Traffic Classification Using Machine Learning Models in Electromagnetic Nano-Networks

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Abstract: The proliferation of Nano-sensors linked to wireless electromagnetic Nano-networks has raised the volume of traffic in numerous ways, but it has also opened up a lot of new opportunities for the Internet of Nano-things. When a nano-network is linked to the Internet by micro or nano gateways, it becomes more difficult to evaluate its general operation and classify the various flows that take place inside. Machine learning has been shown to be the most promising method, while port-based analysis and load-based analysis have also proved beneficial in the past. Finding the best model to analyse the massive amounts of data generated by real-world Nano-networks is difficult because machine learning algorithms have such a profound effect on traffic classification and overall network performance evaluation.

Keywords: Nano-Networks, Nano-Sensors, Supervised Machine Learning Algorithms, Port-based technique, Load-based technique.

1.Introduction

The emergence of nanotechnology has opened up new possibilities for perception and action. A plethora of innovative applications await nano-sensors in the domains of medicine, ecology, industry, and defence, thanks to their detection, computing, and network/Internet communication capabilities. Diagnostic and therapeutic applications of nano-sensors are widespread in the biomedical sector. Human body communication and health tracking systems incorporate nano-sensors, enabling clinicians to remotely access and monitor patients' vitals; these systems also find usage in medical body area networks. With the use of wearable health trackers, physicians can keep tabs on critical signals like heart rate, blood pressure, and respiration rates in real time, allowing for more precise diagnosis and treatment. Environmental monitoring using nano-nodes is vital for tracing the spread of infectious illnesses in public spaces.Another approach to reducing air pollution levels is the use of nano-filters, which improve air quality by removing dangerous compounds.

2.Literature Survey

In this study, the author compares the effectiveness of five distinct machine learning algorithms, including the KNN and Tuning variants, the SVM and Tuning variants, and the Tuning and Tuning variants of the Random Forest variant. Decision Tree (both tuned and untuned versions), Simple Bayes. By "tuning," we mean training the algorithm with different sets of parameters to see whether the accuracy can be

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improved. Nano-network traffic is analyzed and classified using supervised machine learning methods.

3.ALGORITHMS

Random forest algorithm

Each simple decision tree in this model is divided at random, using just some of the characteristics available for that tree's splits. Additionally, the training data used to construct .

K-NN

K-Nearest Neighbour is based on the time-tested Supervised Learning technique; it is one of the most basic Machine Learning algorithms.

Decision Tree algorithm

The goal is to create a model that can predict a desired outcome using only a few elementary decision rules inferred from the available data..

SVM

One of the most fundamental Machine Learning algorithms, K-Nearest Neighbour stems from the tried-and-true Supervised Learning method.

Naive Bayes

When compared to more complex algorithms, the Naive Bayes classifier can be lightning quick.

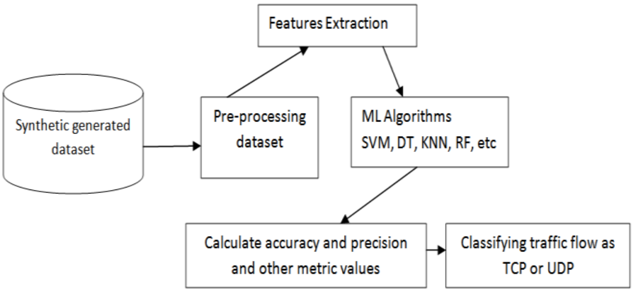

Fig.1. Architecture Diagram

4. RESULT AND DISCUSSION

If you want to mimic the protocol stack and electromagnetic nano-network communication, you should utilise NanoSim, an event-based NS3 simulator. The user can customise the simulator's random packet generation by adjusting the packet size in the message processing unit.

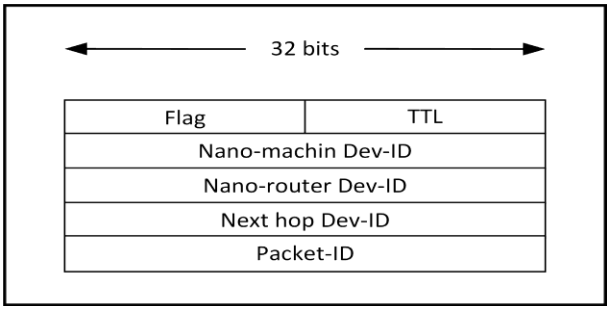

Fig.2. Nano-network message header format

TABLE 1. A portion of the suggested work addressing machine learning-based traffic classification in the literature.

Traffic classification	Machine learning type	Infrastructure	Application
Proposed in [20]	Semi-supervised learning	IP backbone network	Improve QOS of the ISP network
Proposed in [21]	Supervised learning	IP backbone network	Improve QOS of the campus network
Proposed in [33]	Deep learning	IoT network	Smart cities network
Proposed in [22]	Supervised learning	IP backbone network	Improve QOS of the ISP network
Proposed in [23]	Supervised learning	IP backbone network	Improve QOS of the ISP network
Proposed in [24]	Supervised learning	IP backbone network	Smart cities network
Proposed in [32]	Supervised learning	IoT network	Healthcare application
Proposed in [34]	Supervised learning	WBASN	Military and healthcare applications

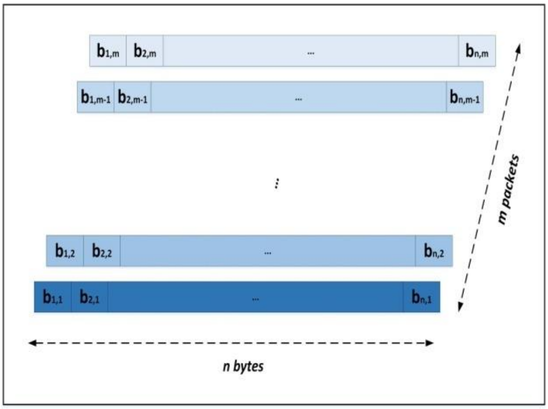

Fig:3-Dataset Features Exploratıon

Table-2 Input features for micro/nano-gateway traffic prediction and classification

Field	Feature description
flag_id	Flag identification
ttl	Time to live
source_dev_id	Source nano-device identification
sender_dev_id	Sender nano-device identification
next_hop_dev_id	Next hop nano-device identification
packet_id	Packet identification
source_mac	Source MAC address
destination_mac	Destination MAC address
source_IP	Source IP address
destination_IP	Destination IP address
transport_protocol	IP transport protocol number
source_port	Source port number
destination_port	Destination port number
payload	Message
payload_size	Message size
header_size	Header size
packet_size	Packet size

Table-3 Labels for the micro/nano-gateway traffic forecast and classification output.

Field	Label description
nn0	Nano-to-nano-communication packet
nn1	Nano-to-Internet-communication packet
tcp	TCP packet
udp	UDP packet

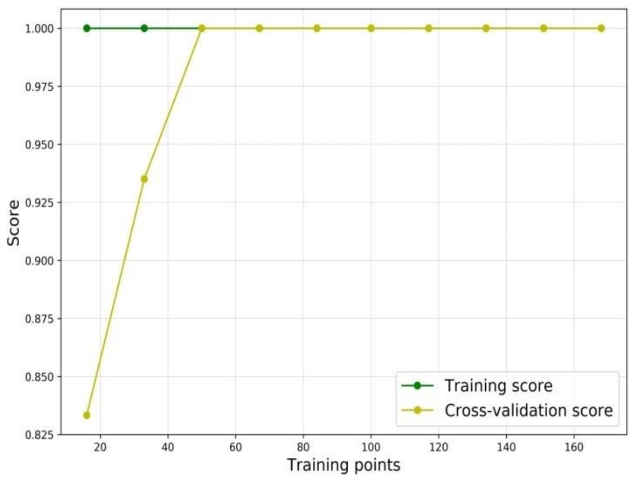

Fig-4: Unoptimized DTC model learning curves.

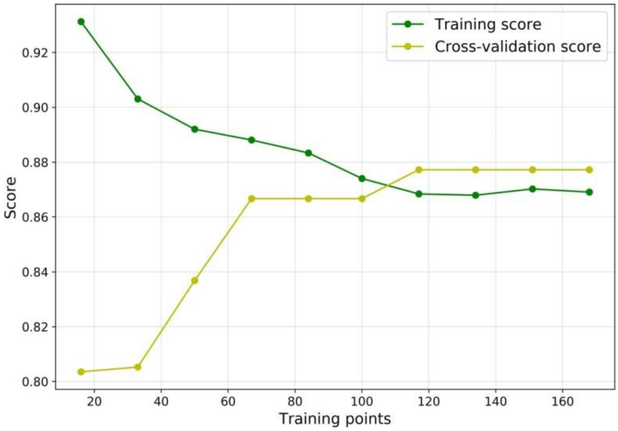

Fig-5: Learning curves for DTC model optimisation

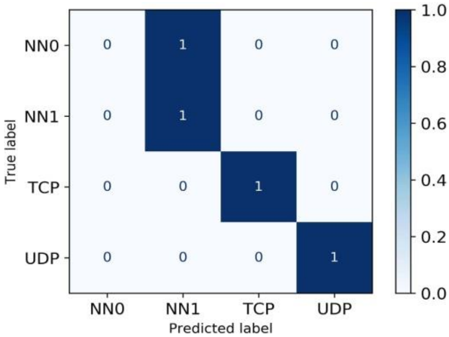

Fig-6: Normalised confusion matrix for the DTC model-optimised.

5. Conclusion

In order to mimic the stress that drivers experience in the actual world, the suggested models employ a multitude of pre-trained networks. Automatically enhancing the detection performance with seven pre-trained networks—Google LeNet, DarkNet-53, ResNet-101, InceptionResNetV2, Xception, DenseNet-201, and InceptionV3—features were retrieved from electrocardiogram (ECG) scalogram images.

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