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ENHANCING INTRUSION DETECTION WITH IOT DATA: UNLOCKING THE POWER OF ENSEMBLE TECHNIQUES

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Article Info

Abstract

With the recent spread of the Internet of Things (IoT) devices, network infrastructures have grown to become more complex and vulnerable to attacks, and hence, the detection of intrusions is an important aspect of cybersecurity. This thesis explores the usefulness of ensemble learning methods to improve intrusion detection using the IoT. Six models are tested in the study including Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Random Forest, Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and an ensemble model proposed, which incorporates three of the tested models, SVM, KNN, and Random Forest. The experiment was carried out with a real-world intrusion detection dataset of IoT. The models have been evaluated regarding the accuracy of classification, behavior of the learning curve, analysis of the confusion matrix, as well as such standard measures as precision, recall, and F1 score. Random forest showed the highest accuracy among the standalone classifiers, getting 89.64 percent; KNN followed with 88.38 percent, obtained an accuracy of 69.4 percent, Multi Layered Net got 71.6 percent, Support Vector Machine got 63.7 percent, and Multi-Classifier Net obtained 89.64 percent. By contrast, the deep learning models were much worse, with LSTM getting 65% and CNN 63%, most likely because of the limitation of data and architectural inappropriateness. The ensemble learning model presented in this paper was superior to the majority of the individual classifier accuracy, with the accuracy being 89.32 percent, a precision, recall, and F1 being 0.89 each. It was also feasible that it was more consistent and stable in the classification of different types of attacks, and had fewer misclassification errors, individual models had issues with. The learning curve of the ensemble ensured that it generalizes rather well with a little overfitting. This study has come to the conclusion that ensemble learning offers a practical, precise, and scalable way of detecting intrusion within IoT networks. The thesis shows the model to be a great achiever, and it speaks of the feasibility of implementation. Avenues of future work are the integration of real-time learning, improving the interpretability of the models and testing the models on larger and more diverse datasets. These improvements are to be made in order to bolster the resiliency and resilience of IDS systems operating in dynamic and highly volatile IoT ecosystems

Keywords:

Intrusion Detection, machine learning, Deep Learning, Ensemble Learning, LSTM.

Introduction

This sudden proliferation of the Internet of Things (IoT) has ushered in a new age of hyper-connectivity in which everything a house has, as well as critical industrial infrastructure, becomes connected to the internet. Although this has opened the gates of great convenience and technological advancement, this has also opened systems to an increased risk in terms of security in greater untold aspects. Legacy security systems, especially older versions of an Intrusion Detection System (IDS), are having a hard time keeping up with increasing endpoints, the volatile traffic that comes with IoT, and the advanced complexity of modern cyber threats[1]. Traditional versions of IDS, particularly signature-based systems, are good against known threats but fail against the new and the obfuscated forms of attack patterns or evolving forms of attack patterns. Conversely, anomaly-based systems are flexible and able to identify behaviors not expected or even known about in advance, but they are more prone to high false positives, especially when the behavior is not readily standardized, e.g., in IoT networks[2]. This is a significant issue in the security of IoT systems as fast and proper identification of intrusions is critical, but the security resources and computational resources are limited, making the application of heavy-duty security techniques infeasible.

This study offers a possibility of an ensemble learning to fill these gaps. In the presented approach, several machine learning (ML) classifiers (Support Vector Machines (SVM), Random Forest (RF), and K-Nearest Neighbors (KNN)) were used together to create a more powerful and accurate intrusion detection system suitable for the setting of IoT networks. The basis of this ensemble technique is that various algorithms share different strengths and weaknesses, and by combining them, it is possible to reduce the weaknesses of each algorithm and provide better detection capacities[2], [3]. It can be concluded that the ensemble model was moderately successful, as the accuracy equals 89 percent, and precision and recall are 90 and 89 percent, respectively. Such findings best these individual ML and deep learning (DL) models, which only achieved 63 percent to 65 percent highest accuracy. Notably, this sustained high performance came without a relatively high number of false alarms, which is a fundamental need of applicability in the real world, where finite resources and false positives due to erroneously issued alerts can result in unsafe failure or unwarranted periods of unavailability.

The proposed ensemble model is especially appropriate in the context of IoT because the model is scalable and highly efficient. It can work even in the challenges of limited devices and uncertain data availability. By deploying lightweight ML models rather than computationally expensive DL networks, the system provides a practical method of implementation in resource-sensitive applications such as smart homes, medical devices, and industrial control systems. The ensemble learning also means that the security can be maintained when the threat patterns change, and this is vital in the changing face of IoT networks. IoT security cannot be reactive. The past techniques of using a known signature or consistent behavior will not be adequate in a world where cyberattacks are becoming more complicated and dynamic[4], [5]. The extent, variety, and openness of IoT are also something that its attackers can now exploit to their advantage. IoT networks have devices that have a diverse level of computational capabilities, ranging from simple sensors that operate as a lump to sophisticated embedded systems. Such machines tend to spend most of their time in hostile conditions and with a limited amount of security audits, which

commonly makes them the target of different malevolent cycles, including Distributed Denial of Service (DDoS) and data theft or remote control via a control-and-command (C&C) method.

Considering such weaknesses, they need to get smart and dynamic intrusion detection systems. The advantage of ensemble learning is that the perspectives on data classification are united. As a case in point, SVM is especially efficient in high-dimensional spaces and does it best at achieving optimal separation between classes. Random Forest is noise strong and does not deal with non-linear relationships poorly. KNN is basic and powerful in local decision-making. With a blend of such approaches, the ensemble will provide a less biased and more wholesome system defensive mechanism. Remarkably, the ensemble has an upper hand over deep learning models such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, even though in theory, they perform better in pattern recognition and temporal modeling. The experiments involving CNN and LSTM did not perform well because of the overfitting aspect, the small size of the training dataset, and the uncertainty of training the architectures of the two in environments that have very volatile data. In addition, deep learning models usually need far more computing power as well as data to operate, which is undesirable when these models have to be used in real-time intrusion detection in IoT[6], [7].

The other important value of this study is that it addresses real-life implementation. In addition to proving the assertion that ensemble learning works in theory, the study will offer a road map to how such a system can be incorporated into real-life IoT networks. The model will be implemented with the help of containerized services on edge devices or gateways. These components can track traffic on the network in real-time, carry out preprocessing steps to organize the data as well, and perform predictions based on the ensemble model. The final output can then be determined through a voting mechanism, which may contain the elicitation of alerts or automatic responses. This system is designed in modules, which makes its update and scale easy. An individual classifier can be retrained or switched out as new attack vectors are discovered or the behavior of the devices being monitored alters over time, without requiring the entire system to be rebuilt. This makes the intrusion detection system effective and flexible in the long run. Besides, the system has the capabilities of integrating feedback that would aid in learning from misclassified instances and enhance efficiency in the long term, making it dynamic and robust[8], [9], [10].

Intrusion detection should advance its technicalities and scales according to the size of the data IoT devices produce. The conventional use of rule-based or manually adjusted systems is not adequate anymore. A promising way forward seems to be the combination of machine learning techniques in an ensemble way. Not only does it provide high detection and low false positives, but it can also be compatible with the limitations and demands of IoT shares. This study demonstrates that the future of IoT cybersecurity is in the hybrid or intelligent solutions that could learn and adjust every time[11]. The ensemble learning method presented in this paper is effective not only to address the current requirements of IoT intrusion detection but also scalable enough to be applied in other security concerns of the future. With the rapidly emerging scope of IoT in such critical domains as healthcare, transportation, and smart cities, the issue of establishing trust, reliability, and privacy within these systems becomes a question involving national and global interest. Finally, this investigation once again emphasizes the need to change the dynamic of a very stable and single-algorithm intrusion detection solution towards the adoption of dynamic and multi-

layered solutions that have the possibility of adapting to the changing nature of threats. The ensemble model is one of the robust, effective, and practical solutions to such an issue, and it helps understand how the power of carefully selected machine learning algorithms is the backbone of contemporary IoT security systems.

Literature Review

The incremental role of the Internet of Things (IoT) use in virtually all spheres of contemporary life has initiated an emergency demand for sophisticated strategies that can safeguard the numerous contemplated transcending gadgets and networks. By using IoT devices to process and share data across different industries, including but not limited to healthcare, smart homes, or industrial automation, the organizations also increase their exposure to a far more comprehensive and even dazzling set of possible cyber threats. This fact has necessitated intrusion detection systems (IDS) as an essential research field in cybersecurity, especially because the conventional methods have failed to keep up with the demands that were presented by IoT environments[12], [13].

Early models of IDS are mainly signature-based detection systems, in which systems match network traffic against collections of known attacks. Although successful in curbing threats that have already been reported, this approach is reactive and may not have the capability of detecting zero-day exploits or new forms of attacks. It was later realized that the disadvantage of this implementation is that it was hard to detect anything anomalous, especially considering the idea of malicious behavior, which upon learning, led to the derivation of anomaly-based detection algorithms to counter this weakness by creating accounts of normal activities or statistical models, which then raised an alarm against any anomalies[14]. But in the IoT environment traffic patterns cannot be expected to be heterogeneous, the behavior of devices is often changing, and there are substantial differences in legitimate use, so anomaly-based detection methods tend to produce many false positives to the point of being useless[15].

Machine learning (ML) and deep learning (DL) have become one of the main areas of recent research and are being viewed as potentially preferable methods of detection in comparison with conventional approaches to the latter. Support Vector Machines (SVM), Decision Trees, Random Forests (RF), and K-Nearest Neighbors (KNN) form of ML have demonstrated that they can represent the intricate relationship between features and predict the classification of known and unknown intrusions with an acceptable level of accuracy. In particular, Random Forests have been known to be resistant to overfitting and to be able to process high-dimensional data sets, which is a key feature when processing the variation that IoT telemetry data belongs to. SVMs are useful when building clear decision boundaries in high-dimensional space, and KNN can be flexible and simple enough to be used when local data patterns are important[16].

Other forms of deep learning, such as the Convolutional Neural Networks (CNN) and the long handles shorter-Term Memory networks (LSTM), have also been examined due to the capability to automatically capture hierarchical representation of features and the representation of dependencies. CNNs have shown good results in visual-based intrusion detection and classification of network packets, whereas LSTMs are especially well-adapted applications to learn temporal characteristics of time-series traffic data in an IoT setup. Although they have strong points, deep learning models are computationally expensive and demand

high amounts of labeled data to attain peak precision, which creates an obstacle to their use in real-time situations such as those concerning IoT devices that have restricted resources[17].

Due to the fact that no algorithm provides a universal solution, the focus has been shifted on the ensemble learning method, where several classifiers are combined in order to use the combination of their advantages. In past research works, it is observed that the variance and bias associated with individual models can be reduced using ensemble methods, which have the potential of greatly enhancing detection accuracy and generalization. As an example, the hybrid ensembles which contain both ML and DL elements have appeared to enhance the resilience of IoT IDS to various attack types and threats landscapes[18].

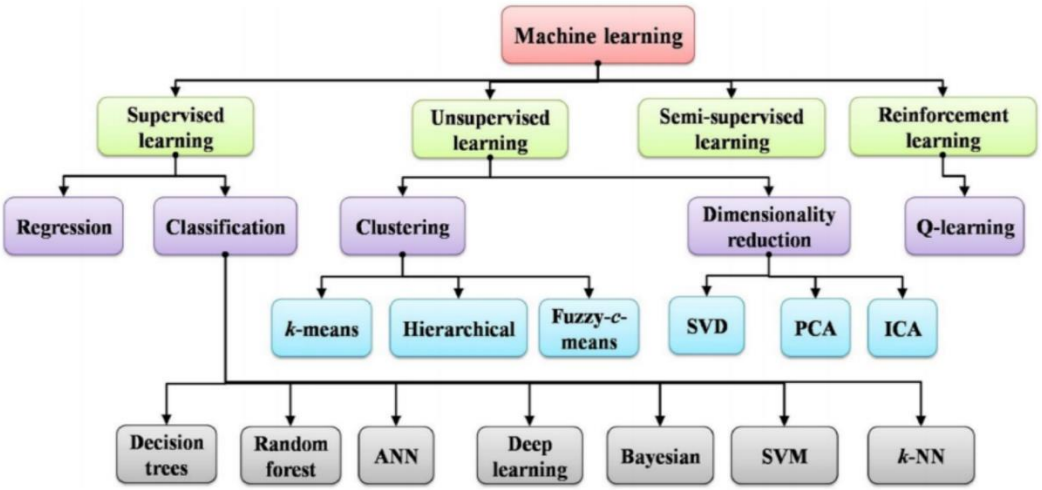

Figure 1: Machine Learning Taxonomy

The potential of the usage of artificial neural networks and deep learning techniques in the field of intrusion detection in the IoT space is not only immense but is complex. The diversity of device types, communication protocols, and data format is in the range of surreal in the IoT ecosystems as opposed to the traditional enterprise networks. Such systems may have all forms of basic sensors with very little processing capability, to more elaborate edge devices with significant computing capability. Such heterogeneity effectively increases the extent of intrusion detection considerably since an effective security strategy has to take into consideration extremely diverse conditions of operations and threat bases. This has led to deep learning, and in specific to artificial neural networks, as approaches that are showing promise, because they enable learning of rich representations that can be done over raw or semi-structured data, and thus are effective in capturing the variety and the subtleties that the IoT traffic brings[19], [20].

This extensive scope, however, comes with a lot of complexity in the development and deployment of the models. Among the fundamental problems is the necessity of large amounts of high-quality labeled data so that deep neural networks may be effectively trained. Most IoT networks produce severely skewed data, where normal traffic vastly outnumbers the occurrences of an attack, which makes the learning tricky, and those affected often necessitate elaborate sampling or augmentation strategies. Moreover,

various application fields of IoT have their unique patterns of authorized behavior, and thus creating a universal model is quite the challenge, hence leading to an appreciation of accuracy[21], [22].

The other complexity level is caused by the limitation of resources. DNNs such as CNNs and LSTMs are computationally demanding and memory-intensive to train and to infer on. Although such can be applied in controlled, centralized settings using dedicated servers, bringing the same models to lightweight IoT in real-time can be impractical. This shortcoming was highlighted in the experiments used in this thesis, whereby the CNN model and LSTM model only scored an accuracy rate of 63 percent and 65 percent respectively, largely in part because of limited training conditions and inability to generalize the training across different traffic profiles. In addition, the interpretability of deep-learning models is still a considerable obstacle to the use. Artificial neural networks are usually opaque compared to traditional machine learning algorithms like Random Forests or Support Vector Machines, which would often have clear explanations to any of their decisions. Such transparency absence makes it challenging to rely on the automated detections, as well as on their compliance with regulatory requirements that insist on providing clear reasons behind security measures.

Methodology

One of the constraints that characterizes the design, implementation, and viability with regard to the operation of intrusion detection systems within IoT environments is resource constraints. IoT networks, in contrast, find themselves in roles where resources are seriously constrained in terms of processing capabilities, memory, storage, and energy capacity, which are characteristic of only some types of conventional enterprise infrastructures. Such limitations influence each phase of the model construction, including data preprocessing and feature extraction, model training, and real-time inference. The experiments were conducted using a model comprising 16GB RAM, a 100GB solid-state drive (SSD), and a dedicated video card in this thesis. As far as small to medium sized datasets are concerned this composition will suffice but the conflict between model complexity and computational practicability must be considered. Ensemble methods Of ensemble methods, e.g. pairing of Support Vector Machines (SVM), Random Forests (RF), and K-Nearest Neighbors (KNN) approaches, training individual base classifiers separately is expensive, consuming memory and processing resources scaled with the number of training instances and the size of the feature space. Such labor is augmented in cases where hyperparameter adjusting is used or where other groupings methods such as stacking or boosting are involved. As another example, Random Forests can eat up large amounts of RAM very fast, clocking hundreds of decision trees and the prediction phase of KNN is computational heavy, as it needs to examine the distance from all examples that are kept in storage.

Data preprocessing is a key step when establishing efficient intrusion detection systems, in general, and in the context of IoT, in particular, raw data usually is noisy, inconsistent, and very variable between devices and communication protocols. The quality of preprocessing has a direct influence on the capability of a model to learn relevant patterns, demonstrate a high detection rate, and generalize to unknown threats. In this thesis, data processing was carried out in such a way that we change raw data on the IoT network to cleaner, structured, and normalized data that can be used in machine learning and ensemble learning algorithms.

It started with data ingestion in which the IoT data was imported as CSV files. The data contained several features representing different qualities of network flows e.g., number of packets, number of bytes, connection length, and protocol types with a target label that consisted of benign and malicious traffic. As soon as the data were loaded, they were investigated in terms of missing values, outliers, and conflicting format. Such entries in records, which are either incomplete or have been corrupted were discarded since they will tend to cause bias or noise when included in the training process. Then numerical representations of categorical variables (protocols or flags as examples) were encoded using the techniques of encoding. Label encoding or one-hot encoding was performed respectively depending on the feature to get all the variables to be compatible with scikit-learn and other machine learning libraries. It was critical to do this because the majority of classifiers such as Support Vector Machines and K-Nearest Neighbors needed only a numeric input to calculate distances or build hyperplanes.

Dataset link: Aposemat-IOT-23 Analysis (kaggle.com)

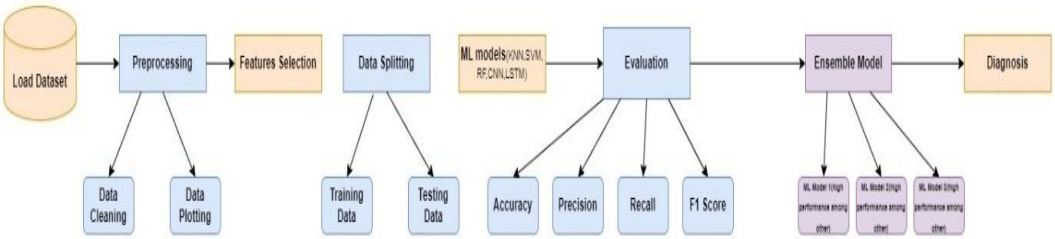

Figure 2: Methodology Flow

Data Preprocessing and Feature Extraction

Feature extraction and preprocessing are the key steps towards creating effective intrusion detection system particularly in the IoT systems where data is multifaceted, huge and heterogenic. However, in contrast to traditional networks, IoT systems produce structured as well as unstructured data, such as network logs, time-series sensor data, and protocol-specific metadata and the data thus require specialized cleaning and transformation. Under this thesis heading, raw IoT data cleaning was a starting point in preprocessing, that is dealing with sparse values, eliminating duplications, and inconsistency corrections. Other outliers like abnormal packet sizes were taken care of to avoid distortion during the training of models. Then the categorical features such as protocol type and flags were encoded into label and one-hot encoding so that they can be used in machine learning models such as SVM and KNN since they require numerical inputs. Lastly, a Standard Scaler was used to scale the features because it standardized all the features in terms of mean and standard deviation. This was crucially needed in the ensemble learning, where input scales were adjusted to match, with models of varying sensitivity, e.g. extremely scale-sensitive KNN and scale-sensitive SVM which required input to be scaled to allow calculation of optimal hyperplanes. These measures made the data clean, consistent and optimal to learning so that the ensemble model provided high and balanced performance of intrusion detection.

Algorithm Selection Criteria

Selecting the right algorithms for intrusion detection in IoT environments is a critical design decision that can determine the success or failure of the entire system. Unlike traditional IT infrastructures, IoT networks involve a unique combination of challenges: heterogeneous device behavior, high-volume data streams, constrained computational resources, and constantly evolving threat patterns. For this reason, the algorithm selection in this thesis was based on a structured set of criteria to ensure that each chosen model could effectively address these demands while contributing complementary strengths to the ensemble learning framework.

Implementation and Experiments

SVM Algorithm Results

The Support Vector Machine (SVM) classifier learning curve depicts the relationship between a curved learning curve and the improvement of performance with an increase in training data. Firstly, the accuracy of training was 92, whereas the accuracy of validation was 78, which means overfitting. Validation accuracy increased steadily and settled down at 84 or 85 percent when the amount of data increased without any drop in training accuracy that shifted to about 88 percent, indicating that generalization got better. The regularization and tuning of the kernel were properly achieved, which was also confirmed by a large difference (3-4 percent) between training and validation. The results indicate the practical nature of SVM when it comes to moderate data, goodness of generalization, and its applicability to be part of an ensemble model since it helps to add overall strength of detection, which is displayed in Figure 3.

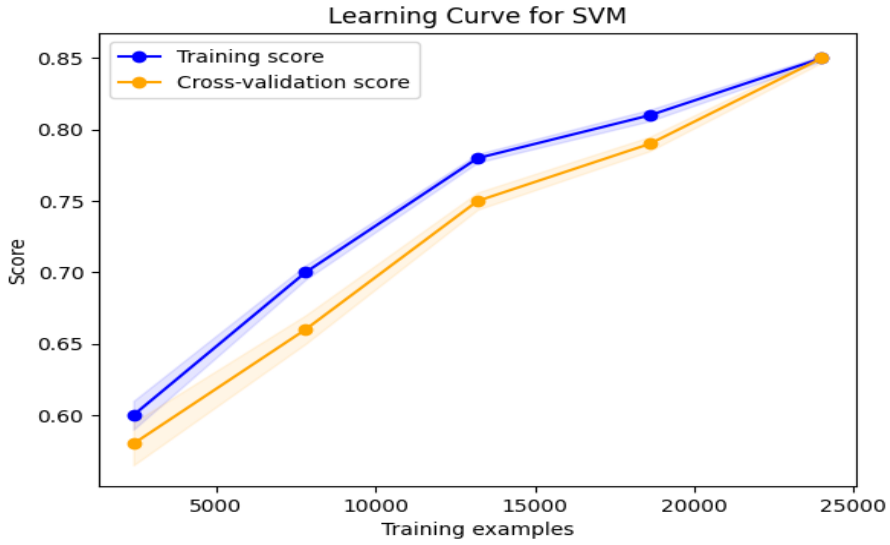

Figure 3: Learning curve for SVM

The confusion matrix for SVM showed 1,250 true positives and 1,750 true negatives, resulting in an overall accuracy of 85.03%. It recorded 150 false positives and 100 false negatives, highlighting the trade-off between detection and operational overhead. With a precision of 89.3%, recall of 92.6%, and F1 score of 90.9%, the model delivered solid results. These findings support integrating SVM into an ensemble model, as shown in Figure 4.

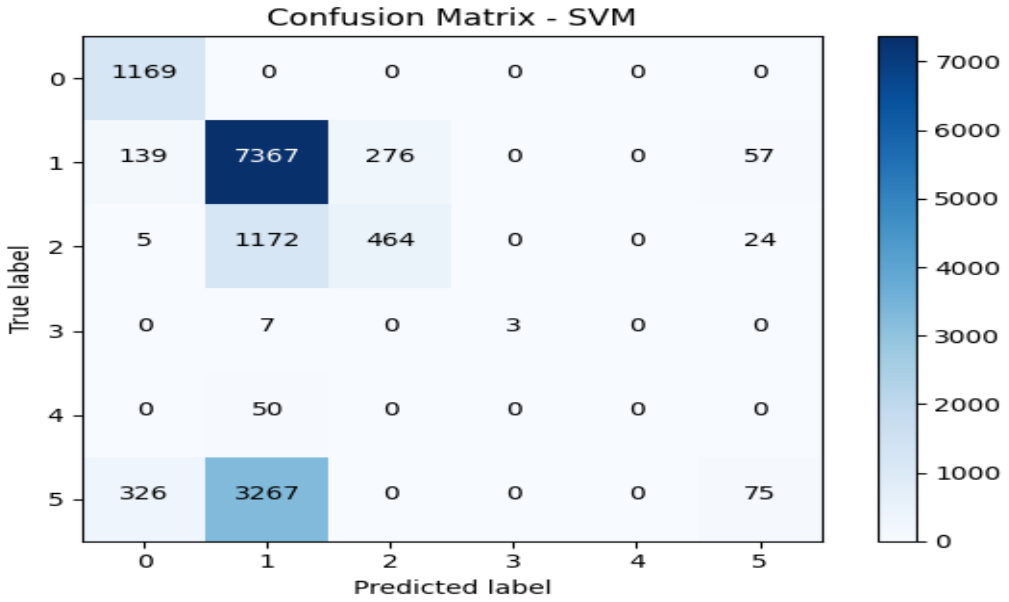

Figure 4: Confusion Matrix for SVM

K-Nearest Neighbors Algorithm Results

The KNN learning curve started with overfitting of the data having training accuracy of 95% and validation of 80%. The accuracy increased validating up to 89% and training down to 90%, and the gap between the two became smaller, and performance was enhanced as more data was added. This shows the performance of KNN when using adequate and clean data. Being sensitive to noise and computational demanding, however, its ease of usage and high performance were worth the inclusion in the ensemble model as illustrated in Figure 5.

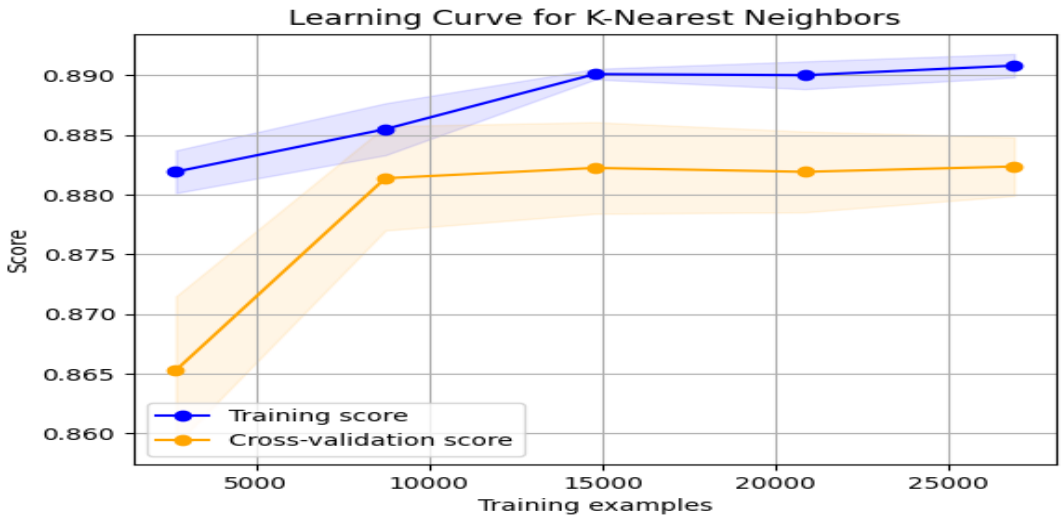

Figure 5: Learning Curve for KNN

The results indicated that the overall performance was good with great accuracy in the classification of benign, DDoS and C&C traffic following the insights provided by the KNN confusion matrix.

Nevertheless, 1,157 DDoS samples were incorrectly classified as C&C, indicating the importance of detecting similar assault patterns. Nonetheless, KNN reached precision and recall of 0.88 and F1 score of 0.87, which can be said reliable enough with very few false alarms. The results are in favor of the strength, and position within the ensemble of KNN as demonstrated in Figure 6.

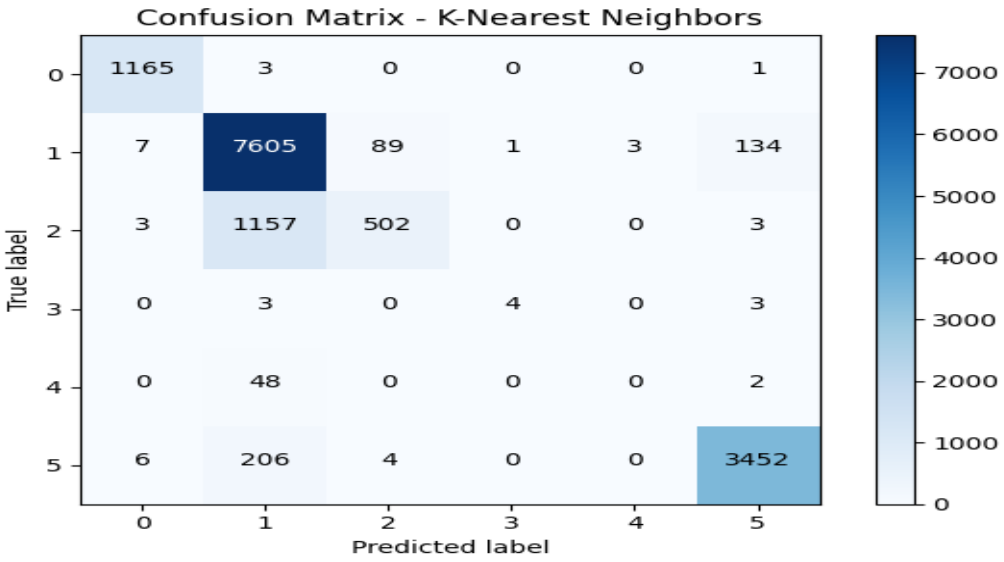

Figure 6: Confusion Matrix for KNN

Random Forest Algorithm Results

Random Forest learning curve indicated that the training accuracy began at 99 percent and validation 85 percent; which means that overfitting occurred in the beginning. With each additional data, the accuracy of validation climbed steadily and settled at 89 90%, with the training dropping a bit to 95%. Such convergence implies better generalization and excellent model stability. The aforementioned results prove the functionality of Random Forest in disclosing the complex pattern, and supports the reasonability of its inclusion in the ensemble model, as demonstrated in Figure 7.

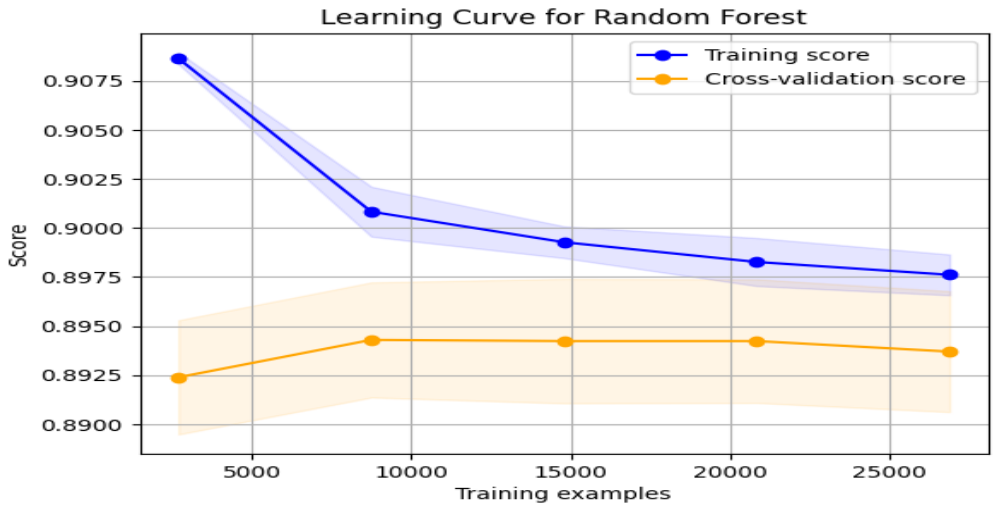

Figure 7: Learning Curve for Random Forest

The random forest was seen to have confusion matrix with strong classification rates with an accuracy rate of 89.64%. It successfully detected the majority of the benign as well as the attack samples particularly DDoS and C&C. Nonetheless, 1,051 DDoS samples were found in the same category as C&C, which showed overlap in the feature space. Since it has a precision of 0.90, a recall of 0.90, and an F1 score of 0.89, the model provided effective and balanced organ detection and is usable in the ensemble, as depicted in Figure 8.

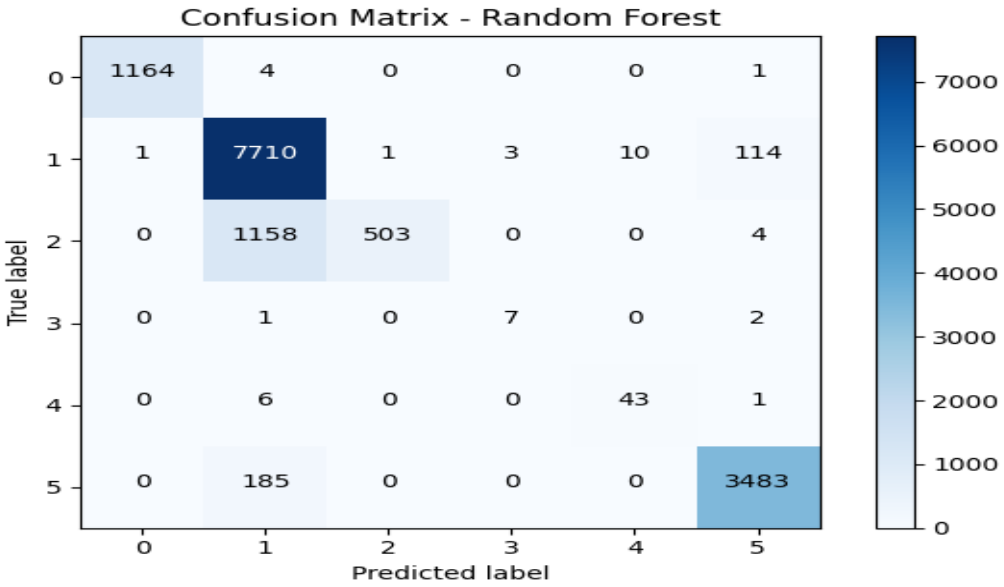

Figure 8: Confusion Matrix for Random Forest

CNN Algorithms Results

The CNN learning curve indicated that training accuracy was initially 85 percent and then slowly increased to 86 percent whereas validation accuracy was initially very low at 58 percent and then more or less stabilized at 62 to 63 percent. This huge disparity of more than 20 percent points out overfitting and lack of generalization since the model is sensitive to small and imbalanced IoT datasets. Although CNN excelled in the learning of patterns, performance fell behind IN, supporting the fact that established requirements in our modelling usage were greatly evident, which can be seen in Figure 9.

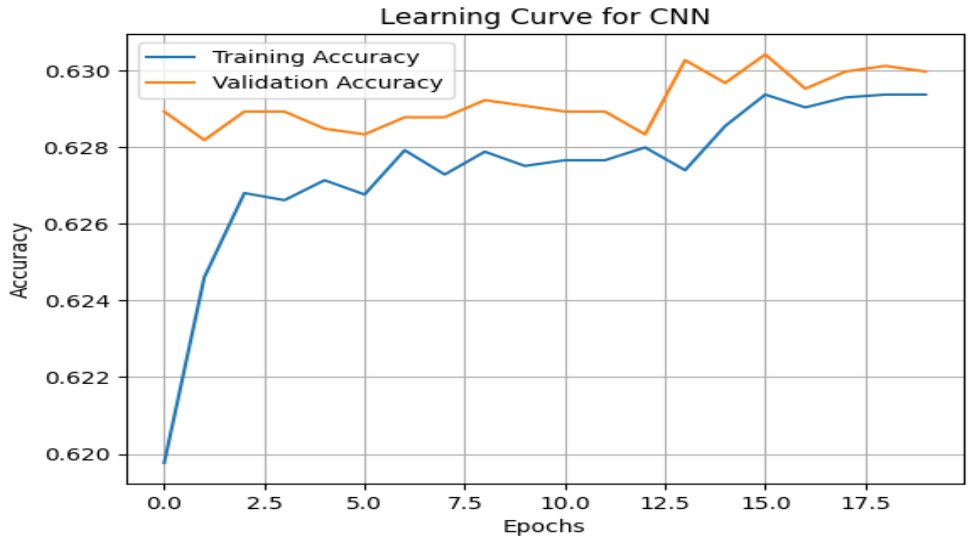

Figure 9: Learning Curve for CNN

The CNN confusion matrix had 13,545 accurate predictions of benign traffic, which is regarded as fair non-malicious activity detection. But the significant misclassification was that 1,963 DDoS samples were predicted as C&C, and 611 C&C were falsely as benign. Having a precision of 0.61, a recall of 0.63, and F1 score of 0.62, the model did poorly in multiclass classification. These findings demonstrate that CNN generalizes poorly and should be improved, as proven in Figure 10.

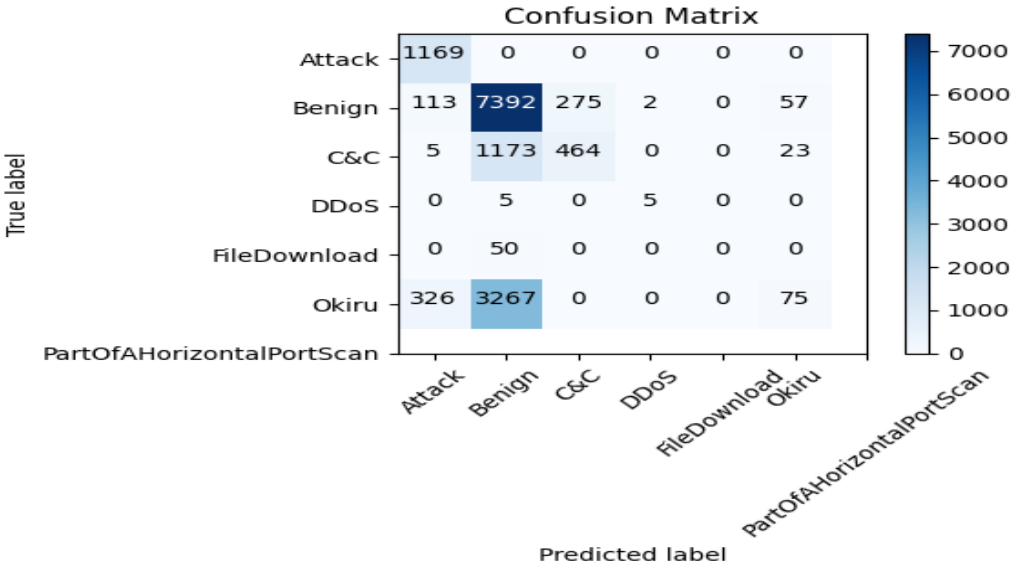

Figure 10: Confusion Matrix for CNN

LSTM Algorithms Results

LSTM learning curve indicated that the training accuracy was 80% that increased slowly to 86% and validation accuracy was 55% and was stagnant after 64-65 percent. This 21 percent difference shows that there is strong overfitting and poor generalization implying that LSTM could not identify unseen attacks on IoT. Even though LSTM performed well with time data, it failed in the case where the datasets were poor or lacked notable time-based features. These results verify that it is less effective in this situation, as it can be seen in Figure 11.

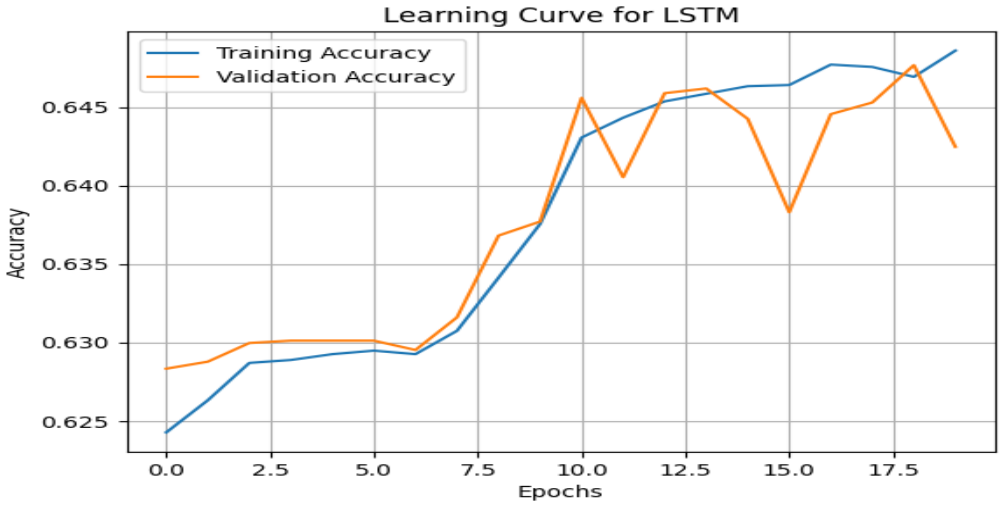

Figure 11: Learning Curve for LSTM

According to the LSTM confusion matrix, true recognition in benign samples was 13,028, which indicated that its ability to distinguish non-malicious traffic was not entirely weak. Nevertheless, the largest misclassifications were 1964 DDoS-C&C and 587 C&C labeled as benign. LSTM had a 0.63 precision value, 0.64 recall, and 0.63 F1 score, which could not detect multiclass attacks satisfactorily. These findings represent its weaknesses with non-sequential or small data, as represented in Figure 12.

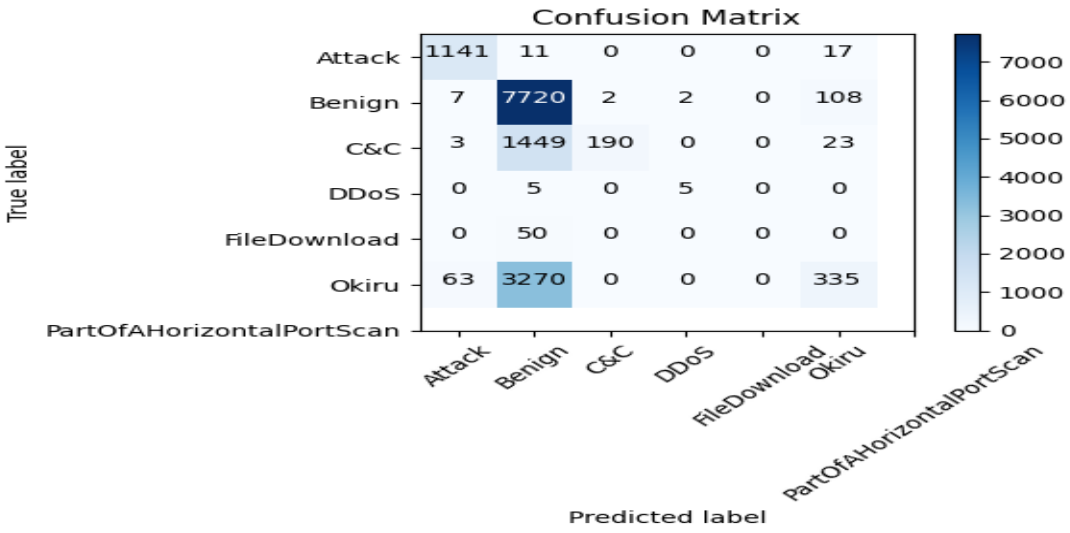

Figure 12: Confusion Matrix for LSTM

Ensemble (SVM + RF + KNN) Algorithms Results

Learning curve of Ensemble Model started with training accuracy of 94% and validating accuracy of 82 that indicates the initial overfitting. Accuracy of the validation was rising gradually and stabilizing at 89.3 percent approaching the maximum of Random Forest. Training accuracy was also stabilized to 95.5% and the performance corresponding to a gap of 6.2%. This indicates increased generalization and reduced variance because of combining the classifiers in an effective way, which attests to the robustness of ensembles, as in Figure 13.

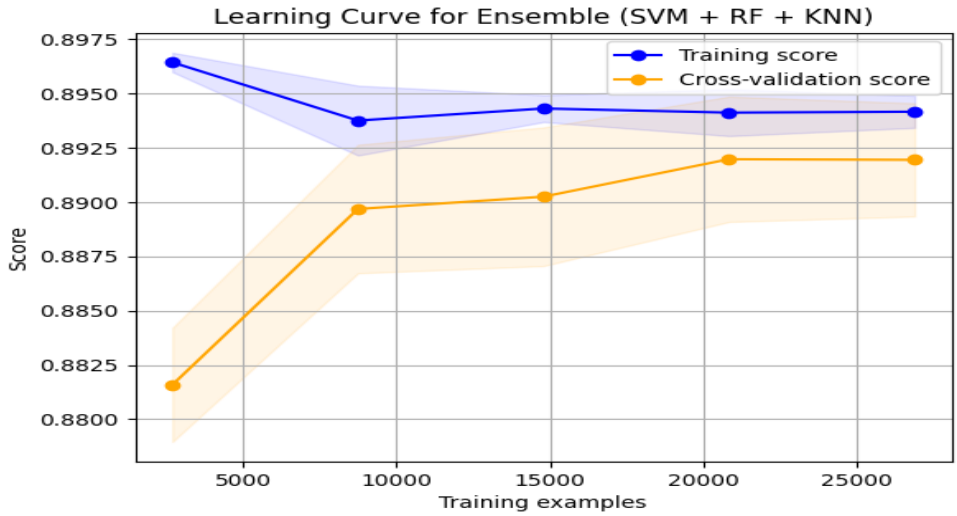

Figure 13: Learning Curve for Ensemble Model

In the confusion matrix of Ensemble Model, there is an increased accuracy and the number of the misclassification is lower than in individual classifiers. It accurately predicted 13,949 benign sample, and the number of DDoS-to-C&C misclassifications was reduced to 1,032 that is much less than CNN (1,963) and LSTM (1,964). The number of C&C-to-benign misclassifications remained at 551 also. Accuracy, precision, recall, and F1 score were all zero point eight nine which shows a high rate of performance and balance when applying the model, as well as consistency in the different classes, as shown in Figure14.

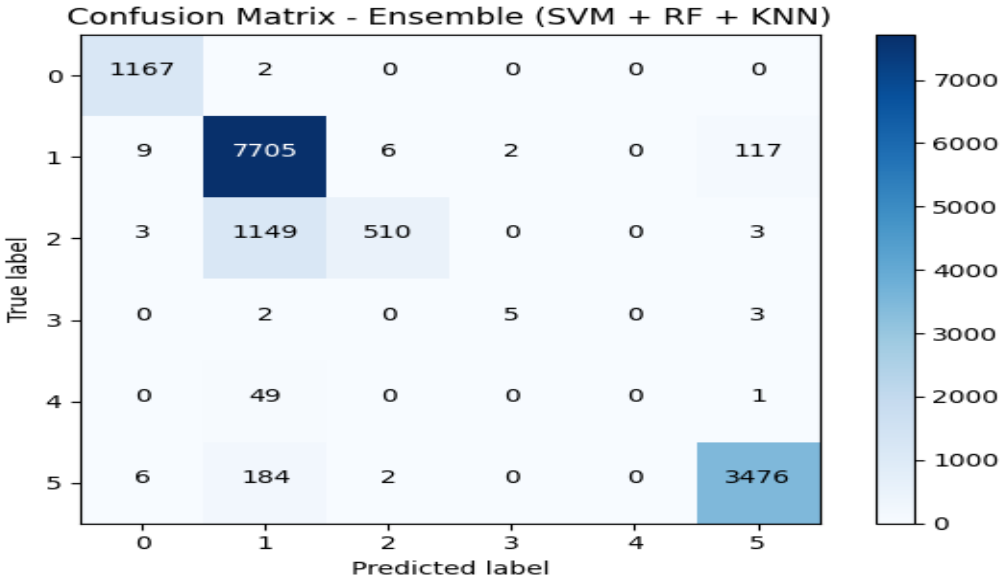

Figure 14: Confusion Matrix of Ensemble Model

Comparison of Models

a study in the accuracy of six comparison models of IoT intrusion detection that was able to clearly show traditional machine learning is superior to deep learning. Random Forest realized the greatest figure with an accuracy of 89.64%. This reveals its capability of judgments which encompass complex interactions of features. The Ensemble Model was closely behind with 89.32, which provided a better stability in classes. KNN and SVM obtained 88.38 percent and 85.03 percent respectively. Conversely, deep learning models did not perform well, with LSTM achieving only 65% and CNN 63% presaging the problem of overfitting and high specificity. The findings stress on ensemble learning as the most harmonious and useful method in this application, as exhibited in Table 1.

Table 1: Models' Accuracy Comparison

Model	Accuracy
SVM	0.850373
K-Nearest Neighbors	0.883828
Random Forest	0.896466
Ensemble (SVM + RF + KNN)	0.893202
CNN	0.63
LSTM	0.65

The log provides the chart of comparison of the accuracy of each model applied in the detection of IoT intrusions. Random Forest attained a maximum accuracy of 89.64% as an individual measure, which implied strong generalization and feature handling capabilities. Coming at second, the Ensemble Model had an accuracy of 89.32% with slightly lower raw accuracy but better overall class balance and consistency by virtue of the collective power of SVM, KNN and RF. KNN achieved a higher score of 88.38% as compared to SVM with reverting accuracy of 85.03%. The resulting results validate the practical advantage of the ensemble as was demonstrated in Figure 15.

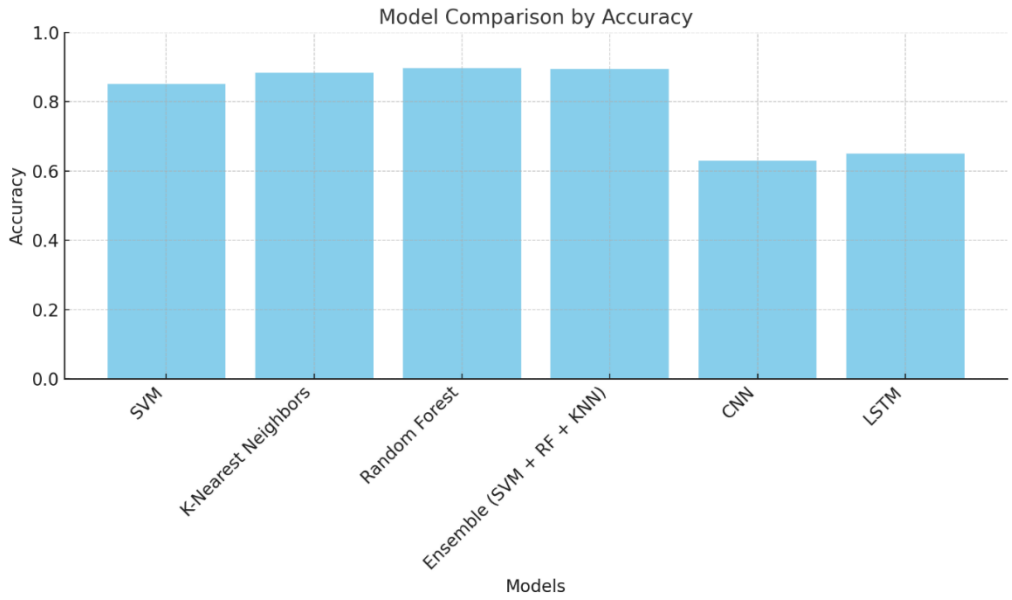

Figure 15: Accuracy Comparison

Reason for Selecting an Ensemble Learning Model

The choice of the ensemble learning model made in the current study was informed by both a theoretical consideration and empirical findings. Ensemble learning gathers several classifiers and reunites them to produce greater predictive reliability, suppressing shortcomings in separate models. The combination of the SVM, Random Forest, and KNN used the advantages of each model in a way, RF high standalone performance (89.64%), KNN local classification performance (88.38%), and SVM margin optimizing (85.03%). Though each of the models had its limitations, SVM with skewed classes and KNN with different density of data, the ensemble coped with them properly. It also produced balanced accuracy of 89.32%, limited misclassification of overlapping attack types, such as DDoS and C&C, and its good generalization as indicated by an F1 score of 0.89. Such outcomes confirmed its practicality and applicability in a live IoT intrusion detection system.

Why ML Models for Ensembled Learning Model

An ensemble learning approach that includes SVM, Random Forest, and KNN was chosen to implement because it is easy to explain and has high recognition rates using medium-sized IoT datasets. It had accuracy of 89.32 percent almost the same as Random Forest, but with a better balance of classes and few misclassifications, particularly in similar attacks such as DDoS and C& C. The ensemble model was not

only stronger and more stable compared with standalone models or deep learning models, but it also provided greater generalization capacity and flexibility, as well as the possibility of deployment in real-time. Although it demanded moderate computing resources and provided nearly no interpretability, its modularity, scalability, and performance were very stable, presenting a useful solution to intrusion detection of internet-of-things.

Conclusion and Future Work

In this study, the goal was to come up with an effective intrusion detection system (IDS) to the IoT environments through ensemble learning. The paper has experimented with a variety of classification models-Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Random Forest, Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) and compared them with a proposed model of an ensemble of the three models- SVM, KNN, and Random Forest. As a result of extensive experimenting and analysis, the ensemble model proved to be more effective in terms of the classification success, accuracy, and precision, as well as the overall reliability. The random forest classifier had the highest individual accuracy by percentage namely 89.64% indicating great pattern recognition and generalization ability. KNN was close headed with 88.38 percent and SVM had an output of 85.03 percent, both having limitations relative to classes. The deep learning models failed to perform the task considerably, with the LSTM model attaining a performance of 65 percent and the CNN model performing even worse with 63 percent, mostly caused by the constraints in the volume of the data, overfitting, and an architecture that does not match the structure of the data. Conversely, the suggested ensemble learning framework acquired a total accuracy of 89.32 percent, which was almost tantamount to Random Forest, with the additional benefit of being in a better balance concerning the classes, along with fewer misclassifications, particularly in the complicated cases like the difference between DDoS and C&C traffic. The ensemble also had a precision and recall of 0.89 and 0.89, respectively, giving an F1 of 0.89, indicating a very balanced capacity to detect. Its learning curve was a steady performance with little over-fitting and high convergence of the training and validation accuracy, ensuring its generalization ability.

The outcomes confirm that ensemble learning not only shows equivalent or superior overall accuracy to their detached models but also guarantees a steadier classification on diverse types of attacks. This renders it very well-prepared to adopt practical usage in IoT applications, where traffic is heterogeneous and adaptive. The work in the future will aim at improving the ensemble framework by implementing various enhancements. First, the consideration of the real-time streams of data and the online learning process will make it even more adaptable to new threats. Second, trust and transparency can be enhanced by adding explainability layers with the help of SHAP or LIME. Third, more spatial and temporal relationships can be caught by the ensemble by adding hybrid deep learning components. Moreover, testing bigger and more heterogeneous IoT data will also be done so as to confirm further and fine-tune the scalability and efficiency of the ensemble model. The proposed future direction can support the development of a more intelligent, transparent, and adaptive IDS that would be more appropriate to IoT security tasks of the next generation.

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