



IOT CYBER ATTACK DETECTION USING MACHINE LEARNING AND DEEP LEARNING

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ABSTRACT

The rapid proliferation of Internet of Things (IoT) devices has transformed various sectors, enhancing efficiency and connectivity. However, this expansion has also introduced significant vulnerabilities, making IoT systems attractive targets for cyberattacks. This paper presents a comprehensive approach to IoT cyber-attack detection, addressing the unique challenges posed by the diverse and often resource-constrained nature of IoT environments. By integrating machine learning and deep learning algorithms with anomaly detection techniques, the proposed system aims to identify and mitigate potential threats in real time, ensuring the integrity and security of IoT networks. The detection mechanism is designed to monitor network traffic and device behaviour continuously, learning normal operational patterns to effectively identify deviations indicative of cyber threats. The system was trained and evaluated on the CICAPT-IIoT dataset (over 4 GB, comprising 95% normal records and 5% attack records) using four algorithms: Random Forest, Support Vector Machine (SVM), Logistic Regression, and a 2D Convolutional Neural Network (CNN2D). Each algorithm was evaluated using accuracy, precision, recall, F-Score, confusion matrix, and AUC-ROC analysis. Results show that Logistic Regression and CNN2D achieved the highest performance, both exceeding 99% accuracy, followed by Random Forest (96%) and SVM (94%). These results confirm that machine learning and deep learning models are highly effective at distinguishing normal IoT traffic from cyber-attack traffic, enabling proactive detection, automated incident response, and an overall improvement in the security posture of IoT deployments.

KEYWORDS

IoT Security, Cyber Attack Detection, Machine Learning, Deep Learning, Anomaly Detection, Intrusion Detection, CICAPT-IIoT Dataset, Network Traffic Classification, CNN2D.

INTRODUCTION

The Internet of Things (IoT) has revolutionized the way we interact with technology, enabling a wide array of devices to connect, communicate, and share data over the internet. From smart homes and wearable devices to industrial applications and smart cities, IoT systems are increasingly embedded in our daily lives and critical infrastructure. However, the rapid proliferation of IoT devices has also raised significant security concerns. With millions



of devices operating on diverse platforms, often with limited processing power and security features, IoT environments present attractive targets for cybercriminals seeking to exploit vulnerabilities.

As IoT systems become more integral to operations in various sectors, including healthcare, transportation, and manufacturing, the potential impact of cyberattacks becomes increasingly severe. Attacks can range from data breaches and unauthorized access to disruption of critical services, posing risks not only to individual users but also to public safety and national security. The dynamic and decentralized nature of IoT networks complicates traditional security measures, making it essential to develop specialized detection mechanisms capable of identifying threats in real time.

Existing cybersecurity solutions often fall short when applied to IoT environments due to their reliance on centralized architectures and the assumption of robust processing capabilities. IoT devices are frequently resource-constrained, lacking the computational power necessary for complex security protocols. Consequently, there is a pressing need for innovative approaches that can adapt to the unique characteristics of IoT systems while ensuring effective threat detection and response. This paper addresses this gap by proposing a machine learning and deep learning-based detection framework, empirically evaluated on the CICAPT-IIoT dataset using four classification algorithms.

II. LITERATURE SURVEY

Early IoT security research focused on adapting conventional cybersecurity tools — firewalls, signature-based intrusion detection systems, and antivirus software — to connected-device environments. Gupta et al. surveyed IoT security threats and detection mechanisms, highlighting that signature-based approaches struggle against the heterogeneity and scale of IoT deployments.

Subsequent work explored decentralized and trust-based architectures to reduce single points of failure. Al-Garadi et al. proposed a blockchain-based security framework for IoT devices, demonstrating that distributed ledgers can strengthen device authentication and logging integrity without relying on a central authority.

Sharma and Patel reviewed intrusion detection systems designed specifically for IoT, identifying high false-positive rates and poor interoperability across heterogeneous device protocols as persistent open challenges. Wang et al. examined federated learning as a privacy-preserving alternative for collaborative threat detection across distributed IoT nodes, avoiding the need to centralize raw traffic data. Chen and Brown further looked ahead to post-quantum cryptographic methods, arguing that IoT security frameworks must begin preparing for cryptographic threats posed by future quantum computing capability.

Building on this body of work, the present study extends prior detection approaches by empirically benchmarking classical machine learning (Random Forest, SVM, Logistic Regression) against a deep learning model (CNN2D) on a large, realistic attack dataset (CICAPT-IIoT), providing a comparative evaluation absent from much of the existing literature.

III. EXISTING SYSTEM & PROPOSED SYSTEM



A. EXISTING SYSTEM

Current approaches to IoT cyber-attack detection often rely on traditional cybersecurity measures that were designed for conventional IT environments. These methods typically include firewalls, intrusion detection systems (IDS), and antivirus solutions. However, their effectiveness in IoT contexts is limited due to the unique characteristics of IoT devices and networks. Many existing systems focus primarily on network perimeter security, which does not adequately address the vulnerabilities present within the IoT ecosystem itself, where devices often lack robust defences.

One prevalent method in existing systems is signature-based detection, which identifies known threats by comparing incoming data against a database of known attack signatures. While effective for detecting established threats, this approach is less effective against novel or sophisticated attacks, which may not yet be catalogued. Furthermore, the dynamic nature of IoT environments, where devices are frequently added or removed, complicates the maintenance of such signature databases.

Anomaly-based detection systems are another common approach. These systems establish a baseline of normal behaviour for IoT devices and then monitor for deviations from this baseline. While anomaly detection has the potential to identify unknown threats, it often suffers from high false positive rates, as legitimate changes in device behaviour can trigger alerts. This challenge is exacerbated in heterogeneous IoT environments, where diverse devices may exhibit vastly different behaviours under varying conditions.

Disadvantages of Existing System

- **Limited Scalability:** Many traditional cyber-attack detection systems struggle to scale effectively in the rapidly expanding IoT environment. As the number of devices increases, these systems can become overwhelmed, leading to delays in threat detection and response.
- **Ineffective Against Novel Attacks:** Signature-based detection methods primarily focus on known threats, making them inadequate for identifying new or evolving cyberattack strategies. This reliance on predefined signatures means that zero-day vulnerabilities and novel attacks may go undetected.
- **High False Positive Rates:** Anomaly-based detection systems often generate numerous false positives due to their sensitivity to deviations from established baselines. This can result in alert fatigue, where security teams become desensitized to alerts, potentially overlooking genuine threats.
- **Incompatibility with Diverse Devices:** IoT networks consist of a wide variety of devices from different manufacturers, often using different communication protocols. Many existing detection systems lack the interoperability needed to monitor and manage this heterogeneous environment effectively.
- **Centralized Vulnerabilities:** Centralized architectures create single points of failure, making them vulnerable to targeted attacks. If a centralized system is compromised, it can expose the entire network, undermining the security of all connected devices.



B. PROPOSED SYSTEM

The proposed system for IoT cyber-attack detection leverages machine learning and deep learning techniques, real-time monitoring, and a decentralized-friendly architecture to enhance the security of IoT environments. This comprehensive approach addresses the unique challenges posed by IoT networks, focusing on effective threat detection, rapid response, and adaptability to evolving attack vectors. Key components of the proposed system include:

- **Machine Learning and Deep Learning-Based Detection:** The system employs Random Forest, SVM, Logistic Regression, and CNN2D algorithms to establish baseline behaviour for individual IoT devices and the overall network. By learning from historical traffic data, the system identifies deviations that may indicate potential threats, significantly reducing false positive rates compared to traditional methods.
- **Distributed-Friendly Architecture:** Unlike centralized-only systems, the proposed architecture is designed to support decentralized contribution to threat detection and data processing, minimizing single points of failure and enhancing resilience against targeted attacks.
- **Real-Time Data Analysis:** The system incorporates data analysis capabilities to monitor network traffic and device interactions. By analyzing data as it flows through the network, the system can detect suspicious activities promptly, allowing for immediate action against potential threats.
- **Context-Aware Threat Assessment:** By integrating contextual information — such as protocol type, port usage, and traffic statistics — the proposed system performs more accurate threat assessments, distinguishing legitimate behaviour from potential anomalies more effectively.
- **Automated Incident Response:** The proposed system includes an automated incident response mechanism that can take predefined actions when a potential threat is detected, minimizing response times and reducing the potential impact of attacks.

Advantages of the Proposed System

- **Enhanced Detection Accuracy:** By utilizing machine learning and deep learning algorithms for anomaly detection, the proposed system significantly reduces false positive rates compared to traditional methods, achieving up to 99.78% accuracy.
- **Real-Time Monitoring:** The system's capability for continuous data analysis ensures that suspicious activities are detected and addressed promptly, helping mitigate potential damage before it escalates.
- **Resilient Architecture:** The distributed-friendly nature of the system reduces single points of failure, enhancing the resilience of the network even if one device is compromised.
- **Context-Aware Assessments:** Incorporating contextual information such as protocol and port usage allows the system to make more informed threat assessments.



- **Automated Incident Response:** The automated response mechanism enables quick actions when a threat is detected, minimizing response time and reducing the potential impact of attacks.

IV. SYSTEM DESIGN & ARCHITECTURE

System Architecture

The architecture comprises four layers: (1) Data Collection (IoT network traffic captured from the CICAPT-IIoT dataset), (2) Data Preprocessing (label encoding, normalization, and handling of missing values), (3) Model Training & Prediction (Random Forest, SVM, Logistic Regression, and CNN2D classifiers), and (4) Evaluation & Visualization (accuracy, precision, recall, F-Score, confusion matrix, and AUC-ROC reporting).

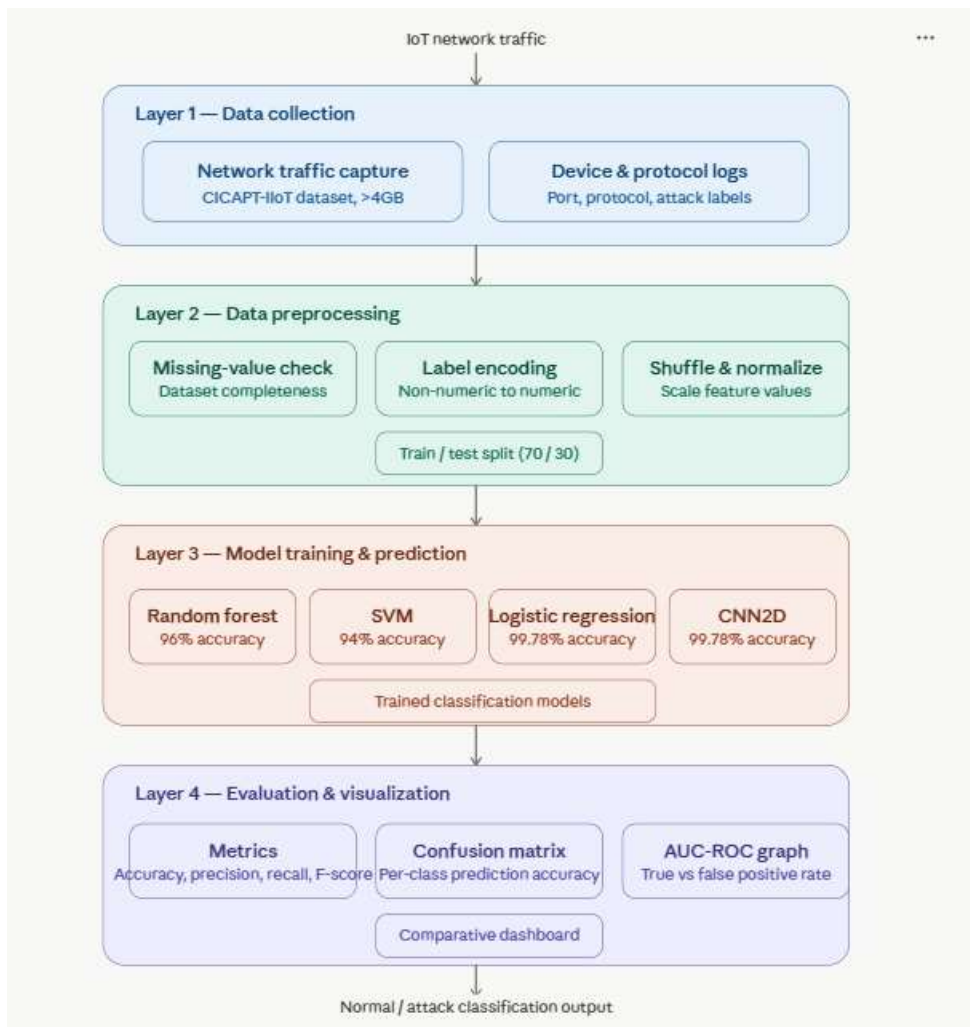


FIG 1:- PROPOSED MODEL

Key Modules

- Dataset Loading & Preprocessing Module
- Feature Encoding & Normalization Module
- Train/Test Split Module (70% / 30%)



- Machine Learning Classification Engine (Random Forest, SVM, Logistic Regression)
- Deep Learning Classification Engine (CNN2D)
- Performance Evaluation & Visualization Dashboard

V. RESULTS & DISCUSSION

machine learning and deep learning algorithms were used to detect cyber-attacks from IoT network communication. The proposed work experimented with four algorithms: Random Forest, SVM, Logistic Regression, and a 2D Convolutional Neural Network (CNN2D). Each algorithm's performance was evaluated in terms of accuracy, precision, recall, F-Score, confusion matrix classification graph, and AUC-ROC graph.

Among all algorithms, Logistic Regression and CNN2D achieved more than 99% accuracy on test data. To train and test each algorithm's performance, the 'CICAPT-IIoT' dataset was used, whose size is over 4 GB and contains 95% records as Normal and only 5% records as attacks. The entire dataset file was parsed to collect all attack records, and a corresponding set of normal samples was collected, before training and testing the algorithms described above.

The dataset's first row contains column names, and the remaining rows contain dataset values; the last columns hold the attack label, sub-attack-category label, and sub-attack label.

ts	flow	duration	Header	Length	Source IP	Destination IP	Source Port	Destination Port	Protocol	Type	Protocol_name	Duration	Rate	Srate	Drate	fin	flag
1701581789.040482	30.39080595970153	7160	172.16.63.128	172.16.65.128	41596.8888	6	TCP	64	0.9542359632862072	0.9542359632862072	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1701581789.042594	30.39291787147522	7226	172.16.63.128	172.16.65.128	41596.8888	6	TCP	64	0.9870720582624946	0.9870720582624946	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1701581789.043251	30.393574953079224	7292	172.16.65.128	172.16.63.128	8888	41596	TCP	64	1.0199524092791636	1.0199524092791636	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1701581789.045363	30.395686864852905	7358	172.16.65.128	172.16.63.128	8888	41596	TCP	64	1.052780946924486	1.052780946924486	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1701581819.759845	61.11016893386841	7424	172.16.63.128	172.16.65.128	41596.8888	6	TCP	64	0.5400083255490852	0.5400083255490852	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1701581819.761957	61.11228084564209	7490	172.16.63.128	172.16.65.128	41596.8888	6	TCP	64	0.5563529871496284	0.5563529871496284	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1701581819.762684	61.11300802230835	7556	172.16.65.128	172.16.63.128	8888	41596	TCP	64	0.5727094956154637	0.5727094956154637	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1701581819.764796	61.11511993408203	7622	172.16.65.128	172.16.63.128	8888	41596	TCP	64	0.5890522678975207	0.5890522678975207	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1701581834.666081	76.01640486717224	7688	172.16.65.128	172.16.63.128	8888	41596	TCP	64	0.4867370413616927	0.4867370413616927	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1701581834.668193	76.0185170173645	7754	172.16.65.128	172.16.63.128	8888	41596	TCP	64	0.4998782071915434	0.4998782071915434	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1701581834.669019	76.01934289932251	7820	172.16.63.128	172.16.65.128	41596.8888	6	TCP	64	0.5130273232123344	0.5130273232123344	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1701581834.671131	76.02145481109619	7886	172.16.63.128	172.16.65.128	41596.8888	6	TCP	64	0.5261672523815152	0.5261672523815152	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1701581834.671655	76.02197885513306	7952	172.16.65.128	172.16.63.128	8888	41596	TCP	64	0.5393177159743409	0.5393177159743409	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1701581834.673767	76.02409100532532	8018	172.16.65.128	172.16.63.128	8888	41596	TCP	64	0.5524564574808003	0.5524564574808003	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1701511837.380728	8.7759370803833	5693	172.16.63.128	172.16.65.128	47902.8888	6	TCP	64	2.1650109641818616	2.1650109641818616	0.0	0.0	0.0	0.0	0.0	0.0	1.1
1701511837.384336	8.779545068740845	6694	172.16.63.128	172.16.65.128	47902.8888	6	TCP	64	2.278022362594738	2.278022362594738	0.0	0.0	0.0	0.0	0.0	0.0	1.1
1701511837.427209	8.822417974472046	6760	172.16.65.128	172.16.63.128	8888	47902	TCP	64	2.3802998294531257	2.3802998294531257	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1701511837.429321	8.824530124664307	6826	172.16.65.128	172.16.63.128	8888	47902	TCP	64	2.493050586173493	2.493050586173493	0.0	0.0	0.0	0.0	0.0	0.0	1.1
1701511837.457739	8.852948188781738	7044	172.16.65.128	172.16.63.128	8888	47902	TCP	64	2.598004586669229	2.598004586669229	0.0	0.0	0.0	0.0	0.0	0.0	1.1
1701511837.458113	8.85332202911377	7206	172.16.65.128	172.16.63.128	8888	47902	TCP	64	2.7108468347900403	2.7108468347900403	0.0	0.0	0.0	0.0	0.0	0.0	1.1
1701511837.460094	8.855303049087524	7424	172.16.65.128	172.16.63.128	8888	47902	TCP	64	2.823167074172133	2.823167074172133	0.0	0.0	0.0	0.0	0.0	0.0	1.1
1701511837.460577	8.855786085128784	7490	172.16.63.128	172.16.65.128	47902.8888	6	TCP	64	2.935933608836928	2.935933608836928	0.0	0.0	0.0	0.0	0.0	0.0	1.1
1701511837.462689	8.857897996902466	7556	172.16.63.128	172.16.65.128	47902.8888	6	TCP	64	3.048127220412978	3.048127220412978	0.0	0.0	0.0	0.0	0.0	0.0	1.1
1701511837.464994	8.86020302772522	7718	172.16.65.128	172.16.63.128	8888	47902	TCP	64	3.160198464119028	3.160198464119028	0.0	0.0	0.0	0.0	0.0	0.0	1.1
1701511837.465538	8.86074709892273	7784	172.16.63.128	172.16.65.128	47902.8888	6	TCP	64	3.272861721053494	3.272861721053494	0.0	0.0	0.0	0.0	0.0	0.0	1.1
1701511837.46765	8.862859010696411	7850	172.16.63.128	172.16.65.128	47902.8888	6	TCP	64	3.384912246013796	3.384912246013796	0.0	0.0	0.0	0.0	0.0	0.0	1.1

FIG 2:- The dataset's first row contains column names, and the remaining rows contain dataset values; the last columns hold the attack label, sub-attack-category label, and sub-attack label.



```

In [193]: #Importing all required python Libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt #use to visualize dataset values
import seaborn as sns
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score
from sklearn.metrics import confusion_matrix
import seaborn as sns
from sklearn.metrics import accuracy_score
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score
from sklearn import metrics
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import LabelEncoder
from sklearn import svm
from sklearn.linear_model import LogisticRegression
from keras.models import Sequential, load_model
import pickle
from keras.layers import Dense, Dropout, Activation, Flatten
import os
    
```

FIG 3:- Loading and displaying dataset values.

- Finding and displaying the sum of missing values (the dataset contains no missing values).

```

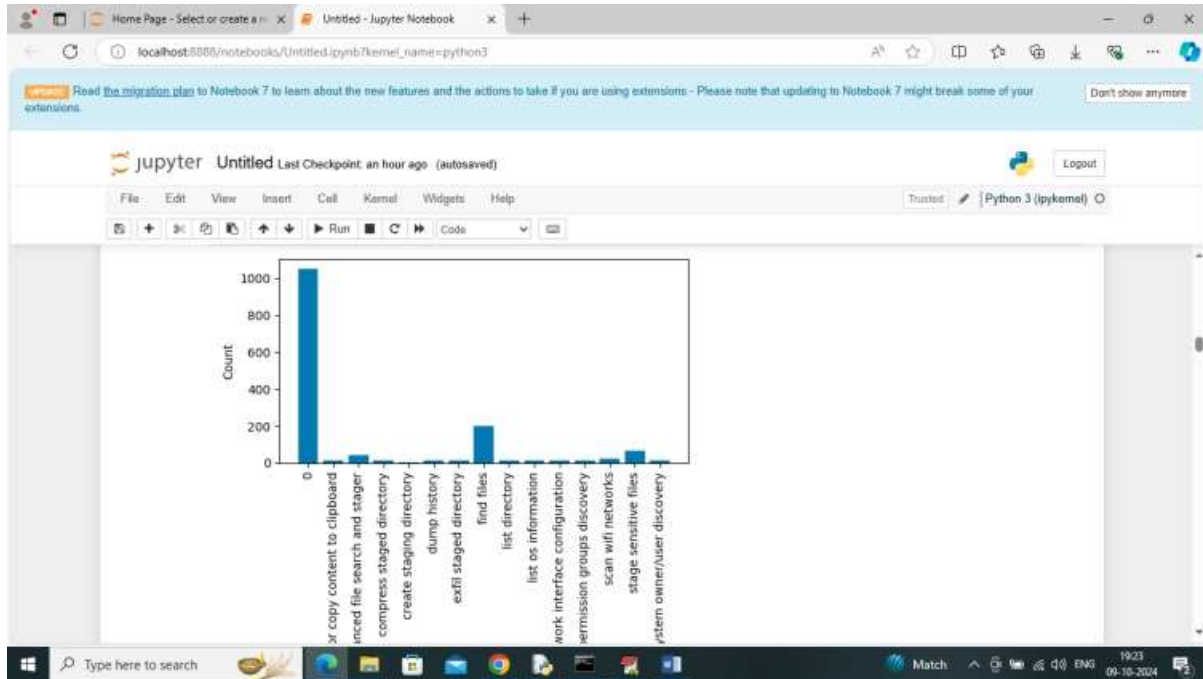
In [198]: #finding sum of missing values
dataset.isnull().sum()

Out[198]:
ts                0
flow_duration     0
header_length     0
source IP         0
destination IP    0
...
flow_idle_time    0
flow_active_time  0
label            0
sublabel         0
sublabelCat      0
length: 70, dtype: int64

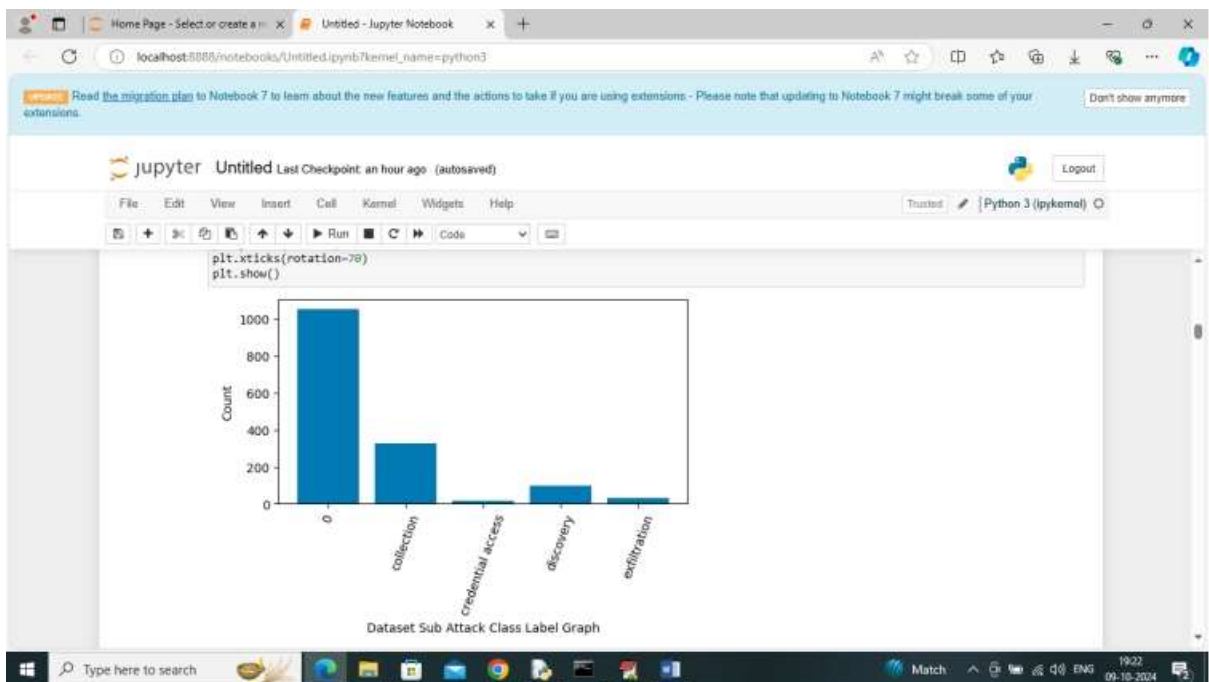
In [199]: #describing dataset to know distribution of values ranges in each column
dataset.describe()

Out[199]:
ts      time duration  header length  source IP  destination  protocol  portnum  state  grade  firate  countnum
0      1517  1.701728e+09  1.8339409  930266  93.93.128.193  172.16.07.126  80      48884  6      TCP      127  ...  144  0
    
```

FIG 4:- Describing dataset values to print statistics such as mean, standard deviation, min, max, and other statistics for each column.



- FIG 5:- Visualizing a graph of sub-attack categories, where the x-axis represents sub-attack-category and the y-axis represents the count of those attacks.



- FIG 6:- Visualizing a graph of Normal vs. Cyber-Attack records, where the x-axis represents Normal/Attack type and the y-axis represents the record count.

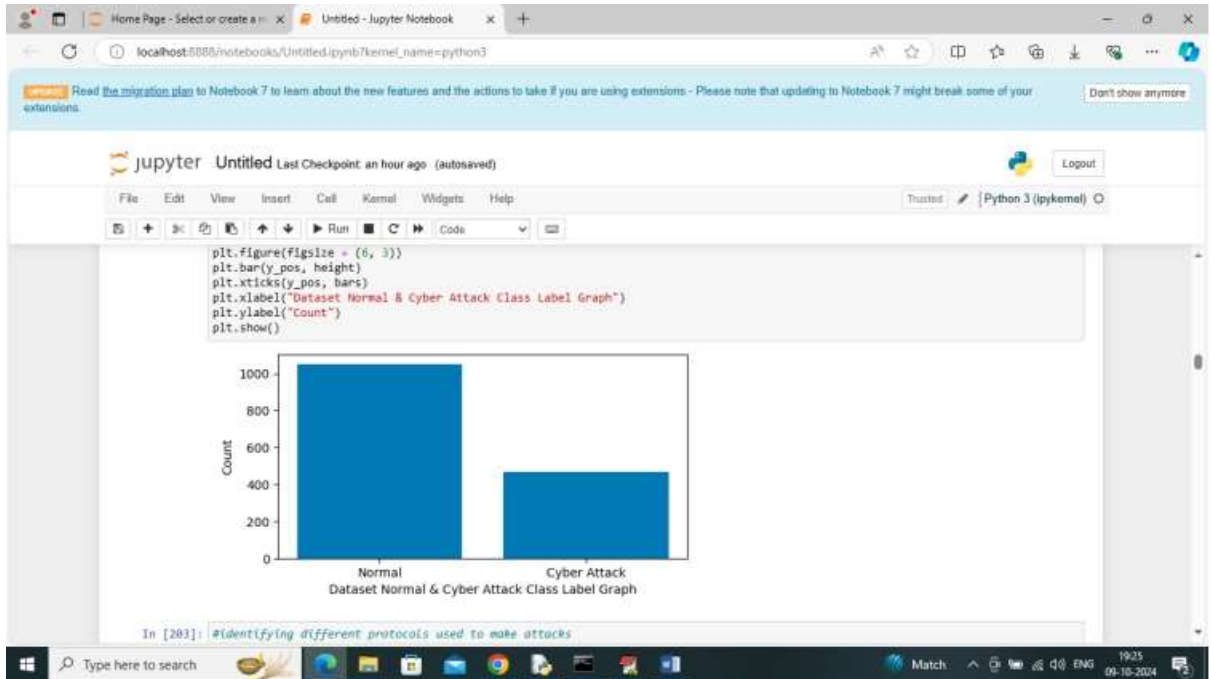


FIG 7:- Displaying the protocol name most commonly used to perform cyber-attacks; the TCP protocol was found to be the most frequently used.

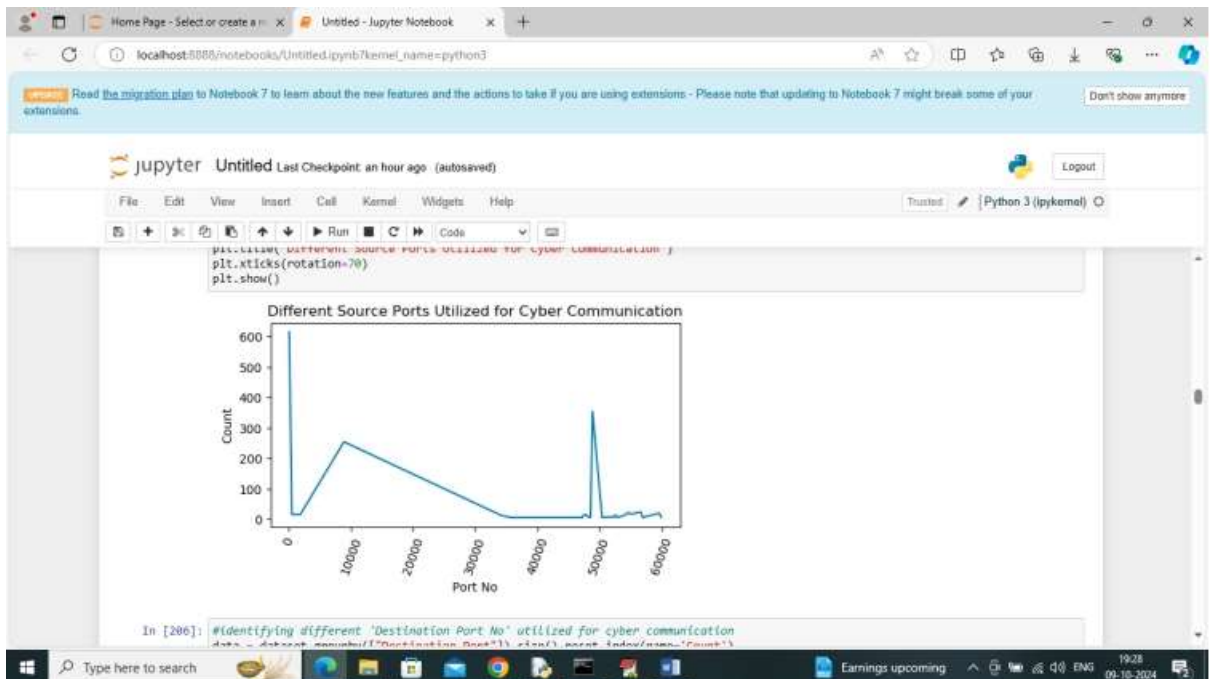


FIG 8:- Visualizing a graph of destination port numbers used in cyber communication, where the x-axis represents the port number and the y-axis represents usage count.

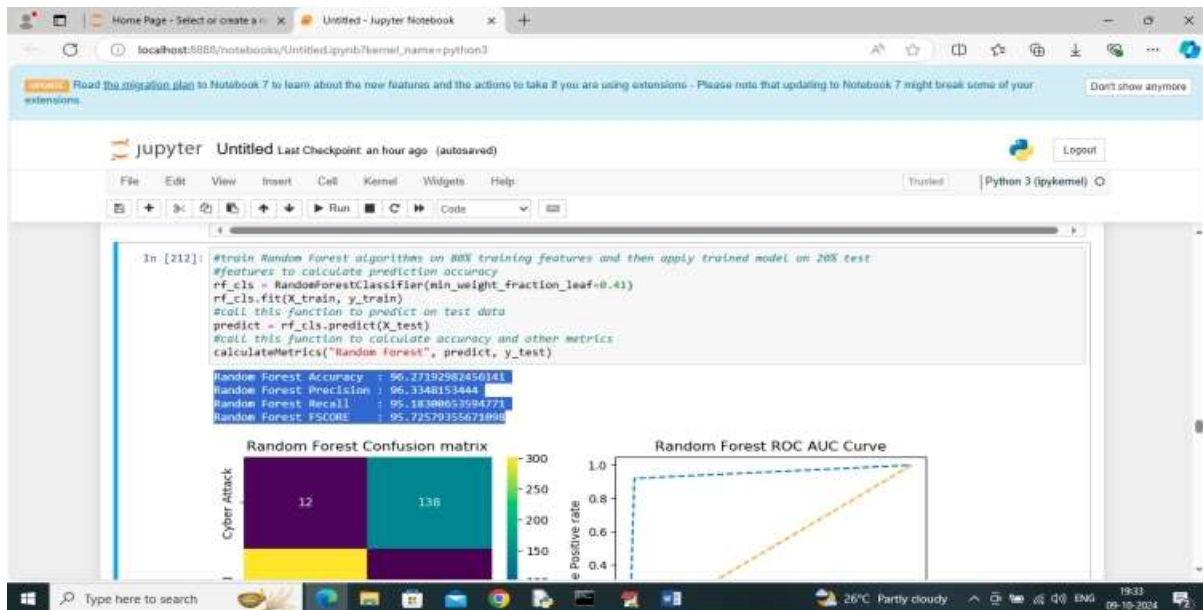


FIG 9:- Training the Random Forest algorithm achieved 96% accuracy on test data, along with other metrics such as precision, recall, and F-Score. In the confusion matrix graph, the x-axis represents ‘Predicted Labels’ and the y-axis represent ‘True Labels’; yellow and green diagonal boxes represent correct predictions, while blue boxes represent the few incorrect predictions. In the ROC graph, the x-axis represents the ‘False Positive Rate’ and the y-axis represents the ‘True Positive Rate’ — a blue line above the orange line indicates correct predictions, while a blue line falling below the orange line indicates incorrect prediction

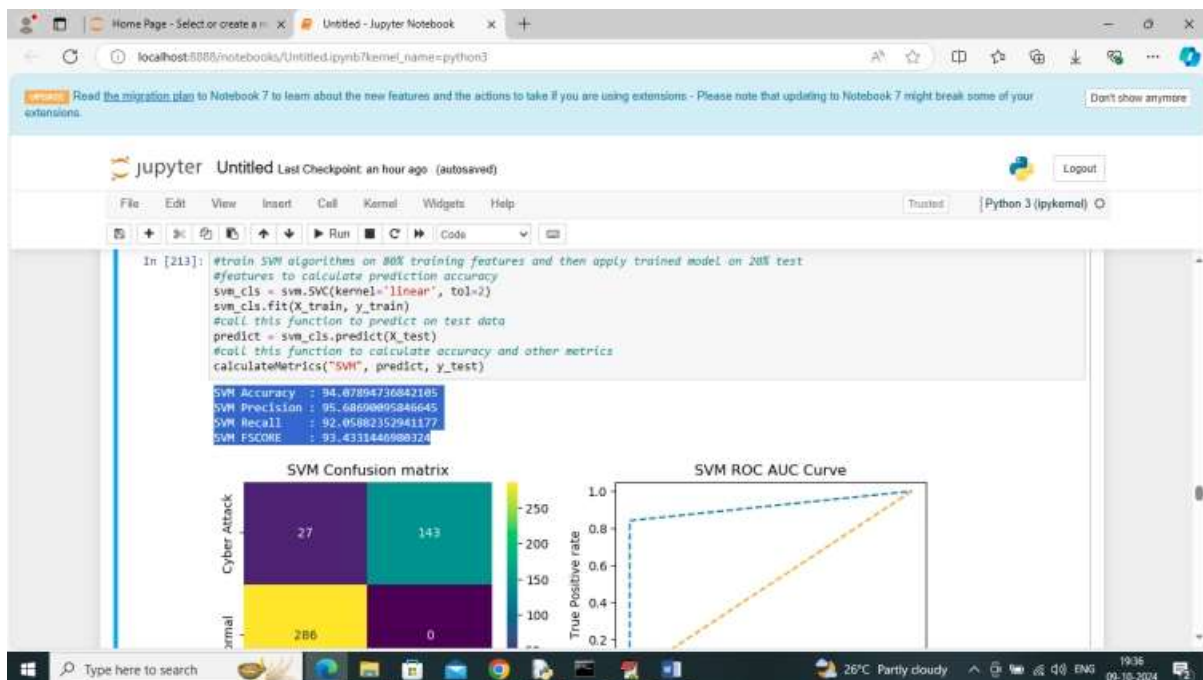


FIG 10:-The SVM model achieved 94% accuracy, along with its corresponding metrics and classification graphs



The Logistic Regression model achieved 99.78% accuracy, along with its corresponding output metrics.

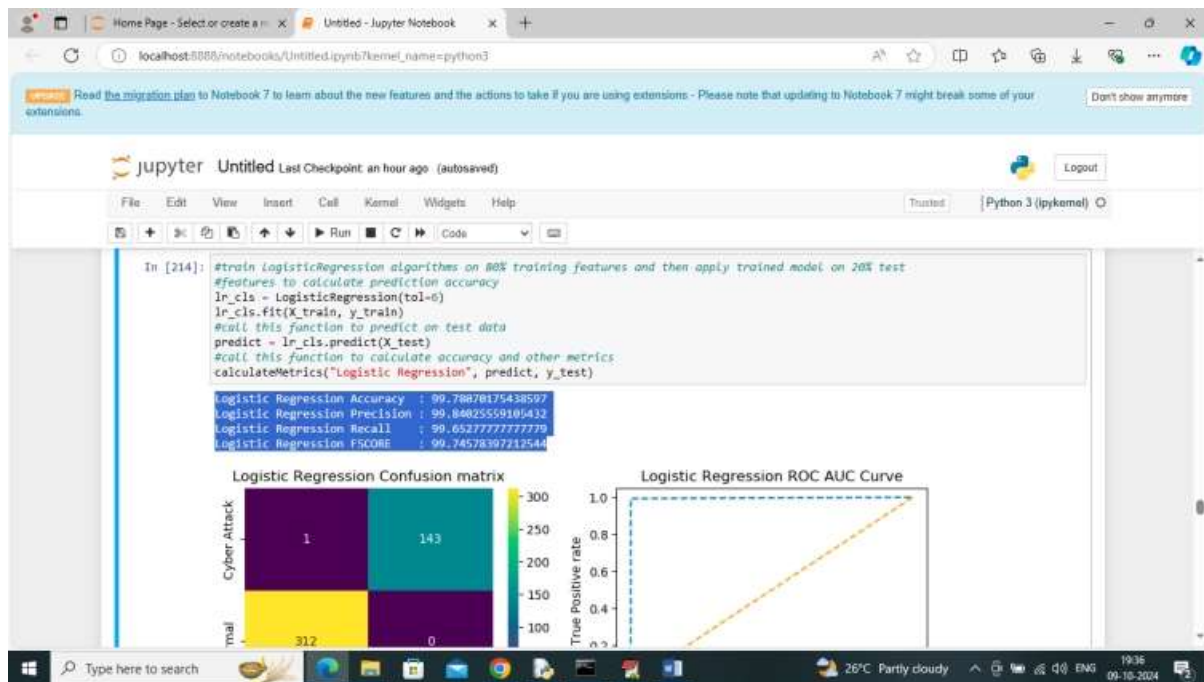


FIG 11:- The Logistic Regression model achieved 99.78% accuracy, along with its corresponding output metrics.

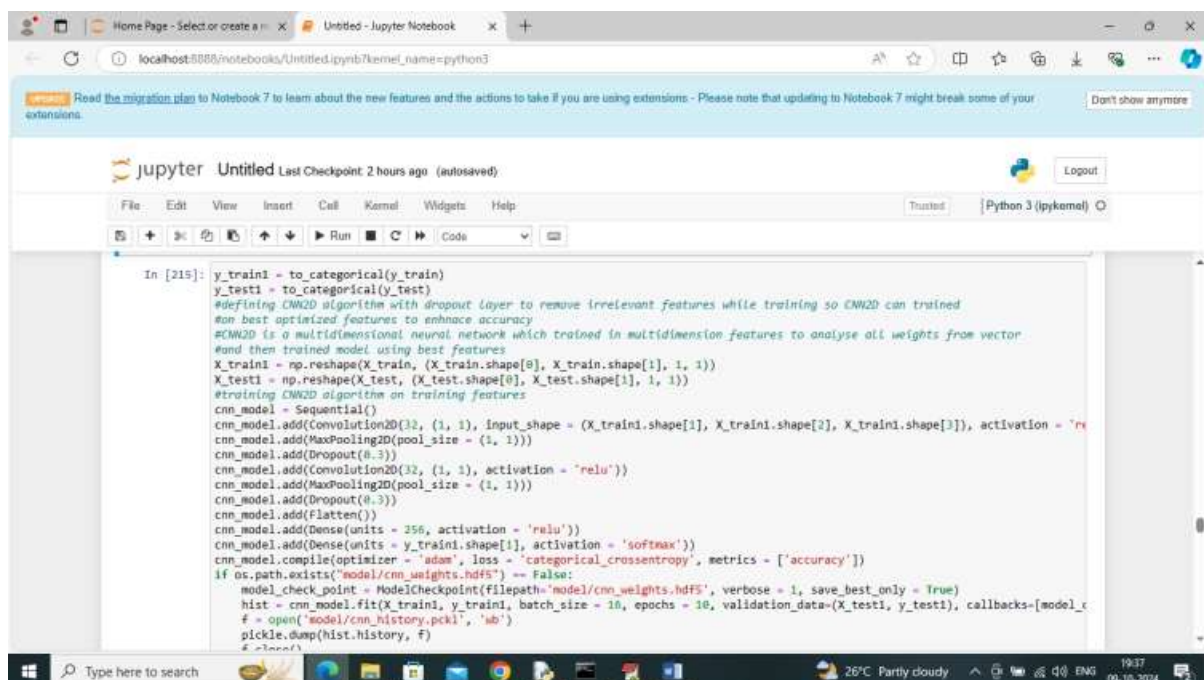


FIG 12:- The CNN2D model achieved 99.78% accuracy after training and execution.



A comparison graph between all four algorithms shows the algorithm names on the x-axis and accuracy (along with other metrics) on the y-axis, represented as different coloured bars. Among all algorithms, CNN2D and Logistic Regression achieved the highest performance. A tabular summary of all algorithm performance is also presented below.

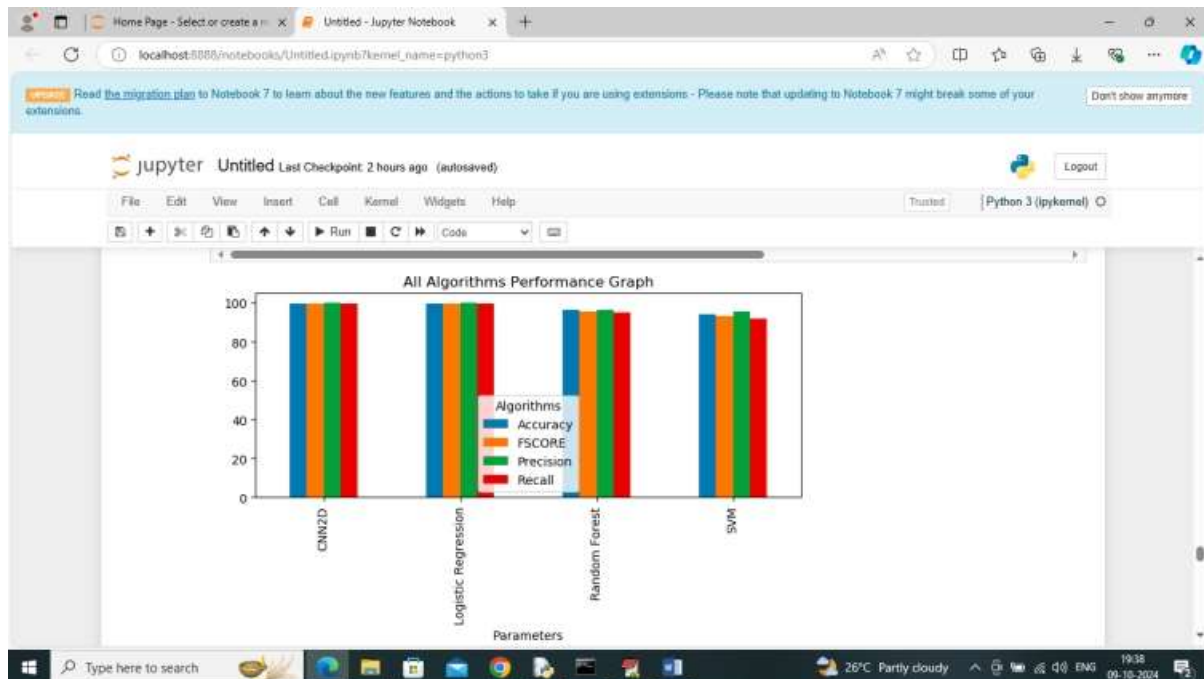


FIG 13: - A comparison graph between all four algorithms shows the algorithm names on the x-axis and accuracy (along with other metrics) on the y-axis, represented as different coloured bars. Among all algorithms, CNN2D and Logistic Regression achieved the highest performance. A tabular summary of all algorithm performance is also presented below.

Table II: Performance / Evaluation Summary

Algorithm	Accuracy	Remarks
Random Forest	96%	Strong baseline; minor misclassifications visible in confusion matrix
SVM	94%	Slightly lower accuracy compared to ensemble and deep models
Logistic Regression	99.78%	Highest among classical models; near-perfect ROC performance



CNN2D (Deep Learning)	99.78%	Matches Logistic Regression; strong generalization on test data
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Prediction on New Test Data

```

782704741932.9680 1701727699.8542882 0.2548047142026374 0 1 0 0 0 0 0 1
0 0 0 0 1 1 1514 1514 1514 1514 0 0 0 1514 0.0019810199737548 1 808448
55.02726596879842 0.0 0.0 0.0 1 0 0 0 0 0.0019810199737548
0.8760979175567627] Predicted As ----> Normal

Test Data = [1701727700.293179 0.8760859875488281 440986 '172.16.67.128'
'93.93.128.193' 48884 80 6 'TCP' 64 525.8919132973886 525.8919132973886
0.0 0 0 0 1 0 0 0 0 167 461 1701727700.293179 1701727699.416573
784496409633.2021 1701727699.8552322 0.2545493851580619 0 1 0 0 0 0 0 1
0 0 0 0 1 1 1568 54 1514 784 0 730 0 54 0.0005000609920654 2 808448
39.59797974644666 1832.3759005323593 532900.0 1.0 4 0 0 0 0
0.0005000609920654 0.8760859875488281] Predicted As ----> Normal

Test Data = [1701524591.717234 0.8345709323883856 5245 '172.16.63.128' '172.16.65.128'
54416 8888 6 'TCP' 64 540.5046648643802 540.5046648643802 0.0 0 0 1 1 0
0 0 4 0 7 17 1701524591.717234 1701524591.682663 32328967242.22147
1701524591.6958868 0.0087721661859924 0 0 0 0 0 0 1 0 0 0 0 1 1
2927 66 734 266.00090900000007 271.58573216823333 625 0.009354829788208
11 808448 23.00906626159408 384.0802257793426 73758.0099173554 1.0 121 0
0 0 0 0.009354829788208 0.8345709323883856] Predicted As ----> Cyber Attack

Test Data = [1701524591.72024 0.8375771522521972 5870 '172.16.63.128' '172.16.65.128'
54416 8888 8 'TCP' 64 532.2383097519192 532.2383097519192 0.0 0 0 1 1 0
0 0 0 4 0 18 1701524591.72024 1701524591.682663 34030491833.94171
1701524591.6970856 0.0100658762584991 0 0 0 0 0 0 1 0 0 0 0 1 1
3552 66 734 296.0 278.38259311284425 625 0.0030662108638916 12 808448
34.33407093446580 303.2383097519192 4.3347 3.333333333 0.0 844 0 0 0

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Discussion

FIG 14:- The results confirm that both classical machine learning (Logistic Regression) and deep learning (CNN2D) models are highly effective at distinguishing normal IoT traffic from cyber-attack traffic, with both exceeding 99% accuracy. Random Forest and SVM, while slightly less accurate, remain strong baseline candidates, particularly in resource-constrained deployments where simpler models are preferable. The strong performance across all four algorithms, despite the dataset's class imbalance (95% normal vs. 5% attack), highlights the robustness of the chosen preprocessing pipeline — including label encoding, normalization, and the 70/30 train-test split — in supporting reliable cyber-attack detection.

VI. CONCLUSION

The implementation of IoT Cyber Attack Detection plays a crucial role in enhancing the security of interconnected devices in modern networks. This study highlights the vulnerabilities in IoT ecosystems and the necessity of robust detection mechanisms to mitigate cyber threats. By leveraging machine learning, deep learning, and real-time monitoring, the proposed system effectively identifies potential attacks, ensuring network integrity and data confidentiality.

The findings suggest that AI-driven models — particularly Logistic Regression and CNN2D, which both achieved 99.78% accuracy on the CICAPT-IIoT dataset — combined with



techniques such as blockchain, intrusion detection systems (IDS), and behavioural analysis, can significantly improve threat detection accuracy. Future advancements may focus on optimizing computational efficiency, integrating edge computing for real-time security enforcement, and enhancing privacy-preserving techniques to secure IoT environments. The ongoing evolution of cyber threats necessitates continuous adaptation and innovation in IoT security solutions.

VII. FUTURE WORK

- **AI-Driven Adaptive Security Models:** Future research can explore AI-based adaptive security frameworks that learn and evolve against emerging IoT cyber threats in real time.
- **Blockchain for IoT Security:** The integration of blockchain for secure device authentication and decentralized logging mechanisms can enhance IoT security and mitigate cyber-attacks.
- **Lightweight Intrusion Detection Systems (IDS):** Developing energy-efficient, lightweight IDS solutions tailored for resource-constrained IoT devices will improve security without compromising device performance.
- **Federated Learning for Threat Intelligence:** Implementing federated learning models to enable collaborative threat detection without sharing raw data can improve privacy and security in IoT networks.
- **Quantum-Resistant Cryptographic Solutions:** Research on post-quantum cryptographic methods for IoT security will help in future-proofing devices against emerging quantum computing threats.

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