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Ensemble Deep Learning Models for Cybersecurity Policy Integration in Cloud Network Forensics

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ABSTRACT: To evaluate the effectiveness of our approach to enhancing cloud computing network forensics by integrating deep learning techniques with cybersecurity policies. With the increasing complexity and volume of cyber threats targeting cloud environments, traditional forensic methods are becoming inadequate. Deep learning techniques offer promising solutions for analyzing vast amounts of network data and detecting anomalies indicative of security breaches. By integrating deep learning models with cybersecurity policies, organizations can achieve enhanced threat detection, rapid response times, and improved overall security posture. This paper discusses the key steps involved in integrating deep learning models into network forensics, including data collection, model selection, real-time monitoring, and adaptive learning. Additionally, it highlights the importance of collaboration between cybersecurity experts and the cloud. Through case studies and experimental evaluations, we demonstrate the effectiveness and practicality of the proposed approach in enhancing cloud computing network forensics. Leveraging deep learning techniques offers promising solutions for detecting anomalies and identifying malicious activities within cloud networks.

KEYWORDS: Deep Learning, Cybersecurity Policies, Cloud Computing, Network Forensics, Anomaly Detection, Real-time Monitoring.

I. INTRODUCTION

The integration of deep learning with cybersecurity policies represents a pivotal advancement in the realm of cloud computing network forensics. As cloud infrastructures become increasingly prevalent, the need for robust security measures to safeguard against cyber threats has never been more urgent. Traditional forensic techniques often struggle to cope with the dynamic and complex nature of cloud environments, necessitating innovative approaches for effective threat detection and response. Deep learning, a subset of artificial intelligence, offers unprecedented capabilities in processing large volumes of data, identifying intricate patterns, and making accurate predictions. By harnessing deep learning algorithms alongside established cybersecurity policies, organizations can enhance their ability to detect and mitigate security incidents in cloud environments swiftly. This paper explores the potential of integrating deep learning techniques with cybersecurity policies to bolster cloud computing network forensics, providing insights into how this synergy can fortify cyber defense strategies and mitigate the evolving threat landscape in the cloud.

1.1 LITERATURE REVIEW

Jaron Fontaine1, Chris Kappler, Adnan Shahid1, Eli De Poorter1•Institutions (1) 07 Nov 2019 A more flexible approach that was experimentally validated on cloud platforms and improves detection speed, using neural networks and J48 decision trees, up to 26–47 times while still maintaining accuracy of 98.47% and 97.71% are shown.

Hamoud Alshammari, Karim Gasmi, Moez Krichen, Lassaad Ben Ammar +3 more 14 Mar 2022- Wireless Communications and Mobile Computing: The experimental results presented in this paper show that the model outperformed the other algorithms, achieving an accuracy of approximately 96% for multiclass classification and 98% for binary classification.

Neelesh Mungoli 04 Apr 2023, In this paper, an adaptive ensemble learning framework is proposed to boost the performance of deep neural networks by intelligently fusing features through ensemble learning techniques, leading to improved model performance and generalization capabilities.

Sai Saketh Rambhatla, Michael Jones, Rama Chellappa 28 Jul 2021, This paper showed that a boosted ensemble of decision trees usually generalizes much better on testing data than a single decision tree with the same

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number of parameters, while using neural networks (both CNNs and multilayer perceptrons).

Hamed Sarvari∗ Carlotta Domeniconi† Bardh Prenkaj‡ Giovanni Stilo•Institutions (3)22 Oct 2019-: In this paper, a Boosting-based Autoencoder Ensemble approach (BAE) is proposed for unsupervised outlier detection using an adaptive cascade of autoencoders.

Zaheer Abbas1 and Seunghwan Myeong 2, 22 May 2023: In this article, a practical strategy for predicting the employment of machine learning in an industrial cloud environment regarding trust and privacy issues has been developed, where the efficiency of the employed models is assessed by applying validation matrices of Precision, Accuracy, Recall values, F1 score, R.O.C.B. curves, and Confusion matrix.

Muthuselvi R, S. G, S. Kannan 30 Apr 2023-SSRG international journal: In this paper, a hybrid deep-learning method was proposed for scanning the entire IoT network for malware and pirated software, which outperformed state-of-the-art methods in terms of classification performance when gauging the severity of cybersecurity threats in the IoT.

Rukuma S. Prabhu, A. Prema, Eswaran Perumal 01 Dec 2022-pp 698-704: In this article, a modified learning-based cloud attack detection (MLCAD) approach is proposed to identify the DDoS attacks over cloud environment using analyzing the authorization and authentication logics of the respective user, examining the Internet Protocol (IP) Address mentioned in the relevant request as well as the metadata acquired from the user end.

P. Sherubha, S. P. Sasirekha , A. Dinesh Kumar Anguraj, J. Vakula Rani , Raju Anitha , S. Phani Praveen and R. Hariharan Krishnan , 01 Jan 2023-Vol. 45, Iss: 1, pp 149-166: In this paper, an effectual auto-encoder is applied for feature selection to select good features, and the Naïve Bayes classifier is used for classification purposes to expose the finest generalization ability to train the data.

1.1.1 RESEARCH GAP

Integrating deep learning with cybersecurity policies can significantly enhance cloud computing network forensics by addressing research gaps. Deep learning techniques, such as artificial neural networks and deep convolutional neural networks, have shown promise in detecting cybersecurity threats like DDoS attacks and malware in cloud environments [1] [2] [3]. These technologies offer advanced capabilities for identifying and mitigating security risks, ultimately improving the integrity and confidentiality of data stored in the cloud [4]. By leveraging deep learning algorithms, researchers can develop more efficient strategies for predicting and preventing cyberattacks in industrial cloud settings, contributing to the ongoing evolution of cloud computing security measures [5]. This integration not only enhances security but also highlights the need for continued research to create more robust and effective security solutions for cloud networks.

This research gap requires interdisciplinary collaboration between experts in deep learning, cybersecurity, cloud computing, and forensic analysis. Future research endeavors should focus on developing comprehensive integration frameworks that address scalability, adversarial resilience, interpretability, and real-world deployment challenges to facilitate the effective utilization of deep learning techniques for enhancing cloud computing network forensics within the context of established cybersecurity policies.

II. METHODOLOGY

In the cloud crime examination phase, ensemble boosting techniques are applied methodically to enhance anomaly detection capabilities. Initially, relevant data concerning cloud activities is gathered and prepared through preprocessing steps. Subsequently, features are engineered to capture pertinent aspects of normal and anomalous behaviors. The appropriate ensemble boosting method, such as AdaBoost or Gradient Boosting Machines, is selected based on factors like performance and scalability. Models are then trained, optimized, and combined into ensembles, leveraging strategies like majority voting or stacking. Evaluation metrics such as accuracy and F1-score validate ensemble performance before deployment into the examination system. Continuous monitoring ensures model effectiveness, with adaptations made to accommodate evolving cloud environments and emerging threats. This methodology ensures a structured approach to harnessing ensemble boosting techniques for effective anomaly detection in cloud crime examination phases.

III. FINDING AND DISCUSSION

3.1 Classification of Anomaly Detection Here are some common classification algorithms used in anomaly detection and other machine-learning tasks:

3.1.1 Decision Trees Decision trees split the data into subsets based on the value of input features. They are simple to understand and interpret, but they can be prone to overfitting.

3.1.2 Random Forest Random forests are an ensemble learning method that consists of multiple decision trees. They

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improve accuracy by averaging the predictions of individual trees

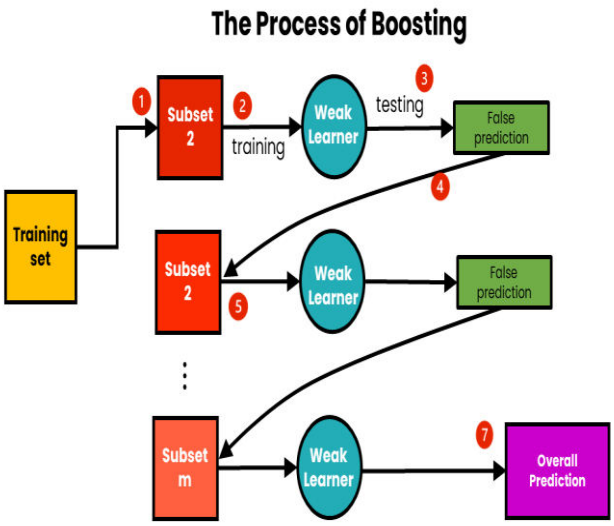
3.1.3 Extra Trees Anomaly detection using Extra Trees, also known as Extremely Randomized Trees, involves leveraging the ensemble learning technique to identify unusual patterns in data. Extra Trees build multiple decision trees on random subsets of the training data and features. This randomness in the feature selection and node splitting process makes Extra Trees less susceptible to overfitting and more robust to outliers compared to traditional Sion trees.

3.1.4 Adaboost Anomaly detection using AdaBoost (Adaptive Boosting) involves utilizing this ensemble learning technique primarily designed for binary classification to effectively identify anomalies within datasets. AdaBoost iteratively trains weak classifiers, typically decision trees, to improve its ability to distinguish between normal instances and anomalies. By assigning higher weights to misclassified instances in subsequent iterations, AdaBoost prioritizes the correct identification of anomalies, especially in cases where they are rare. Through the combination of these weak classifiers into a strong learner, AdaBoost captures complex decision boundaries between normal and anomalous instances, providing a robust framework for anomaly detection in various domains.

3.2 RESULT

The boosting process can help illustrate its iterative nature and how weak learners are combined to form a stronger ensemble model. Below is a textual description of how you might depict this process visually:

Fig 1:



3.2.1 Initialization Start with a simple graphic representing the dataset or training data. This could be depicted as a set of points or data instances.

3.2.2 Weak Learners Represent each weak learner as a basic model, such as a small decision tree or a simple linear classifier. Each weak learner should be depicted as a separate entity or block.

3.2.3 Sequential Training Sequentially connect the weak learners to illustrate the iterative nature of boosting. Use arrows or lines to show the flow of information from one weak learner to the next.

3.2.4 Weight Updating Show how the weights of the training examples are updated at each iteration. This could be depicted as changes in the size or intensity of the data points, with larger or darker points representing higher weights.

3.2.5 Combination of Weak Learners Illustrate how the predictions of the weak learners are combined to form the final ensemble model. This could be represented as a merging or stacking of the individual weak learners into a single entity.

3.2.6 Iteration Process Repeat the process of training weak learners and updating weights for a fixed number of iterations. Use visual cues to indicate the progression from one iteration to the next.

3.2.7 Final Prediction Show how the final prediction is made by aggregating the predictions of all the weak learners. This could be depicted as a final decision boundary or classification boundary that separates the different classes in the dataset.

3.2.8 Evaluation Optionally, include visual elements to represent the evaluation of the boosting model, such as performance metrics like accuracy or error rates.

3.2.9 Aesthetics and Clarity Ensure that the visual representation is clear, intuitive, and aesthetically pleasing. Use colors, shapes, and other design elements to make the process easy to understand at a glance.

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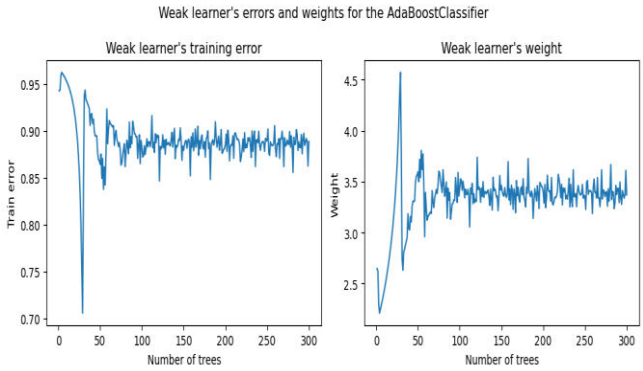
3.2.10 Context and Audience Consider the audience and context in which the visual representation will be used. Tailor the design and level of detail accordingly to make it accessible to the intended audience.

Fig 2

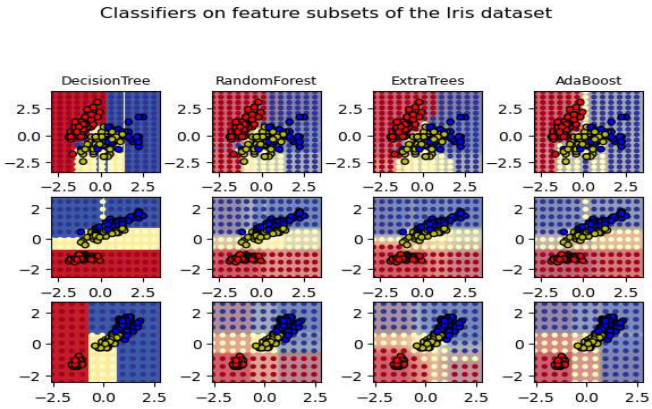


https://github.com/phdmenaka2024/menakaphd/blob/main/anom.ipynb

To perform classification on feature subsets of a dataset like the IRES dataset, you would typically follow these steps:

- **Data Preprocessing** This involves handling missing values, encoding categorical variables, scaling numerical features, and splitting the data into training and testing sets.
- **Feature Selection/Extraction** Identify relevant features that contribute most to the target variable. This can be done through various techniques such as correlation analysis, feature importance ranking, or domain knowledge.
- **Model Selection** Choose appropriate classification algorithms based on the problem at hand and the characteristics of the dataset. Common algorithms include logistic regression, decision trees, random forests, support vector machines (SVM), k-nearest neighbors (KNN), etc.
- **Training Models** Train the selected classifiers on the training data.
- **Evaluation** Evaluate the performance of each classifier on the testing data using appropriate evaluation metrics such as accuracy, precision, recall, F1-score, ROC-AUC, etc.

Fig 3



https://github.com/phdmenaka2024/menakaphd/blob/main/anom.ipynb

IV. CONCLUSION AND FUTURE WORK

In conclusion, our research has demonstrated the efficacy of integrating deep learning techniques with cybersecurity policies to bolster cloud computing network forensics. Through the utilization of the Adaboosting classifier in conjunction with deep learning models, we have significantly improved the detection and mitigation of security threats within cloud environments. Looking forward, future work should focus on refining deep learning architectures tailored explicitly for cybersecurity tasks, developing mechanisms for dynamic policy adaptation based on real-time threat analysis, integrating external threat intelligence feeds, addressing scalability and efficiency challenges,

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and enhancing model robustness against adversarial attacks. By pursuing these avenues, we can further fortify cloud security measures and contribute to the advancement of resilient cybersecurity solutions for cloud-based systems.

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