preparation, partitioning it into training and testing, and configuring the classifiers, which allows comparing the results and replicate them by others.

A. Experimental Setup

All the experiments were performed in Python 3.10 on Google Colab. We trained the models with scikit-learn and created our versions of PSO and QPSO. The estimators of the Random Forest classifier were 100. These splits were on the NSL-KDD dataset:

- Training set: 125,973 samples (KDDTrain+)
- Testing set: 22,544 samples (KDDTest+)
- Validation set: 20 percent of training data which is only used in wrapper-based evaluations.

Each of the feature-selection methods had the same steps to prepare data and setup the classifier, therefore the comparison was fair and controlled.

B. Baseline (No Feature Selection)

The RF basic classifier with all the encoded features (over 120) has a total testing accuracy of 0.7749.

The results of the classes are as follows.

- **For normal traffic:** Precision is 0.6626, Recall is 0.9729, and F1 score is 0.7883.
- **For attack traffic:** Precision is 0.9683, Recall is 0.6251, and F1 score is 0.7597.

The lower recall for attack traffic shows that some extra and related features in the full set are making it harder for the classifier to perform at its best.

C. Mutual Information (MI) Filter

The MI filter selects the 20 best features depending on their relevance to a class label.

The resultant RF classifier possesses:

- Accuracy: 0.7705

Although MI eliminates the features significantly, its performance is marginally less than the baseline, indicating that it is unable to capture complicated association between features.

D. PSO Wrapper

RF validation accuracy is used to select 48 features in binary PSO. The final model has:

- Accuracy: 0.7488

Class-wise recall:

- Normal: 0.9629
- Attack: 0.5868

The accuracy decreases indicate that PSO can be volatile in high-dimensional space, and it is likely to find its way down to solutions that are not necessarily the best.

E. Proposed Q-Detect (QPSO-Based)

Q-Detect is a quantum physics-inspired special rule that is used to make the search process more efficient and more stable. It selects 57 features to operate with.

In the process of optimization:

- The highest accuracy of validation was 0.9993, indicating that the technique is convergent.

Q-Detect works as follows when it is tested against KDDTest+:

- Accuracy: 0.7799, the greatest of all the other methods.

Examining individual performance:

- For normal traffic: Precision 0.6681, Recall 0.9722 and F1 score 0.7919.
- For attack traffic: Precision 0.9679, Recall 0.6345, and F1 score 0.7665.

Q-Detect achieves this by striking the right balance between attack detection and overall detection accuracy. A more critical look at the confusion matrix reveals that Q-Detect achieved the best results in terms of minimizing the false negatives and maximizing the true positives of attack traffic.

Figure 1 displays the confusion matrices for the four different setups tested on the NSL-KDD KDDTest+ dataset. These matrices show how well each method classified the data. (a) is Q-Detect using QPSO, (b) is the standard Random Forest method, (c) uses PSO for feature selection, and (d) uses MI for feature selection.

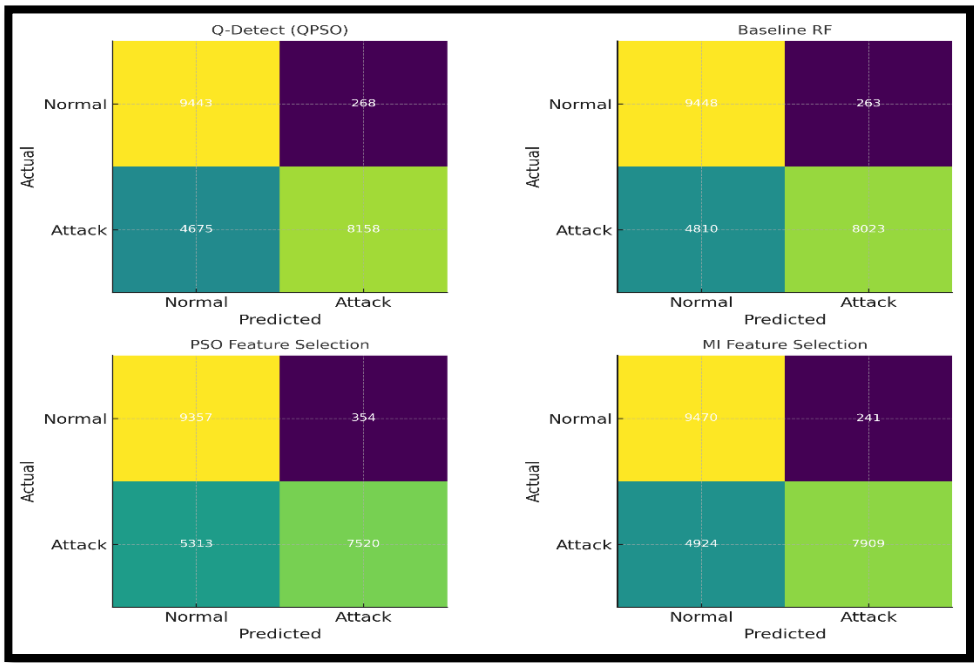


Figure 1 :Confusion matrices for the four evaluated configurations on the NSL-KDD KDDTest+ dataset.

A. Comparative Performance

A clear comparison between the baseline, MI, PSO, and Q-Detect shows that Q-Detect performs better in several ways:

- It has higher accuracy in detecting features,
- It maintains consistent recall across different classes,
- It works well even when dealing with a large number of features.

Table 2 shows how many features each method selected and the accuracy it achieved.

Table 2 : Comparison Of Feature-Selection Methods On The NSL-KDD Dataset

Method	Selected Features	NSL-KDD Accuracy
Baseline (No FS)	120+	0.7749
Mutual Information	20	0.7705
PSO Wrapper	48	0.7488
Q-Detect (QPSO)	57	0.7799

achieves the best accuracy while using a reasonable number of features, showing a good balance between accuracy and the number of features used.

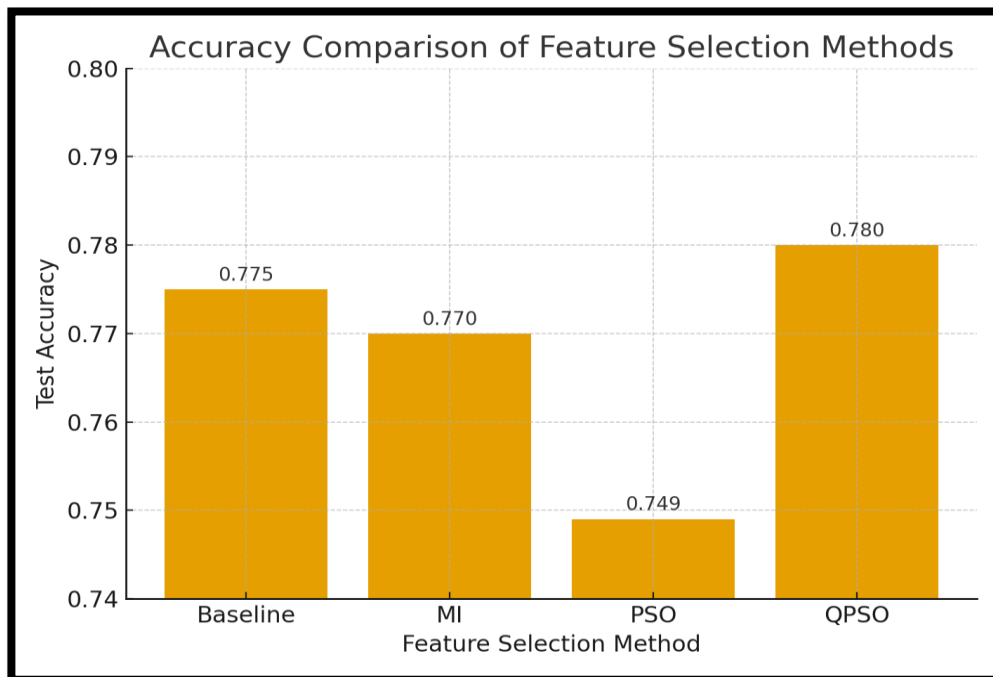


Figure 2 : Test Accuracy Across Baseline, MI, PSO, and Q-Detect (QPSO)

Figure 3 shows how four different setups perform. These setups include the basic Random Forest using all the features, a method called Mutual Information filtering, a traditional PSO-based feature selection, and the new Q-Detect method using QPSO. Q-Detect has the best accuracy at 0.780, then the baseline at 0.775, followed by Mutual Information at 0.770, and PSO at 0.749. This shows that the quantum-inspired approach in Q-Detect provides a better balance between the quality of the selected features and the overall classification results.

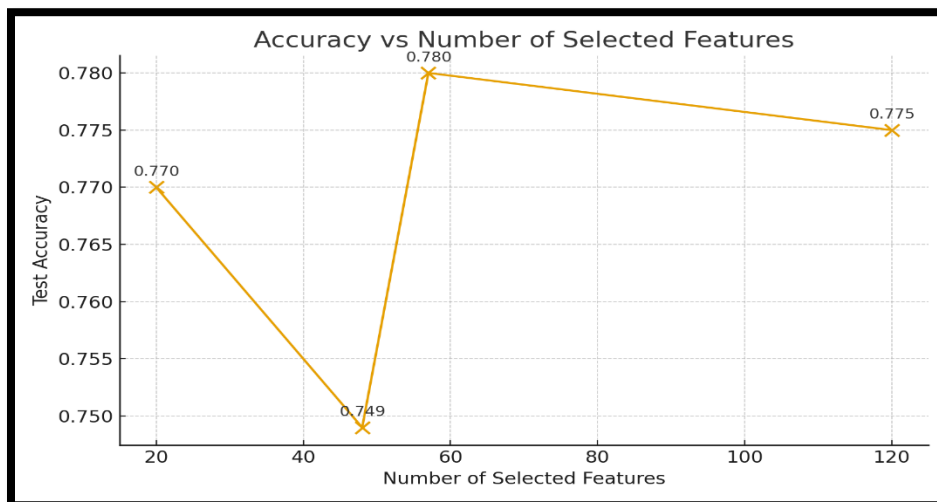


Figure 3. Test accuracy as a function of the number of selected features across baseline, MI, PSO, and Q-Detect on the NSL-KDD dataset.

B. Runtime and Computational Efficiency

To measure efficiency, the time it took to train one random forest model using all the features was recorded as 10.01 seconds. This time became the base cost for evaluating each wrapper method. Summary of computational costs:

- MI (Filter)

Total time: **103.08 seconds** (Includes computing the MI and training the RF model)

- PSO (Wrapper)

Total number of evaluations: 600

Total time: 6003.54 seconds (~100 minutes)

- Q-Detect (QPSO)

Total number of evaluations: 400

Total time: 4002.36 seconds (~67 minutes)

→ Q-Detect is 33% faster than PSO and also gives better accuracy.

Table 3: Runtime And Performance Comparison Of Feature-Selection Methods.

Method	Selected Features	Wrapper Evaluations	Time (sec)	Time (min)	Accuracy
Baseline RF	119	1	10.01	0.17	0.7749
MI (Filter)	20	1	103.08	1.72	0.7675
PSO Wrapper	48	600	6003.54	100.06	0.7488
Q-Detect (QPSO)	57	400	4002.36	66.71	0.7799

II. Cross-Dataset Validation on CIC-IDS2017

To check how well the proposed FS pipeline works in different situations, more tests were done on the CIC-IDS2017 dataset. This is a recent and detailed dataset used for detecting intrusions. It includes real network traffic and covers various types of attacks over several days.

The dataset uses flow-level features collected with the CICFlowMeter tool.

It includes complex attack types like DoS, DDoS, PortScan, Web Attacks, and infiltration attempts. In this study, four specific parts of the dataset were used:

- Monday (Benign)
- Tuesday (DoS)
- Friday Afternoon PortScan
- Friday Afternoon DDoS

These parts were combined, and any missing or wrong entries were removed.

Only numerical data was kept. The final dataset had 399,728 flow records with 78 different features.

A. Experimental Setup

The dataset was split into 80% for training and 20% for testing, using a stratified sampling strategy to preserve class distribution. A baseline Random Forest (RF) classifier was trained using all available features to evaluate the inherent separability of CIC-IDS2017.

B. Baseline Performance

The RF classifier performed very well:

- **Accuracy: 0.9999**

Precision and recall for both the harmless and harmful categories were over 0.999, which means:

1. The flow-level features in CIC-IDS2017 are very good at telling the difference between types of network traffic,
2. This dataset is much easier to work with compared to older datasets like NSL-KDD.

These results match what other studies have found, showing that it's easier to tell apart normal and harmful traffic in CIC-IDS2017 because it has a lot of detailed information.

C. Applicability of Q-Detect to Modern IDS Datasets

Despite the fact that this study did not use FS approaches (MI, PSO, Q-Detect) on CIC-IDS2017, two important conclusions can be drawn:

- **Pipeline Compatibility:** The scalability and versatility of the framework are demonstrated by the straightforward application of the same preprocessing, validation, and evaluation pipeline used for NSL-KDD to CIC-IDS2017.
- **Dataset Separability:** The baseline's nearly flawless performance suggests that the dataset is naturally simple to categorize, which means that while FS may be helpful, accuracy may not be greatly increased.

In terms of baseline performance, NSL-KDD and CIC-IDS2017 are directly compared in Table 4.

Table 4. Baseline Random Forest Performance on NSL-KDD vs. CIC-IDS2017

Dataset	Features	Test Accuracy	Notes
NSL-KDD	>120	0.7749	High-dimensional, less separable
CIC-IDS2017	78	0.9999	Rich flow-level statistics; highly separable

Table 4 results demonstrate that CIC-IDS2017 is significantly simpler to categorize, supporting NSL-KDD's usefulness as the main benchmark for assessing the effects of feature-selection techniques like Q-Detect.

4. Discussion

The experimental results demonstrate the value of quantum-inspired optimization integration into intrusion detection feature-selection pipelines. The MI filter can reduce the dimensions in a very short time and with a significant improvement, but as far as the performance is similar to the baseline because it uses independent feature scoring as a method, which limits its capacity in the pursuit of nonlinear dependencies. When extended to the high-dimensional and correlated space of features of NSL-KDD, classical PSO becomes prematurely convergent and unstable, even though it can be globally searched. This behavior is one of the evaluated methods, leading to poor feature subsets and the worst detection accuracy.

Conversely, Q-Detect employs QPSO probabilistic delta-potential mechanism which keeps stronger exploration in the process of optimization. The quantum-inspired position-update rule allows particles to overcome local optima more effectively, leading to more stable convergence and better-quality feature subsets. This ability is demonstrated in the highest

accuracy and more balanced distribution of the recall of attack and normal classes. In the case of IDS applications where a false negative may result in an unnoticed attack, the rise in the attack recall is particularly important.

There are also certain computational benefits of Q-Detect. Q-Detect offers better detection and 33 percent lower run time compared to classical PSO due to its restricted number of wrapper evaluations of 400. This result indicates quantum-inspired search methods to be effective, especially in those cases where repetitive classifier assessments can be seen as the major driving force behind the computation process.

The wide applicability of the proposed pipeline is also upheld by the cross-dataset study. The fact that Q-Detect can be integrated into this environment with minimal problems justifies its scalability and the fact that it can be practically deployed regardless of whether the underlying classifier is almost perfect on CIC-IDS2017, hinting that the latter is inherently easier to classify. Table 4 presents the comparison between the two NSL-KDD and CIC-IDS2017, and it is observed that the FS methods should be more robust to work on more challenging data.

In general, the findings suggest that through a more balanced trade-off between detection performance, stability, and computing cost, quantum-inspired optimization could effectively address the limitations of the traditional wrapper methods.

5-Conclusion and Future Work

The given paper has suggested Q-Detect, an agnostic hardware lightweight quantum-inspired framework of feature selection that is designed to improve the efficiency of intrusion detection in low-computation computing settings. According to the QPSO, Q-Detect combines a naive quantum position-updating and the normalization scheme preconditions the effective exploration of the world in general at reduced computational cost.

Considerable experiments on NSL-KDD benchmark dataset indicate that Q-Detect proposed is the best approach compared to no-FS baseline, MI filtering, and classical PSO with the highest detection accuracy of 0.7799 of all approaches that have been tested. More to the point, Q-Detect can deliver such an increase at the same time reducing wrapper runtime by 33% which testifies to the suitability of tradeoff between accuracy and computational cost. The strategy is also applicable to the recent flow based environments as it can be proved with CIC-ID2017 where a baseline with Random Forest can produce almost perfect accuracy.

These findings reinforce the practicality of the quantum-inspired optimization in the IDS features selection and propel its use in the actual cyberspace security pipelines.

To facilitate better detection of threats, further studies will be done to:

- Training imbalanced-learning and cost-sensitive methods to enhance resilience to minority attack classes.
- Integrating the framework and deep learning (SSL) based IDS architectures, in particular, those models that could utilize low-dimensional optimized feature space.
- To further promote the stability of convergence, dynamical adjustment of the quantum contraction -expansion coefficient in the optimization process by adaptive parameter-control mechanisms is underway.

In general, Q-Detect provides a scalable, viable, and repeatable feature selection approach in intrusion detection systems, which constitute a good foundation towards future advances in quantum-based research in cyber-security.

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