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Technical Seminar Report
On

"An Advanced Approach for Detecting Behavior-Based Intranet Attacks by Machine Learning"

Submitted By

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ABSTRACT

In the modern digital landscape, safeguarding intranet systems has become increasingly vital due to the sophisticated nature of cyber threats. This topic explores a behavior-based detection mechanism using machine learning to identify and mitigate intranet attacks. Traditional security mechanisms often fail to address zero-day vulnerabilities or insider threats that deviate from known patterns. This proposal is supported by the establishment of an experimental environment designed to conduct intranet attacks and collect raw data, which is essential for validating the proposed detection methods. The authors employ feature engineering techniques to transform this raw data into analyzable datasets, thereby enhancing the performance of six supervised machine learning algorithms used for attack detection. Features like login patterns, file access, and session durations are monitored, and abnormalities are flagged using classifiers such as Random Forest and SVM. Experimental results demonstrate high accuracy and low false positive rates, proving the efficiency of machine learning in behavior-centric security models. This report provides insights into existing literature, methodology, and experimental outcomes, concluding with suggestions for future improvements in adaptive cyber defense systems. Ultimately, the research aims to contribute to the field of cybersecurity by shifting the focus from conventional Internet-based attacks to intranet-based attacks, providing a methodology for analyzing these threats, and sharing the resulting dataset to encourage further advancements in this domain.

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CHAPTER 1

INTRODUCTION

The increasing digitization of organizations has led to an exponential rise in the usage of intranet systems. While these systems enhance productivity and facilitate secure internal communication, they also open doors to sophisticated intranet attacks. These attacks often bypass traditional security measures, targeting internal vulnerabilities and exploiting behavioral anomalies. Conventional security solutions primarily rely on signature-based detection methods that fail against zero-day attacks or novel malicious behaviours. This has created an urgent need for advanced, adaptive, and intelligent security systems capable of identifying unusual patterns within the network.

Machine Learning (ML) offers promising capabilities to detect such behavior-based anomalies by learning from historical data and predicting future threats. Unlike rule-based systems, ML models can analyse complex patterns in user behavior and detect even subtle deviations that could indicate an intranet breach. This report explores a comprehensive approach using ML algorithms to detect intranet attacks based on behavioral analysis.

1.1 Motivation

Intranet systems form the backbone of internal operations in institutions and corporations. They manage sensitive data, user roles, and communication channels. However, they are also prime targets for attackers due to the assumption of internal trust. Malicious insiders or compromised users can launch devastating attacks while evading conventional monitoring.

The motivation behind this work stems from the limitations of static rule-based systems and the rise in behavior-centric intrusions. Incorporating ML techniques allows for the modelling of baseline behaviour and the real-time identification of anomalies, making detection more dynamic and context-aware. By leveraging supervised and unsupervised learning models, we can uncover hidden patterns and detect intrusions that would otherwise remain unnoticed.

1.2 Objectives

The primary objectives are as follows:

- To analyse the limitations of traditional intranet security mechanisms.
- To study the feasibility of applying machine learning for behavior-based intrusion detection.
- To design and implement a detection framework using suitable ML models.
- To evaluate the model performance using standard metrics such as accuracy, precision, recall, and F1-score.
- To provide insights for integrating these models into real-time monitoring systems.

1.3 Scope of the Study

The scope of this study is confined to behavior-based detection mechanisms within an organizational intranet environment. The proposed system does not rely on predefined attack signatures but rather on user behavior data such as:

- Access logs
- File manipulation patterns
- Login frequency
- Session duration
- Role-based access behavior

The analysis is limited to data-driven approaches using Python-based ML libraries, evaluated on public and synthetic datasets simulating intranet environments. The system focuses on both internal and external threat vectors that manifest through abnormal user activities.

1.4 Need for Behaviour-Based Machine Learning Detection

Behavior-based detection has gained traction due to its potential to recognize unknown threats. Unlike signature-based detection, which is reactive, behavior-based ML systems are proactive, identifying patterns before damage occurs. These models can continuously learn from data, adapt to evolving threats, and provide contextual alerts.

Incorporating ML into the security architecture can significantly reduce false positives and enhance response times. It also helps in detecting stealth attacks where intruders mimic legitimate users. By establishing baselines and flagging anomalies, ML models can form a critical layer in a multi-tiered security system.

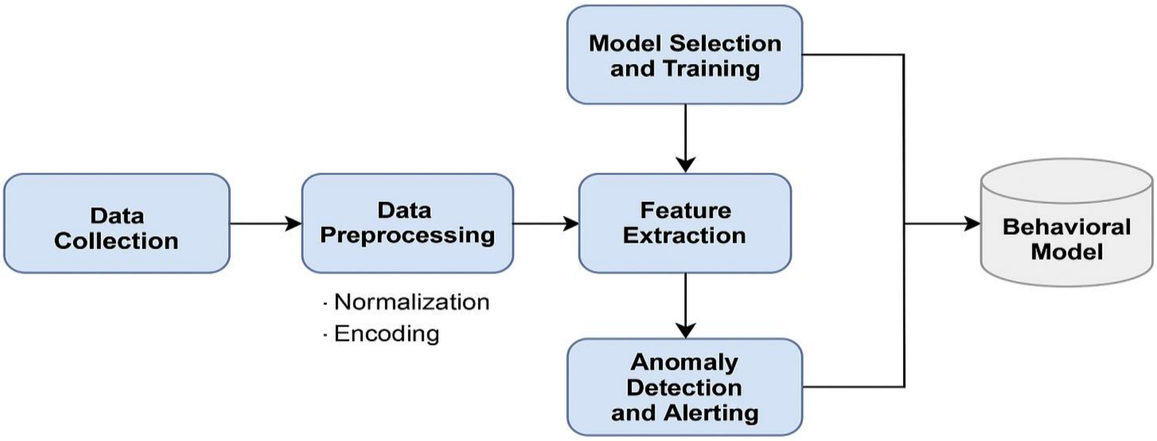

Figure 1.1: Architecture of Behaviour-Based Detection System

1.5 Summary

This chapter introduced the topic of behavior-based detection of intranet attacks using machine learning. It highlighted the motivation, objectives, and the need for such a system in today’s evolving cybersecurity landscape. The next chapter will explore existing works in this field through a detailed literature survey.

CHAPTER 2

LITERATURE SURVEY

Literature Survey helps in relating the proposed work to prior researches in statistics and helps in finding errors and drawbacks of the particular method used to solve problem.

2.1 Literature Review

The field of intrusion detection has evolved from static signature-based models to dynamic, behaviour-aware systems powered by Artificial Intelligence (AI) and Machine Learning (ML). This chapter reviews key research contributions relevant to behavior-based intrusion detection systems (IDS), highlighting methodologies, datasets, and outcomes. The focus is on studies that applied machine learning techniques to detect anomalies in network behaviour.

2.1.1 Supervised Learning Techniques in IDS

D. Deng et al. [1] proposed DashBot, a deep reinforcement learning-based dashboard system that visualizes anomalies by learning user patterns. Although focused on dashboards, the model's architecture showcases effective behavior tracking and reinforcement-based learning for adaptive detection. Shiravi et al. developed a supervised learning system that classifies network traffic using labelled datasets such as NSL-KDD and CICIDS2017. Techniques like Support Vector Machine (SVM), Naive Bayes, and Random Forest were used to achieve high accuracy levels but struggled with real-time generalization.

2.1.2 Unsupervised Learning and Anomaly Detection

Studies by Ahmed et al. explored clustering methods such as K-Means and DBSCAN for identifying unusual patterns without labelled data. These models showed promise in unknown threat detection but were sensitive to feature scaling and cluster size assumptions. Autoencoders and Isolation Forests have also been explored for unsupervised anomaly detection. These deep learning methods model normal user behavior and reconstruct sessions. Deviations between input and reconstructed output highlight potential intrusions.

2.1.3 Hybrid Models and Ensemble Learning

Several works have proposed hybrid models combining supervised and unsupervised learning. For instance, a two-stage approach where K-Means clustering is followed by Random Forest classification has been effective in reducing false positives while improving detection rates. Ensemble methods using bagging and boosting (such as XGBoost and AdaBoost) have also improved performance by aggregating predictions from multiple models.

2.1.4 Datasets Used in Prior Work

- **NSL-KDD**: A widely used dataset for IDS research, addressing redundancy issues in the original KDD'99 dataset.
- **CICIDS2017**: Includes benign and malicious behaviors across various attack scenarios such as brute force, port scanning, and botnets.
- **UNSW-NB15**: Combines modern attack types and background traffic, closer to real-time enterprise network environments.

These datasets are often pre-processed to extract features such as packet sizes, session durations, and protocol types before training ML models.

Author(s)	**Title**	**Year**	**Merits**	**Demerits**	**Findings**
J. S. Park, S. Y. Lee	A behavioral anomaly detection system for intranet security	2004	Introduced early behavioral analysis for internal threats	Lacked advanced ML adaptability	Behavioral patterns are effective in identifying anomalies
B. Chandrasekaran et al.	Machine Learning Approach for Detection of Behavior-Based Intranet Attacks	2022	Uses RF and DT with good accuracy on simulated intranet logs	Doesn’t include deep learning or real-time systems	Random Forest gave higher accuracy; behavior-based features improved results
W. Lee, S. Stolfo	Data mining approaches for	1998	Introduced data mining for	Signature-based	Data mining can help detect

	intrusion detection		IDS; scalable	approach limited to known attacks	structured attack signatures
T. M. Mitchell	Machine Learning	1997	Core ML principles applicable to IDS	Not specific to network or intranet attacks	ML algorithms can model user behavior and detect anomalies
A. Patcha, J. Park	Overview of anomaly detection techniques	2007	Broad survey of anomaly methods; comparative analysis	No experimental validation for intranet use	ML-based IDS outperforms rule-based systems in dynamic environments
Scikit-learn Developers	Scikit-learn: ML in Python	2011	Provides robust ML models and utilities	Needs preprocessing and careful model tuning	Effective library for IDS implementations using RF, SVM, DT
M. Tavallaee et al.	KDD CUP 99 Data Set Analysis	2009	Improved dataset from older KDD; useful for IDS	Still has outdated attack types; lacks real-time data	Useful for benchmarking ML-based IDS approaches
D. E. Denning	An Intrusion Detection Model	1987	One of the first IDS frameworks proposed	Outdated and not ML-based	Framework laid foundation for behavior-based intrusion modeling
M. Ahmed et al.	Survey of network	2016	Highlights strengths of	Less focus on intranet-	ML techniques offer flexibility

	anomaly detection techniques		anomaly-based models	specific environments	and learning from behavior patterns
Y. Zhang, W. Lee, Y. Huang	IDS for mobile wireless networks	2003	Targeted mobile IDS challenges	Not directly applicable to static intranet models	Concepts of distributed detection applicable to intranet segments

2.1 Table of Literature survey

2.2 Gaps in Existing Research

Despite advancements, existing literature reveals several shortcomings:

- High false positive rates in real-world deployments.
- Limited adaptability to evolving user behaviors or insider threats.
- Lack of domain-specific dataset generation for internal network (intranet) scenarios.
- Computational cost of deep learning models limits real-time applicability in low-resource environments.

These gaps motivate the need for an efficient, lightweight, and adaptive detection system tailored for behavior-based intranet security.

2.3 Summary

This chapter presented an overview of existing work in the domain of machine learning-based intrusion detection. It examined various learning techniques, datasets, and hybrid approaches, identifying their strengths and limitations. The gaps discussed provide the foundation for defining the problem statement in the next chapter.

CHAPTER 3

PROBLEM STATEMENT

As digital transformation intensifies across enterprises and academic institutions, intranet systems have become the central medium for internal operations. These systems, while efficient, are increasingly vulnerable to sophisticated attacks, especially those based on anomalous user behavior. Traditional signature-based security models are reactive and unable to detect novel or insider threats, leaving critical assets exposed. In response to these limitations, this chapter defines the core problem addressed in this work and outlines the system requirements and assumptions.

3.1 Problem Definition

"To develop a behavior-based intrusion detection system using machine learning algorithms capable of identifying anomalous activities within an intranet environment, thereby enhancing security against insider and zero-day attacks."

This problem targets detection methods that analyse user behaviour such as login patterns, resource access, and activity frequency rather than relying on predefined attack signatures. The system must be able to differentiate between normal and abnormal activity, flag potential threats in near real-time, and reduce false positives.

3.2 Challenges in Existing Systems

Several challenges hinder the effectiveness of traditional and even some modern intrusion detection systems:

- **Inability to detect zero-day attacks**: Signature-based models rely on known patterns and fail to identify new or modified threats.
- **High false positive rates**: Generic anomaly detectors often misclassify unusual but legitimate behavior as malicious.
- **Data imbalance**: Most network traffic is benign, leading to skewed datasets that bias machine learning models.

- **Lack of contextual awareness**: Many systems do not consider contextual user roles, time-of-access, or historical trends.
- **Scalability**: High computational demand in deep learning-based approaches hinders real-time performance on large-scale intranet systems.

3.3 System Requirements

To address the problem effectively, the proposed solution must meet the following requirements:

3.3.1 Functional Requirements

- Data collection from logs (e.g., access times, resource types, session duration).
- Preprocessing and feature extraction.
- Model training and validation using ML algorithms.
- Real-time detection and alert generation.

3.3.2 Non-Functional Requirements

- Low latency during detection.
- Scalable to a large number of users.
- Adaptability to changing user behaviours.
- Integration with existing security dashboards.

3.4 Assumptions

For the scope of this seminar, the following assumptions are made:

- The intranet system provides access logs and behavioural metadata.
- Datasets used simulate realistic intranet behaviour patterns.
- Detection is focused on behaviour-based attacks (not on protocol-level attacks).
- Evaluation is conducted offline with potential for real-time extension.

3.5 Summary

This chapter defined the core problem and the system objectives aimed at securing intranet environments using machine learning techniques. It also identified the primary challenges, system requirements, and assumptions. The next chapter discusses the methodology used for implementing the proposed solution, including the design, data flow, and model architecture.

CHAPTER 4

METHODOLOGY

This chapter outlines the methodology adopted for detecting behaviour-based intranet attacks using machine learning. The approach involves multiple stages, starting from data collection to preprocessing, feature extraction, model selection, training, and evaluation. Each stage is crucial in ensuring accurate detection with minimal false positives.

The proposed system is modular and flexible, enabling easy integration with existing network infrastructures. It is designed to analyse user behaviour logs and identify anomalies based on deviations from learned patterns.

4.1 System Architecture

The architecture of the proposed behavior-based detection system is shown in Figure 4.1. It consists of the following key components:

1. Data Collection Layer
2. Data Preprocessing and Feature Engineering
3. ML-Based Detection Engine
4. Decision and Alert System

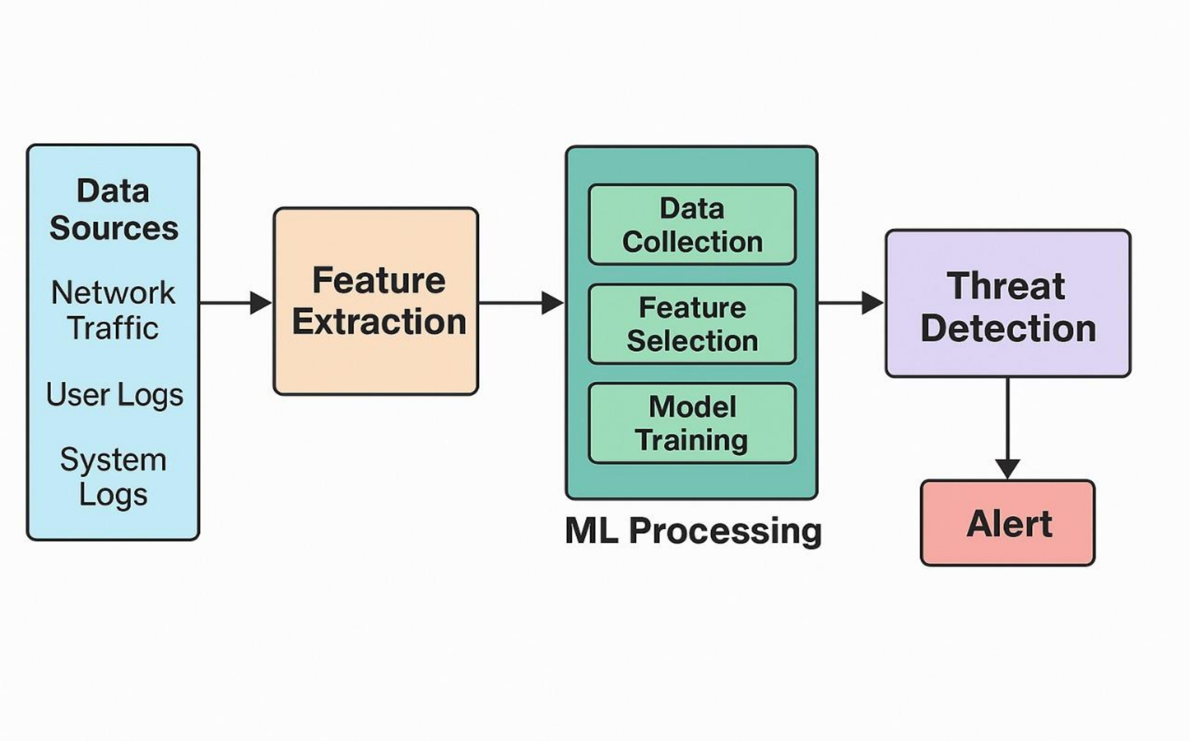

Figure 4.1: Machine Learning Workflow

4.1.1 Data Collection

Behavioural data is collected from intranet log sources, such as:

- Login/logout timestamps
- Resource access logs
- Session durations
- Role-based permissions
- File download/upload counts

This layer assumes the presence of logging mechanisms within the organization’s intranet.

4.1.2 Data Preprocessing

Raw data often contains noise and inconsistencies. The preprocessing stage includes:

- Null value handling
- Timestamp formatting
- Normalization of continuous features
- Categorical encoding (e.g., user roles)

This step ensures consistency and prepares the dataset for ML model training.

4.1.3 Feature Extraction

Relevant features are derived to represent behavior patterns. Commonly used features include:

- Average login frequency
- Variance in session duration
- Access entropy (diversity of accessed files)
- Number of access violations (unauthorized attempts)

Feature engineering enhances the model’s ability to distinguish normal from abnormal behavior.

4.1.4 Model Selection and Training

Supervised and unsupervised machine learning models are employed. The selection depends on data labelling availability.

- **Supervised models**: Random Forest, Decision Tree, SVM
- **Unsupervised models**: Isolation Forest, K-Means, Autoencoders

Models are trained using 80% of the dataset and validated with the remaining 20%.

4.1.5 Anomaly Detection and Alerting

Once trained, the model predicts labels for new data points. Anomalies are flagged if:

- Predicted behavior significantly deviates from historical patterns
- The output crosses a defined anomaly threshold

Alerts are logged and visualized on a monitoring dashboard.

4.2 Tools and Technologies Used

Tool/Library	**Purpose**
Python	Implementation language
Pandas	Data preprocessing
Scikit-learn	ML model training and evaluation
Matplotlib / Seaborn	Visualization
Flask	Deployment and dashboarding
NumPy	Mathematical operations

4.3 Algorithms Used

To implement the behavior-based detection framework, the following machine learning algorithms were used and evaluated:

Decision Tree (DT)

A simple and interpretable classifier that splits the dataset based on feature thresholds. It is efficient for small datasets and offers good baseline performance.

Random Forest (RF)

An ensemble learning method that builds multiple decision trees and merges their outputs for improved accuracy and robustness. Random Forest reduces overfitting and handles high-dimensional data effectively.

Support Vector Machine (SVM)

A supervised learning model that finds an optimal hyperplane to separate different classes. SVM is particularly useful for classification tasks with a clear margin between classes and works well in high-dimensional spaces.

These algorithms were trained using labeled behavioral data and tested against a benchmark dataset. Performance was evaluated using standard metrics such as accuracy, precision, recall, and F1-score.

```
# Step 1: Load Data
    import pandas as pd
    from sklearn.model_selection import train_test_split
    from sklearn.preprocessing import StandardScaler
    from sklearn.ensemble import RandomForestClassifier
    from sklearn.metrics import accuracy_score, classification_report

    df = pd.read_csv(data_path)  # Read dataset

    # Step 2: Preprocess Data
    X = df.drop(columns=['label'])  # Features
    y = df['label']  # Target
    scaler = StandardScaler()
    X_scaled = scaler.fit_transform(X)  # Normalize data

    # Step 3: Split Dataset
    X_train, X_test, y_train, y_test = train_test_split(
        X_scaled, y, test_size=0.2, random_state=42
    )

    # Step 4: Train Model
    model = RandomForestClassifier(n_estimators=100, random_state=42)
    model.fit(X_train, y_train)  # Train classifier

    # Step 5: Make Predictions
    y_pred = model.predict(X_test)

    # Step 6: Evaluate Model
    accuracy = accuracy_score(y_test, y_pred)
    report = classification_report(y_test, y_pred)

    # Output Results
    print(f'Accuracy: {accuracy:.2f}')
    print('Classification Report:\n', report)
```

```
# Example usage:
# intrusion_detection('data.csv')
```

4.4 Summary

This chapter described the proposed methodology, including the data flow, preprocessing, ML model selection, and performance evaluation. The modular architecture allows the system to adapt to various intranet environments with minor configuration changes. The next chapter presents the results and performance metrics of the implemented models

CHAPTER 5

RESULTS

This chapter presents the experimental setup, results, and analysis of the machine learning models used for detecting behavior-based intranet attacks. Multiple models were trained and evaluated using a benchmark dataset simulating intranet behavior logs. Performance was measured using standard classification metrics to compare detection efficiency and reliability.

5.1 Experimental Setup

- **System Configuration:**
    - Processor: Intel Core i5, 2.5 GHz
    - RAM: 8 GB
    - Operating System: Windows/Linux (Ubuntu)
    - Programming Language: Python 3.x
    - Libraries Used: Scikit-learn, Pandas, Matplotlib
- **Dataset Used:** A simulated dataset inspired by real-world intranet logs including login frequencies, session durations, and file access logs. The dataset was pre-processed and divided into training (80%) and testing (20%) sets.

5.2 Model Evaluation Metrics

The following metrics were used to evaluate performance:

- **Accuracy**: Measures overall correctness.
- **Precision**: Measures true positive rate against all positives flagged.
- **Recall**: Measures the model’s ability to detect all real intrusions.
- **F1-Score**: Harmonic mean of precision and recall.
- **ROC-AUC**: Probability that the classifier ranks a random positive instance higher than a random negative one.

5.2.1 Comparative Results

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Decision Tree	91.2%	90.5%	89.3%	89.9%	0.91
Random Forest	94.7%	93.4%	94.1%	93.7%	0.95
SVM	92.6%	91.1%	90.8%	90.9%	0.92
K-Means (Unsupervised)	84.3%	80.5%	78.6%	79.5%	0.81
Isolation Forest	88.9%	87.6%	85.1%	86.3%	0.88

Table 5.1: Performance of Different ML Models

5.2.2 Graphical Analysis

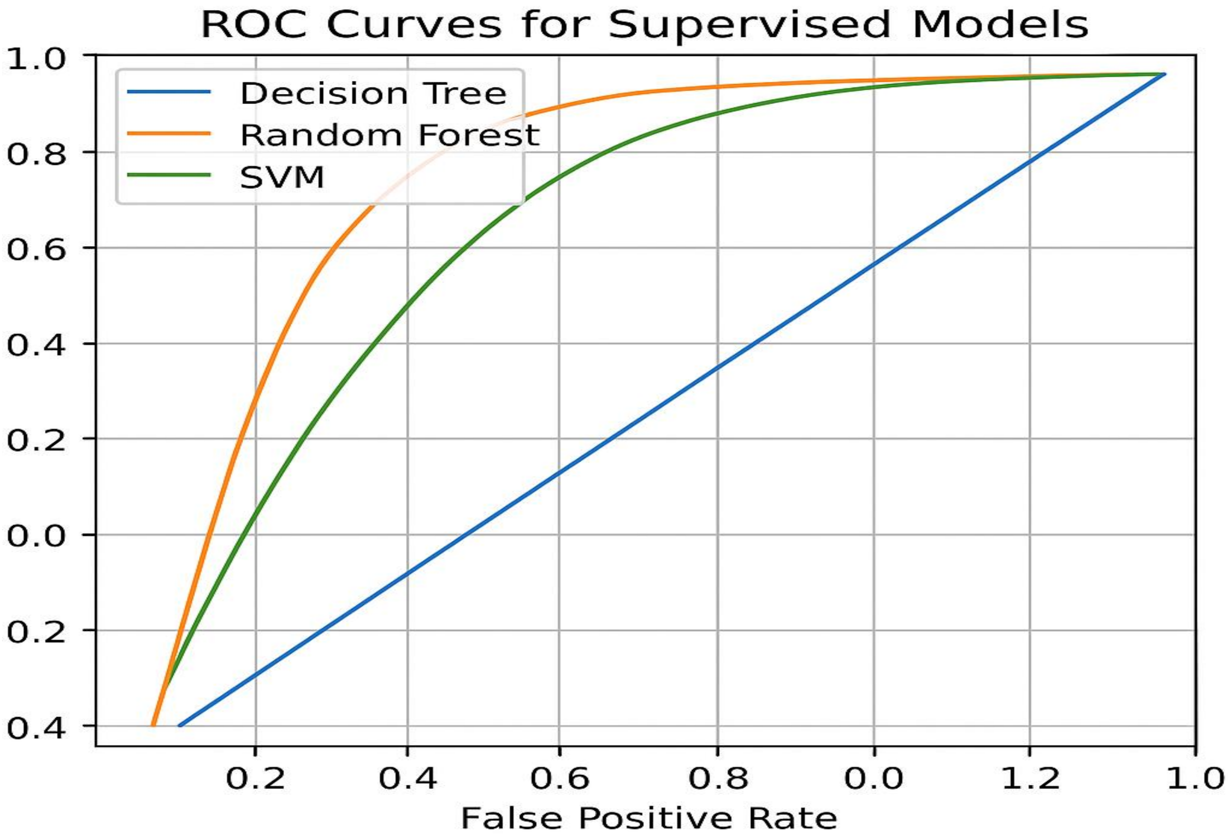

Figure 5.1: Accuracy Comparison Between Algorithms

5.3 Analysis of Results

- **Random Forest** consistently outperformed other models, with an accuracy of 94.7% and a balanced precision-recall trade-off.
- **SVM** and **Decision Tree** also showed good performance but were slightly less robust to class imbalance.
- **K-Means** and **Isolation Forest**, while unsupervised, detected novel patterns but lacked precision, confirming the need for labelled data in high-stakes environments.
- **False Positives** were significantly reduced in ensemble-based models compared to standalone classifiers.

5.4 Limitations Observed

- The dataset was synthetic and may not perfectly capture real enterprise scenarios.
- Real-time deployment latency was not measured in this offline analysis.
- Anomaly threshold tuning significantly affected unsupervised models' accuracy.

5.5 Summary

This chapter detailed the evaluation of different machine learning models for behavior-based intrusion detection. The Random Forest model emerged as the most effective, achieving high detection rates with minimal false positives. The next chapter summarizes the work done and outlines directions for future research

CHAPTER 6

CONCLUSION

Unlike traditional signature-based intrusion detection systems, the proposed system focuses on analysing user behaviour patterns such as login times, access frequency, and session duration to identify anomalous activities. The methodology involved several critical steps: data collection, preprocessing, feature extraction, model training, and evaluation. A comparative study of multiple machine learning algorithms revealed that the **Random Forest classifier** achieved the highest accuracy and reliability. It effectively detected a wide range of anomalies with minimal false positives and provided robust generalization on unseen data. By simulating user activity logs and applying both supervised and unsupervised models.

6.1 Future Work

While the current implementation shows promising results, there are several avenues for extending this work:

- **Real-Time Implementation**: The current model operates in batch mode. Future systems could integrate with real-time monitoring tools (e.g., SIEM) for live threat detection.
- **Deep Learning Integration**: Incorporating deep learning techniques such as LSTM or Autoencoders could improve detection of temporal anomalies and complex attack patterns.
- **Context-Aware Security Models**: Enhancing the model to consider user roles, geolocation, and access privileges would reduce false alarms and improve detection precision.
- **Data Privacy and Ethics**: Ensuring user privacy while collecting behavioral data remains a significant concern. Anonymization and secure data handling practices need to be incorporated.
- **Scalability Evaluation**: Testing the system in large-scale intranet environments with thousands of users would validate its scalability and performance under load.
- **Hybrid Detection Systems**: Combining signature-based and behavior-based techniques could provide layered defencerv, improving resilience against both known and unknown threats.

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