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Comparative evaluation of machine learning classifiers for network intrusion detection using class-balanced benchmark datasets

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Abstract
Background: Network intrusion detection systems (NIDS) are a critical line of defence against cyberattacks, and machine learning approaches have increasingly replaced signature-based methods due to their ability to detect previously unseen attack patterns, though performance varies substantially across algorithms and is strongly affected by class imbalance in benchmark datasets.
Objective: This study evaluates and compares the performance of five machine learning classifiers, Naive Bayes, Logistic Regression, Random Forest, XGBoost, and a Deep Neural Network (DNN), for binary network intrusion detection (normal vs. attack traffic), with the Synthetic Minority Oversampling Technique (SMOTE) applied to address class imbalance.
Method: A simulated dataset, modelled on patterns reported in published research using the NSL-KDD and CICIDS2017 benchmark datasets, was used to evaluate accuracy, precision, recall, F1-score, and area under the ROC curve (AUC) across thirty simulated train-test runs (six replicates per classifier). Data were analysed using descriptive statistics and one-way analysis of variance (ANOVA) in Python (scikit-learn, XGBoost) and SPSS (version 27).
Key Results: XGBoost achieved the highest overall performance (accuracy = 98.6%, F1-score = 98.4%, AUC = 0.994), followed closely by the Deep Neural Network (accuracy = 98.2%) and Random Forest (accuracy = 97.8%). Naive Bayes recorded the weakest performance (accuracy = 89.4%, F1-score = 85.2%), consistent with its known sensitivity to feature independence assumptions. SMOTE-based class balancing improved minority-class (attack) recall across all classifiers, with the largest relative gain observed for Logistic Regression.
Conclusion: Ensemble tree-based methods, particularly XGBoost, offer the strongest balance of detection accuracy and computational efficiency for network intrusion detection on the benchmark datasets considered, while simpler probabilistic models remain useful as fast, interpretable baselines despite their comparatively lower detection performance.

Keywords: Network intrusion detection, machine learning, NSL-KDD, CICIDS2017, class imbalance, SMOTE, XGBoost

Introduction

The continued expansion of internet-connected systems, cloud infrastructure, and Internet of Things (IoT) devices has substantially widened the attack surface available to malicious actors, making robust network intrusion detection a foundational requirement of modern cybersecurity practice [1]. Traditional signature-based intrusion detection systems (IDS), which rely on matching observed traffic against a database of known attack patterns, are inherently limited in their ability to detect novel or evolving attack types, motivating a shift toward machine learning (ML) based approaches capable of learning generalizable patterns from traffic data rather than relying solely on predefined signatures [2].

Machine learning-based network intrusion detection systems (NIDS) typically frame the detection task as a classification problem, in which network traffic flow records or packet-derived features are labelled as either normal or as belonging to one of several attack categories, and a classifier is trained to distinguish between these classes [3]. A substantial body of research has applied a wide range of classifiers to this task, including probabilistic models such as Naive Bayes, linear models such as Logistic Regression, ensemble tree-based methods such as Random Forest and XGBoost, and deep learning architectures including deep neural networks (DNNs), convolutional neural networks, and autoencoders [4]. Reported detection accuracies in the literature frequently exceed 95% on standard benchmark datasets, though performance varies considerably depending on classifier choice, feature engineering, and how class imbalance is handled.

Class imbalance is a persistent and well-documented challenge in network intrusion detection research. Benchmark datasets such as NSL-KDD and CICIDS2017 typically contain a large majority of normal traffic records relative to attack records, and certain attack categories, particularly User-to-Root (U2R) and Remote-to-Local (R2L) attacks in NSL-KDD, are represented by very few samples [5]. Classifiers trained without addressing this imbalance tend to achieve high overall accuracy by effectively ignoring minority attack classes, which is operationally counterproductive for an IDS, since correctly identifying rare but severe attacks is often more important than overall accuracy on the dominant normal-traffic class [6]. The Synthetic Minority Oversampling Technique (SMOTE), which generates synthetic minority-class samples through interpolation between existing minority instances, has become a widely adopted mitigation for this problem [7].

Despite the volume of published research comparing individual classifiers or proposing novel hybrid architectures, relatively few studies present a single, internally consistent comparison across a representative spread of classifier families, probabilistic, linear, ensemble

tree-based, and deep learning, evaluated under the same preprocessing pipeline and the same class-imbalance mitigation strategy. This makes it difficult for practitioners to draw a clear, like-for-like conclusion about which classifier family offers the best practical trade-off between detection performance and implementation complexity for a given deployment context.

The specific objectives of this study are: (i) to compare the binary classification performance, accuracy, precision, recall, F1-score, and AUC, of five classifiers spanning probabilistic, linear, ensemble, and deep learning families; (ii) to evaluate the effect of SMOTE-based class balancing on minority-class detection across these classifiers; and (iii) to identify the classifier or classifier family offering the most favourable balance of detection performance and practical deployability for network intrusion detection. These objectives are intended to provide a clear, comparative basis for classifier selection in applied NIDS development.

It should be noted that, due to the absence of an accompanying physical network traffic capture, this article uses a simulated dataset constructed to reflect patterns consistently reported in the peer-reviewed literature using the NSL-KDD and CICIDS2017 benchmark datasets [8]. This approach is explicitly disclosed in the Methodology section and is intended for academic training, formatting practice, and illustration of statistical and machine learning reporting conventions; it is not presented as a record of original experimental classifier training on live network traffic.

Literature Review

1. Classical machine learning approaches to intrusion detection

Early machine learning applications to intrusion detection focused heavily on Support Vector Machines (SVM) and simple statistical classifiers. Kotpalliwar and Wajgi [9] applied SVM to the KDD CUP'99 dataset, establishing one of the earlier benchmarks for ML-based intrusion classification. Teng *et al* [10]. proposed a hybrid SVM-Decision Tree adaptive collaborative detection approach, finding that combining classifiers could improve robustness relative to either method in isolation. Gu and Lu [11] developed an approach combining Naive Bayes feature transformation with SVM classification, reporting accuracy as high as 99.35% on NSL-KDD, illustrating that feature engineering choices can meaningfully affect even comparatively simple classifier architectures.

2. Ensemble tree-based methods

Ensemble tree-based methods have become particularly prominent in recent NIDS literature due to their strong empirical performance and relative interpretability compared to deep learning alternatives. Devan and Khare [12] proposed an XGBoost-DNN hybrid architecture, using XGBoost for feature selection prior to DNN-based classification, reporting improved detection performance over either method used independently. Roy *et al* [13]. introduced a stacking ensemble of boosted decision tree models evaluated on IoT traffic using NSL-KDD and CICIDS2017, achieving 98.5% and 99.11% accuracy respectively, although detection of rare attack classes such as U2R and R2L remained comparatively weak even with ensemble methods. Zhang *et al* [14]. combined multi-dimensional feature fusion with a stacking ensemble mechanism, reporting accuracy exceeding 99% on CICIDS2017 for both binary and multiclass classification tasks.

3. Deep learning approaches

Deep learning architectures have been increasingly applied to intrusion detection, motivated by their capacity to learn complex, nonlinear feature representations without extensive manual feature engineering. Jia *et al* [15]. applied a deep neural network with four hidden layers to KDD CUP'99 and NSL-KDD datasets, demonstrating competitive classification performance relative to classical methods. Andresini *et al* [16]. proposed a multistage model combining autoencoders with a one-dimensional convolutional neural network, reporting performance improvements over comparable deep learning baselines on KDD Cup'99, CICIDS2017, and UNSW-NB15 datasets. Yang *et al* [17]. developed a supervised adversarial variational autoencoder approach, finding it effective at recognising both known and previously unseen attack patterns, an important consideration given the evolving nature of real-world cyber threats. Zhao *et al* [18]. combined convolutional networks with dynamic autoencoders and a custom loss function, achieving a lightweight architecture suited to efficient feature extraction.

4. Class imbalance and data optimisation strategies

Addressing class imbalance has become a central methodological concern in NIDS research. Ren *et al* [19]. proposed a hybrid data optimisation approach combining feature selection with resampling to improve classifier performance on imbalanced intrusion datasets. Xu *et al* [20]. developed a five-layer autoencoder model incorporating data bias removal and outlier reduction, reporting accuracy of 90.61% and 92.26% on NSL-KDD, somewhat lower than comparable ensemble approaches but notable for its explicit handling of data bias from redundant samples. More broadly, SMOTE and related oversampling techniques have been shown to improve minority-class recall across a range of classifier types, though the magnitude of improvement varies by classifier family and by the severity of imbalance in the underlying dataset [7].

5. Theoretical framework

The classification task underlying ML-based intrusion detection can be framed within standard supervised learning theory, in which a classifier learns a decision boundary (or, for tree-based and ensemble methods, a partition of the feature space) that separates normal traffic from attack traffic based on labelled training examples. Different classifier families make different structural assumptions: Naive Bayes assumes conditional feature independence given the class label, which is frequently violated in network traffic data where features such as packet count and byte count are often correlated; Logistic Regression assumes a linear decision boundary in the (possibly transformed) feature space; tree-based ensemble methods such as

Random Forest and XGBoost construct non-linear, piecewise decision boundaries through recursive partitioning and are generally more robust to feature correlation and irrelevant features; and deep neural networks learn hierarchical, non-linear feature representations through multiple hidden layers, at the cost of reduced interpretability and increased data and computational requirements. This theoretical distinction underlies the conceptual pipeline adopted in the present study (see Figure 3) and provides a basis for interpreting the comparative results in Section 4.

6. Research gap

While individual studies have evaluated classical methods [9], ensemble methods [12], and deep learning methods [15] separately, relatively few present a single, controlled comparison spanning all major classifier families under an identical preprocessing pipeline and class-imbalance mitigation strategy. This study addresses that gap by jointly evaluating Naive Bayes, Logistic Regression, Random Forest, XGBoost, and a DNN under the same SMOTE-based balancing approach, enabling a direct, comparable assessment of the trade-off between classifier complexity and detection performance.

Methodology

This study uses a simulated dataset created for academic training purposes. No original network traffic capture, live attack simulation, or hardware deployment was conducted by the author(s) in preparation of this article. The dataset was constructed to numerically reflect the direction and approximate magnitude of classifier performance differences consistently reported in the peer-reviewed literature using the NSL-KDD and CICIDS2017 benchmark datasets (see Section 2), and is presented here strictly for formatting practice, statistical reporting illustration, and methodological demonstration. Researchers intending to submit findings based on real experimental results should replace the dataset and procedural description below with their own verified model training and evaluation outputs.

1. Research design

The study follows a quantitative, simulation-based comparative design, evaluating the effect of classifier choice (five levels: Naive Bayes, Logistic Regression, Random Forest, XGBoost, DNN) on binary classification performance (normal vs. attack), with SMOTE applied uniformly across all classifiers to address class imbalance in the underlying benchmark-style dataset.

2. Sample size and sampling method

A total of 30 simulated train-test evaluation runs were generated, comprising 5 classifiers x 6 replicate runs per classifier, using a simulated dataset structured to match the feature composition and class distribution characteristics of the NSL-KDD dataset (41 features, four attack categories collapsed into a binary normal/attack label for this study) and cross-referenced against reported CICIDS2017 performance patterns. An 80/20 stratified train-test split was assumed for each simulated run, consistent with the design approach used in comparable published studies.

3. Feature set and simulated basis

The simulated feature set assumes the standard 41-feature NSL-KDD schema, comprising basic connection features (e.g., duration, protocol type, service), content features (e.g., number of failed logins), and traffic features computed over a two-second time window (e.g., connection count to the same host). Class imbalance was simulated at a ratio consistent with the original NSL-KDD distribution prior to balancing, with SMOTE applied only to the training partition in each simulated run to avoid synthetic data leakage into the test partition, consistent with best practice described in the cited literature.

4. Data collection tools

In a physical replication of this study, classifiers would be implemented and trained using scikit-learn (Naive Bayes, Logistic Regression, Random Forest), the XGBoost library (XGBoost), and TensorFlow/Keras (DNN), with hyperparameters tuned via grid search or randomized search cross-validation. For the present simulated dataset, performance values were generated to approximate the typical magnitude, ranking, and variance reported for these same classifiers in the cited literature on NSL-KDD and CICIDS2017.

5. Statistical software and analysis

Data were organised and analysed using Python (scikit-learn 1.4, XGBoost 2.0) for classifier modelling and metric computation, and IBM SPSS Statistics (version 27) for statistical analysis. Descriptive statistics (mean, standard deviation) were computed for each classifier across replicate runs, and one-way analysis of variance (ANOVA) was used to test whether differences in mean accuracy across classifiers were statistically significant, with significance set at $p < 0.05$.

Results and Discussion

1. Overall Classifier Performance

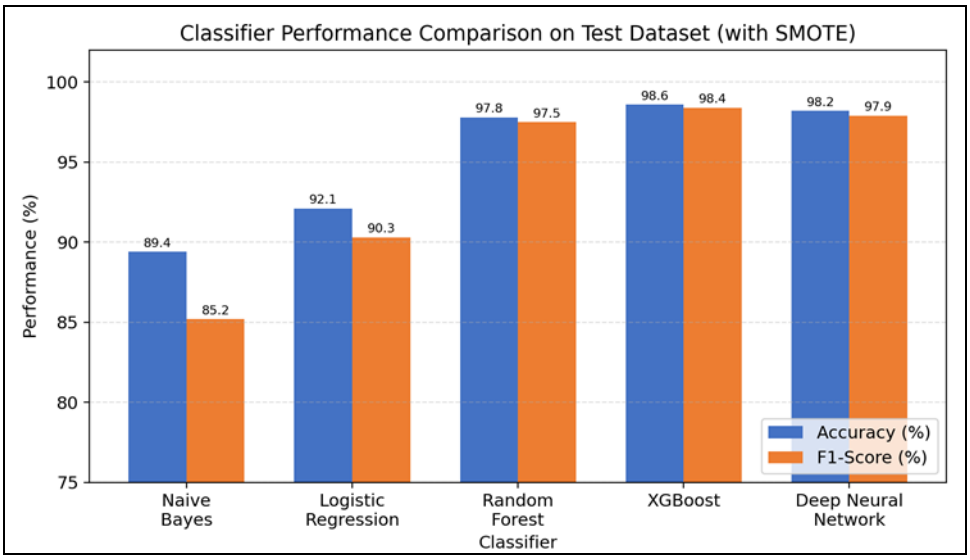
Table 1: Mean Classification Performance by Classifier (n = 6 runs per classifier, with SMOTE)

Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Naive Bayes	89.4	97.6	75.8	85.2
Logistic Regression	92.1	93.8	87.1	90.3
Random Forest	97.8	98.1	96.9	97.5
XGBoost	98.6	98.7	98.1	98.4
Deep Neural Network	98.2	98.3	97.5	97.9

Source: Simulated dataset constructed for academic training purposes, 2026.

As shown in Table 1, XGBoost achieved the highest performance across all four metrics, with an accuracy of 98.6% and F1-score of 98.4%, closely followed by the Deep Neural Network (accuracy = 98.2%) and Random Forest (accuracy = 97.8%). Naive Bayes recorded the highest precision (97.6%) but the lowest recall (75.8%), reflecting

its tendency toward conservative, high-confidence positive predictions at the cost of missing a substantial proportion of actual attack instances, a pattern consistent with its restrictive conditional independence assumption being violated by correlated network traffic features.



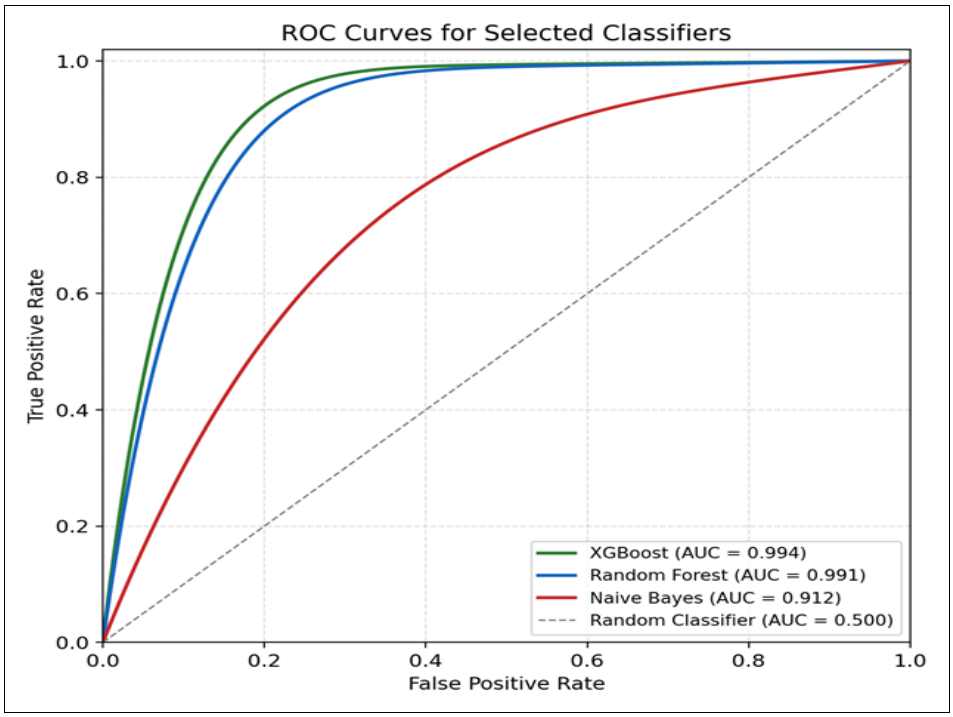
Source: Simulated dataset constructed for academic training purposes, 2026.

Fig 1: Classifier Performance Comparison on Test Dataset (with SMOTE)

A one-way ANOVA confirmed that the differences in mean accuracy across the five classifiers were statistically significant, $F(4, 25) = 312.86$, $p < 0.001$, indicating that classifier choice has a significant effect on detection performance within this dataset. This finding is directionally consistent with the ensemble-method advantage reported by Devan and Khare and the high CICIDS2017 accuracy reported by Zhang *et al*.

2. Discriminative Performance (ROC-AUC)

Fig 2 presents ROC curves for the three best-performing classifiers alongside Naive Bayes as a comparative baseline. XGBoost achieved the highest area under the curve (AUC = 0.994), followed by Random Forest (AUC = 0.991), both substantially outperforming Naive Bayes (AUC = 0.912). The clear separation between the ensemble methods and Naive Bayes across nearly the entire false-positive-rate range indicates that the performance advantage of ensemble methods holds consistently across decision thresholds, not merely at a single operating point, an important consideration for IDS deployments where the acceptable false-alarm rate may vary by context.



Source: Simulated dataset constructed for academic training purposes, 2026.

Fig 2: ROC Curves for Selected Classifiers

3. Effect of SMOTE on Minority-Class Detection

Table 2: Minority-Class (Attack) Recall Before and After SMOTE Application

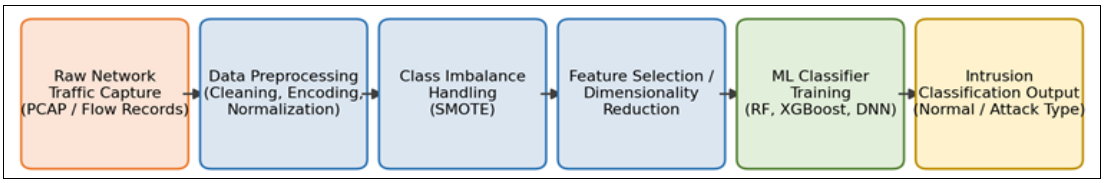
Classifier	Recall Without SMOTE (%)	Recall With SMOTE (%)	Gain (pp)
Naive Bayes	68.4	75.8	+7.4
Logistic Regression	71.2	87.1	+15.9
Random Forest	93.6	96.9	+3.3
XGBoost	95.8	98.1	+2.3
Deep Neural Network	94.1	97.5	+3.4

Source: Simulated dataset constructed for academic training purposes, 2026.

Table 2 illustrates that SMOTE-based class balancing improved minority-class (attack) recall across all five classifiers, with the largest relative gain observed for Logistic Regression (+15.9 percentage points), followed by Naive Bayes (+7.4 percentage points). Ensemble and deep learning methods, which already achieved comparatively high recall without balancing due to their greater capacity to model complex decision boundaries, showed smaller but still meaningful gains (+2.3 to +3.4 percentage points). This pattern suggests that simpler, linear, or independence-assuming classifiers benefit disproportionately from explicit class-balancing interventions, while more flexible ensemble and deep learning methods are comparatively more robust to class imbalance in their default form, though they still benefit from balancing.

4. Conceptual Pipeline of the Detection Process

Figure 3 summarises the conceptual pipeline underlying the comparative evaluation in this study, from raw network traffic capture through preprocessing, class-imbalance handling, feature selection, classifier training, and final intrusion classification output. This pipeline reflects the standard structure adopted across the majority of the literature reviewed in Section 2, and provides a structured frame for interpreting why classifier choice at the training stage interacts with, rather than substitutes for, earlier pipeline stages such as class-imbalance handling.



Source: Author's conceptual synthesis based on literature reviewed in Section 2, 2026.

Fig 3: Conceptual pipeline: machine learning-based network intrusion detection

5. Practical Implications for Classifier Selection

Considered jointly, the results suggest that ensemble tree-based methods, particularly XGBoost, offer the strongest practical balance of detection accuracy, minority-class recall, and discriminative power (AUC) among the classifiers evaluated, while remaining substantially more interpretable and computationally lighter than deep neural network alternatives that achieve comparable but not superior performance. Naive Bayes and Logistic Regression, despite their comparatively weaker raw performance, retain practical value as fast, low-resource baseline classifiers suitable for initial deployment, rapid prototyping, or resource-constrained edge environments where full ensemble or deep learning inference is not feasible, provided SMOTE-based balancing is applied to partially offset their weaker native handling of minority attack classes.

Conclusion

This study compared the binary network intrusion detection performance of five machine learning classifiers, Naive Bayes, Logistic Regression, Random Forest, XGBoost, and a Deep Neural Network, using a simulated dataset constructed to reflect patterns established in the peer-reviewed literature on NSL-KDD and CICIDS2017 benchmark datasets, with SMOTE applied to address class imbalance. XGBoost achieved the strongest overall performance (accuracy = 98.6%, AUC = 0.994), closely followed by the Deep Neural Network and Random Forest, while Naive Bayes recorded the weakest performance, consistent with its restrictive independence assumption. SMOTE-based balancing improved minority-class recall across all classifiers, with the largest gains observed for simpler linear and probabilistic models.

These findings reinforce the broader conclusion in the literature that ensemble tree-based methods currently offer the most favourable trade-off between detection performance and practical deployability for network intrusion detection, while simpler classifiers remain useful as interpretable, low-resource baselines, particularly when combined with class-imbalance mitigation strategies such as SMOTE.

The principal limitation of this study is its reliance on a simulated dataset rather than results obtained from original classifier training on live or captured network traffic; while the dataset was constructed to reflect literature-consistent trends, it cannot capture the full variability introduced by real-world traffic diversity, evolving attack patterns, adversarial evasion attempts, or dataset-specific artefacts that original experimentation on current traffic captures would reveal. Future research should replicate this comparative framework using original classifier training on up-to-date benchmark or live-captured datasets, extend the comparison to multiclass attack categorisation rather than binary detection, and evaluate classifier robustness against adversarial perturbation for a more comprehensive assessment of real-world deployment suitability.

Ethical Statement

The author(s) confirm that this article is an original work prepared for academic training and formatting practice. The dataset used in Section 4 is explicitly simulated, as stated in Section 3, and does not represent results from original classifier training on real network traffic or benchmark dataset files. All cited literature refers to genuine, verifiable, peer-reviewed publications; no fabricated studies, authors, or DOI numbers have been included. Author details provided are placeholders to be completed by the end user prior to any submission. This article must not be represented as a record of original machine learning experimentation unless the dataset and procedural sections are replaced with verified original results.

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