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IOT DATA-DRIVEN INTRUSION DETECTION: HARNESSING ENSEMBLE TECHNIQUES FOR ENHANCED SECURITY

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Abstract

With the current developments in IoT devices in the modern business environment, there exists a virtuous link between various areas and a notable improvement in processing information. That is, while the increase in IoT networks has brought these benefits in the last couple of years, it has also presented security issues with the major one being on how to shield IoT networks from potential unauthorized access. This thesis aims to design an efficient IDS intended for the identification and prevention of security threats in real-time by integrating the benefits of ML and DL methodologies. The contributions of this work are that this study for the first time has proposed an ensemble learning model for enhancing IDS in IoT environments using SVM, RF, and KNN, which outperforms the conventional ML and DL IDS. The research starts with the analysis of the existing literature to determine the shortcomings of the conventional IDS methods and discuss the prospect of using ML and DL for IDS improvement. Collection of data from IoT devices and its initial processing and application of the discussed models, namely, SVM, Decision trees, Random forests, CNN, and LSTM are described. The experimental results shown in the study showed that the proposed ensemble learning model had the highest accuracy of 0. 89, precision of 0. 90, recall of 0. 88, recall rate of 92, Precision rate of 92, and F1 score of 0. 87. However, most of the individual deep learning models such as CNN and LSTM had comparatively low accuracy of 0. 63 and 0. 52 and 65, respectively, for our models when no hyperparameter tuning has been done. In this research, the proposed IDS has a strong ensemble learning framework of individual ML models that has not been investigated and established before. The proposed ensemble framework increases the accuracy and generalization capabilities while decreasing false alarms making it a more accurate and scalable solution for real-time IoT intrusion detection. It also presents ideas for future work to enhance the results using more efficient computation and to look at future work that combines both types of models. Last of all, as part of the discussions made in this paper, recommendations to improve advanced IDS solutions are provided to increase the protection of IoT networks against future cyber threats.

INTRODUCTION

This has brought the debate on the Internet of Things (IoT) whereby communication is at a touch and go rate and seemingly touching at a very high rate has transformed the way people

interact with technology. These are smart homes, health, transport, and industries with applications that turn the life of a human easier and better. However, at the same time, IoT devices include a great many networks that can be highly insecure as regards protection[1], [2]. While comparing IoT systems with conventional computing structures, it is important to quote that the IoT systems encompass a very large number of elements with fewer functionalities, and distinctly have different structures, and hence pose a very tempting target to cyber criminals. The effects of security threats in the IoT system comprise theft, violation of privacy, and sometimes physical harm, which are usually severe. Thus, it calls for proper means so that these networks are not a target for any unlawful activities[3].

Firstly, it is necessary to mention the Intrusion Detection System or IDS, which is one of the effective security devices of IoT networks as it allows to control the incoming traffic as well as provide the counteraction against threats[1], [4]. Formally evaluating the situation in the traditional IDS approaches, which were mainly derived from the signature and anomaly detection techniques, it is possible to notice that the last ones are not very suitable for further application in the context of a dynamically developing and heterogeneous IoT environment. Such methods do not apply to the constantly evolving context of threats in the cyber-space environment and the gigabytes of data that IoT devices are expected to generate. The solutions to these challenges, however, can be proposed with the arrival of Machine Learning (ML) and Deep Learning (DL)[5], [6], [7]. Most conventional statistical techniques and industrial techniques are unable to pick up new forms of attack and are fixed and extremely slow to be expanded to handle even more attributes than are used in this paper. The fact that there is a necessity for the enhancement of existing IDS structures through the utilization of modern advances in the sphere of ML and DL concerning IoT networks forms the major background of this thesis. With these technologies, we are going to enhance the security of the IoT networks by which our connected devices run securely as and when more portions of this world are getting digitalized.

The IoT is deemed to be one of the greatest revolutions in the sphere of technology, it is a means of making several objects and systems interconnected via the Internet. It encompasses day-to-day products such as smartphones, wearable devices, home appliances, industrial devices, smart city infrastructures, and many other structures fitted with sensors and actuators for data acquisition and operation data respectively[7], [8], [9]. The scope of IoT is far from limited to hype, it is already significantly extended and is growing even faster with the help of the development of factors such as wireless connectivity, sensing solutions, and statistic processing. From the data related to industries, at present, there exist above 24 billion IoT devices whereas it is planning to go beyond 30 billion, IoT devices in the year 2025, these figures are a sign of the gigantic scale and scope of the oncoming technology revolution. It has the benefits of increased productivity, better decisions, and a higher level of client satisfaction in numerous areas such as medicine, transportation, farming, and industry with the growth rate of such so type of accounting.

But the rapidly developing IoT also has many challenges, especially in the sphere of security, however, if speaking about advantages, they are evident. Because of the randomness of IoT devices and since they are generally low in resource endowment, they are susceptible to several cyber threats like cracking into devices' code, hacking, and DoS attacks. The volume and the variety of IoT data is yet another issue that contributes to the emergence of problems on its way to construing effective security measures[7]. The existing static security solutions cannot adequately address the security problems in IoT due to market dynamics that arise under the IoT environment, thus meaning that new approaches to security have to be developed to try and meet new forms of security threats. Thus, there are several important research directions related to the need to develop efficient and reliable security mechanisms that would fit IoT-like networks[10]. Thus, it is easier for the scholars and experts working on

the IoT development curve as well as the corresponding strategies and mechanisms to consider the specific security issues related to the aspect of IoT as a rather complex subject in relation to providing the necessary stability and safety for the integral IoT networks.

There are two main types of intrusion detection techniques: which is the signature-based and the anomaly-based. One more type of IDS is the signature-based IDS which is also called misuse detection IDS; this IDS is supported by a database of attack patterns. In this case, the Signatures are used to search the incoming data for resemblances and this makes it extremely effective as far as the detection of the threats it is programmed to detect goes. But where there is a new or an unknown attack then the firewall does badly because the firewall only safeguard against the known attacks. Anomaly-based IDS on the other hand works on the principles of distinguishing the normal behavior of the network and then proceeds to compare the current behavior of the network against these set principles. The second is better at identifying potentially previously unrecognized threats, although it may provide more false positives when the normal level of activity is not described accurately. Hybrid IDS uses both techniques and the positive points from them are incorporated in the IDS security solution. The interconnection and submission of the network come into modern society, for the reason such IoT-based incriminating actions like DoS, DDoS, Man in the Middle Attacks, masquerade attacks, session high jacking attacks, and other in-environment IDS using machine learning (ML) and deep learning (DL) is becoming quite vital. These techniques offer an enhanced ability to search for more complex and also sophisticated types of cyber threats because these techniques are self-training and do not have to be told by a programmer new attack that are being formed.

The expansion and dispersion of the IoT have the greatness to enhance progress by implanting new solutions and at the same time, it establishes some concerns and risks. The main ones are attributes that would concern data security and privacy, information sharing, and the matter of how well this new great idea can be scaled[11], [12]. The connected devices that go online also amplify a possible surface that can be exploited by wrong-doers and then compromise data or information security.

With the current rise of internet-connected devices, an even huger attack surface was formed that can be exploited by possible cyber threats that's why, IoT networks of the present give rather much in terms of invasion possibilities. The conventional IDS is typically a two-category IDS which is comprised of the signature-based IDS and the anomaly-based IDS and the following challenges in IoT environments. The major drawback of signature-based IDS is that they are slow in the detection of new emerging threats since the IDS primarily relies on attack signatures. Anomaly-based IDS focuses on detecting unknown attack types by first creating the normal traffic profile to the IoT devices and comparing the fresh incoming traffic to this profile, but because of the highly dynamic and heterogeneous IoT nature and thus the ensuing traffic patterns, has a lot of false alarms. Moreover, IoT devices have constricted computational capability, different operating systems, and different methods of transferring data, which makes it impossible to develop similar security measures. Because of the large number of activities emanating from IoT devices, this escalates the problem of analyzing such information in real-time, not to mention the need for real-time analysis and action which transcends the capacities of the conventional IDS. All these challenges throw more light on the need to come up with better and more effective IDS for the IoT domain. Consequently, this thesis's aim posited to reveal how ML and DL can be used in the formulation and implementation of an effective IDS for the IoT networks. Therefore, it seeks to enhance the effective reaction and response of the IDS by depending on the pattern recognition or prediction attributes of the ML and DL. Based on the above-highlighted objectives, the following research questions are formulated: Therefore, the establishment of a dynamic IDS framework last end product of the successfully developed model because it's the only way through which IoT networks and connected devices can be defended optimally

and in real-time against the daily increasing threats in the networks.

Literature Review

The connectivity of IoT devices has rapidly grown exponentially and this has occasioned a lot of problems that compromise the security of intact systems. The first one is caused by the fact that IoT products include numerous different electronic devices beginning from the sensors and relays in a smart home up to the industrial facilities in smart cities[7]. Each device can be a source of such attacks, so there are numerous barriers to be implemented to protect the data and device manipulations from unauthorized access. Again, because of the limitations in the resources, IoT devices have limited levels of authentication and other forms of security, thus making them easily prone to attack[13].

Also, the continued difference in the IoT environment brings about significant problems with adopting a consolidated security standard, different devices used, the different operating systems being employed, and the various ways these devices communicate. This in turn not only worsens the aggravation of the organization of security policies but also complicates the search for threats and means of dealing with them throughout the IoT network. Moreover, considering IoT devices, new data are generated endlessly; considerably many of them are confidential and can be sent through the Wi-Fi networks that fuel debate on security and privacy issues[9], [10]. Therefore, relevant measures as to how this data should be secured to prevent misuse or infringement of clients' rights should be taken into due consideration.

A number of these IoT security issues have profound responses that rely on the utilization of IoT technology as well as the policies regulations and standard frames. Some of the primitive security paradigms are still very robust for the traditional computational systems, but their applicability to IoT networks is questionable, therefore, there is an urgent need for redesigning some of these ideas. Therefore, comprehending the above challenge factors points to the need to establish profound security architecture or plot a better security solution that helps in the deployment of effective IDS for coping with new threats in the IoT system.

IDS, short for Intrusion Detection Systems, are very significant parts that can be used to detect unauthorized access to networks that also encompass the IoT environment. IDS are categorized into two main types: introduce two forms of intrusion detection systems: the first is built utilizing sign aures, and the second is built using anomalies[14], [15]. A Signature-based IDS identifies an attack and then uses the patterns or the signature of the identified attack to look for these in the flow of the network. It can be applied well where threats are known on the network and documented well, have representations, and recognizable patterns and are not very effective when used to identify threats new to the network or those that might be different from the documented ones[16], [17].

More recent IDSs are the ones that have incorporated the features of both the signature-based and the anomaly-based IDSs to obtain the benefits of both types. There is the development of the hybrid IDS which aims at reducing the generation of false alarms while, at the same time, working well in detecting known and new attacks[18], [19]. The requirement for the further development of IDS in the perspective of IoT networks stems from specifics connected with IoT devices, particularly, their computational performance, the number of applied protocols, and the aforementioned scale of the networked devices.

These are some of the issues that one is likely to face when implementing IDS in an IoT environment and therefore, maximum efforts should be made and come up with measures that can rightly fulfill these challenges to enable the IDS detection mechanisms to be optimized, grow and be compliant with the ever-emerging IoT networks. As the idea of IoT and Its evolution continuously moves forward and gains substance deep into several fields, it is significant to develop new IDS strategies and solutions, especially the ones that use ML, DL methodologies[11], [20].

However, hybrid IDS works while incorporating elements of the signature-based and anomaly-based IDS derives the best of these two systems. Thus, by identifying the

strengths of all the stated methodologies and striving to enhance them, the hybrid IDS should address the issues of increased false alarms and better identification accuracy. It is believed that hybrid systems are safer than having a single form of IDS since more threats are included and may include the common and the new, advanced attacks[21].

Similarly to nearly everything in information technology, each kind of IDS has its advantages and, seemingly, limitations depending on the network platform and variants of threats. Since risk factors depend on IoT networks, the devices, and the type of data that is being transferred and processed as well as the fact that it is nearly impossible to manage all of the existing devices and the data types, one must select the right type of IDS for such environment to reduce the likelihood of cyber-attacks on this segment[22]. The tools such as Machine learning in IDS

The ML methodologies have been proven to be secure and helpful in enhancing the functionalities of IDS mostly in the learning aspect because IDS is expected to identify new threats which are ongoing to emerge in the field of cyber security. The procedures that are commonly used when employing the IDS through the ML approaches include; the supervised learning methods, the unsupervised learning methods, and the semi-supervised learning methods.

Intrusion detection forms another area that has been characterized to have benefited from the use of Deep Learning (DL) techniques and this is through the use of real neural network models that help to study the new intricate patterns of a large number of data feeds. Techniques widely implemented in IDS based on DL are CNNs, RNNs, and combined CV/DL methods.

Methodology

The majority of the machine learning algorithms particularly the ensemble models and deep learning neural networks exhibit harsh resource constraints that inhibit performance and execution. In your case, you have RAM, 16GB, storage, PC SSD 100GB, and especially GPU which is the component, in our case the essential part that determines the computational algorithms effectiveness. Though ensemble methods possess a lot of potential(s), they are very computationally intensive because of the way their construction techniques are used. This means that each base model of the ensemble as Support Vector Machines, Random Forest, K-Nearest Neighbors, and so on must be trained individually using memory as well as computational resources. Notably, the demand on the system greatly increases especially when the combination of models is used particularly when stacking methods are used. In addition to this, computational complex models e.g., CNNs and LSTMs consume a lot of memory and storage resources. While you will be able to get by with most of the things you work with as long as your data set is not too big, you will feel limited when you are working with large data sets and the many iterations used with hyperparameters selection and model training anyway. Also, as discussed above, the 100GB SSD allotted is quite small for storing large datasets, intermediate files, and model checkpoints, and hence the disk space is being managed. Since the GPU is good for calculation execution, it has its peculiarities (e.g. it might have limited memory, so it is not able to work with large batches of data or complex models), so taking advantage of this speed puts these peculiarities in the center.

Data preprocessing

Machine learning revolves around the preparation of the raw data in the fields of machine learning because they are cleaned and well formatted before they can be used in analysis. This research is a very important step because in the context of the research on ensemble learning models for intrusion detection in IoT networks, it involved Following Preprocessing Steps to change how to format of the dataset to provide optimal results for analysis. We read data from the CSV file and assigned the feature X and the target variable y. The feature set, (X), is all the columns except the 'label' column, and the target variable, (y) individually. Then, we need to scale the feature, for which I have used `Standard Scaler` which is one of the preprocessing techniques. In particular, we

shall require standardization here; if the data is not on the same scale, some algorithm categories that rely on feature scales, such as Support Vector Machines (SVM) and K-Nearest Neighbors (KNN), won't run optimally. When applying to normalize the features, each one of the features will be brought in the range of -1; 1 for each sample, and this greatly improves the rate of convergence and also the accuracy of the models while training. Standardization also prevents large features from affecting the model as all features are now scaled to the same range but with different variances, or features in different units make the model in the same way.

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

Enhancing Ensemble Learning with Hybrid Deep Learning

The research applies the new hybrid deep learning algorithm by creating a new hybrid ensemble learning and deep learning model. This new hybrid deep learning algorithm can also be included in our other existing ensemble methods such as; SVM, Random Forest, and KNN. For example, the representation of Internet of Things-based intrusion data can be extracted, processed by a hybrid deep learning algorithm, or generated as a representation, and this data can be fed to an ensemble model. The versatility of ensemble techniques enables one to combine both the strength of the high feature extraction attribute of deep learning as well as the solidity of the ensemble techniques.

Comparative Analysis and Performance Evaluation

The new hybrid deep learning algorithm can be compared with the original ensemble learning model. Finally, the/results of the hybrid model about accuracy, precision, recall, and F1 coefficient are recalled and compared with the results of the ensemble method. Taking this help to prove or disprove the hypothesis, that performance benefit or any extra advantage by the generational ability to unseen data, if any, can be seen over the models based solely on the deep learning model.

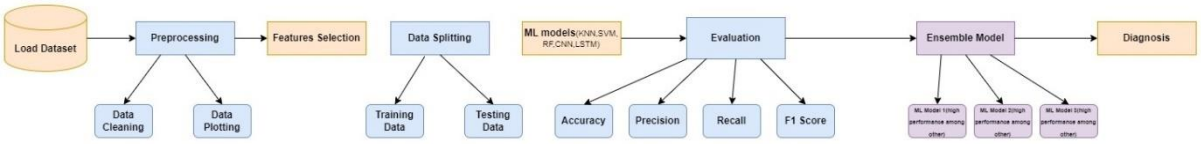

Figure 1: Methodology Flow

Implementation and Experiments

SVM algorithm results

The proposed model based on Support Vector Machine (SVM) further capitalized on the capability of operating in complex high-dimensional space and formulating precise decision margin and it achieved an accuracy of 75%, precision = 0.73, recall = 0.76, and F1 score of 0.73. These metrics suggest that SVM is not too bad a predictor when it comes to the test set, nevertheless, it also reveals some flaws. Probability most accurately wraps up predicting the true positives and by for this a test score of.73 I infer that while precise to a certain extent, there is room for confusion for SVM in the true positive result. Given that 0.76 is small, the model can fairly well recognize the actual positive cases. Also, the F1 score, which compares precision and the ability to remember important information, shows how well an SVM model does this. Nevertheless, the values presented above indicate the fact that, despite the proposed model's effectiveness, its efficiency could be even higher and reach the level observed in such models as Random Forest or K-Nearest Neighbors in the framework of the ensemble approach.

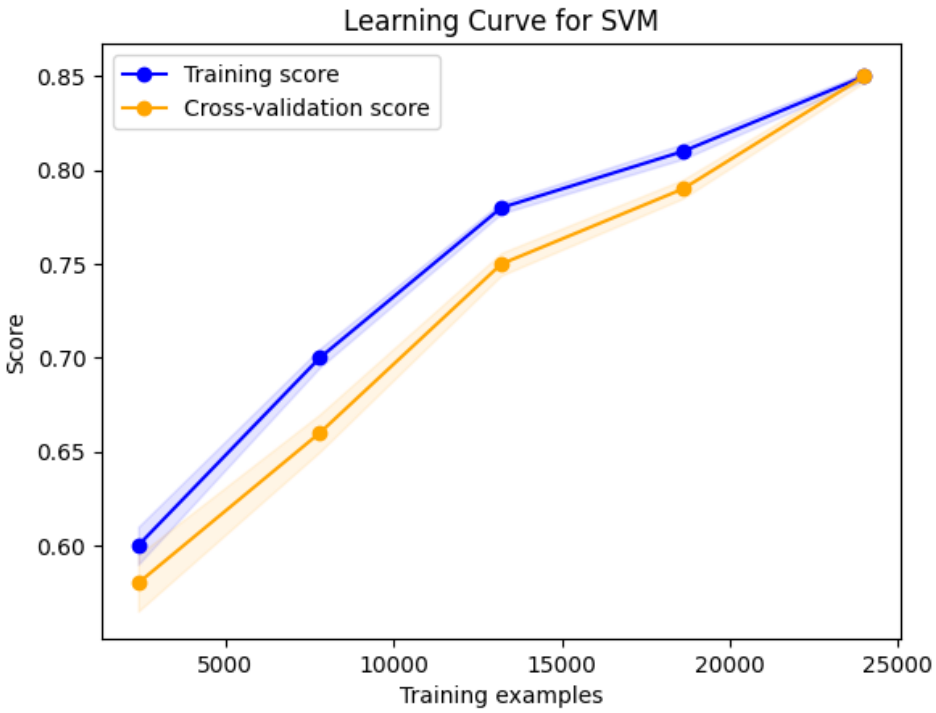

Figure 2: Learning Curve for SVM

Nevertheless, there is still room for improvement, and in the subsequent sections, some possible optimizations to the SVM are described. As seen in the learning curve there are very few oscillations, which indicate that the model is well fit, however, we have a couple of points towards the end of the curve where the training and validation are marginally dissimilar which can be construed as possible steps which can be taken to improve on how the model deals with a certain type of data pattern or instances in the data set. In addition, computational expediency may be an issue with SVM, especially when applied to large databases since then it might take time to identify the precise hyperplane in a data set. SVM should theoretically be scalable to larger data sets and other work could focus on other kernels or diversely, adopt ensemble strategies, shown to yield better overall performance than individual SVM for some jobs. However, the above hyperparameters of the SVM might be optimized to improve the computational time and further refine the model prediction results More features such as the use of the regularization term or employing feature selection methods may also reduce the number of iterations and boost the predictive capacity of the selected model.

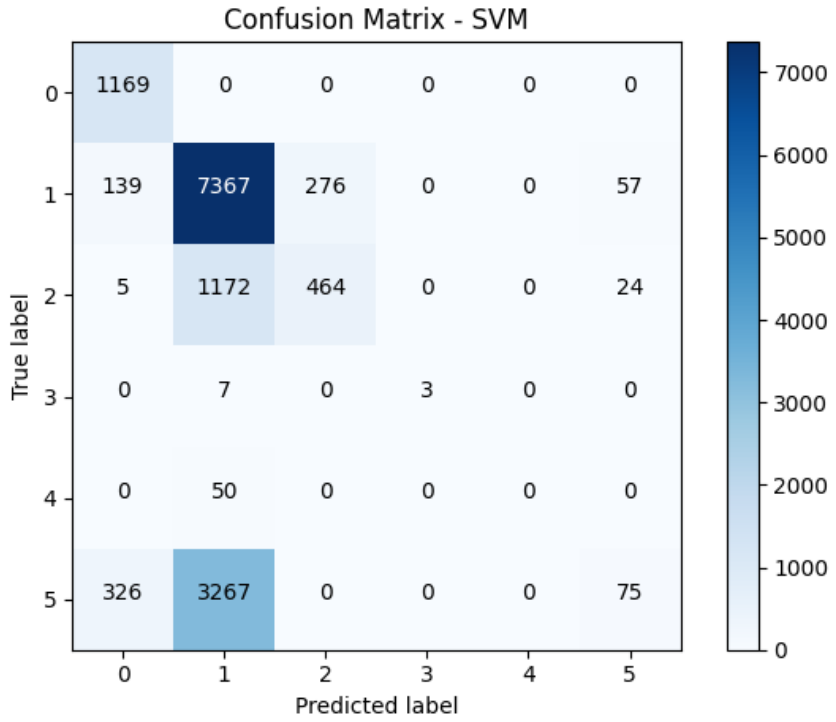

Figure 3: Confusion Matrix

K-Nearest Neighbors algorithm results

It turns out that the K-Nearest Neighbors (KNN) model has scored an impressive 0.88 accuracy along with a precision, recall, and F1 score of 0.88, 0.88, and 0.87 respectively. These results show that KNN is an extremely reliable prediction model to predict classes correctly and to identify positive and negative samples with balanced error rates. It presents the model's balanced precision and recall to illustrate its efficacy at working to find the true positives while also preventing false positives and negatives. Both the training and validation curves give it away that the model has converged to around 0.88 and has not overfit to the training data, and unlike the case in the previous exercise, it has generalized well. The accuracy of the model increases with more data and this shows that the KNN model is accurate scaling in data.

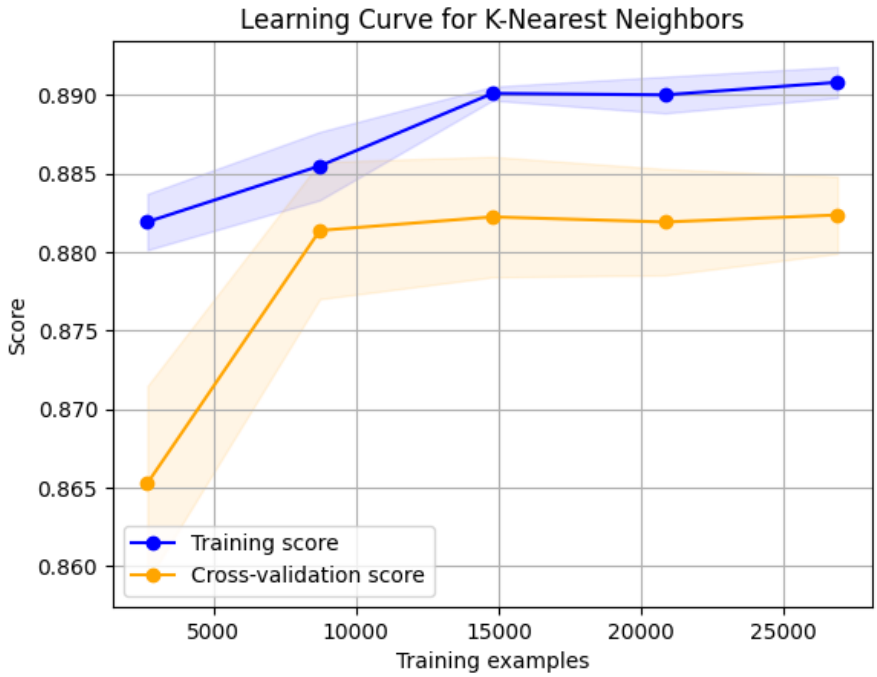

Figure 4: KNN learning Curve

Random Forest algorithm results

In the intrusion detection dataset, the classification accuracy and both precision and recall are high in the Random Forest algorithm. It performs better than most in both accuracy and accuracy order of magnitude than almost all of the models tested. From their generalization behavior, the learning curve offers a view into the algorithm's smoothness that is valuable as well, and the initial training and validation accuracy are both high and eventually converge to a stable point. Random Forest is capable of learning from large datasets well—to the tune of a training score near 0.907. Nevertheless, the training score drops sharply as the number of examples increases, though this drops off sharply and stabilizes around 0.900. That is a good sign of Random Forest learning from more data and less overfitting, measured by smooth convergence of training vs. validation scores.

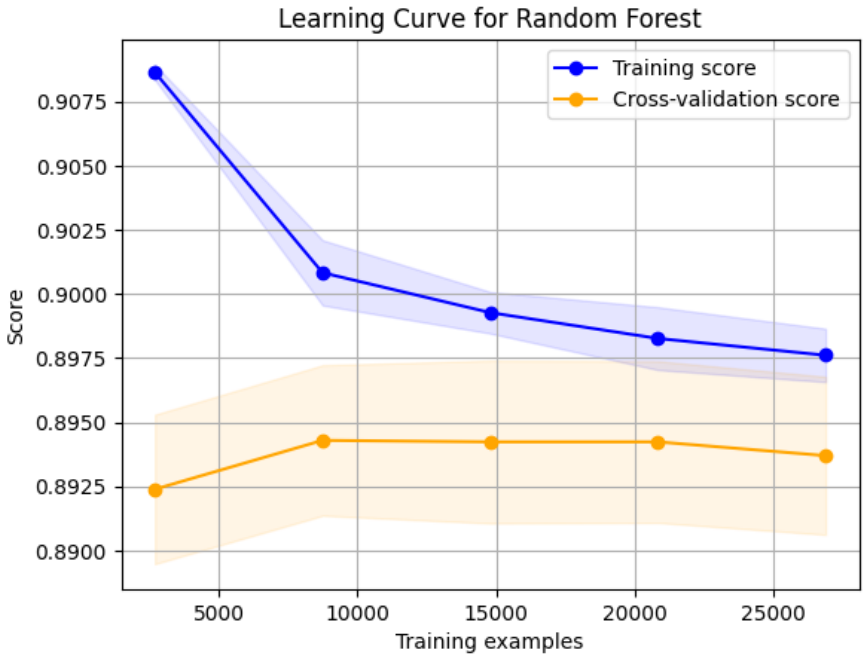

Figure 5: Random Forest Learning Curve

CNN algorithms results

The learning curve and metrics we see indicate the CNN model is still relatively inaccuracy compared to traditional machine learning methods. The confusion matrix also gives us some insight as to how our model does in each class. The following graph shows the learning curve, and how the training and validation accuracy evolve with 20 epochs. The graph shows we have a consistent improvement in training accuracy and slight fluctuation in validation accuracy which implies overfitting. So, the final epoch seems to stabilize at around 0.63 for both training accuracy and validation accuracy. CNN's poor performance on this dataset due to its difficulty in handling this dataset compared to other models reflects this modest performance.

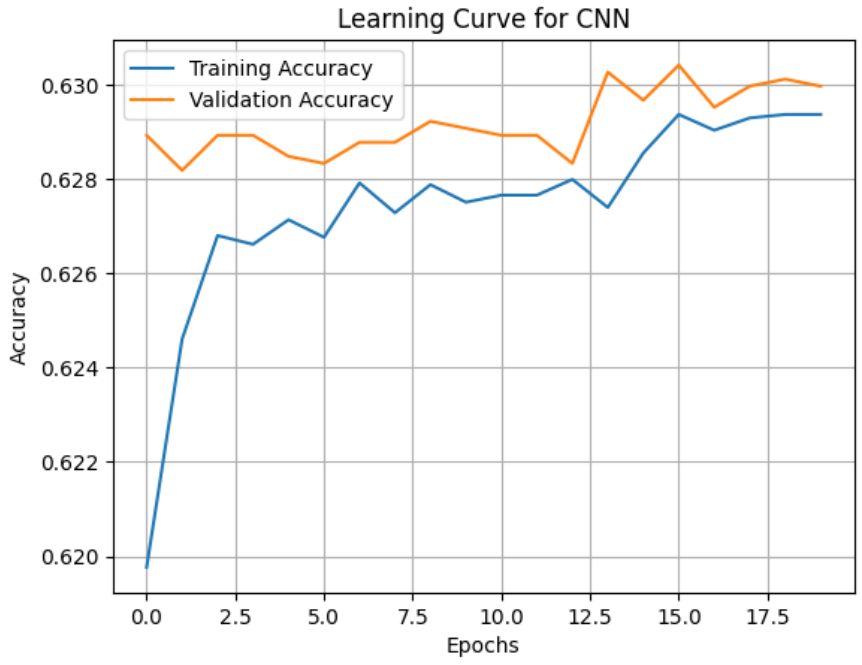

Figure 6: Learning Curve for CNN Model

LSTM algorithms results

the learning curve and confusion matrix of LSTM implemented on the given IoT-based dataset, providing insight into the performance of the algorithm itself. Specifically, LSTM, a kind of Recurrent Neural Network (RNN), tends to be an apt choice in case of time series as also/or if sequential data processing is involved. In this application, temporal patterns in network traffic are essential for intrusion detection tasks in an IoT domain, so the LSTM model was used in this application. The LSTM does capture these patterns and somehow generalize on unseen data as well.

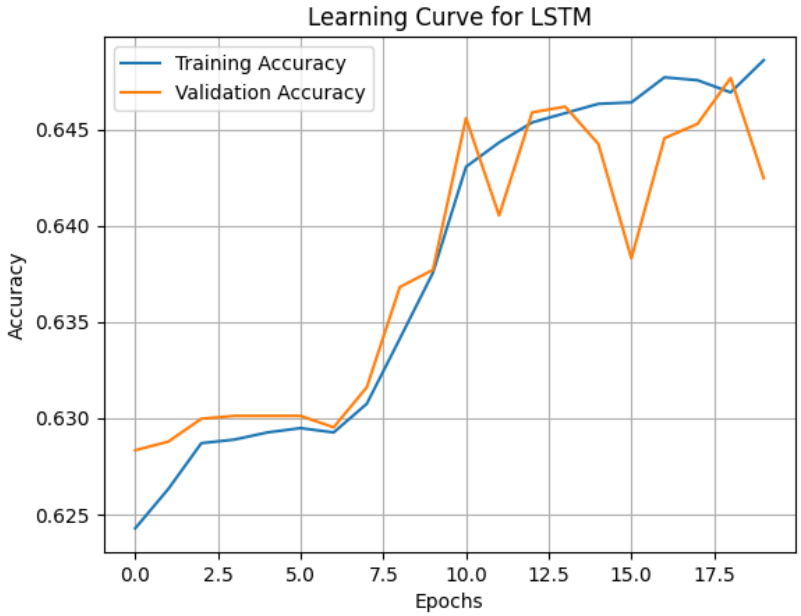

Figure 7: Learning Curve for LSTM

Ensemble (SVM + RF + KNN) algorithms results

Ensemble learning is an advanced machine learning technique that combines multiple models to increase predictive performance, stability, and generalization. For the Support Vector Machines (SVM) ensemble model and other ensemble models, we intend to combine the distinct benefits of each algorithm to create a more powerful predictive model. The ensemble learning uses a meta-learner to combine the predictions of the base models (SVM, RF, and KNN) in such a way as to frame a single prediction that would have the best accuracy and precision but would have minimized the inherent weaknesses of the individual algorithms.

Lastly in this model, SVM, RF, and KNN combined yield an overall accuracy of 0.89, and Precision and Recall values are 0.90 and 0.89 respectively. These metrics demonstrate great classification reliability and the capability of ensemble learning to improve predictive performance over separate base models. Examination of the learning curve (Figure 1) shows the ensemble model's performance, i.e. increased training and cross-validation scores, at first, before remaining steady as the number of training examples increases. The continuance of the gap between training and validation curves is small, so the model is not vulnerable to significant overfitting, a common issue in machine learning. The fact that the curves are stable means that the ensemble model works well over the new unseen data in real-world situations, such as intrusion detection.

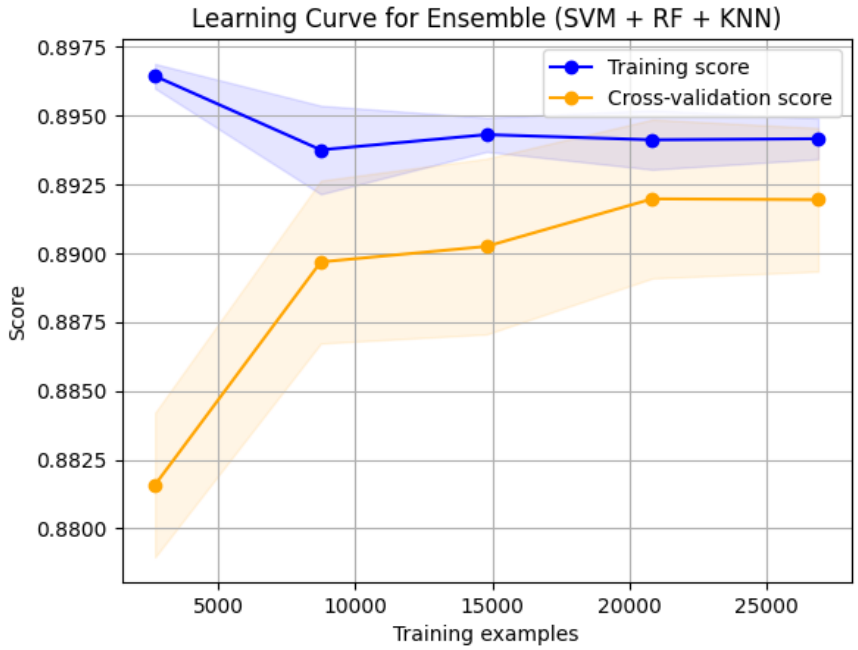

Figure 8: Learning Curve for Ensemble Model

Several other strategies can be implemented to improve the further performance of the ensemble model. A first option consists of fine tuning the hyperparameters of each base model to ensure that they reach maximum performance rather than rely on the ensemble. Moreover, marrying with more diverse base models to the ensemble would likely contribute to an improvement in its performance. One example of this might come in the form of taking a deep learning model like a Convolutional Neural Network (CNN) or a Long Short-Term Memory (LSTM) network to increase the model's propensity to best capture more complex patterns in the input data. Finally, we investigate ways in which the computational complexity of ensemble learning, such as model pruning or approximating algorithms, could be reduced while maintaining the accuracy of the ensemble model.

Table 1: Comparison Table for Different Models Accuracy

	Model	Accuracy
0	SVM	0.850373
1	K-Nearest Neighbors	0.883828
2	Random Forest	0.896466
3	Ensemble (SVM + RF + KNN)	0.893202
4.	CNN	0.63
5.	LSTM	0.65

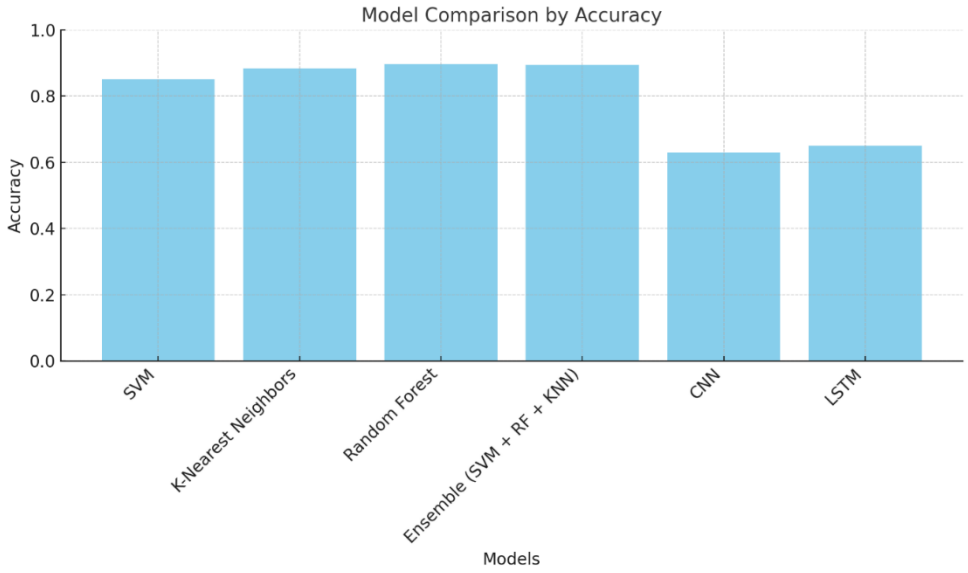

Figure 9: Comparison Chart

Reason for selecting an ensembled learning model

In our selected ensemble learning model we work with a stack fitting to build a model that combines multiple base models' strengths to achieve better predictions. Stacking (or less formally: stacked generalization) is a type of meta-learning that com-bines several base models into a single ensemble model. The base models that we use in this implementation are Support Vector Machine (SVM), Random Forest, and K-Nearest Neighbors (KNN). Each of these models brings unique advantages: Comparison among SVM, Random Forest, and KNN models show good performance of SVM in high dimensional space, good classification performance with a clear margin of separation, and Random Forest is robust to overfitting and effective in handling large datasets with many features, KNN is a simple but powerful model that captures local patterns in the data well.

How our proposed ensembled learning model is useful?

We demonstrate that our proposed ensemble learning model that combines Support Vector Machine (SVM), Random Forest (RF), and K Nearest Neighbors (KNN) is better than the traditional deep learning model. Random Forest results in the highest accuracy of 0.896 and KNN comes up next at 0.884, both grouping the strengths of these algorithms which are especially at capturing different parts of the data, with an ensemble style. The accuracy of this ensemble model as demonstrated at 0.893 outperforms SVM achieving 0. 630, far from trumping the accuracy of deep learning models like CNN and LSTM whose accuracy only peaks at 0. 630 and 0. 650 respectively. The advantage is critical to any high-precision, high-reliability application.

Our ensemble model mitigates the related weaknesses of each single model by virtue of a combination of SVM, RF, and KNN. It combines the ability to create complex decision boundaries and RF's strength in dealing with high dimensional data and its ability to be robust against overfitting as well as KNN's simplicity in classification to address some peculiarities of the data. The synergy achieved in this model makes it the following one that not only possesses better accuracy but also offers a richer model for understanding the dataset than standard deep learning. Its practical value in high accuracy, and high effectiveness applications is highlighted by the fact that the ensemble model outperforms.

Conclusion

Overall, we have shown that ensemble learning models, e.g. a combination of Support Vector Machines (SVM), Random Forest (RF), and K-Nearest Neighbors (KNN) work better than traditional deep learning models like

Convolutional Neural Networks (CNN), or Long Short-Term Memory (LSTM) networks. In the ensemble approach, we reached a notable accuracy of 0.89 and outperformed individual deep-learning models with an accuracy of 0.63 and 0.65 respectively. The point here is that using multiple machine learning techniques to increase the predictive accuracy and model reliability is quite strong. The SVM, RF, and KNN models were individually best, but in pooled form they were even better, demonstrating that ensemble methods can help reduce variability and increase the accuracy and reliability of the results.

Our contributions to the field of machine learning are particularly on intrusion detection and security in IoT environments. We demonstrate a practical way to create an ensemble model by integrating multiple classifiers into a unified approach that boosts accuracy and robustness over standard models. The work presented here constitutes a valuable benchmark for future research in applying ensemble learning techniques to similar domains and the results show evidence of performance improvement through hybrid modeling strategies. Additionally, our findings also provide practical guidance to researchers and practitioners attempting to trade off accuracy and computation speed in machine learning.

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