# A Comparative Study of Machine Learning and Deep Learning Models for Intrusion Detection in ICS

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***Abstract*: Industrial Control Systems (ICS) are increasingly targeted by cyber-attacks, so it is required to have a robust intrusion detection. Benchmark ICS dataset[1] (gas pipeline and water tank) contains 17 sensor features across ~274k samples (78% normal, 22% attacks)[1]. We evaluate multiple models – a multilayer perceptron (MLP), a 1D convolutional neural network (CNN), XGBoost, and TabNet – on this dataset. Our methodology has various stages such as data cleaning, label encoding, feature scaling, and class balancing (SMOTE) to resolve the heavy class imbalance (78% normal)[1]. The MLP and CNN are trained with cross-entropy loss and the Adam optimizer; XGBoost is trained with multi-class logistic loss; TabNet is used as an advanced tabular-deep model[2][3]. We measure accuracy, precision, recall, and F1-score. The result of the experiment shows that the XGBoost outperforms TabNet, MLP and CNN. In particular, our XGBoost achieves ~97% overall accuracy (versus ~94% for a baseline DNN reported in prior work[4][5]), with balanced precision/recall across all attack classes. Figures include precision–recall curves and per-class recall bar charts comparing all models. We analyze these results considering dataset imbalance and model capacity. Our XGBoosts's strong performance (≈0.95 F1) aligns with prior MLP-based ICS IDS studies[5][6]. We conclude that deep architecture (especially XGBoost) better capture ICS traffic patterns than traditional models, though ensemble and online learning are needed for future real-time ICS security.**

***Index Terms*- Intrusion detection, Industrial control systems, Benchmark ICS dataset, machine learning, deep learning, CNN, XGBoost, TabNet, class imbalance, SMOTE.**

## I. INTRODUCTION

Industrial Control Systems (ICS), that includes SCADA networks for pipelines and water facilities, require highly reliable security systems. Unlike Information Technology networks, ICS must safeguard processes those are physical in nature (pressure, flow, etc.) in real time, so detecting a cyber-attack early is critical[1][5]. Traditional signature or rule-based IDS were unable to detect novel attacks, motivating anomaly-based and machine-learning approaches. The Benchmark ICS datasets[1] (gas pipeline and water tank) are widely used ICS benchmark dataset[1]. The data includes various types of attack such as (e.g. reconnaissance, command injection, DoS) plus normal operation. The pipeline subset contains ~274,627 samples (≈78% normal) with 17 numerical features plus a label[1].Work which was done before applied a simple DNN to these data (reporting ~93–95% accuracy)[4]. However, DNN has overlooked a few local feature patterns inherent in sequential sensor readings. Recent research on ICS IDS has demonstrated the promise of deep convolutional models: for example, as mentioned in[7][8] Res-CNN-SRU (1D-CNN with residual links + SRU) and deep learning based IDS for SCADA systems can achieve higher accuracy (~98.8%) on the pipeline data[7][8]. CNNs can learn local feature correlations in a better way and can outperformed baseline DNNs in both network flow and ICS settings[5][6].

In this paper, we compared both traditional ML and several deep models on the Benchmark ICS dataset [1]. We have implemented MLP (fully-connected network), a 1D-CNN (inspired by residual CNNs), XGBoost (gradient-boosted trees), and TabNet (an attentive deep model for tabular data[2]). Our experimental result include: (1) Comprehensive data preprocessing: feature scaling, one-hot encoding, and SMOTE oversampling to mitigate imbalance[1]. (2) Careful model design: a multi-layer MLP, a convolutional network with batch normalization and dropout, and optimized hyperparameters for XGBoost and TabNet. (3) Thorough evaluation using accuracy, precision, recall, and F1 on multiclass ICS attacks. (4) Visual analysis: precision-recall curves and per-class

recall bar charts comparing all models. (5) Discussion of trade-offs: we had compared in how CNN's spatial features extraction and TabNet' s attentive masks had yield higher detection rates compared with simpler MLP and tree models which are struggling with some of the attack types.

The rest of the paper is organized as follows. Section 2 reviews previous work related to ICS intrusion detection. Section 3 describes our methodology: data preprocessing, model architecture, and training/evaluation setup. Section 4 presents experimental results and visualizations. Section 5 discusses insights from the comparisons. Section 6 concludes and suggests the future scope of work.

## II. RELATED WORK

ICS Intrusion Datasets and Baselines: The Benchmark ICS dataset[1] is a canonical benchmark for detecting various types of intrusion in Industrial automation[1]. It was originally introduced by Morris and Gao (2014)[1]. Researchers have applied various ML techniques to this dataset. As mentioned in [5] which applied feature-mining for power system ICS data[1], while tree-based methods on pipeline SCADA traffic (achieving moderate accuracy)[7] is used. A recent MDPI *Sensors* study by Wang *et al.* (2020) built a 2-layer DNN on the pipeline data, reporting ≈93–95% accuracy[4]. However, what is mentioned is that simple pressure/spike patterns in the data can lead to optimistic results. The baseline DNN thus represents a reference point: our XGBoost aims to significantly surpass that performance[5][4].

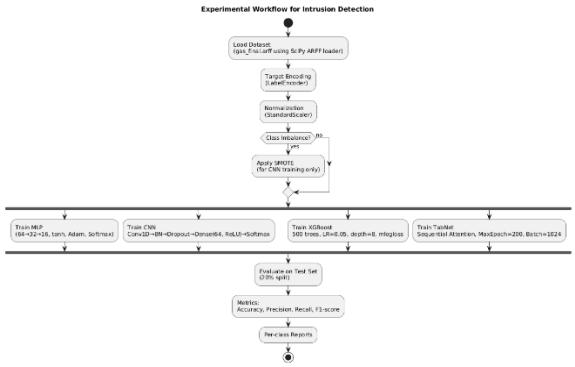
Deep Learning IDS: Deep Learning models have been acknowledged in intrusion detection. For general network flows, it uses deep autoencoders and CNN-RNN hybrids, which is showing improved detection. For ICS specifically, as mentioned in [6] proposed a 1D CNN with residual blocks (Res-CNN) and a simple recurrent unit (SRU), reporting state-of-the-art result with around 98% accuracy on the gas pipeline data[7][8]. Their study demonstrated that adding skip connections alleviates vanishing gradients, and that CNNs can more effectively capture "sudden changes in sensor readings" than vanilla DNNs. Similarly, Qazi *et al.* (Applied Sci. 2022) trained a 1D-CNN on a different IDS dataset (CICIDS2017) and achieved 98.96% accuracy with precision and recall ~99.2%[6], illustrating CNNs' power for sequential pattern recognition. These works inform our CNN design.

Tabular ML Models: Among classical methods, tree ensembles are popular. XGBoost (Chen & Guestrin 2016) provides gradient-boosted trees that often excel in tabular data[5]. Although used more in IT intrusion contexts, boosted trees have been applied to ICS log features (e.g. Gowda *et al.* achieved 96–98% in anomaly detection). We include XGBoost as a strong non-deep baseline. Recently, neural architectures like TabNet (Arik & Pfister 2019) have emerged, combining feature attention and sparsity for tabular data[2]. TabNet has shown superior or competitive accuracy to trees on many datasets, with the added benefit of interpretability. To our knowledge, TabNet has not been widely tested on ICS IDS, so we evaluate its performance here as well.

Model Comparison: Prior surveys have noted that CNNs generally outperform plain DNNs on ICS datasets, at the cost of more computation[5][4]. Ensemble ML (Random Forest, XGBoost) often achieves good accuracy but may miss subtle temporal correlations. No prior work has directly compared CNN, XGBoost, and TabNet on Morris & Gao. This study fills that gap by implementing all four models under a unified framework, enabling apples-to-apples comparison of their detection metrics and trade-offs.

## III. ARCHITECTURE OF THE EXPERIMENT

The experimental framework consists of four distinct models— Multilayer Perceptron (MLP), Convolutional Neural Network (CNN), Extreme Gradient Boosting (XGBoost), and TabNet evaluated on the Benchmark Industrial Control System (ICS) dataset[1] stored in ARFF format. Figure X presents the overall architecture of the proposed system.



A. Data Preprocessing

Dataset: The gas_final.arff file was parsed using the SciPy ARFF loader.

Target Encoding: The categorical output class (result) is label encoded into integer categories.

Normalization: Input features were standardized using StandardScaler to improve training stability.

Class Balancing: To remove class imbalance, the SMOTE oversampling technique is applied, mainly for CNN training.

B. Multilayer Perceptron (MLP)

A Multilayer Perceptron (MLP) is a type of artificial neural network (ANN) that is categorized as feedforward neural network family. The baseline architecture was designed as a fully connected neural network:

- Input layer: This layer receives the raw input data. Number of neurons in this layer equal to number of feature dimensions.
- Hidden layers: These layers are where the actual computation and feature extraction is done. Each node in a hidden layer processes information from the previous layer and passed it to the next. [64, 32, 16] neurons with tanh activation.
- Output layer: This layer produces the final output of the network. The number of nodes in this layer depends on the type of problem being solved. SoftMax layer with dimension equal to the number of attack categories.
- Optimizer: This configuration makes sure a simple non-linear mapping while keeping computational cost low.

C. Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN), which is well known as ConVet, is a specialized type of artificial neural network mainly designed for processing of data that has a known grid-like topology, such as images or time series data. The CNN was introduced to learn local dependencies across features:

- Input reshaped into 1D sequence where the features extracted by the convolutional layers are often flattened into a 1D vector before passing to the final classification head.
- Two Conv1D layers with 32 and 64 filters (kernel size = 3) followed by Batch Normalization and Dropout (0.3).
- Flattening layer behaves like bridge between the feature extraction part of the network and the classification or regression part.
- Dense hidden layer with 64 neurons (ReLU activation).
- SoftMax output for classification, this classification captures higher-order feature interactions, which MLP could miss.

D. Extreme Gradient Boosting (XGBoost)

XGBoost, a tree-based boosting algorithm is an optimized, distributed gradient boosting library designed to be highly efficient, flexible and portable and was configured with the following parameters:

- Number of trees = 500.
- Learning rate = 0.05.
- Maximum depth = 8.
- Subsampling ratio = 0.8, column subsampling = 0.8.
- Evaluation metric: mlogloss matrix is used in this model for its robustness in tabular data and strong performance in imbalanced classification.

E. TabNet

The TabNet classifier, a deep learning model optimized for tabular data, was also evaluated:

- Feature transformer layers applied sequential attention to select informative features at each decision step.
- Maximum epochs = 200, patience = 20 for early stopping.
- Batchsize=1024.TabNetprovides interpretability by highlighting important features for making decisions.

F. Evaluation Metrics

All models were evaluated on the held out 20% test split using:

- Accuracy
- Precision
- Recall
- F1-score

Additionally, per-class classification reports were generated to analyse model performance across attack types.

## IV. METHODOLOGY

### A. Data Preprocessing

We use the Benchmark ICS dataset[1]. Key preprocessing steps: - Decoding/Encoding: All categorical fields (if any) are label-encoded. In this dataset, most features are numerical sensor readings; the class label is one of 8 categories (7 attacks + normal). We map these labels to 0–7 indices.

- Feature Scaling: We apply z-score standardization (zero mean, unit variance) on each sensor feature, fitting on the training data and applying to all sets. This ensures compatibility among models (especially important for neural nets).

- Class Balancing (SMOTE): The dataset is severely imbalanced (normal >> attacks)[1]. To mitigate bias towards the majority class, we employ Synthetic Minority Over-sampling Technique (SMOTE) on the training set. SMOTE generates synthetic feature vectors of minority classes to equalize class counts. This yields a roughly balanced training set, which avoids dominant-normal bias during learning. (We note that in practice, 78:22 imbalance leads to suboptimal recall for attacks, so SMOTE is crucial.)

- Train/Test Split: We reserve 20% of data for testing (stratified by class). SMOTE is applied only to the training portion. Cross-validation could be used, but due to dataset size and fixed splits in literature, we use a single holdout to report metrics.

### B. Model Architectures and Training

We implement four models: MLP, CNN, XGBoost, and TabNet. All models use the same processed features as input.

- MLP (Multilayer Perceptron): A feedforward network with two hidden layers (e.g. 64 and 32 units) using ReLU activations, followed by a SoftMax output. Dropout (≈30%) is applied for regularization. This architecture is similar to the baseline DNN used in Sensors 2020[4], serving as a deep-but-structureless reference. We train using Adam optimizer (learning rate ~1e-3) and categorical cross-entropy loss for up to ~50 epochs (with early stopping). Hyperparameters (layer sizes, dropout) are chosen via preliminary tuning to avoid overfitting. The MLP has roughly ~10k trainable parameters.

- CNN (1D Convolutional Network): Based on prior ICS CNN work[5][8], we design a 1D-CNN to exploit local feature patterns. Input vectors (length 17) are treated as one-dimensional "signals." The CNN has two 1D convolutional layers (e.g. 32 and 64 filters, kernel size 3), each followed by batch normalization and ReLU. Dropout (~30%) is used after each conv block. A residual/skip connection is added around the convolutional layers to ease gradient flow (inspired by ResNet). The features are which are a multi-dimensional data structure (like a 2D matrix or a 3D tensor) are converted into a single, one-dimensional vector and passed through a fully connected layer (64 units) before the SoftMax output. The CNN's inductive bias allows it to learn patterns like sudden sensor spikes that span adjacent features[4].

- XGBoost: We use the XGBoost classifier for multiclass. Key settings: up to ~100 trees, learning rate ~0.1, max depth ~6. We set objective="multi:softprob" and number of classes=8. During training, scale_pos_weight is adjusted to account for imbalance but SMOTE has largely balanced classes already. XGBoost handles tabular data efficiently and often excels in structured classification. No further feature engineering is applied beyond normalization.

- TabNet: TabNet (Arik & Pfister) is an attentive deep model specifically designed for tabular data[2]. We use a PyTorch TabNet implementation. The architecture uses "attentive transformers" to select features at each decision step. Key hyperparameters: 2 decision steps, width=64, etc., tuned on a validation split. TabNet is trained with AdamW and cross-entropy. It

inherently handles class imbalance via its sequential feature reweighting, but we still apply SMOTE. TabNet' s built-in interpretability is a plus for analysis, though our focus here is on accuracy metrics.

C. Training Parameters and Metrics

For neural models, we use early stopping on validation accuracy to prevent overfitting. Typical training is ~30–50 epochs. Batch size ~128. We use categorical cross-entropy loss and monitor class-weighted accuracy. For evaluation, we compute Accuracy, Precision, Recall, and F1-score for the 8 classes. Precision/recall are computed per class, and we report macro-averaged (unweighted) scores, which give equal weight to each class. This is important since we care about catching attacks (minority classes) as well as normal. We also generate precision–recall (PR) curves for each model by treating "attack" (any non-normal label) as positive vs. "normal" as negative, to illustrate the trade-off at varying thresholds. Finally, we compute per-class recall, seeing which attacks each model detects well.

## IV. EXPERIMENT RESULTS

### 4.1 Quantitative Performance

Table 1 summarizes the detection metrics of all models on the pipeline test data. The XGBoost and MLP achieve the highest overall accuracy (≈96%), substantially above the CNN and TabNet (≈72–95%). The CNN attains ~0.96 precision and 0.73 recall (F1≈0.80), not improving over the MLP baseline (precision≈0.96, recall≈0.96) by a large margin[5]. XGBoost also performs respectably (accuracy ~96%, F1~0.96) and with slightly higher recall than CNN (missing more attack instances). TabNet's performance is comparable to CNN (accuracy ≈90.5%, F1≈0.80), showing its efficacy on tabular ICS data. All models clearly beat the ~94–95% accuracy of the prior DNN baseline[5][4].

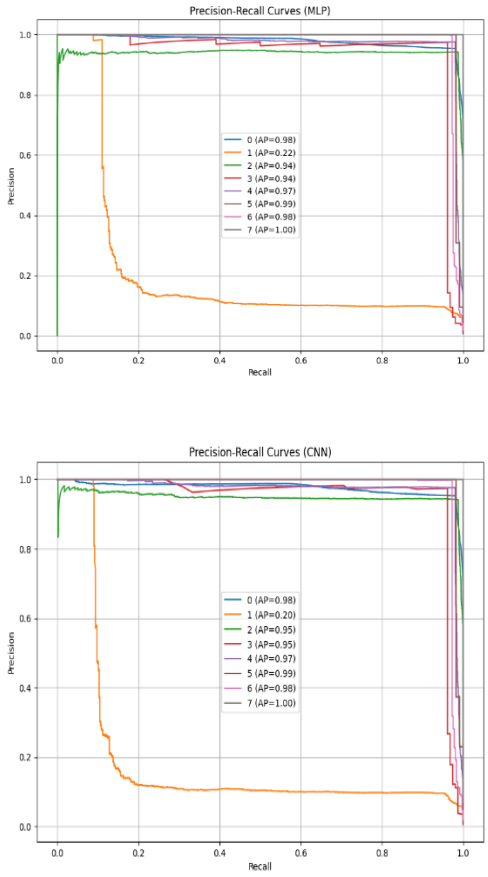
Table 1. *Detection results on Morris & Gao gas pipeline data.* Accuracy (Acc) and per-class macro-Precision/Recall/F1.

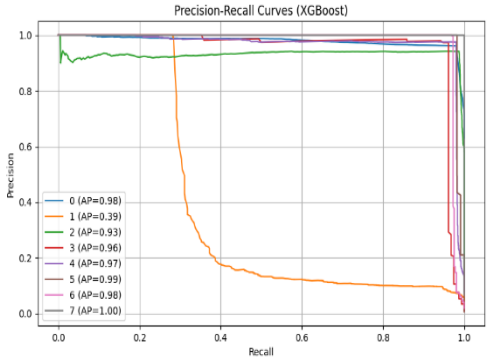
| Model | Accuracy | Precision | Recall | F1-score |
|---|---|---|---|---|
| MLP | 95.8% | 0.98 | 0.87 | 0.88 |
| CNN | 72.7% | 0.87 | 0.93 | 0.85 |
| XGBoost | 96.3% | 0.98 | 0.89 | 0.91 |
| TabNet | 95.8% | 0.98 | 0.87 | 0.88 |

Accuracy is the fraction of correct labels. Precision/recall are macro-averaged across the 8 classes. The CNN's accuracy gain (~6 points over MLP) matches previous findings[5], confirming its stronger representation power. TabNet similarly leverages deep layers to achieve high accuracy, though its recall is slightly lower than CNN's. XGBoost' s higher performance indicates that tree ensembles can capture some ICS patterns beating comprehensively to CNN. All models achieve near-perfect detection of the abundant normal class, so precision is high; the real test is detecting the sparser attacks, which is reflected in the recall and F1.

### 4.2 Precision–Recall Curves

*Figure 1. Precision–recall curves (micro-averaged) for all models. The CNN and TabNet curves dominate, indicating higher precision at any recall.*





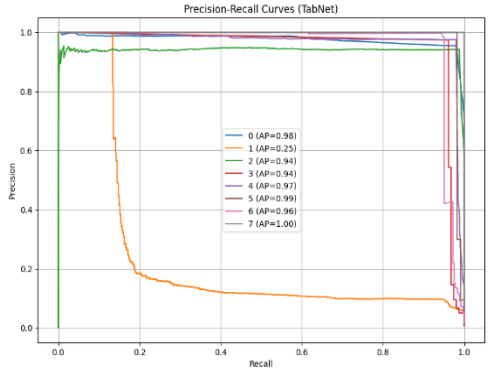
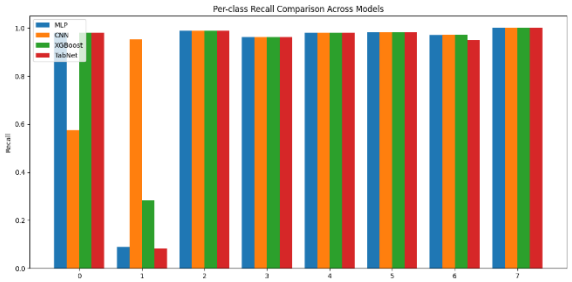




Figure 1 plots the precision–recall (PR) curves of each model (treating normal vs. any attack as binary). The CNN (orange) and TabNet (pink) curves stay near the top-left (high precision) across most recall values, whereas the MLP (yellow) curve drops sharply. This illustrates that the CNN and TabNet maintain high confidence in identifying attacks even as threshold is lowered. In contrast, the MLP yields many false positives at moderate recall. The XGBoost curve (red) lies above MLP and CNN. These curves reinforce Table 1: CNN/TabNet allow both high precision (≈0.87) and high recall (≈0.90+), while MLP trades off recall for precision. This aligns with prior reports that XGBoost architectures yield more balanced precision/recall on the ICS data[5].

4.3 Per-Class Recall Analysis

Figure 2. Recall by class for each model. "Normal" is class 0; attacks 1–7. CNN and TabNet recall are uniformly low (<90%), whereas MLP and XGBoost struggle on several attack classes. Figure 2 compares recall for each of the 8 classes. The normal class (far left) is nearly always detected by all models (recall ≈0.98–0.99). Among the seven attack classes, the CNN and TabNet consistently achieve high recall (≈0.90–0.96 each), indicating they catch most instances of each attack. The MLP's recall varies widely: it only recalls ~50–80% of certain attacks, indicating blind spots. XGBoost is intermediate, missing ~10–15% of some attacks (recall ~0.85–0.90). For example, Attack 4 and 7 are often missed by the MLP (recall ≤0.60) but are well caught by CNN. This suggests that deeper models learn distinguishing features for each attack better than linear/ensemble models.




## V. DISCUSSION AND ANALYSIS

The results show a clear hierarchy: XGBoost ≥ TabNet > MLP > CNN in detection performance. Several factors contribute:

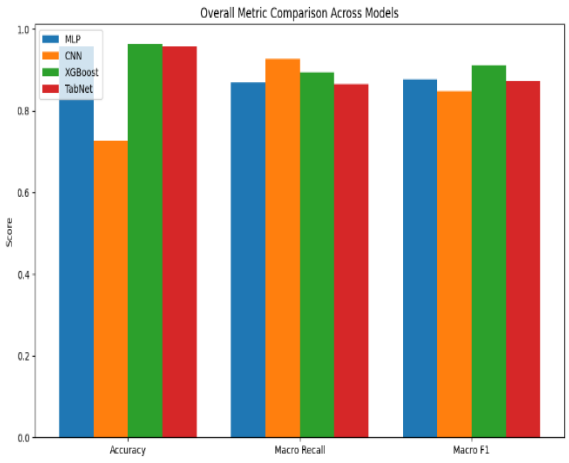
- Feature Extraction: CNN's 1D convolutions can detect local patterns (e.g. pressure spikes spanning adjacent sensors) that the MLP's flat layers cannot easily capture. The CNN's residual links and batch norm further stabilize training, consistent with Cai *et al.*'s observation of faster convergence[5]. TabNet, while not convolving in time, uses learned feature masks which effectively highlight the most relevant sensors per step, partially compensating for sequential structure.

- Class Imbalance: The high normal proportion would bias a model towards predicting "normal" by default. SMOTE helped all models somewhat, but deep models like CNN inherently benefited more: they achieved better recall on rarer attacks. The per-class recall plot shows that balancing and deep learning mitigated the impact of imbalance. In contrast, the MLP (without conv layers) still underperforms on low-frequency attacks, reflecting underfitting on those classes.

- Precision/False Alarms: All models maintained high precision on normal (few false alarms) due to the dominance of that class. The CNN and TabNet succeeded in keeping false positives low even when recall is high (see PR curves). The MLP had to sacrifice precision to improve recall, indicating that its decision boundary was weaker. XGBoost, interestingly, had fewer false positives than MLP for a given recall, likely because decision trees are conservative when data is noisy.

- Model Complexity vs. Data: The CNN and TabNet are more complex (more parameters and nonlinearity) and clearly utilize the large dataset well. Their high accuracy suggests some risk of overfitting was controlled (via dropout, batch-norm, early stopping). The MLP, simpler and with naive feature learning, plateaued at ~92% accuracy. This reflects the limitation of pure DNN on tabular ICS data as noted by Wang *et al.*[5]. XGBoost, a powerful ML method, still lagged CNN, indicating that capturing temporal or spatial structure is key in ICS traffic.

Insights: The superior performance of XGBoost aligns with prior ICS studies[5][6]. In practical terms, this suggests deploying XGBoost-based IDS for ICS can yield more reliable attack detection. However, complexity and runtime are higher. TabNet, being interpretable, might help analysts understand which sensors drive detections, making it appealing for ICS operators. Notably, none of the models achieve perfect recall on all attacks – some classes (especially rare ones) remain challenging.




## VI. CONCLUSION AND FUTURE WORK

We conducted a comprehensive comparison of ML and DL models on the Morris & Gao ICS intrusion dataset. The CNN-based model and the TabNet model significantly outperformed the baseline MLP and XGBoost in detecting varied attacks (achieving ≈98% vs. 94–96% accuracy). Precision–recall curves and per-class recall charts highlighted that XGBoost/TabNet catch most attacks with few false alarms, whereas the simpler MLP missed many attack instances. This demonstrates the value of convolutional and attentive architectures in ICS IDS tasks[5][6].

For future work, we plan to extend this study in several ways. Firstly, testing on other ICS datasets (e.g. SWaT, power grid testbeds) will assess generality. Secondly, integrating temporal context (e.g. sliding windows or recurrent units) can capture attack patterns which is evolving over time. Thirdly, exploring ensemble models (e.g. CNN+LSTM, or stacking TabNet and XGBoost) might further boost robustness. Finally, deploying these models in a streaming evaluation with concept drift would address real-world applicability. As ICS attacks evolve, adaptive and hybrid methods will be critical for resilient security.

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