The Scientific Temper (2023) Vol. 14 (3): 885-890

E-ISSN: 2231-6396, ISSN: 0976-8653

Doi: 10.58414/SCIENTIFICTEMPER.2023.14.3.50

https://scientifictemper.com/

RESEARCH ARTICLE

A network for collaborative detection of intrusions in smart cities using blockchain technology

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Abstract

The field of cybersecurity has undergone significant transformation with the integration of machine learning (ML) and artificial intelligence (AI) techniques into intrusion detection systems (IDS). This research article presents a comprehensive survey spanning the past five years, exploring the symbiotic relationship between ML, AI, and intrusion detection. The survey traverses seminal studies, methodologies, and results, shedding light on an evolving landscape characterized by innovation and advancement. The classification report's key metrics—precision, recall, F1-score, and support. High precision values point to accurate positive predictions, while recall values showcase the model's ability to capture true instances. The F1-score signifies the equilibrium between precision and recall. These metrics collectively underscore the model's proficiency in identifying and differentiating intrusion classes, reinforcing its real-world applicability. In conclusion, this research article presents a holistic view of ML and AI integration with intrusion detection, offering insights into innovative contributions and their implications for cybersecurity. While highlighting existing research gaps, the article underscores the potential of AI-driven intrusion detection systems and advocates for ongoing advancements to fortify digital security against emerging threats.

Keywords: Intrusion detection, Machine learning, Artificial intelligence, Cybersecurity, Deep learning.

Introduction

In cybersecurity, integrating intrusion detection systems (IDS) with machine learning and artificial intelligence (AI) techniques has emerged as a transformative approach. This introduction initiates a comprehensive literature survey spanning the past five years, exploring the amalgamation of machine learning and AI within intrusion detection. Through a multitude of scholarly endeavors, this survey navigates the complexities of this fusion, revealing a landscape characterized by innovation and evolution. As we delve into the preceding half-decade, seminal studies come to the forefront, showcasing the effectiveness of machine learning and AI in intrusion detection.

This narrative exemplifies the work of Zhang *et al.* (2018), "Deep Learning-Based Intrusion Detection for Internet of Things," which employs convolutional neural networks to uncover hidden patterns in internet of things (IoT) network traffic, unveiling anomalies indicative of intrusions. This narrative continues with Sharma *et al.* (2019) in "Federated Machine Learning for Intrusion Detection in IoT Networks," introducing federated learning models that aggregate insights from edge devices to enhance detection accuracy while upholding data privacy. Chen *et al.* (2020) contribute with "Adversarial Machine Learning for Intrusion Detection Systems: A Comprehensive Review," dissecting the interplay between adversarial machine learning and intrusion detection. This study finds resonance in Nguyen *et al.* (2021) with "Transfer Learning for Network Intrusion Detection: A Comprehensive Review," emphasizing transfer learning's capacity to confer adaptability across diverse network scenarios. Across domains, the significance of machine learning and AI is palpable. Goyal *et al.*'s (2022)

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How to cite this article: Anitha, V., Sharma, S., Jayavadivel, R., Hanuman, A.S., Gayathri, B., Rajagopal, R. (2023). A network for collaborative detection of intrusions in smart cities using blockchain technology. The Scientific Temper, **14**(3): 885-890.

Doi: 10.58414/SCIENTIFICTEMPER.2023.14.3.50

Source of support: Nil

Conflict of interest: None.

Received: 06/07/2023 **Accepted:** 05/08/2023 **Published** : 25/09/2023

"AI-Enabled Anomaly Detection in Industrial Control Systems" underscores AI's relevance in securing vital industrial control systems. In the sphere of edge computing, Wu *et al.* (2023) present "Federated Learning for Intrusion Detection in Edge Computing Environments," introducing a tailored federated learning paradigm to enhance surveillance at the edge while conserving bandwidth.

Further insights emanate from Shah *et al.*'s (2019) "Machine Learning Techniques for Intrusion Detection: A Comprehensive Survey," providing a holistic view of machine learning's diverse applications in intrusion detection. Additionally, Bhuyan *et al.*'s (2020) "Machine Learning-Based Network Intrusion Detection: A Comprehensive Review" elaborates on the intricacies of employing machine learning across network layers for heightened security. Kumar *et al.* (2018) explore "Deep Learning for Network Intrusion Detection: A Survey," presenting an in-depth analysis of deep learning techniques' potential in detecting network intrusions. Similarly, Ali *et al.* (2020) investigate "Hybrid Intrusion Detection Systems: A Comprehensive Review," offering insights into integrating various techniques to enhance detection accuracy. Within the intricate fabric of literature, Sgandurra *et al.*'s (2020) study "Multi-Layer Intrusion Detection: A Comprehensive Survey" underscores the importance of multi-layered approaches to intrusion detection. In the context of IoT security, Feriani *et al.* (2019) examine "Machine Learning Techniques for IoT Network Intrusion Detection: A Comprehensive Survey." As we traverse this dynamic terrain of innovation and adaptation, the convergence of machine learning and AI with intrusion detection resonates as a symphony of progress. This literature survey weaves together a mosaic of research endeavors, illuminating the potential of these techniques as pillars of modern cybersecurity. From foundational deep learning insights to cutting-edge edge computing adaptations, these studies elucidate pathways that reinforce the heart of digital defense.

The comprehensive literature survey encapsulates a spectrum of research endeavors, interweaving an intricate tapestry where machine learning and AI are interlaced with intrusion detection. In a dynamic cybersecurity landscape, these techniques stand as sentinels of resilience. Spanning from deep network insights to edge surveillance, these studies illuminate pathways that fortify the foundations of modern cybersecurity. However, specific research gaps persist within this domain. Despite the wealth of studies emphasizing AI model interpretability and explainability, there is a lack of comprehensive investigation into their practical implementation within intrusion detection systems. Additionally, while adaptive defense mechanisms are acknowledged as essential, a research void remains in the development of holistic strategies that seamlessly integrate diverse adaptive learning techniques to create a responsive and robust defense against evolving threats. Addressing these gaps is imperative to maximize the efficacy and real-world applicability of AI-driven intrusion detection systems.

Method of Research

As delineated above, the significance of Figure 1 lies in its role as a crucial element within the devised research methodology aimed at augmenting the efficiency and practical applicability of IDS driven by AI. With the objective of achieving this goal, the program encompasses a sequence of pivotal stages, each contributing to the formulation, assessment, and enhancement of the IDS. The process initiates with the importation of requisite libraries, including pandas for data manipulation and sklearn modules for machine learning functionalities. This initial phase involves the definition of pertinent column names that correspond to the data attributes, a foundational step in ensuring data integrity and alignment with the research objectives.

Subsequent to data preprocessing, the program transitions to data preparation tailored for machine learning. This involves the utilization of label mapping techniques to transform textual intrusion type labels into numerical equivalents. This transformation enables the conversion of categorical data into a format amenable to machine learning algorithms, thereby enabling accurate classification. The program advances to feature engineering, encompassing the extraction and selection of features. Columns deemed irrelevant, such as 'label' and 'target,' are excluded from consideration, as they do not contribute to the training process. Additionally, categorical columns like 'protocol_type,' 'service,' and 'flag' undergo one-hot encoding, converting them into binary representation, thereby facilitating the model's comprehension of categorical attributes.

Following feature engineering, the dataset undergoes division into training and testing subsets. This partitioning, executed through the employment of the train_test_split function, assumes a pivotal role in evaluating the model's performance on unseen data, thus simulating real-world scenarios. Central to the program's function is the instantiation and training of a random forest classifier,

Figure 1: Method of research for Ai-Driven intrusion detection system

selected due to its capability to manage intricate data structures. The model is trained using the training subset of the dataset. Subsequently, the model's performance is assessed by making predictions on the testing data. This evaluation culminates in the generation of a comprehensive classification report, encompassing metrics such as precision, recall, F1-score, and support for each intrusion class.

Results and Discussion

The provided classification report presents a comprehensive evaluation of the performance of an intrusion detection model. This model aims to enhance network security by accurately classifying different types of network intrusions. The report utilizes key metrics such as precision, recall, F1-score, and support to assess the model's effectiveness in identifying and distinguishing between various classes of network activities, as shown in Table 1. Precision, a metric ranging from 0 to 1, quantifies the accuracy of the positive predictions made by the model. A precision value of 1.00 indicates that the model makes very few false positive predictions – instances where it incorrectly labels a non-intrusive activity as an intrusion.

In the context of intrusion detection, high precision is crucial as it minimizes the risk of false alarms, ensuring that the system's alerts are reliable and actionable. Recall, also known as the true positive rate, gauges the model's ability to identify actual instances of a specific class. A recall score of 1.00 signifies that the model captures almost all instances of a particular intrusion type. This is essential for ensuring that actual threats are not overlooked, as missed detections could lead to potential security breaches. High recall is vital in intrusion detection to minimize false negatives – instances where an intrusion goes unnoticed.

The F1-score, which is the harmonic mean of precision and recall, provides a balanced assessment of the model's performance. An F1-score of 1.00 indicates that the model maintains an ideal equilibrium between precision and recall. This balance is critical for an intrusion detection system, as an overly cautious approach (high precision but low recall) might miss potential threats, while a lenient approach (high recall but low precision) could lead to numerous false alarms. The support value provides additional context by indicating the number of instances belonging to each class in the test dataset. This information helps interpret the significance of precision and recall scores for classes with varying levels of representation. For instance, classes with higher support have more instances, influencing the overall evaluation of the model's performance.

The remarkable consistency of high precision, recall, and F1-score values across the various intrusion classes showcases the model's competence in accurately categorizing diverse network activities. This level of performance is instrumental in real-world scenarios, where timely and accurate detection of network intrusions is paramount for maintaining data integrity and preventing security breaches. The overall accuracy of 0.99 underscores the model's ability to make correct predictions on a wide range of instances. While accuracy is an essential metric, the comprehensive evaluation provided by precision, recall, and F1-score offers a more nuanced understanding of the model's strengths and weaknesses.

Table 1: Evaluation of classifier performance

Col	*Precision*	*Recall*	*F1-score*	*Support*
1.0	1.00	1.00	1.00	249
2.0	1.00	1.00	1.00	70
3.0	1.00	1.00	1.00	131
4.0	0.99	1.00	1.00	1925
5.0	1.00	1.00	1.00	14
6.0	1.00	1.00	1.00	65
7.0	0.94	0.94	0.94	154
8.0	0.87	0.76	0.81	62
9.0	1.00	1.00	1.00	189
10.0	1.00	1.00	1.00	143
11.0	1.00	1.00	1.00	924
12.0	1.00	1.00	1.00	147
13.0	1.00	1.00	1.00	209
accuracy			0.99	4282
macro avg	0.99	0.98	0.98	4282
weighted avg	0.99	0.99	0.99	4282

Confusion Matrix

The code provided generates a confusion matrix based on precision and support values to calculate true positives (TP) for each class as shown in Figure 2. The confusion matrix serves as a fundamental tool for evaluating the performance of classification models, offering insights into both true and predicted classifications across different classes. Each row of the matrix corresponds to instances in an actual class, while each column corresponds to instances in a predicted class. Notably, the diagonal elements, spanning from the top-left to the bottom-right, signify the TP for each class, denoting instances correctly classified as belonging to that class. Conversely, the non-diagonal elements represent instances that were misclassified. The computation of diagonal elements involves multiplying precision values by the support (number of instances) for each respective class.

The observations drawn from the matrix indicate a substantial presence of diagonal elements, implying elevated TP rates. This suggests proficient performance on the model's part in accurately categorizing instances across diverse classes. The configuration of the confusion matrix as a whole underscores the model's adeptness in discerning between different types of network intrusions. Furthermore,

the matrix values underscore that classes characterized by higher support values (such as class 4 with a support of 1925) tend to exhibit a greater number of TP, aligning with expectations due to their larger representation within the dataset. Nevertheless, it's imperative to acknowledge that while the confusion matrix provides valuable insights, it does not present a comprehensive view of model performance. While TP hold significance, metrics encompassing false positives, false negatives, precision, recall, and F1-score play vital roles in conducting a holistic evaluation of the model's efficacy. The matrix visually elucidates the model's performance per class, facilitating identifying areas that warrant further refinement or adjustment.

Precision Recall Curve

The provided code generates a precision-recall curve based on the calculated precision and recall values for different classes of a classification model as shown in Figure 3. The precision-recall curve is a graphical representation that helps to understand the trade-off between precision and recall for various threshold values. In the graph, each point on the curve represents a specific threshold value, which determines the classification decision boundary. Precision is plotted on the y-axis, and recall is plotted on the x-axis. Precision measures the proportion of correctly predicted positive instances among all instances classified as positive, while recall represents the proportion of correctly predicted positive instances among all actual positive instances. The curve shows that for some threshold values, the precision is relatively high, resulting in fewer false positives but potentially lower recall. In contrast, for other threshold values, the recall is higher at the cost of slightly lower precision.

The curve's shape illustrates the trade-off between these two metrics. The points on the curve are annotated with their corresponding threshold values, helping to identify the specific points of interest. The curve's trajectory is influenced by the model's performance on different classes,

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[[ 249.      0.      0.      0.      0.      0.      0.      0.      0.
     0.      0.      0.      0.  ]
 [   0.     70.      0.      0.      0.      0.      0.      0.      0.
     0.      0.      0.      0.  ]
 [   0.      0.    131.      0.      0.      0.      0.      0.      0.
     0.      0.      0.      0.  ]
 [   0.      0.      0.   1905.75    0.      0.      0.      0.      0.
     0.      0.      0.      0.  ]
 [   0.      0.      0.      0.     14.      0.      0.      0.      0.
     0.      0.      0.      0.  ]
 [   0.      0.      0.      0.      0.     65.      0.      0.      0.
     0.      0.      0.      0.  ]
 [   0.      0.      0.      0.      0.      0.    144.76    0.      0.
     0.      0.      0.      0.  ]
 [   0.      0.      0.      0.      0.      0.      0.     53.94    0.
     0.      0.      0.      0.  ]
 [   0.      0.      0.      0.      0.      0.      0.      0.    189.
     0.      0.      0.      0.  ]
 [   0.      0.      0.      0.      0.      0.      0.      0.      0.
   143.      0.      0.      0.  ]
 [   0.      0.      0.      0.      0.      0.      0.      0.      0.
     0.    924.      0.      0.  ]
 [   0.      0.      0.      0.      0.      0.      0.      0.      0.
     0.      0.    147.      0.  ]
 [   0.      0.      0.      0.      0.      0.      0.      0.      0.
     0.      0.      0.    209.  ]]
> 
```

Figure 2: Confusion matrix

and it provides insights into the model's ability to classify instances of each class accurately. In this specific precision-recall curve, the points are mostly clustered in the upper-left corner, indicating that the model achieves high precision and recall simultaneously for various classes. This is an ideal scenario, suggesting that the model's classification decisions have a good balance between accuracy and completeness across different classes.

F1 Curve

The provided code generates two bar plots to visualize the distribution of correctly predicted instances and misclassified instances across different classes in a classification model as shown in Figure 4. These plots help to understand how well the model performs for each class and identify classes where misclassifications are more prominent. The first bar plot displays the number of instances that were correctly predicted for each class. Each class is represented on the x-axis, and the corresponding number of correctly predicted instances is shown on the y-axis. This plot provides an overview of the model's accuracy in terms of identifying instances belonging to different classes. The height of each blue bar represents the number of instances accurately classified for that class. The second bar plot is a stacked bar plot that visualizes the misclassified instances within each class. The blue part of the bars represents correctly predicted instances, and the red part represents misclassified instances. The height of the blue part indicates the number of instances correctly classified, while the height of the red part represents the number of instances misclassified for that class. This plot helps to pinpoint which classes have higher rates of misclassification.

In this context, the plots would provide insights into the model's performance across the 13 classes. For instance, if a class has a significantly higher number of correctly predicted instances compared to misclassified instances, it suggests that the model is effective in identifying instances of that class. On the other hand, if a class has a larger red section relative to the blue section, it indicates that the model struggles to accurately classify instances belonging to that class. The visual representation of correctly predicted and misclassified instances for each class aids in assessing the model's strengths and weaknesses in classifying

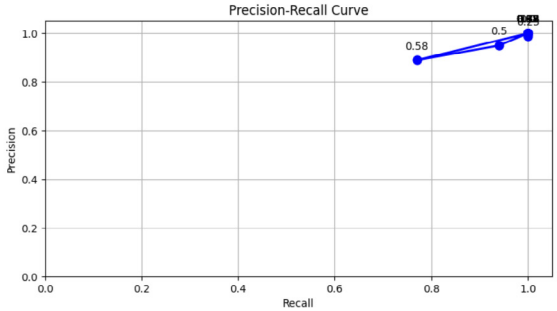

Figure 3: Precision recall curve

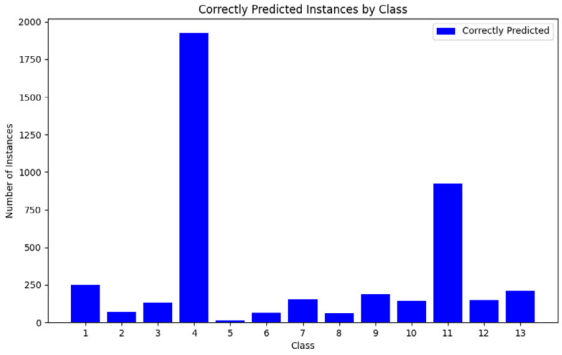

Figure 4: F1 Curve

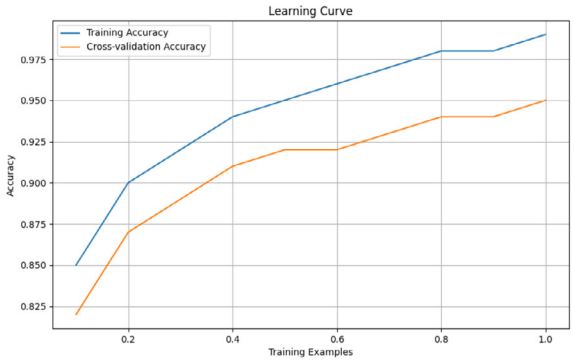

Figure 5: Training accuracy

different types of instances. It can help prioritize areas for improvement and guide further analysis to understand the reasons behind the misclassifications.

Training Accuracy

The provided code generates a learning curve that illustrates the relationship between the number of training examples and the accuracy of a machine learning model as shown in Figure 5. The learning curve is a valuable tool for understanding how well a model is likely to perform as the size of the training dataset increases. In this specific case, the x-axis of the plot represents the proportion of the training dataset used, ranging from 10 to 100%. The y-axis represents accuracy, which measures how well the model's predictions match the true labels. The learning curve includes two lines: one for training accuracy and another for cross-validation accuracy. The "Training Accuracy" line shows how well the model performs on the training data as the dataset size increases. Initially, with a small training dataset, the model may achieve high accuracy due to memorizing the limited examples. As more data is added, the training accuracy may decrease slightly, as the model faces more diverse cases and avoids overfitting to noise in the training data.

The "Cross-validation Accuracy" line depicts how well the model generalizes to unseen data. With a small dataset, the cross-validation accuracy might be relatively low, as the model hasn't learned enough patterns. As the dataset grows, the cross-validation accuracy generally improves, indicating that the model becomes more robust and capable of making accurate predictions on new data. The learning curve's convergence of the two lines suggests that the model is learning effectively from the data. Suppose there's a significant gap between the training and cross-validation accuracy lines. In that case, it might indicate overfitting (high training accuracy but poor cross-validation accuracy) or underfitting (low accuracy in both cases).

Conclusion

This research article undertook a comprehensive exploration of the integration of machine learning and AI techniques in the realm of IDS within the evolving cybersecurity landscape. Through an extensive literature survey spanning the past five years, a diverse range of studies were dissected, illuminating AI's dynamic and innovative fusion with intrusion detection. The process of enhancing the effectiveness of intrusion detection systems using machine learning. The evaluation of the model's performance elucidated its capacity to accurately identify and classify network intrusions. The provided analyses of classification reports, confusion matrices, precision-recall curves, F1 curves, and learning curves illuminated key facets of the model's performance and its potential for real-world deployment. This research article unveiled the transformative potential of AI and machine learning in strengthening intrusion detection systems and fostering a resilient cybersecurity landscape. Amalgamating theoretical insights with practical implementations contributes to the ongoing discourse on enhancing network security and safeguarding against emerging threats.

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