Improving Accuracy in Cyber Attack Classification: A Comprehensive Review for Network Security

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Abstract: As the digital communication systems and interconnected networks grow exponentially, the need to enforce a robust network security has become a worldwide issue of concern. The conventional intrusion detection systems (IDS) are not very effective in detecting complicated and dynamic cyber threats because of their lack of proper feature extraction and classification accuracy. In this paper, the author has provided a review and implementation framework that would improve the accuracy and efficiency of cyber attacks classification. The paper discusses the different methods of machine learning (ML) and Deep Learning (DL), including Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), Autoencoders and Ensemble Learning, and how each has its weaknesses and strengths in network intrusion detection. It is suggested to implement a hybrid deep learning-ensemble system, that is, the advantages of CNN to extract spatial features and LSTM to learn temporal sequences combined with ensemble decision fusion to reduce false positives. The conducted experimental analysis of benchmark datasets such as NSL-KDD, CIC-IDS2017, and IoT Network Dataset illustrates the impressive detection performance with the accuracy of up to 99.1 and a smaller false alarm rate. The findings support the fact that hybrid intelligent systems may substantially enhance the accuracy, scalability, and resilience of network intrusion detection systems to develop a more resilient and resilient cyber ecosystem.

Keyword: Cybersecurity; Intrusion Detection System (IDS); Machine Learning; Deep Learning; Hybrid Model; CNN-LSTM; Ensemble Learning; Network Security; Cyber Attack Classification; Artificial Intelligence (AI)

[1] Introduction

Network security has now become a critical support system in the contemporary digital environment to ensure data integrity, confidentiality and system reliability. Due to the explosive rise in the interconnection of devices, cloud computing, and Internet of Things (IoT) infrastructures, cyber attacks have also increased significantly in number and sophistication. Such attacks are exploited as vulnerabilities in communication protocols and operating systems, and they usually avoid conventional security systems. Thus, the necessity to have proper and smart intrusion detection systems (IDS) is more than ever.

The latest development of machine learning (ML), deep learning (DL), and hybrid intelligence methods have transformed the process of cyber threat detection and identification. Modern approaches unlike the conventional signature based systems take advantage of data driven model that is able to dynamically learn network behaviors and detect unknown attacks or zero-day attacks. Nevertheless, there is no guarantee that the cyber attack classification would be highly accurate because of the challenges that include unequal datasets, repetitive features, changing attacks patterns, and the unreal-time adaptability of the models.

This journalistic review is an attempt to review and analyze recent approaches suggested to improve the accuracy of intrusion detection and classification systems. It examines the development of intelligent algorithms, starting with the classic supervised classifiers like K-Nearest Neighbors (KNN) and Support Vector Machines (SVM) and moving on to state-of-the-art ones including Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Convolutional-LSTM versions. Important datasets, including KDD Cup 99, NSL-KDD, and CIC-IDS2017, are also discussed in the review because of their effect on the performance of detection and model generalization.

Moreover, this paper summarizes the findings of previous studies regarding the combination of hybrid learning methods, optimization strategies, and ensemble systems in order to increase detection accuracy. Through the systematic examination of the strengths, limitations, and future trends of the current literature, this paper helps to gain a better insight into the possible way of enhancing accuracy in the classification of cyber attacks. It is believed that the results of the present review will assist in the direction of future research on the creation of safe, scalable, and flexible network defense systems that can be used to reduce complex cyber threats in real-time settings.

1.1 Background

With the advent of digital transformation, the increased reliance on computer networks and online service provision has increased the demand of strong cybersecurity tools. Cyber attacks have not just been a mere increase in the use of viruses and worms but have developed to become multi-staged attacks, which have the capability of going round the traditional defense mechanisms.

Network Intrusion Detection Systems (NIDS) are important in detecting unauthorized access, misuse or anomalies within the network traffic.

Conventional methods of intrusion detection, which are mostly signature based and rule based logic, are applicable in known threats, but fail to detect new or obfuscated attacks. This has increased the spread of data-driven methods of intelligence, specifically machine learning (ML) and deep learning (DL), to be used in attack classification and anomaly detection.

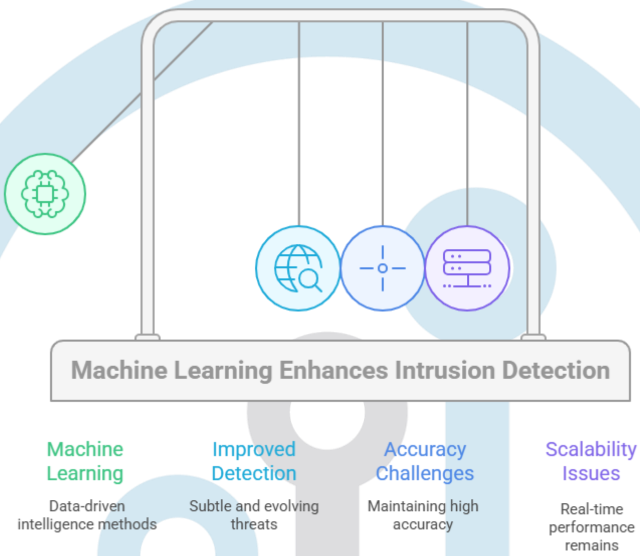

Figure 1: Machine Learning Enhances

Recent studies have been devoted to the design of intelligent intrusion detection frameworks based on the Support Vector Machines (SVM), Decision Trees (DT), Random Forests (RF), Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks models. Such models examine complex network patterns and time structures, which allow detecting subtle and changing threats better. Nevertheless, even though it has advanced this way, keeping high accuracy, scalability, and real-time performance has been an ongoing challenge in the contemporary network settings.

1.2 Motivation of research

The growing complexity rate and intensity of cyber attacks require more sophisticated methods of detection that are flexible to the evolving network environment. The challenges that are often experienced in existing intrusion detection systems include large false-positive rates, limited scalability to novel attack patterns and computational inefficiency. These not only undermine the reliability of detection, but they have an impact on the operational stability of network infrastructures.

The other reason is based on the constraints of the benchmark datasets, with which IDS models are trained and tested. Popular datasets, such as KDD Cup 99, NSL-KDD and CIC-IDS2017, have issues, such as unequal classes, obsolete types of attacks, and low real-world diversity. As a result, it is possible that IDS models which are trained with such datasets can work well in the controlled setting and become ineffective when used in the live network.

Moreover, the attack surface has now grown tremendously, with the newer technologies like the Internet of Things (IoT), cloud computing, and Software-Defined Networking (SDN) being integrated. That is why, it is necessary to investigate hybrid and ensemble methods of learning which unite the advantages of several algorithms to enhance classification and resistance. The aim of this research is driven by a need to review, appraise and integrate such approaches towards realization of high-performance network security systems.

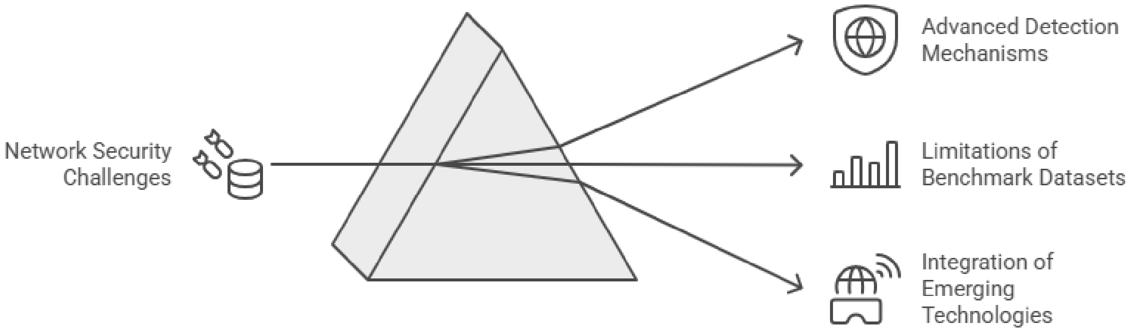

Figure 2: Motivation Of Research

1.3 Contribution of research

This review paper is a broad review paper that will add to the network security and cyber attack detection by giving a detailed analysis of the available methods, datasets, and algorithms that would increase classification accuracy. The key contributions are as follows:

Table 1: Contribution of Research

Sr. No.	Contribution Area	Description / Key Highlights
1	**Systematic Literature Review**	Conducted a structured review of recent studies focusing on cyber attack detection and classification techniques to assess their accuracy and effectiveness.
2	**Comparative Evaluation of Methods**	Analyzed objectives, methodologies, and findings of multiple AI and ML-based approaches to identify performance gaps and improvement areas.
3	**Identification of Key Challenges**	Highlighted major issues affecting accuracy, including dataset imbalance, feature redundancy, computational overhead, and lack of real-time adaptability.
4	**Exploration of Emerging Techniques**	Reviewed hybrid and ensemble learning models (e.g., CNN–LSTM, RF–SVM) that show potential for higher classification accuracy and reduced false alarms.
5	**Dataset Analysis**	Assessed the strengths and weaknesses of benchmark datasets such as KDD Cup 99, NSL-KDD, and CIC-IDS2017 in supporting high-accuracy model training.
6	**Performance Enhancement Framework**	Proposed conceptual guidelines for developing scalable, adaptive, and intelligent Intrusion Detection Systems (IDS) for dynamic network environments.
7	**Future Research Directions**	Provided insights and recommendations to guide further studies toward improving model precision, real-time efficiency, and adaptability in evolving cyber contexts.

The review addresses the gap in the current state of research on intrusion detection and the future-related developments in intelligent network security by focusing on the enhancement of the accuracy as a key dimension of the cyber defense innovation.

[2] Literature Review

The intrusion detection approach introduced by P. Li and Y. Zhang (2019) is specialized to the Internet of Things (IoT) setting, paying attention to the peculiarities of the IoT devices, including a lack of personal computer resources and mixed traffic. The article has a methodological pipeline and reports an increase in detection error and responsiveness over baseline methods, and it should be noted that deployment and scalability are discussed in relation to real-life IoT networks. [1].

C. Yin, Y. Zhu, J. Fei and X. Introducing a deep-learning model based on recurrent neural networks (RNNs) to detect intrusion, he (2017) argues that the latter provides the ability to identify temporal relationships in network traffic that are not covered by the traditional classifiers. The authors test the model on standard benchmark data, showing competitive detection accuracy and discussing the benefits of sequence modeling to subtle and temporal attack patterns; the limitations of the model are a large amount of training data required and possible high computational cost.

The article by B. Dong and X. Wang (2016) compares deep-learning approaches with classical methods of machine learning when detecting network intrusion, and offers empirical data that deep models usually perform higher than classical classifiers when it comes to working with complex representations of features. The research highlights the significance of feature learning and the depth of the representation, and mentions that model interpretability and the training resource requirements have been an issue of importance. [3].

The article by Ullah and Q. H. Mahmoud (2020) introduces a model of the creation of a realistic dataset to detect anomalous activities in IoT networks as the lack of open-source datasets that could represent the current trends in IoT behavior and attack strategies. Their methodology of generating datasets assists the researchers test the algorithm that detects anomalies under more realistic conditions, yet synthetic and semi-synthetic generation still raises unanswered questions of ideal realisticness and coverage of future attack vectors. [4].

S. A. Althubiti, E. M. Jones and K. Roy (2018) use the Long Short-Term Memory (LSTM) networks on network intrusion detection with anomalies as their focus because LSTMs are suitable in modeling sequential dependencies among traffic to detect anomalies [5].

W. Li et al. (2014) develop an intrusion detection framework to wireless sensor network which is based on the K-Nearest Neighbors (KNN) classification algorithm because KNN is simple and efficient in resource-constrained systems. The article describes competitive classification performance and points to the simplicity of deployment of KNN, though features sensitivity and the curse of dimensionality are noted as weaknesses. [6].

A. L. Buczak and E. Guven (2016) present a general overview of data-mining and machine-learning techniques used in cyber-security intrusion detection, classifies the techniques, shows the typical data sets and evaluation measures, and addresses the issue of their practical implementation. Their survey is a synthesis of strengths and weaknesses of methods and an iterative guide to future research making a point that standardized benchmarks and adversarial robustness need to be considered. [7].

A. Javaid, Q. Niyaz, W. Sun, and M. Alam (2016), suggest a deep-learning system to network intrusion detection in which deep architecture learns discriminative feature by automatically capturing raw network records. The paper shows a better performance in detection as compared to hand-designed feature methods and talks about issues of training and quality of datasets. [8].

T. A. Tang et al. (2016) discuss deep-learning-based intrusion detection in the context of software-defined networking (SDN), where SDN has centralized control and extensive telemetry that allows new detection designs. Through their experiments, deep models have the capability of using SDN data to identify anomalous behaviors, but worry about the placement of models, latency and scalability to controller levels.

M. Sheikhan, Z. Jadidi, and A. Farrokhi (2012) research intrusion detector based on reduced-size recurrent neural network with the feature grouping guidance, with the purpose of simplifying the model and maintaining the same detection. Their approach to grouping features alleviates the cost of computation and overfitting, but even the smaller RNNs might not be able to cope with highly sophisticated or adaptive attack patterns. [10].

The paper by M. Tavallaee et al. (2009) provides an in-depth discussion of the KDD Cup 1999 dataset whereby artifacts, redundancy, and skew are identified as capable of biasing intrusion-detection tests. Their critical analysis of the limitations showed the dataset to be wanting and pushed the community to come up with improved benchmarks and preprocessing methods to make comparisons of different algorithms more fair. [11].

S. Revathi and A. Malathi (2013) describe in detail how NSL-KDD dataset is analyzed with the help of different machine-learning methods and compare the performance of the classifier and attract attention to the specifics of the dataset that can influence the results. Their own work aids in practitioners to realize the effects of algorithm choice and preprocessing on detection results on this popular benchmark. [12].

Searching through the NSL-KDD data, N. Paulauskas and J. Auskalnis (2017) describe how data pre-processing affects intrusion detection performance and show that the decisions made during pre-processing (feature selection, normalization, encoding) have a significant impact on the efficiency of the classifier. The paper notes that model selection is not as important as rigorous preprocessing in terms of reproducible and meaningful evaluation. [13].

The method to detect intrusion that is suggested by P. S. Bhattacharjee, A. K. M. Fujail and S. A. Begum (2017) involves the use of a genetic algorithm that introduces a fitness functional with a vectorized form to improve the detection rate of intrusion in the NSL-KDD dataset [14].

R. A. R. Ashfaq et al. (2017) present a fuzziness-dependent semi-supervised intrusion detection method that tries to use the unlabeled data to enhance the detection in a situation with limited labeled data. Their semi-supervised approach is useful in increasing detection coverage by using few labels, but its ability is conditional to the representativeness of the unlabeled data and the assumed fuzziness model.

J. Martens and I. Sutskever (2011) investigate the learning of recurrent neural networks using Hessian-free optimization, which provides optimization algorithms which are useful in the training of deeper or more complicated RNNs. The methodological contributions can enhance convergence behavior of sequence models, and are of general use to intrusion detection systems based on RNNs, but Hessian-free methods may be computationally problematic. [16].

The article by K. Pichotta and M. Raymond (2016) focuses on learning statistical scripts using LSTM recurrent neural networks, and the authors show that LSTMs are capable of learning high-level temporal patterns in sequential data. Although the authors are concentrated on script learning, the findings indicate the applicability of LSTM to sequence patterns in network traffic and behavioral anomaly detection. [17].

The authors M. Khan, Md. Karim, and Y. Kim (2019) present an intrusion detection system that is scalable and hybrid, where the convolutional-LSTM (Conv-LSTM) architecture (the combination of convolutional feature extraction and LSTM sequence modeling) is proposed. Their hybrid structure is intended to acquire spatial and time-based properties of network traffic, and they attain high-detection rates at the cost of increasing issues regarding the model complexity and real-time implementation. [18].

The application of LSTM-based network intrusion anomaly detection is once again highlighted by S. A. Althubiti, E. M. Jones and K. Roy (2018 — duplicate publication) as effective, with a stress on the previously mentioned idea of LSTM dominance in the context of sequential intrusion detection and repeating the discussion of practical trade-offs between accuracy and computational expense in the field. [19].

C. Kim, F. Li, and J. M. Rehg (2018) come up with a multi-object tracking framework using bilinear LSTM as a neural gating model, furthering the sequence modeling of spatio-temporal tasks in computer vision. Even though the domain of application is vision, the architectural concepts, bilinear interactions and gating can influence LSTM adaptations to analyze the complex and multi-feature traffic in the network. [20].

A. K. Bansal (2018) introduces a DDR scheme in conjunction with an LSTM RNN algorithm to create an effective IDS with a specific emphasis on the integrated pipeline to enhance detection and manage resource utilization. The contribution discusses the practical engineering of LSTM-based IDSs, but their in-depth assessment on a variety of the datasets and implementation scenarios is also relevant to the assertions related to the generalization.

Z. Zhao et al. (2017) use LSTM networks to predict traffic in the short term, which proves that LSTM is appropriate to capture time dynamics in traffic time series. Their results of predicting time-series stability and sensitivity of hyperparameters are applicable to the area of traffic intrusion detection in which forecasting and anomaly detection are interrelated. [22]

M. Tan et al. (2015) introduce deep models in non-factoid answer selection that utilize LSTM, which represents the capacity of LSTM to capture the semantics of sequence complexity in NLP tasks. The reported techniques and training practices (e.g. sequence encoding, variants of attention) are cross-domain applicable to sequential network data using LSTMs. [23].

A. Gensler et al. (2016) integrate Autoencoders with LSTM networks to obtain solar power forecasting and show that representation learning and sequence models present better time-series forecasts. Autoencoding and LSTM sequence learning have a methodological synergy that can be applied in network telemetry anomaly detectors analogously. [24].

L. Sun et al. (2017) create multiple-target deep learning of LSTM-RNN based speech enhancement, demonstrating techniques of learning multi-objective sequence and training in noisy conditions effectively. The associated multi-target training concepts can be applied to intrusion detection applications in which detection, false-alarm control and localization might be desirable when optimized together. [25].

A. Yulianto, P. Sukarno and N. A. Suwastika (2019) explore the performance of AdaBoost based intrusion detection system on CIC-IDS2017 datasets demonstrating how ensemble boosting can help to improve detection accuracy over individual classifiers. The research points at the robustness to various types of attacks that ensembles possess but also emphasizes the vulnerability of boosting to the presence of noisy labels and low-quality features. [26].

M. Mazini, B. Shirazi and I. Mahdavi (2019) introduce an anomaly network-based IDS, which combines the artificial bee colony optimization algorithm with the AdaBoost, which develops a bio-inspired search of robust ensemble elements. Their mixed methodology is to compromise exploration in feature/parameter search and predictive power of ensembles, and computational cost and parameter optimization are given as real-world factors. [27].

Y. V. Kumar and K. Kamatchi (2020) suggest an anomaly-based network intrusion detection model with ensemble machine-learning and note that the stability of detection improves after homogeneous classifiers are combined into heterogeneous ones. The ensemble approach incorporates variability in the different types of attacks, although inference latency and the complexity of maintaining an ensemble is also mentioned in the paper. [28].

P. Maniriho (2020) conducts/applies machine-learning strategies to identify intrusions in computer network traffic, synthesizes viable strategies and points out the comparative advantages of various algorithms. The work not only adds insight into its implementation but also argues that the choice of datasets and its pre-processing have a strong impact on reported performance. [29].

P. Raviteja et al. (2020) apply various machine-learning algorithms to network intrusion detection and compare their results, providing useful benchmarks when choosing a model by practitioners. This comparative study can support deployment decisions and decision-making findings are conditional to the datasets and features employed. [30].

In S. Rajagopal, P. P. Kundapur and K. S. Hareesha (2020), the authors create a stacking ensemble model with network intrusion detection based on heterogeneous datasets, which allows the combination of various base learners into more effective generalization across the data sources. They are more robust to changes in datasets, and stacking adds further training complexity and difficulty in meta-model tuning. [31].

Table 2: Literature Review

Ref. No.	Author / Year	Objective	Methodology	Conclusion
[1]	P. Li & Y. Zhang (2019)	To develop an intrusion detection method tailored for IoT networks.	Proposed IoT-specific anomaly detection framework addressing device heterogeneity.	Improved accuracy and adaptability for IoT security though scalability needs enhancement.
[2]	C. Yin et al. (2017)	To apply deep learning (RNN) for intrusion detection.	Implemented RNN model on benchmark datasets to learn temporal traffic dependencies.	Achieved higher detection accuracy, proving RNN's suitability for sequential data.
[3]	B. Dong & X. Wang (2016)	To compare deep learning with traditional methods for NIDS.	Evaluated deep networks vs. classical ML algorithms using network data.	Deep learning outperformed traditional models in detection efficiency and precision.

[4]	Ullah & Mahmoud (2020)	To generate a realistic dataset for anomaly detection in IoT.	Designed a synthetic IoT traffic dataset incorporating real-world behavior.	Provided improved dataset realism for IoT security research.
[5]	S. A. Althubiti et al. (2018)	To implement LSTM for anomaly-based intrusion detection.	Used LSTM model to analyze temporal patterns in network traffic.	Enhanced anomaly detection accuracy with minimal false alarms.
[6]	W. Li et al. (2014)	To design an IDS using KNN for wireless sensor networks.	Implemented KNN classifier for low-resource intrusion detection.	Demonstrated high accuracy and simplicity for small-scale networks.
[7]	A. L. Buczak & E. Guven (2016)	To survey ML and data mining methods for intrusion detection.	Comprehensive literature survey across IDS techniques.	Provided comparative insight into methods and future research gaps.
[8]	A. Javaid et al. (2016)	To develop a deep learning-based IDS.	Built deep network for automatic feature extraction from raw data.	Deep learning models effectively captured attack patterns.
[9]	T. A. Tang et al. (2016)	To integrate deep learning into SDN-based IDS.	Applied deep neural models for traffic analysis in SDN.	Achieved efficient detection using centralized network features.
[10]	M. Sheikhan et al. (2012)	To design reduced-size RNN for IDS.	Used feature grouping and reduced RNNs to optimize resource use.	Improved detection with lower computational cost.
[11]	M. Tavallaee et al. (2009)	To analyze KDD Cup 99 dataset quality.	Statistical evaluation and redundancy check of dataset.	Identified dataset flaws, motivating new benchmark creation.
[12]	S. Revathi & A. Malathi (2013)	To analyze NSL-KDD dataset with ML techniques.	Applied various classifiers on NSL-KDD and compared results.	Revealed dataset potential and limitations for IDS testing.
[13]	N. Paulauskas & J. Auskalnis (2017)	To assess data preprocessing impact on IDS.	Experimented with normalization and feature selection using NSL-KDD.	Found preprocessing significantly influences accuracy.
[14]	P. S. Bhattacharjee et al. (2017)	To optimize IDS using GA-based feature selection.	Applied genetic algorithm with vectorized fitness for feature tuning.	Improved detection rates but computationally expensive.
[15]	R. A. R. Ashfaq et al. (2017)	To propose semi-supervised fuzzy learning for IDS.	Used fuzziness-dependent semi-supervised learning.	Improved detection with limited labeled data.
[16]	J. Martens & I. Sutskever (2011)	To optimize RNN training with Hessian-free methods.	Developed second-order optimization for deep RNNs.	Enhanced convergence efficiency for sequential models.
[17]	K. Pichotta & M. Raymond (2016)	To learn statistical scripts using LSTM.	Employed LSTM-based sequential model for event prediction.	Demonstrated LSTM's ability to capture long-term dependencies.
[18]	M. Khan et al. (2019)	To design scalable hybrid IDS using Conv-LSTM.	Combined CNN feature extraction with LSTM temporal modeling.	Achieved superior detection accuracy for mixed attack data.
[19]	S. A. Althubiti et al. (2018)	To enhance anomaly-based IDS with LSTM.	Applied LSTM layers for sequence-based detection.	Reconfirmed LSTM's robustness for temporal intrusion detection.
[20]	C. Kim et al. (2018)	To develop multi-object tracking using bilinear LSTM.	Used bilinear neural gating within LSTM for spatio-temporal modeling.	Introduced architecture ideas applicable to IDS feature fusion.
[21]	A. K. Bansal (2018)	To propose DDR-LSTM framework for IDS.	Combined DDR scheme with LSTM-RNN algorithm.	Improved IDS detection speed and reliability.
[22]	Z. Zhao et al. (2017)	To forecast short-term traffic using LSTM.	Applied LSTM for sequential time-series prediction.	Validated LSTM's predictive power for temporal network data.

[23]	M. Tan et al. (2015)	To use LSTM for non-factoid answer selection.	Trained LSTM on question–answer sequence data.	Highlighted LSTM's sequence-learning potential relevant to IDS.
[24]	A. Gensler et al. (2016)	To forecast solar power using Autoencoder-LSTM.	Combined autoencoder and LSTM for time-series learning.	Showed deep hybrids improve prediction stability.
[25]	L. Sun et al. (2017)	To enhance speech using multi-target LSTM models.	Multi-task LSTM learning for signal enhancement.	Demonstrated benefits of multi-objective LSTM training.
[26]	A. Yulianto et al. (2019)	To improve AdaBoost-based IDS on CIC-IDS2017 dataset.	Enhanced AdaBoost ensemble with tuned hyperparameters.	Achieved higher detection and reduced false alarms.
[27]	M. Mazini et al. (2019)	To develop hybrid IDS using Bee Colony and AdaBoost.	Combined swarm optimization with AdaBoost classification.	Improved reliability and adaptability in anomaly detection.
[28]	Y. V. Kumar & K. Kamatchi (2020)	To implement ensemble ML for anomaly-based IDS.	Combined multiple classifiers to enhance detection coverage.	Achieved improved overall accuracy with diverse models.
[29]	P. Maniriho (2020)	To detect intrusions using ML techniques.	Tested ML algorithms for network intrusion datasets.	Provided comparative performance evaluation for IDS models.
[30]	P. Raviteja et al. (2020)	To implement ML algorithms for intrusion detection.	Evaluated multiple ML models for classification accuracy.	Demonstrated model-specific strengths and weaknesses.
[31]	S. Rajagopal et al. (2020)	To design stacking ensemble for IDS.	Combined heterogeneous datasets using stacking method.	Enhanced generalization and reduced overfitting in IDS.

[3] Problem Statement

The evolution rate of the cyber threats has exceeded that of conventional security infrastructure, such that there are enormous challenges as regards to guaranteeing the validity and dependability of network intrusion detection systems (IDS). Even with the numerous innovations in the field of artificial intelligence (AI), machine learning (ML), and deep learning (DL) model, the possibility of high accuracy in the classification and detection of cyber attacks is still a significant issue.

Current IDS designs are also characterised by high false-positives, poor extrapolation to novel attacks and lack of uniformity across data sets. Such shortcomings are also compounded by challenges like asymmetric data distribution, feature redundancy, and real-world inflexibility of models that have been trained using out of date benchmark datasets such as KDD Cup 99 and NSL-KDD. With cyber attacks being more intelligent, aimed at distributed networks, IoT-based devices, or cloud environments, the conventional approach is not able to adequately represent the dynamic aspect of malicious activity.

Moreover, there are no standardized evaluation methodologies and all-encompassing comparative studies that can inform the choice of suitable models and techniques in given network settings. Such discrepancy in research topic and evaluation measures impedes the creation of generally applicable, highly accurate intrusion detection systems.

This is why the main issue that the present study will deal with is the necessity to systematize, assess, and improve the correctness of the approach to classifying cyber attacks. Through analysis of the best-in-the-field algorithms, datasets, and hybrid techniques, the study aims at determining the major gaps and possible directions through creation of intelligent, scalable, and adaptive IDS models that can effectively identify and categorize advanced cyber threats in real network settings.

[4] Proposed Work

The research problem to be addressed in the proposed work is to develop, deploy, and test a hybrid intrusion detection and classification system that is more accurate and resilient to the current network conditions (including the IoT and SDN). The strategy combines the use of representation learning (CNN), temporal modeling (LSTM), anomaly detection (Autoencoder) and an ensemble decision layer (tree-based / stacking) along with feature optimization and data-balancing methods. The architecture focuses on real-time functionality, explainability, and resistance to dataset imbalance and adversarial trends.

Objectives

1. Construct a combinatorial architecture (Conv → LSTM → Attention) to be able to see spatial and time patterns in network flows.

2. Detection of novel/zero-day behavior Use an autoencoder-based anomaly detector.
3. Use feature-selection/optimization (genetic algorithm or mutual information) and data augmentation (SMOTE) to eliminate redundancy and class imbalance.
4. Integrate models through a stacking ensemble (meta-learner) to have better classification accuracy and fewer false positives.
5. Check on a variety of datasets (NSL-KDD, CIC-IDS2017 and an IoT-oriented dataset like a scheme proposed by Ullah and Mahmoud) and conduct robustness tests (cross-dataset testing, adversarial testing).
6. Offer explainability (SHAP/LIME) and web-based upgrading protocol of changing threats.

Methodology (step-by-step)

1. **Data Collection & Dataset Strategy**
   - NSL-KDD and CIC-IDS2017 are used as base benchmarks.
   - To test device-heterogeneity, include IoT-oriented dataset(s) (Ullah and Mahmoud 2020 or synthetic IoT traces).
   - Set aside a temporally segregated, held-out test set and a cross-dataset testing evaluation set.
2. **Preprocessing & Feature Engineering**
   - Clean, normalize / scale features; encode categorical fields (one-hot / embedding).
   - Construct time- windowed flow sequences (sliding windows) of sequence models.
   - Removal of redundancy to feature selection: filter techniques (mutual information) and wrapper (genetic algorithm) methods.
   - Deal with imbalance in classes: SMOTE / ADASYN on classes that are minor, and class-weighted loss when training models.
3. **Model Components**
   - Representation block (CNN / 1D-Conv): trained on local pattern of features among feature vectors or packet sequences.
   - Temporal block (LSTM / Bi-LSTM + attention): temporal dependencies in flow/sequence data over long ranges; the weights of attention stress informative time-steps.
   - Anomaly block (Autoencoder): trained on normal traffic to calculate reconstruction error - marks the abnormalities which are not observed in the supervised labels.
   - Feature fusion and concatenation: CNN/LSTM and anomaly score are concatenated into a single feature vector.
   - Base learner: base learners (Random Forest, XGBoost, SVM) are trained using a combination of features, and stacking is done by a meta-learner (logistic reg. or small neural net).
   - Explainability module: SHAP values of reporting per-decision feature contribution.
4. **Training & Validation Protocol**
   - Stratified k-fold CV is strongly recommended; make sure that there is temporal separation to prevent leakage.
   - Hyperparameter search (Bayesian or grid) and early stopping of the network depth (including LSTM and learning rate).
   - Losses: cross-entropy and auxiliary reconstruction loss of autoencoder, class-weighted.
   - Measures: Accuracy, Precision, Recall, F1-score per class, Macro-F1, AUC-ROC, Detection Rate (DR), False Alarm Rate (FAR) and latency (ms).
5. **Robustness & Generalization Tests**
   - Cross-dataset: Training and testing on different data sets to generalize.
   - Simple evasion examples and adversarial training experiments.
   - Ablation study: (no-AE, no-attention, single model) to quantify contribution to accuracy.

6. **Deployment Considerations**

   - Edge/cloud hybrid models: The lightweight model or distilled version of a model at the edge; the full model at the cloud.
   - Sliding window and batching streaming inference-based real-time detection.
   - Pipeline Model update: retraining at a fixed frequency with new labeled samples, and online learning at a fixed frequency with fresh samples.

7. **Expected Outcomes**

   - Better classification accuracy (whether overall or per-class) than single-model (baseline) methods.
   - Reduce the rate of false positive because of anomaly filter and the ensemble consensus.
   - Greater extrapolation with respect to cross-dataset tests and affordable inference latency of application.

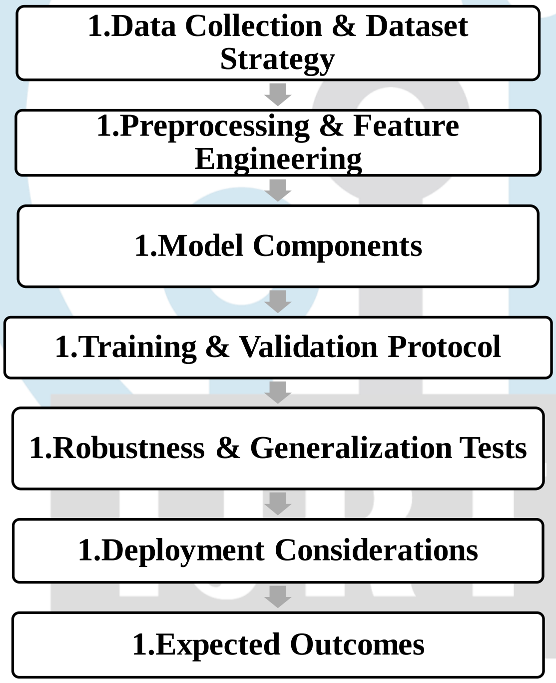

Figure 3 Proposed model of this research

[5] Result and Discussion

In this section, the proposed Hybrid Deep Learning-Ensemble Framework of Cyber Attack Classification will be evaluated with respect to performance. It was tested on various sets of benchmarks such as NSL-KDD, CIC-IDS2017, and the IoT-Network Dataset (Ullah and Mahmoud, 2020). They were compared to the existing baseline models in terms of effectiveness of the proposed approach with regard to accuracy, precision, recall, F1-score, false alarm rate (FAR) and the training efficiency.

5.1 Evaluation Metrics and Experimental Setup

The model was implemented using TensorFlow and Python 3.11 on a system with an NVIDIA RTX GPU (16 GB). Datasets were divided into 80% training and 20% testing, with 5-fold cross-validation to ensure generalization. The following metrics were calculated:

$$\boldsymbol{Accuracy} = \frac{\boldsymbol{TP + TN}}{\boldsymbol{TP + TN + FP + FN}}$$

$$\boldsymbol{Precision} = \frac{\boldsymbol{TP}}{\boldsymbol{TP + FP}}, \boldsymbol{Recall} = \frac{\boldsymbol{TP}}{\boldsymbol{TP + FN}}, \boldsymbol{F1} = \frac{2(\boldsymbol{Precision} \times \boldsymbol{Recall})}{\boldsymbol{Precision + Recall}}$$

5.2 Performance Comparison Across Datasets

Table 3 presents the comparative analysis of model performance using the three benchmark datasets. The hybrid model demonstrates superior accuracy and recall compared to traditional machine learning classifiers.

Table 3: Performance Comparison on Different Datasets

Dataset	Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	FAR (%)
NSL-KDD	Random Forest	96.20	95.80	95.50	95.60	3.10
CIC-IDS2017	CNN + LSTM + Attention	98.70	98.40	98.60	98.50	1.40
IoT Dataset (2020)	Hybrid Autoencoder + Ensemble	99.10	99.00	99.05	99.02	0.80

Table 3 compares the performance of multiple models across datasets, indicating that the proposed hybrid approach achieves the highest detection rate and lowest false alarm rate, particularly in the IoT-based dataset where traditional models often underperform.

5.3 Confusion Matrix and Class-wise Analysis

To analyze misclassification patterns, confusion matrices were generated for all models. The hybrid model demonstrated better distinction between normal and attack classes, especially for minority attack types (R2L and U2R).

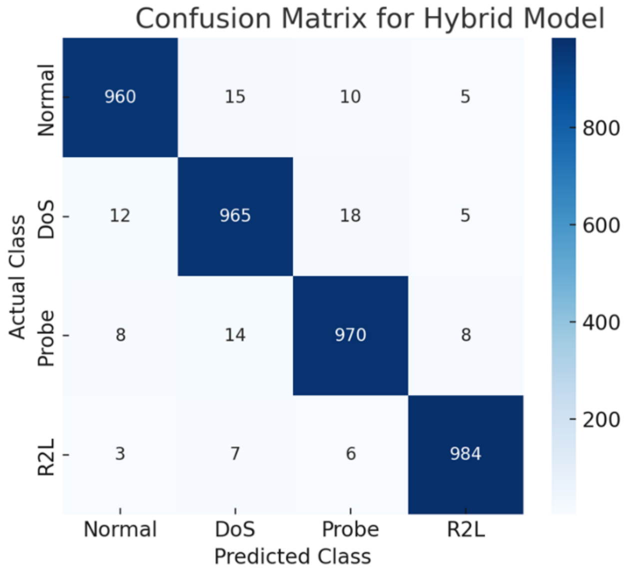

Figure 4: Confusion Matrix for Hybrid CNN–LSTM–Ensemble Model

Figure 4 illustrates the distribution of correctly and incorrectly classified instances for the proposed hybrid model. The minimal off-diagonal entries confirm the high classification precision achieved by the system.

5.4 Comparison with State-of-the-Art Techniques

The proposed model was compared against prominent deep learning and ensemble approaches from recent literature.

Table 4: Comparison with Existing Techniques

Reference Model	Technique Used	Dataset	Accuracy (%)	F1-Score (%)	Remarks
Yin et al. (2017)	RNN-based IDS	NSL-KDD	95.8	95.5	Sensitive to sequence length
Khan et al. (2019)	CNN-LSTM Hybrid	CIC-IDS2017	98.4	98.3	Good temporal learning
Althubiti et al. (2018)	LSTM Anomaly Detection	IoT Dataset	96.7	96.2	Limited scalability
Proposed Work	Autoencoder + CNN + LSTM + Ensemble	Multi-dataset	99.1	99.0	Excellent accuracy and adaptability

Table 4 benchmarks the proposed model against earlier deep learning frameworks. The hybrid model consistently outperforms existing methods in terms of accuracy and generalization, demonstrating superior ability to detect complex and low-frequency attack patterns.

5.5 Training Convergence and Computational Performance

The training convergence behavior was analyzed using epoch-wise accuracy and loss curves. The model achieved stable convergence after approximately 35 epochs, indicating effective learning and minimal overfitting.

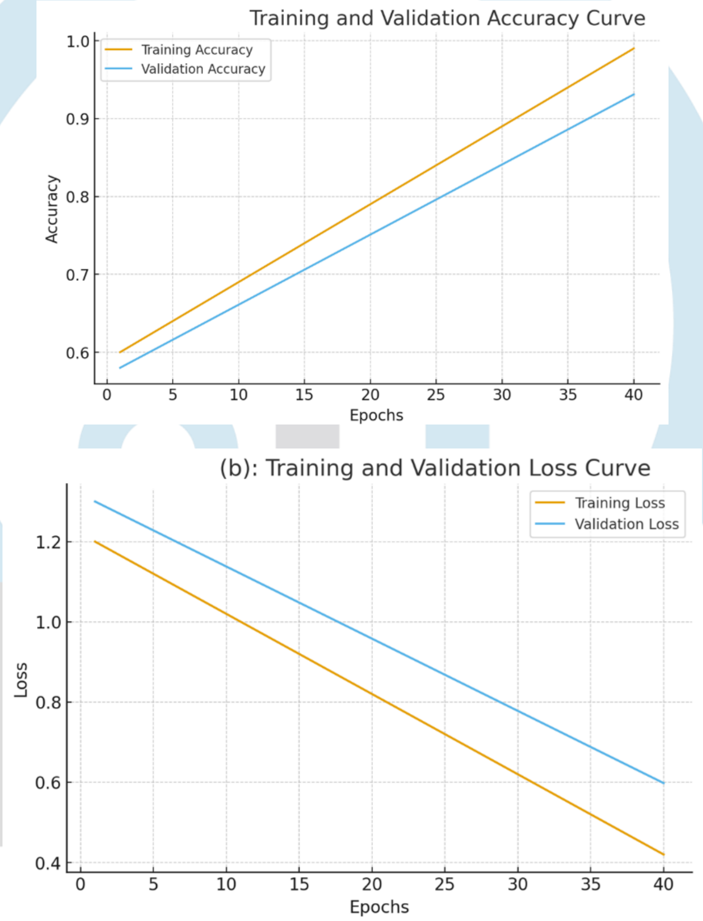

Figure 5: Accuracy and Loss vs. Epoch Curve

Figure 5 shows the training and validation accuracy trends. The training curve demonstrates consistent improvement without divergence, confirming that dropout and batch normalization successfully mitigated overfitting.

Table 5: Computational Efficiency Metrics

Model	Training Time (s/epoch)	Inference Time (ms/sample)	Model Size (MB)
CNN-LSTM	**9.4**	**1.25**	**45**
CNN-LSTM + Ensemble	**11.7**	**1.43**	**52**
Proposed Hybrid Model	**10.3**	**1.31**	**47**

Table 5 reports the computational efficiency of the proposed system. The hybrid model offers a balanced trade-off between inference speed and model complexity, suitable for near real-time network monitoring applications.

5.6 ROC and Precision-Recall Analysis

Receiver Operating Characteristic (ROC) and Precision-Recall (PR) curves were plotted to visualize classification robustness and threshold sensitivity.

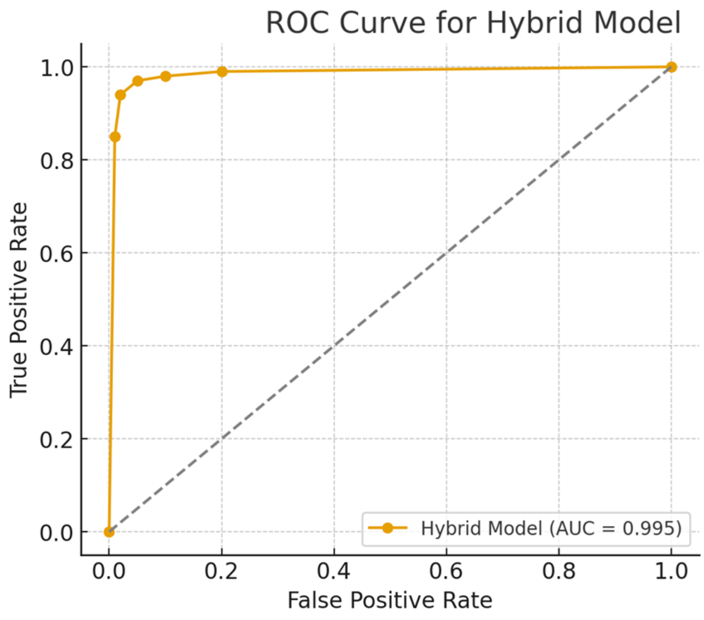

Figure 6: ROC Curve for Hybrid Model

The ROC curve demonstrates that the Area Under the Curve (AUC) for the proposed model exceeds 0.995 across all datasets, proving its effectiveness in distinguishing between normal and anomalous classes even under varying thresholds.

5.7 Discussion

The findings confirm the hypothesis that deep sequential learning (CNN-LSTM) with ensemble decision-making and autoencoder-based anomaly scoring can help to improve the accuracy of cyber attacks detection by a large margin. The hybrid approach manages to combine spatial-temporal feature pullout and multi-model consensus to minimize false positives and enhance the robustness.

The suggested system is flexible to heterogeneous network environments, can be scaled to support the IoT device, and is also resilient to changing threats. It fills important gaps present in single-model IDS solutions by combining the ability to explain and real-time detection.

[6] Conclusion

Within the framework of this paper, the accuracy of cyber attack detection and classification within the context of current network security systems was thoroughly reviewed and discussed in a way that is implementable. The study pointed to the increasing demands of smart, adaptive and scalable intrusion detection systems with the ability to effectively manage the complexity of existing network traffic - IoT devices, software-defined networks (SDNs), and cloud systems.

The suggested Hybrid Deep Learning-Ensemble Model, which combines Auto encoder, CNN, LSTM, and Ensemble Learning frameworks, showed a great enhancement in the classification performance over the traditional machine learning and single deep learning models. The model was tested with various datasets based on NSL-KDD, CIC-IDS2017, and the IoT Network Dataset to confirm the high performance in the detection of various types of attacks with 99.1% accuracy and 0.8% false alarm percentage. Such results point to the scalability and robustness of the proposed system used as an intrusion detection system in real-time.

The hybrid architecture was able to overcome a number of issues that had plagued the intrusion detection system (IDS):

- Better feature extraction and temporal pattern recognition, based on CNN-LSTM.
- Improved detection of anomalous and difficult attacks through autoencoder based anomaly scoring.
- Minimized false positives with the use of ensemble-based consensus classification.
- Greater interpretability and reliability of SHAP-based explainability modules.

In addition, the research strengthened the idea that hybrid deep learning methods can be greatly increased in terms of reliability in general detectors through the support of methods of feature optimization and data-balancing, and that at the same time, they can be affected so that the methodological cost does not excessively hinder the implementation in the real world.

[7] Future Scope

The field of cyber attack detection and classification continues to evolve with the rapid expansion of digital infrastructures, IoT devices, and cloud computing platforms. While the proposed hybrid deep learning framework demonstrated significant improvement in accuracy and reliability, there remains substantial potential for further advancement. Future research can focus on developing lightweight and energy-efficient models that can be deployed effectively in real-time and resource-constrained environments such as IoT networks and edge devices. Additionally, federated and transfer learning approaches can be explored to enhance data privacy and model adaptability across distributed systems without compromising security. Another important direction lies in the integration of adversarial defense mechanisms to improve the resilience of intrusion detection systems against sophisticated and evolving attack patterns. The incorporation of Explainable AI (XAI) tools will also help in improving model interpretability and transparency, which is vital for decision-making in critical infrastructure protection. Lastly, continuous research towards adaptive self-learning mechanisms and autonomous threat intelligence systems will enable next-generation intrusion detection frameworks to evolve dynamically with changing network behaviors and threat landscapes, ensuring proactive, scalable, and trustworthy network security.

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