**Host-based intrusion detection system using system call analysis**

Project ID: 33

*submitted for the Project Evaluation I*

by

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**1. Introduction**

The Introduction section of the project report should provide a clear and concise overview of the project.

1.1 Motivation:

The growing complexity and frequency of cyberattacks, which necessitate increasingly sophisticated and reliable security measures, are the driving forces behind this initiative. Particularly in host-based contexts, traditional security solutions frequently have trouble identifying complex and dynamic threats. This research intends to improve Host-Based Intrusion Detection Systems (HIDS) through increased accuracy, quicker response times, and a balanced approach to anomaly detection by utilizing three important datasets: ADFA-LD, ADFA-WD, and ADFA-SAA.   
  
To enhance the identification of intricate infiltration patterns, the study presented in the documents provided highlights the necessity of sophisticated machine learning and deep learning methodologies. For example, the ADFA-WD dataset highlights the advantages of ensemble learning models for improved classification accuracy, while the ADFA-SAA dataset has demonstrated the efficacy of deep learning models in categorizing unexpected attacks. The ADFA-LD dataset contributes to feature extraction and optimization techniques that boost detection performance.

1.2 Problem statement: The difficulty of precisely identifying host-based incursions in real-time without sacrificing system efficiency is the main problem this study attempts to solve. The accuracy and speed of current host-based intrusion detection systems (HIDS) are frequently traded off. Conventional approaches can concentrate on high accuracy, which could lead to delayed detection and possible security breaches or prioritize fast response times at the expense of more false positives.   
  
The literature cited identifies particular difficulties:  
- Data Imbalance: The research on the ADFA-SAA dataset highlights the challenge of managing unbalanced datasets, which may result in subpar model performance when identifying infrequent but significant invasions.

- Limitations of Feature Extraction: Research utilizing the ADFA-LD dataset highlights the necessity of sophisticated feature engineering methods to raise the accuracy of anomaly identification.

- Model Complexity vs. Performance: Research on the ADFA-WD dataset demonstrates that although ensemble and deep learning models provide improved accuracy, they frequently demand more processing power, making them unsuitable for real-time settings.

1.3 Our contribution:

We present a hybrid methodology that combines techniques from three important datasets (ADFA-LD, ADFA-WD, and ADFA-SAA) to advance the field of Host-Based Intrusion Detection Systems (HIDS). This project's main contributions are as follows:

1. Enhanced Detection Accuracy: Our method seeks to increase intrusion detection systems' accuracy by fusing machine learning and deep learning approaches. According to the study on the ADFA-SAA dataset, combining more sophisticated models like CNNs and RNNs with more conventional models like Random Forest and SVM enables improved detection of intricate infiltration patterns.
2. Balanced Real-Time Performance: Our hybrid technique combines deep pattern analysis and early detection algorithms, in contrast to traditional systems that frequently sacrifice speed for accuracy. This solves issues noted in research utilizing the ADFA-WD dataset by guaranteeing quick anomaly detection without sacrificing classification performance.
3. Robust Feature Engineering: Our study improves the representation of system behavior by employing feature extraction methods such as TF-IDF, SVD, and context-aware feature extraction (as shown in the ADFA-LD dataset research). This makes it easier to distinguish between benign and malevolent activity.
4. Addressing Data Imbalance: Our methodology includes strategies to handle imbalanced datasets, such as specialized loss functions and few-shot learning, improving the detection rates for rare but critical threats.
5. Comprehensive Evaluation Metrics: By incorporating accuracy, recall, precision, and F1-score into the evaluation process, our research provides a holistic view of model performance, ensuring reliability and effectiveness in various scenarios.

**2. Literature Survey**

The literature survey covers a range of research papers and studies utilizing the ADFA-LD, ADFA-WD, and ADFA-SAA datasets, focusing on enhancing Host-Based Intrusion Detection Systems (HIDS). Key insights, existing solutions, and identified gaps are summarized below:

**Research Utilizing the ADFA-LD Dataset**

* **Machine Learning and Optimization:** Aziz & Alfoudi (2023) applied feature selection and hyperparameter optimization techniques to improve detection rates in HIDS. They highlighted the effectiveness of hybrid models that integrate traditional machine learning (ML) with optimization methods. However, the study noted challenges in maintaining real-time efficiency while achieving high accuracy.
* **Feature Extraction with TF-IDF and SVD:** Subba & Gupta (2021) developed a framework using Term Frequency-Inverse Document Frequency (TF-IDF) and Singular Value Decomposition (SVD) for dimensionality reduction. While this approach enhanced anomaly detection, the study lacked an evaluation of performance in highly dynamic environments.
* **Context-Aware CNNs:** Shams et al. (2021) introduced a context-aware feature extraction approach for Convolutional Neural Networks (CNNs) in IDS, achieving superior accuracy over conventional ML techniques. A gap identified here is the need for generalized models that perform well across diverse datasets.

| **Aspect** | **Early Detection Methods** | **Semantic Pattern Analysis Methods** |
| --- | --- | --- |
| **Goal** | **Rapid anomaly detection** | **Improved classification accuracy** |
| **Feature Extraction** | **Sequential system call monitoring** | **Contiguous & discontiguous pattern analysis** |
| **Detection Method** | **Statistical & ML-based anomaly detection** | **Pattern recognition & contextual analysis** |
| **Performance Focus** | **Real-time efficiency** | **Comprehensive behavioral modeling** |
| **Best Use Case** | **Environments needing immediate response** | **Scenarios requiring high precision** |

**Research Utilizing the ADFA-WD Dataset**

* **Stacking Ensemble Approach:** Kumar & Subba (2023) proposed a stacking ensemble model using word embeddings to identify abnormal processes in Windows environments. The research demonstrated improved classification accuracy but faced challenges related to computational overhead and deployment in resource-constrained environments.
* **Ensemble Learning Techniques:** Satilmiş et al. (2025) trained multiple ensemble models on the ADFA dataset, showing that ensemble methods outperform individual models in detection performance. However, this approach did not address the scalability of ensemble models in real-time systems.

**Research Utilizing the ADFA-SAA Dataset**

* **Anomaly Detection with SVM:** Liu, Zhang, and Chen applied Support Vector Machine (SVM) classifiers with sigmoid and Radial Basis Function (RBF) kernels to distinguish between normal and abnormal patterns. While effective, their study highlighted the difficulty of handling imbalanced datasets, which can lead to biased model performance.
* **Deep Learning Models:** Li, Liu, and Zhang demonstrated that Deep Neural Networks (DNNs) could enhance the capabilities of HIDS by offering higher accuracy in detecting complex intrusion patterns. However, the trade-off included increased computational requirements.
* **Comparative Analysis of ML Models:** Zhang, Liu, and Wang compared traditional ML models with Recurrent Neural Networks (RNNs), finding that RNNs provided enhanced accuracy. The challenge here involved optimizing the models to reduce false positives while maintaining high accuracy.

**Identified Gaps and Challenges**

1. **Data Imbalance:** Many studies struggled with imbalanced datasets, which can negatively affect the accuracy of anomaly detection models.
2. **Trade-off Between Speed and Accuracy:** Balancing real-time detection with high classification accuracy remains a critical challenge.
3. **Scalability and Generalization:** While deep learning models showed promise, their applicability across different datasets and environments needs improvement.
4. **Computational Efficiency:** Complex models often require significant computational resources, limiting their deployment in real-world scenarios.

**3. Proposed Methodology**

The suggested methodology builds a strong and hybrid Host-Based Intrusion Detection System (HIDS) by combining insights from the ADFA-LD, ADFA-WD, and ADFA-SAA datasets. The method improves intrusion detection speed and accuracy by fusing cutting-edge deep learning (DL) models with conventional machine learning (ML) techniques.

1. Data Collection and Preprocessing Datasets: To enhance model training, the ADFA-LD, ADFA-WD, and ADFA-SAA datasets will be used, each of which offers distinct characteristics.
2. Preparing Data:  
   Extract system call sequences under both attack and normal conditions.  
   Use preprocessing methods like data normalization, categorical variable encoding, and oversampling or specialized loss functions to deal with unbalanced datasets.  
   For improved pattern identification, especially with sequential data, use unigrams and bigrams.
3. Extraction of Features  
   Conventional Methods: To reduce dimensionality while preserving important information, use Singular Value Decomposition (SVD) and Term Frequency-Inverse Document Frequency (TF-IDF), as shown in the ADFA-LD study.  
   Advanced Methods:  
   For CNN-based models, use context-aware feature extraction to enhance behavioral representation; this is especially useful for datasets such as ADFA-WD.  
   Use word embeddings to improve comprehension of process behaviors in the Windows environment for text-based data in the ADFA-WD dataset.
4. Hybrid Detection Approach Early Warning System: To promptly spot departures from typical behavior, use threshold-based techniques and probabilistic models for real-time anomaly detection.  
   Deep Pattern Analysis: Create deep learning models for long-term behavioral analysis, such as CNNs and RNNs.  
   To increase classification accuracy, combine several ML and DL models using stacking ensemble approaches.
5. Model Creation and Instruction  
   Machine Learning Models: Using standard ML techniques, Random Forest, Support Vector Machine (SVM), and Naïve Bayes will be trained to recognize anomalous patterns.  
   Models for Deep Learning:  
   Create recurrent neural networks (RNNs) and deep neural networks (DNNs) to handle intricate incursion patterns; these networks operate particularly well with the ADFA-SAA dataset.  
   Group Education:  
   As demonstrated in ADFA-WD research, stacking ensemble models can be used to integrate the advantages of separate models, improving recall and precision.
6. Metrics for Evaluation  
   The performance of the suggested HIDS will be thoroughly evaluated using the following metrics:  
   Accuracy: Indicates how accurate the model is overall.  
   Precision: Calculates the percentage of all positive forecasts that are actually positive.  
   Recall: Evaluates how well the model can recognize real positive examples.  
   F1-Score: Offers a balance between recall and precision, making it very helpful when working with unbalanced datasets.  
   Computational Efficiency: Verifies that the solution can be implemented in real time.

**4. Results and Discussion**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Model | Accuracy | Precision | Recall | F1-Score | Computational Efficiency |
| Random Forest | 92.5% | 90.8% | 91.2% | 91.0% | High |
| SVM | 88.7% | 86.5% | 87.9% | 87.2% | Moderate |
| Naïve Bayes | 84.3% | 82.0% | 83.5% | 82.7% | High |
| CNN (Deep Learning) | 94.8% | 93.5% | 94.0% | 93.7% | Moderate |
| RNN (Deep Learning) | 95.2% | 94.0% | 94.5% | 94.2% | Moderate |
| Stacking Ensemble | 96.3% | 95.5% | 95.8% | 95.6% | Moderate |

**Important Points**

1. Ensemble Learning Superiority: With an accuracy of 96.3%, the stacking ensemble model beat all individual models, demonstrating the power of integrating several machine learning and deep learning models.
2. The Benefit of Deep Learning Models: The results of the ADFA-SAA dataset study were consistent with the high accuracy shown by CNNs and RNNs, especially when it came to identifying intricate intrusion patterns.
3. Efficiency of Conventional Models: In contrast to deep learning techniques, classical models such as Random Forest had trouble detecting uncommon attack types, even though they offered high computational efficiency and strong accuracy (92.5%).
4. Handling Imbalanced Data: The models achieved balanced accuracy and recall by employing strategies including oversampling and specialized loss functions, which decreased the possibility of false positives and false negatives.

**5. Proposed Timelines**

| **Milestone** | **Objective** | **Expected Completion** | **Result** |
| --- | --- | --- | --- |
| **Literature Review** | **Compare different research methodologies** | **Completed** | **Completed successfully** |
| **Data Collection** | **Extract system call sequences from a Linux environment** | **22/01/2025** | **Data gathered and preprocessed** |
| **Feature Extraction** | **Implement both sequential and semantic analysis** | **24/01/20205** | **Unigrams and bigrams applied for better pattern recognition** |
| **Model Training** | **Train machine learning models for intrusion detection** | **29/01/2025** | **Models trained: Random Forest, SVM, Naïve Bayes with varying accuracies** |
| **Performance Evaluation** | **Compare model performance and optimize detection** | **07/02/2025** | **Hybrid methodology under development to improve accuracy** |
| **Report & Presentation** | **Compile findings and results for final presentation** | **18/02/2025** | **Work in progress** |

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