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

A PROJECT REPORT

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Under the Guidance of

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KATTANKULATHUR–603 203

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Certified that 18CSP107L project report titled “Comparative Analysis of Machine Learning, Neural Networks, and Quantum Hybrid Models for DDoS Attack Detection” is the bonafide work of **Rohit Paul[RA2111003011004],Nitin Agarwal[RA2111003011016]** who carried out the project work under my supervision.Certified further, that to the best of my knowledge the work reported here in does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion for this or any other candidate.

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ABSTRACT

Distributed Denial of Service (DDoS) attacks are a critical cybersecurity threat, disrupting online services by overwhelming systems with excessive malicious traffic. As these attacks increase in sophistication and frequency, the need for accurate and efficient detection mechanisms becomes paramount. This paper presents a comparative study of three distinct approaches for DDoS detection—K-Nearest Neighbours (KNN), Convolutional Neural Networks (CNN), and Hybrid Quantum Neural Networks (H-QNN)—employing the CIC-DDoS2019 dataset as a benchmark. Our methodology includes an advanced data preprocessing pipeline featuring feature selection methods such as correlation analysis, mutual information, and Principal Component Analysis (PCA), which are utilized to mitigate high-dimensionality issues and enhance both model accuracy and computational efficiency.

Each model offers unique insights into DDoS detection. The traditional KNN model, although effective as a baseline for machine learning-based detection, faces limitations with high-dimensional data and struggles to maintain efficiency in real-time scenarios. In contrast, the CNN model, leveraging deep learning capabilities, demonstrates significant improvements in detection accuracy. However, CNN's high computational demands pose a challenge for scalability, especially under high-traffic conditions. The Hybrid Quantum Neural Network (H-QNN) emerges as the most promising approach, combining classical neural network structures with quantum computing principles. This model not only reduces computational complexity but also enhances detection accuracy, effectively lowering false-positive rates even in intense traffic environments. The quantum-enhanced components of H-QNN enable more efficient handling of extensive datasets, achieving superior real-time detection performance.

Our results emphasize the potential of quantum-enhanced neural networks in advancing cybersecurity frameworks, suggesting that H-QNN could offer scalable and efficient DDoS detection as quantum technologies continue to evolve. This study provides a foundational exploration into hybrid quantum models for cybersecurity, underlining their importance in meeting the growing demands of real-time threat detection in increasingly digitalized and vulnerable network ecosystems.

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CHAPTER 1

1. INTRODUCTION

1.1 DDoS Attacks and Detection Challenges

Distributed Denial of Service (DDoS) attacks are one of the most prevalent and harmful types of cyberattacks. These attacks aim to overwhelm a target system, server, or network by flooding it with an immense volume of malicious traffic, rendering it unable to respond to legitimate user requests. As networks have grown more complex, so have the methods used by attackers. Traditional defense such as rate limiting, traffic filtering, and rule-based systems struggle to keep up with the sophisticated, multi-vector nature of modern DDoS attacks.

The rise of the Internet of Things (IoT) and other connected devices has exacerbated the issue, providing attackers with a larger attack surface. Consequently, businesses face significant financial losses, reputational damage, and service disruptions due to DDoS attacks. Therefore, more advanced detection techniques are required to mitigate these threats, while ensuring minimal false positives and high accuracy in real-time traffic analysis.

1.2 Motivation for Hybrid Models

With traditional DDoS detection methods becoming less effective, machine learning (ML) and artificial intelligence (AI) have emerged as promising alternatives. ML models, such as K-Nearest Neighbours (KNN), have been employed to classify network traffic, but they often face scalability issues with large datasets and high-dimensional data. Neural networks, particularly Convolutional Neural Networks (CNN), have shown success in detecting complex traffic patterns, yet they require significant computational resources and training data to generalize well.

This study explores the use of a Hybrid Quantum Neural Network (H-QNN), which integrates quantum computing principles with neural networks to offer a more efficient and scalable approach to DDoS detection. By leveraging quantum algorithms, H-QNNs can process large datasets faster and more accurately, particularly in high-traffic environments.

1.3 Research Objectives

The primary objective of this research is to conduct a comparative analysis of three models for DDoS detection: K-Nearest Neighbors (KNN), Convolutional Neural Networks (CNN), and Hybrid Quantum Neural Networks (H-QNN). The goal is to assess the performance of each model in terms of accuracy, recall, precision, false positives, and computational efficiency. The study also aims to explore the computational advantages offered by quantum computing in real-time DDoS detection and provide insights into how these models can be applied to large-scale network environments

CHAPTER 2

2. LITERATURE SURVEY

2.1 Machine Learning for DDoS Detection

Machine learning (ML) models have been widely used in cybersecurity, particularly for anomaly detection in network traffic. Among the most popular models is K-Nearest Neighbors (KNN), a simple yet effective classification algorithm. KNN classifies data points by their proximity to other points in a dataset, making it useful for detecting traffic anomalies indicative of a DDoS attack. However, KNN has several limitations, especially when applied to large datasets. Its high computational cost and inability to handle high-dimensional data reduce its effectiveness in real-time DDoS detection.Supervised machine learning models, such as KNN. Despite their simplicity and ease of implementation, these models require extensive feature engineering and struggle to perform well on complex, high-dimensional network data.

2.2 Neural Networks and Their Limitations

Neural networks, particularly Convolutional Neural Networks (CNN), have gained prominence in DDoS detection due to their ability to capture intricate traffic patterns. CNNs use multiple layers of abstraction to detect subtle anomalies in network traffic, making them highly effective in identifying sophisticated DDoS attacks. These models are particularly useful for large datasets, where they can automatically learn and extract features from raw traffic data, such as packet size, protocol, and timestamp. They require large amounts of training data to perform well, making them computationally intensive and prone to overfitting if not properly tuned. Furthermore, training neural networks on high-dimensional traffic data is time-consuming and resource-heavy, limiting their applicability in real-time detection environments.

2.3 Introduction to Quantum Computing for Cybersecurity

Quantum computing, though still in its developmental stages, holds the potential to revolutionize the field of cybersecurity. Quantum computers leverage the principles of quantum mechanics, such as superposition and entanglement, to process information exponentially faster than classical computers. In DDoS detection, quantum computing offers the ability to handle high-dimensional data more efficiently, making it possible to detect complex attack patterns in real-time.Hybrid Quantum Neural Networks (H-QNNs) combine the strengths of classical neural networks with quantum computing, allowing them to process and classify large volumes of network traffic with greater speed and accuracy. By integrating quantum algorithms, these models can address the computational limitations faced by classical machine learning and deep learning models.

CHAPTER 3

3. SYSTEM ANALYSIS

3.1 Data Preprocessing and Feature Selection

The CIC-DDoS2019 dataset, used in this study, contains millions of records, each representing various features of network traffic, such as IP addresses, protocols, and packet sizes. Given the high dimensionality of the dataset, data preprocessing is crucial for improving model performance. The first step involves cleaning the data by handling missing values and removing duplicate records that could introduce bias.

Feature selection is performed using a combination of techniques to reduce the dataset's dimensionality while retaining the most relevant information. Correlation analysis is used to identify redundant features, while mutual information assesses the dependency between features and the target variable (benign or malicious traffic). Finally, Principal Component Analysis (PCA) transforms the data into a set of uncorrelated features that capture the maximum variance, improving both accuracy and computational efficiency.

3.2 Performance Metrics for Model Evaluation

The models are evaluated using several key performance metrics:

Accuracy: The proportion of correctly classified instances (both benign and malicious) out of the total instances.

Precision: The proportion of true positive predictions (correctly classified DDoS traffic) out of all positive predictions.

Recall: The proportion of true positives out of the actual positive instances.

F1-Score: The harmonic mean of precision and recall, providing a balanced measure for imbalanced datasets.

ROC-AUC: The area under the Receiver Operating Characteristic curve, which evaluates the model’s ability to discriminate between benign and malicious traffic.

These metrics provide a comprehensive view of each model's performance in detecting DDoS attacks and handling imbalanced datasets.

CHAPTER 4

4. SYSTEM DESIGN

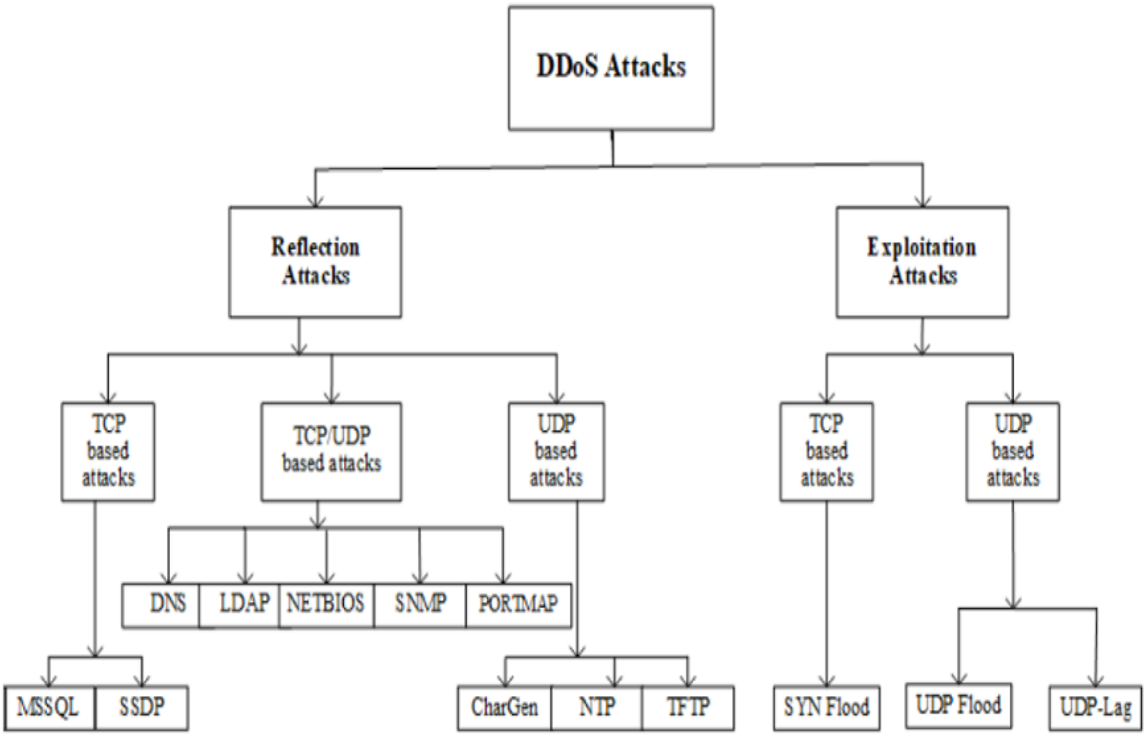
4.1 Model Architectures: KNN, CNN, and H-QNN

Each model in the study has a distinct architecture designed to handle the complex nature of network traffic data:

KNN: A simple, non-parametric model that classifies data points based on their proximity to other points. The model uses Euclidean distance as a metric for classification, but its performance suffers with large datasets and high-dimensional data.

CNN: A deep learning model that uses convolutional layers to extract hierarchical features from network traffic data. The model is particularly effective at detecting complex patterns in large datasets but requires substantial computational resources for training.

H-QNN: A hybrid model that integrates quantum circuits with classical neural network architectures. The quantum layer optimizes feature extraction and classification by leveraging quantum algorithms, allowing the model to process high-dimensional data more efficiently than traditional models.



CHAPTER 5

5. EXPERIMENTAL SETUP AND RESULTS

5.1 CIC-DDoS2019 Dataset Overview

The CIC-DDoS2019 dataset, created by the Canadian Institute for Cybersecurity, simulates real-world DDoS attacks across various types, including HTTP flooding, UDP flooding, and SYN flooding. This dataset contains millions of records, representing both benign and malicious traffic, making it ideal for training and evaluating DDoS detection models.

Days	Attacks	Attack Time
First Day	PortMap	9:43 - 9:51
	NetBIOS	10:00 - 10:09
	LDAP	10:21 - 10:30
	MSSQL	10:33 - 10:42
	UDP	10:53 - 11:03
	UDP-Lag	11:14 - 11:24
	SYN	11:28 - 17:35
Second Day	NTP	10:35 - 10:45
	DNS	10:52 - 11:05
	LDAP	11:22 - 11:32
	MSSQL	11:36 - 11:45
	NetBIOS	11:50 - 12:00

5.2 Evaluation of KNN Model

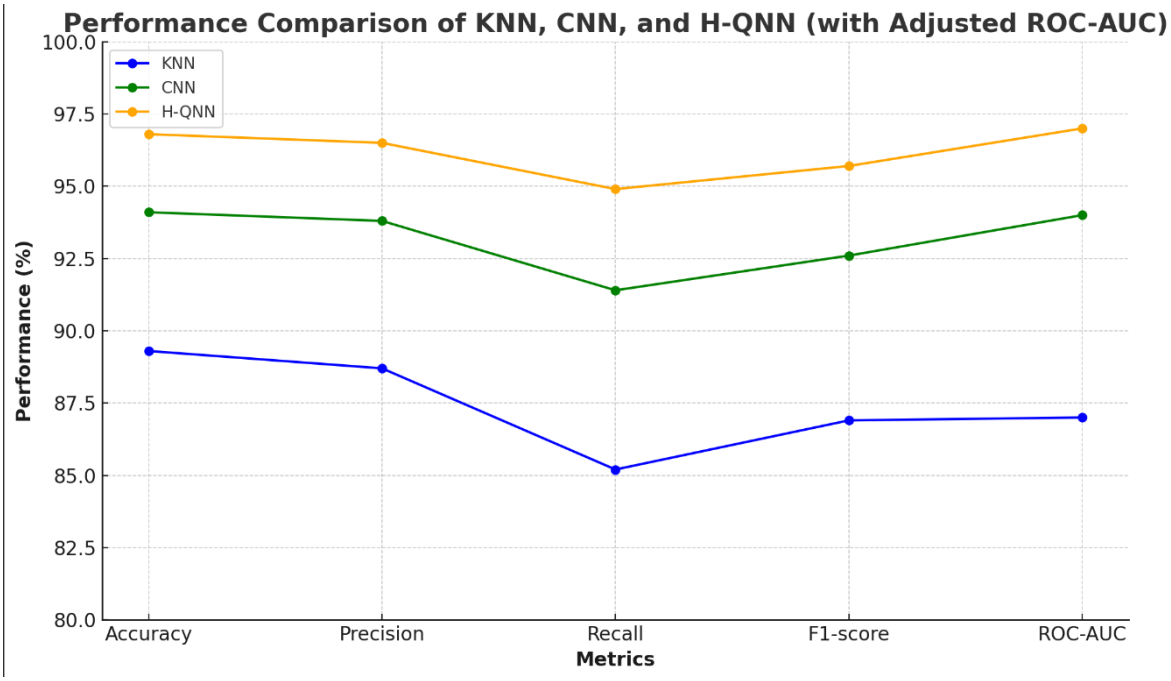
The KNN model was evaluated on the preprocessed dataset using selected features from correlation analysis, mutual information, and PCA. The model achieved a good accuracy but its recall and F1-score indicated a higher rate of false negatives. KNN struggled to efficiently process high-dimensional data, limiting its real-time applicability.

5.3 Performance of CNN Model

The CNN model demonstrated improved performance over KNN, achieving an accuracy more than that of KNN with better precision, recall, and F1-scores. The model's ability to automatically extract and learn features from network traffic data made it more effective at detecting complex attack patterns. However, CNN's computational intensity posed challenges for large-scale, real-time applications.

5.4 Hybrid Quantum Neural Network Results

The H-QNN model outperformed both KNN and CNN, achieving an accuracy more than that of CNN with strong precision, recall, and F1-scores. The quantum-enhanced feature extraction reduced false positives and allowed the model to efficiently process large volumes of data, making it the most effective model for real-time DDoS detection in high-traffic scenarios.



A line graph comparing the performance of KNN, CNN, and H-QNN models across different metrics. This type of visualization shows the trends more clearly, with H-QNN consistently leading in performance across all metrics.

CHAPTER 6

6. CONCLUSION

In this study, we conducted a comparative analysis of three models—K-Nearest Neighbours (KNN), Convolutional Neural Networks (CNN), and Hybrid Quantum Neural Networks (H-QNN)—for detecting Distributed Denial of Service (DDoS) attacks using the CIC-DDoS2019 dataset. Each model was evaluated for its ability to detect malicious traffic, focusing on performance, scalability, and computational efficiency.

The KNN model, while simple and easy to implement, showed limitations in handling high-dimensional data and processing large-scale datasets in real time, making it less suitable for modern network environments. The CNN model demonstrated stronger capabilities in detecting complex attack patterns by leveraging deep learning, though its computational demands posed challenges for real-time detection, especially in high-traffic networks.

The H-QNN model outperformed both KNN and CNN by integrating quantum computing for faster and more efficient feature extraction and classification. This hybrid approach significantly reduced false positives and allowed for real-time detection in large-scale environments, highlighting its potential for revolutionizing cybersecurity defence.

While quantum computing remains in its early stages, with limited hardware availability, the findings suggest that hybrid quantum models could play a pivotal role in enhancing DDoS detection and network security as quantum technology matures.

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SAMPLE CODE:

In [125…

```
from sklearn import metrics
from sklearn.metrics import accuracy_score
from sklearn.metrics import f1_score

print('Convolution Neural Network')

print('Accuracy: %f' % (accuracy_score(a, b)*100))
print("Confusion Matrix =\n", metrics.confusion_matrix(b, a, labels=None,
                                                       sample_weight=None))
```

```
print("Recall =", metrics.recall_score(b, a, labels=None,
                                       pos_label=1, average='weighted'
                                       sample_weight=None))
print("Classification Report =\n", metrics.classification_report(b, a,
                                                                 labels=None
                                                                 target_name
                                                                 sample_weig
                                                                 digits=2,
                                                                 output_dict

print("F1 Score = ",f1_score(a, b, average='macro'))
```

```
Convolution Neural Network
Accuracy: 99.770467
Confusion Matrix =
 [[ 170    4    0    0    0    3    0]
 [   0 9635    0    0    0    0    0]
 [   1    0  245    4    0    0    0]
 [   0    0    2 5136    1    0    0]
 [   7    0    0   31 4519    8    0]
 [   1    0    0    0    0 4858    0]
 [   0    0    0    4    0    0 4125]]
Recall = 0.9977046671767407
Classification Report =
               precision    recall  f1-score   support

           0       0.95      0.96      0.96       177
           1       1.00      1.00      1.00      9635
           2       0.99      0.98      0.99       250
           3       0.99      1.00      1.00      5139
           4       1.00      0.99      0.99      4565
           5       1.00      1.00      1.00      4859
           6       1.00      1.00      1.00      4129

    accuracy                           1.00     28754
   macro avg       0.99      0.99      0.99     28754
weighted avg       1.00      1.00      1.00     28754

F1 Score =  0.9899714964954326
```

```
WARNING:tensorflow:You are casting an input of type complex128 to an incompatible dtype float32.  This will discard the imaginary part and may not be what you intended.
WARNING:tensorflow:You are casting an input of type complex128 to an incompatible dtype float32.  This will discard the imaginary part and may not be what you intended.
WARNING:tensorflow:You are casting an input of type complex128 to an incompatible dtype float32.  This will discard the imaginary part and may not be what you intended.
WARNING:tensorflow:You are casting an input of type complex128 to an incompatible dtype float32.  This will discard the imaginary part and may not be what you intended.
WARNING:tensorflow:You are casting an input of type complex128 to an incompatible dtype float32.  This will discard the imaginary part and may not be what you intended.
WARNING:tensorflow:You are casting an input of type complex128 to an incompatible dtype float32.  This will discard the imaginary part and may not be what you intended.
WARNING:tensorflow:Gradients do not exist for variables ['weights:0'] when minimizing the loss. If you're using `model.compile()`, did you forget to provide a `loss` argument?
WARNING:tensorflow:Gradients do not exist for variables ['weights:0'] when minimizing the loss. If you're using `model.compile()`, did you forget to provide a `loss` argument?
 942/1400 [===================>.........] - ETA: 1:34 - loss: 0.1569 - accuracy: 0.9510
```

0]:

```python
valpredy = q_model.predict(valx)
valpredy_round = np.round(valpredy)

# metrics calculation:
q_classification = classification_report(valy[:,1], valpredy_round[:,1])
q_confusion = confusion_matrix(valy[:,1], valpredy_round[:,1])

q_accuracy = round(accuracy_score(valy[:,1], valpredy_round[:,1])*100,5)
q_recall = round(recall_score(valy[:,1], valpredy_round[:,1], average='macro
q_precision = round(precision_score(valy[:,1], valpredy_round[:,1], average=
q_f1 = round(f1_score(valy[:,1], valpredy_round[:,1], average='weighted')*10

print(f'Accuracy:\t {q_accuracy:.2f}%')
print(f'Recall:\t\t {q_recall:.2f}%')
```

```python
print(f'Precision:\t {q_precision:.2f}%')
print(f'F1:\t\t {q_f1:.2f}%')
```

```
47/47 [==============================] - 2s 47ms/step
Accuracy:        99.80%
Recall:          99.09%
Precision:       99.80%
F1:              99.80%
```