

Evaluation of Machine Learning Model for Network Anomaly Detection: Support Vector Machine

ABSTRACT

Effective network anomaly detection plays a pivotal role in safeguarding digital assets against evolving cyber threats in cybersecurity. This study aims to evaluate the performance of Support Vector Machine (SVM) models with different kernel types for network anomaly detection. Leveraging the neural structured learning - knowledge discovery in database (NSL-KDD) dataset, the research investigates SVM models employing linear, polynomial, radial basis function (RBF), and sigmoid kernels. The study employs experimentation methodologies, including data preprocessing, model training, and evaluation, to assess each SVM kernel's accuracy and F1 score. The findings reveal varying performances across kernel types, with linear and polynomial kernels exhibiting superior accuracy and F1 scores compared to RBF and sigmoid kernels. These results shed more light on the effectiveness of SVM kernels in detecting network anomalies and provide insights for future research and development in cybersecurity.

Keywords: Network Anomaly Detection, Support Vector Machine, SVM Kernels, NSL-KDD Dataset, Cybersecurity.

1. INTRODUCTION

In today's interconnected world, where data communication plays a pivotal role in every aspect of our lives, ensuring the security and integrity of computer networks has become paramount. With the exponential growth of network traffic and the increasing sophistication of cyber threats, the need for effective intrusion detection systems (IDS) has never been greater. An intrusion detection system is a crucial component of network security, tasked with identifying and mitigating malicious activities and unauthorized access attempts within a network environment [1].

Traditionally, intrusion detection systems have relied on rule-based techniques and signature-based detection methods to identify known patterns of malicious behaviours [2]. While these methods have been somewhat effective, they often struggle to detect novel and previously unseen attacks. As cyber threats continue to evolve and become more sophisticated, there is a growing need for intrusion detection systems that can adapt and learn from the ever-changing network landscape. Hence, Machine learning (ML) techniques have emerged as promising tools for network anomaly detection, offering the potential to detect previously unseen attacks and adapt to changing threat scenarios. Among the various ML algorithms, Support Vector Machine (SVM) has garnered significant attention for its effectiveness in classifying data points into different categories based on their features [3].

SVM is particularly well-suited for intrusion detection tasks due to its ability to handle high-dimensional data and its robustness against overfitting.

The aim of this research work was to evaluate the performance of Support Vector Machine models for network anomaly detection. By leveraging SVM's capabilities in identifying patterns and anomalies within network traffic data, thereby seeking to assess its effectiveness in detecting various types of cyber threats and distinguishing between normal and malicious network activities [4]. Through rigorous experimentation and analysis of different kernels, this work intends to gain insights into the strengths and limitations of SVM-based intrusion detection systems and provide valuable guidance for the development of more robust and reliable network security solutions.

The Neural Structured Learning knowledge discovery in database (NSL-KDD) dataset, short for "NSL-KDD Network Intrusion Detection Dataset," is a widely used benchmark dataset in the field of network intrusion detection [2]. It serves as a standard reference for evaluating the performance of machine learning models in detecting various types of network attacks and anomalies. Originally derived from the KDD Cup 1999 dataset, the NSL-KDD dataset addresses some of the limitations and biases present in the original dataset, making it more suitable for modern intrusion detection research. The dataset contains a comprehensive collection of network traffic data captured from a simulated computer network environment, encompassing both normal and malicious activities [5].

There have been a lot of researches in recent times in the area of machine learning based intrusion detection. Divekar et al [6] explored the vulnerability of Internet of Things (IoT) systems to cyberattacks due to changes and advancements in the IoT environment. The work highlighted the potential harm to physical and business assets resulting from these attacks. To address these security concerns, the authors employed various machine learning (ML) approaches, including Logistic Regression, Decision Tree, K-nearest Neighbor (KNN), Random Forest, and Support Vector Machine. Using the NSL-KDD dataset, these ML approaches were compared based on evaluation measures such as accuracy, precision, F1-score, and recall to predict and visualize attack threats effectively.

In [7], eight machine learning (ML) techniques were applied to detect intrusions, including neural networks, KNN, SVM, random forest, trees, AdaBoost, naive Bayes, and stochastic gradient descent (SGD). Using the NSL-KDD dataset, these ML techniques were trained and tested to classify network and operating system records into one of 24 possible attacks. The performances of these ML methods were analyzed and compared, with random forest achieving the highest performance. This study investigates more than four ML classifiers on this dataset, utilizing the same set of tools.

A machine learning-based methodology was proposed for detecting intrusions in computer networks [8]. The methodology consists of four main phases: preprocessing, feature selection, parameter optimization, and classification. Correlation Based Feature Selection was used to select the most significant features. For classification, Random Tree, AdaBoost, K-Nearest Neighbor (KNN), and Support Vector Machine (SVM) algorithms were employed, while particle swarm optimization is utilized for parameter optimization. The proposed method was evaluated on two extensive datasets, namely NSL-KDD and CIC-DDOS2019, to assess its effectiveness in intrusion detection.

Sekhar C, Pavani K, and Rao MS [9] focused on the potential of Software Defined Network (SDN) as the next-generation network architecture and addresses security concerns for its large-scale deployment. To enhance the accuracy of Network Intrusion Detection Systems (NIDS), the paper applied various Machine Learning (ML) and Deep Learning (DL) models.

The NSL-KDD dataset was used to evaluate the performance of these algorithms and through extensive experiments, the paper demonstrates that the F-measure rate can reach up to 87.72% for multiclass labels on the NSL-KDD dataset with twenty-two features using the K-Nearest Neighbors (KNN) algorithm. Furthermore, the k-Nearest Neighbor model outperformed other ML models in multiclass classification, as observed in numerous experiments.

A novel approach that integrates feature selection and classification for the NSL-KDD Cup 99 intrusion detection dataset using Support Vector Machine (SVM) was proposed in [10]. The goal was to enhance intrusion classification efficiency by employing a reduced set of input features extracted from the training data through feature selection, a crucial step in supervised learning that involves identifying important input features while eliminating irrelevant ones to improve classification accuracy. In this research, the SVM classifier was applied to various subsets of input features from the training dataset of NSL-KDD Cup 99 to assess the effectiveness of the proposed approach.

2. METHODOLOGY

2.1 Data Collection and Preprocessing

The study utilized the Google Colab notebook environment with Python programming language, focusing exclusively on the NSL KDD dataset sourced from Kaggle. This dataset, tailored for intrusion detection studies, encompasses diverse features such as protocol types, service types, and connection attributes. Prior to model training, rigorous preprocessing steps were undertaken, including data cleaning, feature selection, and normalization, to ensure data integrity and consistency.

2.2 Performance Comparison

A comparative analysis of SVM models with different kernels was conducted, focusing on their accuracy and F1-score. This analysis will enable the discernment of the relative performance of each kernel in accurately identifying cyber threats and classifying network traffic.

In Support Vector Machine (SVM), kernels are essential components that enable the algorithm to handle non-linear classification tasks effectively. Kernels function by transforming the input data from the original feature space into a higher-dimensional space, where it becomes easier to separate classes with a hyperplane [11]. This transformation allows SVM to capture complex relationships in the data and create non-linear decision boundaries. The types of kernels used in SVM and considered in the work are discussed in the following subsections:

2.2.1 Linear kernel

The linear kernel is the simplest and most commonly used kernel in SVM. It computes the dot product between feature vectors in the original input space, resulting in a linear decision boundary. The decision boundary separates classes by a straight line or hyperplane. Linear kernels are suitable for datasets where classes can be effectively separated by a linear boundary.

2.2.2 Polynomial kernel

The polynomial kernel introduces non-linear decision boundaries by computing the dot product raised to a specified power between feature vectors [12]. This allows SVM to capture more complex relationships in the data that cannot be separated by straight lines. The degree parameter controls the degree of the polynomial, influencing the flexibility of the decision boundary. Higher degrees result in more complex decision boundaries.

2.2.3 Radial basis function (RBF) kernel

The RBF kernel, also known as the Gaussian kernel, measures the similarity between data points based on their Euclidean distance in the original feature space. It maps the data into a higher-dimensional space using a Gaussian similarity measure [13]. The RBF kernel is highly flexible and can capture complex non-linear relationships in the data. It is capable of creating decision boundaries of varying shapes and complexities, making it suitable for a wide range of datasets. The parameters of the RBF kernel, such as gamma (γ) and C, control the smoothness of the decision boundary and the trade-off between model complexity and accuracy.

2.2.4 Sigmoid Kernel

The sigmoid kernel computes the similarity between data points using the hyperbolic tangent function. It maps the data into a higher-dimensional space, allowing SVM to handle non-linear relationships [12]. However, sigmoid kernels are less commonly used compared to linear, polynomial, and RBF kernels. They are suitable for specific datasets with non-linear relationships, but generally may not perform as well as other kernels.

Fig. 1 shows the simulated map from synthetic data of the learning behaviour for linear, polynomial, RBF and Sigmoid SVM kernels.

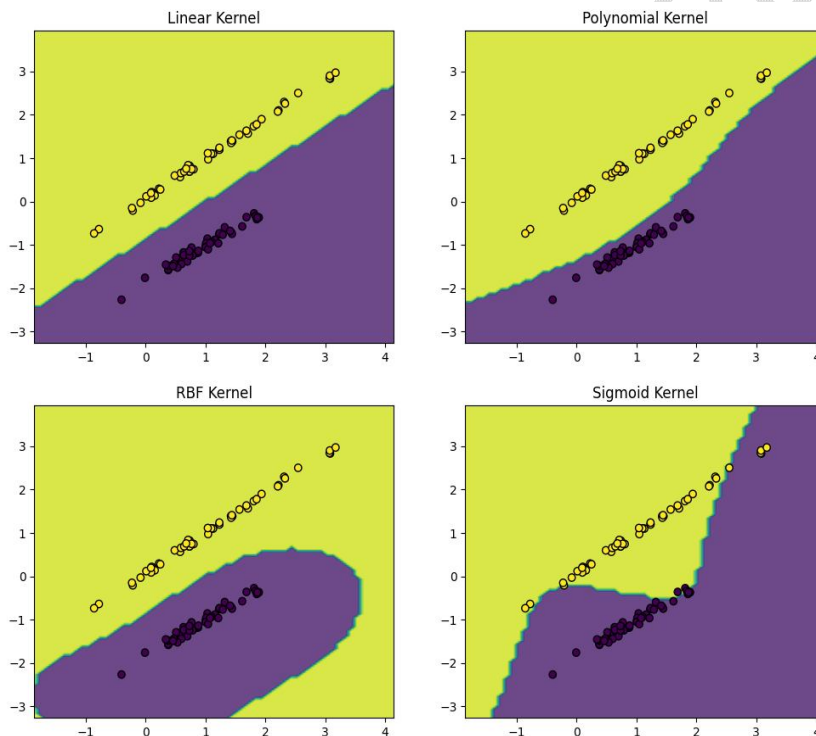


Fig. 1. Kernels in Support Vector Machine [Author]

2.3 Model Training and Evaluation

The scikit-learn (Sklearn) library is used to facilitate the training of Support Vector Machine (SVM) models with four distinct kernels: linear, polynomial, radial basis function (RBF), and sigmoid. Through stratified cross-validation, the dataset was divided into training and testing sets to maintain class the balance. Subsequently, SVM models were trained on the training

data and evaluated using standard performance metrics, namely accuracy and F1-score, to gauge their efficacy in detecting network anomalies and classifying network traffic.

2.3.1 Metrics

Since the data may only have one of four statuses, true or false, positive or negative, T_P was used to connote the true positive values which is the number of instances correctly classified as positive, F_P used to represent the false positive values which is the number of instances incorrectly classified as positive, T_N denoted true negative values which states the number of instances correctly classified as negative and F_N deployed to signify the false negative value which is the number of instances incorrectly classified as negative. The precision, sensitivity, F1 score and accuracy were calculated for the different SVM kernels using Equations 1-4 [14].

The precision or measure of the proportion of correctly predicted positive instances out of all instances predicted as positive was calculated using Equation 1.

$$Precision = T_P / (T_P + F_P) \quad (1)$$

The proportion of correctly predicted positive instances out of all actual positive instances is known as the sensitivity or recall. It was determined using Equation 2.

$$Recall = T_P / (T_P + F_N) \quad (2)$$

F1 score or F-measurement is the harmonic mean of precision and recall. It provides a balance between precision and recall and was calculated using Equation 3.

$$F1 - Score = 2 \left[\frac{(Precision \times Recall)}{(Precision + Recall)} \right] \quad (3)$$

The accuracy measures the proportion of correctly classified instances (both positive and negative) out of all instances. It is calculated as shown in Equations 4.

$$Accuracy = (T_P + T_N) / (T_P + F_P + T_N + F_N) \quad (4)$$

The Macro average which calculates the average performance metric, such as precision, recall, or F1 score, across different classes independently and the Weighted average which considers the average performance metric by assigning specific weights to each class based on their importance. They were calculated using Equations 5 and 6 [7].

$$MacroX = \frac{1}{N} \times \sum X_i \quad (5)$$

$$Weighted_X = \frac{\sum (X_i \times C_i)}{\sum C_i} \quad (6)$$

Where N is the number of classes, C is the number of instances in the class and X represent the precision metric under consideration such as Precision, Recall, F1 Score

2.3.2 Algorithm

Model training and evaluation was achieved using Algorithm 1.

Algorithm 1: Model Training and Evaluation

1. Start
2. Load dataset from Google Drive df

3. Encode_Categorical_Features(df)
4. Split data into training and testing sets: X_train, X_test, y_train, y_test
5. Standardize features: X_train_scaled,)
6. Define kernel type= ['linear', 'poly', 'rbf', 'sigmoid']
7. f_scores = []
8. accuracies = []
9. Train and evaluate SVM model for each kernel type
10. FOR EACH kernel IN kernel_types:
 - svm_classifier = Initialize_SVM(kernel)
 - svm_classifier.fit(X_train_scaled, y_train)
11. Make predictions
12. Evaluate the model:
 - f_score
 - accuracy
13. Store results
14. Print results
15. Plot_F_Score_Comparison
16. Plot_Accuracy_Comparison
17. END

Fig. 2 shows the simulated heat map generated.

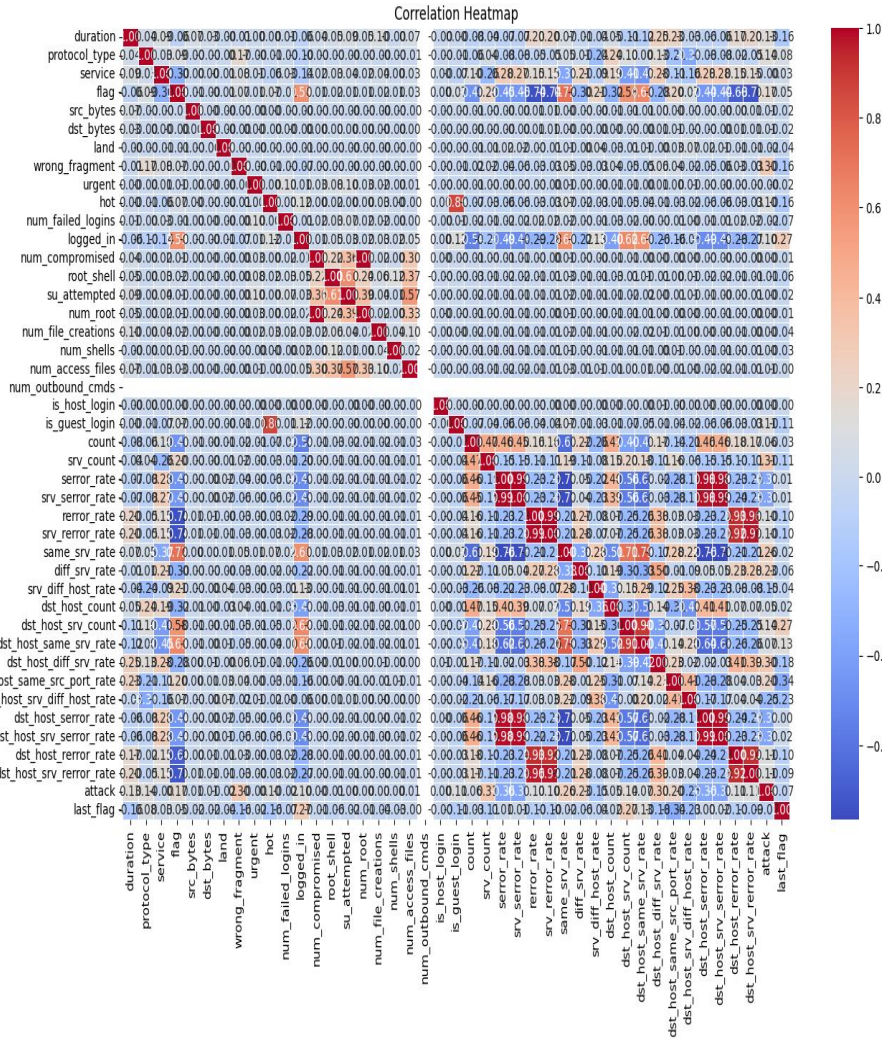


Fig. 2. Correlation Heat Map [Author]

3. RESULTS AND DISCUSSION

3.1 Results

THE ATTACK CLASS MAPPINGS AND THE RESULTS OBTAINED FROM THE DIFFERENT KERNELS SIMULATIONS ARE HERE PRESENTED. THE PROVIDED RESULTS PRESENT AN EVALUATION OF SUPPORT VECTOR MACHINE (SVM) MODELS WITH DIFFERENT KERNEL TYPES FOR NETWORK ANOMALY DETECTION.

3.1.1 Attack class mapping NSL KDD

- 0. Back: Refers to a network attack attempting to overwhelm a system or network resource, causing denial of service.
- 1. Buffer Overflow: Involves exploiting a program's buffer overflow vulnerability to execute malicious code.
- 2. FTP Write: Indicates an attack where unauthorized users attempt to write or transfer files via the FTP service.

3. Guess Password: Involves attempting to gain unauthorized access by repeatedly guessing passwords.
4. IMAP: Stands for Internet Message Access Protocol, an attack involving unauthorized access or manipulation of email accounts using IMAP.
5. IPSweep: Refers to scanning a range of IP addresses to identify live hosts on a network.
6. Land: A type of network attack where a malicious packet is crafted to cause a system to respond to itself.
7. Loadmodule: Involves loading a malicious module or code into a system to exploit vulnerabilities.
8. Multihop: Indicates a network attack involving multiple intermediate hosts to conceal the true origin of the attack.
9. Neptune: Denotes a denial-of-service attack that floods the target with traffic, rendering it unavailable.
10. Nmap: Stands for Network Mapper, an attack using the Nmap tool to discover and map network hosts.
11. Normal: Represents normal network traffic, not associated with any malicious activity.
12. Perl: Involves exploiting vulnerabilities in Perl scripts or applications.
13. PHF: Stands for "Personal Home Page," an attack attempting to exploit the CGI program used for accessing personal webpages.
14. Pod: Refers to a network attack that attempts to overload the target system's resources.
15. Portsweep: Indicates scanning multiple hosts for open ports, often as a precursor to an attack.
16. Rootkit: Involves installing software to gain unauthorized access while concealing its presence.
17. Satan: Refers to a network attack using the tool Satan, which performs security vulnerability assessments.
18. Smurf: Denotes a type of denial-of-service attack that floods a network with spoofed ICMP echo requests.
19. Spy: Suggests espionage-related activity, possibly involving unauthorized access to sensitive information.
20. Teardrop: A denial-of-service attack involving fragmented packets designed to crash the target system.
21. Warezclient: Indicates a client involved in downloading or distributing pirated software.
22. Warezmaster: Denotes a central figure or server coordinating the distribution of pirated software.

3.1.2 Results of Linear Kernel SVM

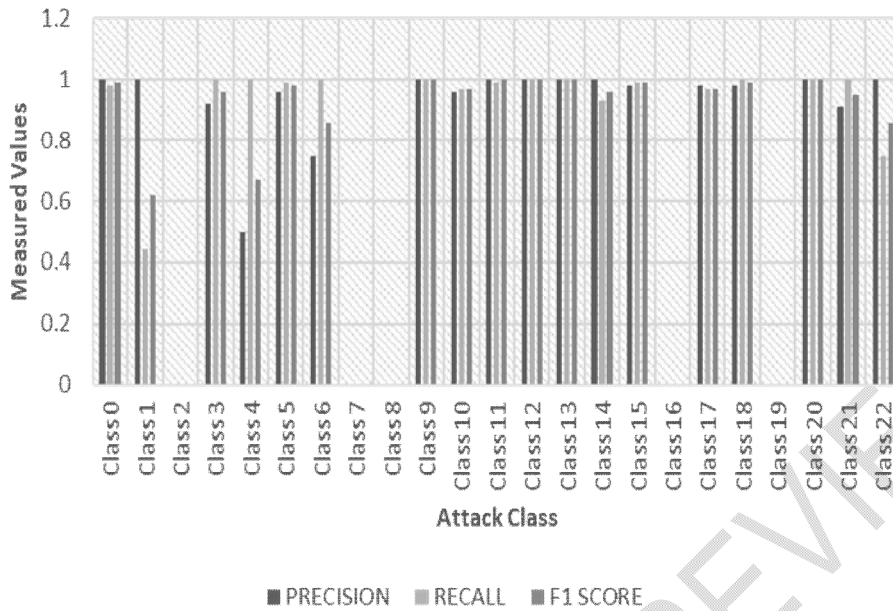


Fig. 3. Linear Kernel Attack Classification Results

The Linear Kernel SVM achieved a high accuracy of 99.47% and an F-score of 99.47%. The macro average F-score was 0.79, indicating variability in performance across different classes, while the weighted average was 0.99, showing strong overall performance. The classification report highlighted excellent precision and recall for most classes, especially with several achieving a perfect score (e.g., classes 0, 11, 12, 13, 20). However, some classes like 1, 7, 8, 16, and 19 had significantly lower performance, with zero recall and F-scores.

3.1.3 Results of Poly Kernel SVM:

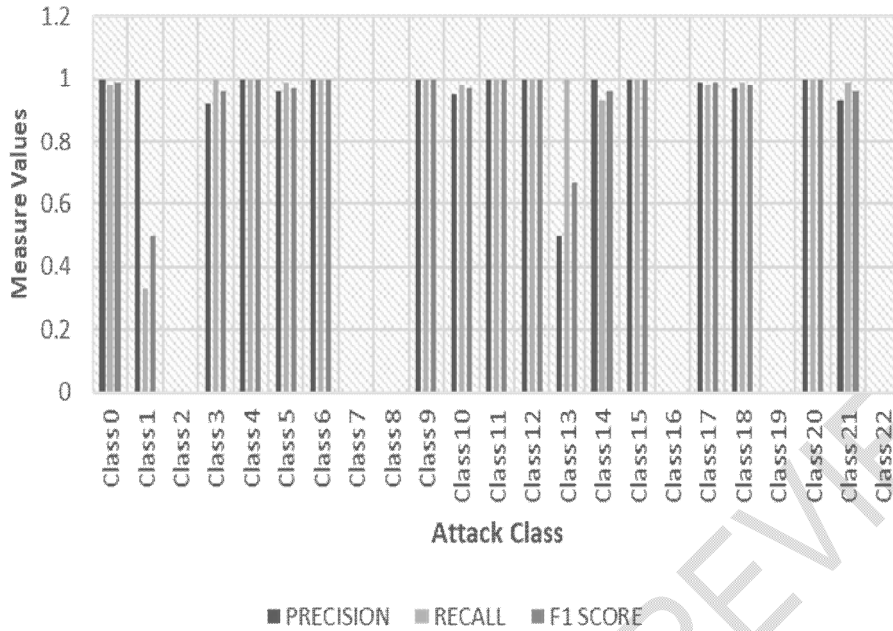


Fig. 4. Poly Kernel Attack Classification Results

The Poly Kernel SVM demonstrated an accuracy of 99.55% and an F-score of 99.53%. The macro average F-score was 0.72, suggesting notable variation in performance between classes, while the weighted average was 1.00. The classification report showed high precision and recall for many classes, with several achieving perfect scores (e.g., classes 0, 4, 6, 9, 11, 12, 20). Nonetheless, certain classes such as 1, 7, 8, 16, 19, and 22 showed poor performance, with zero recall and F-scores.

3.1.4 Results of Rbf Kernel SVM:

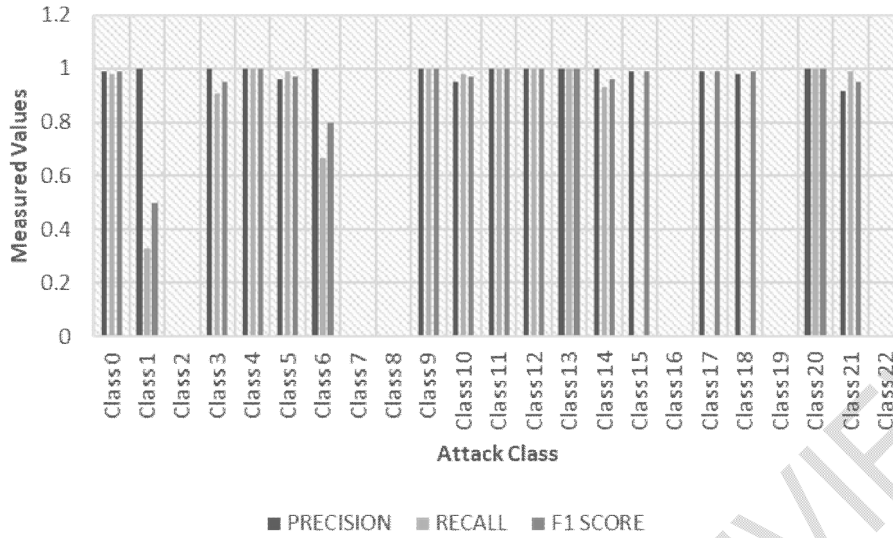


Fig. 5. Kbf Kernel Attack Classification Results

The RBF Kernel SVM recorded an accuracy of 99.55% and an F-score of 99.53%. The macro average F-score was 0.48, indicating considerable variation in performance across classes, and the weighted average was 0.92. The classification report indicated high precision and recall for several classes, particularly those achieving perfect scores (e.g., classes 0, 4, 9, 11, 12, 13, 20). However, classes such as 1, 7, 8, 16, 19, and 22 had very low performance, with zero recall and F-scores.

3.1.5 Results for Sigmoid Kernel SVM:

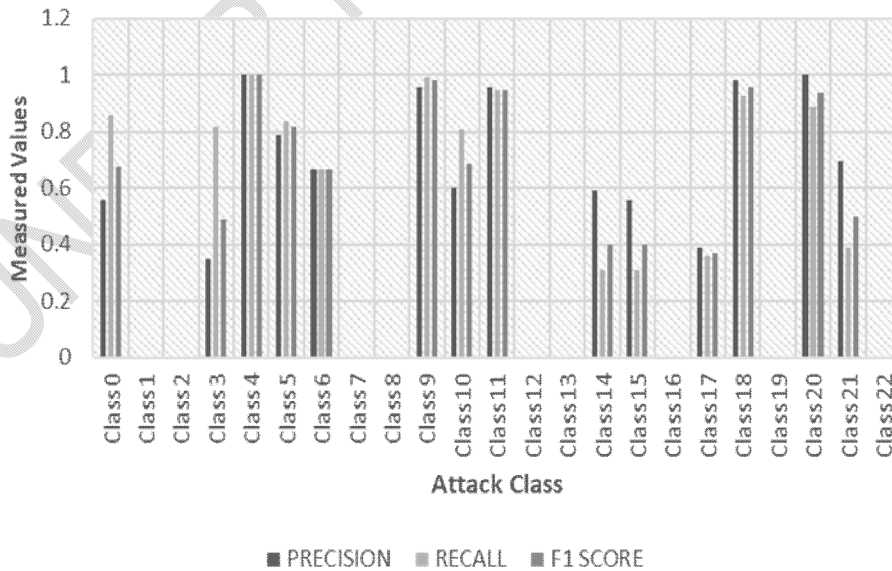


Fig. 6. Sigmoid Kernel Attack Classification Results

The Sigmoid Kernel SVM achieved a lower accuracy of 92.11% and an F-score of 91.80%. The macro average F-score was 0.79, and the weighted average was 0.99. The classification report revealed varying performance, with some classes like 4, 9, 11, and 20 achieving high precision and recall. However, several classes such as 1, 8, 12, 13, 16, 19, and 22 performed poorly, with zero recall and F-scores. This kernel showed considerable inconsistency and lower overall effectiveness compared to the other kernels.

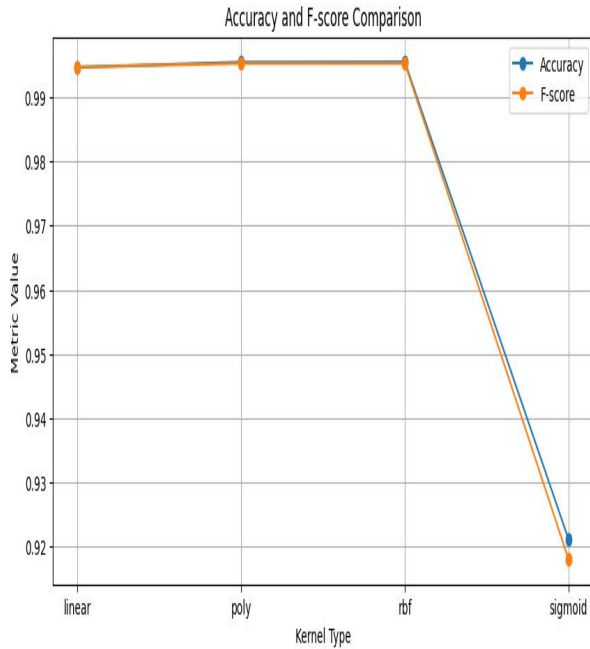


Fig. 7. Accuracy and F-scores comparison

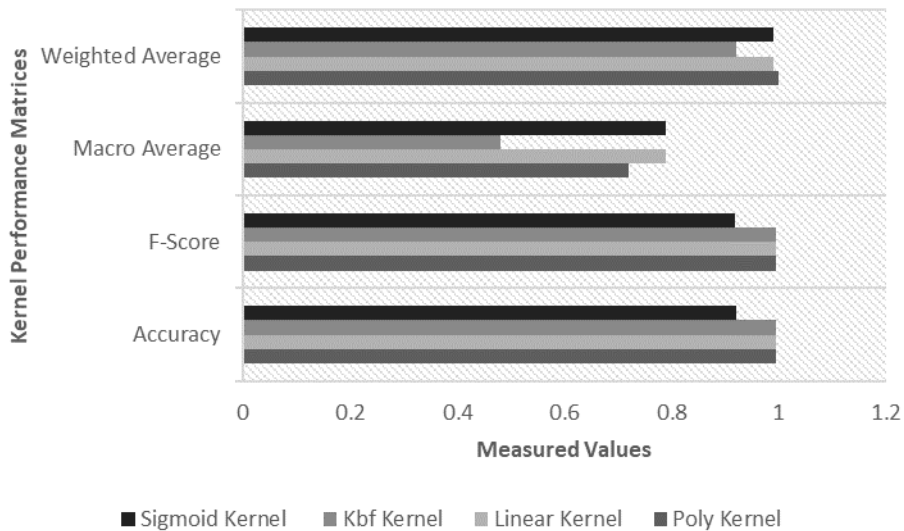


Fig. 8: Kernel Performance Analysis

4.0 Discussion

The SVM models exhibit high accuracy and F1-scores across all kernel types, indicating their effectiveness in classifying network traffic and detecting anomalies.

The accuracy values range from approximately 92% to 99.55%, demonstrating the models' ability to correctly classify the majority of instances in the dataset. The linear and polynomial kernel SVMs demonstrate the highest accuracy and F1-scores among all kernels, indicating their robust performance in capturing the underlying patterns in the data. The radial basis function (RBF) kernel SVM performs slightly lower than the linear and polynomial kernels but still achieves high accuracy and precision.

In contrast, the sigmoid kernel SVM exhibits noticeably lower accuracy and F1-scores compared to other kernels, suggesting its limited suitability for network anomaly detection in this scenario.

The results underscore the importance of selecting an appropriate SVM kernel for network anomaly detection tasks.

Linear and polynomial kernels demonstrate superior performance, making them preferable choices for this application.

The findings also highlight the need for further investigation into the factors influencing the performance of different SVM kernels, such as dataset characteristics and feature representation.

SVMs with different kernels have different hyperparameters that need to be tuned for optimal performance. Inadequate tuning of hyperparameters, such as the regularization parameter for linear SVM and the kernel coefficient for RBF SVM, could lead to suboptimal results.

4. CONCLUSION

The study presents an evaluation of Support Vector Machine (SVM) models with different kernel types for network anomaly detection. The experiments and analysis aimed to discern the performance characteristics of each SVM kernel and their implications for network security applications.

The findings of the research offer valuable insights into the comparative effectiveness of SVM kernels in accurately classifying network traffic and detecting anomalies. Notably, the linear and polynomial SVM kernels emerged as top performers, showcasing robust performance in capturing underlying patterns within the data. These kernels exhibited high accuracy and F1-scores, underscoring their suitability for anomaly detection tasks. Conversely, the sigmoid kernel SVM demonstrated comparatively lower accuracy and F1-scores, indicating its limited effectiveness in capturing the complexity of network traffic and identifying anomalies. Despite its computational efficiency, the sigmoid kernel may not be well-suited for nuanced anomaly detection scenarios.

Our research underscores the importance of informed model selection in network security applications. By understanding the strengths and limitations of different SVM kernels, practitioners can make judicious decisions in deploying intrusion detection systems. Moreover, our findings highlight the need for ongoing research to explore novel approaches and hybrid models that leverage the strengths of multiple kernels for enhanced anomaly

detection capabilities. Machine learning can be beneficial in many ways, and it is necessary to study its functionality in many cases. For instance, machine learning can be of great value in anomaly detection in devices through vibration analysis [15], in rain attenuation analysis [16, 17], In energy systems monitoring and performance prediction [18, 19] and in monitoring and evaluation of spectrum occupancy [20, 21] and network performance monitoring [22].

In conclusion, the study contributes to advancing anomaly detection techniques and developing resilient network security solutions. By providing empirical evidence and actionable insights, the research contributes to the empowerment of cybersecurity professionals in their efforts to safeguard critical network infrastructures against evolving cyber threats. Through continued collaboration and research endeavours, we can further strengthen the resilience of modern network systems and mitigate the risks posed by malicious activities.

Building upon the findings of this research, several avenues for future exploration may emerge, offering opportunities to advance the field of network anomaly detection and enhance cybersecurity practices. Investigating the efficacy of hybrid models that combine multiple SVM kernels or integrate SVM with other machine-learning techniques could yield improved anomaly detection capabilities. Hybrid approaches have the potential to leverage the strengths of different algorithms and enhance overall performance. Experimenting with ensemble learning techniques, such as bagging or boosting, in conjunction with SVM models could lead to more robust and resilient anomaly detection systems. Ensemble methods harness the collective intelligence of multiple models to achieve superior performance compared to individual classifiers.

The study's findings provided valuable insights into the effectiveness of SVM kernels for network anomaly detection. By comparing their accuracy and F1-score, the most suitable kernel for detecting specific cyber threats was identified, thereby contributing to the ongoing discourse in network security research.

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