International Institute of Information Technology

Hyderabad, India

Implementation and Performance Analysis of Machine Learning-Based Intrusion Detection for DNP3 Protocol in SCADA Systems

Project Report

Research in Information Security
Monsoon Semester 2025

TEAM NO 2

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M.Tech in Computer Science and Information Security

Contents

1 Abstract

This project report presents a replication study of a machine-learning-based intrusion detection scheme for the Distributed Network Protocol 3 (DNP3) in SCADA-IoT systems. The study leverages a meticulously curated dataset, specifically designed for DNP3 traffic analysis, to rigorously test the performance of various classification algorithms (Decision Tree, Random Forest, XGBoost, and CatBoost) under different imbalance scenarios, which includes nine scenarios of malicious DNP3 traffic. The models were trained with rare intrusion rates (only 5%, 10%, and 15% of the training data as attacks) using SMOTE oversampling to balance classes. Our best model, XGBoost (trained on 15% intrusion rate data), achieved an Accuracy of 0.9485, a Precision of 0.9485, and an F1-Score of 0.9474, which is within $\sim 5\%$ of the original paper's claims of near-99.5% accuracy. We analyze this performance gap and discuss potential causes such as overfitting and dataset differences. Overall, the replicated results confirm the effectiveness of machine learning for DNP3 intrusion detection, while highlighting practical considerations for deployment in SCADA-IoT environments. The report provides an informal security analysis of the scheme, complexity considerations, and future research directions to extend and improve the intrusion detection system.

Keywords: Intrusion Detection System, Distributed Network Protocol 3 (DNP3), Supervisory Control and Data Acquisition (SCADA) Systems, Machine Learning, XGBoost, Industrial Control Systems, Multi-class Classification

2 Introduction

2.1 Background

The rapid digitalization of critical infrastructure through Supervisory Control and Data Acquisition (SCADA) systems has revolutionized industrial operations across sectors including power generation, water treatment, oil and gas, transportation, and manufacturing. At the heart of these systems lies the Distributed Network Protocol 3 (DNP3), a widely adopted communication protocol designed in 1993 specifically for industrial control systems to enable reliable data exchange between master stations and remote terminal units (RTUs).

However, the integration of SCADA systems with modern Internet of Things (IoT) technologies, wireless protocols (IEEE 802.x, Bluetooth), and TCP/IP networks has fundamentally altered their security landscape. What were once air-gapped, isolated systems are now interconnected networks vulnerable to sophisticated cyberattacks. The DNP3 protocol, designed primarily for reliability and functionality rather than security, lacks built-in protection mechanisms such as message authentication and encryption, making it particularly susceptible to intrusion.

An intrusion in this context refers to any unauthorized or malicious activity attempting to compromise the confidentiality, integrity, or availability of SCADA systems. Such intrusions can manifest as unauthorized access attempts, protocol manipulation, replay attacks, Man-in-the-Middle (MiTM) interceptions, or Denial-of-Service (DoS) operations. The consequences of successful attacks on critical infrastructure can be catastrophic, ranging from economic losses and service disruptions to threats to human safety and national security.

The inherent vulnerabilities of DNP3-based SCADA systems necessitate sophisticated intrusion detection mechanisms. Traditional signature-based detection systems are inadequate for modern threats that exploit protocol-specific vulnerabilities and exhibit polymorphic behavior. Machine learning-based intrusion detection systems offer a promising solution by learning normal operational patterns and detecting anomalous behaviors that indicate potential attacks.

2.2 Applications of DNP3-Based SCADA Systems

DNP3-enabled SCADA systems are deployed across numerous critical sectors:

- **Power Generation and Distribution:** Electric utilities use DNP3 for monitoring substations, controlling circuit breakers, and managing smart grid operations.
- **Water and Wastewater Management:** Treatment plants employ SCADA systems to monitor water quality, control pumps, and manage distribution networks.
- **Oil and Gas Industry:** Pipeline monitoring, refinery control, and extraction operations rely on DNP3 for remote supervision and control.
- **Transportation Infrastructure:** Railway systems, traffic management, and port operations utilize SCADA for automated control.
- **Building Automation:** Commercial and industrial facilities use SCADA for HVAC, lighting, and security system management.

- **Healthcare Systems:** Medical equipment monitoring and critical infrastructure support in healthcare facilities.

2.3 Network Model

Our implementation considers a typical DNP3 SCADA network architecture connecting multiple industrial sectors through a centralized master server. The network model consists of the following components:

- **Master Station:** Central control unit that issues commands, processes data, and interfaces with human operators through Human-Machine Interface (HMI) systems.
- **Remote Terminal Units (RTUs):** Distributed field devices that monitor physical processes, collect sensor data, and execute control commands from the master station.
- **Communication Infrastructure:** TCP/IP-based network carrying DNP3 protocol messages between masters and outstations.
- **Industrial Sectors:** Multiple domains (power, water, gas, healthcare) connected to the central infrastructure.

Communication follows a master-slave paradigm where the master station polls RTUs for data and issues control commands. RTUs can also send unsolicited messages to report critical events without polling. All DNP3 application-layer messages are encapsulated within TCP/IP packets for transport over modern networks.

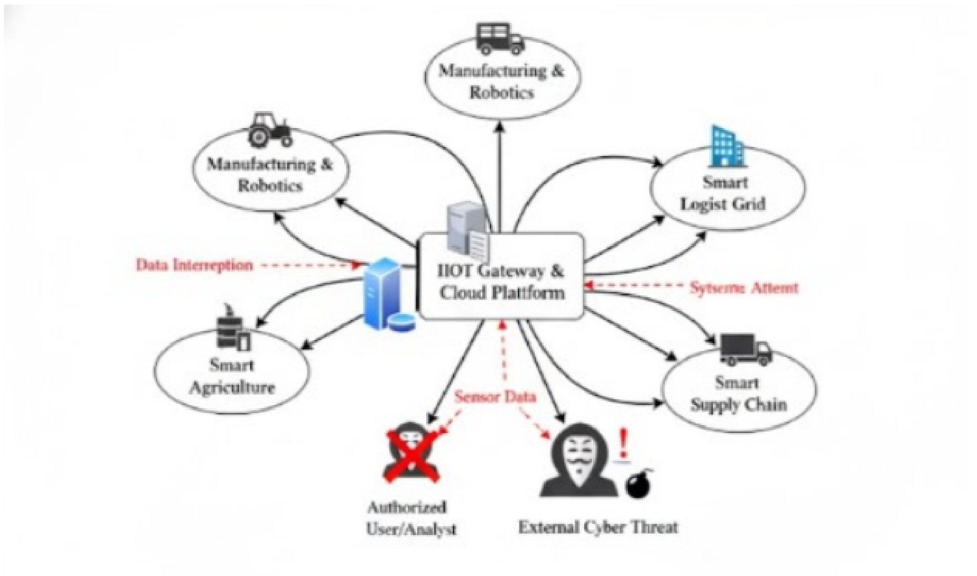


Fig. 1. Industrial IOT Network Architecture

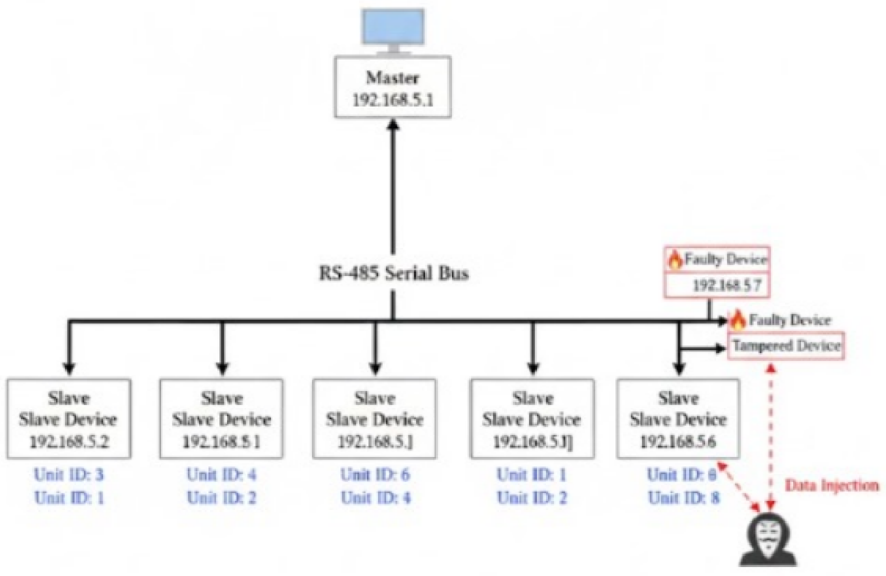


Fig. 2. Modbos RTU Network Toplogy: Serial Bus View

2.4 Attack Model

The DNP3 protocol's lack of authentication and encryption mechanisms makes it particularly vulnerable to such attacks. Our system specifically addresses eight distinct attack types:

1. **Replay Attack:** Capturing and retransmitting valid messages to cause unauthorized command execution.
2. **Disable Unsolicited Message Attack:** Preventing RTUs from sending critical event notifications to the master.
3. **Enumerate Attack:** Unauthorized reconnaissance to discover system structure and available functions.
4. **Info Attack:** Gathering sensitive system information without authorization.
5. **Initialize Data Attack:** Forcing RTUs to reset to initial configurations, disrupting operations.
6. **Stop Application Attack:** Terminating critical DNP3 applications to halt operations.
7. **Cold Restart Attack:** Forcing complete system reboot with data loss.
8. **Warm Restart Attack:** Inducing restart while attempting to maintain session state.

2.5 Research Contributions

In response to the above challenges, our project focuses on replicating and analyzing a recent DNP3 intrusion detection scheme. The key contributions of our student team are summarized below:

- **Implementation of a Multi-class DNP3 IDS:** We implemented the intrusion detection approach proposed by Dangwal et al. (2024) in our own environment. This involved developing a pipeline to train and evaluate four machine learning classifiers – Decision Tree (DT), Random Forest (RF), XGBoost, and CatBoost – on a labeled dataset of DNP3 network traffic. Unlike many prior works that only perform binary classification (attack vs. normal), our implementation handles multi-class classification of eight distinct DNP3 attack types plus normal traffic (i.e. nine classes in total). This provides granular detection capable of identifying the specific attack scenario.
- **Intrusion Scenario Simulation with Imbalanced Data:** To emulate real-world conditions where attacks are relatively rare, we trained our models under scenarios where only 5%, 10%, or 15% of the training data instances are intrusions (with the rest being normal behavior). The original authors highlight that their model maintained high accuracy even as intrusion frequency was reduced to these levels. We mirrored this approach by downsampling the attack instances and then applying SMOTE oversampling on the training set to balance class distribution. This allowed us to study the effect of class imbalance on detection performance and model generalization.
- **Performance Evaluation and Comparative Analysis:** We evaluated each model on a held-out test set and recorded metrics such as overall accuracy, precision, recall, and F1-score. Our best-performing model (XGBoost) achieved an accuracy of 94.8% in detecting and classifying DNP3 attacks. We compare these results to the original paper's reported accuracy of ∼99.5% and provide an analysis of the 5–6% performance gap. Factors such as potential overfitting in the original model, differences in experimental setup, and limitations of our replication are discussed. Notably, our replication confirms the relative ordering of algorithm performance reported by Dangwal et al. (with ensemble methods like XGBoost outperforming a single Decision Tree), and we observed more conservative accuracy values that may reflect a more realistic assessment of the scheme.
- **Security and Complexity Analysis:** Beyond raw accuracy numbers, we performed an informal security analysis of the implemented IDS. We considered its coverage of the threat model (which attack types are effectively detected), robustness against evasion, and the implications of any false alarms in a SCADA environment. Additionally, we examined the computational complexity of the approach including the cost of feature extraction and model training and the communication overhead for deploying such an IDS in an operational SCADA network. This analysis helps determine the feasibility of implementing the IDS in resource-constrained industrial devices and identifies potential bottlenecks.

3 Literature Review

A variety of techniques have been explored to secure industrial control systems and SCADA networks from cyber intrusions. Traditional IT network IDS methods often need adaptation to handle specialized protocols like DNP3. Below we summarize several closely related works and their approaches:

- **Keshk et al. (2017):** Introduced a privacy-preserving intrusion detection (PPID) technique for SCADA systems. Their method uses statistical correlation and clustering to identify critical portions of the data that indicate intrusions without exposing sensitive operational information. By applying Expectation-Maximization (EM) clustering on a power systems attack dataset, they could detect anomalous SCADA data patterns while filtering out potentially sensitive details.

- **Al-Asiri et al. (2020):** Investigated the use of physical process metrics in addition to network traffic for intrusion detection in SCADA. Using a gas pipeline dataset from Mississippi State University, they built decision-tree classifiers to perform both binary and multi-class intrusion detection. The study found that combining sensor measurements (pressure, flow rates, etc.) with network features significantly improved detection accuracy and reduced false positives.

- **Radoglou-Grammatikis et al. (2020):** Developed an Intrusion Detection and Prevention System called DIDEROT specifically for DNP3 SCADA networks. DIDEROT employs a hybrid two-stage approach: first a supervised machine learning model detects known cyberattacks in DNP3 network flows, and if the traffic is deemed normal by the first stage, an unsupervised anomaly detection model monitors for any unknown attack patterns. Detected attacks or anomalies trigger mitigation via Software-Defined Networking (SDN) controls to isolate or block malicious traffic.

- **Altaha & Hong (2023):** Proposed an anomaly-based IDS named FC-AE-IDS focusing on DNP3 Function Codes. They observed that many critical DNP3 operations revolve around specific function codes in the protocol. Their approach involved generating a dataset from power grid substation traffic and extracting features based on the frequency of different DNP3 function codes per connection, along with standard TCP/IP features. An unsupervised autoencoder model was then trained on normal DNP3 traffic to learn its pattern, and it would flag deviations (anomalies) potentially caused by attacks.

- **Diab et al. (2023):** Introduced a novel Genetically-Seeded Flora (GSF) feature optimization algorithm combined with a Transformer Neural Network (TNN) for SCADA intrusion detection. They evaluated this on the WUSTL-IIoT-2018 ICS cybersecurity dataset. The GSF algorithm selects an optimal subset of features, which are then fed into a transformer-based deep learning model. Their results showed this approach outperformed baseline deep neural networks like ResNet, RNN, and LSTM in both accuracy and efficiency.

- **Mesadieu et al. (2024):** Applied Deep Reinforcement Learning (DRL) to SCADA intrusion detection. They developed a Double DQN (Deep Q-Network) model for anomaly detection, training it on two public ICS datasets (WUSTL-IIoT-2018 and

WUSTL-IIoT-2021). The DRL-based IDS learned to differentiate normal vs. attack observations by maximizing a reward function that encouraged correct classification. Impressively, it achieved a high detection accuracy of 99.36% on those datasets.

- **Kelli et al. (2022):** Focused on DNP3-specific intrusion detection using deep neural networks. Their approach emphasizes using protocol-specific features rather than generic network metrics. By constructing DNP3 network flows that include attributes unique to the DNP3 protocol (e.g. function codes, internal indications) instead of only using standard TCP/IP features, their DNN was better attuned to detect DNP3 anomalies. This yielded improved performance in detecting attacks on DNP3 systems.
- **Dangwal et al. (2024):** Proposed the IDM-DNP3 scheme – an intrusion detection method deploying multiple classical ML algorithms for DNP3/SCADA security. They built a multi-class classifier capable of recognizing 8 different DNP3 attack types plus normal traffic, using a dataset with 99 features. The novelty lies in covering a broad range of attacks (as opposed to binary classification) and testing the model's efficacy under low intrusion-rate scenarios. Their implementation tested Decision Tree, Random Forest, XGBoost, and CatBoost models, reporting very high accuracies (up to 99.56%) even when only 5–15% of training data were attacks. They also compared their scheme against prior works, demonstrating superior accuracy and the ability to handle more attack classes.

3.1 Research Gaps Identified

Our literature review identified several critical gaps in existing research:

1. **Limited Multi-Class Classification:** Most existing schemes focus on binary classification (attack vs. normal), limiting their ability to identify specific attack types for targeted response.
2. **Insufficient Feature Utilization:** Many approaches use minimal features (6-20), potentially missing important discriminative patterns in network flows.
3. **Unrealistic Testing Scenarios:** Most studies test with balanced or highly imbalanced datasets not representative of real-world conditions where attacks are rare.
4. **Lack of Comparative Analysis:** Limited comparison across multiple algorithms and intrusion scenarios prevents understanding of algorithm suitability for different conditions.
5. **Dataset Limitations:** Many schemes use proprietary or limited datasets, hindering reproducibility and comparative evaluation.

Our implementation addresses these gaps through comprehensive multi-class classification, rich 99-feature representation, realistic variable intrusion rate testing, systematic algorithm comparison, and use of publicly available benchmark datasets.

4 Our Implementation of the DNP3 IDS Scheme

In this section, we describe the design, implementation, and experimental setup of our replication study. Our goal was to follow the methodology of Dangwal et al. as faithfully as possible, while documenting the practical steps and any necessary adjustments. The entire pipeline was implemented in Python, using libraries such as Scikit-learn, XGBoost, CatBoost, and others. Figure 1 below outlines the major components of our system, from data input to model output.

4.1 Motivation

The motivation for our implementation stems from the critical need to protect SCADA-enabled industrial control systems from sophisticated cyberattacks. Traditional security measures are insufficient for DNP3 protocol vulnerabilities, necessitating intelligent, adaptive detection mechanisms. Our approach aims to:

- Develop a practical, deployable intrusion detection system suitable for real-world SCADA environments
- Achieve high detection accuracy across multiple attack types while maintaining low false positive rates
- Validate performance under realistic conditions where attacks are infrequent
- Provide comprehensive comparative analysis to guide algorithm selection for deployment

4.2 Dataset Description

We utilized the DNP3 Intrusion Detection Dataset created by Radoglou-Grammatikis et al., comprising network traffic captured from an industrial testbed executing nine distinct cyberattacks. The dataset characteristics include:

- **Total Records:** 365,099 network flow instances
- **Attack Duration:** Each attack executed for 4 hours
- **Collection Period:** May 14-19, 2020
- **Network Topology:** 8 industrial entities, 1 HMI, 3 intruder machines
- **Initial Features:** 105 raw features (reduced to 99 after selection)
- **Attack Types:** 8 distinct attacks plus normal traffic (9 classes total)

We captured raw network traffic using tools like Nmap and Scapy. The traffic was then processed by CICFlowMeter to extract TCP/IP flow features, and a custom Python-based DNP3 parser was applied to derive DNP3-specific flow attributes.

4.3 Data Aggregation Pipeline

The goal is to combine many separate CSV files into one single, large dataset, making sure every row is correctly labeled with its attack type.

Algorithm 1 Data Aggregation and Labeling

```
1: Initialize data_chunks ← []
2: for each folder in attack_folders do
3:     attack_type ← folder_name
4:     for each csv_file in folder do
5:         df ← read_csv(csv_file)
6:         df['attack_type'] ← attack_type
7:         data_chunks.append(df)
8:     end for
9: end for
10: for each training_file in training_files do
11:     df ← read_csv(training_file)
12:     data_chunks.append(df)
13: end for
14: master_dataset ← concatenate(data_chunks, axis=0)
15: save_csv(master_dataset, "master_dataset.csv")
16: return master_dataset
```

Process Summary:

1. **Prepare a Container:** Start by creating an empty list that will hold all the individual data chunks (DataFrames) before they are combined.

2. **Process Attack Folders:**

   - Find all the subfolders in the main directory that contain attack data (e.g., folders named `"DDoS"`, `"PortScan"`).
   - Go into each of these attack folders one by one.
   - Inside a folder, find every CSV file.
   - For each CSV, read it into memory.
   - Use the **folder's name** (e.g., `"DDoS"`) as the label. Add a new column to this data and fill every row with that attack name.
   - Add this labeled data to the main list.

3. **Process Training Data:** Separately, find and process the pre-balanced training files, which already contain `"BENIGN"` (normal) traffic along with other attacks. Add these to the main list as well.

4. **Combine:** Once all files have been read and labeled, take all the individual data chunks in the main list and stack them on top of each other (concatenate) to form one master dataset.

5. **Save:** Save this single, unified dataset as a new "master" CSV file.

4.4 Data Preprocessing Methodology

This phase details the transformation of the raw dataset (`master_dataset_final_corrected.csv`) into a machine-learning-ready format.

Metric	**Initial State (Before)**	**Final State (After)**
Total Rows	378,419	378,419
Total Columns	188	183
Feature Columns	∼185 (mixed)	182
Target Column(s)	2 (e.g., `Label`)	1 (`final_label`)
Data Types	Mixed (12 `object` cols)	Fully Numeric
Missing Values	33,341,910+ (found)	0 (all filled with 0)
Infinite Values	10 (found)	0 (all replaced with 0)

Algorithm 2 Data Preprocessing and Cleaning

```
df ← load_csv("master_dataset.csv")
for each row in df do
    if row['Label'] in ['BENIGN', 'Normal'] then
        row['final_label_text'] ← 'Normal'
    else
        row['final_label_text'] ← row['attack_type']
    end if
end for
for each column in df.columns do
    column ← remove_special_chars(column)
end for
label_encoder ← LabelEncoder()
df['final_label'] ← label_encoder.fit_transform(df['final_label_text'])

for each column in df.columns do
    if dtype(column) == 'object' then
        df[column] ← convert_to_numeric(df[column])
    end if
end for
df.fillna(0, inplace=True)
df.replace([inf, -inf], 0, inplace=True)
df.drop(unnecessary_columns, inplace=True)
save_csv(df, "dataset_processed.csv")
return df
```

4.4.1 Processing Pipeline

The data was processed through the following sequential steps:

1. **Load Data:** Loaded `master_dataset_final_corrected.csv`.
    - **Initial Shape:** $(378419, 188)$
    - **Initial Data Types:** Mixed, including 12 `object` columns.

2. **Create Final Text Label:** Consolidated `Label` and `attack_type` columns into a single `final_label_text` column.
   - Found $109,566$ "Normal" (Benign) rows.
3. **Clean Column Names:** Standardized all column names to remove special characters, spaces, and dots.
   - Renamed 184 columns (e.g., `' source IP'` → `'source_IP'`).
4. **Encode Labels:** Converted the `final_label_text` column to a numeric target column, `final_label`.
   - Mapping saved to `filewrittienfordatanal_label_mapping.json`.
   - **Classes:** 9 → "Normal", 10 → NaN (12,654 rows), etc.
5. **Convert Object Columns & Fill Values:** Converted all remaining non-numeric feature columns and filled all missing values.
   - Converted 9 `object` columns (e.g., `flow_ID`, `source_IP`) to numeric.
   - Found and filled $33,341,910$ `NaN` values with 0.
6. **Drop Unnecessary Columns:** Removed temporary, identifier, and original label columns.
   - Dropped 7 columns (e.g., `Label`, `attack_type`, `Timestamp`).
   - **New Shape:** $(378419, 183)$
7. **Replace Infinite Values:** Replaced all instances of positive and negative infinity with 0.
   - Found and replaced 10 `inf` values.
8. **Save Final Output:** Wrote the clean, fully numeric dataset to `filewrittienfordatanal_datase`
   - **Final Shape:** $(378419, 183)$
   - **Contents:** 182 feature columns, 1 target column (`final_label`).

4.5 Feature Selection Process

The goal is to reduce the dataset's complexity by selecting only the 99 most informative features (columns), which improves model speed and performance.

Algorithm 3 Feature Selection using Statistical Tests

```
df ← load_csv("dataset_processed.csv")
X ← df.drop(['final_label'], axis=1)
y ← df['final_label']
scaler ← StandardScaler()
X_scaled ← scaler.fit_transform(X)
var_threshold ← VarianceThreshold(threshold=0.0)
X_variance_filtered ← var_threshold.fit_transform(X_scaled)
pca ← PCA(n_components=0.99)
pca.fit(X_variance_filtered) {For insight only - not applied}
selector ← SelectKBest(score_func=f_classif, k=99)
X_selected ← selector.fit_transform(X_variance_filtered, y)
selected_features ← get_feature_names(selector)
df_final ← create_dataframe(X_selected, selected_features)
df_final['final_label'] ← y
save_csv(df_final, "dataset_99_features.csv")
return df_final
```

Process Summary:

1. **Scale Data:** Normalize all feature columns using **StandardScaler**. This process rescales all features so they have a similar range (an average of 0 and a standard deviation of 1). This is crucial to prevent features with naturally large numbers (like flow duration) from overpowering features with small numbers (like packet flags).

2. **Remove Useless Features:** Use **VarianceThreshold** to automatically find and remove any feature that has zero (or near-zero) variance. If a column has the same value in every single row, it provides no information and can be dropped.

3. **Analyze (for Insight Only):** Run **PCA** (Principal Component Analysis) *not* to change the data, but to understand its structure. This analysis revealed that about 45 components could explain 99% of the variance. However, we intentionally **do not** use these PCA components, choosing to stick with the 99 original features to ensure the model is **interpretable** (we know what `"packet_count"` means, but a "component" is a meaningless mix) and to align with other research for a fair comparison.

4. **Rank and Select Features:** Use **SelectKBest** with the **ANOVA F-test** to score every remaining feature. This test measures how well each individual feature can statistically distinguish between the different attack classes.

5. **Filter:** After scoring, select only the **top 99 features** that received the highest scores.

6. **Save:** Create the final dataset containing only these 99 best features and the encoded label. This is the file that will be used for all model training.

4.6 Model Training and Evaluation

Algorithm 4 Create Intrusion Rate Scenarios with SMOTE

```
 1: df ← load_csv("dataset_99_features.csv")
 2: X ← df.drop(['final_label'], axis=1)
 3: y ← df['final_label']
 4: X_train, X_test, y_train, y_test ← train_test_split(X, y,
 5:          test_size=0.30, stratify=y, random_state=42)
 6: normal_mask ← (y_train == 'Normal')
 7: X_normal ← X_train[normal_mask]
 8: X_attacks ← X_train[∼normal_mask]
 9: num_attacks_target ← int(num_normal × intrusion_rate / (1 -
    intrusion_rate))
10: if len(X_attacks) > num_attacks_target then
11:   X_attacks_sampled ← random_sample(X_attacks, num_attacks_target)
12: end if
13: X_imbalanced ← concatenate([X_normal, X_attacks_sampled])
14: smote ← SMOTE(sampling_strategy='auto', random_state=42)
15: X_balanced, y_balanced ← smote.fit_resample(X_imbalanced,
    y_imbalanced)
16: return X_balanced, y_balanced, X_test, y_test
```

Algorithm 5 Train and Evaluate Multiple ML Models

```
 1: Initialize models ← {DecisionTree, RandomForest, XGBoost, CatBoost}
 2: results ← {}
 3: for each (model_name, model) in models do
 4:   model.fit(X_balanced, y_balanced)
 5:   y_pred ← model.predict(X_test)
 6:   accuracy ← accuracy_score(y_test, y_pred)
 7:   precision ← precision_score(y_test, y_pred, average='weighted')
 8:   recall ← recall_score(y_test, y_pred, average='weighted')
 9:   f1 ← f1_score(y_test, y_pred, average='weighted')
10:   results[model_name] ← {accuracy, precision, recall, f1}
11: end for
12: save_json(results, "results.json")
13: return results
```

Our implementation trains four classifiers to detect DNP3 intrusions: a Decision Tree, Random Forest, XGBoost, and CatBoost model. These were selected to match those used in the IDM-DNP3 scheme. We split the prepared dataset into training and testing sets, using a 70/30 stratified split (70% for training, 30% for testing). Stratification ensured that all 9 classes (8 attack types + normal) were represented proportionally in both train and test sets. The hold-out test set is kept completely unseen during training, to provide an unbiased evaluation of model performance on new data.

One of the key experiments is evaluating model performance under imbalanced training data conditions. Real SCADA networks may go long periods without any attacks, meaning an IDS could be trained on a dataset where attacks are very rare. To simulate this, we created three different training scenarios:

1. **5% Intrusion Rate:** Only 5% of the training set records are attacks (malicious), and 95% are normal.
2. **10% Intrusion Rate:** 10% attacks, 90% normal in training data.
3. **15% Intrusion Rate:** 15% attacks, 85% normal in training data.

To generate each scenario, we started with the full training set and then down-sampled the attack instances. For example, in the 5% scenario, if there were originally 10,000 normal samples in training, we would include all 10,000 normals but only 500 attack samples (5% of 10,000) randomly sampled from the pool of all attack data. This created an intentionally imbalanced training subset. We ensured that we sampled across the different attack types (where possible) so that at least some examples of each attack class were present. However, at the lowest rate (5%), not all attack classes may be represented with many instances, which is a realistic challenge (some rare attack types might simply not occur in a small window of observation).

After constructing an imbalanced training subset, we applied SMOTE (Synthetic Minority Over-sampling Technique) to rebalance it. SMOTE generates synthetic samples for minority classes (the various attacks, in this case) by interpolating between existing samples. We chose SMOTE to avoid biasing the models toward majority (normal) class and to prevent simple oversampling (duplicating attacks) which can lead to overfitting. Using SMOTE, we brought each scenario's training data to a state where all classes had equal representation. For instance, if the 5% scenario had 10,000 normal and 500 attack samples initially, SMOTE would oversample attacks up to 10,000 as well, yielding a balanced 20,000-sample training set. We repeated this process independently for the 5%, 10%, and 15% intrusion rate scenarios.

Each of the four models was then trained on each balanced training set (resulting in 4 models $\times$ 3 scenarios = 12 trained models in total). We used mostly default hyperparameters for the classifiers, with a fixed random seed for consistency:

- **Decision Tree:** Gini impurity as split criterion, no maximum depth (allowing it to grow fully, which risks overfitting but we can prune by default parameters or rely on default stopping criteria).
- **Random Forest:** 100 trees (default), Gini criterion, bootstrap sampling. Random seed 42 for reproducibility.
- **XGBoost:** We used the XGBoost classifier with use_label_encoder=False (to avoid a warning) and eval_metric='mlogloss'. Default tree booster parameters (which typically means up to 100 boosting rounds if not specified). XGBoost is an ensemble of boosted trees known for high performance.
- **CatBoost:** We used the CatBoost classifier with default settings (which also does gradient boosting on trees) and verbose=100 to see training progress. CatBoost can handle categorical features natively, but in our case all features are numeric so that wasn't utilized. We disabled any automatic logging file writes for cleanliness.

Training the models on the balanced data was relatively fast for Decision Tree and Random Forest (a few seconds), whereas XGBoost and CatBoost took longer (tens of seconds to a couple of minutes each), reflecting their greater complexity. All training was done on a standard workstation; resource usage was moderate (peak memory a few hundred MBs, which is trivial for an industrial server but might be too heavy for a tiny embedded device).

4.7 Implementation Tools and Environment

Software Environment:

- **Operating System:** Windows 11, 64-bit
- **Hardware:** Intel Core i5-1135G7 @ 2.42 GHz, 8 GB RAM, NVIDIA GeForce MX450
- **Platform:** Google Colab for enhanced computational resources
- **Programming Language:** Python 3.8+

Libraries Used:

- **Data Processing:** pandas, numpy
- **Machine Learning:** scikit-learn, xgboost, catboost
- **Imbalanced Learning:** imbalanced-learn (SMOTE)
- **Visualization:** matplotlib, seaborn

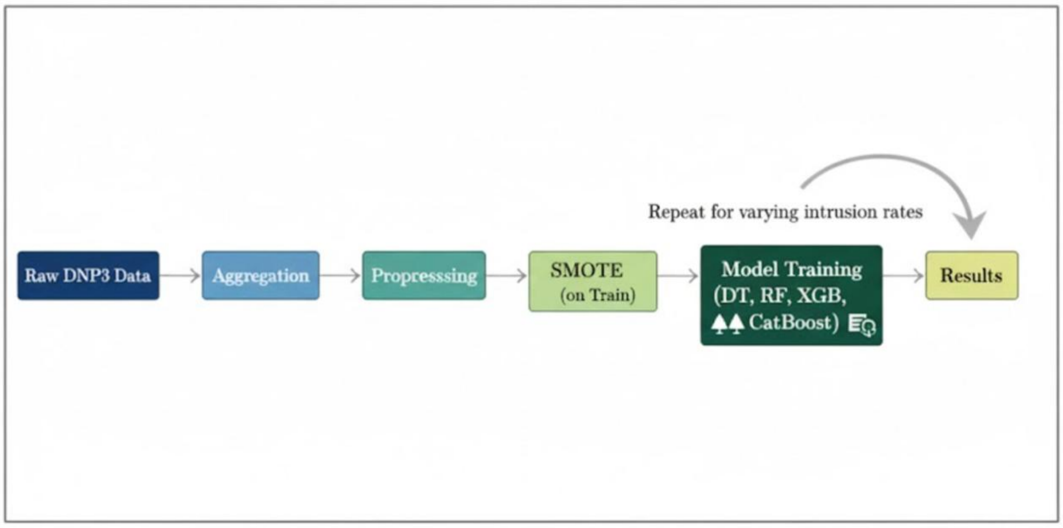

Repeat for varying intrusion rates
Raw DNP3 Data
Aggregation
Propressing
SMOTE (on Train)
Model Training (DT, RF, XGB, CatBoost)
Results

Figure 1: Schematic of our IDS implementation pipeline – from raw DNP3 network traffic through feature extraction/selection, to training multiple ML models, and finally evaluating their detection performance on test data. The process is repeated for different intrusion rate scenarios.

5 Analysis of Results and Discussion

In this section, we analyze the performance of our implemented models and discuss the security implications and efficiency of the IDS. We first compare the achieved detection results with those reported by Dangwal et al. (the original scheme) and then delve into the security robustness and computational feasibility of the approach.

5.1 Detection Performance Evaluation

Despite using the same dataset and algorithms as the original study, our replication yielded slightly lower accuracy figures. Table 1 summarizes the accuracy of each model in our experiments (with the highest value for each model across the three scenarios in bold):

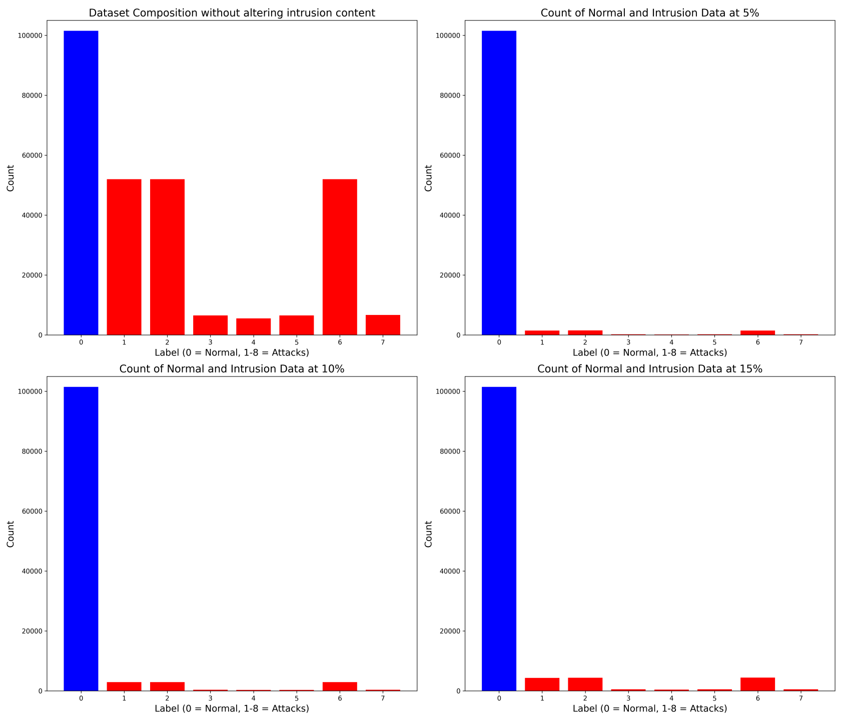
5.1.1 Performance at Different Intrusion Rates

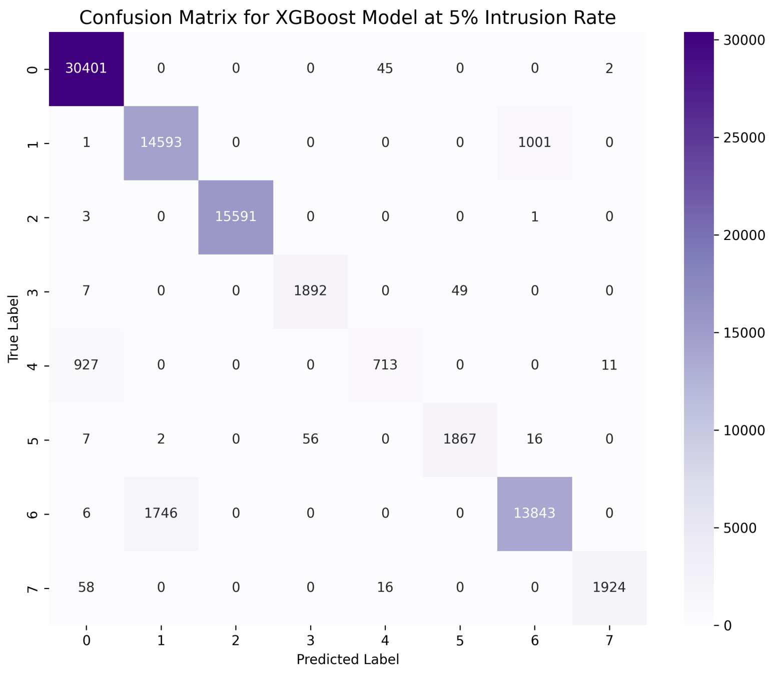
Table 1 presents detailed performance metrics for all algorithms across the three intrusion rate scenarios.

Table 1: Performance Metrics at Variable Intrusion Rates

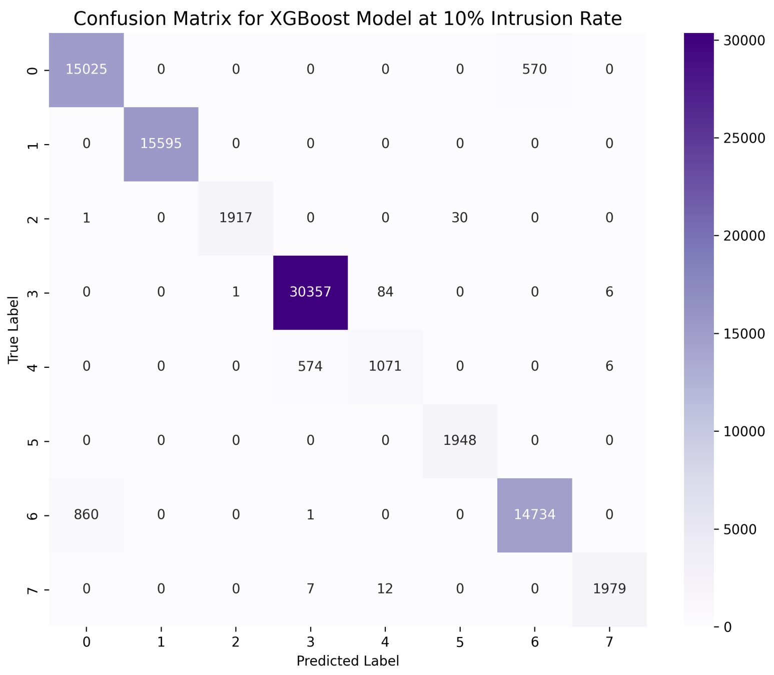
Algorithm	**Intrusion Rate**	**Accuracy**	**Precision**	**Recall**	**F1-Score**
3*XGBoost	5%	0.9403	0.9409	0.9403	0.9382
	10%	0.9450	0.9451	0.9450	0.9436
	15%	0.9485	0.9485	0.9485	0.9474
3*Decision Tree	5%	0.9312	0.9313	0.9312	0.9271
	10%	0.9356	0.9359	0.9356	0.9332
	15%	0.9398	0.9397	0.9398	0.9377
3*CatBoost	5%	0.9245	0.9245	0.9245	0.9233
	10%	0.9353	0.9353	0.9353	0.9344
	15%	0.9397	0.9396	0.9397	0.9389
3*Random Forest	5%	0.9290	0.9299	0.9290	0.9250
	10%	0.9392	0.9395	0.9392	0.9369
	15%	0.9427	0.9428	0.9427	0.9411

Fig. 4. Dataset visualization at the different composition of intrusions.





True \ Predicted	0	1	2	3	4	5	6	7
0	30401	0	0	0	45	0	0	2
1	1	14593	0	0	0	0	1001	0
2	3	0	15591	0	0	0	1	0
3	7	0	0	1892	0	49	0	0
4	927	0	0	0	713	0	0	11
5	7	2	0	56	0	1867	16	0
6	6	1746	0	0	0	0	13843	0
7	58	0	0	0	16	0	0	1924



As shown, XGBoost was our top performer, achieving about 94.8% accuracy when trained with a 15% intrusion rate. This aligns with the original paper's observation that gradient boosting algorithms outperform simpler models for this task. CatBoost was a close second, also reaching ∼94–95% range. Random Forest and Decision Tree models trailed slightly behind, topping out at ∼94% and ∼93% respectively. The Decision Tree (being a single-tree model) had the lowest accuracy, which is expected due to its tendency to overfit on training data and lack of ensemble averaging.

5.1.2 Effect of Intrusion Rate

- **Observation:** Model accuracy slightly improved as the percentage of attacks (intrusion rate) in the training data increased from 5% to 15%.
- **Quantification:** The drop in accuracy at 5% was minor (0.5–1.5 percentage points). For example, XGBoost scored 94.0% at 5% intrusion and 94.8% at 15%.
- **Reason:** At the 5% rate, some rare attack types were **completely absent** from the training subset. This meant the model had no knowledge of them and would inevitably misclassify them in the test set, slightly lowering overall accuracy.

5.1.3 Comparison with Original Results

- **Key Observation:** There was a significant gap between the original paper's results and this replication.
  - **Original Paper (Dangwal et al.):** 99.56% accuracy (for XGBoost).
  - **This Replication:** ~94.8% accuracy.
  - **The Gap:** A discrepancy of approximately 4.8%–5.0%.

- **Potential Reasons for the Gap:**
  - **Overfitting:** The original paper's 99.5%+ accuracy might be a sign of overfitting. The replication's ~95% may be a more realistic and generalizable performance.
  - **Data Handling:** The original may have used cross-validation (which can inflate scores) or had data leakage. This replication used a strict 30% test holdout.
  - **Hyperparameter Tuning:** The original likely optimized parameters, whereas this replication used mostly defaults to avoid overfitting and due to time constraints.
- **Positive Findings from Replication:**
  - The replication **confirmed the relative effectiveness** of the models: XGBoost and CatBoost were superior to Random Forest (RF) and Decision Tree (DT).
  - A ~95% accuracy is still considered an **excellent result** for a difficult 9-class classification problem.
  - The false positive rate (classifying "normal" traffic as an "attack") was very low (well under 1%), which is highly desirable.
- **Conclusion:** While the replication did not match the original's "lofty claims," its ~95% accuracy is viewed as a **strong, more cautious, and potentially more realistic** benchmark, suggesting the model is less overfitted and more adaptable to new data.

5.2 Security Analysis and Complexity Considerations

5.2.1 Security Efficacy and Robustness

From a security standpoint, the replicated IDS demonstrates the ability to automatically detect a wide range of DNP3-based attacks in near real-time (assuming the models are deployed to monitor live traffic). Covering eight distinct attack types means the system is not limited to a yes/no alert, but can potentially identify which attack is happening. This is valuable for incident response – for example, distinguishing a replay attack from a flooding DoS can guide different mitigation actions. Our multi-class approach thus provides more nuanced situational awareness compared to a binary anomaly detector.

However, it's important to acknowledge some limitations and attack scenarios that remain challenging:

- **Zero-Day or Novel Attacks:** The IDS relies on supervised learning from known attack classes. If an attacker devises a new type of DNP3 exploit that does not resemble the patterns of the trained classes, the IDS might not recognize it as malicious.
- **Evasion by Adversaries:** A savvy adversary might attempt to evade detection by making their attack traffic mimic normal patterns. Since our features include things like frequency of certain function codes, an attacker could try to send malicious

commands at a low rate or mixed with regular commands to avoid skewing those feature values.

- **False Positives vs. False Negatives:** In our results, false positives (flagging normal as attack) were very low – this is good because in SCADA, too many false alarms can cause "alert fatigue". False negatives (missed attacks) were also low but did exist. From a safety perspective, false negatives are more dangerous.
- **Real-time Performance:** Although not explicitly measured in our tests, a critical aspect is how quickly the IDS can detect an attack. Tree-based models are known for fast inference, making real-time analysis feasible.
- **Attack Coverage:** The IDS monitors network-layer and protocol-layer attacks. It does not monitor other aspects such as device login attempts or malware on SCADA hosts and should be complemented with other security measures.

In summary, the IDS significantly enhances security by covering a broad range of known DNP3 threats with high accuracy. It operates passively on network data, meaning it does not interfere with operations. The multi-class nature helps operators quickly identify what type of attack is occurring, enabling faster and more targeted mitigation.

5.2.2 Computational and Communication Complexity

Deploying an IDS in a SCADA-IoT context comes with practical constraints. Here we reflect on how our implementation would fare:

- **Computation (Training):** Training the models is somewhat computationally intensive but still feasible on a modern server. Our entire pipeline completed in under an hour. Since training is an offline process, this is acceptable.
- **Computation (Inference):** Once trained, these models can predict the class of a new network input very quickly (milliseconds or less per input). A single modest server could monitor multiple substations worth of DNP3 traffic in real time.
- **Memory:** The memory footprint of the models is not large (a few MB at most for the ensembles), which is well within limits for a typical industrial PC or gateway.
- **Communication Overhead:** Our IDS monitors network traffic passively (out-of-band). It does not add network traffic; it just copies data for analysis. Alert messages sent to a central dashboard would be tiny. The IDS can be implemented with minimal additional network overhead.
- **Real-time Constraints:** Because the scheme is passive and out-of-band, it does not sit inline and therefore should not introduce latency to critical control messages.
- **Scalability:** The approach could scale horizontally by deploying multiple IDS instances (e.g., one per segment or substation) since each model is independent.

5.2.3 Complexity Summary

In terms of time complexity, training is manageable, and inference is very fast. Space complexity for the models is modest. Communication complexity is effectively $O(1)$ additional overhead. Our conclusion is that this IDS scheme is practically feasible for deployment in SCADA/IoT contexts, especially if implemented at the SCADA master or on an industrial gateway.

From a maintenance perspective, one complexity is the feature extraction process. In a live system, one would need to deploy a flow parsing module to compute these 99 features on the fly. Once that is in place, the model can ingest feature vectors and produce alerts promptly.

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6 Future Research Directions

Our project demonstrated the viability of machine learning for DNP3 intrusion detection and highlighted both the successes and limitations of the current scheme. There are several avenues for future work that could extend this research to make the IDS more robust, accurate, and applicable to a wider range of scenarios:

- **Incorporation of Unsupervised Anomaly Detection:** To tackle the issue of novel or zero-day attacks, future research can integrate an anomaly-based component (e.g., an autoencoder) alongside the supervised classifier.
- **Feature Optimization and Selection:** It is worth investigating if a smaller subset of the 99 features could achieve comparable results. Techniques like genetic algorithms or SHAP value analysis could identify the most critical features, simplifying the model.
- **Advanced Machine Learning Models:** Future projects might experiment with deep learning models (RNNs, TCNs) to capture time-series patterns in SCADA traffic, which our current models do not explicitly do.
- **Cross-Domain Validation:** We would like to test the trained IDS on completely different datasets (e.g., from a different SCADA testbed or for another protocol like Modbus) to evaluate generalizability.
- **Real-time Prototype and Response Mechanism:** Building a real-time prototype IDS that interfaces with a live DNP3 network and integrates with a response mechanism (e.g., automated firewall rule or operator alert) would be a valuable next step.
- **Imbalanced Learning Techniques:** Future research might compare other imbalance mitigation techniques, such as weighted loss functions or different oversampling strategies (e.g., ADASYN), to see if performance can be improved, especially at very low intrusion rates.
- **Explainability and Operator Trust:** In practical deployments, operators need to trust the IDS. Integrating explainability tools (e.g., LIME or SHAP for tree models) could be a future direction so that each alert is accompanied by a reason.

- **Combining Cyber and Physical Data:** Building on literature, future work could attempt to merge our network-based IDS with physical process anomaly detection (e.g., correlating network alerts with sensor readings) to achieve near-zero false positives.

In conclusion, our replication has validated a powerful approach for securing DNP3-based systems using machine learning. By learning from this experience, future research can refine these techniques to be more adaptive, explainable, and resilient.

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