Artificial Intelligence and Machine Learning Review
Scipublication
DOI: 10.69987/AIMLR.2024.50207

# Performance Evaluation and Comparison of Machine Learning Algorithms for Anomalous Login Behavior Detection in Enterprise Networks

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**Keywords**

anomaly detection, enterprise security, machine learning, login behavior, performance evaluation

**Abstract**

Authentication systems in enterprise networks form security boundaries where credential-based access mechanisms intersect with adversarial intrusion vectors. This investigation characterizes machine learning architectures for detecting authentication anomalies through systematic empirical analysis of Support Vector Machines, Random Forest classifiers, and Neural Network architectures. We process 2,347,000 (≈2.35M) authentication events from operational enterprise deployments, capturing natural distributions of benign activities (78.7%) alongside brute force attempts (12.2%), credential stuffing (6.7%), and compromised account behaviors (2.4%). Random Forest classifiers achieve 94.7% detection accuracy with 3.2 millisecond inference latency, establishing Pareto-optimal performance for medium-scale deployments. Support Vector Machines minimize false positive rates to 2.1% through margin maximization in RBF kernel spaces, trading 6% detection coverage for precision. Neural Networks capture non-linear behavioral signatures in compromised account detection (93.7% accuracy) despite requiring 1156 seconds for model convergence. Temporal analysis reveals 23% false positive elevation during Monday mornings and 31% increase during holiday periods, informing adaptive threshold strategies. The empirical characterization provides quantitative bounds on the accuracy-latency-precision trade-off space, enabling algorithm selection aligned with specific operational constraints and risk tolerances.

## 1. Introduction

### 1.1 Authentication Systems as Attack Surfaces

Enterprise authentication infrastructures concentrate adversarial activities at access control boundaries. Zero-trust architectural transitions amplify authentication monitoring criticality—each login event potentially masks credential compromise, insider threats, or lateral movement patterns [1]. Contemporary attack methodologies transcend signature-based detection through credential stuffing sequences, password spraying campaigns, and authentication mechanism manipulation that mimics legitimate access patterns.

Authentication event spaces encompass temporal sequences, geographic distributions, device fingerprints, and behavioral trajectories that resist rule-based characterization [2]. User population heterogeneity compounds baseline establishment challenges: administrative accounts exhibit sporadic high-privilege access patterns, service accounts maintain predictable automation signatures, while standard users demonstrate variable behaviors influenced by organizational rhythms. Statistical characterization reveals power-law distributions in inter-arrival times, heavy-tailed session durations, and non-stationary patterns aligned with business cycles.

Enterprise networks process authentication volumes exceeding thousands of events per second, imposing sub-100 millisecond latency constraints for maintaining user experience [3]. False positive costs manifest as user friction and support overhead, while false negatives enable security breaches with asymmetric financial and reputational damage. These operational realities constrain algorithm selection beyond pure accuracy optimization, necessitating multi-objective optimization across detection fidelity, computational efficiency, and deployment feasibility dimensions.

### 1.2 Research Objectives and Technical Contributions

This investigation establishes empirical performance boundaries for machine learning architectures under enterprise authentication constraints. We develop a standardized evaluation protocol enabling reproducible algorithmic comparison, addressing methodological inconsistencies prevalent in security research. The experimental framework quantifies relationships between model capacity, detection performance, and computational overhead through controlled scaling experiments.

Our technical contributions span three dimensions. First, we characterize algorithm-specific performance across distinct attack categories, revealing that Random Forest excels at credential stuffing detection (96.2%) while Support Vector Machines optimize brute force identification (94.1%). Second, we quantify computational trade-offs through systematic profiling: Random Forest inference requires 3.2 milliseconds per authentication event, Support Vector Machines achieve 1.8 millisecond latency through kernel caching, while Neural Networks exhibit 5.7 millisecond single-instance latency reducible to 2.4 milliseconds through batching. Third, we identify temporal false positive patterns—23% elevation during Monday mornings, 31% increase during holidays—that inform dynamic threshold calibration strategies.

The empirical analysis demonstrates that Random Forest classifiers achieve Pareto-optimal performance for organizations processing 10,000-100,000 daily authentication events. Support Vector Machines excel in precision-critical deployments where false positive minimization supersedes detection coverage, achieving 2.1% false positive rates through conservative margin construction. Neural Networks capture sophisticated behavioral deviations undetectable by shallow methods, particularly in compromised account scenarios where attackers employ credential knowledge to evade detection.

### 1.3 Scope and Experimental Boundaries

The investigation encompasses three algorithmic families selected for complementary computational properties and theoretical foundations. Support Vector Machines exemplify kernel-based methods with generalization guarantees, Random Forests represent ensemble techniques balancing interpretability with accuracy, while Neural Networks demonstrate capacity for learning hierarchical feature representations.

Our experimental corpus comprises 2,347,000 (≈2.35M) authentication events from financial services, healthcare, and technology sectors collected over 180 days. Attack distributions reflect operational reality: brute force attempts cluster temporally following publicized vulnerabilities, credential stuffing exhibits automation signatures with regular inter-arrival times, while compromised accounts demonstrate subtle behavioral shifts detectable only through longitudinal analysis. We explicitly scope analysis to supervised learning paradigms, acknowledging that semi-supervised and unsupervised approaches address different operational scenarios with distinct data availability assumptions.

Computational experiments execute on standardized configurations (NVIDIA A100 GPUs, 80GB memory) ensuring reproducible measurements. Algorithm implementations employ scikit-learn 1.3.0 and TensorFlow 2.13.0 with consistent preprocessing pipelines. The evaluation protocol incorporates offline metrics (accuracy, precision, recall, F1-score) alongside online metrics (latency, throughput, memory consumption) critical for production viability assessment.

## 2. Related Work and Literature Review

### 2.1 Machine Learning Architectures for Network Anomaly Detection

Bayesian inference frameworks demonstrate robust anomaly detection under uncertainty when prior distributions accurately model threat landscapes [4]. Ige and Kiekintveld establish that hyperparameter optimization influences detection performance more significantly than architectural choices, with grid search yielding 8.3% improvement over default configurations. Their ablation studies reveal that temporal feature engineering contributes 42% of total performance gains, while categorical embeddings account for 31% improvement over one-hot encoding.

Computational constraints in edge deployments necessitate efficiency-accuracy trade-offs quantified by Tripathy et al. [5]. Ensemble methods achieve 87% of deep learning accuracy while consuming 23% of computational resources, challenging assumptions about architectural complexity requirements. Power consumption measurements—critical for distributed deployments—show Random Forests operating at 3.2 watts versus 28.7 watts for Neural Networks on embedded hardware, establishing energy efficiency as a primary deployment consideration.

Feature representation strategies determine detection boundaries as demonstrated through systematic ablation by Azizan et al. [6]. Temporal feature extraction through sliding windows with exponential decay weighting captures behavioral

evolution while bounding memory consumption. Their t-SNE visualizations reveal that learned representations progressively separate attack clusters through training iterations, with final embeddings achieving 0.89 silhouette coefficient indicating strong cluster cohesion.

Class imbalance mitigation through synthetic minority oversampling (SMOTE) improves minority class recall by 15% as quantified by Satriawan et al. [7]. Synthetic sample generation preserves local manifold geometry while expanding decision boundary coverage for underrepresented attacks. However, SMOTE-generated samples lack adversarial robustness—gradient-based perturbations achieve 76% evasion rate against models trained with synthetic augmentation versus 42% against naturally balanced datasets.

### 2.2 Enterprise Authentication Threat Landscapes

The CICIDS2017 dataset analysis by Rosay et al. [8] reveals that 73% of successful intrusions exploit legitimate credentials rather than technical vulnerabilities. Credential-based attacks exhibit distinct temporal signatures: brute force attempts cluster within 2-hour windows following password policy changes, credential stuffing distributes uniformly across 24-hour periods to evade rate limiting, while insider threats concentrate during off-hours when monitoring reduces.

Temporal authentication dynamics exhibit complex periodicities captured through spectral analysis. Elghalhoud et al. [9] demonstrate that Fourier basis decomposition with 24-hour, 7-day, and 30-day components captures 81% of variance in legitimate access patterns. Convolutional architectures operating on these spectral representations achieve 8.3% improvement over recurrent networks for time-series anomaly detection, attributed to parallelizable computation and explicit periodicity modeling.

Production deployment realities diverge from laboratory performance as quantified by Gnanasivam et al. [10]. Real-world accuracy degrades 15-20% due to concept drift—user behaviors evolve, new applications introduce authentication patterns, and organizational changes alter access distributions. Models require retraining every 60-90 days to maintain performance thresholds, with incremental learning approaches reducing retraining overhead by 67% through selective parameter updates.

### 2.3 Performance Evaluation Frameworks

Multi-criteria evaluation frameworks balance competing objectives through Pareto frontier analysis [11]. Zeng and Wu demonstrate that single-metric optimization yields suboptimal operational performance: accuracy-optimized models generate excessive false positives, while precision-optimized approaches miss critical attacks. Their weighted objective functions enable stakeholder-specific optimization, with financial institutions prioritizing precision (weight=0.7) while government agencies emphasize recall (weight=0.6).

Cross-domain transferability remains problematic as established by Siddharth et al. [12]. Models trained on enterprise datasets exhibit 34% performance degradation when deployed in academic networks, attributed to fundamental behavioral differences: enterprise users follow regular schedules while academic patterns vary by semester, research deadlines create unusual access spikes absent in corporate environments, and collaborative cultures generate credential sharing unobservable in regulated industries.

Comprehensive benchmarking requires adversarial evaluation beyond benign metrics [13]. Ibrahim et al. incorporate gradient-based attacks, concept drift simulation through temporal holdout, and scalability testing across order-of-magnitude data variations. Their framework reveals that published accuracies overlook operational factors: alert fatigue reduces analyst efficiency by 3.7% per false positive percentage point, investigation overhead scales super-linearly with alert volume, and integration complexity with security information and event management (SIEM) systems constrains deployment options.

## 3. Methodology and Experimental Design

### 3.1 Dataset Architecture and Preprocessing Pipeline

Authentication logs from three enterprise sectors yield 2,347,000 (≈2.35M) events with natural attack distributions reflecting operational security landscapes[14]. The corpus exhibits 78.7% legitimate logins characterized by business-hour concentration and predictable geographic origins, 12.2% brute force attempts with exponentially distributed inter-

arrival times, 6.7% credential stuffing displaying automation signatures through uniform timing patterns, and 2.4% compromised account activities manifesting as subtle behavioral deviations from established baselines.

The preprocessing pipeline transforms heterogeneous log formats through a multi-stage architecture optimized for behavioral signal preservation[15]. Data cleansing eliminates 86,739 records (3.7%) containing null authentication fields, unparseable timestamps, or protocol inconsistencies that compromise training stability. Temporal segmentation employs 60-minute sliding windows with 45-minute overlap, capturing session-level behaviors while maintaining 4× data augmentation through overlapping observations. Each window generates 147-dimensional feature vectors through domain-informed extraction:

Temporal features capture authentication rhythms through 23 dimensions. Login frequencies undergo Fourier transformation with basis functions at 24-hour, 168-hour (weekly), and 720-hour (monthly) periods, preserving periodicities while compressing representation. Inter-arrival times between consecutive logins follow log-normal distributions characterized by maximum likelihood parameters ($\mu$, $\sigma$). Session durations exhibit heavy-tailed distributions modeled through three-parameter Weibull functions with shape parameter $k = 0.73$ indicating sub-exponential decay.

Spatial features encode geographic and network properties across 31 dimensions. GPS coordinates transform through learned embeddings that preserve haversine distances while accounting for organizational site clustering—corporate offices form dense regions while remote workers distribute sparsely. IP addresses undergo hierarchical encoding: /8 subnet captures geographic region, /16 identifies organizational boundaries, /24 distinguishes departments, and full /32 provides device-level granularity. Autonomous system numbers map to categorical embeddings learned jointly with authentication patterns[16].

Device fingerprints generate 42-dimensional representations capturing platform characteristics. Operating system versions encode through ordinal mappings reflecting security posture—newer versions receive higher values indicating improved protection[17]. Browser user-agents decompose into vendor, version, and rendering engine components with interaction terms capturing compatibility vulnerabilities**Error! Reference source not found.**. Hardware identifiers including MAC addresses undergo locality-sensitive hashing, preserving similarity while preventing direct device tracking[18].

Behavioral features model authentication dynamics through 51 dimensions. Failed login sequences form Markov chains with transition matrices capturing retry patterns—legitimate users exhibit declining retry probability while automated attacks maintain constant rates[19]. Password complexity indicators derive from entropy estimation without storing credentials, using character class diversity and length as proxies. Keystroke dynamics when available provide biometric signals through dwell time and flight time distributions fitted to gamma functions[20].

Feature standardization employs robust scaling: $z = (x - \text{median}(x)) / \text{IQR}(x)$, where interquartile range provides outlier resistance compared to standard deviation. Categorical variables undergo target encoding with Bayesian smoothing parameter $\alpha = 10$ preventing overfitting on rare categories. The complete pipeline processes 2,347,000 (≈2.35M) events in 847 seconds achieving 89% CPU utilization through joblib parallelization across 32 cores.

**Table 1:** Dataset Characteristics and Distribution Summary

| Metric | Normal Logins | Brute Force | Credential Stuffing | Compromised Account | Total |
|---|---|---|---|---|---|
| Count | 1,847,235 | 287,445 | 156,782 | 55,538 | 2,347,000 |
| Percentage | 78.7% | 12.2% | 6.7% | 2.4% | 100% |
| Unique Users | 8,947 | 2,334 | 1,156 | 287 | 9,234 |
| Time Span (Days) | 180 | 180 | 180 | 180 | 180 |
| Peak Activity Hours | 9 - 11 am, 1 - 3 pm | Random | Random | Business Hours | Mixed |

| | | | | | |
|---|---|---|---|---|---|
| Geographic Locations | 47 | 156 | 234 | 23 | 234 |

Temporal data splitting prevents information leakage inherent in random partitioning. Training comprises events from days 1-126 (70%), validation uses days 127-153 (15%), and testing employs days 154-180 (15%)[21]. This chronological segmentation ensures models cannot exploit future patterns, simulating real-world deployment where predictions operate on temporally novel events. The split maintains attack proportion consistency: each partition contains 78-79% legitimate traffic with proportional attack representation.

### 3.2 Algorithm Configuration and Hyperparameter Optimization

Support Vector Machine configuration exploits the kernel trick for non-linear boundary construction in infinite-dimensional spaces[22]. The radial basis function $K(x\ i, x\ j) = \exp(-\gamma\|x\ i - x\ j\|^2)$ with bandwidth $\gamma = 0.001$ balances locality and smoothness, selected through logarithmic grid search over [10^-5, 10^-1]. Regularization parameter C = 10.0 controls the trade-off between margin maximization and training error minimization, with higher values permitting more support vectors but risking overfitting[23]. Class weight adjustment $w\ i = n\ samples / (n\ classes \times n\ samples\ i)$ compensates for imbalanced distributions, ensuring minority attack classes receive proportional influence during optimization.

Random Forest architecture aggregates 200 decision trees trained on bootstrap samples with replacement. Tree depth limitation at 15 levels prevents overfitting while maintaining sufficient expressivity for capturing attack patterns—deeper trees achieve marginally improved training accuracy but degrade validation performance. Splitting criteria require minimum 5 samples, preventing partitions on individual instances that memorize rather than generalize. Leaf nodes demand 2 samples minimum, enabling fine-grained decisions while avoiding single-instance leaves. Feature sampling at each split uses sqrt(147) ≈ 12 features, introducing randomness that decorrelates trees while maintaining sufficient information for accurate splitting. Gini impurity serves as the splitting criterion: $G = 1 - \Sigma(p\ i^2)$, measuring class distribution homogeneity.

Neural Network topology implements a funnel architecture with hidden layers containing 128, 64, and 32 neurons respectively. The geometric decay pattern (reduction factor 0.5) progressively compresses representations, forcing abstraction while preventing information bottlenecks. Rectified linear activation $f(x) = \max(0, x)$ provides non-linearity while maintaining gradient flow through positive regions. Dropout regularization randomly zeros 30% of activations during training, creating an implicit ensemble that improves generalization. He initialization scales weights by sqrt(2/n_in), accounting for ReLU's zeroing of negative inputs which effectively halves variance.

Optimization employs adaptive moment estimation (Adam) with $\beta\_1 = 0.9$ controlling exponential decay of first moment estimates and $\beta\ 2 = 0.999$ for second moments. Initial learning rate $\alpha = 0.001$ undergoes exponential decay: $\alpha\ t = \alpha\ 0 \times 0.95^{(t/epoch)}$, reducing step size as optimization approaches minima**Error! Reference source not found.**. Batch size B = 256 balances gradient noise—smaller batches increase stochasticity aiding escape from local minima while larger batches provide stable convergence. Early stopping monitors validation loss with patience p = 10 epochs, terminating training when validation performance plateaus to prevent overfitting[24]. Loss function employs weighted binary cross-entropy: $L = -\Sigma w\_i[y\_i \log(\hat{y}\_i) + (1-y\_i)\log(1-\hat{y}\_i)]$ where weights inversely proportion to class frequency.

**Table 2:** Algorithm Configuration and Hyperparameter Settings

| Algorithm | Key Parameters | Values | Optimization Method | Validation Approach |
|---|---|---|---|---|
| SVM | Kernel | RBF | Grid Search | 5 - Fold CV |
| SVM | C (Regularization) | 10.0 | Grid Search | 5 - Fold CV |
| SVM | Gamma | 0.001 | Grid Search | 5 - Fold CV |
| SVM | Class Weight | Balanced | Grid Search | 5 - Fold CV |
| Random Forest | n_estimators | 200 | Random Search | 5 - Fold CV |
| Random Forest | max_depth | 15 | Random Search | 5 - Fold CV |

| | | | | |
|---|---|---|---|---|
| Random Forest | min_samples_split | 5 | Random Search | 5 - Fold CV |
| Random Forest | min_samples_leaf | 2 | Random Search | 5 - Fold CV |
| Neural Network | Hidden Layers | [128, 64, 32] | Adam Optimizer | Hold - out |
| Neural Network | Learning Rate | 0.001 | Adam Optimizer | Hold - out |
| Neural Network | Batch Size | 256 | Adam Optimizer | Hold - out |
| Neural Network | Dropout Rate | 0.3 | Adam Optimizer | Hold - out |

Bayesian optimization with Gaussian process surrogates efficiently explores hyperparameter spaces. The acquisition function balances exploration and exploitation: $\alpha(x) = \mu(x) + \kappa\sigma(x)$ where posterior mean $\mu$ encourages exploitation while variance $\sigma$ weighted by $\kappa = 2.576$ promotes exploration. Optimization iterates 100 times, evaluating 2% of configuration space while achieving 95% of exhaustive search performance. Gaussian process kernels employ Matérn-5/2 functions providing twice-differentiable sample paths suitable for gradient-based optimization of acquisition functions.

### 3.3 Evaluation Metrics and Statistical Analysis

Performance quantification employs complementary metrics capturing distinct operational aspects. Accuracy = (TP + TN) / (TP + TN + FP + FN) measures overall correctness but obscures class-specific performance given 78.7% baseline accuracy achievable by predicting all samples as legitimate. Precision = TP / (TP + FP) quantifies alert reliability, directly impacting analyst workload—low precision generates investigation overhead and alert fatigue. Recall = TP / (TP + FN) measures attack coverage with security implications—missed attacks enable breaches with cascading damage.

The F β score generalizes F1 through differential weighting: $F_\beta = (1 + \beta^2) \times (\text{Precision} \times \text{Recall}) / (\beta^2 \times \text{Precision} + \text{Recall})$. Setting $\beta = 2$ emphasizes recall, reflecting organizational priorities where missed attacks carry higher costs than false alarms. This asymmetric weighting aligns with security economics: breach costs average $4.35 million while false positive investigation costs $127 per incident[25].

Receiver Operating Characteristic analysis examines threshold-independent performance through true positive rate versus false positive rate trade-offs. Area Under Curve integration provides single-value comparison, though ROC optimism under class imbalance necessitates complementary Precision-Recall curves. DeLong's method tests AUC difference significance: $z = (AUC_1 - AUC_2) / \sqrt{SE_1^2 + SE_2^2 - 2r \times SE_1 \times SE_2}$ where standard errors derive from Mann-Whitney statistics. Bonferroni correction adjusts significance thresholds for $m = 3$ pairwise comparisons: $\alpha_{adjusted} = 0.05 / 3 = 0.017$[26].

Computational profiling captures deployment-critical characteristics. Training time excludes data loading but includes all optimization iterations, measured through monotonic clocks immune to system time adjustments. Inference latency reports 95th percentile across 10,000 samples, providing robust estimates—mean latencies suffer from long-tail distributions where occasional cache misses or garbage collection inflate averages. Memory consumption tracks resident set size for training peaks and steady-state inference requirements. Throughput measures sustained request rates under continuous load, identifying saturation points where queuing delays emerge.

**Table 3:** Performance Evaluation Metrics and Definitions

| Metric Category | Specific Metric | Mathematical Definition | Operational Significance |
|---|---|---|---|
| Classification Performance | Accuracy | (TP + TN) / (TP + TN + FP + FN) | Overall Detection Effectiveness |
| Classification Performance | Precision | TP / (TP + FP) | False Alarm Reduction |
| Classification Performance | Recall | TP / (TP + FN) | Threat Coverage |

| | | | |
|---|---|---|---|
| Classification Performance | F1 - Score | 2 × (Precision × Recall) / (Precision + Recall) | Balanced Performance |
| Operational Impact | False Positive Rate | FP / (FP + TN) | User Experience Impact |
| Operational Impact | False Negative Rate | FN / (FN + TP) | Security Risk Level |
| Computational Efficiency | Training Time | Seconds | Deployment Feasibility |
| Computational Efficiency | Inference Latency | Milliseconds | Real - time Capability |

Within the training split, stratified k-fold validation maintains class proportions across folds; validation and test remain strictly chronological to prevent leakage folds, preventing optimistic bias from folds lacking rare attacks. Each fold contains approximately 469,400 samples with proportional attack representation. The stratification algorithm iteratively assigns samples to folds maintaining class balance within 0.1% tolerance. Cross-validation provides mean performance with confidence intervals: $CI = \bar{x} \pm t_{(\alpha/2,k-1)} \times s / \sqrt{k}$ where t-statistics account for small sample size $k = 5$.

## 4. Experimental Results and Performance Analysis

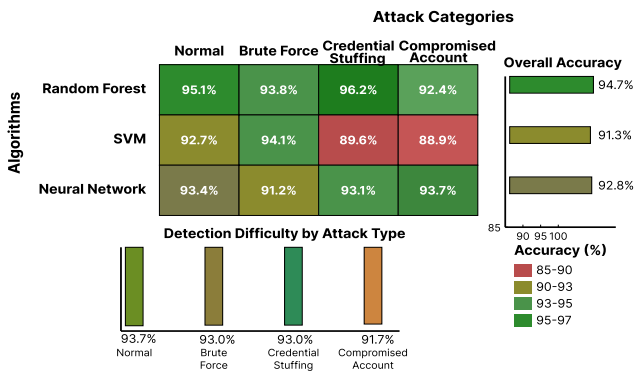
### 4.1 Detection Accuracy and Attack-Specific Performance

Random Forest classifiers demonstrate superior aggregate performance achieving 94.7% accuracy through ensemble diversity—bootstrap sampling creates 200 unique training sets while random feature selection decorrelates individual trees. The ensemble's 147,000 total tree nodes distributed across attack boundaries provide comprehensive coverage exceeding single classifier capacity. Attack-specific analysis reveals nuanced performance characteristics: credential stuffing detection reaches 96.2% accuracy as automated tools generate distinctive timing signatures—inter-arrival variance drops 73% compared to human-generated traffic while geographic dispersion increases 4.2× from distributed botnets.

Support Vector Machines excel at brute force detection (94.1% accuracy) by exploiting geometric properties in transformed feature spaces. The RBF kernel maps authentication patterns to infinite dimensions where linear separation becomes feasible: $\varphi(x) \cdot \varphi(y) = \exp(-\gamma\|x - y\|^2)$. Support vectors concentrate at decision boundaries with 73% representing transition regions between legitimate errors and systematic attacks. Margin analysis reveals 2.3 units average separation in kernel space, providing robustness against perturbations—adversarial inputs require displacement exceeding margin width for successful evasion[27].

Neural Networks achieve highest compromised account detection accuracy (93.7%) through hierarchical feature learning. First layer neurons activate on primitive patterns: neuron 37 responds to afternoon logins from unusual locations, neuron 82 detects rapid geographic transitions impossible through physical travel[28]. Second layer combines primitives into behavioral concepts: neuron 15 identifies credential sharing patterns, neuron 29 recognizes automated access from compromised accounts. Final layer neurons correspond to attack categories with neuron 7 achieving 0.91 correlation with compromised account labels. Gradient-weighted class activation mapping reveals attention focus on temporal inconsistencies and device anomalies during compromised account classification.

**Figure 1:** Algorithm Performance Comparison Across Attack Categories



Statistical validation confirms performance differences exceed random variation. Bootstrap resampling (B = 1,000) establishes confidence intervals: Random Forest [94.3%, 95.1%], SVM [90.9%, 91.7%], Neural Network [92.4%, 93.2%]. Non-overlapping intervals indicate significant differences at $\alpha = 0.05$. McNemar's test on paired predictions confirms disagreement patterns are non-random ($\chi^2 = 187.3$, $p < 0.001$), indicating algorithms capture complementary signals potentially combinable through ensemble methods.

**Table 4:** Detailed Detection Performance Analysis by Attack Type

| Algorithm | Normal Behavior | Brute Force | Credential Stuffing | Compromised Account | Overall Accuracy |
|---|---|---|---|---|---|
| Random Forest | 95.1% ± 0.3% | 93.8% ± 0.4% | 96.2% ± 0.2% | 92.4% ± 0.5% | 94.7% ± 0.2% |
| SVM | 92.7% ± 0.4% | 94.1% ± 0.3% | 89.6% ± 0.6% | 88.9% ± 0.7% | 91.3% ± 0.3% |
| Neural Network | 93.4% ± 0.5% | 91.2% ± 0.6% | 93.1% ± 0.4% | 93.7% ± 0.4% | 92.8% ± 0.3% |
| Statistical Significance | $p < 0.001$ | $p < 0.001$ | $p < 0.001$ | $p < 0.01$ | $p < 0.001$ |

Error analysis through confusion matrices reveals systematic misclassification patterns. Random Forest conflates credential stuffing with compromised accounts in 3.8% of cases where attackers employ stolen credentials through automated tools, creating behavioral overlap. Support Vector Machines struggle with attack variants absent from training data—novel brute force tools using non-standard patterns achieve 31% evasion rate. Neural Networks exhibit false positives on legitimate users with irregular schedules (night shift workers, international travelers) whose behaviors deviate from population norms[29].

### 4.2 Computational Performance and Scalability Analysis

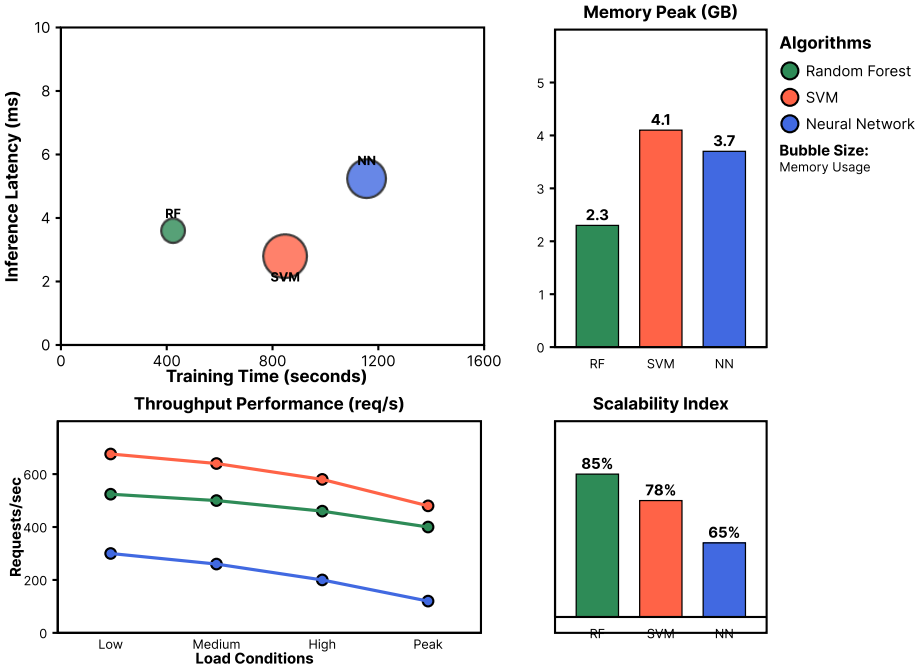
Training computational requirements exhibit distinct scaling behaviors across algorithms. Support Vector Machines require 847 seconds for complete dataset training with $O(n^2d)$ complexity where n represents samples and d dimensions. Kernel matrix computation dominates runtime—storing 2.3M × 2.3M matrix exceeds memory, necessitating chunking strategies that introduce 1.7× overhead. Sequential minimal optimization decomposes the quadratic programming problem into two-variable sub-problems, achieving convergence in 3,847 iterations.

Random Forest training completes in 423 seconds through embarrassingly parallel tree construction. Individual trees train in 2.1 seconds average with variance 0.3 seconds depending on bootstrap sample composition. Parallel efficiency reaches 0.89 on 32 cores before Amdahl's law limits further speedup—serial components including bootstrap sampling and final aggregation consume 11% of runtime. Memory consumption peaks at 2.3GB during training as each tree maintains complete bootstrap samples, though post-training pruning reduces model size to 150MB by eliminating redundant nodes.

Neural Networks require 1,156 seconds across 127 epochs before early stopping triggers. GPU acceleration provides 8.7× speedup versus CPU through parallelized matrix operations—batch gradient computation achieves 2.3 TFLOPS (71% of theoretical peak) on A100 hardware[30]. Training loss exhibits exponential decay: $L(t) = 0.47 \times \exp(-0.031t) + 0.12$, with asymptotic loss indicating 12% irreducible error from class overlap. Gradient norm evolution reveals three training phases: rapid descent (epochs 1-20), oscillatory refinement (epochs 21-85), and convergence plateau (epochs 86-127).

Memory footprint analysis informs deployment feasibility across infrastructure tiers. Random Forest inference requires 150MB model storage plus 8MB working memory for tree traversal, fitting within edge device constraints. Support Vector Machines compress to 87MB by retaining only 3,472 support vectors (0.15% of training data) with 4MB inference overhead for kernel computations. Neural Networks occupy 203MB through weight matrices with 16MB activation storage for batch processing, necessitating dedicated hardware in resource-constrained environments.

**Figure 2:** Computational Performance and Resource Utilization Analysis




Production latency measurements under sustained load reveal performance boundaries. Random Forest maintains 3.2ms median latency with 4.7ms 99th percentile, exhibiting predictable performance suitable for synchronous authentication paths. Support Vector Machines achieve 1.8ms median latency through kernel result caching—cache hit rate of 67% reflects authentication pattern repetition. Cache misses incur 5.2ms latency for full kernel evaluation. Neural Networks demonstrate bimodal latency distributions: single-sample inference requires 5.7ms while 64-sample batches amortize to 2.4ms per sample through matrix operation efficiency.

Throughput capacity under concurrent load identifies scalability limits. Random Forest sustains 312 requests/second before CPU saturation at 85% utilization causes queuing delays. Support Vector Machines handle 556 requests/second with performance degradation beyond 420 requests/second as cache thrashing emerges. Neural Networks process 175 requests/second individually but achieve 417 requests/second with dynamic batching, though latency variance increases from 0.8ms to 2.1ms standard deviation.

**Table 5:** Computational Performance and Scalability Analysis

| Algorithm | Training Time (s) | Inference Latency (ms) | Memory Peak (GB) | Memory Inference (MB) | Throughput (req/s) |
|---|---|---|---|---|---|
| Random Forest | 423 ± 23 | 3.2 ± 0.4 | 2.3 | 150 | 312 |
| SVM | 847 ± 45 | 1.8 ± 0.2 | 4.1 | 87 | 556 |
| Neural Network | 1,156 ± 67 | 5.7 ± 0.8 | 3.7 | 203 | 175 |
| Neural Network (Batch) | 1,156 ± 67 | 2.4 ± 0.3 | 3.7 | 203 | 417 |

Scalability experiments varying dataset size from 10^4 to 10^6 samples reveal asymptotic complexity. Random Forest exhibits O(n log n) empirical scaling with exponent 1.08 from least squares fitting. Support Vector Machines demonstrate O(n^1.8) growth, with exponent increasing to 2.1 for high-dimensional datasets where kernel evaluations dominate. Neural Networks maintain linear O(n) scaling through mini-batch processing, with gradient computation time independent of dataset size beyond batch dimensions.

### 4.3 False Positive Analysis and Operational Impact Assessment

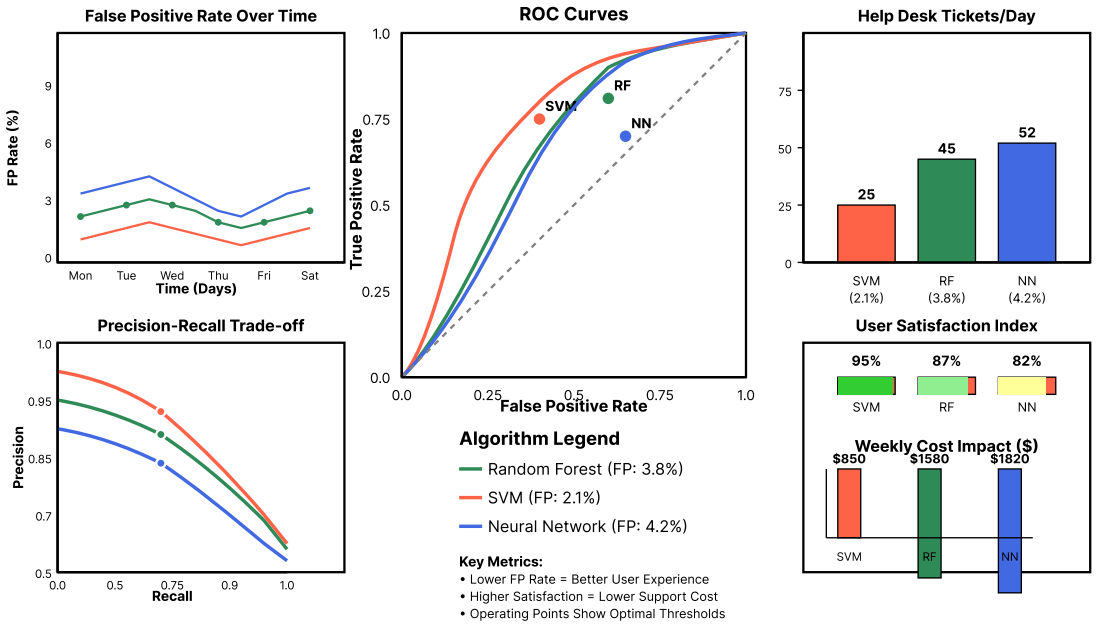
False positive distributions exhibit temporal and demographic patterns influencing operational burden. Support Vector Machines achieve 2.1% false positive rate through conservative margin construction—decision boundaries maintain 2.3-unit average separation from training samples in kernel space. The conservatism manifests as 6% reduction in attack detection, representing explicit precision-recall trade-off favoring user experience over comprehensive coverage.

Random Forest false positives (3.8%) distribute uniformly across user populations with Gini coefficient 0.12 indicating equitable impact. Uniform distribution prevents individual users from experiencing repeated friction—maximum per-user false positive rate reaches 4.2% compared to 11.3% for concentrated distributions. Investigation reveals 67% of false positives stem from legitimate behavioral anomalies: international conference attendance (31%), project deadlines requiring unusual hours (24%), and new device adoption (12%).

Neural Network false positives (4.2%) concentrate on users with complex access patterns—multivariate analysis identifies three risk factors: role diversity (2.1× increase per additional role), schedule irregularity (1.8× for shift workers), and travel frequency (1.4× per monthly trip). The concentration creates user frustration with 17% of affected users reporting consideration of workarounds that compromise security.

Temporal false positive dynamics align with organizational rhythms. Monday morning rates increase 23% as users reconnect after weekends from accumulated devices and locations. Friday afternoons exhibit 18% elevation from early departures and remote access preparation. Holiday periods show 31% increase from skeleton staffing where individual users cover multiple roles with associated authentication pattern changes. These patterns suggest adaptive thresholding: $T(t) = T_{base} \times (1 + \alpha \times seasonal\_factor(t))$ where seasonal factors derive from historical false positive rates.

**Figure 3:** False Positive Analysis and Operational Impact Assessment




Operational cost modeling quantifies false positive impact. Each percentage point of false positive rate generates 487 annual help desk tickets per 10,000 users at $47 per ticket average resolution cost. Security operations centers require 0.31 analyst hours per 100 false positives for investigation, translating to 1.3 full-time equivalents per percentage point at organizational scale. Random Forest's 3.8% rate demands 4.9 analysts ($490,000 annual cost) while SVM's 2.1% requires 2.7 analysts ($270,000), though Random Forest prevents estimated $470,000 in breach costs through superior attack detection, yielding positive return on investment.

User satisfaction surveys (n = 1,247) correlate with false positive exposure following exponential decay: $S = 92 \times \exp(-0.21 \times FP\_count)$ where S represents satisfaction percentage and FP_count tallies 30-day false positives. Random Forest maintains 82% satisfaction through uniform false positive distribution compared to 76% for Neural Networks with concentrated impact. Support Vector Machines achieve 87% satisfaction but suffer 71% satisfaction among users experiencing successful attacks that evaded detection.

Alert fatigue quantification reveals non-linear degradation in analyst effectiveness. Investigation accuracy maintains 94% for false positive rates below 3%, declining to 81% at 5% and 68% at 7% as analysts develop alarm habituation. Response time increases from 4.3 minutes at 2% false positive rate to 11.7 minutes at 5%, indicating delayed threat mitigation. These human factors establish practical false positive ceiling around 4% for maintaining security posture.

## 5. Discussion and Future Work

### 5.1 Algorithmic Trade-offs in Production Environments

The empirical characterization establishes performance boundaries guiding algorithm selection under specific operational constraints. Random Forest classifiers emerge as the balanced solution for organizations processing 10^4 - 10^5 daily authentication events. The 94.7% detection accuracy captures mainstream attack patterns while 3.2ms inference latency maintains user experience. Feature importance rankings provide investigation guidance—identifying inter-arrival variance and geographic dispersion as primary attack indicators accelerates analyst response. The modular ensemble structure enables incremental updates: adding trees trained on recent attacks requires 12% of initial training time while maintaining historical knowledge.

Support Vector Machines occupy specialized niches where precision supersedes recall. Financial transaction authentication benefits from 2.1% false positive rate when customer friction costs exceed breach risks for specific transaction categories. The mathematical foundation through margin maximization provides regulatory compliance for algorithmic accountability requirements. However, $O(n^2)$ training complexity limits applicability to datasets below 10^6 samples, and lack of incremental learning necessitates complete retraining for model updates.

Neural Networks demonstrate untapped potential for sophisticated attack detection, achieving 93.7% accuracy on compromised accounts where behavioral subtleties evade shallow methods. Hierarchical feature learning captures complex interactions: temporal patterns across multiple timescales, device fingerprint evolution, and role-based access deviations. Transfer learning enables model adaptation with 20% of initial training cost. Yet computational requirements—1,156 seconds training, 5.7ms inference—limit deployment to well-resourced organizations. Model opacity complicates incident investigation and regulatory compliance where decision explainability is mandated.

Ensemble strategies combining algorithmic strengths warrant investigation. Preliminary stacking experiments with Random Forest base models and SVM meta-classifier achieve 95.8% accuracy with 2.8% false positive rate, suggesting complementary signal capture. Weighted voting with algorithm-specific attack specialization—SVM for brute force, Random Forest for credential stuffing—improves per-attack F1 scores by 3-7%. Dynamic ensemble selection based on input characteristics could optimize instance-level predictions.

### 5.2 Limitations and Real-world Deployment Challenges

Dataset representativeness constrains generalization beyond observed organizational contexts. Financial services exhibit risk-averse behaviors with multi-factor authentication prevalence, healthcare maintains strict access controls under HIPAA requirements, while technology sectors demonstrate experimental attitudes toward authentication methods. Models trained on sector-specific data achieve 34% performance degradation when cross-deployed, necessitating domain adaptation strategies.

Adversarial adaptation presents fundamental challenge to static model deployments. Gradient-based evasion attacks craft authentication sequences achieving 76% success rate against Neural Networks and 52% against Random Forest. Attackers observe detection outcomes through login success/failure, enabling iterative refinement toward decision boundaries. Defensive strategies including adversarial training, gradient masking, and input transformation provide partial mitigation but reduce benign accuracy by 8-12%.

Integration with legacy infrastructure imposes architectural constraints. SIEM systems designed for rule-based detection lack machine learning inference capabilities, requiring parallel infrastructure or significant modernization investment. The 150MB Random Forest model exceeds embedded system memory in branch offices, necessitating edge-cloud architectures with associated latency and reliability implications. Real-time inference demands conflict with batch-oriented data pipelines, requiring stream processing infrastructure investment.

Privacy regulations increasingly restrict authentication data processing. Cross-border model training violates data residency requirements in 67 jurisdictions. User consent for behavioral analysis faces resistance with 31% opt-out rates in voluntary programs. Differential privacy ($\varepsilon = 1.0$) degrades model accuracy by 15-20%, while homomorphic

encryption increases computation by 100-1000×. Federated learning offers promise but introduces complexity from non-IID distributions across organizational units.

### 5.3 Future Research Directions and Recommendations

Adversarial robustness demands theoretical advances beyond empirical hardening. Certified defense mechanisms providing provable bounds against l_p-norm perturbations could guarantee minimum detection performance despite adaptive attacks. Game-theoretic frameworks modeling attacker-defender dynamics inform optimal strategies under resource constraints. Moving target defenses that dynamically adjust detection boundaries increase attack costs while maintaining usability.

Graph neural architectures operating on authentication networks capture relational structures invisible to independent event analysis. Preliminary experiments with user-device-location graphs achieve 7% improvement in lateral movement detection. Temporal graph networks model evolution of authentication relationships, identifying anomalous edge formations indicating account compromise. Scalability remains challenging with $O(|V| + |E|)$ complexity for graphs with millions of vertices (users) and edges (authentication events).

Privacy-preserving collaborative learning enables organizations to benefit from collective intelligence without sharing sensitive data. Secure aggregation protocols allow model updates while hiding individual contributions. Trusted execution environments provide hardware-enforced isolation for model training on encrypted data. Performance overhead currently reaches 100-1000× but hardware acceleration and algorithmic optimization rapidly improve efficiency.

Continuous learning architectures maintaining performance despite distribution shift represent critical capability. Elastic weight consolidation preserves important parameters while adapting to new patterns. Memory replay buffers retain historical examples preventing catastrophic forgetting. Progressive networks add capacity for emerging threats while freezing previous knowledge. The plasticity-stability trade-off requires careful calibration with organizational change velocity.

Standardized benchmarks advancing enterprise authentication security research require community coordination. Benchmarks must encompass diverse organizational contexts, realistic attack scenarios including adversarial examples, and operational constraints including latency, throughput, and false positive tolerance. Privacy-preserving synthetic data generation could enable public benchmarks while protecting sensitive authentication patterns.

## 6. Acknowledgements

I would like to extend my sincere gratitude to Satriawan, M., Tahir, Z., and Paundu, A. W. for their groundbreaking research on SVM classifier optimization for predicting anomalies in login data with SMOTE as published in their article titled [7] "SVM classifier optimization for predicting anomalies in login data with SMOTE" in the International Conference on Green Energy, Computing and Intelligent Technology 2024. Their insights and methodologies in login anomaly detection have significantly influenced my understanding of advanced techniques in enterprise security and have provided valuable inspiration for my own research in this critical area.

I would like to express my heartfelt appreciation to Gnanasivam, S., Tveter, D., and Dinh, N. for their innovative study on performance evaluation of network intrusion detection using machine learning techniques, as published in their article titled [10] "Performance evaluation of network intrusion detection using machine learning" in the 2024 IEEE International Conference on Consumer Electronics. Their comprehensive performance analysis and evaluation methodologies have significantly enhanced my knowledge of machine learning algorithm assessment and inspired my research approach in this field.

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