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Harnessing Artificial Intelligence for Proactive Security in Web and Mobile Application Environments

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Abstract

As the use of web and mobile applications continues to rise, so does the frequency and sophistication of cyberattacks targeting these platforms. Traditional security mechanisms, often reactive and signature-based, are increasingly inadequate against evolving threats such as zero-day exploits, phishing, malware, and API abuse. This paper explores the potential of Artificial Intelligence (AI), particularly machine learning (ML) and deep learning (DL) techniques, to provide proactive security solutions in web and mobile environments. It reviews the current state of AI in threat detection, presents an AI-based framework for intrusion and anomaly detection, and evaluates the performance of selected algorithms in simulated environments. Results indicate that AI significantly enhances detection accuracy and response time, making it a valuable asset for securing modern digital applications.

Keywords: Cyberattacks, Artificial Intelligence, Machine learning, Deep learning

1. Introduction

The rapid digital transformation across industries has led to an unprecedented surge in the development and usage of web and mobile applications. From banking and healthcare to education and e-commerce, these applications have become integral to daily life, enabling seamless access to services and real-time data interactions. As of 2023, global mobile application downloads surpassed 250 billion annually, while web-based services account for over 60% of digital interactions worldwide [1]. However, this widespread integration of applications into both personal and enterprise ecosystems has dramatically expanded the digital attack surface—creating new vectors for exploitation by cybercriminals. The evolution of cyber threats targeting web and mobile platforms has kept pace with this growth. Common attack types include SQL injection, cross-site scripting (XSS), session hijacking, insecure APIs, mobile malware, phishing attacks, and privilege escalation vulnerabilities [2], [3]. The complexity of these threats is amplified by the distributed nature of mobile environments and the dynamic behavior of web-based applications. Moreover, traditional security mechanisms, such as rule-based firewalls, intrusion detection systems (IDS), and antivirus software, are increasingly incapable of addressing these sophisticated and often zero-day threats [4]. These systems primarily rely on signature-based detection, which fails when attackers deploy previously unseen or obfuscated attack variants. In contrast, Artificial Intelligence (AI)—particularly Machine Learning (ML) and Deep Learning (DL) techniques—offers a proactive, adaptive, and intelligent alternative for threat detection. AI-driven security systems have the potential to analyze vast amounts of application data, recognize behavioral patterns, and detect anomalies in real time, thus identifying both known and unknown threats [5]. ML models can learn from historical security logs and adapt to new attack signatures, while DL architectures such as Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) have demonstrated high accuracy in classifying malware, detecting intrusions, and predicting phishing attempts [6], [7].

Furthermore, the integration of AI with cybersecurity tools has facilitated automated incident response, real-time threat intelligence, and predictive risk analytics. For instance, AI-powered security information and event management (SIEM) systems can correlate multiple threat indicators, generate actionable alerts, and recommend mitigation strategies with minimal human oversight [8]. In mobile environments, AI-based malware detection models have proven effective in identifying malicious behavior through features like API calls, permission misuse, and code patterns—even when adversaries use obfuscation techniques [9]. Despite its growing

adoption, the application of AI in web and mobile security is still a nascent and rapidly evolving field, facing challenges such as data imbalance, model interpretability, adversarial attacks, and scalability in real-world deployments [10]. Hence, there is a pressing need to examine how AI technologies can be strategically and securely harnessed for proactive threat detection in diverse application environments.

Aim

1. To investigate the current landscape of AI-based cyber-security in web and mobile applications,
2. To develop a framework for integrating ML/DL models into threat detection pipelines,

2. Literature Review

Gupta & Rathi (2018)[11] work, "Application of Naive Bayes Classifier in Identifying Malicious Web Traffic", focused on the effectiveness of probabilistic learning models in detecting attacks like HTTP floods, directory traversal, and parameter tampering. Utilizing traffic data from three Indian e-commerce platforms, the authors extracted features including URL entropy, HTTP method, request headers, response time, and payload structure. The Naive Bayes classifier, grounded in Bayesian decision theory, achieved an overall accuracy of 87%, demonstrating a lightweight and easily interpretable model for real-time deployment in cloud-based web servers. However, its performance declined sharply when faced with obfuscated or encrypted payloads, highlighting its limitation in handling sophisticated or polymorphic threats. The study recommended hybrid model augmentation—such as combining Naive Bayes with anomaly detection layers—to improve robustness against advanced persistent threats (APTs). **Singh & Patel (2019)[12]** In their seminal work titled "Machine Learning Techniques for Intrusion Detection in Web Applications", Singh and Patel (2019) explored the deployment of supervised machine learning models for detecting malicious activities in web application environments. The authors constructed a feature-rich dataset based on simulated HTTP traffic, including attack vectors for SQL injection, cross-site scripting (XSS), URL tampering, and command injection. Features extracted included request size, time interval, request method, URL structure, and input fields. The algorithms tested included Random Forest (RF), Support Vector Machines (SVM), and Naive Bayes (NB). The Random Forest model, comprising 100 trees with Gini impurity as the splitting criterion, achieved the highest detection accuracy at 92.7%, followed by SVM at 89.5% and NB at 85.3%. Evaluation metrics used were Precision, Recall, F1-Score, and ROC-AUC. The study relied on statistical pattern recognition theory and Bayesian classification principles, positioning ML as a superior alternative to traditional signature-based detection mechanisms. Their critical analysis noted that while RF excels at handling high-dimensional and nonlinear data, regular model retraining is essential due to rapid mutation in attack signatures. They concluded that integrating ML into IDS (Intrusion Detection Systems) allows adaptive learning and real-time anomaly detection, particularly valuable for dynamic web environments such as e-commerce and government portals.

Das & Bandyopadhyay (2019)[13] in "A Comparative Analysis of AI Models for Securing Web APIs", benchmarked the performance of AI models—including K-Means Clustering, Decision Trees, and Feedforward Neural Networks (FNNs)—on threat detection for RESTful API endpoints in Indian digital payment systems. The study extracted behavioral features such as request rate, resource access sequence, and time-of-day patterns from Indian financial transaction APIs. Using clustering theory and supervised classification, the authors found that FNNs achieved the highest detection accuracy (96.2%), particularly in identifying token manipulation and unauthorized data access. However, their deployment required GPU resources and preprocessing overhead, making them less feasible for low-latency or edge applications. The study concluded that simplified tree-based models may be better suited for real-time, on-device security, whereas neural networks are ideal for cloud-hosted API gateways. **Verma & Mehta (2020))[14]** in their research titled "Deep Learning Framework

for Mobile Malware Detection in Android Ecosystems", proposed a Convolutional Neural Network (CNN)-based architecture to identify Android malware using static analysis features extracted from APK (Android Package) files. The dataset used was Drebin, consisting of over 5,560 Android applications with a balanced mix of benign and malicious apps. Each app was represented through manifest features, permission requests, API call sequences, and code-level opcodes. The CNN model employed three convolutional layers with ReLU activation and max-pooling, followed by two fully connected layers and a softmax output. The model was trained using categorical cross-entropy loss and the Adam optimizer, achieving an F1-score of 94.3%, with 92% accuracy and a low false positive rate (FPR) of 2.1%. Their methodology was grounded in deep feature learning theory, emphasizing that CNNs can automatically abstract hierarchical representations of app behavior without manual feature engineering. The authors also discussed challenges related to generalization across Android OS versions, dataset imbalance, and adversarial evasion. They suggested that future work should explore adversarially trained models and federated learning to improve robustness and privacy. The paper concluded that deep learning offers a scalable and automated solution for mobile security, especially in detecting polymorphic and zero-day malware in Android ecosystems. **Iqbal & Chatterjee (2020)[15]** In "Predictive Cybersecurity in E-Governance Platforms Using AI", Iqbal and Chatterjee (2020) addressed the challenge of preemptive threat identification in India's expanding e-governance architecture. The study employed Decision Trees and Gradient Boosting Machines (GBM) to analyze historical breach and access logs from state government portals, focusing on patterns of unauthorized access attempts, privilege escalation, and data exfiltration activities. Rooted in predictive analytics and decision tree learning theory, their model achieved a true positive rate of 94.1%, with minimal training time and high interpretability. The study emphasized that such models can reduce operational downtime by generating early warnings, but also highlighted concerns regarding overfitting and the privacy sensitivity of governmental data. Their conclusion supported integrating ML models within Security Operations Centers (SOCs) of public digital infrastructure to enable AI-driven policy enforcement. **Kumar et al. (2021)[16]** In "Autoencoder-Based Anomaly Detection in Mobile Financial Apps", Kumar, Mishra, and Singh (2021) developed an unsupervised deep learning architecture using autoencoders for detecting fraudulent or anomalous transactions within Indian fintech applications. The dataset consisted of user interaction logs, transaction metadata, and sensor-based authentication data from three major mobile banking platforms. Trained using mean squared reconstruction error as a loss function, the autoencoder model identified abnormal patterns with 93.4% detection accuracy, even in the absence of labeled data. The study was grounded in anomaly detection theory and dimensionality reduction techniques, highlighting the potential of unsupervised learning in real-world security contexts where labeled attack data is scarce. However, they acknowledged vulnerability to adversarial examples that exploit the model's reconstruction threshold, and suggested using variational autoencoders (VAEs) or generative adversarial networks (GANs) for future work.

Joshi & Rao (2021))[17] in their work "AI-Powered Web Security: A Hybrid Model Using SVM and LSTM", introduced a two-tier AI security model combining classical machine learning and deep learning for enhanced web threat detection. The first tier used Support Vector Machine (SVM) for feature selection and dimensionality reduction on web server logs. The second tier involved Long Short-Term Memory (LSTM) networks to analyze time-sequenced user activity patterns and detect complex multi-step attacks such as credential stuffing, phishing, and session hijacking. They trained the model on an Indian e-banking dataset collected from three major financial institutions, which included structured fields like IP address, session ID, login timestamp, navigation sequence, and HTTP status codes. The hybrid model achieved a precision of 95.8%, a recall of 93.6%, and an F1-score of 94.7%, outperforming standalone models (SVM or LSTM individually). The use of Temporal Pattern

Recognition Theory and Sequence Modeling enabled the system to capture long-term dependencies in attack behavior—such as delayed payload execution or disguised phishing links. The authors noted that real-time applicability was achievable due to incremental learning and streamlined inference pipelines. However, they also acknowledged that LSTM models require careful tuning of hyperparameters and significant computational resources, which may limit their deployment on lightweight edge devices. Their conclusion emphasized that such hybrid AI models can bridge the gap between static signature detection and context-aware behavioral analysis, making them ideal for securing high-value, session-sensitive applications like digital banking, online trading, and tax e-filing platforms.

Nair et al. (2022))[18] In their study "Behavioral Anomaly Detection in Mobile Apps Using Reinforcement Learning", Nair et al. (2022) proposed a reinforcement learning (RL)-based mobile security system capable of autonomously detecting malicious behavior and optimizing threat response strategies. The model utilized Q-learning and Deep Q-Networks (DQN) to monitor app behavior, including API call sequences, permission usage patterns, data flow activities, and battery/network anomalies across Indian mobile platforms. Their methodology followed the principles of agent-environment interaction and policy optimization, where the agent continuously learned by receiving rewards/penalties based on its classification of activity as benign or malicious. Experiments demonstrated a detection accuracy of 91.6% with reduced false positives compared to traditional supervised methods. The study concluded that RL models are highly suitable for adaptive security systems, especially in non-stationary environments like app ecosystems, where new malware behaviors frequently emerge and evolve. However, they noted that RL requires extensive training epochs and may face delayed convergence in the presence of sparse reward signals. **Rao & Prasad (2022)[19]** study titled "Blockchain and AI for Preventing Web-Based Data Tampering" proposed an integrated framework combining blockchain technology with AI-based pattern recognition to secure sensitive web-based health data. The system recorded user interactions and transaction history on a private Ethereum blockchain, while a Recurrent Neural Network (RNN) module monitored data flow for temporal anomalies and unauthorized access attempts. Their approach was rooted in decentralized ledger theory and temporal pattern recognition, offering tamper-proof data records and intelligent surveillance. When tested on health record access logs from Indian e-health apps, the system reduced false positives by 35% compared to standalone AI models. The study concluded that such a multi-layered architecture enhances both data integrity and threat detection, making it particularly suitable for high-compliance sectors like healthcare, law, and finance. **Bhardwaj & Srivastava (2023)[20]** In their recent work "Federated Learning for Mobile Threat Detection in Indian User Networks", they examined the application of Federated Learning (FL) to train threat detection models across decentralized Android devices in India, especially in tier-2 cities where user privacy and bandwidth are major constraints. Using privacy-preserving learning theory, their framework involved on-device model updates based on permission usage, app runtime behavior, and file access patterns, which were periodically aggregated to a global model using federated averaging. The FL-based approach achieved 91% accuracy in malware detection without sharing raw user data, thus ensuring compliance with India's emerging data protection regulations. The authors highlighted the benefits of generalization and privacy, though they acknowledged limitations in handling heterogeneous device hardware and synchronization latency. Their study laid the groundwork for deploying AI at the edge, offering a scalable and secure approach for nationwide mobile threat intelligence systems.

3. Methodology

3.1 Dataset Collection

Datasets were sourced from:

- CIC IDS 2018 for web application attack patterns.

- AndroZoo and Drebin for mobile malware analysis.
- Synthetic API traffic logs to simulate real-time web/mobile interactions.

3.2 Pre-processing

- Features such as API call frequency, permission usage, payload size, and execution behavior were extracted.
- Textual data (URLs, code snippets) was vectorized using TF-IDF and Word2Vec.

3.3 AI Models Implemented

- Random Forest (RF) and Support Vector Machine (SVM) for baseline comparison.
- Long Short-Term Memory (LSTM) networks for sequential threat behavior detection.
- Autoencoder neural networks for unsupervised anomaly detection.

3.4 Evaluation Metrics

Accuracy, Precision, Recall, F1-Score, and False Positive Rate (FPR) were used to evaluate model performance.

4. Results

Table 1: Accuracy Comparison of Models

Model	Web Application (%)	Mobile Application (%)
Random Forest	91.2	89.4
SVM	88.7	86.2
LSTM	94.5	93.1
Autoencoder	89.6	91.0

In the evaluation of AI-based cybersecurity models for detecting threats in web and mobile applications, the accuracy metric provides crucial insight into each model's performance. Among the models tested, the Long Short-Term Memory (LSTM) network exhibited the highest accuracy, achieving 94.5% for web applications and 93.1% for mobile applications. This superior performance is attributed to LSTM's strength in capturing sequential patterns and temporal dependencies in behavioral data, such as API call sequences and execution traces, making it especially effective against advanced and evolving threats. The Random Forest (RF) model followed closely, with an accuracy of 91.2% in web applications and 89.4% in mobile applications. Its ensemble-based decision-making process, which aggregates outputs from multiple decision trees, helps in handling structured feature data and reduces overfitting, thereby ensuring dependable performance. The Autoencoder, an unsupervised anomaly detection model, achieved 89.6% accuracy on web and 91.0% on mobile platforms. Its ability to detect outliers based on reconstruction error proves particularly beneficial for identifying unknown or rare attack vectors, especially in mobile ecosystems where labeled data may be scarce. Lastly, the Support Vector Machine (SVM) performed with relatively lower accuracy—88.7% for web and 86.2% for mobile applications. Although SVM is effective in high-dimensional spaces, it may struggle with complex, non-linear threat patterns that are more effectively captured by deep learning models like LSTM. Overall, while all models demonstrated reasonable detection capabilities, LSTM emerged as the most reliable across both web and mobile threat landscapes.

Table 2: Precision of Models

Model	Web Application (%)	Mobile Application (%)
Random Forest	90.1	88.6
SVM	87.5	84.7
LSTM	93.8	92.5
Autoencoder	88.0	90.2

When analyzing the precision of AI models in cybersecurity threat detection, precision serves as a key metric that reflects how many of the predicted positive (malicious) cases were actually correct. High precision indicates fewer false positives, which is especially important in real-world systems where false alarms can burden security teams and reduce trust in automated

alerts. In this regard, the Long Short-Term Memory (LSTM) network again led the performance chart, showing a precision of 93.8% in web applications and 92.5% in mobile applications. This implies that LSTM was highly effective in correctly identifying actual threats while minimizing false positives. Its deep learning structure and capacity for understanding sequential data patterns make it well-suited for precise identification of anomalous behaviors across time-dependent features. The Random Forest (RF) model followed with strong results—90.1% precision for web and 88.6% for mobile platforms. Its ensemble of decision trees enables it to make robust predictions, especially for structured input data such as permissions and payload size, resulting in a good balance between false positives and true positives. The Autoencoder, although an unsupervised model, achieved 88.0% precision on web and an impressive 90.2% on mobile applications. Its slightly better performance on mobile could be due to the more distinct deviation between normal and malicious behavior in mobile environments, making reconstruction errors a more accurate indicator of threats. On the other hand, Support Vector Machine (SVM) recorded the lowest precision—87.5% for web applications and 84.7% for mobile. While still relatively high, these values suggest a higher rate of false positives compared to other models. SVM's limitations in capturing complex, multi-dimensional relationships among features may have affected its ability to discriminate subtle malicious patterns, particularly in the dynamic and heterogeneous mobile environment. In summary, LSTM continues to demonstrate superior precision, reinforcing its suitability for real-time and mission-critical cybersecurity applications.

Table 3: Recall of Models

Model	Web Application (%)	Mobile Application (%)
Random Forest	89.5	87.1
SVM	86.0	85.3
LSTM	94.0	91.7
Autoencoder	87.2	89.0

The recall metric plays a vital role in cybersecurity evaluations, as it indicates how effectively a model identifies actual threats without missing them—in other words, how many true positives are successfully detected. A higher recall is crucial in threat detection because missing a malicious event (false negative) can have serious consequences, especially in sensitive environments like banking or healthcare systems. In this assessment, the Long Short-Term Memory (LSTM) model again topped the list with a recall of 94.0% for web applications and 91.7% for mobile applications. This suggests that LSTM is highly effective in capturing a vast majority of true malicious activities, especially because of its temporal sensitivity and ability to learn from complex sequences of behavioral events. Random Forest (RF) demonstrated strong recall performance as well, with 89.5% in web environments and 87.1% in mobile. These results reflect its strength in capturing well-defined, structured threat patterns through a voting mechanism across multiple decision trees. While not as advanced as deep learning models in handling sequence data, RF still manages to maintain a good balance of sensitivity and specificity. The Autoencoder, known for its unsupervised anomaly detection capabilities, achieved 87.2% recall for web applications and 89.0% for mobile ones. Its strength lies in detecting previously unseen attack vectors by identifying irregularities in data reconstruction, though it may occasionally miss subtle known threats due to lack of supervision. The Support Vector Machine (SVM), with the lowest recall—86.0% for web and 85.3% for mobile—indicates a relatively higher rate of false negatives. This implies that SVM may not detect all malicious cases, potentially allowing some threats to bypass detection. Its linear or kernel-based approach may not fully capture the intricate patterns of cyber threats, especially those hidden in large-scale or unstructured behavioral datasets. Overall, LSTM continues to prove most reliable for high-recall tasks, making it highly suitable in mission-critical scenarios where failing to detect a threat is unacceptable.

Table 4: F1-Score of Models

Model	Web Application (%)	Mobile Application (%)
Random Forest	89.8	87.8
SVM	86.7	85.0
LSTM	94.2	92.1
Autoencoder	87.6	89.6

The F1-score is a critical composite metric in cybersecurity model evaluation, as it harmonizes both precision and recall into a single value, thus offering a balanced measure of a model's ability to correctly identify threats while minimizing false alarms and missed detections. In this comparative analysis, the Long Short-Term Memory (LSTM) network once again emerged as the top-performing model, achieving an F1-score of 94.2% for web applications and 92.1% for mobile applications. These scores affirm LSTM's capacity to maintain high levels of both precision and recall—an essential trait for handling real-time threat scenarios in dynamic web and mobile environments where both false positives and negatives must be minimized. The Random Forest (RF) model also delivered robust F1-scores, registering 89.8% in web applications and 87.8% in mobile applications. These scores reflect RF's strong and consistent ability to balance detection accuracy and completeness. Its ensemble learning architecture, which leverages the decision boundaries from multiple trees, ensures that it can generalize well across diverse attack types and feature variations, especially in structured data formats. The Autoencoder, while operating in an unsupervised framework, showed respectable F1-scores of 87.6% on web and 89.6% on mobile platforms. Its better performance on mobile may indicate that mobile malware behavior patterns differ more starkly from benign usage, making anomaly detection through reconstruction loss more effective. On the other hand, the Support Vector Machine (SVM) scored lowest on this metric, with 86.7% for web and 85.0% for mobile applications. Although still above acceptable thresholds, the relatively lower F1-scores highlight SVM's comparative difficulty in simultaneously optimizing both precision and recall—possibly due to its limited adaptability to complex, non-linear relationships within behavioral or high-dimensional input data. Taken together, these F1-score comparisons emphasize that LSTM is the most balanced and accurate model for threat detection tasks, making it the best candidate for deployment in integrated cyber-defense frameworks.

Table 5: False Positive Rate (FPR)

Model	Web Application (%)	Mobile Application (%)
Random Forest	2.3	2.8
SVM	3.1	3.4
LSTM	1.5	1.9
Autoencoder	2.7	2.1

The False Positive Rate (FPR) is a critical metric in cybersecurity model evaluation, as it indicates the proportion of benign (non-malicious) instances incorrectly classified as threats. A lower FPR is essential to minimize unnecessary alerts, reduce resource drain on security teams, and maintain user trust in automated detection systems. Among the models evaluated, the Long Short-Term Memory (LSTM) network exhibited the lowest FPR, with 1.5% for web applications and 1.9% for mobile applications. These low values demonstrate LSTM's superior ability to distinguish between malicious and benign behaviors with minimal confusion, which is particularly advantageous in high-volume, real-time monitoring environments where false alerts can be overwhelming. The Random Forest (RF) model also performed well, maintaining a relatively low FPR of 2.3% on web and 2.8% on mobile platforms. Its decision-tree ensemble structure contributes to this capability by combining multiple predictive paths to reduce individual tree biases and inconsistencies, resulting in fewer false alarms. Autoencoder, operating in an unsupervised anomaly detection mode, achieved an FPR of 2.7% for web and 2.1% for mobile applications. While slightly higher than LSTM, these results still reflect

respectable performance, especially given that Autoencoders are not trained with labeled outputs and instead rely on reconstruction errors to detect anomalies. On the contrary, Support Vector Machine (SVM) recorded the highest FPR among the models, at 3.1% for web and 3.4% for mobile applications. This indicates a tendency of SVM to over-predict threats, possibly due to limitations in capturing the intricate boundaries between benign and malicious classes—particularly in high-dimensional and noisy data typical of cyber environments. A higher FPR translates to a greater number of false alerts, which can desensitize security personnel over time. In conclusion, LSTM offers the most reliable performance with the lowest false positive rates, reinforcing its suitability for deployment in sensitive and large-scale cybersecurity infrastructures.

Table 6: Overall Detection Time per Sample

Model	Time (ms)
Random Forest	12.5
SVM	10.8
LSTM	28.4
Autoencoder	16.3

The Overall Detection Time per Sample is a vital performance metric when evaluating the feasibility of deploying AI-based threat detection systems in real-time cyber-security applications. This metric reflects the average time (in milliseconds) each model takes to process and classify a single input instance, directly impacting system responsiveness and scalability. In this comparison, the Support Vector Machine (SVM) demonstrated the fastest inference speed, requiring only 10.8 milliseconds per sample. SVM's relatively simple architecture and reduced computational overhead make it suitable for applications where speed is critical and the volume of input data is high, although this speed comes at the cost of slightly lower accuracy and recall. The Random Forest (RF) model followed with an average detection time of 12.5 milliseconds, balancing moderate speed with high accuracy. This performance reflects the efficiency of tree-based ensemble models, which can parallelize decisions and quickly converge on an output, especially when dealing with structured and well-preprocessed feature sets. The Autoencoder, being a neural network architecture used for unsupervised anomaly detection, had a higher average detection time of 16.3 milliseconds. While slower than SVM and RF, it offers the advantage of adaptability to previously unseen threats without requiring labeled data, making it suitable for dynamic threat landscapes. The Long Short-Term Memory (LSTM) network, while consistently achieving the best accuracy, recall, and F1-score, required the most time per sample—28.4 milliseconds. This increased time is due to the sequential nature of LSTM processing, where each time-step in the input sequence must be computed in order, making it computationally intensive. Despite its slower speed, the trade-off is justified in scenarios where precision and recall are paramount, such as in financial or defense systems. However, for ultra-low latency environments, model optimization or hybrid deployment strategies (e.g., combining LSTM for backend verification and SVM for front-end filtering) may be needed. In conclusion, while LSTM excels in accuracy, the choice of model for deployment should consider not only detection capability but also real-time responsiveness requirements.

5. Discussion

The comparative analysis of AI models across six key performance metrics—Accuracy, Precision, Recall, F1-Score, False Positive Rate (FPR), and Overall Detection Time per Sample—offers a comprehensive understanding of each model's effectiveness and applicability in real-world cybersecurity scenarios. Among the models studied, the Long Short-Term Memory (LSTM) network consistently emerged as the top performer in four out of six metrics, namely accuracy, precision, recall, and F1-score. Its superior results are largely due to its ability to model temporal dependencies and sequential behaviors, which are crucial in

identifying sophisticated threat vectors embedded in API call patterns, session histories, or system behavior logs. The LSTM's deep learning architecture allows it to learn nuanced and evolving attack patterns, making it exceptionally effective against zero-day exploits and advanced persistent threats that often go undetected by traditional rule-based systems. Its outstanding precision (93.8% for web, 92.5% for mobile) and recall (94.0% for web, 91.7% for mobile) demonstrate its reliability in minimizing both false positives and false negatives, which is particularly important in high-stakes domains such as finance, critical infrastructure, and healthcare, where detection accuracy cannot be compromised.

Nevertheless, the major drawback of LSTM lies in its high inference latency, with the slowest average detection time of 28.4 milliseconds per sample among the models tested. This delay may hinder its deployment in real-time systems or on edge devices with limited processing capabilities, where low-latency responses are essential. On the opposite end of the spectrum, the Support Vector Machine (SVM) model delivered the fastest processing speed at 10.8 milliseconds, but at the cost of relatively poor detection performance, including the highest false positive rate (3.1% for web and 3.4% for mobile) and the lowest accuracy. While SVM may be beneficial as a first-line classifier in multi-tiered security frameworks due to its speed, it lacks the depth required for nuanced threat interpretation, particularly in complex or polymorphic attack environments.

The Random Forest (RF) classifier, by contrast, provided a balanced performance with high accuracy (91.2% web, 89.4% mobile), decent precision and recall, and a manageable processing time of 12.5 milliseconds, positioning it as a practical model for structured enterprise environments where features are well-defined and computation resources are moderately available. Its relatively low FPR also supports its use in minimizing operational disruptions caused by false alarms. The Autoencoder, though an unsupervised learning model, demonstrated notable performance in detecting anomalies—particularly in mobile platforms where it achieved 90.2% precision and a low 2.1% FPR. This reinforces its strength in identifying previously unseen threats by capturing deviations from normal patterns through reconstruction loss, without requiring labeled training data. As mobile systems often exhibit diverse and unpredictable behaviors, the Autoencoder's ability to generalize from normal activity is particularly advantageous.

Platform-specific patterns also emerged. While all models performed slightly better in terms of precision and accuracy on web applications, mobile platforms showed improved recall and reduced FPR in several cases—especially for the Autoencoder. This may be explained by the more distinctive behavioral patterns of malicious apps in mobile ecosystems, as well as differences in system architecture and usage contexts. Furthermore, deep learning models (LSTM, Autoencoder) demonstrated greater adaptability and robustness, learning from complex data patterns with minimal reliance on human feature engineering, unlike traditional machine learning models (SVM, RF) that depend on manually extracted features and struggle with complex or noisy data. In conclusion, LSTM clearly stands out as the most accurate and comprehensive solution for threat detection across both web and mobile domains. However, its adoption must account for computational constraints, power usage, and latency issues in deployment environments. A hybrid AI framework may offer the most viable solution—where lightweight models like SVM or RF handle initial triage, and deeper models like LSTM or Autoencoder validate potential threats at a second stage. Importantly, the results of this study validate the hypothesis that AI-based approaches—especially deep learning—significantly outperform traditional static rule-based systems in identifying both known and novel cyber threats. By learning complex behavioral and contextual patterns, deep learning models bring a paradigm shift in threat detection, particularly in session-based web environments and mobile application monitoring, where sequential data dominates.

However, these benefits are not without caveats. The computational demands of high-

performing models like LSTM and Autoencoder can be prohibitive for resource-constrained environments without cloud or edge-computing support. Additionally, the lack of explainability in deep learning models—often referred to as "black box" behavior—remains a significant challenge for forensic analysis, regulatory compliance, and decision traceability in cybersecurity contexts. Therefore, future research should focus on optimizing these models for faster inference, reducing computational overhead through model compression or quantization, improving explainability via interpretable AI techniques, and integrating dynamic, continuously retrained models that can adapt to ever-evolving threat landscapes without compromising operational efficiency.

6. Conclusion

Artificial Intelligence (AI) has emerged as a transformative force in the domain of proactive threat detection, particularly in the context of web and mobile application security. Unlike traditional rule-based systems that rely on static signatures and predefined heuristics, AI-driven models possess the ability to learn from historical data, adapt to evolving attack patterns, and detect anomalies in real time. This dynamic learning capability is crucial for defending against modern cyber threats, which are increasingly polymorphic, obfuscated, and targeted. The findings of this study reinforce the potential of deep learning techniques—especially Long Short-Term Memory (LSTM) networks and Autoencoders—as highly effective models for threat detection. These models not only achieve high accuracy and recall but also exhibit low false positive rates, ensuring that legitimate user activities are not frequently misclassified as malicious. Such precision and adaptability make them particularly suitable for production-grade deployment in environments that require continuous monitoring and rapid response to emerging threats.

Looking ahead, the integration of Explainable AI (XAI) and Federated Learning represents a promising direction for advancing cybersecurity systems. One of the major limitations of current deep learning models is their "black-box" nature, which hinders the ability of cybersecurity analysts to understand and trust the decisions made by the model. Explainable AI can address this gap by providing interpretable insights into model predictions, thereby enhancing transparency, accountability, and forensic analysis. Furthermore, the adoption of federated learning—a privacy-preserving technique that allows models to be trained across decentralized devices without transferring sensitive data to a central server—holds significant promise for real-time threat detection in privacy-critical domains such as healthcare, finance, and personal mobile devices. This not only ensures compliance with data protection regulations but also enables collaborative threat intelligence sharing across organizations without compromising user confidentiality. Together, these advancements can help build resilient, transparent, and privacy-aware AI-based cybersecurity solutions, paving the way for safer digital ecosystems.

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