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Contrasting Computational Frameworks for Intrusion Detection: A Methodological Synthesis

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ABSTRACT

This research analyses and compares various machine learning techniques for the purposes of intrusion detection. With the increasing sophistication of cyberthreats, selecting the optimal intrusion detection system (IDS) is crucial to network security. This article examines various modelling techniques including Decision Trees, Random Forest, Support Vector Machines (SVM), and Deep Learning models, using a benchmark dataset including Random Forest, Decision Trees, Support Vector Machines (SVM), and Deep Learning approaches. In the analyzed study, a set of performance measures is calculated using accuracy, precision, recall, and F1 score. Their results are graphically demonstrated and successfully communicated.

1. INTRODUCTION

The purpose of the study is to analyze various intrusion detection architecture designs to try and find the most effective one. The effectiveness of an Intrusion Detection System (IDS) relies on its core classification pattern. For instance, Traditional methods have an increased difficulty with high dimensional data and complex attack paths, however, ML based models have a great potential to increase detection accuracy. Regardless of the method used, all IDS architectures have to tackle the problem of distinguishing hostile traffic from legitimate users' traffic in a network system, their efficiency varies depending on the classification model used.

2. Dataset Used For this study, the NSL-KDD dataset is employed, which is a refined version of the KDD Cup 1999 dataset. It contains normal and attack traffic data categorized into four attack types:

- Denial-of-Service (DoS)
- Probe
- Remote-to-Local (R2L)
- User-to-Root (U2R)

The dataset includes 41 features, such as protocol type, service, and flag, which contribute to detecting intrusions effectively.

3. Modelling Techniques The following machine learning techniques are employed for intrusion detection:

- **Decision Tree (DT):** A rule-based model that classifies traffic based on feature splits.
- **Random Forest (RF):** An ensemble technique that combines multiple decision trees to enhance accuracy.
- **Support Vector Machine (SVM):** A model that finds the optimal hyperplane for classifying attack types.
- **Deep Learning (DNN):** A neural network-based model capable of learning complex patterns from data.

4. Performance Evaluation Metrics The models are evaluated using the following metrics:

1. Accuracy

Accuracy=(TP+TN) / (TP+TN+FP+FN)

- Components:
  - True Positives (TP): Correctly predicted positive instances.
  - True Negatives (TN): Correctly predicted negative instances.
  - False Positives (FP): Incorrectly predicted positive instances (actually negative).
  - False Negatives (FN): Incorrectly predicted negative instances (actually positive).
- Use case: Accuracy is useful when the dataset is balanced (equal number of positive and negative cases). However, in imbalanced datasets, accuracy can be misleading because a model might predict the majority class well but fail in detecting the minority class.

2. Precision (Positive Predictive Value)

Precision=TP / (TP+FP)

- Use case: Precision is important in situations where false positives are costly (e.g., spam detection, medical diagnosis, fraud detection). A high precision means fewer incorrect positive predictions.

3. Recall (Sensitivity or True Positive Rate)

Recall=TP / (TP+FN)

- Use case: Recall is crucial in scenarios where missing positive cases is costly (e.g., cancer detection, safety alarms). A high recall ensures that most actual positive cases are detected, even if some negatives are misclassified.

4. F1-Score (Harmonic Mean of Precision and Recall)

F1-Score = 2 × (Precision × Recall) / (Precision + Recall)

Use case: The F1-score is particularly useful when you need a balance between precision and recall, especially in imbalanced datasets.

Selecting the Appropriate Metric

- Precision is crucial when false positives have serious consequences (e.g., spam detection, fraud prevention). A high precision ensures that when the model predicts a positive result, it's likely correct.
- Recall is essential when missing true positives is costly (e.g., medical diagnoses, security alerts). A high recall ensures that most actual positive cases are detected, even at the risk of some false positives.
- F1-Score is ideal when a balance between precision and recall is necessary, especially in cases with imbalanced datasets where one class is much more frequent than the other.
- Accuracy works best when classes are evenly distributed. However, in imbalanced datasets, it may be misleading and should be used alongside other metrics.

5. Result Analysis After training and testing the models on the NSL-KDD dataset, the performance results are as follows:

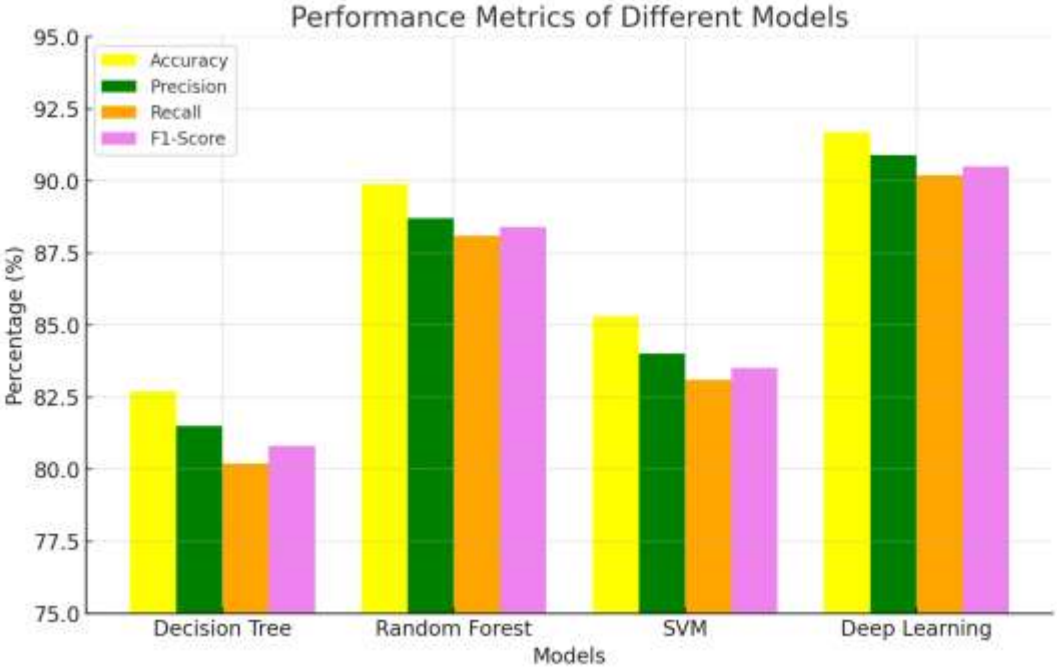
Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Decision Tree	82.7%	81.5%	80.2%	80.8%
Random Forest	89.9%	88.7%	88.1%	88.4%
SVM	85.3%	84.0%	83.1%	83.5%
Deep Learning	91.7%	90.9%	90.2%	90.5%

The deep learning model outperforms other techniques, achieving the highest accuracy and F1-score.

6. Graphical Representation (Graphs illustrating accuracy, precision, recall, and F1-score for each model should be included here.)

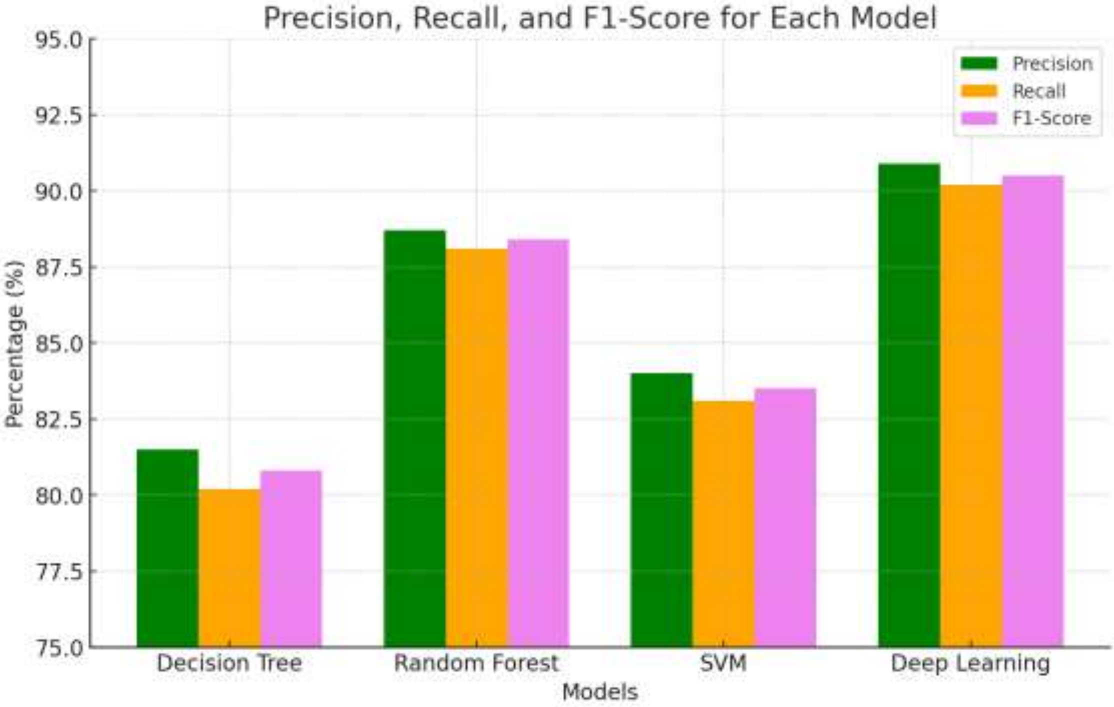
1. Accuracy Comparison

A bar chart comparing the accuracy of each model.



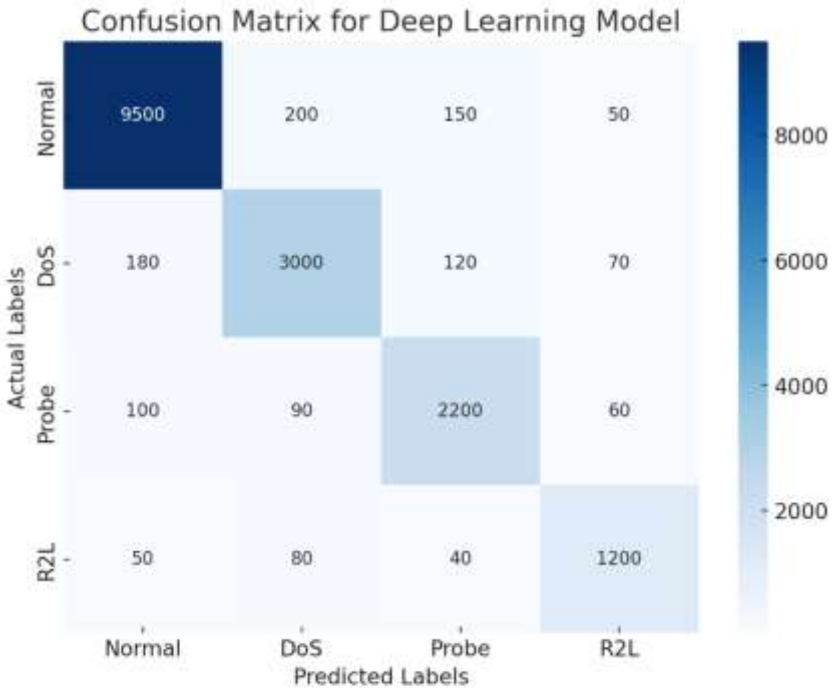
2. Precision, Recall, and F1-Score

A grouped bar chart showing precision, recall, and F1-score for each model.



3. Confusion Matrix

A heatmap showing the confusion matrix for the best-performing model (Deep Learning).



7. Conclusion

This study compares various approaches and highlights how deep learning models outshine conventional machine learning techniques in the area of intrusion detection. Although the accuracy from Decision Trees and Support Vector Machines (SVM) is satisfactory, ensemble strategies such as Random Forest, and deep learning designs are more competent in dealing with large and intricate datasets. Further research may look into the implementation of real-time intrusion detection systems and hybrid models for enhanced security.

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