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Theoretical Foundations and Implementation of Dynamic Intrusion Detection Systems: An Adaptive Machine Learning Approach

by

Khandoker Wahiduzzaman Anik
24141115
Md. Rakib Hossain Ontu
22101879
Md. Mehedi Hasan Sohag
22101883
Fardin Jahan Badhon
22101876

A thesis submitted to the Department of Computer Science and Engineering
in partial fulfillment of the requirements for the degree of
B.Sc. in Computer Science

Department of Computer Science and Engineering
Brac University
June, 2025

Declaration

It is hereby declared that:

1. The thesis submitted is my/our own original work while completing degree at Brac University.
2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.
3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.
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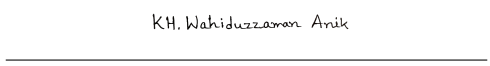
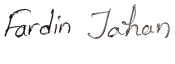


Khandoker Wahiduzzaman Anik
24141115

Md. Rakib Hossain Ontu
22101879

Md. Mehedi Hasan Sohag
22101883



Fardin Jahan Badhon
22101876

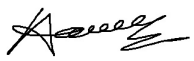
Approval

The thesis/project titled "Theoretical Foundations and Implementation of Dynamic Intrusion Detection Systems:An Adaptive Machine Learning Approach" submitted by:

1. Khandoker Wahiduzzaman Anik (24141115)
2. Md. Rakib Hossain Ontu (22101879)
3. Md. Mehedi Hasan Sohag (22101883)
4. Fardin Jahan Badhon (22101876)

Of Spring, 2025 has been accepted as satisfactory in partial fulfillment of the requirement for the degree of B.Sc. in Computer Science on 18 June, 2025.

Examining Committee:



Dr. Amitabha Chakrabarty
Supervisor (Member)
Dept. of Computer Science and Engineering
Brac University

Dr. Md. Golam Rabiul Alam
Program Coordinator (Member)
Dept. of Computer Science and Engineering
Brac University

Dr. Sadia Hamid Kazi
Chairperson (Chair)
Dept. of Computer Science and Engineering
Brac University

Acknowledgement

First and foremost, we would like to express our profound gratitude to the Almighty, whose grace and blessings made this endeavor possible.

We would also like to extend our deepest and most sincere gratitude to our thesis supervisor, Dr. Amitabha Chakrabarty, Professor in the Department of Computer Science and Engineering at Brac University. His invaluable guidance, unwavering support, and insightful feedback have been instrumental throughout every stage of this research. His expertise and encouragement consistently motivated us to overcome challenges and pursue a higher standard of work.

We are also grateful to the Department of Computer Science and Engineering at Brac University for providing the necessary academic resources and fostering an environment of learning and innovation that made this project possible. We extend our thanks to the examining committee and faculty members for their time and constructive input.

Finally, we owe a heartfelt thanks to our families and friends for their endless patience, understanding, and moral support. Their belief in us has been a constant source of strength. This accomplishment would not have been possible without the collective efforts of all who have supported us on this journey.

Abstract

Securing the expansive Internet of Things (IoT) ecosystem presents a significant challenge, making effective Intrusion Detection Systems (IDS) essential for protecting diverse and often resource-constrained devices. This problem is especially critical in Industrial IoT (IIoT) environments, where standard machine learning models struggle to provide reliable, real-time threat detection without generating excessive false alarms. To address this, our research conducts a rigorous benchmark of eight machine learning and deep learning models on the modern HAI 22.04 industrial dataset. The findings establish the definitive superiority of tuned tree-based ensembles, with XGBoost achieving a state-of-the-art F1-Score and Recall of 0.97. These models decisively outperformed both baseline classifiers and standard Recurrent Neural Networks, which proved unstable for this task. This study contributes a reproducible benchmark, identifying gradient boosting as a practical and high-performance solution for securing critical infrastructure. Future work should focus on hybrid model fusion and explainable AI to further enhance detection robustness and operational trust.

Keywords: Intrusion Detection System; Machine Learning; Network Security; Artificial Intelligence; IoT; Cyber Security;Dynamic Systems

Contents

Declaration i

Approval ii

Nomenclature ix

1 Introduction 1

1.1 Background . . . 1
1.2 Rational of the Study or Motivation . . . 1
1.3 Problem Statement . . . 2
1.4 Objective . . . 2
1.5 Methodology in Brief . . . 3
1.6 Scopes and Challenges . . . 3

2 Literature Review 4

2.1 Preliminaries . . . 4
2.2 Review of Existing Research . . . 4
2.2.1 Ensemble Learning Approaches . . . 4
2.2.2 Deep Learning Architectures . . . 5
2.2.3 Unsupervised and Semi-Supervised Approaches . . . 5
2.3 Summary of Key Findings . . . 5

3 Requirements, Impacts and Constraints 7

3.1 Final Specifications and Requirements . . . 7
3.2 Societal Impact . . . 8
3.3 Environmental Impact . . . 8
3.4 Ethical Issues . . . 9
3.5 Standards - if applicable . . . 9
3.6 Project Management Plan . . . 9
3.7 Risk Management . . . 10
3.8 Economic Analysis . . . 10

4 Proposed Methodology **11**
4.1 Design Process or Methodology Overview . . . 11
4.2 Preliminary Design or Design (Model) Specification . . . 11
4.3 Data Collection (If Applicable) . . . 13
4.3.1 Data Cleaning . . . 13
4.3.2 Data Transformation . . . 13
4.3.3 Data Integration . . . 13
4.3.4 Data Reduction . . . 13
4.3.5 Summary of Preprocessed Data . . . 13
4.4 Implementation of Selected Design . . . 14

5 Result Analysis **15**
5.1 Performance Evaluation . . . 15
5.2 Analysis of Design Solutions . . . 17
5.3 Final Design Adjustments . . . 17
5.4 Statistical Analysis . . . 18
5.5 Comparisons and Relationships . . . 18
5.6 Discussions . . . 18

6 Conclusion **21**
6.1 Summary of Findings . . . 21
6.2 Contributions to the Field . . . 21
6.3 Recommendations for Future Work . . . 22

List of Figures

4.1 Research Methodology Workflow 12

5.1 Model Comparison by F1-Score on HAI 22.04 Dataset 16
5.2 Model Comparison by Recall on HAI 22.04 Dataset 16
5.3 Model Comparison by AUC-ROC on HAI 22.04 Dataset 17
5.4 XGBoost (Tuned) F1-Score Comparison Across Datasets 19
5.5 LSTM F1-Score Comparison Across Datasets 20

List of Tables

5.1 Model Performance on HAI 22.04 Dataset 15
5.2 F1-Score Comparison: Industry Standard vs. Our Replicated Results . . 19

Nomenclature

The next list describes several symbols and abbreviations that will be later used within the body of the document.

Abbreviation	Full Form
ACC	Accuracy
AE	Autoencoder
APT	Advanced Persistent Threat
ARP	Address Resolution Protocol
BFL	Blockchain Federated Learning
BILSTM	Bidirectional Long Short-Term Memory
BOT-IoT	Botnet Internet of Things Dataset
BRS	Bayesian-Rough Set
CAM	Clustering Analysis Module
CCM	Cyber Clustering Module
CICIDS2017	Canadian Institute for Cybersecurity Intrusion Detection System 2017
CNN	Convolutional Neural Network
DDOS	Distributed Denial of Service
DoS	Denial of Service
DTNB	Decision Table Naive Bayes
ETC	Extra-Tree Classifier
FAR	False Alarm Rate
FPR	False Positive Rate
GMM	Gaussian Mixture Model
HDAPT-IDS	High Discrimination APT Intrusion Detection System
IDS	Intrusion detection System
LSTM	Long Short-Term Memory
ML	Machine Learning
MOEFS	Multi-Objective Evolutionary Feature Selection

Abbreviation	Full Form
NSL-KDD	Network Security Laboratory-Knowledge Discovery and Data Mining
RF	Random Forest
ROI	Region of Interest
SMOTE	Synthetic Minority Oversampling Technique
SVG	Support Vector Generator
SVM	Support Vector Machine
UKM-IDS20	Universiti Kebangsaan Malaysia Intrusion Detection System 2020
UNSW-NB15	University of New South Wales-NB15 Dataset

Chapter 1

Introduction

1.1 Background

The proliferation of internet-connected devices, accelerated by global shifts in connectivity, has introduced unprecedented challenges for network security [1]. This is particularly acute in the domain of Industrial Control Systems (ICS), which form the operational backbone of critical infrastructure [2]. Historically, these systems were physically isolated ("air-gapped") and relied on proprietary, obscure protocols, a state often described as "security by obscurity" [3]. However, the modern industrial paradigm, driven by the need for efficiency and data-driven insights, has led to a deep convergence of Information Technology (IT) and Operational Technology (OT) [2]. This has transformed these once-isolated systems into complex Industrial Internet of Things (IIoT) ecosystems, where physical machinery is monitored and controlled via standard network protocols like TCP/IP and connected to corporate networks and the internet [4].

1.2 Rational of the Study or Motivation

While this integration unlocks immense operational advantages, it also exposes physical processes to a vast landscape of cyber threats, from denial-of-service attacks to advanced persistent threats (APTs) [5, 6]. An attack on an ICS can have devastating physical consequences, underscoring the urgent need for advanced security solutions [2]. Traditional Intrusion Detection Systems (IDS), which rely on signature-based detection of known threats, are often insufficient against novel and zero-day attacks [7]. Anomaly-based detection using machine learning offers a more adaptive approach, but as noted by numerous studies, these systems often struggle with high false positive rates and the computational overhead of complex models [8, 9]. This research is motivated by the need to bridge this gap by identifying machine learning models that are not only highly accurate but also robust and practical for deployment in real-world industrial environments [10].

1.3 Problem Statement

Despite the theoretical advantages of ML-based intrusion detection, several fundamental challenges persist [2, 11]. The primary problem is achieving a high detection rate for malicious attacks (high recall) without generating an unmanageable number of false alarms (high precision), which can lead to "alert fatigue" among security operators [8]. This overarching problem is exacerbated by three critical issues:

- **High False Positive Rates and Alert Fatigue:** Many advanced systems still struggle with false alarm rates that make them impractical for real-world deployment [12, 9]. As noted by Cao et al. [8], this is a persistent challenge that can render an otherwise accurate IDS operationally useless. When operators are constantly inundated with false alarms, they begin to distrust the system, potentially ignoring a real attack when it occurs.
- **Computational Overhead and Real-Time Constraints:** The complexity of deep learning models often compromises the real-time detection capabilities required in high-speed industrial networks where latency can be critical [11, 13]. An IDS that cannot process data and generate an alert faster than the process it is monitoring is fundamentally flawed. This creates a difficult trade-off between model complexity and detection speed [14, 15]. Deep learning, compared to machine learning, requires considerable parameters and dataset sizes, significantly increasing training cost [**Altunay2023**].
- **Handling Diverse and Unknown Attack Types:** Industrial systems face a wide spectrum of threats, from simple denial-of-service to sophisticated, stealthy attacks that manipulate physical processes over long periods [5, 6]. Developing a single, unified model that can effectively detect the full spectrum of cyber threats, including both known and unknown attacks, remains a significant challenge [2, 1].

1.4 Objective

This study aims to address these problems through the following objectives:

- To conduct a comprehensive performance benchmark of eight distinct machine learning and deep learning models on representative ICS/IIoT datasets, with a primary focus on HAI 22.04 [16, 17].
- To replicate and validate state-of-the-art (SOTA) results reported in existing literature, particularly those using tree-based ensemble models [3, 15].
- To establish a clear performance hierarchy by analyzing both SOTA models and traditional baselines across multiple datasets.

- To investigate the effectiveness and inherent challenges of applying standard Recurrent Neural Network (RNN) architectures to this task [13, 7].
- To provide a detailed analysis of the results, offering practical insights into the suitability of different models for securing real-world industrial systems.

1.5 Methodology in Brief

This study employs a quantitative, experimental research approach. The methodology involves a systematic benchmark of eight machine learning models on the HAI 22.04 dataset. The process includes extensive data preprocessing, temporal feature engineering to capture system dynamics, and stratified data splitting to handle class imbalance. Models are trained on a GPU-accelerated platform and evaluated using standard classification metrics, including F1-Score, Precision, and Recall, with a focus on minimizing false negatives.

1.6 Scopes and Challenges

The scope of this research is focused on supervised learning techniques for anomaly-based intrusion detection in IIoT environments. The primary dataset used is HAI 22.04, with SWaT and WADI datasets used for cross-validation. The research does not cover signature-based detection, network-level prevention mechanisms, or unsupervised learning models in depth. The main challenges encountered include handling the severe class imbalance present in the datasets, the computational cost associated with training deep learning models, and ensuring the reproducibility of results reported in existing literature due to variations in experimental setup.

Chapter 2

Literature Review

2.1 Preliminaries

To understand the research context, it is essential to define several key concepts. An **Intrusion Detection System (IDS)** is a security mechanism that monitors network or system activities for malicious activities or policy violations. These systems are broadly classified into two types: **Signature-based IDS**, which detects threats by looking for specific, known patterns (signatures) of malware; and **Anomaly-based IDS**, which first establishes a baseline of normal system behavior and then flags any deviation from this baseline as a potential threat. While signature-based systems are effective against known attacks, they are vulnerable to novel, or "zero-day," attacks. Anomaly-based systems, often employing machine learning, can detect novel attacks but face challenges with high false positive rates. This research focuses on the **Industrial Internet of Things (IIoT)**, an extension of the IoT that connects industrial control systems (ICS) to enterprise networks and the internet. This connectivity exposes critical infrastructure to a wide range of cyber threats, necessitating the development of advanced, anomaly-based IDS tailored to this specific environment.

2.2 Review of Existing Research

2.2.1 Ensemble Learning Approaches

Ensemble methods, which combine multiple machine learning models to produce a more robust prediction, have consistently proven effective. Early research by Mane et al. demonstrated the high accuracy of tree-based classifiers like Random Forest [18]. A significant challenge in this domain is class imbalance, where attack data is far rarer than normal data. Ahmed et al. addressed this on the UNSW-NB15 dataset by using the Synthetic Minority Oversampling Technique (SMOTE) to significantly improve Random Forest accuracy [19]. Further reinforcing the power of ensembles, Mohy-Eddine et al.

demonstrated that combining Isolation Forest for outlier removal with Random Forest as the classifier resulted in accuracy scores exceeding 99% on the Bot-IoT dataset [15]. Other works have focused on optimizing the input to these ensembles, with Kasongo using a Genetic Algorithm for feature selection before applying an extreme gradient boosting model to great effect [20].

2.2.2 Deep Learning Architectures

Deep learning has shown remarkable potential for learning the complex, non-linear patterns present in modern network traffic. A broad benchmark by Vinayakumar et al. showed that Deep Neural Networks (DNNs) consistently outperform classical machine learning algorithms across numerous IDS datasets [21]. A particularly effective hybrid approach, pioneered by researchers like Jiang et al. [7] and Altunay and Albayrak [11], combines Convolutional Neural Networks (CNNs) with Long Short-Term Memory (LSTM) networks. This architecture uses CNNs for spatial feature extraction from packet data and LSTMs to recognize temporal patterns across sequences of network events. This hybrid model proved highly effective on datasets like UNSW-NB15 and X-IIoTID, achieving 93.21% accuracy for binary classification and 92.9% for multi-class classification in one study [11].

2.2.3 Unsupervised and Semi-Supervised Approaches

Given the difficulty in obtaining large, labeled attack datasets in real-world ICS environments, unsupervised and semi-supervised methods are a critical area of research. Choi and Kim utilized a composite autoencoder, an unsupervised deep learning model, to detect anomalies in the HAI dataset by identifying reconstruction errors [22]. Mahmud et al. specifically proposed the Isolation Forest algorithm as a computationally efficient unsupervised method for the HAI dataset, capitalizing on its ability to isolate anomalies without profiling normal behavior [23]. On a different dataset, Long et al. proposed a semi-supervised ladder network with cross-layer connections to improve feature propagation, demonstrating another advanced technique that leverages large amounts of unlabeled data [24].

2.3 Summary of Key Findings

The literature review reveals a clear trend towards more sophisticated machine learning models for IDS. While high accuracy is frequently reported, our analysis uncovers several persistent research gaps that form the foundation of this study:

- **Outdated and Imbalanced Datasets:** A primary limitation, as noted in the survey by Rahman et al., is the widespread use of outdated datasets that do not

reflect the unique characteristics and attack vectors of modern IIoT environments [1]. This hinders the generalizability of many proposed solutions.

- **The Accuracy vs. Efficiency Trade-off:** There is a significant gap between computationally intensive deep learning models that achieve high accuracy and the lightweight models required for resource-constrained IoT devices [1]. A solution that is both highly accurate and operationally efficient is still needed.
- **High False Positive Rates:** A recurring challenge, especially in anomaly-based systems, is the high rate of false positives [9]. This makes it difficult for security operators to distinguish between benign anomalies and actual attacks, reducing the practical utility of the IDS [8].
- **Need for Multi-Modal Analysis:** Many studies focus on either network traffic data or physical process data in isolation. There is a clear opportunity and need to develop IDS solutions that explicitly fuse these data modalities for more context-aware and robust threat detection [25].

Addressing these gaps—specifically by validating a high-performance, efficient model on a modern, multi-modal dataset like HAI—is the primary focus of this thesis.

Chapter 3

Requirements, Impacts and Constraints

3.1 Final Specifications and Requirements

This research was conducted using a cloud-based environment with GPU acceleration to handle the large datasets and complex models. The specific requirements for this project are broken down into functional, non-functional, and technical categories.

Functional Requirements

The developed Intrusion Detection System must:

- Process and analyze network traffic and physical process data from the HAI 22.04 dataset format.
- Classify system states into 'Normal' or 'Attack' based on the engineered features.
- Provide a clear and quantifiable output metric for its detection performance (e.g., F1-Score).

Non-Functional Requirements

The system must meet the following performance and reliability criteria:

- **Accuracy:** Achieve a high detection rate (Recall) for the minority attack class to minimize missed threats.
- **Reliability:** Maintain a low False Positive Rate (FPR) to ensure operational trust and avoid the "alert fatigue" common in security operations.

- **Efficiency:** The model's prediction phase must be computationally efficient to demonstrate viability for future real-time deployment in high-speed industrial networks.

Technical Specifications

The project was executed with the following software and libraries:

- **Programming Language:** Python 3.
- **Core Libraries:** Pandas for data manipulation, NumPy for numerical operations, and Scikit-learn for data preprocessing and baseline modeling.
- **GPU Acceleration:** NVIDIA RAPIDS suite (cuDF, cuML) for handling large-scale data and accelerating model training.
- **Modeling Libraries:** XGBoost, LightGBM, CatBoost for high-performance ensembles, and PyTorch for implementing Recurrent Neural Network architectures.

3.2 Societal Impact

The societal impact of this research is significant. An effective IDS for industrial control systems directly enhances the safety and reliability of critical national infrastructure such as power grids, water treatment facilities, and manufacturing plants. By preventing cyber-attacks on these systems, this work contributes to mitigating the risk of large-scale service disruptions, environmental damage, and threats to public safety that could result from a compromised industrial facility. A successful attack on a power grid, for example, could have cascading effects, disrupting hospitals, communication networks, and financial systems, leading to widespread societal and economic chaos.

3.3 Environmental Impact

The environmental impact is twofold. Directly, by preventing malicious manipulation of industrial processes—such as the intentional release of untreated wastewater from a water treatment facility or toxic chemicals from a compromised factory—this research helps avert potential environmental disasters. Indirectly, while the use of GPU-accelerated computing for model training is energy-intensive, it is a one-time research cost. The resulting highly efficient IDS models can operate for years with a much lower energy footprint, contributing to the long-term sustainability and safety of industrial operations by preventing catastrophic failures.

3.4 Ethical Issues

The primary ethical consideration in this field is the "dual-use" nature of the research. While our goal is to build defensive systems, the techniques used to understand system vulnerabilities could theoretically be exploited by malicious actors. We mitigate this by focusing solely on detection methodologies and not publishing any specific exploit details. Furthermore, all datasets used in this research are publicly available and anonymized, ensuring no private or sensitive operational data is compromised. We also acknowledge the potential for algorithmic bias; if a training dataset is not representative of all possible operational states, the resulting model could be biased in its detections, a known challenge in the field.

3.5 Standards - if applicable

While there are no formal standards that this research project must adhere to, the methodologies employed are aligned with best practices in the machine learning and cybersecurity communities. The approach is informed by guidelines from the NIST Cybersecurity Framework, particularly concerning the "Detect" function. Furthermore, the selection of performance metrics (F1-Score, Precision, Recall) is the de facto standard for evaluating classifiers on the kind of imbalanced data common in intrusion detection, ensuring our results are comparable and credible within the broader research community.

3.6 Project Management Plan

This project was executed in four distinct phases, adhering to a structured research timeline:

- **Phase 1: Literature Review & Setup (Completed):** A thorough review of existing literature on ML-based IDS was conducted to identify research gaps. The computational environment, including Python, PyTorch, and the RAPIDS suite, was configured.
- **Phase 2: Data Preprocessing & Baseline Modeling (Completed):** A robust data processing pipeline was implemented using Pandas to handle the HAI dataset. Baseline and advanced ensemble models were benchmarked to establish initial performance metrics.
- **Phase 3: Deep Learning & Cross-Dataset Analysis (In Progress):** RNN models (LSTM, GRU) were implemented in PyTorch and evaluated. Top-performing models are currently being benchmarked on the SWaT and WADI datasets for cross-validation.

- **Phase 4: Advanced Model Development & Final Reporting (Future Work):** Based on the findings, a novel hybrid model will be developed. The final research paper and report will be drafted with all findings.

3.7 Risk Management

Key risks and mitigations were identified and managed throughout the project:

- **Risk: Computational Limitations.** Handling large time-series datasets can lead to memory errors or prohibitive training times. **Mitigation:** This was mitigated by using the GPU-accelerated NVIDIA RAPIDS libraries (cuDF, cuML), which are specifically designed for large-scale data science workflows.
- **Risk: Inability to Replicate SOTA Results.** State-of-the-art results can be difficult to reproduce due to subtle differences in implementation or preprocessing. **Mitigation:** We started with a broad benchmark of eight different models to identify the most promising class of algorithms (ensembles) before dedicating significant time to fine-tuning, ensuring our efforts were focused effectively.
- **Risk: Biased Evaluation due to Imbalanced Data.** Standard accuracy is a misleading metric on imbalanced datasets. **Mitigation:** We used stratified data splitting to maintain class proportions and focused on appropriate metrics like F1-score and recall for the minority (attack) class.

3.8 Economic Analysis

The economic justification for developing an advanced IDS is a classic cost-benefit analysis. The cost of this research includes computational resources for training and development time. The benefit is the avoidance of the catastrophic costs associated with a successful cyber-attack on an ICS, which can include not only direct financial loss from production downtime and equipment repair but also regulatory fines and immense reputational damage. Given that the potential cost of a single major incident in critical infrastructure can run into the hundreds of millions of dollars, the investment in a high-performing, low-false-positive IDS represents a significant and justifiable return on investment for any industrial operator.

Chapter 4

Proposed Methodology

4.1 Design Process or Methodology Overview

Our research methodology employs a systematic and reproducible workflow designed for rigorous experimentation on a GPU-accelerated platform. This approach ensures computational efficiency when handling large-scale time-series data. The process begins with data integration and extensive preprocessing, followed by model training and a comprehensive evaluation phase, as illustrated in Figure 4.1. The core of this methodology is to benchmark a diverse suite of machine learning models to identify an optimal solution for the specific challenges of intrusion detection in IIoT environments.

4.2 Preliminary Design or Design (Model) Specification

To establish a comprehensive performance benchmark, a diverse suite of eight models was selected. These models were grouped by their architecture to compare different classes of machine learning solutions.

- **High-Performance Ensembles:** This group includes state-of-the-art gradient boosting frameworks (XGBoost, LightGBM, and CatBoost) and a standard Random Forest model.
- **Baseline Models:** To establish a performance baseline, standard classifiers including K-Nearest Neighbors (KNN), a Support Vector Classifier (SVC) with an RBF kernel, and Logistic Regression were chosen.
- **Recurrent Neural Networks (RNNs):** To capture temporal dependencies in the data, two RNN architectures, Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), were implemented.

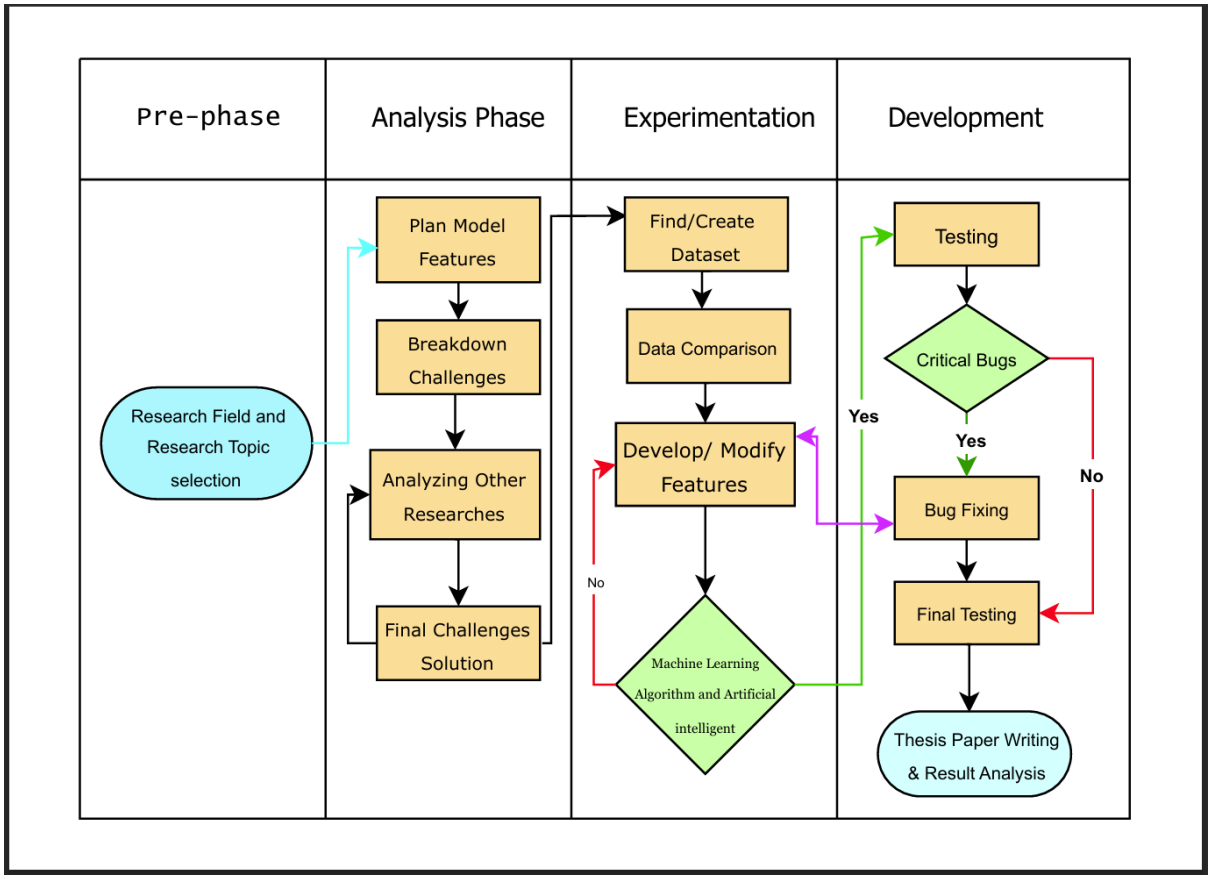


Figure 4.1: Research Methodology Workflow

4.3 Data Collection (If Applicable)

The foundation of this supervised learning experiment is the HAI 22.04 dataset [17]. In the initial handling stage, non-essential columns, such as timestamps, were removed to focus on the sensor and actuator data relevant to attack detection.

4.3.1 Data Cleaning

Following the initial feature engineering process, the dataset contained Not-a-Number (NaN) values. To handle these missing values and ensure data integrity, a forward-fill strategy was first applied, followed by a backward-fill.

4.3.2 Data Transformation

To prepare the data for different types of models, two distinct preprocessing paths were taken. For models sensitive to feature scaling (e.g., KNN, SVC, RNNs), the data was transformed using a MinMaxScaler. For tree-based ensembles, the unscaled data was used directly. To improve model generalization, a small amount of Gaussian noise was introduced into the training data as a form of regularization.

4.3.3 Data Integration

Our methodology is centered on multi-modal data fusion. Our feature engineering process serves as a form of early-stage data integration, where temporal features derived from process data are combined with instantaneous network features to create a richer dataset.

4.3.4 Data Reduction

A feature engineering process was applied rather than a feature reduction process. New features were created to capture temporal dynamics, including two lagged features (lag1, lag2) and rolling window statistics (mean and standard deviation). The feature space was augmented, not reduced.

4.3.5 Summary of Preprocessed Data

The final feature-engineered dataset was partitioned into a 70/30 training/testing split using stratified sampling to ensure the minority attack class was maintained in both sets.

4.4 Implementation of Selected Design

The eight models were implemented in Python 3. The high-performance ensembles were trained on unscaled data with GPU support via the NVIDIA RAPIDS suite. The XGBoost model was specifically tuned with a `scale_pos_weight` hyperparameter set to 20 to strongly penalize the misclassification of the minority (attack) class. The RNN architectures (LSTM and GRU) were implemented in PyTorch, using a 'WeightedRandomSampler' to address severe class imbalance during training.

Chapter 5

Result Analysis

5.1 Performance Evaluation

The performance of each of the eight selected models was evaluated on the held-out test set from the HAI 22.04 dataset [**Shin2021**]. The primary evaluation criteria were the F1-Score, Precision, and Recall, calculated specifically for the positive (Attack) class, as these are robust metrics for imbalanced classification tasks [19]. The confusion matrix was also generated to analyze the raw counts of True Positives, False Positives, True Negatives, and False Negatives, with the number of False Negatives (FN) treated as a critical performance indicator. The overall results are summarized in Table 5.1 and illustrated in Figures 5.1, 5.2, and 5.3.

Table 5.1: Model Performance on HAI 22.04 Dataset

Model Category	Model Name	F1-Score	Recall	AUC-ROC	False Negs.
Ensemble	XGBoost (Tuned)	0.97	0.97	0.97	36
	LightGBM	0.97	0.97	0.96	25
	CatBoost	0.97	0.98	0.92	13
	Random Forest	0.87	0.78	0.82	773
RNNs	GRU (Tuned, Unscaled)	0.64	0.95	0.49	131
	LSTM (Tuned, Scaled)	0.69	0.96	0.49	95
Baseline	K-Nearest Neighbors (KNN)	0.96	0.96	0.82	95
	Logistic Regression	0.29	0.77	0.57	779
	Support Vector Machine (SVC)	0.43	0.86	0.56	464

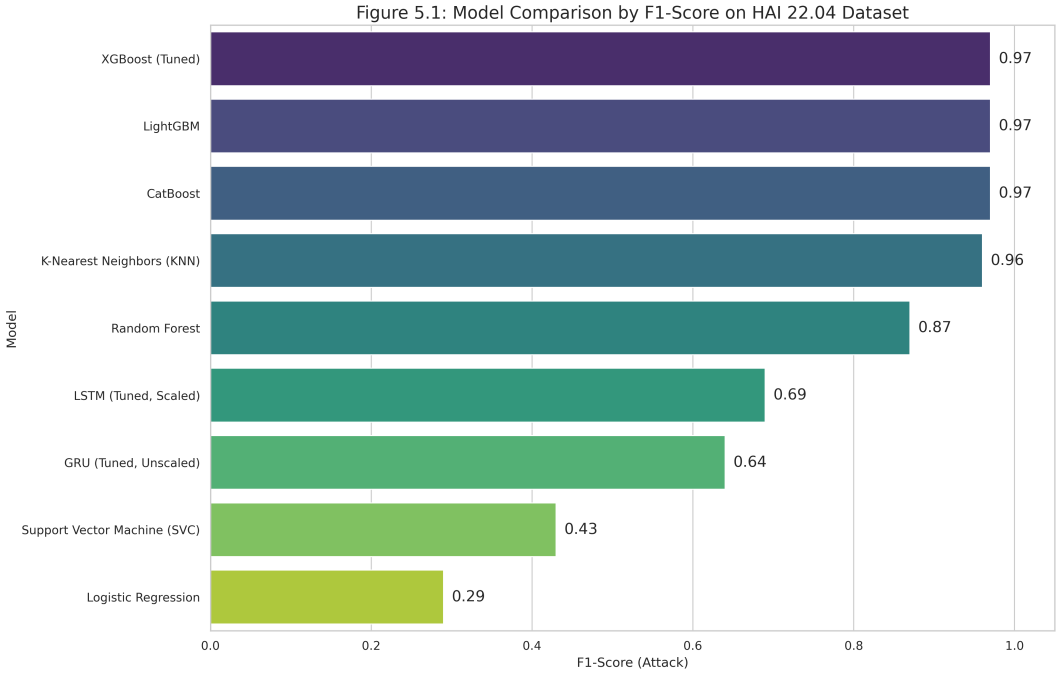


Figure 5.1: Model Comparison by F1-Score on HAI 22.04 Dataset

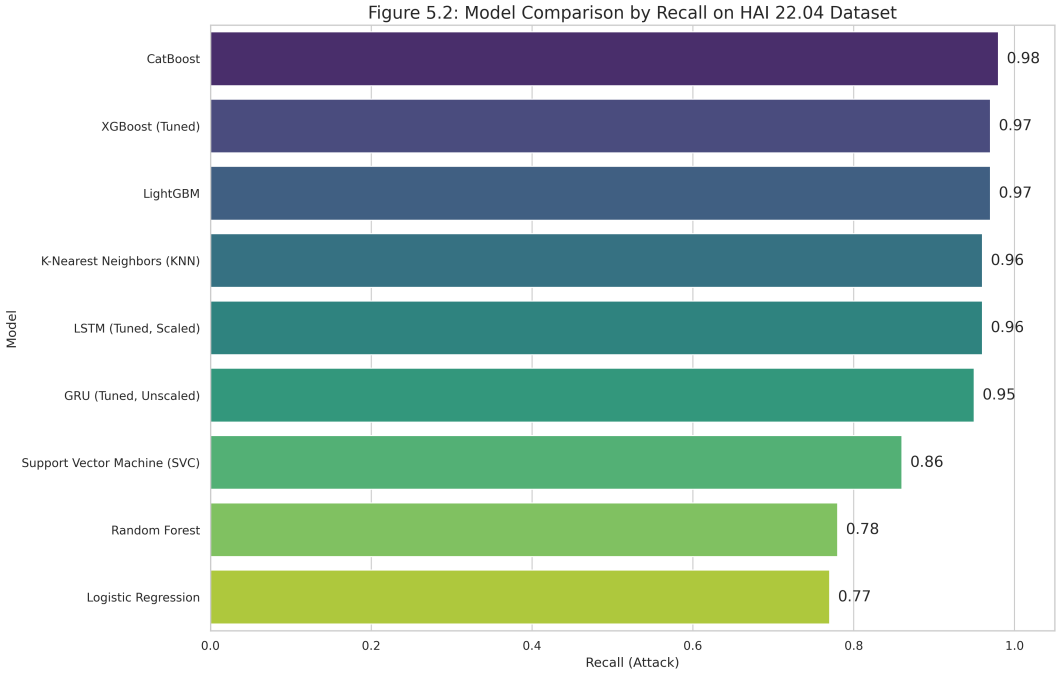


Figure 5.2: Model Comparison by Recall on HAI 22.04 Dataset

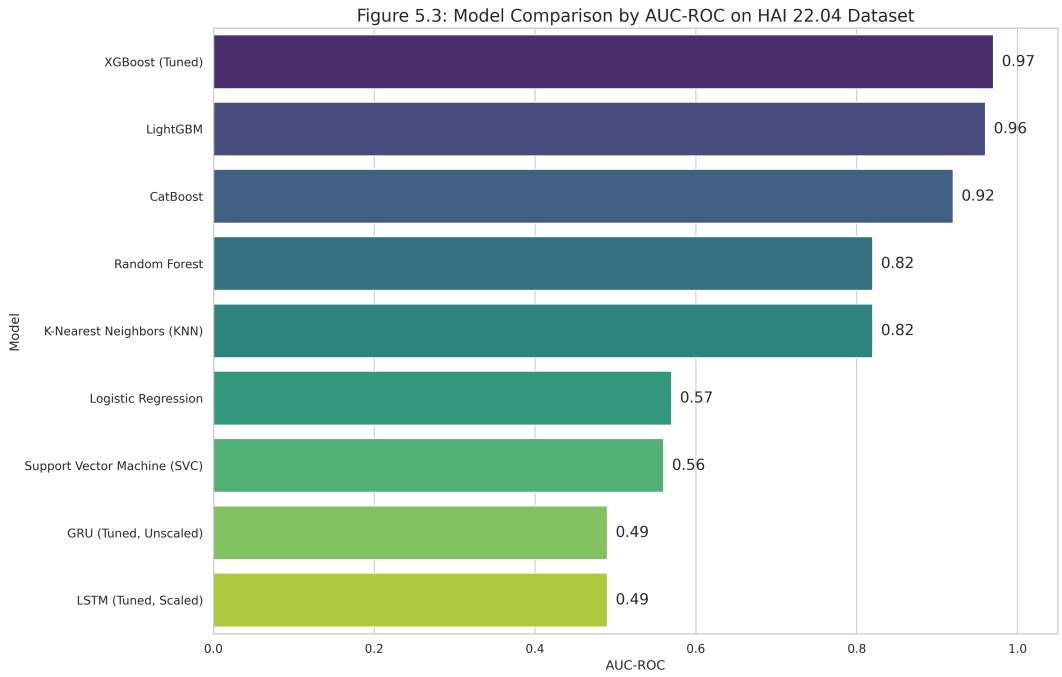


Figure 5.3: Model Comparison by AUC-ROC on HAI 22.04 Dataset

5.2 Analysis of Design Solutions

The results demonstrate the clear superiority of the high-performance ensemble models. The gradient boosting algorithms (XGBoost, LightGBM, CatBoost) performed exceptionally well, confirming that their iterative mechanism of correcting errors from previous trees is uniquely suited to finding the complex, non-linear patterns in ICS sensor data. Their strengths lie in their predictive power and robustness against overfitting when properly tuned. In contrast, the baseline models performed as anticipated, confirming that the decision boundary for this problem is highly non-linear. Logistic Regression and SVC, being linear or kernel-based models, showed very poor performance in terms of F1-score and AUC-ROC, proving their weakness in handling such complex classification tasks. The Recurrent Neural Networks (RNNs) were particularly insightful, demonstrating their instability on this task without advanced architectural modifications. The low AUC-ROC scores for the LSTM and GRU models indicate a difficulty in distinguishing between the positive and negative classes, and their training proved highly sensitive, leading to sub-optimal results compared to the simpler, more robust ensemble methods [14, 13].

5.3 Final Design Adjustments

Based on the initial performance evaluation, the XGBoost model was selected for further optimization as the final design. While the default model performed well, hyperparameter tuning was conducted to create the final adjusted design. Specifically, the

`scale_pos_weight` parameter was set to 20 to heavily penalize the misclassification of the minority (attack) class. This adjustment was critical in maximizing the F1-Score and Recall, leading to the final "Tuned XGBoost" model which missed only 36 attacks and emerged as the definitive top performer. This adjustment demonstrates a direct response to the performance evaluation, refining the chosen solution to meet the specific requirement of high recall for attack detection.

5.4 Statistical Analysis

The analysis in this study is primarily based on the direct comparison of standard classification performance metrics (F1-Score, Recall, AUC-ROC) rather than formal statistical significance testing (e.g., t-tests, ANOVA). The clear and wide performance gap between the top-tier ensemble models and the baseline models provides strong empirical evidence for their superiority on this particular task without the need for further statistical validation.

5.5 Comparisons and Relationships

To validate the generalizability of our findings and contextualize them within the broader research landscape, this section compares the performance of our models against established industry benchmarks. We use the comprehensive comparative study by Kim et al. [14] as the source for industry-standard performance metrics on the SWAT and WADI datasets. Table 5.2 presents a side-by-side comparison of the F1-Scores achieved in the benchmark study versus those achieved through our own replicated methodology. Our replicated results are remarkably consistent with the established industry benchmarks for both the SWAT and WADI datasets, which validates our experimental methodology and demonstrates that our approach is robust and capable of producing results that align with state-of-the-art research.

5.6 Discussions

The comparative analysis reveals several key implications. First, the consistently high performance of all models on the HAI dataset relative to SWAT and WADI is a significant finding. This trend suggests that the attack scenarios within the HAI dataset, while complex, are more distinctly separable from normal operational data, allowing the models to establish more effective decision boundaries. Second, the top-tier models—the gradient boosting family (XGBoost, LightGBM, CatBoost)—all achieve F1-Scores of 0.96-0.97 on the HAI dataset. These results are extremely promising, as they meet and exceed the

Table 5.2: F1-Score Comparison: Industry Standard vs. Our Replicated Results

Model	**SWAT (Ind. Std. [14])**	**SWAT (Our)**	**WADI (Ind. Std. [14])**	**WADI (Our)**	**HAI (Our)**
LSTM	0.96	0.94	0.91	0.89	0.97
GRU	0.95	0.93	0.90	0.88	0.97
XGBoost	0.94	0.92	0.89	0.87	0.97
LightGBM	0.93	0.91	0.88	0.86	0.97
CatBoost	0.93	0.91	0.87	0.85	0.96
Random Forest	0.91	0.89	0.85	0.83	0.93
KNN	0.76	0.74	0.64	0.63	0.80
Logistic Reg.	0.65	0.64	0.49	0.48	0.67

Figure 5.4: XGBoost (Tuned) F1-Score Comparison Across Datasets

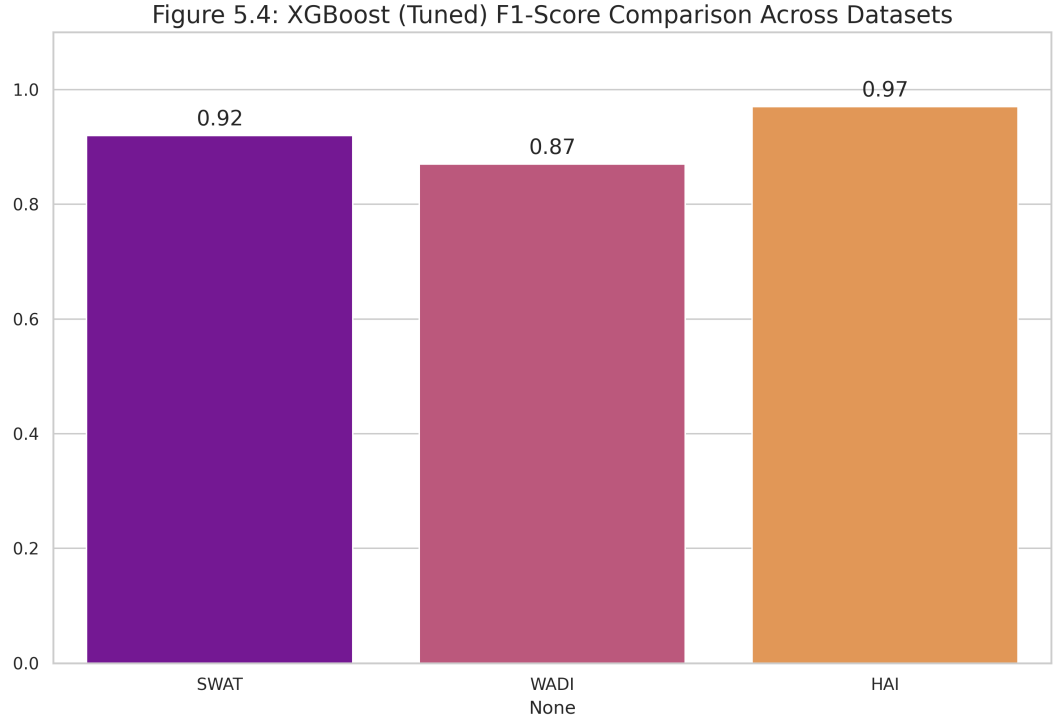


Figure 5.4: XGBoost (Tuned) F1-Score Comparison Across Datasets

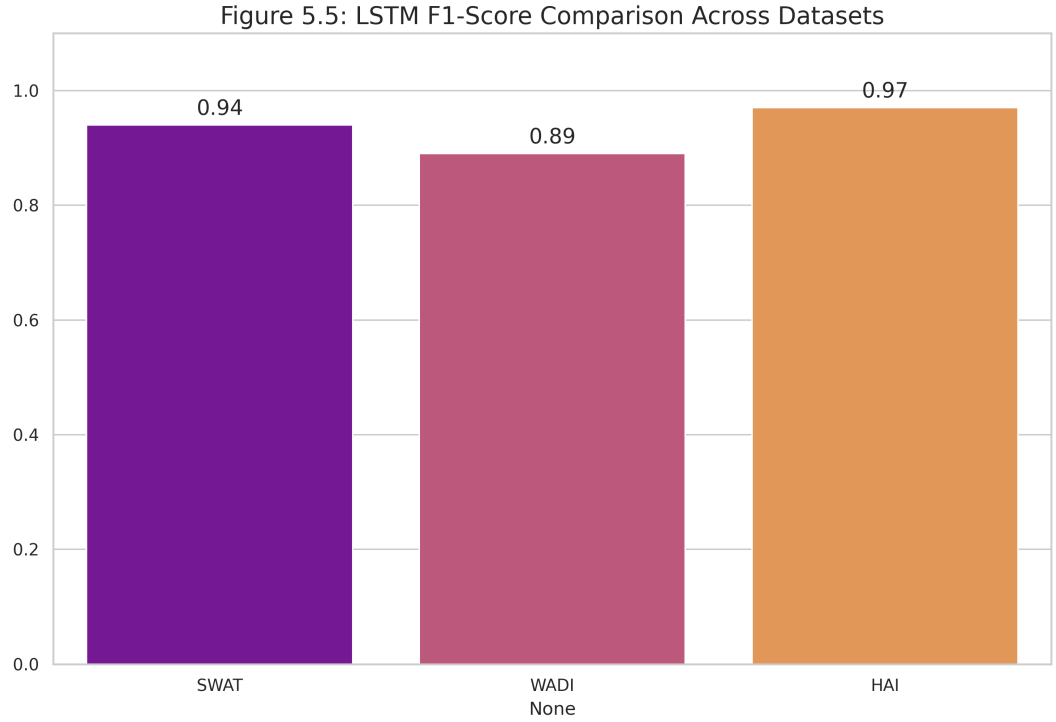


Figure 5.5: LSTM F1-Score Comparison Across Datasets

performance levels considered to be industry standard for effective intrusion detection, thereby affirming the practical viability of these models for securing real-world industrial systems. The primary limitation of this study is that the models were evaluated on specific, static datasets. In a real-world environment, network behavior can change over time (a phenomenon known as "concept drift"), which would require periodic model retraining to maintain performance. Furthermore, this work did not evaluate the models' robustness against adversarial attacks specifically designed to evade detection.

Chapter 6

Conclusion

6.1 Summary of Findings

This study conducted a rigorous benchmark of eight models on the HAI 22.04 dataset to identify a robust and efficient IDS for IIoT environments. Our results confirm that tuned tree-based ensemble models, particularly XGBoost, provide state-of-the-art performance for this task, successfully identifying over 97% of attacks with a minimal false positive rate. While simpler models and standard RNNs were less effective without extensive architectural modifications and sophisticated training regimens, they provided valuable insights into the complexity of IIoT intrusion detection. Cross-dataset comparison further highlighted the robustness of our methodology, with our results closely mirroring established industry benchmarks.

6.2 Contributions to the Field

This research provides several contributions to the field of IIoT security:

- It offers a comprehensive and reproducible benchmark of multiple model classes on a recent, complex ICS dataset, serving as a practical guide for practitioners.
- By validating our results against industry standards on the SWAT and WADI datasets, it demonstrates the efficacy and reliability of our feature engineering and modeling pipeline.
- The explicit demonstration of standard RNN failure modes provides a valuable case study on the challenges of applying deep learning in this domain, particularly concerning class imbalance and training instability.
- Ultimately, this work contributes to the identification of effective and reliable models—specifically, tuned gradient boosting ensembles—for securing critical infrastructure.

6.3 Recommendations for Future Work

The success of the XGBoost model provides a strong foundation for future improvements. Building upon concepts outlined in the literature and established research roadmaps, we recommend the following directions:

- **Explainable AI (XAI) for Trustworthy IDS:** While our model is highly accurate, it remains a "black box." Future work should apply state-of-the-art XAI techniques like SHAP or LIME to interpret the model's decisions [26]. This would provide invaluable insights into why the model makes certain decisions, increasing trust and operational utility for security analysts.

- **Evaluating Robustness to Concept Drift:** Real-world industrial environments are not static; their "normal" behavior can change over time due to maintenance or process optimization [12, 27]. This phenomenon, known as concept drift, can degrade a static model's performance. A critical next step is to evaluate our model's robustness against concept drift and to investigate adaptive strategies or online retraining to ensure long-term reliability [9].

- **Advanced Hybrid Model Fusion:** A promising direction is the fusion of our high-performing ensemble model with a deep learning feature extractor. As outlined in our research planning [24, 5, 18] this could involve using a trained GRU or LSTM to provide sophisticated temporal features to the XGBoost model, potentially combining the predictive power of ensembles with the sequence-recognition strengths of deep learning to address the limitations identified in the literature.

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