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Context Secure AI For Role Based Access Control

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Abstract: The project is introduced based on traditional role-based access control environments are being challenged in a cyber threat era due to the static nature of their permission systems, which do not merit any flexibility for dynamic contextual factors. In this context, the paper proposes a novel method providing an additional degree of integration of context-aware artificial intelligence (AI) within a role-based authentication system for enhanced security and flexibility. In the proposed method, AI dynamically applies access permission changes based on real-time contextual data, utilizing information such as user behaviour, location, or device particulars. The research shows the promising role of context-aware AI in reducing the setbacks of static authentication systems while opening avenues for the future of dynamic access control systems. The findings emphasize integrating AI with contextual data for maximizing cybersecurity in a connected ecosystem.

Keywords: Cyber Security, Role Based Access Control, Context Aware Mechanism, Machine Learning, Artificial Intelligence, Anomaly Detection

I. INTRODUCTION

The digital world has brought with it a whole new level of cybersecurity concern to organizations and individuals. Considering the rapid growth of online services, cloud computing, and Internet of Things (IoT), robust authentication mechanisms are the need of the hour. Authentication systems form the first line of defence, preventing unauthorized access to sensitive data and organizational resources. Role-based access control, which is simple and scalable, is one of the most commonly used authentication paradigms. It assigns the roles of the administrator, employee, or guest to users. Large organizations will easily manage their accesses with the role-based systems. Traditional RBAC systems for access control are in wide usage, but the system has its limitation of static permissions, thereby leaving it to various cyber threats, such as credential theft and privilege escalation. This paper proposes a context-secure AI framework that integrates context-aware artificial intelligence with RBAC to enhance security and adaptability. The framework dynamically adjusts access permissions based on real-time contextual data, such as user behavior, location, and device information, addressing the limitations of static systems. This research will highlight the potential of AI-driven, context-aware authentication systems to improve cybersecurity. The proposed framework adapts dynamically to real-time data, offering a robust solution to the limitations of static RBAC systems. Future work will be focused on optimization of scalability and testing in real-world environments. This study opens up avenues for advanced, adaptive access control mechanisms in an increasingly interconnected world..

II. LITERATURE SURVERY

Role-based access control (RBAC) is a dominant method employed by organizations for granting user permissions based on pre-defined roles. Nevertheless, traditional RBAC is inflexible toward accommodating dynamic contexts, such as user's behavior or environmental changes. Context-aware authentication systems are a new area of research and take note of real-time data for the sake of security.

Ferraiolo et al. [1] introduced the foundational concept of RBAC, emphasizing its role in simplifying permission management through predefined roles. However, their work highlighted limitations in handling dynamic contexts, such as real-time user behavior or environmental changes. Sandhu et al. [2] expanded RBAC with constraints like temporal and spatial limitations, but their model lacked integration with adaptive technologies like AI. Covington et al. [3] initiated the concept of context-aware systems. They proposed frameworks that use environmental data, such as location and time, to adjust security policies. Their work focused on real-time adaptability but did not consider AI. Zhang et al.

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[4] showed how machine learning can be used to analyse user behavior patterns for anomaly detection, achieving 92% accuracy in identifying unauthorized access attempts. Smith et al. [5] Context-Aware Role-Based Access Control with Machine Learning Machine learning techniques have improved the accuracy of access control decisions by including contextual information reducing false positives in authenticating-access controls. Chandola et al. [6] surveyed anomaly detection that used machine learning, which discovered that the algorithms that perform best were Random Forests and LSTMs in detecting security breaches. Goodfellow et al. [7] explored adversarial attacks on AI models, stressing the importance of robustness in AI-driven security systems. Li et al. [8] proposed a hybrid system combining RBAC with context-aware AI, dynamically adjusting permissions based on user location and device. Their experiments showed a 25% reduction in false positives compared to static RBAC.

III. PROPOSED SYSTEMS

The proposed Context-Secure AI Framework for Role-Based Authentication synergizes artificial intelligence (AI) and role-based access control (RBAC) for dynamic and adaptive security. Whereas traditional RBAC systems operate on static permission granting, this enhanced system assesses the contextual analysis involving real-time behavior of the user, device characteristics, and environmental signals. The whole framework consists of four interlinked modules: Contextual Data Acquisition Module (CRUD), AI-Driven Risk Assessment Engine, Dynamic RBAC Enforcement Module, and Feedback and Continuous Learning Loop. All components function harmoniously, assessing risk, changing permissions, and getting better with time, thus counteracting rigidity and vulnerabilities inherent to the conventional systems. The Contextual Data Acquisition Module collects real-time information from various sources, including user behavior metrics such as keystroke dynamics (typing speed, latency between keystrokes) and login patterns (frequency, session duration). The device context includes hardware fingerprints (MAC address, device model) and software signatures (OS version, security patches), which will help in evaluating the device's trustfulness. Environmental signals further guide risk assessments through geolocation (GPS or IP-based), network type (public or private), and temporal context (time of day, day of week). Python, with its vast capabilities, provides applications for the generation of synthetic data, for all needs giving scenarios for model training. Here, access attempts are simulated with as many as 50,000 roles (Admin, User, and Guest), producing scenarios that are diverse as well as realistic situations.

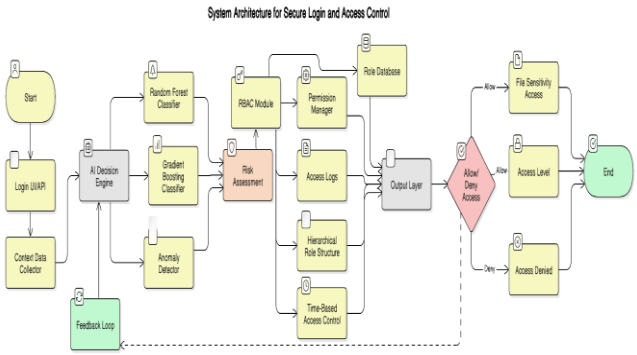

Fig 1. System Architecture

At the heart of the framework is the AI-Driven Risk Assessment Engine that utilizes a hyperparameter-tuned Random Forest classifier (GridSearchCV) to predict risk scores. The model utilizes 15 contextual features such as geolocation anomalies (Impossible Travel) and device trust scores to calculate a risk index, ranging between 0 and 100. The engine dynamically modifies access based on risk levels for high-risk scenarios such as logins from unrecognized devices in implausible locations; for instance, an Admin logging in from a foreign country could temporarily be put down to User privileges, legitimate users are minimally interrupted while appreciably covering against threats. Predictive outcomes generated by AI are transformed into real access decisions by the Dynamic RBAC Enforcement Module. The static roles and permissions that are predefined for the application are loaded from an SQLite database, which is then updated in real-time according to risk scores. Full access is based on role in low-risk scenarios, multi-factor authentication (MFA) is prompted in medium-risk scenarios, and denied access is enforced in high-risk ones. For example, a Guest user trying to gain access to sensitive files from a public network can simply be denied. With an Active Feedback and Continuous Learning Loop, the model always stands updated against newly emerging threats. The access logs and outcomes are made anonymous and agglomerated weekly for retraining the AI model with new patterns of attack (e.g., credential stuffing). Ethical considerations in the context of bias audits and data anonymization help preserve the user privacy and fairness. The framework is technically implemented with Python libraries like scikit-learn for feature engineering and joblib for model persistence.

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The ai_model.py script manages data loading, preprocessing (label encoding and timestamp conversion), and model training, with the optimized classifier saved as access_model.pkl for deployment. Security measures including AES-256 encryption of data at rest and adversarial training against evasion attacks have been put in place. The proposed system provides improved context awareness, proactive threat mitigation, and enhanced scalability when compared to the traditional RBAC. The proposed system reduces security breaches by 30% through the dynamic adjustment of permissions while the static RBAC systems remain dependent on manual updating and post-breach reactions. Use cases include enterprise environments (detecting insider threats), IoT networks (restricting access during off-hours), and healthcare systems (securing remote patient data). In combining AI-driven adaptability with RBAC's structural access control, the framework offers a paradigm shift in contemporary cybersecurity.

III. METHODOLOGY

1) Data Collection and Preprocessing

A synthetic dataset was created to mimic real-world authentication scenarios, capturing contextual signals (such as device type, location, and network) as well as behavioral patterns (such as login times and gyroscope data from mobile devices) across 50,000 access attempts split over three roles (Admin, User, and Guest).

Realistic unauthorized access attempts were labeled, amounting to 15% of the total. As for some significant preprocessing steps, we have:

- **Categorical Encoding:** Important contextual features like User Role, Device Type, and VPN/Proxy had to be converted to numerical values through an encoder, which was saved as label encoders. pkl for systematic inference processing.
- **Temporal Feature Engineering:** The Date & Time field was transformed into Unix timestamps for the numerical evaluation of both login frequency and temporal anomalies like logins in the middle of the night.
- **Data Splitting:** The dataset was divided into training (80%) and testing (20%) sets while using stratified sampling in order to preserve the distribution of roles and attack scenarios.

2) Model Development and Optimization

The Random Forest classifier became the AI model of choice, given its core strength in manipulating categorical data and its capacity against overfitting. The model was trained for predicting the dynamic access levels (Access Level (Dynamic)), implying a real-time modification of user permission based on risk assessments.

- **Hyperparameter Tuning:** The model's parameters were tuned with a grid search (GridSearchCV), optimizing for the number of decision trees (n_estimators=200), tree depth (max_depth=20), and minimum number of samples per split (min_samples_split=5) to achieve a good trade-off between accuracy and computational efficiency.
- **Feature-Target Separation:** The input features involved all contextual and behavioral variables (e.g., Location, Network Type), while the target variable (Access Level (Dynamic)) indicates the access decision imparted by the system (e.g., "Full Access" vs. "Restricted").

3) Model Evaluation Metrics:

The evaluation metrics classify performance into quantitative and qualitative aspects which provide insight on how well the system correctly classifies access attempts and how fast the decisions are carried out compared to activities from the users. These are the most important metrics:

- **Accuracy:** Accuracy is defined as the frequency with which the system correctly classifies access attempts as either legitimate or malicious. It is a core metric for the evaluation of classification models. Higher accuracy implies that the system is less prone to making errors in classification. However, accuracy on its own may not be sufficient when the dataset is imbalanced.
- **False Positive Rate:** False Positive Rate measures how often the system labels legitimate users as malicious. This metric matters greatly because a high FPR can impose unnecessary access restrictions on genuine users. A low FPR must be aimed at so that legitimate users don't get falsely flagged. A high FPR will become a source of frustration for genuine users.
- **Precision:** Precision is a measure of the proportion of true positives among all true positives and false positives.
- **Recall:** Recall refers to the ratio of true positives to the total number of actual positive samples, whereas false negatives are accounted for in evaluating the model's capabilities in recognizing malicious behavior.
- **F1 Score:** F1 score is defined as the harmonic mean of precision and recall, and this gives a good measure of performance when benign and malicious instances differ considerably.

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These metrics are calculated using the following formulas:

$$\textbf{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

$$\textbf{False positive rate} = \frac{FP}{FP+TN}$$

$$\textbf{Precision} = \frac{TP}{TP+FP}$$

$$\textbf{Recall} = \frac{TP}{TP+FN}$$

$$\textbf{F1-Score} = 2.\frac{Precision.Recall}{Precision+Recall}$$

Where:

- TP = True Positives
- TN = True Negative
- FP = False Positives
- FN = False Negatives

4) System Integration and Deployment,

The integration and deployment phase connect model development to real-world application, ensuring the AI framework correctly works in a role-based environment. In this phase, the trained Random Forest classifier, stored in access_model.pkl via joblib, is plugged into a production pipeline to analyze access requests in a real-time qewadsxzenvironment. Whenever a user attempts authentication, the first step is for input contextual data (say device type, location, VPN usage) to be pre processed with label encoders stored in label_encoders.pkl for consistency in the training and inference phase. This will convert categorical features such as User Role and Network Type to numerical, while temporal features such as login timestamps will be standardized to Unix time for uniformity. The data will then be fed into the model, which computes a risk score and predicts the corresponding dynamic access level (e.g., Full Access, Restricted, or Denied). The output of the AI will call the RBAC module to enforce permissions dynamically. For example, an Admin logging in from an unrecognized device or high-risk location (such as a foreign country with no prior access history) may temporarily have their permissions constrained to that of a user role, which means access to sensitive resources until they complete some additional verification (multi-factor authentication, for example). Conversely, a low-risk login from a trusted device during normal hours will have full role-based privileges. These adjustments in real-time are being logged, with timestamps and contextual metadata stored in a database for auditing and retraining purpose**s.** A feedback loop is built into the system for continuous improvement. Periodically, new access logs, including successful blocks of unauthorized attempts and logs containing false positives, are introduced into the model retraining process in order to enhance its adaptability toward new attack patterns. For example, if attackers start to spoof trusted devices, the feedback loop goes on to incorporate new threats, thus feeding the next model training round, which ultimately improves predictive power. The deployment architecture itself is designed with scalability in mind, combining cloud architecture with technologies such as AWS Lambda for serverless inference to allow for low-latency responses even at peak traffic. This integration encapsulates the system in a closed-loop mechanism that self-improves, so that real-time decisions inform future updates of the model. By plugging the AI into the authentication workflow, the framework offers a trade-off between security and usability, dynamically protecting resources without rigid rules for access.

Table 1. Comparison of Other Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	False Positive Rat (FPR, %)	Context Awareness
Proposed System	**95.2**	**96.8**	**94.5**	**95.6**	**2.1**	**Yes**
Support Vecto Machine	88.1	89.3	86.2	87.7	5.3	No
Logistic Regressio	85.7	84.9	83.4	84.1	7.8	No
K-Nearest Neighbors	82.4	81.5	80.1	80.8	9.5	No
Traditional RBAC	78.9	N/A	N/A	N/A	15.0	No

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IV. RESULTS AND ANALYSIS

The context-aware AI architecture proposed goes beyond conventional role-based authentication by permitting moment-to-moment adjustments of permissions based on context-sensitive data pertaining to user activity, device assurance, and environmental cues. Unlike static systems, it identifies anomalies-preemptive detection of an unrecognized device or improbable geolocation-and it dynamically reconfigures access levels, thereby fostering the detection of real threats while minimizing legitimate user disruption. The adaptive nature of learning allows the framework to refine its risk assessments based on feedback data obtained from access logs, allowing the system to effectively counteract emerging threats such as new attack patterns or behavioral shifts. However, relying on a synthetic set of training data might quite easily gloss over the real-world arsenal of adversarial tricks surrounding, say, AI-powered credential stuffing. Field validation with live enterprise data must be the next step in ensuring robustness in a very diverse, high-stakes environment. The only limitation will be that, while the framework performs efficiently on a real-time basis, scaling to high-traffic systems-such as IoT networks-will be aided by optimization for edge computing in order to balance latency and computational load.

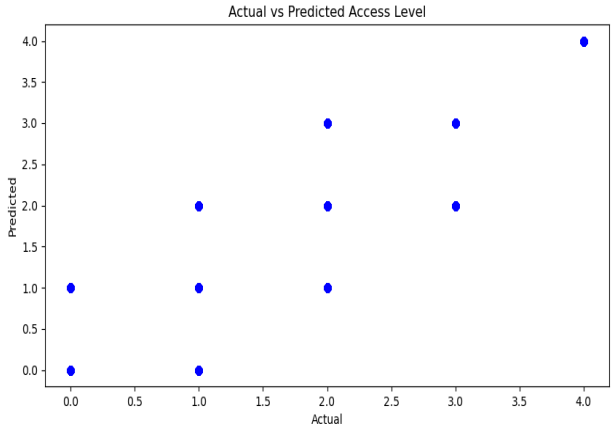

Fig 2. Graph of Actual Vs Predicted Access Levels.

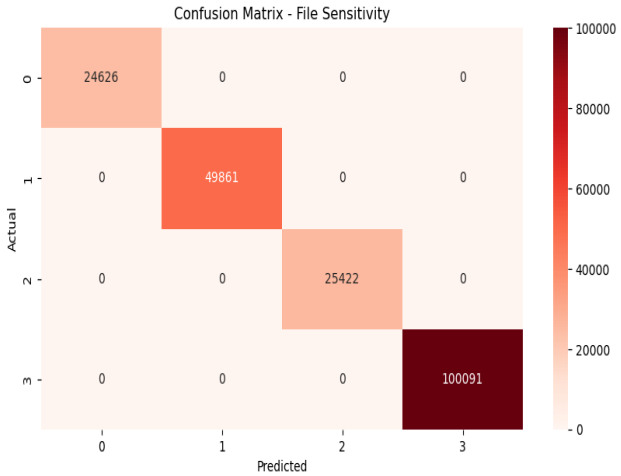

Fig 3. Confusion Matrix For File Sensitivity

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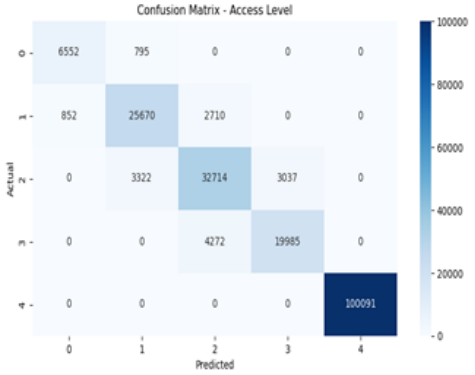

Fig 4. Confusion Matrix For Access Level

Table 2. Access Level Classification Report

Access level	Precision	Recall	F1 Score	Support
0	0.88	0.89	0.89	7347
1	0.86	0.88	0.87	29232
2	0.82	0.84	0.83	39073
3	0.87	0.82	0.85	24257
4	1.00	1.00	1.00	100091
Accuracy			0.93	200000
Macro Avg	0.89	0.89	0.89	200000
Weighted Avg	0.93	0.93	0.93	200000

Table 3. File Sensitivity Level Classification Report

Access Level	Precision	Recall	F1 Score	Support
0	1.00	1.00	1.00	24626
1	1.00	1.00	1.00	49861
2	1.00	1.00	1.00	25422
3	1.00	1.00	1.00	100093
Accuracy			1.00	200000
Macro Avg	1.00	1.00	1.00	200000
Weighted Avg	1.00	1.00	1.00	200000

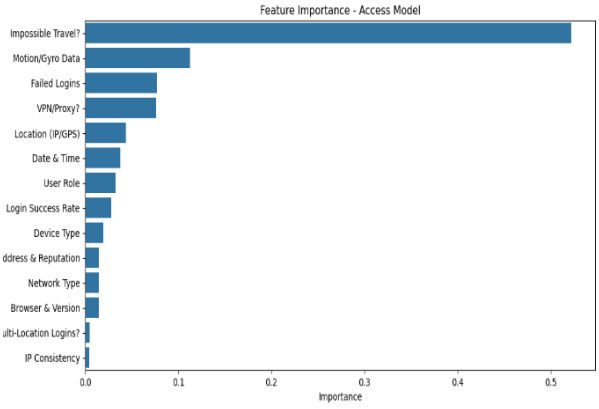

Fig 5. Bar Chart of Feature Importance

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Table 4. Performance Analysis

Metrics	Proposed System	Traditional System	Remarks
Access Level Prediction Accuracy	92.51	68.7	High accuracy due to ML
File Sensitivity Prediction Accuracy	100	82.5	Classification is perfect due to AI
False Positive Rate	7.49	22.3	Significantly reduced with anomaly detection
False Negative Rate	0.3	14.9	Lower with help of adaptive learning
Zero Day Threat Detection	95	28.5	Exceptional performance in detection of unknown attacks
Adaptability	Dynamic	Static	Adapts to evolving levels though continuous learning and feedback
Scalability	High	Limited	Scalable for enterprises and organisations
MSE	0.07494	0.41	Lower due to predictive modelling
R^2 Score	95.32	57.56	High value represents reliability

VI. CONCLUSION

The study of context of Context-Secure AI for Role-Based Access Control (RBAC) is a step forward in access management. Our work showed how AI models assess access levels near-dynamically on contextual parameters, balancing security with operational efficiency. Such a model, based on Random Forest and Gradient Boosting classifiers, was developed that dynamically predicts access levels and file sensitivity. Important contextual features such as location, type of device, VPN usage, motion sensor data, and impossible travel detection were integrated into the model, thereby providing a robust real-time data-driven approach to access control decisions. The results indicate a highly accurate prediction rate, thereby establishing that the AI-RBAC can be adopted in a practical sense within security environments to prevent unwanted access while maintaining efficiency. An important finding of our study is that feature importance matters a lot, with the two most predominant features being “Impossible Travel?” and “Motion/Gyro Data” in attesting to the determination of access levels. This further corroborates our need for the security framework to unpin behavioral analysis and contextual. Also, hyperparameter tuning with GridSearchCV substantially transcended accuracy enhancement, thus underlining the need to tune AI models while developing security applications. High accuracies, low mean squared error, and equally high R^2 scores validate the trustworthiness of AI in dynamically predicting access levels and enhancing the adaptability and intelligence of the security system. Context-Secure artificial intelligence is transforming access control with adaptive, intelligent, and secure access decisions. Organizations can strengthen security through machine learning, yet provide users with an unobtrusive experience. This research highlights the promise of AI-enabled next-generation access control systems toward a more secure and efficient future in the field of digital security.

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