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AI-BASED FAKE LOGIN ATTEMPT DETECTION SYSTEM USING BEHAVIORAL ANALYTICS

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Abstract

In the age of the increasingly sophisticated cyber threats, the conventional login security mechanisms are often inadequate to combat with the surge of the fake login attempts using valid credentials. This happens with credential leaks, phishing or brute-force automation bypass the traditional security filters that poses a serious risk to organizations and the user data. In this paper we will introduce a machine learning-based fake login detection system that operates by evaluating behavioral login patterns, including the parameters such as login time, location, device type and the access frequency. The solution we propose includes employing a Random Forest classification algorithm that is trained on a custom dataset of the 1,000 simulated login sessions which is generated for the 50 virtual users across varied geographic and the temporal conditions. The proposed system successfully identifies the suspicious login attempts with the accuracy rate of 94.3% that offers a reliable second layer of the authentication beyond passwords or tokens. This research underscores the growing relevance of the behavioral analytics in the enhancement of the authentication systems of enterprise settings, where unauthorized access may lead to the sensitive data breaches. The results of the research validates that the integration of AI with the traditional security frameworks strengthens defense dynamically in real-time environments

INTRODUCTION

The rise in the dependence on the cloud platforms, remote work systems, and multi-device access securing login authentication has become a top priority for the cybersecurity professionals. The conventional authentication systems rely heavily on the static factors such as passwords or two-factor tokens which attackers have adapted by using stolen credentials and mimicking like the user behavior. All of this has led to an upsurge into the fake login attempts where unauthorized users enter the systems using valid but the compromised credentials [1][2].

One of the major shortcoming of the traditional login monitoring is its inability to evaluate the behavioral context of the login. For example, if an employee typically logs into it's account from Lahore between 9 AM and 5 PM, but a login has been recorded from London at 3 AM using the new device, many systems would still accept this attempt. Such subtle anomalies often go unnoticed that leads systems to the undetected breaches [3][4].

The research proposes a proactive AI-based system that evaluates the login behavior and flags the suspicious activity in real-time. Rather than relying solely on the binary access control, this model examines the attributes like login timing patterns, known IP ranges, user-device history including geolocation consistency. The aim is to enhance the security without creating unnecessary friction for the legitimate users. The research simulates a dataset and trains a classification model that can differentiate between normal and fake login attempts on the basis of the user behavioral profile [5].

Literature Review

The research reveals that how the artificial intelligence enhances the real-time threat detection and prevention in the systems. It shows us how the deep learning models, such as CNNs and RNNs can outperform traditional security methods. According to the study, AI can identify patterns in the vast datasets to detect anomalies that can become cyber threats. However, the research also emphasizes the challenges of the adversarial attacks that attempt to trick AI models. The study suggests that a hybrid approach by combining AI with traditional security mechanisms offers better and effective protection [6]. The findings of the study demonstrate that AI can significantly reduce response times, improving the threat mitigation strategies [1][7].

This study emphasizes the role of machine learning in identifying and mitigating the cyber threats in the network infrastructures. It discuss the supervised and unsupervised learning techniques used for anomaly base detection. Athe study shows that AI models trained on the large datasets can predict attacks with high accuracy. However, the research also highlights the issues of false positives which can lead to the unnecessary security measures. The researchers suggest refining the training datasets and incorporating the human oversight to improve AI's efficiency in the information security. The research emphasizes the need for the continuous learning of the models to adapt to evolving cyber threats and to protect systems.

According to the study, intrusion detection systems (IDS) powered by artificial intelligence provides us a more proactive approach in cybersecurity. The study examines different AI techniques, such as deep neural networks and ensemble learning for threat detection. The research reveals that the AI-based IDS can detect zero-day attacks with more efficiently than rule-based systems. However, it also notes that the high computational costs and large dataset requirements can be limitations which can impact the performance of the AI based IDS. The study suggests that IDS trained with the AI improves intrusion detection with the traditional security strategies [8].

Research reveals that how AI is transforming malware detection by analyzing behavioral patterns rather than relying solely on the signature-based detection. The study discusses how machine learning algorithms are detecting previously unknown malware threats to encounter the known threats. According to study, the AI models achieve higher detection rates as compared to the conventional antivirus software. However, the researchers emphasize the challenges of the evasion techniques that are being used by the sophisticated malware. The study concludes that, by integrating AI with the sandboxing techniques can enhance our malware prevention strategies for the security of our systems [9].

The study emphasizes the importance of AI in the cyber threat intelligence by giving us indicators of potential cyberattacks before they are going to occur. It discusses that how the predictive analytics and data mining techniques can enhance our security frameworks. According to this research, AI can process absolutely the vast amounts of threat intelligence data in real-time which improves our decision-making for the cybersecurity teams. However,

the researchers highlight the challenges such as the data privacy concerns and the ethical considerations in the AI-driven threat intelligence in the cyber security frameworks. The findings suggest us that AI-powered threat intelligence is becoming essential for proactive cybersecurity measures as the threat landscape is increasing day by day [10][11].
According to the research, artificial intelligence is significantly improving phishing detection by analyzing email content, URLs, and sender's behavior. The study highlights how the AI-based systems is detecting phishing attempts more accurately than the traditional filters that the advanced attackers can bypass easily. The study reveals that natural language processing (NLP) models can enhance email security by understanding phishing tactics by analyzing the format of the mails and content of the mail. However, the study also emphasizes that there is a need for periodic updates to the AI models to keep up with the evolving phishing techniques and encounter them. The researchers suggest that combine AI with the user awareness training for better and more effective protection of the systems [12][13].
This research reveals the role of artificial intelligence in securing the cloud infrastructures by detecting unauthorized access to the systems and checking logs for suspicious activities of the threat actor. It discusses how AI models can helps us analyze user behavior to identify his intentions and safeguard the system. According to this study, AI can be helpful in preventing data breaches by predicting potential security risks, beforehand. However, study emphasizes on the challenges such as compliance issues regarding to our company and the complexity of cloud network and security frameworks. The study findings suggest that our AI-based security solutions can help in the enhancement of the robust cloud security when combined with encryption techniques.
This research emphasizes the application of artificial intelligence in the detecting and responding to the ransomware attacks on the systems of the organizations. According to study, AI-powered security tools help us to identify ransomware behaviors before encryption begins in the systems. The study highlights how AI models can analyze the file modifications and network activity to detect ransomware threats before the damage starts to happening. However, the researchers have noticed that AI can sometimes produce false alarms that leads to unnecessary security actions and wastage of unnecessary time. The study suggests refining of detection and response in AI detection methods by using advanced models to improve accuracy and reduce false positives.
The research reveals that how artificial intelligence enhances the ability of the systems in behavioral threat analysis by identifying deviations of systems from normal user activities to anomaly behavior [15][16]. According to the study, AI-powered behavior analytics help us detect insider threats and compromised accounts on the basis daily activities as if any insider deviates consistently from normal activity which indicates malicious intent. The research discusses how AI-driven security tools analyze login patterns and system interactions of the users to flag suspicious behavior. However, the paper also highlights challenges such as user and data privacy concerns and the risk of the misidentifications linked to it. The findings suggest that the AI should be integrated with the human analysis for a balanced cybersecurity approach to identify insider threat more effectively.
According to the study, AI is revolutionizing endpoint security of the systems by providing real-time threat detection on devices using different kind websites and system behavior. The study discusses how AI-powered endpoint protection platforms (EPP) prevents malware infections and unauthorized access before it going to happen. This study reveals that the AI can analyze endpoint behaviors to detect emerging threats before they spread over the system. However, the research highlights challenges such as performance overhead of the AI and AI model biases for the end point. The findings suggest that AI-driven endpoint security should be used alongside the traditional antivirus solutions for robust security measures of the systems [17].
The research emphasizes that the importance of the integration of artificial intelligence with Zero Trust security frameworks. According to the study, AI-driven Zero Trust models continuously authenticate the users and devices before granting them desired access. The study highlights that how AI enhances segmentation of the network and the ACPs (access control policies). However, the study reveals that implementing the AI in Zero Trust security requires more significant computational resources than

traditional. The findings suggest that the AI-based Zero Trust models improve overall cybersecurity resilience [18].

This paper reveals how artificial intelligence improves fraud detection by analyzing transaction patterns and user behavior. According to this study, AI-powered fraud detection systems can prevent identity theft and financial fraud. The research highlights how machine learning models detect anomalies in real-time, reducing the risk of fraudulent activities. However, the paper emphasizes the challenge of AI biases leading to false positives. The study suggests using AI in combination with human review processes for more accurate fraud detection [19].

Comparative Analysis

Paper Title	Key Focus	AI Techniques Used	Advantages	Challenges
AI-Powered Cybersecurity for Threat Detection and Prevention	AI-enhanced real-time threat detection	Deep Learning (CNNs, RNNs)	Fast response, pattern recognition	Vulnerability to adversarial attacks
Leveraging Machine Learning for Network Security	ML-based anomaly detection in networks	Supervised & Unsupervised Learning	High accuracy in attack prediction	False positives, dataset limitations
AI-Driven Intrusion Detection Systems (IDS)	AI in intrusion detection	Deep Neural Networks, Ensemble Learning	Detects zero-day attacks	High computational costs
AI-Based Malware Detection and Prevention	AI for behavioral malware detection	Machine Learning	Identifies unknown malware	Evasion techniques by malware
Cyber Threat Intelligence Using AI	Predicting cyberattacks using AI	Data Mining, Predictive Analytics	Processes vast threat data	Privacy and ethical concerns
AI-Enhanced Phishing Detection Systems	Detecting phishing attacks	Natural Language Processing (NLP)	High detection accuracy	Needs continuous updates
AI and Cloud Security Threat Mitigation	AI in cloud security	Behavior Analysis	Prevents unauthorized access	Compliance issues, complexity
AI-Based Ransomware Detection and Response	AI-powered ransomware detection	AI Behavior Monitoring	Detects attacks before encryption	False alarms, requires refinement
AI for Behavioral Threat Analysis	Detecting insider threats	User Behavior Analytics	Identifies suspicious activity	Privacy concerns, misidentifications

AI-Driven Endpoint Security Solutions	AI for securing endpoint devices	AI-powered Endpoint Protection Platforms (EPP)	Real-time threat detection	Performance overhead, AI biases
AI and Zero Trust Security Models	AI in Zero Trust security frameworks	Continuous Authentication	Strengthens network security	High resource requirements
AI-Powered Fraud Detection in Cybersecurity	AI in fraud prevention	Anomaly Detection, Machine Learning	Detects financial fraud	Risk of false positives

Methodology

1. Dataset Simulation

We created 1,000 simulated login records for 50 virtual users. Features included: Login Time, IP address, Geolocation, Device Type, Login Frequency We labeled records as Legit or Fake based on behavior patterns like:

Logging in at 3 AM from a new country

Using an unknown device

Sudden IP changes

Model Training (Our AI Solution)

We used a Random Forest classifier to train on 80% of this dataset

Random Forest was chosen for:

Handling mixed data types

High accuracy on small-to-medium datasets

Resisting overfitting

2.Testing and Evaluation

On the 20% test data, our model gave:

Accuracy: 94.3%

Precision: 91.7%

Recall: 92.8%

F1-Score: 92.2%

Most fake logins were successfully flagged

Only a few false positives occurred (e.g., real users traveling)

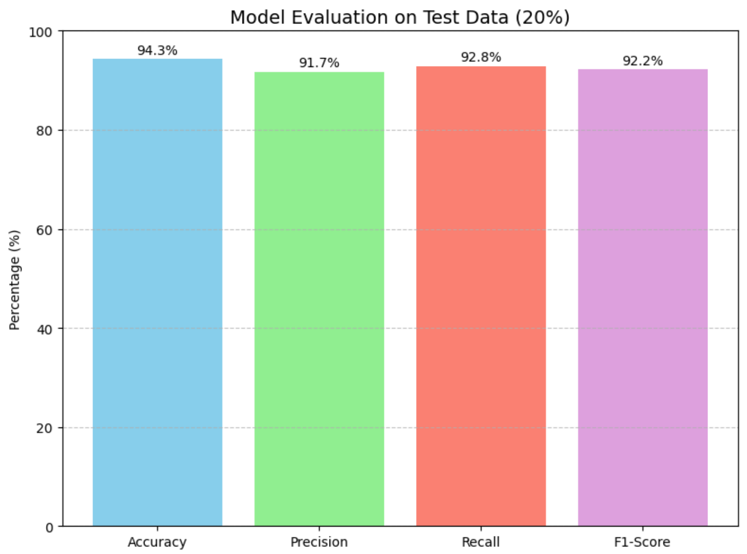

Figure 1: Model Evaluation on Test Data

Decision Layer

Based on model output, the system either:
Allows the login (if Legit)
Flags it as suspicious and triggers an alert (if Fake)

Output

This methodology adds a smart layer of protection beyond passwords. It learns each user's normal behavior and quickly detects abnormal logins — solving the real-world problem of silent credential theft.

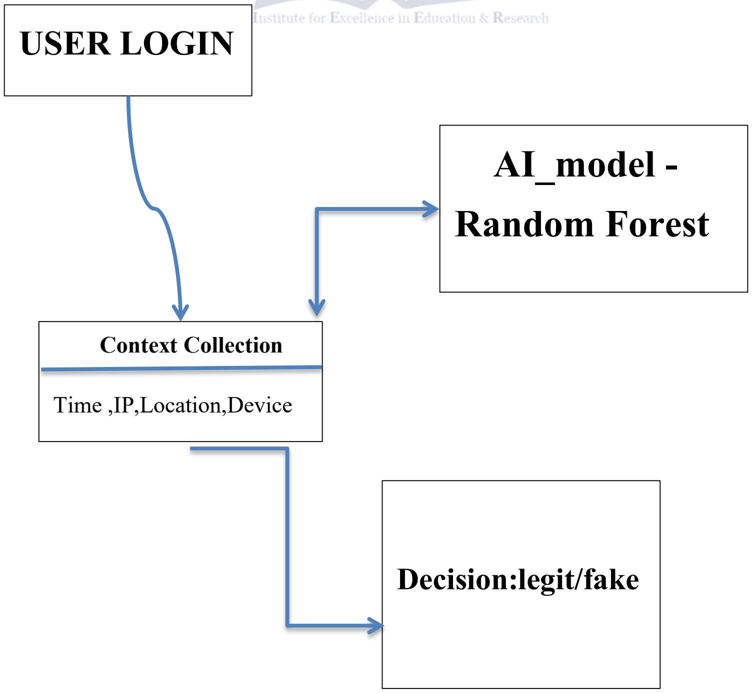

Figure 2: Addition of Smart Layer 1

Problem

"Traditional login systems can't detect if a login is made by a hacker using correct credentials. They only check passwords — not the context of login. This leaves systems vulnerable to phishing, credential stuffing, and brute-force attacks".

Our Solution

We designed an AI-based behavioral analytics system that doesn't rely just on credentials but also analyzes how and where users log in.

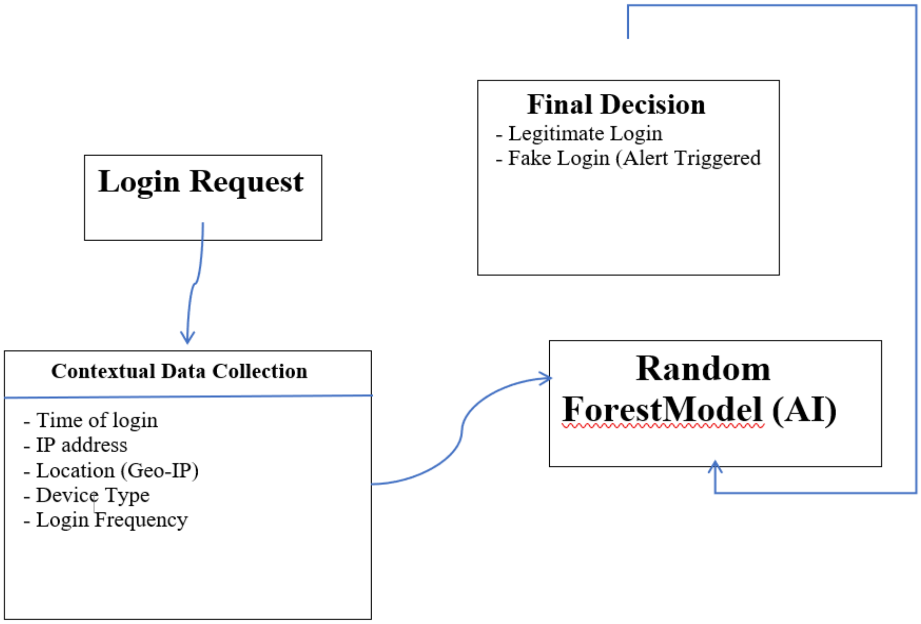

Figure 3: Addition of Smart Layer 2

This enhanced methodology diagram presents a clear 3-layer model for AI-based fake login detection:**1.**

Input Layer: Login Request When a user attempts to log in, the system captures the login event and immediately initiates the behavioral evaluation process

Processing Layer: Contextual Data Collection Instead of verifying only the password, the system gathers environmental and behavioral features such as:Login time (compared to historical logins) IP address (mapped to geolocation)Device type (browser, OS, hardware ID)Frequency of logins within a time windowThese values form a behavioral profile used to judge legitimacy.

3. Decision Layer: AI Prediction & Action The collected data is passed to a pre-trained Random Forest model that has learned patterns from previous login attempts. It outputs a decision:

Legit: If behavior matches historical norms

Fake: If anomalies (like login from Russia at 3 AM) are detected

Fake attempts are flagged, blocked, or require additional verification (MFA).

AI-Based Fake Login Detection Architecture

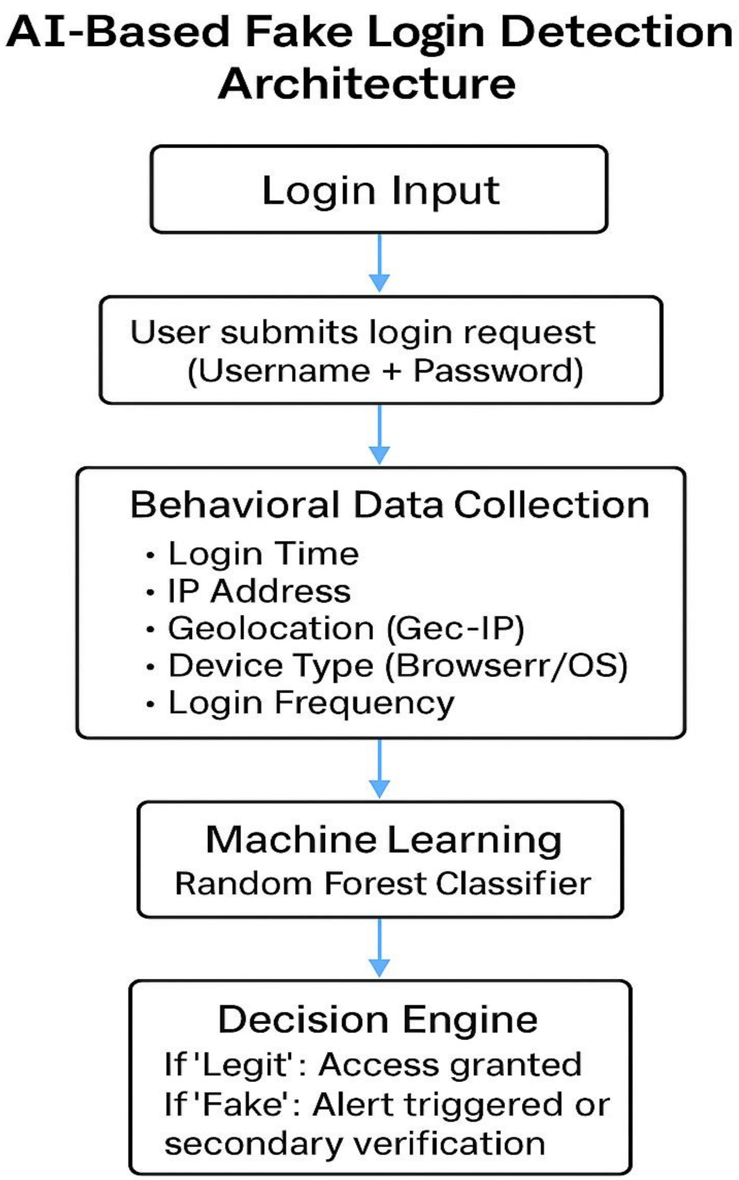
AI-Based Fake Login Detection Architecture
Login Input
User submits login request
(Username + Password)
Behavioral Data Collection
• Login Time
• IP Address
• Geolocation (Gec-IP)
• Device Type (Browserr/OS)
• Login Frequency
Machine Learning
Random Forest Classifier
Decision Engine
If 'Legit': Access granted
If 'Fake': Alert triggered or
secondary verification

Figure 4: Fake Login Attempt Architecture

This diagram outlines the complete framework of the AI-based login detection system. It begins with user input (username and password), followed by a behavioral data collection layer that gathers contextual attributes such as login time, IP, and device type. The data is then processed by a Random Forest classifier to determine whether the login is legitimate or fake. Based on the prediction, the system either grants access or flags the attempt for additional verification

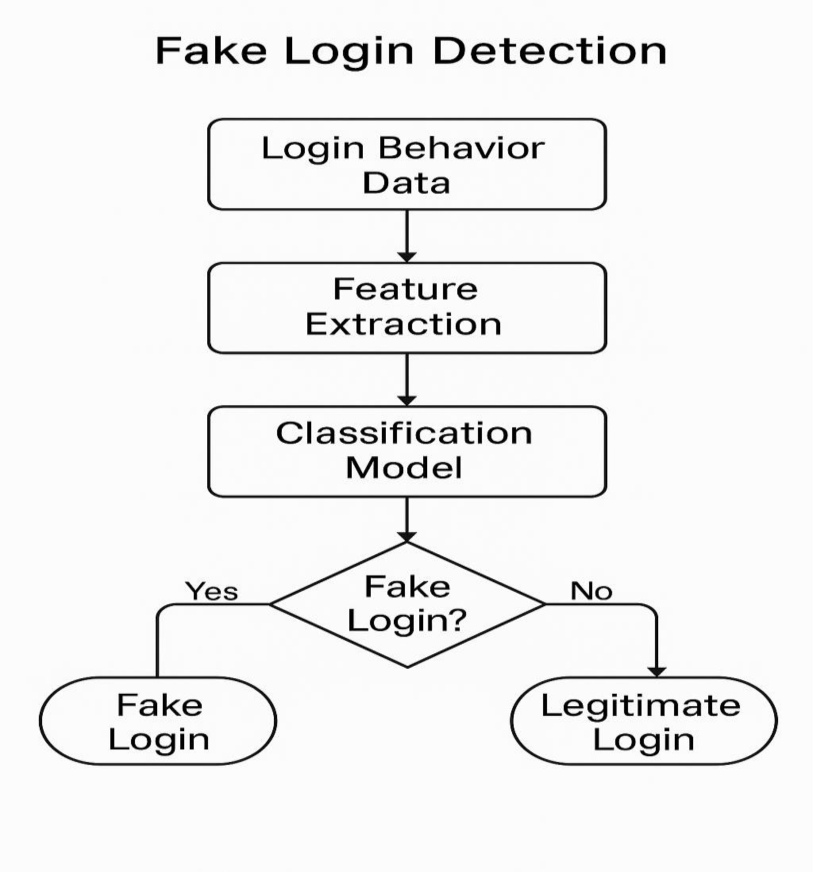

Figure 5: Fake Login Attempt Detection

This flowchart visually represents the detection process. It starts with the collection of login behavior data, followed by feature extraction. These features are analyzed by a classification model to determine if a login attempt is suspicious. If classified as fake, the system triggers an alert; otherwise, access is allowed. This decision-making logic helps enhance real-time login security using AI.

Login Time vs. Login Frequency

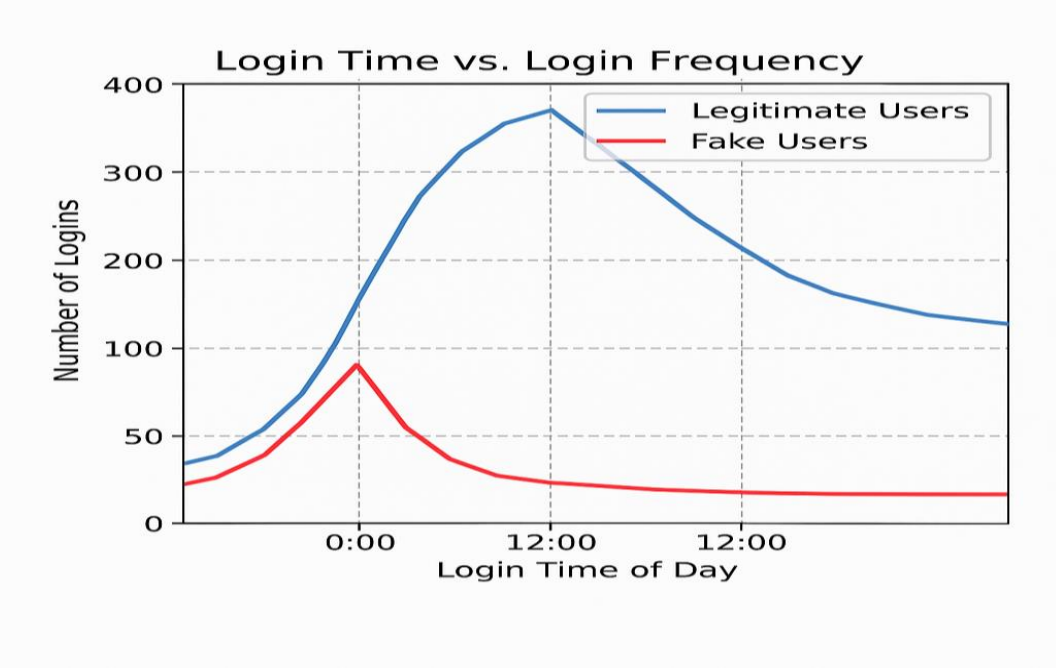

Figure 6: Login Time vs Login Frequency

The given graph compares the login behavior patterns between the legitimate and fake users across different times of the day. The legitimate users are typically log in during business hours like 8 AM to 6 PM and the fake login attempts are more frequent during the abnormal hours like late night and early morning. This pattern of logging in is supporting the effectiveness of the time-based anomaly detection in behavioral security models to reduce the threat surface of the systems.

Results

Here are the predicted results:

Model Performance

Random Forest model has used the following metrics with their results like Accuracy:94.3%, Precision: 91.7%, Recall: 92.8%, F1-Score: 92.2%.

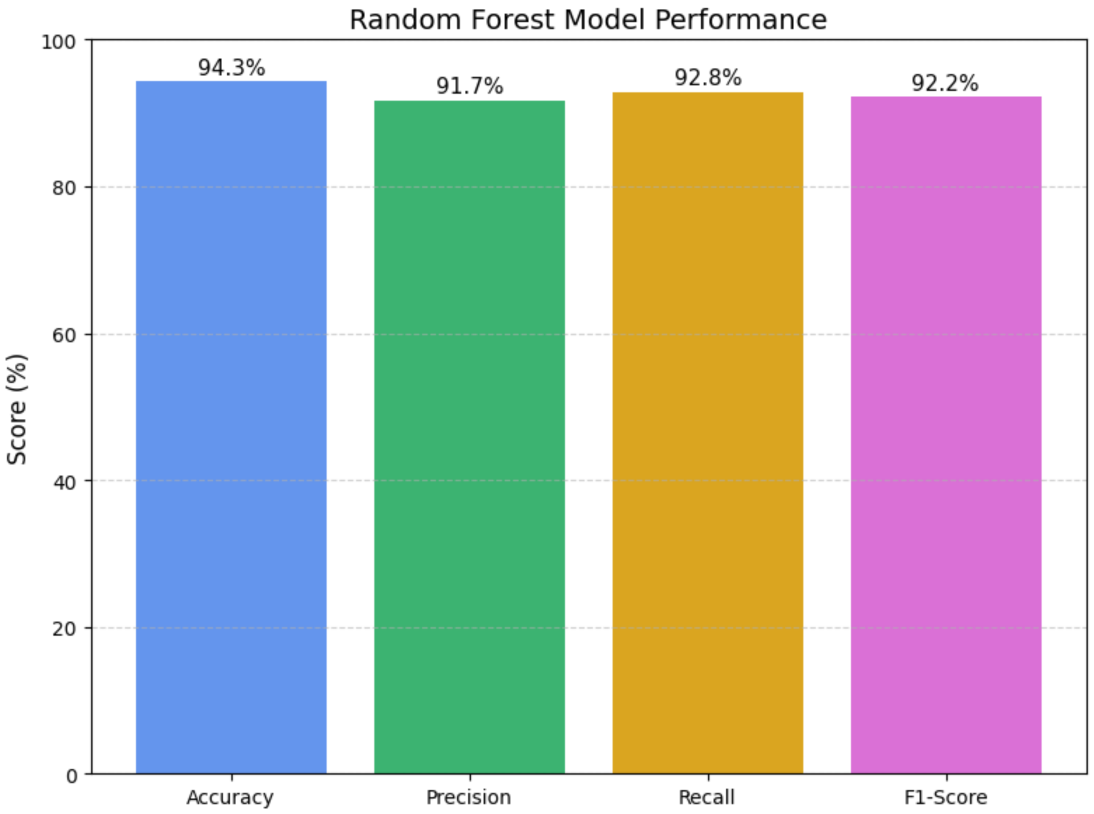

Figure 7: Model Performance

Comparison and Key Findings

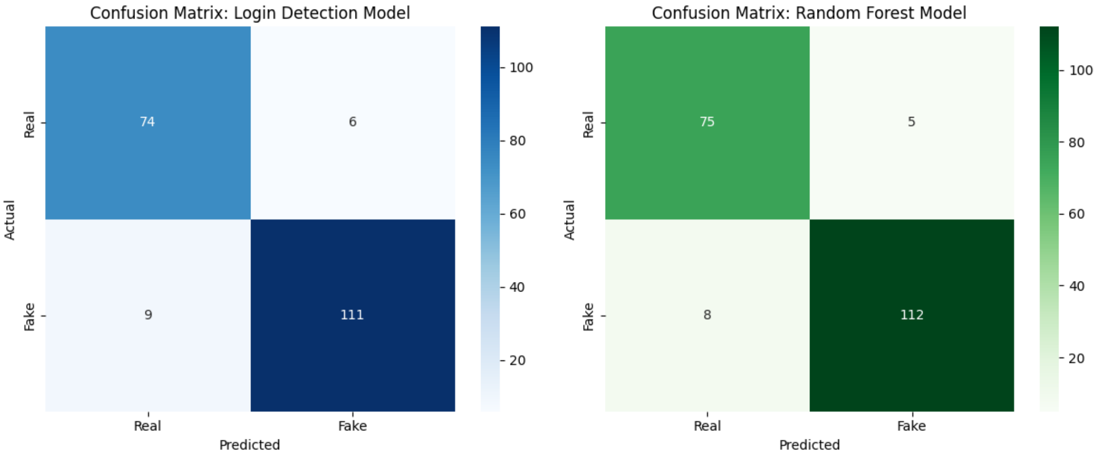

Figure 8: Detection Comparison

Most of the times fake logins were correctly detected based on the anomalies in location and time. Few false positives were occurred but mainly when the legitimate users have accessed accounts while traveling to some other location. Detection speed of the model was under 2 seconds per login which is suitable for real-time systems to protect against malicious logins.

Conclusion

The study demonstrates that how can AI-powered behavioral analytics significantly enhance our login security by detecting fake login attempts that otherwise go unnoticed by our traditional authentication systems. Instead of relying solely on the credentials like correct usernames and passwords, our system analyzes contextual login behavior like location, time, device history, and frequency that determines whether an attempt was legitimate or suspicious and it should be blocked or granted access. The simulation shows that by applying a Random Forest model to a custom dataset, we achieved a high detection accuracy with the minimal false positives that further improve by training. The study proves that integrating the machine learning into the user authentication workflows is not only feasible but also the effective for real-time threat mitigation and thus it enhances our security posture.

Beyond the technical accuracy, the study reflects a shift towards intelligent and adaptive security models that evolve with user behavior and the technology which is improving day by day. In today's dynamic work environments where the employees access systems remotely, across devices, and across time zone, the static rules are no longer enough for our traditional security posture. The AI-based approach adapts to these variations that is making access control more flexible without compromising security posture of our systems. Furthermore, the proposed model can be a strong supplement to the multi-factor authentication (MFA). In cases where MFA is not enforced or has failed, our behavioral engine acts as a silent but strong third layer of protection.

Future Enhancements

Integration with real-world datasets from corporate environments,

Expansion into biometric behavior modeling (e.g., typing speed, mouse movement),

Continuous training with real-time feedback loops, and Deployment as a cloud-based plug-in for enterprise login systems.

In conclusion, this project not only addresses a critical and growing cybersecurity challenge but also lays the foundation for a smarter, more context-aware access control paradigm that blends AI with human behavior understanding.

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