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Evaluation of Machine Learning Techniques for Network Intrusion Detection Systems

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Abstract:
Intrusion Detection Systems (IDS) are critical for safeguarding network security by monitoring and analyzing network traffic for suspicious activities. This paper presents a comparative study of three machine learning algorithms—K-Nearest Neighbors (KNN), Logistic Regression, and Decision Tree classifiers—using a publicly available dataset from Kaggle. The objective is to evaluate the performance of these algorithms in detecting network intrusions, comparing their accuracy, precision, recall, F1-score, and computational efficiency. The results highlight the strengths and weaknesses of each model, providing insights into their suitability for real-world IDS applications.

Keywords: Intrusion Detection System, Artificial Intelligence, Machine Learning, Network Security, Real-time Detection, Threat Detection.

1. Introduction:

With the proliferation of the internet and the increasing reliance on digital communication, network security has become a paramount concern. As organizations and individuals alike conduct an ever-growing portion of their activities online, the potential risks associated with cyber threats have escalated. In this interconnected digital ecosystem, the integrity and confidentiality of sensitive information are constantly under threat from malicious actors seeking to exploit vulnerabilities in network infrastructure [3-53].

Intrusion Detection Systems (IDS) serve as a frontline defense against these threats, playing a vital role in identifying potential breaches and preventing unauthorized access to network resources. By continuously monitoring network traffic for suspicious activities and patterns indicative of malicious behavior, IDS act as vigilant guardians, alerting administrators to potential threats in real-time.

This paper investigates the effectiveness of three commonly used machine learning classifiers—K-Nearest Neighbors (KNN), Logistic Regression, and Decision Tree—in the context of intrusion detection.

2. Material and Methods:

2.1 Material:

Numerous studies have been conducted to enhance the performance of IDS using machine learning techniques. Previous research highlights the importance of feature selection, algorithm choice, and parameter tuning in achieving high detection rates. For instance, A. Patel et al. (2013) demonstrated the effectiveness of combining different machine learning models for improving IDS performance. This paper builds upon these insights by providing a comparative analysis of KNN, Logistic Regression, and Decision Tree classifiers using a Kaggle dataset.

2.2 Methodology

2.2.1 Dataset

The dataset used in this study is sourced from Kaggle and contains features indicative of normal and malicious network traffic. The dataset consists of various attributes that describe the characteristics of network connections, such as duration, protocol type, service, flag,etc. It includes labeled instances of both normal and attack traffic. This labeling facilitates supervised learning approaches, enabling the training of machine learning models to distinguish between benign and malicious network activity.

2.2.2 Data Preprocessing

Data preprocessing is a crucial step in preparing the dataset for machine learning models. The preprocessing steps include:

- **Handling Missing Values**: Missing values within the dataset are addressed using the forward fill method, ensuring that gaps in the data are filled with appropriate values derived from neighboring instances.
- **Encoding Categorical Data**: Categorical features are transformed into numerical representations through one-hot encoding. This transformation facilitates the incorporation of categorical variables into machine learning models.
- **Normalization**: To maintain consistency and comparability across different features, all attributes are normalized. This normalization process involves scaling the features to ensure they possess a mean of zero and a standard deviation of one, thereby preventing any single feature from disproportionately influencing the learning process.

2.2.3 Feature Selection

Feature selection is performed to reduce dimensionality and improve model performance. Techniques such as correlation analysis and recursive feature elimination are applied to identify the most significant features. This helps in reducing noise and computational overhead.

2.2.4 Machine Learning Models

2.2.4.1 K-Nearest Neighbors (KNN)

KNN is a non-parametric, instance-based learning algorithm that classifies a data point based on the majority class of its K-nearest neighbors in the feature space. It is simple to implement but can be computationally expensive, especially with large datasets.

2.2.4.2 Logistic Regression

Logistic Regression is a linear model used for binary classification tasks. It estimates the probability of a binary outcome using a logistic function. It is computationally efficient and interpretable but may struggle with non-linear relationships.

2.2.4.3 Decision Tree

Decision Tree is a non-linear model that splits the data into subsets based on the most significant feature at each node, forming a tree-like structure. It is easy to interpret and can handle complex decision boundaries but is prone to overfitting.

2.2.5 Model Evaluation

The models are evaluated using metrics such as accuracy, precision, recall, F1-score, and computational time. Cross-validation is employed to ensure the robustness of the results..The evaluation metrics are defined as follows:

- **Accuracy**: The proportion of true results among the total number of cases examined.
- **Precision**: The proportion of true positive results in all positive results predicted by the model.
- **Recall**: The proportion of true positive results in all actual positive cases.
- **F1-score**: The harmonic mean of precision and recall, providing a balance between the two.
- **Computational Time**: The time taken to train and test the model.

Through rigorous evaluation, the study aims to identify the most suitable model for intrusion detection applications, considering both performance and computational considerations

3. Results and Discussion:

3.1 Experimental Setup

The dataset is divided into training and testing sets with a ratio of 80:20. Standardization is applied to the features to ensure uniformity across different scales. The models are implemented using Python and the scikit-learn library.

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3.2 Performance Metrics

In this study, we evaluated the performance of three different classifiers—KNeighborsClassifier, LogisticRegression, and DecisionTreeClassifier—on a dataset aimed at distinguishing between normal and anomaly instances. The models were assessed based on their confusion matrices, precision, recall, F1-scores, and overall accuracy. Below, we present a detailed analysis of each model's performance, supported by a table summarizing the key metrics.

Table 1: Summary

Model	Accuracy	Precision	Recall	F1-score	Computational Time
K-Nearest Neighbors	0.98	0.98	0.98	0.98	12.5 s
Logistic Regression	0.92	0.93	0.92	0.92	5.8 s
Decision Tree	0.99	1.00	0.99	0.99	9.2 s

3.3 Analysis

K-Neighbors Classifier Analysis and Discussion

The K-Neighbors Classifier (KNN) model displayed a high level of performance with an overall accuracy of 98%. The precision, recall, and F1-score for both normal and anomaly classes were consistently high at 0.98, indicating the model's robust ability to correctly identify both normal and anomaly instances while minimizing false positives and false negatives.

Table 2: Comparison of k-NN Parameters

Metric	Normal	Anomaly	Overall
Precision	0.98	0.98	0.98
Recall	0.98	0.98	0.98
F1-Score	0.98	0.98	0.98
Accuracy			0.98

Strengths:

- **Local Structure Learning:** KNN excels in leveraging the proximity of data points, effectively capturing the local structure of the data. This makes it particularly effective in distinguishing between normal and anomalous instances.
- **Balanced Performance:** The model's high precision and recall for both classes indicate a balanced and robust performance.

Limitations:

Computational Complexity: KNN requires significant computation, especially with large datasets, as it calculates the distance between the query instance and all the training samples.

- **Memory Usage:** The need to store all the training data makes KNN memory-intensive.
- **Feature Sensitivity:** KNN's performance can degrade with the presence of irrelevant or redundant features, necessitating careful feature selection and scaling.

Logistic Regression Analysis and Discussion

Analysis

The Logistic Regression model achieved an accuracy of 92%, with precision scores of 0.94 for normal instances and 0.91 for anomalies. Recall was 0.89 for normal and 0.95 for anomaly instances, indicating the model's better capability in correctly identifying anomalies. The F1-scores were 0.92 for normal and 0.93 for anomalies, reflecting a good balance between precision and recall.

Table 3: Performance Metrics for Decision Classifier Models

Metric	Normal	Anomaly	Overall
Precision	0.94	0.91	0.92
Recall	0.89	0.95	0.92
F1-Score	0.92	0.93	0.92
Accuracy			0.92

Discussion:

Strengths:

- **Baseline Performance:** Logistic Regression serves as a reliable baseline model, performing well with linearly separable data.
- **Interpretability:** The model is straightforward to interpret, providing insights into the influence of individual features.

Limitations:

- **Linear Assumption:** The model assumes a linear relationship between features and the log odds of the outcome, which may not hold in all scenarios, limiting its ability to capture complex patterns.
- **Sensitivity to Outliers:** Logistic Regression can be adversely affected by outliers.

- **Flexibility:** The model lacks flexibility compared to non-linear models like KNN and Decision Trees.

Decision Tree Classifier Analysis and Discussion

Analysis

The Decision Tree model exhibited exceptional performance with an accuracy of 99%. The model achieved near-perfect precision and recall for both normal and anomaly instances, with precision at 0.99 for normal and 1.00 for anomalies, and recall at 1.00 for normal and 0.99 for anomalies. Both classes had an F1-score of 0.99.

Table 4: Evaluation of Various Classifier Algorithms

Metric	Normal	Anomaly	Overall
Precision	0.99	1.00	0.99
Recall	1.00	0.99	0.99
F1-Score	0.99	0.99	0.99
Accuracy			0.99

Discussion

Strengths:

- **Non-linear Relationship Handling:** Decision Trees are adept at capturing non-linear relationships and interactions between features, contributing to their superior performance.
- **Interpretability:** The tree structure provides clear interpretability, making the decision-making process easy to understand.
- **Performance:** High precision and recall across both classes indicate robust performance.

Limitations:

- **Overfitting:** Decision Trees are prone to overfitting, particularly when they become too deep, although this was not evident in the current results.
- **Bias:** The model can be biased if certain features dominate the decision process.
- **Instability:** Small changes in the data can result in different tree structures, leading to variability in results.

4. Conclusion

This paper presents a comparative analysis of KNN, Logistic Regression, and Decision Tree classifiers for intrusion detection using a Kaggle dataset. The results highlight that no single model outperforms others across all metrics, emphasizing the importance of context in model selection. Among the tested models, the Decision Tree Classifier demonstrated the best performance, with the highest accuracy, precision, recall, and F1-scores across both normal and anomaly classes. The K-NeighborsClassifier also performed well but has limitations related to computational complexity and feature sensitivity. Logistic Regression, while effective, lagged behind in handling complex, non-linear patterns due to its inherent linear nature.

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