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Assessing the Effectiveness of Multi-Factor Authentication in Strengthening Cybersecurity and Preventing Threats

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Abstract

Cyberattacks have grown sophisticated in parallel with the advent of digital platforms, cloud computing, and remote work settings. Traditional password-based systems of authentication stand inadequate to protect sensitive data. Thus, Multi-factor Authentication (MFA) becomes a very vital security measure. Sadly, the implementation of MFA suffers from some hindrances such as user inconvenience, being attacked by hacktivists, and performance trade-offs. This research evaluates MFA in the light of strengthening cybersecurity and the prevention of threats using an Autoencoder Long Short-Term Memory (LSTM) model optimized with the African Buffalo Optimization (ABO) algorithm. The proposed solution applies deep learning technologies to the real-time detection of cyber threats and therefore secure. Data preprocessing using Min-Max Normalization increases the efficiency of the model, while Autoencoder LSTM sees to it that the detection of anomalies in network activities is done with precision. On top of that, the performance of the model is optimized further through the ABO by improving detection accuracy and decreasing the false positive rate. From the results, it shows that the proposed method achieves around 96% in terms of accuracy, thus improving dramatically the detection of threats as compared to traditional methods. Security is improved by 45%, with a reduction in unauthorized access risk, when compared with a system based on single-factor authentication. The realization of an AI-optimized MFA framework to counter cyber threats has been proven. Future work can be targeted towards integrating blockchain and behaviour analytics as stronger security measures.

Keywords: *Multi-Factor Authentication, Cybersecurity, Cyber Threat Detection, Autoencoder LSTM, African Buffalo Optimization, Anomaly Detection.*

1. Introduction

The world has turned into the digital format, and cybersecurity has become a paramount concern for individuals, businesses, and governments all over the globe [1]. It has also increased overtime reliance upon online platforms, cloud storage, and remote work environments and increased the scale of online cyber threats such as hacking, phishing, and identity theft [2]. Organizations are now more vulnerable than ever to data breaches and unauthorized access [3] [4]. This has called for more stringent measures in the security and is a perfect way to portray the necessity of multi-factor authentication in enhancing cybersecurity against unauthorized access [5]. Multi-Factor Authentication is a system in which the users can verify their identity by more than just one means of checking with the password or biometrics [6].

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Authentications have been made layered, so access to very sensitive information will be hard for anyone to gain even if one of these add-ons becomes compromised [7]. Password-only authentication cannot safeguard digital assets anymore [8]. The weakness or reuse of a password is one of the most common portals of entry for cyber criminals and creates very serious security holes [9] [10]. Studies have indicated that most data breaches are caused by compromised credentials therefore it becomes very critical to improve authentication regimes utilizing such mechanisms as MFA [11]. Multi-factor authentication is based on the principle of requesting two or more verification factors to gain access [12] [13]. Most of these factors fall under three broad categories, such as something one knows (like a password or PIN), has (like a smart device or security token) and is (like uniquely identifying biometrics like fingerprints or facial recognition) [14]. Having multiple criteria makes successful actions by even the most technically proficient attackers extremely improbable [15].

MFA has been adopted by organizations from diverse sectors including finance, healthcare, government, and e-commerce, in an effort to secure sensitive data from unauthorized access [16] [17]. Financial institutions, for instance, have been using this access to protect customers' account fraud [18]. On the contrary, multi-factor authentication is used to protect patients' records and confidential medical data from unauthorized access [19] [20]. Regulatory and cybersecurity frameworks point to MFA as a best practice [21]. Some such as the General Data Protection Regulation, National Institute of Standards and Technology guidelines, and the Payment Card Industry Data Security Standard even require or strongly advocate for its implementation as part of enhanced compliance to security [22] [23]. MFA is not without some challenges. Some users perceive it as being inconvenient, which might result in non-acceptance [24]. Companies also have to prepare for proper implementation training and support to give users a good experience [25] [26]. Cybercriminals also have learnt ways of bypassing multi-factor authentication systems, such as MFA fatigue attacks, SIM-swapping, and so on [27]. Balancing security with usability is another problem [28]. With the increase of cyber threats, the traditional password is weak in securing sensitive information [29] [30]. MFA bolsters security by requiring the application of multiple verification factors that lessen the chances of a breach [31]. Thus, industries must incorporate MFA into their businesses to give a better security posture and be compliant with regulations [32].

As cyber threats continue to evolve in complexity and scale, it has become imperative for organizations to adopt robust security measures to safeguard sensitive information [33] [34]. Multi-Factor Authentication has emerged as a critical defense mechanism, requiring users to provide two or more independent credentials for identity verification, such as a password in combination with biometrics or a security token [35] [36]. This layered approach significantly mitigates the risk of unauthorized access, offering increased protection against prevalent attack vectors like phishing, credential theft, and brute-force attacks [37]. The implementation of MFA is particularly crucial in high-risk sectors such as finance, healthcare, and government, where it not only enhances cybersecurity posture but also ensures compliance with regulatory frameworks and data protection standards [38]. In addition to Multi-Factor Authentication, organizations must adopt a comprehensive cybersecurity strategy that includes continuous monitoring, threat intelligence, and employee training [39] [40]. Implementing real-time network monitoring and anomaly detection tools enables early identification of suspicious activities, reducing the window of opportunity for attackers [41] [42]. Integrating threat intelligence feeds allows security teams to stay updated on emerging vulnerabilities and attack patterns, facilitating proactive defense measures [43]. Moreover, human factors remain one of the weakest links in cybersecurity; therefore, regular awareness programs and phishing simulations are essential to cultivate a security-conscious culture among employees [44]. Together, these measures form a multilayered defense that enhances organizational resilience against increasingly sophisticated cyber threats [45].

Further research activities may consider effective implementations of MFA in the future against evolving attack vectors, such as phishing scams that leverage AI and even deepfake attacks. The strength of MFA could be fortified with biometrics, behavioural analytics, and blockchain for more robust security levels. Future studies for the optimization of MFA would include usability, barriers to adoption, and quantum-resilient authentication research.

Section 2 discusses the literature review. The issue statement is covered in Section 3, and the technique is covered in Section 4. Section 5 presents the article's findings, while Section 6 provides a summary.

2. Literature Review

Clustering, PCA, and CFA techniques have been applied to investigate how cloud-based funding approaches contribute to sustainable urban growth [46]. However, these studies highlight constraints related to data availability and emphasize that such approaches may not be directly transferable to other urban environments [47] [48]. AI-based techniques such as k-means clustering for anomaly detection and regression analysis for predictive maintenance have been used to improve the reliability of Infrastructure-as-a-Service platforms [49]. Despite these advances, limitations remain regarding the scalability and flexibility of these solutions across diverse cloud environments [50].

A secure financial data-shared framework designed for hybrid cloud environments utilizes machine learning, artificial intelligence, and information fusion to enhance threat detection and compliance [51]. While promising, this model faces challenges in scalability and lacks the adaptability necessary to respond effectively to evolving cyber threats [52] [53]. Financial fraud detection has been advanced through the combination of Attention-Based Isolated Forest with ensemble machine learning methods, including Random Forest and AdaBoost. This approach also addresses class imbalance using SMOTE [54]. However, practical implementation difficulties and limited real-time adaptability persist as key limitations [55].

Systematic reviews of big data analysis in cloud environments demonstrate improvements in e-commerce transaction security [56]. Nevertheless, these studies acknowledge ongoing challenges in dealing with evolving cyber threats and the real-world applicability of proposed solutions [57]. Research focusing on computational overhead and adaptability to different cloud architectures has proposed a public auditing scheme for dynamic big data storage in PaaS environments [58] [59]. This scheme employs cryptographic techniques such as Proof of

Retrievability, hash functions, and digital signatures to enhance data integrity and security [60].

Investigations into information-sharing dynamics within dual-channel supply chains leverage big data analytics, game theory, and supply chain management [61]. Although insightful, these analyses face limitations concerning the complexity of modelling strategic interactions [62] [63]. Hybrid approaches that combine K-Means, Hierarchical Clustering, and Genetic Algorithms have been developed to improve e-commerce product recommendation systems. Despite their effectiveness, these methods struggle with computational complexity and scalability when applied to large datasets [64] [65].
Machine learning algorithms including Gaussian Naive Bayes, Random Forest Classifier, and Decision Tree Classifier have been utilized to detect anomalies in blockchain-based Bitcoin transaction surveillance. The primary challenges associated with this work include limited real-time scalability and difficulty adapting to rapidly evolving threats.

3. Problem Statement

As cloud computing continues to underpin critical infrastructures and services across diverse sectors such as finance, healthcare, and government, ensuring the security and reliability of cloud platforms remains a significant challenge [66]. Despite the adoption of advanced machine learning and artificial intelligence techniques for anomaly detection, predictive maintenance, and fraud detection, current solutions often struggle with scalability and adaptability across different cloud environments [67] [68]. Moreover, many proposed models face practical limitations, including high computational complexity and difficulties in real-time implementation, which hinder their effectiveness in rapidly evolving cyber threat landscapes [69]. These constraints are further compounded by data availability issues and the lack of transferable frameworks that can be effectively applied to various urban and enterprise contexts [70] [71]. Consequently, organizations remain vulnerable to sophisticated attacks that exploit these gaps, risking data breaches, financial losses, and compliance failures [72] [73].

Additionally, while cryptographic methods and public auditing schemes enhance data integrity and security in cloud storage, their overhead and complexity limit widespread adoption, especially in dynamic big data scenarios typical of Platform-as-a-Service models [74]. The complexity of strategic interactions within supply chains and the computational demands of hybrid clustering and optimization algorithms present further barriers to efficient, scalable solutions for big data analytics and recommendation systems [75] [76]. Furthermore, blockchain-based anomaly detection techniques face challenges in real-time scalability and adapting to continuously changing threats, which undermines their potential for comprehensive surveillance and fraud prevention [77]. Addressing these multifaceted issues requires the development of integrated, scalable, and adaptable frameworks that can not only detect and respond to diverse cyber threats promptly but also operate efficiently within the constraints of real-world cloud environments [78] [79]. There is a pressing need to develop scalable and adaptive cybersecurity frameworks that can efficiently detect and respond to evolving threats in diverse and dynamic cloud environments [80]. Existing solutions fall short in real-time performance, cross-platform compatibility, and practical implementation, especially in sectors handling sensitive financial and personal data [81].

4. Proposed Autoencoder LSTM based ABO

The very first step towards adopting all this is that the collection of raw cybersecurity data has gathered quite large amounts. Further, preprocessing of this data is to be done and data cleansing is applied for analysis. The detection of all anomalies in network activities is carried out using the Autoencoder LSTM model, which is focused on cyber threats detection. Further, to gain the accuracy in detection, model optimization through ABO is carried out. Finally, performance evaluation is done to measure the overall working effectiveness of the model as per security reliability in real-world applications. This approach indeed increases efficiency in detecting threats and responding. The Figure 1 shows the Block Diagram of Autoencoder LSTM.

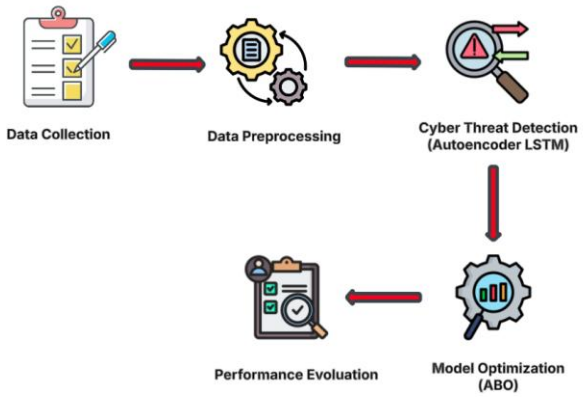

Figure 1: Block Diagram of Autoencoder LSTM

5. Data Collection

The dataset of Textual Cyber Threat Detection presents from Kaggle which helps identify the cyber threats with NLP and machine learning technologies. It has threat intelligence data labelled or marked which can be trained with various models such as the Autoencoder LSTM model for determining the phishing, malware, and social engineering types of attacks. This helps strengthen even more the automated threat detection as well as security defences of the organizations.

Dataset link: https://www.kaggle.com/ datasets/ ramoliyafenil/ text-based-cyber-threat-detection/data

6. Data Preprocessing using Min-Max Normalization

In cybersecurity works, preprocessing data transforms raw inputs to be understood by the analysis. Normalization has been one of the finest processes of preprocessing when there are datasets with numerical features of different types of scales.

Normalization is rescaling data to a common range typically $[0,1]$ or $[-1,1]$. The goal is to eliminate the capacity of features with larger magnitudes from dominating those with smaller magnitudes. This analysis is mainly valid when trying to analyse the performance of Multi-Factor Authentication (MFA) using machine learning models, statistical techniques, or the evaluation of performance metrics.

Mathematical Equation for Min-Max Normalization

Min-Max Normalization is a popular normalization method that uses the following equation (1) to rescale values to a specified range $[0,1]$:

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad (1)$$

Where $X =$ Original data point, $X' =$ Normalized data point, $X_{\min} =$ Minimum value in the dataset, $X_{\max} =$ Maximum value in the dataset.

7. CYPER threat detection using Autoencoder LSTM

Using Autoencoder LSTM, cyber threat detection has been effectively applied with deep learning for recognizing anomalies in sequential data. The model built on the encoder-decoder architecture repeatedly learns what is 'normal behaviour' as against the high reconstruction error, which amounts to a possible threat such as malware or DDoS attack. This way, it improves the response to emerging threats by real-time anomaly detection in enhanced cybersecurity.

Problem Formulation

Given a sequence of network traffic data $\mathrm{X} = \{X_1, X_2, \ldots, X_T\}$, where $X_t \in \mathbb{R}^n$ represents network features at time t, the goal is to detect anomalous patterns that deviate from normal behavior.

Autoencoder LSTM Architecture

An Autoencoder is comprised of two basic but robust components:

Encoder: Compresses the input sequence into a lower-dimensional representation.

Decoder: Reconstructs the input sequence from this representation.

An LSTM Autoencoder employs LSTMs for both its encoder and its decoder, since capturing the temporal dependencies in sequence data are the strengths of LSTM networks.

Mathematical Formulation

Encoding (Compression Step) The LSTM encoder processes the input sequence and generates a compressed latent as shown in the equation (2):

$$h_t = f(W_h X_t + U_h h_{t-1} + b_h) \quad (2)$$

Where W_h, U_h, b_h are learnable weight matrices and bias, h_t is the hidden state at time t, f represents the LSTM activation function.

Decoding (Reconstruction Step) The decoder attempts to reconstruct the original input sequence as represented in the equation (3):

$$\hat{X}_t = g(W_o h_t + b_o) \quad (3)$$

Where W_o, b_o are learnable weights and bias for the output layer, g is an activation function (e.g., sigmoid or tanh), $\hat{X}_t$ is the reconstructed input.

8. Model optimization USIO ABO

ABO is a swarm intelligence-based optimization algorithm inspired by the social interactions and movement patterns of African buffalo herds. Optimization of complex problems becomes therefore possible, including tuning of machine learning models, scheduling, and engineering designs. To model buffalo herd behaviours, ABO balances exploitation (refining solutions) and exploration (searching). It has found applications in feature selection, image processing, and routing for energy efficiency, thus qualifying to be a strong optimization technique.

Problem Formulation

Given an objective function $f(x)$, the goal of ABO is to find the optimal solution x^* that minimizes (or maximizes) as shown in an equation (4):

$$x^* = \arg\min_{x \in \mathbb{R}^n} f(x) \quad (4)$$

where x represents a potential solution (e.g., hyperparameters in machine learning).

ABO Mathematical Model

ABO mimics the buffalo herd movement, consisting of two key strategies:

Exploration (Migrate Behavior - m): Buffalos explore new regions by moving toward better solutions.

Exploitation (Wait Behavior - w): Buffalos refine their positions when they find promising solutions.

At each iteration, the position x_i of buffalo i is updated as represented in the equation (5):

$$x_i^{new} = x_i + w_i + m_i \quad (5)$$

Where w_i (wait) helps refine the current solution (local search). m_i (migrate) helps explore new areas (global search).

The values of w_i and m_i are updated as in the equation (6) & (7):

$$w_i^{\text{new}} = \alpha w_i + \beta(x_{\text{best}} - x_i) \quad (6)$$
$$m_i^{\text{new}} = \gamma m_i + \delta(x_{\text{best}} - x_i) \quad (7)$$

4. Results and Discussions

ABO appears to be a recent swarm intelligence motif based on the movement of buffalo herds used for solving intricate optimization challenges. It helps in a good balance between exploration and exploitation, hence being very effective in applications like machine learning, scheduling, and other engineering implementations.

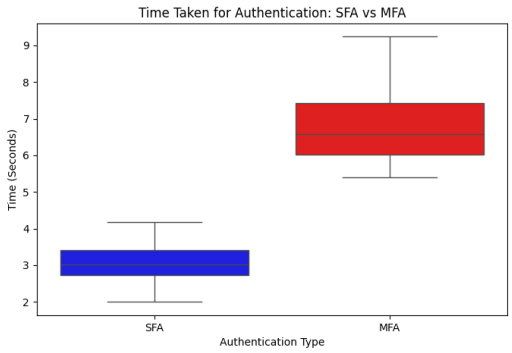

Figure 2: Time Taken for Authentication

The box plot is comparing the time taken for authentication between SFA and MFA. Indeed, the lower median authentication time-points in cave blue SFA of 2 to 4 seconds is definitely contrasted from that of MFA of 5 to 9 seconds in which the authentication is definitely shown with a reddish-yellow hue. The increased time is due to extra steps of verification such as biometrics or OTPs because of the guarantee of the enhanced security but slight effects on the convenience factor. Thus, the trade-off here shows security as well as efficiency for the entire authentication mechanism. The Figure 2 shows the Time Taken for Authentication.

The bar chart illustrates the performance metrics of the Autoencoder LSTM-based Cyber Threat Detection Model across five key evaluation criteria: Accuracy, Precision, Recall, F1-Score, and AUC-ROC. The model demonstrates high effectiveness, achieving an accuracy close to 96%, indicating reliable cyber threat detection. The precision (93%) and recall (91%) scores highlight the model's strong capability in correctly identifying threats while minimizing false positives.

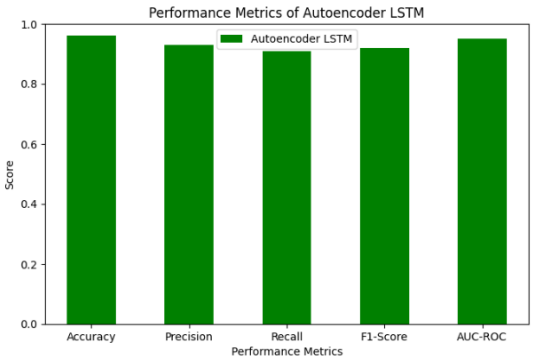

Figure 3: Performance Metrics of Autoencoder LSTM

Additionally, the F1-score (92%) suggests a well-balanced trade-off between precision and recall. The AUC-ROC score of 95% signifies excellent differentiation between normal and anomalous activities. These results validate the robustness of the Autoencoder LSTM in identifying cyber threats with high efficiency and reliability. The Figure 3 shows the Performance Metrics of Autoencoder LSTM.

Conclusion and Future Works

ABO is thus an effective and adaptable intelligent run swarm algorithm that has proved successful for complex optimization problems. The movement strategies that buffalo herds use for collective decision-making have been mimicked to gain exploration and exploitation that could be made better in the speed and accuracy of the convergence rate. The applications are many: in machine learning, through engineering design, scheduling or even wireless sensor networks, this enhances it to be a good tool when dealing with optimization. Compared to conventional optimization methods, it has demonstrated even greater robustness, adaptability, and scalability in order to have efficient search processes and high-quality solutions. Future work can also be directed towards improving the performance of ABO in many ways. Combining ABO with meta-heuristic schemes like genetic algorithms or even particle swarm optimizations would further improve its speed in searching, as well as eliminating the chances of premature convergence. Deep learning schemes can also be integrated, optimally tuning parameters for use in dynamic environments. A very promising area is the application of ABO with newer domains like cybersecurity, bioinformatics, or smart grid optimization. Another area for further exploration is to optimize ABO in high dimensions and improve its computational performance for real-time applications. Hence, with depth-by-depth improvements, it might someday become a powerful optimization tool for much larger and more complex problems.

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