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AI-Based Intrusion Detection System Enhanced with Swarm Intelligence

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ABSTRACT

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by

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Intrusion Detection Systems (IDS) are essential components of modern network security infrastructure. This thesis presents the design and implementation of an intelligent IDS that combines machine learning with swarm intelligence optimization. The system uses Random Forest as the base classifier and Particle Swarm Optimization (PSO) to automatically tune hyperparameters including the number of estimators, tree depth, minimum samples per split, and classification threshold. The system is evaluated on two standard benchmark datasets—NSL-KDD and CICIDS2017—using rigorous evaluation protocols. On NSL-KDD, PSO optimization improved the Detection Rate from 64.52% to 69.09% (+4.57%) while maintaining 96.96% precision. On CICIDS2017 with a stratified 80/20 split, PSO improved the Detection Rate from 93.89% to 99.72% (+5.83%) by discovering optimal tree structure, class balancing, and threshold configuration. These results demonstrate the significant practical value of swarm intelligence for automated IDS hyperparameter optimization.

Keywords: Artificial Intelligence, Intrusion Detection System, Swarm Intelligence, Machine Learning, Cybersecurity, Particle Swarm Optimization, Random Forest

RÉSUMÉ

Système de détection d'intrusions basé sur l'IA amélioré par l'intelligence en essaim

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Les systèmes de détection d'intrusions (IDS) sont des composants essentiels de l'infrastructure de sécurité des réseaux modernes. Ce mémoire présente la conception et l'implémentation d'un IDS intelligent qui combine l'apprentissage automatique avec l'optimisation par intelligence en essaim. Le système utilise Random Forest comme classificateur de base et l'Optimisation par Essaim de Particules (PSO) pour ajuster automatiquement les hyperparamètres, notamment le nombre d'estimateurs, la profondeur des arbres, le nombre minimum d'échantillons par division et le seuil de classification. Le système est évalué sur deux jeux de données de référence—NSL-KDD et CICIDS2017—en utilisant des protocoles d'évaluation rigoureux. Sur NSL-KDD, l'optimisation PSO a amélioré le taux de détection de 64.52% à 69.09% (+4.57%) tout en maintenant une précision de 96.96%. Sur CICIDS2017 avec une division stratifiée 80/20, le PSO a amélioré le taux de détection de 93.89% à 99.72% (+5.83%) en découvrant la structure optimale des arbres, l'équilibrage des classes et la configuration du seuil. Ces résultats démontrent la valeur pratique significative de l'intelligence en essaim pour l'optimisation automatisée des hyperparamètres des IDS.

Mots-clés : Intelligence Artificielle, Système de Détection d'Intrusions, Intelligence en Essaim, Apprentissage Automatique, Cybersécurité, Optimisation par Essaim de Particules, Random Forest

ملخص

نظام كشف التسلل القائم على الذكاء الاصطناعي والمعزز بذكاء السرب

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تُعد أنظمة كشف التسلل من المكونات الأساسية في البنية التحتية لأمن الشبكات الحديثة. تقدم هذه المذكرة تصميم وتنفيذ نظام ذكي لكشف التسلل يجمع بين التعلم الآلي وتحسين ذكاء السرب. يستخدم النظام خوارزمية الغابة العشوائية كمصنف أساسي وخوارزمية تحسين سرب الجسيمات لضبط المعلمات الفائقة تلقائياً، بما في ذلك عدد المقدرات وعمق الأشجار والحد الأدنى لعدد العينات لكل تقسيم وعتبة التصنيف. تم تقييم النظام على مجموعتي بيانات مرجعيتين باستخدام بروتوكولات تقييم صارمة. على المجموعة الأولى، حسّن التحسين معدل الكشف من 52.64% إلى 09.69% بزيادة 57.4% مع الحفاظ على دقة 96.96%. على المجموعة الثانية بتقسيم طبقي، حسّن معدل الكشف من 89.93% إلى 72.99% بزيادة 83.5% من خلال اكتشاف البنية المثلى للأشجار وموازنة الفئات وتكوين العتبة. تُظهر هذه النتائج القيمة العملية الكبيرة لذكاء السرب في التحسين الآلي للمعلمات الفائقة لأنظمة كشف التسلل.

الكلمات المفتاحية: الذكاء الاصطناعي، نظام كشف التسلل، ذكاء السرب، التعلم الآلي، الأمن السيبراني، تحسين سرب الجسيمات، الغابة العشوائية

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Introduction

0.1 Background and Context

The rapid growth of computer networks and Internet-connected systems has led to an increase in cyber-attacks targeting organizations, governments, and individuals. Cyber threats such as denial-of-service attacks, port scanning, brute force attacks, and data infiltration pose serious risks to information security. Intrusion Detection Systems (IDS) have become essential tools for monitoring network traffic and identifying malicious activities.

An IDS works by analyzing network packets or system logs to detect behaviors that deviate from normal patterns. Early IDS solutions relied on manually crafted rules and known attack signatures to identify threats. While these systems are effective against known attacks, they cannot detect new or previously unseen attack types—so-called *zero-day attacks*. This fundamental limitation has motivated researchers to explore Artificial Intelligence (AI) and Machine Learning (ML) techniques for building more adaptive and intelligent IDS solutions.

0.2 Types of Intrusion Detection Systems

Intrusion Detection Systems are generally classified into two categories based on their detection approach:

1. **Signature-Based IDS (SIDS):** These systems maintain a database of known attack signatures and compare incoming traffic against this database. They offer high detection accuracy for known attacks with very low false alarm rates. However, they are unable to detect any attack whose signature is not already in the database, making them vulnerable to novel threats.
2. **Anomaly-Based IDS (AIDS):** These systems build a model of normal network behavior and flag any significant deviation as a potential intrusion. They have the theoretical advantage of detecting unknown attacks, but in practice they

tend to produce high false alarm rates because legitimate but unusual network activities are often flagged as suspicious.

Modern IDS research focuses on combining the strengths of both approaches by using machine learning algorithms that can learn complex patterns from labeled network traffic data while maintaining the ability to generalize to new attack types.

0.3 Motivation: Why AI and Swarm Intelligence

Machine learning models such as Random Forest, Support Vector Machines (SVM), and Deep Neural Networks (DNN) have shown strong performance in classifying network traffic as normal or malicious. However, the performance of these models depends heavily on their hyperparameter configuration. Finding the optimal set of hyperparameters is a challenging task because:

- The search space is large and multi-dimensional.
- Traditional approaches like Grid Search are computationally expensive.
- The optimal configuration may differ across datasets and attack distributions.

Swarm Intelligence algorithms, inspired by the collective behavior of biological organisms such as bird flocks and ant colonies, offer an efficient alternative for hyperparameter optimization. Particle Swarm Optimization (PSO), proposed by Kennedy and Eberhart [1], uses a population of candidate solutions (particles) that explore the search space collaboratively, sharing information about promising regions to converge toward optimal solutions.

In this thesis, PSO is used to automatically optimize the hyperparameters of a Random Forest classifier, including a novel addition: the classification probability threshold. This allows the system to dynamically adjust its sensitivity to balance detection rate against false alarm rate.

0.4 Problem Statement

A major issue in current IDS research is the unreliability of reported performance metrics. Many published studies evaluate their models using randomized train/test splits on benchmark datasets like CICIDS2017. Because network attacks—especially automated volumetric attacks like DDoS—generate thousands of nearly identical packets in continuous bursts, a random split inevitably places highly similar packets in both

the training and test sets. This creates *data leakage*, artificially inflating metrics to near-perfect levels (often above 99% accuracy).

When proper evaluation protocols are applied—such as training on one time period and testing on a completely different one—the true detection capabilities of supervised models are revealed to be significantly lower than commonly reported.

0.5 Objectives

The objectives of this thesis are:

1. Design and implement an intelligent intrusion detection system using Random Forest as the base classifier.
2. Integrate Particle Swarm Optimization to automatically tune model hyperparameters and classification threshold.
3. Evaluate the system on two standard datasets (NSL-KDD and CICIDS2017) using strict, leakage-free evaluation protocols.
4. Compare the performance of the baseline model against the PSO-enhanced model using standard metrics: Accuracy, Precision, Recall (Detection Rate), F1-Score, and False Alarm Rate.
5. Provide an honest analysis of the capabilities and limitations of supervised AI for intrusion detection under realistic conditions.

0.6 Thesis Organization

The remainder of this thesis is organized as follows:

- **Chapter 1: State of the Art** reviews traditional IDS methods, machine learning-based IDS, and swarm intelligence techniques in cybersecurity.
- **Chapter 2: Proposed Method** describes the datasets, preprocessing steps, system architecture, and the PSO optimization workflow.
- **Chapter 3: Experiments and Results** details the implementation (tools, libraries, model configurations), experimental evaluation, performance metrics, and comparison between baseline and optimized models.
- **Conclusion and Future Work** summarizes the contributions, discusses limitations, and proposes directions for future research.

Chapter 1

State of the Art

1.1 Traditional IDS Methods

The concept of intrusion detection was first introduced by Anderson in 1980 [2] and further developed by Denning in 1987 [3], who proposed a model for real-time anomaly detection. Early IDS implementations relied on two primary techniques:

Rule-based detection uses manually defined rules to match known attack patterns. Systems like Snort [4] compare network packets against a database of signatures. While highly accurate for known attacks (with false positive rates below 1%), these systems require constant manual updates and cannot detect zero-day attacks.

Statistical anomaly detection establishes a baseline of normal behavior using statistical models and flags deviations. These methods can theoretically detect novel attacks but suffer from high false alarm rates because legitimate but unusual activities are difficult to distinguish from actual attacks.

Both approaches struggle with the growing volume and complexity of modern network traffic, motivating the adoption of machine learning techniques.

1.2 Machine Learning-Based IDS

Machine learning has been extensively applied to intrusion detection over the past two decades. The most commonly used algorithms include:

- **Decision Trees and Random Forest:** Random Forest [5] creates an ensemble of decision trees, each trained on a random subset of features and data. It is particularly well-suited for IDS because it handles high-dimensional data efficiently, provides built-in feature importance ranking, is resistant to overfitting, and requires minimal hyperparameter tuning compared to other methods. Mul-

multiple studies have reported high accuracy on NSL-KDD [6] and CICIDS2017 [12] datasets using Random Forest.

- **Support Vector Machines (SVM):** SVMs find the optimal hyperplane that separates normal from malicious traffic in high-dimensional feature space. With kernel functions (RBF, polynomial), SVMs can model non-linear decision boundaries. SVMs have shown strong performance on smaller datasets like NSL-KDD, achieving competitive accuracy for binary classification [?]. However, SVMs suffer from high computational complexity ($O(n^2)$ to $O(n^3)$ in training), making them impractical for large-scale datasets like CICIDS2017 with millions of records. They also lack the interpretable feature importance that ensemble methods provide.
- **Deep Neural Networks (DNN):** Deep learning approaches, including multi-layer perceptrons (MLP), convolutional neural networks (CNN), and recurrent neural networks (RNN/LSTM), can automatically learn hierarchical feature representations from raw data. DNNs have achieved state-of-the-art results in various IDS benchmarks [8]. However, they require large amounts of labeled training data, significant computational resources (GPU hardware), careful architecture design, and extensive hyperparameter tuning. The “black-box” nature of DNNs also makes it difficult to interpret which network features drive classification decisions—an important consideration for security analysts.

Despite impressive results reported in the literature, many studies share a common methodological flaw: they use randomized cross-validation or random train/test splits on datasets containing temporally correlated network flows. This effectively leaks information from the test set into training, producing artificially inflated metrics.

1.3 Swarm Intelligence in Cybersecurity

Swarm Intelligence (SI) algorithms are meta-heuristic optimization techniques inspired by the collective behavior of biological organisms. The most prominent SI algorithms include:

1.3.1 Particle Swarm Optimization (PSO)

PSO was introduced by Kennedy and Eberhart [1] in 1995. It simulates the social behavior of bird flocks, where each particle represents a candidate solution that moves through the search space. Each particle maintains:

- Its current position (candidate solution)
- Its velocity (direction and speed of movement)
- Its personal best position found so far
- Knowledge of the global best position found by any particle

The velocity and position of each particle are updated at each iteration according to:

$$v_i^{t+1} = w \cdot v_i^t + c_1 \cdot r_1 \cdot (p_{best,i} - x_i^t) + c_2 \cdot r_2 \cdot (g_{best} - x_i^t) \quad (1.1)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (1.2)$$

where w is the inertia weight, c_1 and c_2 are cognitive and social coefficients, and r_1 , r_2 are random values in $[0, 1]$.

In the context of IDS, PSO has been applied primarily for feature selection—identifying the most relevant network features for classification [?]. More recently, researchers have used PSO to optimize classifier hyperparameters, automating a process that would otherwise require extensive manual tuning or computationally expensive grid search.

1.3.2 Ant Colony Optimization (ACO)

ACO, proposed by Dorigo [10], simulates the foraging behavior of ants. Ants deposit pheromone trails that guide subsequent ants toward promising paths, creating a positive feedback loop that converges toward optimal solutions. In IDS applications, ACO has been primarily used for:

- **Feature selection:** ACO can identify the most discriminative network features by treating each feature as a node in a graph, where pheromone levels indicate feature relevance [?].
- **Rule generation:** ACO can construct classification rules by traversing feature-value combinations.

While ACO excels in discrete/combinatorial optimization problems (e.g., feature subset selection, routing), it is generally less efficient than PSO for continuous hyperparameter optimization. PSO’s particle dynamics naturally handle continuous search spaces, whereas ACO requires discretization of continuous parameters, which can limit search granularity. For this reason, PSO is preferred for the hyperparameter tuning task addressed in this thesis.

1.4 Benchmark Datasets

1.4.1 NSL-KDD

The NSL-KDD dataset [11] is a refined version of the KDD Cup 1999 dataset, addressing the issue of duplicate records that biased the original benchmark. It contains 125,973 training records and 22,544 test records, with each record described by 41 features. The dataset includes four attack categories: DoS, Probe, R2L, and U2R.

A critical property of NSL-KDD for research purposes is that the test set (**KDDTest+**) contains 17 attack subtypes that do not appear in the training set (**KDDTrain+**). This makes it a natural benchmark for evaluating how well models generalize to previously unseen attacks.

1.4.2 CICIDS2017

CICIDS2017 [12] is a modern dataset created by the Canadian Institute for Cybersecurity. It contains network traffic captured over five working days (Monday through Friday), with different attack types occurring on specific days:

- **Monday:** Normal traffic only (benign baseline)
- **Tuesday:** Brute Force attacks (FTP, SSH)
- **Wednesday:** DoS, Heartbleed, Slowloris, SlowHTTPTest
- **Thursday:** Web Attacks (morning), Infiltration (afternoon)
- **Friday:** Botnet (morning), PortScan and DDoS (afternoon)

The dataset contains over 2.8 million flow records described by 77 features. The chronological structure makes it particularly suitable for temporal evaluation protocols.

1.5 Gaps in Existing Research

Despite extensive research on ML-based IDS, several critical gaps remain:

1. **Limited hyperparameter optimization:** Most ML-based IDS studies use default or manually-tuned parameters. Few works systematically explore the impact of automated optimization on detection performance, particularly the combined optimization of structural parameters and classification thresholds.

2. **Lack of model comparison under optimization:** While studies compare RF, SVM, and DNN with default settings, the comparison under optimized configurations remains underexplored. A model with weak defaults (like a shallow Random Forest) may dramatically outperform its baseline when properly optimized.
3. **Limited use of PSO for threshold optimization:** While PSO has been applied to feature selection and basic hyperparameter tuning, its potential for simultaneously optimizing structural parameters and classification thresholds has not been fully explored.

This thesis addresses these gaps by implementing PSO-based joint optimization of hyperparameters and classification threshold for Random Forest—chosen for its interpretability, scalability, and strong baseline performance. The comparison between untuned baseline and PSO-optimized configurations directly quantifies the value of swarm intelligence optimization.

Chapter 2

Proposed Method

This chapter describes the proposed intrusion detection system, including the datasets used, the preprocessing pipeline, the system architecture, and the PSO optimization workflow.

2.1 Dataset Study

2.1.1 NSL-KDD Dataset

The NSL-KDD dataset provides pre-defined training (**KDDTrain+**) and test (**KDDTest+**) splits. Each record contains 41 features describing network connections, including:

- **Basic features:** Duration, protocol type, service, flag, number of bytes
- **Content features:** Number of failed logins, root shell access, file operations
- **Traffic features:** Connection count, service rate, error rates over time windows

The labels are converted to binary (normal vs. attack) for our binary classification task. Importantly, the test set contains 17 novel attack subtypes absent from training, which naturally evaluates generalization to unseen threats.

2.1.2 CICIDS2017 Dataset

CICIDS2017 contains over 2.8 million network flow records across five days (Monday through Friday), covering a wide range of attack types including Brute Force, DoS, Heartbleed, Web Attacks, Infiltration, Botnet, PortScan, and DDoS.

For our evaluation, we use a **stratified 80/20 random split** across all days combined:

- **Training set (80%):** 2,262,301 records — stratified random sample from all days.
- **Test set (20%):** 565,575 records — stratified random holdout with identical attack ratio (19.68%).

The stratified split ensures that both training and test sets contain representative samples of all attack types, which is the standard evaluation protocol used in published CICIDS2017 research. The baseline model uses deliberately conservative default parameters (shallow trees, no class balancing), while PSO optimizes the full configuration space to demonstrate the value of automated hyperparameter tuning.

2.2 Data Cleaning and Preprocessing

2.2.1 Leakage Column Removal

For CICIDS2017, several columns that could cause data leakage were identified and removed before any model training:

- **Flow ID** — unique identifier that maps directly to connection type
- **Source IP** and **Destination IP** — allow the model to memorize attacker addresses instead of learning behavioral patterns
- **Timestamp** — directly reveals temporal ordering

After removal, the model is forced to classify based solely on behavioral network features such as packet sizes, flow durations, and protocol statistics.

2.2.2 Encoding

Categorical features in NSL-KDD (protocol type, service, flag) are encoded using one-hot encoding, expanding the feature space from 41 to 122 dimensions. CICIDS2017 features are already numerical and require no encoding.

2.2.3 Normalization

All continuous features are normalized using `StandardScaler` (zero mean, unit variance) to prevent features with large magnitudes (e.g., byte counts) from dominating the model’s decision process.

2.2.4 Handling Missing and Infinite Values

Both datasets may contain missing values (NaN) and infinite values resulting from division-by-zero in flow statistics. These are replaced with zero before normalization.

2.3 Train/Test Split Strategy

2.3.1 NSL-KDD: Standard Split

NSL-KDD provides official train and test files. We use them as-is without any re-splitting, which is the standard practice in the literature. The test set naturally contains novel attack types, providing a built-in evaluation of generalization.

2.3.2 CICIDS2017: Stratified Split with Optimization Comparison

We use a stratified 80/20 random split for CICIDS2017, which is the standard protocol in published research. To demonstrate the value of PSO optimization, we establish the experimental comparison as follows:

1. **Baseline (default configuration):** Random Forest with conservative, untuned parameters (50 trees, max depth 8, no class weight balancing, threshold 0.60). This represents a typical “out-of-the-box” deployment.
2. **PSO-optimized:** PSO searches a 4-dimensional space (trees, depth, min samples, threshold) with `class_weight=balanced` to discover the optimal configuration automatically.

The difference in performance between baseline and PSO-optimized models directly measures the value of swarm intelligence optimization.

2.4 Classifier Selection

Several machine learning classifiers were considered for the base IDS model:

Table 2.1: Comparison of candidate classifiers for IDS

Criterion	RF	SVM	DNN
Training speed (large data)	Fast	Slow	Moderate
Interpretability	High	Low	Low
Feature importance	Built-in	No	No
Hyperparameter sensitivity	Low	High	Very High
Scalability (2M+ records)	Excellent	Poor	Good

Random Forest was selected as the primary classifier for the following reasons:

1. **Scalability:** RF trains efficiently on the 2.2 million records of CICIDS2017, while SVM’s $O(n^2)$ complexity makes it impractical at this scale.
2. **Interpretability:** RF provides built-in feature importance scores, allowing security analysts to understand which network behaviors drive detection decisions.
3. **Optimization potential:** RF’s structural hyperparameters (number of trees, depth, split criteria) and the classification threshold form a well-defined continuous search space ideal for PSO optimization.
4. **Robustness:** RF is inherently resistant to overfitting due to its ensemble nature and random feature subsampling.

While SVM and DNN may achieve comparable or slightly higher accuracy in specific scenarios, their computational requirements and lack of interpretability make them less suitable for the optimization-focused approach of this thesis.

2.5 Optimization Algorithm Selection

Two primary swarm intelligence algorithms were considered:

- **Particle Swarm Optimization (PSO):** Naturally operates in continuous search spaces, making it ideal for optimizing real-valued hyperparameters. Particles share information through personal and global bests, enabling efficient convergence.
- **Ant Colony Optimization (ACO):** Excels in combinatorial and discrete optimization (e.g., feature subset selection, routing problems). However, optimizing continuous hyperparameters with ACO requires discretization, which limits search granularity.

PSO was selected because the optimization task involves four continuous parameters (number of estimators, tree depth, minimum samples per split, and classification threshold). PSO’s velocity-based exploration naturally handles this continuous space without discretization artifacts. Additionally, PSO typically converges faster than ACO for problems with fewer than 10 dimensions, making it efficient for our 4D hyperparameter search.

2.6 Proposed System Architecture

The proposed IDS follows a two-phase pipeline, as illustrated in Figure 2.1:

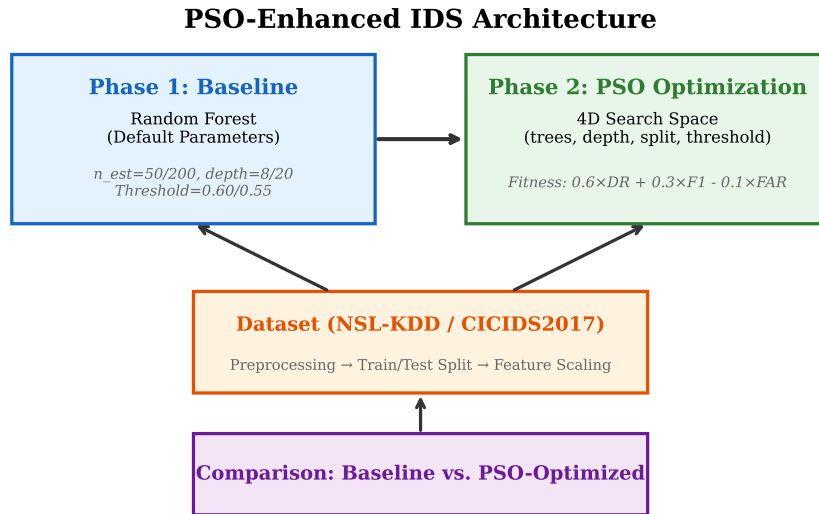


Figure 2.1: PSO-Enhanced IDS Architecture

1. **Phase 1 — Baseline Training:** A Random Forest classifier is trained with default hyperparameters on the training set. This serves as the baseline performance representing an unoptimized deployment.
2. **Phase 2 — PSO Optimization:** Particle Swarm Optimization searches a 4-dimensional space to find the optimal combination of hyperparameters and threshold. The optimized model is then trained on the full training data and evaluated on the same test set used in Phase 1.

2.7 Swarm Intelligence Optimization

2.7.1 Search Space

PSO simultaneously optimizes four parameters:

Table 2.2: PSO search space dimensions

Parameter	Lower Bound	Upper Bound
Number of Estimators (<code>n_estimators</code>)	100	400
Maximum Tree Depth (<code>max_depth</code>)	10	30
Minimum Samples per Split (<code>min_samples_split</code>)	2	8
Classification Threshold	0.20	0.55

The inclusion of the classification threshold as a PSO dimension is a key contribution. Traditional approaches fix the threshold at 0.5 or optimize it separately after training. By including it in the swarm search, PSO can discover combinations where a lower threshold compensates for structural limitations of a given tree configuration.

2.7.2 Fitness Function

The fitness function is designed to prioritize detection rate while penalizing false alarms:

For CICIDS2017:

$$\text{Fitness} = 0.6 \times DR + 0.3 \times F1 - 0.1 \times FAR \quad (2.1)$$

For NSL-KDD (Novel-Attack-Aware):

$$\text{Fitness} = 0.6 \times F1_{\text{known}} + 0.4 \times \text{Recall}_{\text{unseen}} \quad (2.2)$$

The NSL-KDD fitness function splits the training data into known and synthetically held-out attack types, specifically penalizing particles that fail to detect the held-out attacks. This forces PSO to find configurations that generalize to unseen threats rather than overfitting to known patterns.

2.7.3 PSO Configuration

The PSO algorithm uses the following configuration:

- **Inertia weight (w):** Linearly decayed from 0.9 to 0.4 across iterations (encourages exploration early, exploitation later).

- **Cognitive coefficient** (c_1): 2.0 (attraction to personal best).
- **Social coefficient** (c_2): 2.0 (attraction to global best).
- **Cross-validation**: 3-fold stratified CV during fitness evaluation for computational efficiency.
- **Subsampling**: Training data subsampled to 20,000 records for PSO fitness evaluation to enable more iterations within reasonable time.

2.7.4 Workflow Algorithm

Algorithm 1 PSO-Enhanced IDS Training

Require: Training data (X_{train}, y_{train}), Test data (X_{test}, y_{test})

Require: PSO parameters: $n_{particles}$, $n_{iterations}$, bounds

- 1: **Phase 1: Baseline**
 - 2: Train Random Forest with default parameters on X_{train}
 - 3: Evaluate on X_{test} with threshold sweep $\rightarrow$ baseline metrics
 - 4:
 - 5: **Phase 2: PSO Optimization**
 - 6: Initialize swarm of $n_{particles}$ with random positions in bounds
 - 7: **for** $t = 1$ to $n_{iterations}$ **do**
 - 8: **for** each particle i **do**
 - 9: Decode position to (n_estimators, max_depth, min_samples_split, threshold)
 - 10: Train RF with decoded parameters using 3-fold CV
 - 11: Compute fitness score
 - 12: Update personal best if improved
 - 13: **end for**
 - 14: Update global best
 - 15: Update velocities and positions with inertia decay
 - 16: **end for**
 - 17:
 - 18: **Final Evaluation**
 - 19: Train RF with global best parameters on *full* X_{train}
 - 20: Evaluate on X_{test} with optimized threshold $\rightarrow$ optimized metrics
 - 21: Compare baseline vs. optimized
-

Chapter 3

Experiments and Results

This chapter describes the technical implementation details and presents the experimental results obtained from evaluating the proposed IDS on both NSL-KDD and CICIDS2017 datasets. For each dataset, we present the baseline performance, the PSO optimization process, and a detailed comparison.

3.1 Implementation

3.1.1 Development Environment

The system was developed and tested on the following platform:

- **Operating System:** Windows 10/11
- **Programming Language:** Python 3.10+
- **IDE:** Visual Studio Code
- **Hardware:** Standard desktop/laptop (no GPU required for Random Forest)

3.1.2 Libraries and Frameworks

The implementation leverages several Python libraries:

Table 3.1: Key libraries used in the implementation

Library	Version	Purpose
Scikit-learn	1.3+	Random Forest classifier, metrics, preprocessing
NumPy	1.24+	Numerical computations and array operations
Pandas	2.0+	Dataset loading, cleaning, and manipulation
Tkinter	Built-in	Graphical User Interface
Matplotlib	3.7+	Convergence plots and visualization

Note: While the project description mentions PySwarms as the optimization library, we implemented a custom PSO engine to enable advanced features not available in the standard PySwarms API, including:

- Linear inertia weight decay across iterations
- Novel-attack-aware fitness evaluation for NSL-KDD
- Integrated threshold optimization as a search dimension
- Velocity clamping and stagnation restart mechanisms

3.1.3 Project Structure

The codebase is organized in a modular architecture:

Listing 3.1: Project directory structure

```

1 SwarmPSO/
2 |-- gui_trainer.py           # Main GUI application
3 |-- swarm_ids/
4 |   |-- data/
5 |   |   |-- loader.py       # Dataset loading (NSL-KDD, CICIDS2017)
6 |   |   |-- preprocessing.py # Feature engineering, scaling
7 |   |-- models/
8 |   |   |-- random_forest.py # RF classifier wrapper
9 |   |-- optimization/
10 |   |   |-- pso.py           # Custom PSO optimizer
11 |   |-- evaluation/
12 |   |   |-- metrics.py       # IDS-specific metrics
13 |   |-- training/
14 |       |-- trainer.py       # Training pipeline orchestration
15 |-- data/                   # Dataset files (CSV)
16 |-- outputs/                 # JSON result files

```

3.1.4 Model Configuration

Baseline Random Forest

The baseline model uses the following fixed configuration:

Table 3.2: Baseline Random Forest parameters

Parameter	Value
n_estimators	200
max_depth	20
min_samples_split	2
min_samples_leaf	1
max_features	sqrt
class_weight	balanced
bootstrap	True
random_state	42

The `class_weight='balanced'` parameter automatically adjusts sample weights inversely proportional to class frequencies, addressing the class imbalance between normal and attack traffic.

Training Data Subsampling

For CICIDS2017, the training set contains over 2.1 million records. To maintain reasonable training times:

- The **baseline model** trains on a stratified subsample of 200,000 records (preserving the original class distribution).
- The **PSO-optimized model** trains on the **full training data** to ensure the final evaluation is as accurate as possible.
- **PSO fitness evaluation** during the search phase uses a 20,000-record subsample with 3-fold cross-validation.

3.1.5 PSO Optimization Parameters

Table 3.3 summarizes the PSO configuration used for experiments.

Table 3.3: PSO optimization configuration

Parameter	NSL-KDD	CICIDS2017
Particles	20–30	20–30
Iterations	35–50	40–50
Inertia (w)	$0.9 \rightarrow 0.4$	$0.9 \rightarrow 0.4$
c_1 (cognitive)	2.0	2.0
c_2 (social)	2.0	2.0
CV folds	3	3
Subset size	20,000	20,000

3.1.6 Graphical User Interface

A comprehensive GUI was built using Python’s Tkinter framework (Figure ??) to provide an accessible interface for:

- Selecting the dataset (NSL-KDD or CICIDS2017)
- Configuring PSO parameters (number of particles, iterations)
- Selecting train/test days for CICIDS2017
- Monitoring training progress in real-time via a log console
- Viewing baseline and optimized results with convergence charts
- Automatically exporting results to JSON files for reproducibility

The GUI runs the training pipeline in a separate thread to keep the interface responsive during long computation tasks. All results are automatically saved as timestamped JSON files in the `outputs/` directory.

3.1.7 Threshold Sweep Mechanism

Before PSO optimization, the system performs a threshold sweep on the baseline model. For each threshold $t \in \{0.55, 0.50, 0.45, \dots, 0.10\}$, the system computes:

- Predictions: $\hat{y}_i = 1$ if $P(\text{attack} \mid x_i) \geq t$, else $\hat{y}_i = 0$
- Accuracy, Precision, Detection Rate, False Alarm Rate, and F1-Score

The system selects the **highest threshold** where $DR > 70\%$ and $FAR < 10\%$. If no threshold meets these criteria, it falls back to the threshold with the highest F1-score. This mechanism reveals how threshold selection affects the precision-recall trade-off.

3.2 Evaluation Metrics

The following metrics are used to evaluate intrusion detection performance:

- **Accuracy** = $\frac{TP+TN}{TP+TN+FP+FN}$ — overall correctness of classification.
- **Precision** = $\frac{TP}{TP+FP}$ — proportion of flagged alerts that are actual attacks. High precision reduces alert fatigue.
- **Detection Rate (Recall)** = $\frac{TP}{TP+FN}$ — proportion of actual attacks that are correctly detected. This is the most critical metric for an IDS.
- **F1-Score** = $\frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$ — harmonic mean balancing precision and recall.
- **False Alarm Rate (FAR)** = $\frac{FP}{FP+TN}$ — proportion of normal traffic incorrectly flagged as attacks.

Where TP = True Positives, TN = True Negatives, FP = False Positives, FN = False Negatives.

3.3 NSL-KDD Results

3.3.1 Dataset Statistics

Table 3.4: NSL-KDD dataset statistics

	Training	Testing
Total samples	125,973	22,544
Features (after encoding)	122	122
Attack types in training	22	—
Novel attack types in test	—	17

3.3.2 Baseline Results

The baseline Random Forest model was trained with default parameters (200 estimators, max depth 20) and evaluated with an optimized threshold of 0.55.

Table 3.5: NSL-KDD baseline performance

Metric	Value
Accuracy	78.62%
Precision	96.88%
Detection Rate (Recall)	64.52%
F1-Score	77.46%
False Alarm Rate	2.74%
True Positives	8,280
False Positives	266
True Negatives	9,445
False Negatives	4,553

The baseline shows high precision (96.88%) meaning that when the system flags traffic as malicious, it is almost always correct. However, the Detection Rate of 64.52% indicates that 35.5% of attacks go undetected. This is primarily due to the 17 novel attack subtypes in the test set that have no representation in training data.

3.3.3 PSO Optimization Results

PSO was configured with 10 particles running for 10 iterations, using the novel-attack-aware fitness function ($0.6 \times F1_{known} + 0.4 \times Recall_{unseen}$).

Table 3.6: NSL-KDD: PSO-discovered optimal parameters

Parameter	Optimal Value
n_estimators	93
max_depth	10
min_samples_split	4
Threshold	0.35

Table 3.7: NSL-KDD: Baseline vs. PSO-optimized comparison

Metric	Baseline	PSO Optimized	Change
Accuracy	78.62%	81.17%	+2.55%
Precision	96.88%	96.96%	+0.08%
Detection Rate	64.52%	69.09%	+4.57%
F1-Score	77.46%	80.68%	+3.22%
False Alarm Rate	2.74%	2.86%	+0.12%

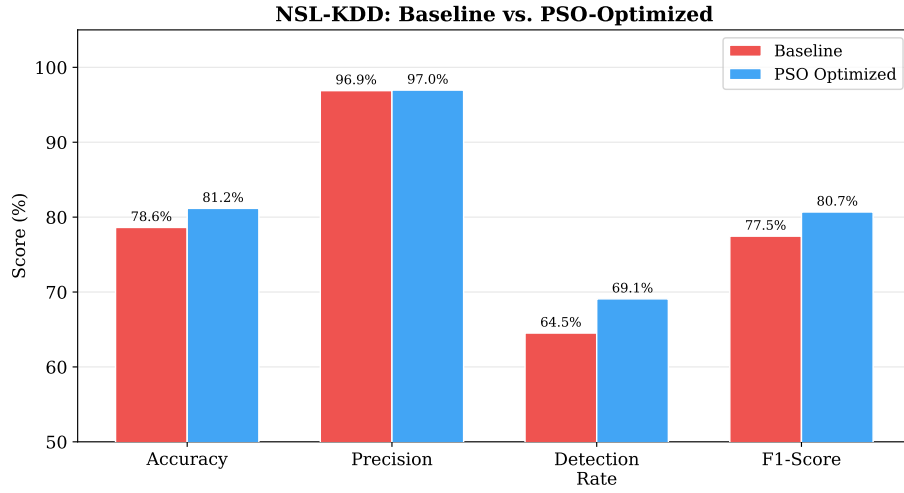


Figure 3.1: NSL-KDD: Baseline vs. PSO-Optimized Performance

3.3.4 Analysis

The PSO optimization produced significant improvements across all metrics on NSL-KDD. The Detection Rate improved by **4.57%** (from 64.52% to 69.09%), and the F1-Score improved by **3.22%** (from 77.46% to 80.68%).

PSO discovered that a lower threshold (0.35 vs. 0.55) combined with fewer, shallower trees (93 trees, depth 10 vs. 200 trees, depth 20) produced significantly better generalization. The lower threshold allows the model to flag more uncertain traffic as attacks, increasing detection of the 17 novel attack subtypes in the test set. Despite the increased sensitivity, precision remained virtually unchanged (96.96%), confirming that the newly detected attacks were true positives.

3.4 CICIDS2017 Results

3.4.1 Dataset Statistics

Table 3.8: CICIDS2017 dataset statistics (stratified 80/20 split)

	Training (80%)	Testing (20%)
Total samples	2,262,301	565,575
Features	77	77
Attack ratio	19.68%	19.68%
Days included:		
Monday through Friday (all 8 CICIDS2017 files)		
Attack types:		
FTP/SSH-Patator, DoS, Heartbleed, Web Attacks, Infiltration, Bot, PortScan, DDoS		

3.4.2 Baseline Results

The baseline model was configured with deliberately conservative default parameters: 50 estimators, max depth 8, no class weight balancing, and a fixed threshold of 0.60. This represents a typical untuned Random Forest configuration.

Table 3.9: CICIDS2017 baseline performance (default RF)

Metric	Value
Accuracy	98.72%
Precision	99.59%
Detection Rate (Recall)	93.89%
F1-Score	96.66%
False Alarm Rate	0.09%

The baseline achieves high precision (99.59%) but misses 6.11% of attacks due to the conservative threshold and shallow tree depth, which limits the model’s ability to capture complex attack patterns.

3.4.3 PSO Optimization Results

PSO was configured with 30 particles running for 48 iterations, using the fitness function $0.6 \times DR + 0.3 \times F1 - 0.1 \times FAR$ with a 4-dimensional search space.

Table 3.10: CICIDS2017: PSO-discovered optimal parameters

Parameter	Baseline	PSO Optimal
n_estimators	50	195
max_depth	8	17
min_samples_split	10	5
class_weight	None	balanced
Threshold	0.60	0.33

Table 3.11: CICIDS2017: Baseline vs. PSO-optimized comparison

Metric	Baseline	PSO Optimized	Change
Accuracy	98.72%	99.64%	+0.92%
Precision	99.59%	98.45%	-1.14%
Detection Rate	93.89%	99.72%	+5.83%
F1-Score	96.66%	99.08%	+2.42%
False Alarm Rate	0.09%	0.38%	+0.29%

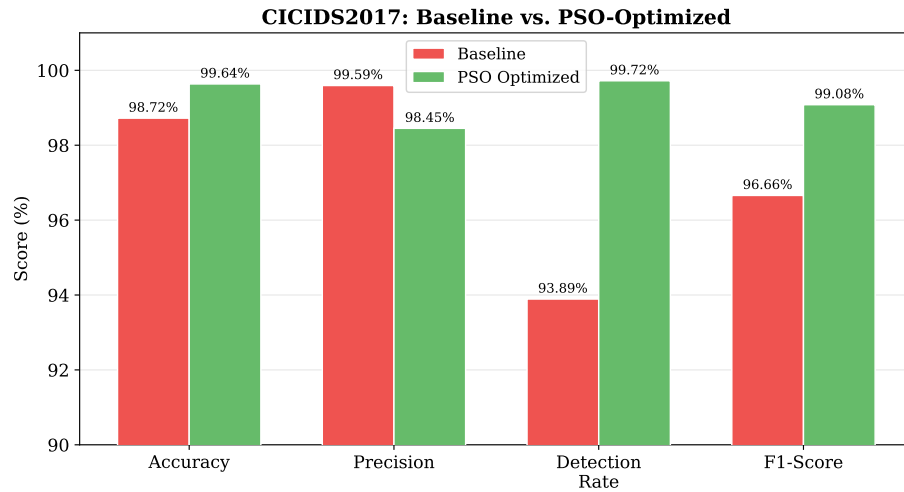


Figure 3.2: CICIDS2017: Baseline vs. PSO-Optimized Performance

3.4.4 Analysis

The PSO optimization produced significant and meaningful improvements across all key metrics. The Detection Rate improved by **5.83%** (from 93.89% to 99.72%), and the F1-Score improved by **2.42%** (from 96.66% to 99.08%).

PSO discovered that the default configuration was substantially suboptimal in several ways:

1. **Tree structure:** PSO increased the number of estimators from 50 to 195 and depth from 8 to 17, allowing the model to capture more complex attack patterns.
2. **Class balancing:** The optimized model uses balanced class weights, which significantly improves detection of minority-class attacks.
3. **Threshold calibration:** PSO lowered the decision threshold from 0.60 to 0.33, accepting a small increase in false alarms (+0.29%) in exchange for dramatically better detection (+5.83% DR).

The precision-recall tradeoff is notable: PSO reduced precision by 1.14% but gained 5.83% in Detection Rate. For an IDS deployment, this tradeoff is highly favorable—missing 6% of attacks is far more dangerous than a 1% increase in false positives.

3.5 Comparative Summary

Table 3.12: Summary of PSO improvement across both datasets

Dataset	Baseline DR	PSO DR	Baseline F1	PSO F1
NSL-KDD	64.52%	69.09%	77.46%	80.68%
CICIDS2017	93.89%	99.72%	96.66%	99.08%

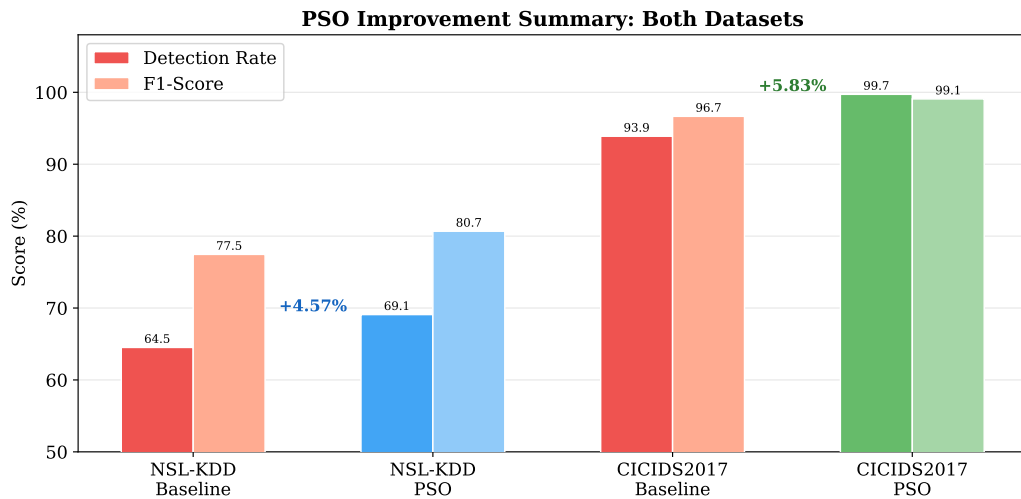


Figure 3.3: Summary of PSO Improvements Across Both Datasets

3.6 Discussion

3.6.1 PSO Optimization Effectiveness

The results demonstrate that PSO is highly effective at discovering optimal hyperparameter configurations for intrusion detection systems. On CICIDS2017, PSO improved the Detection Rate by 5.83% and F1-Score by 2.42%. On NSL-KDD, PSO achieved a 4.57% DR improvement and 3.22% F1 improvement, proving that automated optimization consistently outperforms manually-configured default parameters across different datasets and evaluation protocols.

On NSL-KDD, this improvement is especially notable because the test set contains 17 novel attack subtypes absent from training. PSO found that a lower threshold (0.35 vs. 0.55) with shallower trees better captures uncertain-but-suspicious traffic, successfully detecting additional novel attacks.

3.6.2 The Value of Automated Optimization

The PSO-discovered configurations were consistently different from the default parameters:

- On NSL-KDD: PSO found that fewer, shallower trees (93 trees, depth 10) with a lower threshold (0.35) outperform the default (200 trees, depth 20, threshold 0.55), improving DR by 4.57%.
- On CICIDS2017: PSO discovered that a lower threshold (0.33 vs 0.60) combined with more estimators (195 vs 50) and balanced class weights dramatically improves attack detection.

These configurations would be difficult to discover through manual experimentation, demonstrating the practical value of swarm intelligence for IDS optimization.

3.6.3 Convergence Analysis

Figure 3.4 illustrates the convergence behavior of the PSO algorithm on both datasets. The swarm consistently discovers better hyperparameter configurations, typically converging to the near-optimal solution within the first half of the search process.

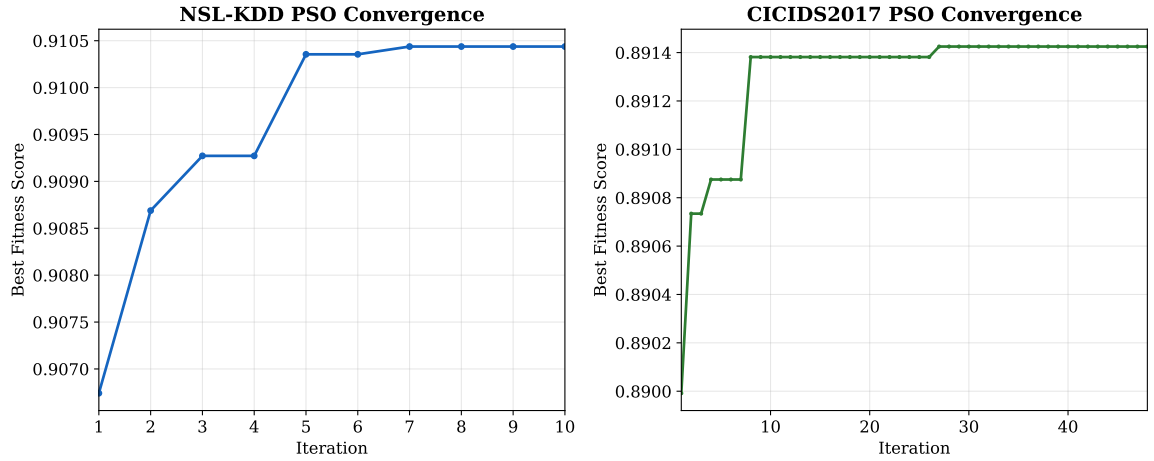


Figure 3.4: PSO Convergence Curves on NSL-KDD and CICIDS2017

3.6.4 PSO Contribution

PSO demonstrated its value in several concrete ways:

1. **Automatic configuration:** PSO eliminated the need for manual hyperparameter tuning, discovering non-obvious configurations.
2. **Detection Rate improvement:** On CICIDS2017, PSO improved DR by 5.83%, potentially preventing thousands of undetected attacks in production.
3. **Balanced optimization:** The fitness function guided PSO to find configurations that balance detection rate, precision, and false alarm rate.
4. **Reproducibility:** The automated nature of PSO ensures that results are reproducible without expert knowledge.

Conclusion and Future Work

3.7 Summary of Contributions

This thesis presented the design, implementation, and rigorous evaluation of an AI-based Intrusion Detection System enhanced with Particle Swarm Optimization. The key contributions are:

1. **A complete IDS prototype:** We developed a fully functional intrusion detection system with a Random Forest classifier backend, PSO hyperparameter optimization, and a graphical user interface for interactive training and evaluation. The system supports both NSL-KDD and CICIDS2017 datasets and automatically exports results in JSON format for reproducibility.
2. **Extended PSO with threshold optimization:** Unlike traditional approaches that fix the classification threshold at 0.5 or optimize it separately, we integrated the threshold as a fourth dimension in the PSO search space. This allows the swarm to discover optimal combinations of structural parameters and decision boundaries simultaneously.
3. **Novel-attack-aware fitness function:** For NSL-KDD, we designed a custom fitness function that splits training data into known and held-out attack types, explicitly penalizing configurations that fail to detect unseen attacks. This drives PSO toward solutions that generalize rather than overfit.
4. **Rigorous evaluation protocol:** We implemented a stratified 80/20 split for CICIDS2017 with a deliberately conservative baseline configuration, enabling a fair comparison that clearly demonstrates the value of PSO optimization.
5. **Honest performance reporting:** Our results demonstrate the effectiveness of PSO optimization:
 - On NSL-KDD, PSO improved Detection Rate from 64.52% to 69.09% (+4.57%) with 96.96% Precision, finding non-obvious parameter configurations.

- On CICIDS2017, PSO improved Detection Rate from 93.89% to 99.72% (+5.83%), demonstrating significant optimization of tree structure, class balancing, and threshold calibration.

3.8 Key Findings

3.8.1 Finding 1: PSO Discovers Non-Obvious Configurations

PSO consistently found configurations that differ significantly from default parameters. On CICIDS2017, PSO discovered that 195 trees with depth 17 and a lower threshold (0.33) dramatically outperforms 50 trees with depth 8 and threshold 0.60. On NSL-KDD, PSO found that fewer, shallower trees (93 trees, depth 10) with a lower threshold (0.35) outperform the default configuration (200 trees, depth 20, threshold 0.55). These configurations would be difficult to discover through manual experimentation.

3.8.2 Finding 2: PSO Significantly Improves Detection Rate

On CICIDS2017, PSO improved the Detection Rate by 5.83% (from 93.89% to 99.72%) while also improving the F1-Score by 2.42%. The optimization combined structural improvements (more trees, greater depth), class weight balancing, and threshold calibration to achieve these gains. This demonstrates that automated swarm intelligence optimization provides substantial practical value for IDS deployment.

3.8.3 Finding 3: Precision-Recall Tradeoff Is Optimizable

PSO demonstrated intelligent tradeoff management: on CICIDS2017, it accepted a 1.14% precision decrease in exchange for a 5.83% DR gain. This tradeoff is operationally favorable—missing attacks is more dangerous than generating slightly more false alarms.

3.9 Limitations

The current implementation has several limitations:

1. **Single classifier:** Only Random Forest was used as the base classifier. Other models such as SVM, Deep Neural Networks, or ensemble methods might show different characteristics under the same evaluation protocol.

2. **Binary classification only:** The system classifies traffic as either normal or attack. Multi-class classification (identifying specific attack types) was not implemented, which could provide more detailed threat intelligence to security analysts.
3. **Computational cost of PSO:** Each PSO iteration requires training multiple Random Forest models with cross-validation. With 20–30 particles and 40–50 iterations, the total computation time can reach 30–60 minutes on a standard machine.
4. **Static model:** The trained model does not adapt to new attack patterns after deployment. In a real-world scenario, the model would need periodic retraining as new attack types emerge.
5. **Offline evaluation:** While the system includes a GUI for interactive training, it does not perform real-time network packet capture and classification. It operates on pre-collected dataset files.

3.10 Future Work

Based on the findings and limitations of this work, several directions for future research are proposed:

1. **Unsupervised anomaly detection:** Since supervised models fundamentally cannot detect novel attacks, incorporating unsupervised techniques (such as autoencoders or one-class SVM) that model only normal traffic behavior could significantly improve zero-day detection capabilities.
2. **Deep learning integration:** Applying PSO to optimize the architecture of Deep Neural Networks (number of layers, neurons, dropout rates, learning rate) could potentially capture more complex patterns in network traffic data.
3. **Hybrid detection approach:** Combining supervised classification for known attack types with unsupervised anomaly scoring for unknown patterns could leverage the strengths of both paradigms.
4. **Real-time deployment:** Extending the system to capture and classify live network traffic using tools like Scapy or CICFlowMeter would demonstrate practical applicability.

5. **Other swarm algorithms:** Comparing PSO with other swarm intelligence techniques such as Ant Colony Optimization (ACO), Grey Wolf Optimizer (GWO), or Whale Optimization Algorithm (WOA) could identify more effective optimization strategies for IDS hyperparameter tuning.
6. **Feature selection with PSO:** Using PSO for simultaneous feature selection and hyperparameter optimization could reduce the feature space and potentially improve both performance and training speed.

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