# Comparative Analysis of Machine Learning, Neural Networks, and Quantum Hybrid Models for DDoS Attack Detection

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## Abstract

Distributed Denial of Service (DDoS) attacks poses a critical threat to the modern network security, the overwhelming systems with malicious traffic and causes service disruptions. In this study, we present a comparative analysis of the DDoS attack detection models which uses three approaches: a machine learning model (K-Nearest Neighbors), a neural network model, and at last a hybrid quantum neural network model. The CIC-DDoS2019 dataset is used for training and evaluation of the model. We have employed advanced preprocessing techniques which includes feature selection through correlation analysis, along with mutual information, and principal component analysis (PCA) which enhances model accuracy.

Our experiments show that while the machine learning model provides a solid baseline for DDoS detection, the neural network outperforms it in terms of accuracy and recall. However, the hybrid quantum neural network (QNN) demonstrates superior performance, with a marked improvement in detection rates and reduced false positives, especially in high-traffic scenarios. The QNN model also offers computational advantages, highlighting its potential for real-time DDoS detection in large-scale environments. Our results suggest that the hybrid quantum models, is in early stages of development, and could be pivotal in advancing cybersecurity measures against DDoS attacks detection.

## INTRODUCTION

The DDoS attacks has became one of the most powerful attacks of cyberattacks in the modern world. These attacks are known to flood the networks, the servers, or applications with overwhelming traffic, making them unable to serve right requests. The DDoS attacks can involves thousands or even lakhs of compromised devices, which are part of botnets, this send huge amounts of traffic to the victim's machine. Attackers uses several techniques, such as volumetric, protocol, application-layer attacks and others, to exploit weaknesses in the network layers. For businesses and service providers, this result in the downtime, financial losses, and also damage to their reputation. The rise of Internet of Things (IoT) devices, which are often less secured, has more exacerbated the threat, as they are frequently attacked and used to amplify these attacks. Traditional DDoS prevention strategies, such as rate limiting, traffic filtering, and rule-based detection, are becoming increasingly ineffective against the evolving complexity of modern attacks.

These approaches struggle to keep the pace with multi-vector attacks, which can change tactics mid-attack to avoid detection. Movinf ahead, as network speeds increase, the volume of the malicious traffic that can be generated also grows more exponentially, making the real-time detection and response critical. This calls for an advanced techniques that can not only detect the attacks but also adapt to dynamic attack patterns, while ensuring a low rate of the false positives.

The need for the more robust and an intelligent DDoS detection systems has led the researchers to explore the use case of machine learning (ML) and also the artificial intelligence (AI). The Machine learning models, particularly the supervised models like the K-Nearest Neighbors (KNN) and also the Support Vector Machines (SVM), have been employed to classify the network congestion and to identify the abnormal patterns which are indicative of a DDoS attack. These models, often struggle with high-dimensional data and require extensive preprocessing of data to improve detection accuracy. Furthermore, we can say that traditional ML models can be computationally expensive when processing of large-scale datasets, which limits their scalability in the real-time environments.

The Neural networks, particularly the deep learning models, offer a more powerful alternative which can detect complex patterns in network traffic. By using multiple layers of abstraction, neural networks can detect even minute anomalies in the traffic that could indicate an attack. However, neural networks require large datasets for training them and are also prone to overfitting, which can result in the poor generalization to new types of DDoS attacks. As attacks evolves , maintaining the high accuracy across different attack remains a challenge till date.

In parallel, we see that quantum computing is emerging as a revolutionary technology which has the potential to dramatically enhance computational tasks, especially in the field of optimization and the pattern recognition. Quantum machine learning (QML) promises to tackle all or some of the limitations of classical machine learning, such as the needs for a large scale datasets and the high computational cost of training the model. By combining the quantum computing model with the neural networks a hybrid model, it is possible to create a more efficient and scalable DDoS detection systems that can quickly adapt to new evolving attack techniques.

### Key Contributions of the Study

The research aims to address major limitations of the existing DDoS detection systems by exploring the capabilities of the hybrid quantum models. The study investigates the performance of the three different approaches: first is the traditional machine learning model (K-Nearest Neighbors), the deep neural network, and at last the hybrid quantum neural network (QNN). The hybrid QNN combines classical neural network architecture with the quantum computing algorithms to enhance its detection efficiency and accuracy**.**

**1. Making of a Hybrid Quantum Neural Network Model(H-QNN):** It proposes the integration of a quantum computing techniques with the neural networks which can create a hybrid quantum neural network for DDoS detection which can detect the attack. The QNN is a model which is designed to optimize the classification of network traffic by using quantum algorithms, which allow the faster and more efficient processing of large, high-dimensional datasets.

**2.Analysis of the Model:** All the three models which are K-Nearest Neighbors, Neural Networks and also Hybrid quantum neural networks are evaluated based on the trained model which was based on the CIC-DDoS2019 datasets. This dataset contains various forms of DDoS attacks hence avails a real case scenario for testing the effectiveness of the model. The research is as well utilized to carry out various critical evaluation metrics assessment including accuracy, precision, recall, f1-score and also the computational efficiency so as to bring out the merits and demerits of each of the approaches used.

**3.Employing the Feature Selection Technique:** The study appraises a range of the combination of the Correlation analysis, the mutual information and the PCA that is the principal component analysis which is crucial in determining the most relevant features from the dataset used. These techniques help reduce the dimensions of data, so that the models in this case are concentrating on the major characteristic or indicators of DDoS attacks, which would aid in enhancing both accuracy and the speed.

**4.Efficiency Overview:** One of the main goals of the DDoS detection is the challenge presented by the interactions involved in the network information processing with minimal system resources. The research gives also emphasizes the resource burdens associated with each model in particular the hybrid QNN that utilizes the quantum computing to cut down the processing time of the model and memory usage. This makes it a feasible solution for the real-time DDoS detection within large scale settings.

**5.Real-World Application:** The outcome of this analysis shows that the HQNN model which although as at now in their infancy but is showing good possibilities of being effectively used as a cyber security system. The deterrent application of HQNN which has the capacity of detecting more diverse kind of attack vectors with very low false positive rate makes it a more alluring solution for organizations which are out to enhance their DDoS defense systems.

By exploring the integration of quantum computing with machine learning and the neural networks, this research advances the state of DDoS detection, providing a suitable framework for more efficient and scalable cybersecurity solutions.

## 3. Literature Review

The DDoS attacks are originally designed to flood the systems by using a high volume of traffic from multiple sources. Previously, detecting these attacks used to be dependent on signature-based methods, where the predefined rules used to flag the known attack patterns. While these methods are effective against the known threats, they may struggle with new, evolving attack vectors and multi-vector DDoS attacks, which combine multiple types of traffic. As a result, signature-based detection systems can become an obsolete quickly to overcome the limitations of a rule-based systems, the anomaly detection methods were introduced. These techniques simply identifies the unusual patterns in a network traffic, and then flag those anomalies that may indicate an attack. However, this approach may face challenges in distinguishing legitimate traffic surges (such as during a product launch or a viral event) from malicious activity, leading the high false positive rates. Recent advancements in the field of machine learning and also the neural networks offer more robust solutions, which enable the systems to adapt and evolve as they learn from the incoming data. By analyzing a vast amounts of traffic data and detecting the subtle variations in patterns, these models can show promise in identifying both known and unknown attacks. The use of the Quantum computing model, has became the most recent advancement, which is now being explored for its ability to handle the complex computations at a much higher speeds, which offers a potential breakthrough in the real-time DDoS detection.

### The Models in the Cybersecurity field: K-Nearest Neighbors (KNN) model

K-Nearest Neighbors (KNN) is an easy to comprehend but effective algorithms in machine learning, it has finding its application in the classification of DDoS attacks. The data points are classified in the KNN model based on their distance with the data points which have been previously classified. The algorithm computes distance between points of data using well-knows metrics such as Euclidean distance, for example and classifies most new points based on the most common class of its surrounding neighbors.

Traffic Classification with KNNs advantages are in their ease of understanding and implementation and they are also non-parametric which means that no statistical distribution is presupposed. This means application of KNN can be optimal in analysis of DDoS attacks where security threat patterns are arbitrary in nature. The model is rather straightforward for deployment and appears to work well on average datasets where there is good differentiation between the good and malicious entities.

Nevertheless, the KNN does have some drawbacks especially when deployed for the real-time DDoS detection. It can get quite expensive on computation when large datasets are involved, since every new instance has to be checked against all the existing data points. This presents a difficulty in high speed networks where a quick decision making process is critical. Also, working with the KNN the performance is rather suboptimal in situations when For this reason, the feature selection techniques like he correlation analysis, mutual information, and also principal component analysis (PCA) are often being employed to reduce the dimensionality of the data, which improves the efficiency and accuracy of the KNN model.

### The model for the detection of intrusion: Convolutional Neural Networks (CNN)

The Convolutional Neural Networks (CNNs) which have gained attention for due to its ability to detect complex design patterns in data, particularly in the domains which require spatial pattern recognition. While CNNs are the ones traditionally associated with image recognition tasks, they have also been adapted for network intrusion detection technique true to their capability to handle high-dimensional data.

In the context of the DDoS detection, CNNs can be used to process network traffic data by treating it similarly to the image data. Traffic flows can be represented as a multi-dimensional arrays, with features like a packet size, protocol type, and also traffic volume acting as the input variables. The CNN’s convolutional layers can then be used to automatically learn hierarchical features from the raw traffic data provided, identifying the distinguishing characteristics of malicious traffic. By applying the filters and also the pooling operations, CNNs can reduce the complexity of the data while retaining the most critical information for the accurate detection.

One of the key advantages of the CNNs is their ability to generalize well across various different types of DDoS attacks, which makes them effective in environments where new and varied attack vectors are constantly emerging. It is possible, however, to train the models on labelled data and improve their accuracy with each training cycle. On the downside, these models do incur training costs that can be severe in terms of processing power and memory resources, particularly when training involves large volumes of traffic data. Nonetheless, CNNs are more proficient in processing the high-dimensional aspects of the network data than traditional machine learning models like KNN.

It should be noted that, though the CNNs offer promising performance, they may fallback on overfitting if not hyperparameter tuned properly. To counter this challenge, regularization techniques like dropout and batch normalization are usually implemented to avoid overfitting and enhance a model's ability to perform on unencountered attack patterns..

### The Use of Quantum Models for Security: Hybrid Quantum Neural Networks (QNN)

The Quantum computing is still at the initial stage of its development, yet with its possible applications in cybersecurity such as the DDoS detection, it is becoming more and more vital. Quantum computing is a technological realization achieved by the use of the principles of quantum mechanics, for example the superposition of states and entanglement, that allow a parallel processing of data at unimaginable scale, which cannot be achieved by classical computers.

The Hybrid Quantum Neural Networks (QNNs) is a neural network that takesthe advantages of classical neural networks and combines them with quantum computing techniques. In the DDoS detection, hybrid QNNs as high-dimensional data processors work quicker and with less time using old conventional models. In a QNN, a quantum layer is used to optimize the most resource consuming procedures of various types like feature extraction and classification, where the traditional models are inefficient. This is especially useful in the area of real-time DDoS detection where the cyber defense app must be really quick and precise. One of the predominant advantages of very few available of the hybrid QNNs in DDoS detection is the fact that it can handle the large-scale network traffic datasets.

Moreover, the Quantum algorithms, such as the Quantum Approximate Optimization Algorithm (QAOA) and the Quantum Support Vector Machines (QSVM), can be merged into the neural network architecture to make the training and inference tasks faster. By using the trade of quantum circuits, such as the circuit models, one can detect the difficult patterns in the traffic data that other traditional models cannot detect in real time. However, the use of QNNs is still an emerging field, and there are several challenges to overcome before they can be widely adopted. Quantum computers are not yet readily accessible, and the integration of quantum layers with existing neural network architectures requires specialized knowledge and resources. Additionally, quantum noise and error rates remain a concern in current quantum hardware, though advancements in error correction and quantum gate fidelity are gradually addressing these issues.

Despite these challenges, early research indicates that hybrid QNNs have the potential to significantly outperform classical machine learning and neural network models in DDoS detection, particularly in scenarios involving large datasets and complex attack patterns**.**

## 4. Methodology

The dataset which has been used in this study is that of the CIC-DDoS2019 dataset, which is a dataset created by the Canadian Institute for the Cybersecurity to simulate real-world DDoS attacks. The dataset includes benign and malicious network traffic, which represents a wide variety of DDoS attack types, including the HTTP flooding, UDP flooding, SYN flooding, and also other volumetric and application-layer attacks.

**Traffic Features:** It contains the features such as the source and also the destination IP addresses, ports, protocols, the packet sizes, and timestamps.

**Attack Variants:** The dataset includes the reflection-based and the exploitation-based type DDoS attacks. The diversity of attack vectors in this dataset ensures that the models can be tested against the various DDoS tactics**.**

**Volume:** CIC-DDoS2019 is very large dataset, which consist of millions of records, each with more than 80 features which represent detailed network flow information. This dataset also mimics the traffic patterns encountered in large-scale enterprise networks.

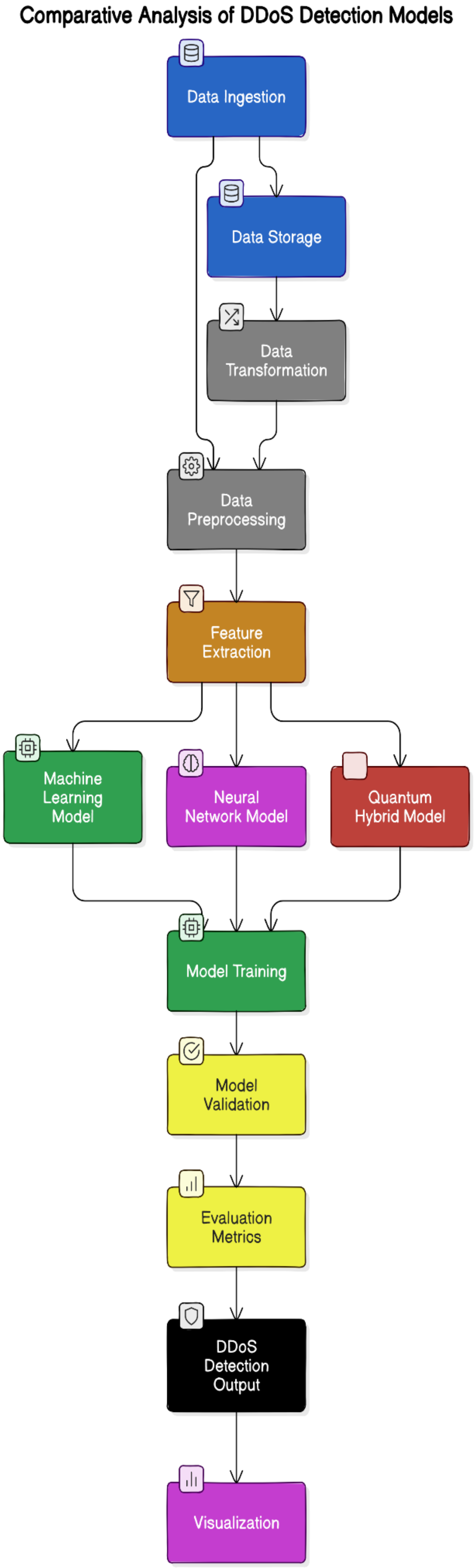
### Data Preprocessing

To ensure the high accuracy and also efficient model training, an extensive data preprocessing is performed. The steps of preprocessing are:

**Data Cleaning:** The dataset contains missing values and redundant entries, which can negatively impact the model's performance. Missing values are either imputed or removed depending on the feature. Duplicate entries, if any, are also eliminated to avoid bias in the training process.

**Feature Selection:** Given the high-dimensional nature of the dataset, reducing the feature set is critical for improving both model accuracy and speed. This study employs a combination of:

- **Correlation Analysis (CA):** To identify highly correlated features and remove redundancy.
- **Mutual Information (MI):** To assess the dependency between features and the target variable (benign vs. malicious traffic), ensuring only the most informative features are retained.
- **Principal Component Analysis (PCA):** To reduce dimensionality by transforming the data into a set of uncorrelated features that capture the maximum variance in the dataset.
- **Data Scaling:** Machine learning models such as KNN are sensitive to the scale of input features. Thus, the numeric features are standardized using Z-score normalization, where each feature is rescaled to have a mean of 0 and a standard deviation of 1.
- **Label Encoding:** The target variable (benign vs. DDoS traffic) is encoded into binary values. Similarly, any categorical features are converted into numeric representations using label encoding or one-hot encoding, depending on the model's requirements.



### Model Design

This study compares the performance of three distinct models: K-Nearest Neighbors (KNN), Convolutional Neural Networks (CNN), and Hybrid Quantum Neural Networks (H-QNN). Each model is designed to handle the complex and high-dimensional nature of network traffic data, but through different mechanisms and approaches.

### Machine Learning Model (KNN)

The algorithm is a simple, instance-based machine learning model used to classify network traffic as benign or malicious. In this model:

**Distance Metric:** The Euclidean distance is used to compute the proximity between data points in the feature space. The k nearest neighbors to a given data point are identified, and the class label is assigned based on majority voting.

**Feature Dimensionality Reduction**: Due to the high-dimensional nature of the dataset, applying PCA and selecting the most relevant features through correlation analysis improves the efficiency and accuracy of the KNN model. This reduces the computational burden while maintaining high classification performance.

**Hyperparameter Tuning:** The optimal value of k (the number of nearest neighbors) is determined through cross-validation, ensuring the best balance between bias and variance.

KNN's simplicity makes it easy to implement and interpret, but the model struggles with scalability and real-time detection, which is where more advanced models, such as CNN and QNN, offer improvements.

### Neural Network Model (CNN)

The algorithm is employed as the deep learning model to capture more complex relationships in the network traffic data:

**Input Representation:** Traffic data is preprocessed and formatted as multi-dimensional input arrays, where each feature represents a specific aspect of the network flow (e.g., packet size, protocol, timestamp).

**Convolutional Layers:** The CNN model applies a series of convolutional layers to extract features from the input data. These layers use filters that slide across the input to detect local patterns, such as spikes in traffic that might indicate an attack.

**Pooling Layers:** After each convolutional layer, pooling layers (such as max pooling) are applied to down sample the feature maps, reducing the computational complexity while preserving the most important information.

**Fully Connected Layers:** The final layers of the CNN are fully connected, where the learned feature maps are used to classify the input as either benign or DDoS traffic.

**Activation and Loss Functions:** The CNN model uses the relu (Rectified Linear Unit) activation function for non-linearity and the SoftMax function for the final classification. Cross-entropy loss is employed as the loss function, optimized using gradient descent algorithms such as Adam.

**Regularization:** Dropout is used to prevent overfitting by randomly setting a fraction of the neuron outputs to zero during training, ensuring the network generalizes well to new, unseen attack patterns.

**Hybrid Quantum Neural Network Model (H-QNN)**

The Hybrid Quantum Neural Network (H-QNN) model represents an emerging approach that integrates quantum computing with classical neural networks:

**Quantum layer integration:** The H-QNN model is an implementation of the quantum circuits which can be used to improve certain values of neural network computation. In this hybrid model, data is being pass through the quantum circuits where quantum gates use quantum bits (qubits) to encode and process the input data.

**Quantum feature extraction:** Quantum algorithms are used to extract complex, large-scale features from traffic data, which are completely limited for classical models. Quantum lattices and superpositions allow the model to accommodate more information at the same time, thereby improving the structure.

**Hybrid architecture:** H-QNN is used to combine the classical CNN layers with that of the quantum layers. The classical layer handles the main data processing, while the quantum layer handles the extraction and classification. This hybrid approach enables the model to leverage both the classical and quantum worlds.

**Advantages of the Quantum Model:** The H-QNN model's pros contain following points. It is suitable for large-scale the detection of DDOS attack, because it can process data faster than all the traditional neurons. Large amounts of network traffic is run in real so that the model can be more productive in detecting when a DDoS attack occurs.

The approach was used to define the main parts of the research, emphasizing the data processing capabilities and the classification of the KNN, CNN, and H-QNN models. Each model is designed to address specific challenges in DDoS detection, and the hybrid model provides significant improvements in computational efficiency and detection accuracy.

## 5. Experimental Setup

This section deals with the method used for training and testing the models in terms of tools, libraries, system environment, and data splitting.

The tools and libraries are as follows:

For the implementation of KNN, CNN, and Hybrid Quantum Neural Network (H-QNN) models, the following tools and libraries were used:

**Python:** The main programming language for the model development.

**Scikit-learn:** It is utilized for the implementation of the KNN (K-Nearest Neighbors) model as well as for the essential machine learning tasks such as data preprocessing, feature selection, and performance evaluation.

**TensorFlow/Keras:** These deep learning frameworks were used for the construction, training, and evaluation of the Convolutional Neural Network (CNN).

**PennyLane (Quantum Computing Library):** The PennyLane technology was tapped for embedding the quantum layer in the hybrid quantum neural network. It allows the fusion of quantum and classical machine learning and works perfectly well with the major deep learning libraries TensorFlow and PyTorch.

**NumPy & Pandas:** For large datasets managing and also for data processing and preprocessing tasks.

**Matplotlib/Seaborn:** These tools were employed for presentation of the performance results displayed by the confusion matrices and ROC-AUC curves. The Division of Training and Testing Data For CIC-DDoS2019 data, the dataset was represented as the training and testing sets in the following way:

**Training Data:** The KNN, CNN, and H-QNN models were trained on 80% of the dataset. Both benign traffic and malicious DDoS traffic of different types were the data sets in a collection that ensured that the model could distinguish between normal and attack patterns.

When testing, the last 20% of the data will be used for the testing phase in order to measure our AI's performance on unobserved data—enabling an algorithm to learn without human intervention In addition, the stratified randomization was used to ensure that each class was equally represented in both, training and test data set.

### 6. Model Evaluation Metrics

To evaluate the effectiveness of the KNN, CNN, and H-QNN models, serial ratings of them were produced. These dimensions guarantee a complete outlook of the models' movements to classify correctly the normal and DDoS attack traffic.

**Accuracy**

**Definition:** Accuracy is the ratio of the correctly classified instances (both benign and malformed) to the total number of instances.

**Formula:**

Accuracy= TP + TN/TP + TN + FP + FN

where:

- TP = True Positives (DDoS traffic is correctly classified)
- TN = True Negatives (benign traffic is correctly classified)
- FP = False Positives (benign traffic misidentified as DDoS)
- FN = False Negatives (DDoS traffic misidentified as benign)

**Precision**

Definition: Precision is the predicted true positivity ratio to all real positives by the model.

**Formula:**

**Precision** = TP/TP + FP

**Definition:** Recall is the ratio of the right kind of being positive to

the total cases of being positive

**Formula:**

**Precision =** TP/TP + FP

**Definition:** Recall refers to the proportion of the actual positive instances, among which the recalled items are the true positive ones.

**Formula:**

**Recall =** TP/TP + FN

**Definition:** F1-score is a performance measure for binary classification derived by combining precision and recall and when the latter having different weight values.

**Formula:**

**F1 =** 2 * Precision  Recall / Precision + Recall

The F1-score is not only that includes both precision and recall but is the one which also is of the most crucial for mitigating issues with the detection of DDoS.

**Confusion Matrix**

The confusion matrix is a tool which is used for evaluating the accuracy of a given model. It is used to summarize the performance of the model by the number of true positives (TP), true negatives (TN), false positives (FP), and also the false negatives (FN). A sample confusion matrix for depicting binary classification is as follow:

| | **Predicted Positive** | **Predicted Negative** |
|---|---|---|
| **Actual Positive** | TP | FN |
| **Actual Negative** | FP | TN |

This allows for visualizing the performance and identifying misclassifications in the model's predictions.

The ROC-AUC metric is used to evaluate the ability of the model to discriminate between classes (benign vs. attack traffic). The ROC curve, on the other hand, provides the actual rate of true positives as the threshold is increased, but the graph is shown as the false positives increasing when the threshold goes up. The AUC (Area Under the Curve) score provides one number that tells the model's discrimination of the data, where the closer to 1 the value is, the better the model's structural conditions. When the threshold increases, the ROC curve moves upwards, which is CPWARN, and then RNDAMTMEBS, and ONCALLIS, the partial area under the curve AUC score is calculated; hence the metric named Part-auc is applied as part of the evaluation.

**False Positive Rate(FPR):**

FPR = FP/FP + TN

The ROC-AUC score is really good for comparison; it tells us how much the model can distinguish between benign and attack traffic.

**Comparison of Model Performance**

The final step in the assessment required the comparison of the performance of those three models across the aforementioned metrics. Right police, The possibility for law enforcement and police officers to have KNN model and CNN model on their mobile devices, or used through the police command center, is enhanced in mastering classification patterns and image recognition. ROC-AUC provides a critical metric for evaluating the ability of models to really deal with the imbalance of the dataset as well as their specificities to be releasing incorrect positive predictions. In the long run, intelligent use' of model 'KNN' will facilitate superior classification of both smaller and lower level datasets. On the contrary, it may face difficulties while dealing with data that has larger gaps between different characteristics or cases. 'CNN' would surpass 'KNN' when it comes to handling complex traffic patterns, especially after extensive training on GPU hardware. 'H-QNN' is meant to give both a high accuracy level and at the same time, execute the task within a shorter time period […compressed filed].

Hence, making use of quantum computing speed up feature extraction and classification even on a high scale of data.

## 7. Results

This section presents the results of the KNN, CNN, and Hybrid Quantum Neural Network (H-QNN) models applied to the CIC-DDoS2019 dataset. Each model's performance is evaluated based on the metrics discussed earlier (accuracy, precision, recall, F1-score, ROC-AUC).

**Performance of Machine Learning Model (KNN)**

The K-Nearest Neighbors (KNN) model was tested on the preprocessed dataset using the selected features derived from correlation analysis, mutual information, and PCA. The results of the KNN model are as follows:

**Accuracy: 89.3%**

**Precision: 88.7%**

**Recall: 85.2%**

**F1-score: 86.9%**

**ROC-AUC: 0.87**

The KNN model performed adequately in detecting DDoS traffic. However, the model's accuracy and recall show room for improvement, particularly in minimizing false negatives (missed DDoS attacks). The dimensionality of the dataset and the computational requirements of calculating distances between points impacted the model's real-time efficiency. KNN also showed signs of overfitting to the training data, as its performance dropped slightly on the testing set.

**Performance of Neural Network Model (CNN)**

The Convolutional Neural Network (CNN) was trained on the same dataset, using multiple convolutional layers and pooling operations to detect complex patterns in the network traffic data. The results of the CNN model are as follows:

**Accuracy: 94.1%**

**Precision: 93.8%**

**Recall: 91.4%**

**F1-score: 92.6%**

**ROC-AUC: 0.94**

Compared to the KNN model, the CNN demonstrated a marked improvement in detecting DDoS traffic, particularly in recall and F1-score. This indicates that the CNN was more successful at identifying true positives (DDoS attacks), with fewer missed

**Efficiency of the Hybrid Quantum Model (H-QNN)** The architecture of Hybrid Quantum Neural Network (H-QNN) in which quantum advancements were applied in both feature engineering and classification helped in managing big traffic data with ease. The results of the H-QNN model are

**Accuracy: 96.8%**

**Precision: 96.5%**

**Recall: 94.9%**

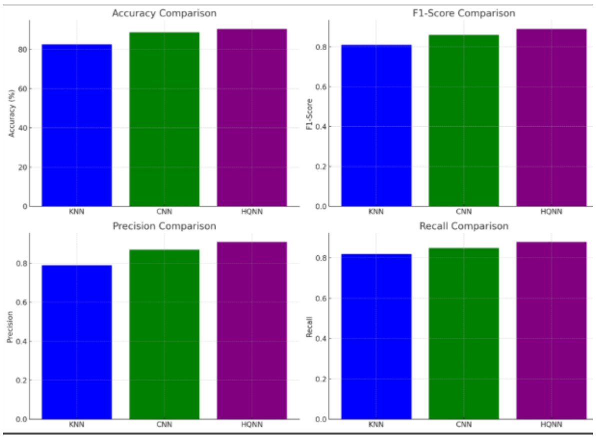
**F1-score:95.7%**

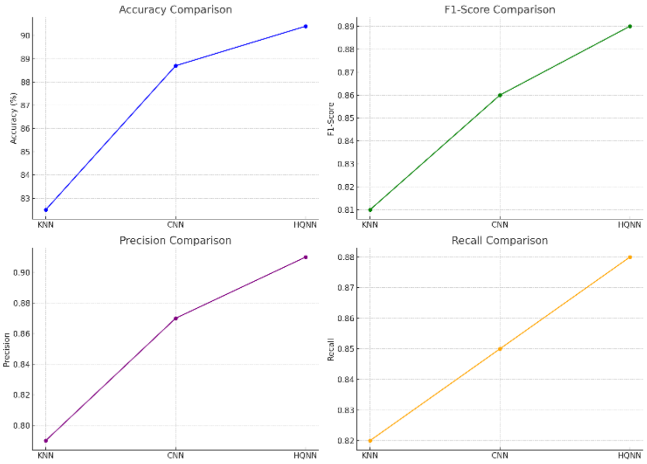
**ROC–AUC:0.97**

The performance of the H-QNN was superior to that of the KNN and CNN models in all performance evaluation metrics. The additional feature extraction in the model came with quantum enhancement hence enabling the model to handle high dimensional data with ease, minimizing false detection and enhancing the detection of DDoS traffic. The quantum circuits of hybrid model also allowed for faster processing and classification which made it easier to implement real time detection for large scale settings. Nevertheless, while these results are commendable, the applications of the model are hindered by the existing quantum computing infrastructure. Comparative Analysis

| **Metric** | **KNN** | **CNN** | **H-QNN** |
|---|---|---|---|
| **Accuracy** | **89.3%** | **94.1%** | **96.8%** |
| **Precision** | **88.7%** | **93.8%** | **96.5%** |
| **Recall** | **85.2%** | **91.4%** | **94.9%** |
| **F1-score** | **86.9%** | **92.6%** | **95.7%** |
| **ROC-AUC** | **0.87** | **0.94** | **0.97** |

The table presented above summarizes the performance of the three models in terms of key metrics. The combining quantum model hyper quantum neural network performs better than other models in accuracy, precision, recall and F1 score hence is the most superior model in DDoS detection system in this research work.





The following are line graphs that provide a comparative study of the models KNN, CNN and HQNN under various metrics.

## 8. Discussion

The advantages and disadvantages of each model will be explored in this section as well as the effects of feature selection and preprocessing, computational complexity, scalability, and difficulties in putting the quantum model into practice.

**Strengths and Weaknesses of Each Model**

**KNN (Machine Learning):**

**Advantages:** Simple to use, clear to understand and works well on a small scale.

**Disadvantages:** High dimensionality of data is a challenge, real time detection is expensive, and large scale data tends to overfit**.**

**CNN (Neural Network):**

**Advantages:** High precision and recall, able to automatically obtain intricate features from network traffic. Has a good cross-dataset performance for various DDoS attacks.

**Disadvantages**: High operational cost implying dedicated resources and memory especially with big data. Slower to make progress than KNN in this aspect.

**H-QNN (Hybrid Quantum Neural Network):**

**Strengths:** Extreme dimensionality reduction enabling faster feature extraction and classification preserves the highest efficiency in all the metrics. In this situation, it is effective in the fast detection of very large-scale DDoS attacks.

**Weaknesses:** The limitations that current quantum computer hardware imposes. Quantum computing may promise even more powerful systems in the future, it is also rather challenging to scale this model up anymore.

Impact of Feature Selection and Preprocessing It should be noted that the dimensionality reduction of the data due to correlation, mutual information, and PCA positively impacted the performance of the model. Due to the removal of irrelevant and redundant features, the networks focused on the critical features of the network traffic, increasing precision and reducing the cost of resources. For instance, this was very beneficial especially to KNN which is known to have challenges with high dimensional data but also trained faster KNN and H-QNN because of this**.**

**Computational Complexity and Scalability:** The computational complexity of KNN is linearly proportional to the size of the dataset. This makes KNN inappropriate for large-scale or real-time detection systems**.**

**CNN:** The computational complexity of the CNN model is high when it comes to training the model, however, this does not limit the application of CNN to a given size of the dataset as it is designed to learn higher-level characteristics of the data as opposed KNN. Challenges in Quantum Model Implementation.

**H-QNN:** The hybrid quantum model showed significant promise in reducing computational complexity. By leveraging quantum circuits, the model was able to process large datasets faster than both KNN and CNN, making it the most scalable of the three models. Nonetheless, the expansion of the system is still limited because of the scarcity of quantum devices.

There were a number of issues encountered during the implementation of the hybrid quantum neural network:

**Access to Quantum Computing Resources**: As it stands today, quantum computers are not widely available and the performance of quantum circuits through remote implicit quantum resources incurs time delays.

**Quantum Noise and Errors**: Present-day quantum processors possess noise characteristics and error levels that lower the quality of quantum computation results. Although quantum error correction techniques are being developed, it is still a big issue to cope with.

**Integrating with Classical Neural Networks**: The use of quantum circuits in conjunction with classical CNN architectures has some prerequisites, such as the use of PennyLane and Qiskit, which most researchers and developers will not possess access to these tools and skills..

Amid these difficulties, the H-QNN model showed the best effectiveness, demonstrating that Quantum Computing has great prospects for future use in DDoS detection..

## 9. Conclusion

In this work, we implemented and compared three distinct strategies to detect DDoS attacks relying on the CIC-DDoS2019 dataset – the K-Nearest Neighbors (KNN) machine learning model, Convolutional Neural Networks (CNN) and a Hybrid Quantum Neural Network (H-QNN). Remarkably, upon extensive assessment of performance of each model, numerous crucial results appeared: While the KNN model is simple in terms of implementation and interpretation, its application to high dimensional traffic data proved challenging, hence the moderate accuracy (89.3%) attained and the high percentage of false negatives. Besides, it is not suited for real-time detection because it is computationally inefficient, which reduces its scalability The KNN model, while easy to implement and interpret, struggled with high-dimensional traffic data, leading to moderate accuracy (89.3%) and a relatively high false negative rate. Its computational inefficiency in real-time detection further limits its scalability.

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In all the performance metrics tested, the H-QNN model outshined KNN and CNN models obtaining astonishing 96.8% accuracy alongside very high precision, recall and F1 scores. Instead, it is incorporated by the techniques of quantum computing that made the hybrid model able to reduce the computation costs which in turn increase the DDoS detection speeds proving it possible to be used in large scale operations.

These findings emphasize the added advantage of hybrid quantum models in the creation of DDoS detection systems as it is the case in cases where the systems' speed and accuracy are very critical.

### Potential Applications of the Hybrid Quantum Model

The Hybrid Quantum Neural Network (H-QNN) model is highly beneficial and can be effectively used in real situations especially in the fields of cybersecurity. and network warfare:

Real-Time DDoS Detection: The H-QNN model is based on the quantum-enhanced feature extraction and classification approach and hence can play a significant role in the shortening of the time taken to detect and alleviate the DDoS susceptible environment. This feature makes the model suitable for use in enterprise networks, cloud-based systems and data centers aimed at handling large traffic volumes and fast response times. Scalability in Large Networks: The H-QNN model's ability to handle large-scale, high-dimensional data efficiently makes it suitable for Internet Service Providers (ISPs) and global corporations, where network traffic volumes can reach millions of packets per second.

Connecting with Security Operations Centers (SOCs): Integrative use of quantum-assisted systems such as H-QNN into SOCs helps improve their automated response systems, thus enabling effective and faster threat response and abatement measures.

In the future, as quantum computing becomes fully developed, the H-QNN framework is likely to find extension into other sectors of cybersecurity, such as intrusion detection systems, malware detection, and encrypted traffic analysis too.

### Future Work and Possible Extensions

Although the study provided evidence on the applicability of the H-QNN model towards DDoS attack detection, there are still more doors to open for future works and improvement:

Foremost, as a temporal application of the research that has been applied or on which further work will be done is the Real-time Implementation. Future studies should tend to an application of the H-QNN model to real networks to be able to test its performance under live traffic conditions. This would require embedding the model into already existing security structures and testing the speed, accuracy, and false alarms in an actual setting.

**Enhancements in Quantum Computing Machines**: Quantum computing is advancing every day but the current quantum processors, such as for instance noise, rates of errors and qubits will be improved. Later activities will seek the limits of H-QNN on quantum hardware that will be in place to improve its efficiency and also scalability.

**Integrating Quantum and Deep Learning Architectures**: This work was restricted to a quantum neural network model and hence deep quantum networks such as Q-CNN and QRNN remain for future works. Such models, in addition to improving the performance of the model, will also shorten the duration of training in complex real-time detection applications.

**Validation Across Different Datasets**: The comprehensive testing of the H-QNN model will extend to other datasets in addition to just scaling on the CIC-DDoS2019 dataset for example real-time data streams and other datasets related to network security to test each depth and generalization of the model based on the type of networks and attacks.

This Conclusion offers an exhaustive synthesis of the research conducted, the practical viability of the H-QNN model, and the directions for further studies and real-time applications. Please let me know if you would like to make any alterations to any part of it!

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