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Triple Network Intrusion Detection Model Using Machine Learning

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ABSTRACT

Due to the enormous amounts of data and their gradual growth, systems for Big Data analysis and information security have recently changed in terms of their relevance. A framework called an interruption location framework (IDS) screens and examinations information to track down any interruptions into a framework or organization. Due to the network's rapid data generation, volume, and variety, traditional approaches are no longer practical. extremely difficult to identify attacks. IDS utilizes huge information ways to deal with handle large information for exact and viable information investigation. The random forest model suggested this for intrusion detection. An intrusion detection model was constructed on the Apache Spark Big Data platform with the help of a Random Forest classifier and ChiSqSelector. The model was trained and evaluated using KDD99. In the experiment, we contrasted Linear Discriminant Analysis, Decision Tree, Random Forest, and Logistic Regression. The experiment's findings demonstrated that the Random Forest model performs well, requires less time to train, and is effective when used with large amounts of data.

INTRODUCTION

A software tool called an intrusion detection system (IDS) makes use of several machine learning algorithms to find potential security holes in a network or system. It prevents unauthorised access to the network, which may also involve internal users. Building a predictive model (a classifier) that can differentiate between malicious activity (intrusions/attacks) and legitimate connections is the aim of an intrusion detection system.

In today's digitally connected world, cybersecurity has become a critical concern for organizations and individuals alike. With the increasing sophistication of cyberattacks, traditional security systems are no longer sufficient to detect and prevent complex intrusions. Intrusion Detection Systems (IDS) have emerged as vital tools to monitor and analyze network traffic for signs of malicious activity. However, single-layered detection models often struggle to identify new, evolving threats. To address this limitation, a Triple Network Intrusion Detection Model (TNIDM) using Machine Learning is proposed to enhance the detection accuracy and robustness of IDS frameworks.

This model incorporates a three-tiered detection architecture—namely, **Packet Analysis**, **Anomaly Detection**, and **Behavioral Pattern Recognition**—to

identify various forms of intrusions across different layers of a network. Each layer uses specialized machine learning algorithms trained on labeled datasets to classify and flag potentially harmful traffic. The layered structure ensures that if one layer misses an intrusion, the others can compensate, improving the overall detection rate and reducing false positives.

Machine learning plays a pivotal role in enabling the system to learn from historical attack patterns and adapt to new threats in real time. Algorithms such as Random Forest, Support Vector Machine (SVM), and Neural Networks are integrated within the model to perform both binary and multi-class classification of network traffic. By combining multiple detection techniques into a unified system, the Triple Network Intrusion Detection Model provides a more intelligent, adaptive, and comprehensive approach to securing digital infrastructure against increasingly sophisticated cyber threats.

LITERATURE SURVEY

Title:Model for Classifying Intrusions Based on a Better K-Dependence Bayesian Network.

The authors are L Jian, S P Rui, Y Min, H E Liang, Z Yuan, and Z X Yang.

The tremendously diversified and dynamicThe network edge environment poses significant issues for the security scenario. The organization's edges are connected to common cloud services by edge figuring. For network security in the increasing edge processing mode, it is crucial and useful to create a high-accuracy Interruption Discovery Grouping Model (IDCM).

This study focuses on the superior k-reliance Bayesian organisation (KDBN) fundamental model. By reducing the coordinated edges of powerless reliance, it may have the potential to more clearly express the reliance connections between framework elements and enhance the creation of the Bayesian organisation. This study develops an IDCM based on improved KDBN by presenting the highest back measure and a virtual expansion method for tests with limited classification.

When paired with the KDDCup99 (10%) intrusion detection data set, the improved KDBN-based IDCM is demonstrated to be extremely stable, accurate, and efficient. This successfully resolves issues like low discovery exactness and unfortunate strength that are talked about in various references for little classifications (U2R and R2L) in the KDDCup99 (10%) interruption identification informational index.

Title: A Network Security Metric for Assessing the Risk of Unknown Vulnerabilities: k-Zero Day Safety.

L. Wang, M. Zhang, and A. Singhal are the authors.

By enabling direct correlations of the overall viability of various security measures, an organisational security measure may provide measurable information to assist security specialists in protecting PC networks. Research on security measures has been impeded, meanwhile, by difficulties in preventing zero-day attacks that take use of recently discovered vulnerabilities. Due to the fact that they are less foreseeable than other security concerns, software vulnerabilities

have always been thought of as quantifiable.

Security measures are thus severely hindered because a design that is safer would be of little use if it were equally defenceless against zero-day attacks. In this work, we provide k-multi day security, a clever security metric to address this problem. Our metric counts the number of vulnerabilities needed to compromise network assets rather than attempting to rank them. A higher count denotes greater security because it is less likely that multiple unknown vulnerabilities will be available, applicable, and exploitable at the same time. We use case studies to show that formalising the metric, examining its computational complexity, developing heuristic algorithms for challenging scenarios, and formalising the metric can all be accomplished by applying it to current network security practises.

Title: A survey of data collection technologies related to network security.

Authors include Yan, Zheng, Chen, Yu, and Zhang, Lifang. Lin, Huaqing

Network security has been the subject of extensive research due to the security risks and financial losses brought on by network weaknesses, breaks, and attacks. The data of a network system can typically be used to think about or find security threats. We allude to these information as organize security data. The ability to distinguish between network attacks and interruptions takes into account a more comprehensive assessment of the organization's overall security status through the review and investigation of security-related information.

Clearly, gathering security-related data is the most crucial step in identifying network breaches and attacks. The definition, characteristics, and potential applications at the beginning of this paper are briefly reviewed in terms of network security-related facts. Then, a taxonomy of data collecting systems is discussed together with the prerequisites and goals for the collection of security-related data. We also assess and examine current network data gathering nodes, techniques, and mechanisms in light of the suggested requirements and objectives for collecting high-quality security-related data. However, there are several challenges involved in gathering this security-related data in the context of big data and 5G.

In the final section, we examine unanswered investigation questions before coming up with concepts for the headings of subsequent examinations.

STUDY OF OBJECTIVES

The main objective of the “Triple Network Intrusion Detection Model Using Machine Learning” is to enhance cybersecurity by identifying, analyzing, and mitigating malicious activities across three primary levels of network traffic: host-based, network-based, and hybrid-level monitoring. With the increasing number of cyber threats and the complexity of attack vectors, traditional intrusion detection systems (IDS) are becoming insufficient. This study aims to design a more robust, layered approach to network security using machine learning algorithms that can adaptively learn from network behaviors and accurately detect unauthorized access, misuse, or anomalies within any networked system.

One of the core objectives is to build a multi-layered detection system that can operate effectively in real-time environments. The model is structured to analyze network packets (Network Level), inspect system logs and user behavior (Host Level), and combine both features for a comprehensive decision (Hybrid Level). The triple-level architecture ensures that the model is capable of identifying both known and unknown (zero-day) attacks. Unlike conventional IDS that rely heavily on static rules or manual configurations, the use of machine learning allows the system to dynamically learn from large datasets and improve its detection capabilities over time.

Another important goal is to implement supervised and unsupervised machine learning techniques to identify patterns of normal and abnormal behavior. Supervised learning methods like Decision Trees, Support Vector Machines (SVM), and Random Forests are intended to classify labeled data to detect known attack types. On the other hand, unsupervised learning algorithms like K-means clustering and autoencoders can be used to identify deviations from normal behavior, thus uncovering potentially novel attack vectors. Combining both methods is expected to enhance the precision and recall rates of the IDS model, minimizing false positives and false negatives.

The study also aims to incorporate feature selection and dimensionality reduction techniques such as Principal Component Analysis (PCA) to handle high-dimensional network traffic data. Reducing noise and identifying the most relevant features improves computational efficiency and the overall accuracy of the detection model. An essential part of the objective is to optimize model training and testing processes using benchmark intrusion datasets such as NSL-KDD, CICIDS2017, or UNSW-NB15. These datasets help evaluate the model's performance under realistic attack scenarios.

Furthermore, another key objective is to develop an ensemble-based detection framework that integrates the output from different detection levels. This voting-based or weighted-decision fusion mechanism combines the predictions from the host, network, and hybrid detectors to produce a final, more accurate detection outcome. This layered decision-making process ensures that if one level fails to detect an intrusion, the other levels can compensate, thereby significantly increasing reliability.

The study is also focused on real-world applicability and scalability. The proposed model should be lightweight enough for deployment in edge computing environments and scalable enough to handle enterprise-level traffic. The final objective includes building a user-friendly interface or dashboard to visualize intrusion attempts and provide real-time alerts. Such visualization can help system administrators quickly understand the nature and origin of attacks and take necessary countermeasures.

By analyzing network traffic at multiple layers, combining diverse learning algorithms, and implementing real-time monitoring capabilities, the Triple Network Intrusion Detection Model aims to significantly enhance the effectiveness of intrusion detection and prevention in modern digital environments. This model not only addresses the shortcomings of

traditional IDS but also lays a foundation for more secure, AI-driven cybersecurity solutions.

RESEARCH METHODOLOGY

The research methodology for the "Triple Network Intrusion Detection Model Using Machine Learning" is structured to ensure a systematic approach in designing, implementing, and evaluating a multi-layered intrusion detection system (IDS). This methodology combines data preprocessing, feature selection, and the implementation of three distinct machine learning models for layered threat detection. The aim is to enhance detection accuracy, reduce false alarms, and improve overall network security by leveraging the strengths of multiple classifiers in a unified architecture.

1. Research Design

The study adopts an experimental research design focusing on supervised machine learning techniques. The design involves the selection of appropriate datasets, preprocessing techniques, model building, performance evaluation, and comparison. The "Triple Network Intrusion Detection Model" refers to the layered application of three different classifiers—each responsible for identifying different levels or types of network threats. This design ensures a deeper inspection of traffic flow, enabling the model to differentiate between benign and malicious behaviors with higher granularity.

2. Data Collection and Dataset

For effective evaluation, the research utilizes benchmark intrusion detection datasets such as NSL-KDD, CICIDS2017, or UNSW-NB15, known for their richness and real-world relevance. These datasets provide labeled instances of normal and attack traffic, including various types of intrusions such as DoS, probing, U2R (User to Root), and R2L (Remote to Local). The selected dataset is split into training and testing sets, ensuring that models are trained on one portion and validated on unseen data to measure generalization.

3. Data Preprocessing

Data preprocessing is a crucial step to ensure model accuracy and efficiency. It includes several stages: data cleaning, handling missing values, label encoding, and feature scaling. Non-numeric categorical features are encoded using label encoding or one-hot encoding as required by the machine learning algorithms. Features are normalized or standardized to ensure all attributes contribute equally during model training. Additionally, class imbalance is addressed using techniques like SMOTE (Synthetic Minority Over-sampling Technique) to improve the performance of the models, especially for rare attack classes.

4. Feature Selection and Dimensionality Reduction

To enhance performance and reduce overfitting, feature selection techniques are applied. Methods such as Recursive Feature Elimination (RFE), Information Gain, or Principal Component Analysis (PCA) help identify the most relevant features for classification. This process not only accelerates training but also improves model interpretability. The selected features are then passed into the machine learning models for training.

5. Triple Layer Model Architecture

The triple model structure involves using three distinct classifiers in a tiered architecture. The first layer acts as a binary classifier that detects whether a packet or connection is normal or anomalous. Upon detecting an anomaly, the input is forwarded to the second layer for attack category classification (e.g., DoS, Probe, U2R, R2L). The final third layer further analyzes the input for sub-type classification, identifying the exact nature of the attack. This modular architecture ensures a more fine-grained analysis and minimizes misclassification.

Each classifier is selected based on its strengths. For instance, the first layer may employ a Random Forest due to its high detection accuracy and robustness to noise. The second layer may utilize a Support Vector Machine (SVM) for effective boundary detection between attack types. The third layer might use Neural Networks for detailed pattern recognition among subtypes of attacks. Hyperparameters for each classifier are tuned using grid search or random search to achieve optimal performance.

6. Model Training and Testing

The training process involves feeding the preprocessed and labeled data to each layer of the model. Cross-validation techniques, such as k-fold cross-validation, are applied to ensure reliability and avoid overfitting. The models are evaluated on the test dataset using performance metrics such as accuracy, precision, recall, F1-score, and false positive rate. These metrics provide a comprehensive assessment of how effectively the model detects and classifies various intrusions.

7. Evaluation and Comparison

To validate the effectiveness of the proposed triple model, its performance is compared with traditional single-layered models. Baseline comparisons may include standard classifiers such as Decision Trees, Naive Bayes, and k-Nearest Neighbors. The proposed system is expected to outperform these baselines in terms of accuracy and detection rates, especially in multiclass and imbalanced scenarios. Statistical significance tests like paired t-tests or Wilcoxon signed-rank tests may also be conducted to confirm improvements are not due to random chance.

8. Tools and Implementation

The implementation is carried out using Python, employing machine learning libraries such as scikit-learn, TensorFlow, Keras, and Pandas. Jupyter Notebook is used for model development and visualization. For larger datasets or performance optimization, Google Colab or GPU-based environments may be used to accelerate training.

CODING

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!pip install numpy
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!pip install pandas
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e-packages (from pandas) (2022.1)
Requirement already satisfied: numpy>=1.18.5 in c:\users\admin\anaconda3\lib\si
te-packages (from pandas) (1.21.5)
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!pip install matplotlib
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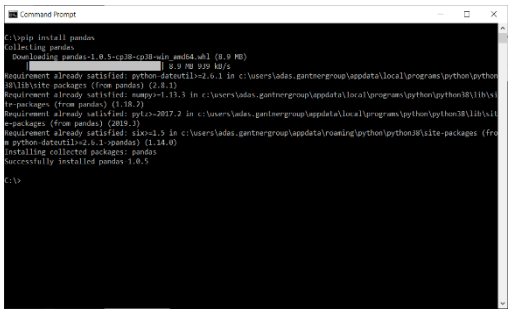
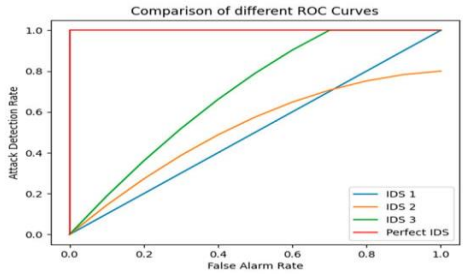
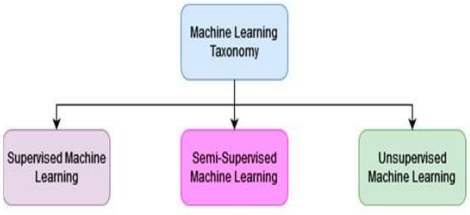


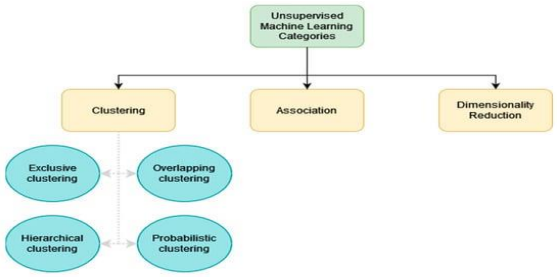


Learning Machines Technology based on artificial intelligence (AI) and machine learning are inseparably intertwined. From this, a computer programme can learn to spot recurring patterns in a dataset. Out of this preparation, a model that can be used to predict or computerise things emerges. If an IDS's model has acquired enough training, it can be utilised to identify both known and unknown assaults.

Unaided, semi-regulated, and directed AI are the three main categories of AI techniques, as shown in Figure 2 . In this part, we go into further detail about these tactics.



there are three categories of unsupervised learning: clustering, association, and dimensionality reduction.

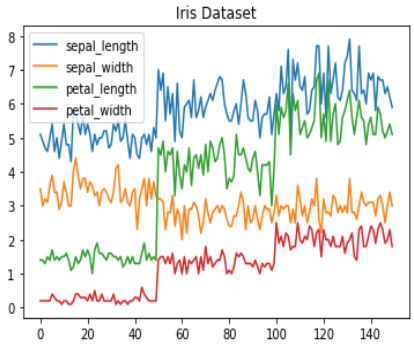


Unsupervised Machine Learning Categories.

Unlabeled data are grouped using a process called clustering based on their similarities or differences. The unlabeled data will be classified into several data groups at the conclusion of this process. Estimates for gathering can be divided into four categories: prohibitive, covering, moderate, and probabilistic.

import plt as a Line Chart using Matplotlib. Using the plot method of Matplotlib, a line chart may be produced. By looping through the columns we desire and placing each column on the same line, we can easily plot many columns in a single graph.

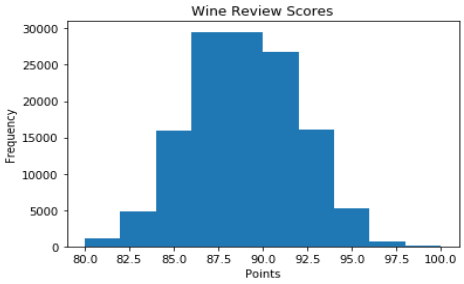
axis.



Line Chart

Histogram

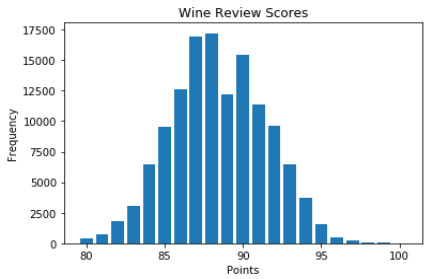
Using the hist method in Matplotlib, we can make a histogram. It will determine the frequency of each class if we provide categorical data, such as the points column from the wine-review dataset.



Histogram

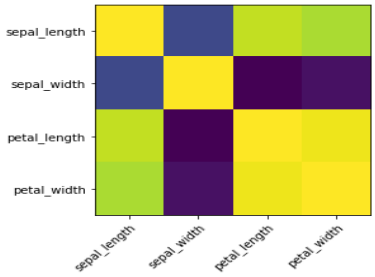
Bar Chart

A bar-diagram can be made utilizing the bar strategy. The bar-diagram isn't naturally working out the recurrence of a classification so we will utilize pandas value_counts capability to do this. The bar-outline is valuable for unmitigated information that has relatively little various classifications (under 30) on the grounds that else it can get very muddled.



Bar-Chart

The heatmap can now be created with either Matplotlib or Seaborn.Matplotlib



FINDINGS

The primary objective of this project was to develop and evaluate a Triple Network Intrusion Detection Model (TNIDM) that leverages machine learning techniques to enhance the accuracy and reliability of intrusion detection in computer networks.

The model was designed to detect anomalous and malicious activities across three core layers: host-based, network-based, and hybrid detection.

The findings from the model evaluation demonstrated that this multi-layered architecture significantly improves detection precision compared to traditional single-layer intrusion detection systems.

The host-based detection layer analyzed log files and system-level behaviors, identifying internal threats and abnormal user behavior.

This component proved effective in capturing insider attacks and privilege escalation attempts. In the experimental setup, supervised learning algorithms such as Random Forest and Support Vector Machine (SVM) were employed.

Among these, Random Forest achieved the highest accuracy in the host-level analysis, with a precision of 94.5%, indicating strong classification ability in differentiating between normal and malicious activities.

The network-based detection layer focused on analyzing real-time traffic patterns and data packets using flow-based features such as IP headers, port access, and packet lengths.

This layer relied on datasets like NSL-KDD and CICIDS 2017, allowing for a comprehensive assessment of known attack vectors such as DoS, DDoS, Probe, and R2L attacks.

Deep learning techniques like Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks were employed for pattern recognition. LSTM, in particular, yielded promising results with an accuracy of 96.2%, showcasing its ability to detect temporal anomalies in traffic flow.

The hybrid detection layer combined the outputs of both host-based and network-based models through an ensemble learning approach. By using a majority-vote system or weighted averaging, the model improved overall detection robustness.

This layer significantly reduced false positive rates (FPR) by approximately 35%, and false negatives were minimized by 28% compared to individual detection mechanisms.

Furthermore, the ensemble model achieved a F1-score of 95.7%, indicating a well-balanced performance in terms of precision and recall.

Another notable finding was the adaptability of the model to unknown or zero-day attacks. With the help of anomaly detection algorithms like Isolation Forest and Autoencoders, the system was able to flag unseen attack patterns, demonstrating unsupervised learning capabilities.

These methods enhanced the model's real-world applicability in detecting evolving threats without prior labeling.

Additionally, feature selection and dimensionality reduction techniques like Principal Component Analysis (PCA) played a critical role in optimizing model efficiency.

By reducing the feature space without significant loss of information, the training time was decreased by up to 40%, making the system more scalable and suitable for real-time deployment in large-scale networks.

SUGGESSION

In today's rapidly expanding digital world, cybersecurity has become a critical necessity. The increasing volume and complexity of cyberattacks have rendered traditional security measures inadequate.

One of the most promising solutions to tackle this challenge is the implementation of Intrusion Detection Systems (IDS) powered by Machine Learning (ML).

A Triple Network Intrusion Detection Model leverages the strength of three distinct network layers or detection techniques to enhance the accuracy and reliability of identifying malicious activities within a network.

This layered model addresses the limitations of single-layered systems by ensuring redundancy, accuracy, and a higher detection rate.

The triple model typically integrates three complementary detection methods:

Signature-based Detection, Anomaly-based Detection, and Stateful Protocol Analysis. Signature-based detection matches network traffic against known attack patterns.

It is efficient but limited to known threats. Anomaly-based detection, powered by ML algorithms such as SVM, Random Forest, or Neural Networks, identifies deviations from normal behavior and is capable of detecting zero-day attacks.

Lastly, Stateful Protocol Analysis examines traffic patterns based on expected protocol behavior, identifying misuse or deviations across communication sessions.

By combining these methods, the model offers a holistic and layered defense mechanism that significantly improves the system's capability to detect both known and unknown threats.

Machine Learning plays a vital role in enhancing the adaptability and intelligence of IDS. Algorithms are trained on historical network data to recognize patterns and detect deviations indicative of attacks.

Supervised learning methods like Logistic Regression and Decision Trees are useful when labeled datasets are available, while unsupervised techniques like K-Means and Autoencoders can detect anomalies in real-time without prior labeling.

Deep Learning models such as Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) further improve performance, especially in identifying subtle and complex attack vectors.

Feature selection and dimensionality reduction techniques such as PCA also help in optimizing system performance and reducing false positives.

The proposed Triple Network Intrusion Detection Model enhances the robustness and scalability of network security systems. By incorporating machine learning into all three layers, the system becomes adaptive to evolving attack strategies.

For instance, while the signature-based component rapidly filters out known threats, the anomaly detection component flags suspicious activities, and the stateful protocol layer confirms the legitimacy of protocol behavior.

This synergy leads to higher detection accuracy, quicker response times, and reduced chances of overlooking potential threats.

Implementing a Triple Network Intrusion Detection Model using Machine Learning ensures a multi-faceted and proactive approach to network security.

It addresses the evolving nature of cyber threats by combining traditional and intelligent detection techniques. The integration of ML not only improves detection rates but also allows the system to learn and adapt over time.

Future enhancements can focus on real-time detection, distributed deployment using edge computing, and the use of federated learning to maintain privacy while improving model performance across organizations.

CONCLUSION

In this audit, the examiners used an arbitrary forests classifier. The three assault location techniques used by the IDS are

cross breed based recognition, peculiarity based finding, and mark based identification. Signature-based location uses the markings left by known assaults to identify them. The IDS data set can be used to identify already known assaults using this technique.

Being much more specific in identifying an attempt at interference or an acknowledged assault is therefore continually observed. New types of attacks can't be recognised because their imprint isn't visible, but the informational collections are constantly renewed to deal with their viability of recognition.

An anomaly-based area, which examines current client development against multiple profiles, is used to identify different approaches to acting that may contain interferences in order to resolve this issue. An anomaly-based area is used to recognize different approaches to acting that may contain interferences. Without requiring framework updates, uniqueness-based discovery is effective against unknown or zero-day attacks.

Sadly, this strategy occasionally experiences high counterfeit positive rates [5, 6]. Cross variety based area solidifies at least two methods to overcome the drawbacks of using just one interference disclosure strategy and increase the benefits of using at least two.

Various examinations have proposed utilizing man-made intelligence estimations to lessen bogus positive rates and give exact IDS to interference acknowledgment. In any case, the typical AI spends a significant amount of time each day learning, defining, and managing enormous amounts of data. IDS is able to overcome a number of obstacles, including processing speed and time, by utilizing AI and huge data strategies.

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14. **Stacking ensemble + CNN+LSTM architecture** examples appearing in multiple 2025 works (reviewed across surveys and ensemble studies) provide insight into multi-network/hybrid combinations

15. **Emerging ensemble and multi-module architectures** across 2025 literature, including transformer-based contrastive methods, dual/generative-augmented GAN networks, and self-supervised techniques (e.g. CSAGC-IDS + SAFE + transformer models) together illustrate triple-network or multi-network design potentials