



ENHANCING TRAFFIC CLASSIFICATION IN NANO-NETWORKS THROUGH SUPERVISED MACHINE LEARNING ANALYSIS

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ABSTRACT

This work focuses on the classification of traffic in nano-networks, which are composed of numerous nano-sensors connected to wireless electromagnetic networks. The increasing number of nano-sensors has led to a significant rise in traffic volumes, requiring effective analysis techniques. Traditional methods like port-based and load-based techniques face challenges in classifying the different types of flows and assessing overall nano-network performance. To address this, the study explores the application of machine learning models for traffic classification and network performance evaluation. Specifically, five supervised machine learning algorithms are utilized to analyze and classify nano-network traffic, collected from operational nano-networks through micro/nano gateways. The aim is to determine the most suitable model for analyzing large volumes of traffic in nano-networks.

KEYWORDS: ML, nano-networks, traffic

1] INTRODUCTION:

Nano-technology has opened up new possibilities in sensing and actuating. Nano-sensors, capable of sensing, computing, and communicating, have enabled advanced applications across various fields such as biomedicine, environment, industry, and defense. In biomedicine, nano-sensors are utilized in drug delivery, medical treatments, health tracking systems, and remote patient monitoring. Environmental applications involve monitoring the spread of diseases, air pollution control using nano-filters, and water quality management. Industrial uses include improving materials, production processes, quality control, and agricultural applications. Nano-networks facilitate wireless communication among nano-devices, forming the Internet of NanoThings (IoNT) through micro/nano-gateways. However, nano-devices face challenges like limited energy, computational power, and storage, as well as data routing and interoperability issues. Overcoming these constraints is crucial for

achieving optimal performance in nano-networks across different applications.

2] LITERATURE SURVEY:

2.1] A. Galal and X. Hesselbachet *al*

A nano-network is a communication network composed of nano-devices at the Nano-scale. Nano-devices face challenges due to their limited processing capabilities and power management. To exploit their functionalities, managing and controlling a complete nano-network with an appropriate architecture becomes crucial. This enables unprecedented applications in biomedicine, environment, and industry. With the advent of the Internet of Things (IoT), the concept of connectivity has evolved, connecting various objects, sensors, and devices. In this paper, we propose a unified architectural model for nano-network communication, incorporating Software Defined Network (SDN), Network Function Virtualization (NFV), and IoT technologies. We discuss the implementation of functions and use cases for nano-devices, along with the

significant challenges and open research issues in this nano-technology paradigm.

2.2]S. Javaid, Z. Wu, H. Fahimet *al*

Introducing a novel approach, this article focuses on an intrabody area nanonetwork (intra-BANN) for noninvasive healthcare monitoring and disease diagnosis. To enhance the computational intelligence and prolong the network lifetime, a unique feedforward neural networks (FFNNs) based data aggregation scheme is designed. The scheme incorporates artificial intelligence attributes and employs data division, labeling, and two different packet types to conserve energy and avoid redundant transmission. Periodic data transmission using FFNN-based techniques optimizes critical information delivery with minimum energy consumption and delay. Additionally, an event-driven data transmission ensures minimal delay and storage overhead for high-priority data. Comparative evaluation with existing schemes demonstrates the superior performance of our proposed framework in terms of residual energy, delay, and packet loss, achieving a 50%-60% improvement.

3] PROBLEM DEFINITION:

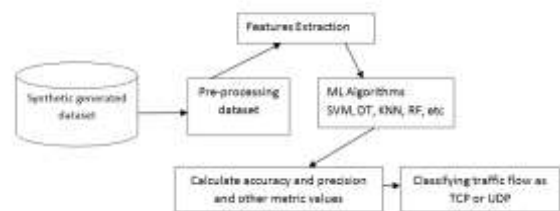
The problem identified in this work is the challenge of classifying nano-network traffic generated by a large number of nano-sensors connected to a wireless electromagnetic nano-network. The increased traffic volumes in the Internet of nano-things pose difficulties in analyzing different flow types and studying overall network performance. Traditional techniques like port-based and load-based classification have limitations, leading to the adoption of machine learning as a promising approach. However, determining the best model for analyzing large volumes of traffic collected in operational nano-networks remains challenging. The focus of the study is on the classification problem, where the captured nano-network traffic is analyzed and classified using five supervised machine learning algorithms in comparison to traditional traffic classification methods.

4] PROPOSED APPROACH:

In propose paper author evaluate performance of 5 machine learning algorithms such as KNN without Tuning, KNN with Tuning, SVM with and without tuning, Random Forest with and without tuning. Decision Tree with and without tuning, Naïve Bayes. Tuning means we will train algorithm with various parameters to check accuracy can be enhance or not.

Supervised machine learning algorithms are used to analyse and classify the nano-network traffic from traditional traffic. Experimental analysis of the proposed models is evaluated and compared to show the most adequate classifier for nano-network traffic that gives very good accuracy and performance score to other classifiers.

5] ARCHITECTURE:



6] PROPOSED METHODOLOGY:

Data Pre-processing:

In this pre-processing phase we collected traffic data characterization mechanism is needed to differentiate between different types of traffic, such as the high-priority and low-priority traffic coming to/from the nano-network, which results in the loss of high-priority or critical information during a high data traffic load. During high data traffic load, packets are randomly dropped and delayed, which increases the delay and packet loss of high priority data.

Traffic classification:

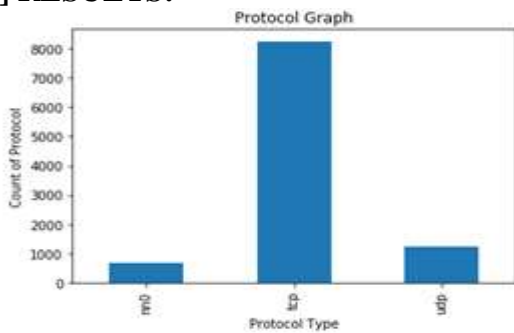
Traffic classification is an important process for telecommunication networks to observe a wide range of operations, measurements and management activities. In nano networks, traffic classification can be useful for performance monitoring, resource provisioning, traffic prioritization, self configuration devices, network management,

QoS and security by identifying unknown traffic or detecting anomaly behavior to maintain adequate nano-communication.

Micro/ Nano Network:

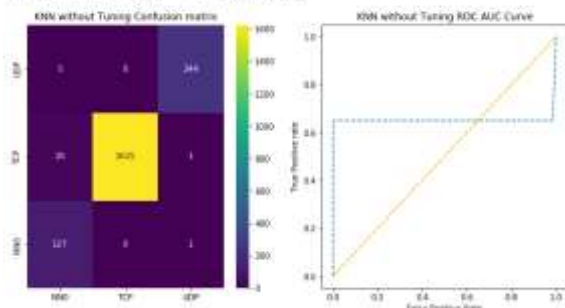
The main objective is to construct a model that accurately classifies nano-network traffic received by a micro/nano-gateway. The dataset is collected from the developed packet generator, which generates nano-packets representing the nano-network traffic associated with background traffic composed of multiple TCP and UDP packets that represent traditional traffic. We have demonstrated the outstanding performance of the DTC, SVM, KNN, RF and NB algorithms for the analysis of traffic received by micro/nano-gateway from both macro and nano wireless communication domains.

7] RESULTS:



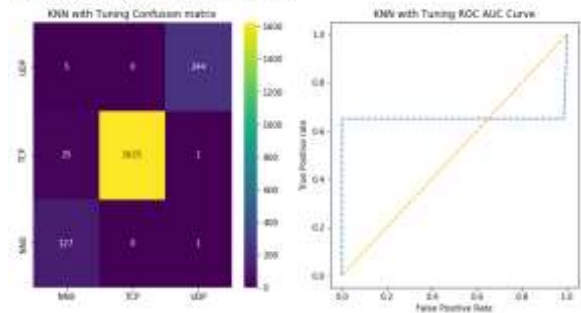
In above graph we are plotting graph of different traffic flow found in dataset such as TCP, UDP and NN0 (Nano)

KNN without Tuning Accuracy : 98.42289672973284
 KNN without Tuning Precision : 93.35957953388864
 KNN without Tuning Recall : 98.5453049072932
 KNN without Tuning FSCORE : 95.43813282993723



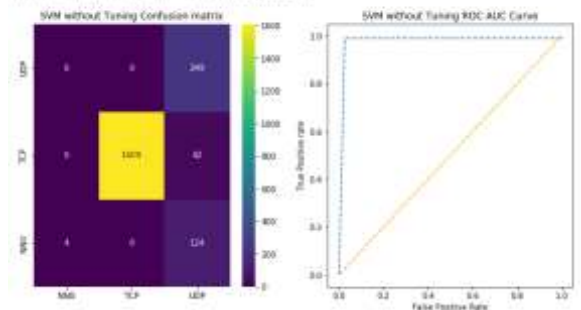
We are training KNN without tuning (grid search parameters) and we got accuracy as 98%

KNN with Tuning Accuracy : 98.42289672973284
 KNN with Tuning Precision : 93.35957953388864
 KNN with Tuning Recall : 98.5453049072932
 KNN with Tuning FSCORE : 95.43813282993723



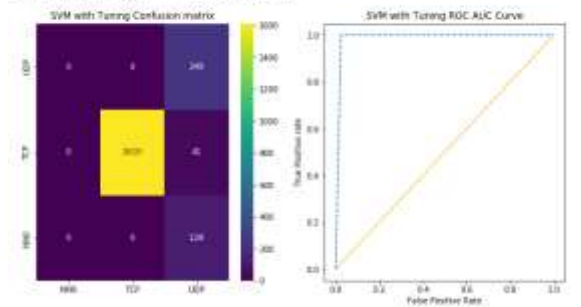
KNN with tuning parameters and we got accuracy as 98%

SVM without Tuning Accuracy : 81.0143950667405
 SVM without Tuning Precision : 86.00000000000007
 SVM without Tuning Recall : 86.00036348663224
 SVM without Tuning FSCORE : 86.92488758677461



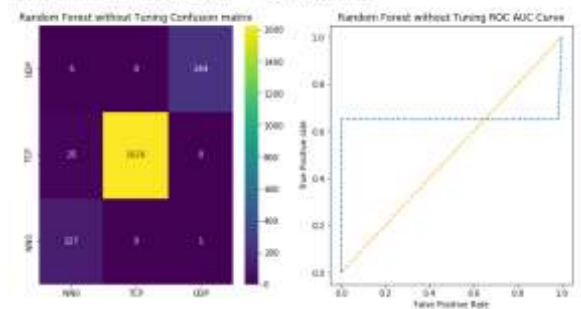
SVM without tuning

SVM with Tuning Accuracy : 91.88000000000000
 SVM with Tuning Precision : 91.880762647988
 SVM with Tuning Recall : 85.838805239249
 SVM with Tuning FSCORE : 87.88179328789518



SVM with tuning

Random forest without Tuning Accuracy : 86.47140029447731
 Random forest without Tuning Precision : 93.40451892668884
 Random forest without Tuning Recall : 60.26549499126253
 Random forest without Tuning FSCORE : 85.71511397839872



Random forest without tuning

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