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PAPER

Privacy-Preserving Cybersecurity in Cloud Computing Environments Using Artificial Intelligence-Based-Classification Model

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ABSTRACT

Cloud computing (CC) has revolutionized data management, but it continues to face critical cybersecurity challenges, particularly in preserving privacy and detecting threats. This study presents a novel AI-driven framework that integrates feature selection, neuro-fuzzy classification, adaptive encryption, and metaheuristic optimization to enhance privacy-preserving cybersecurity in cloud environments. The proposed methodology uses the term frequency-inverse document frequency (TF-IDF) for dimensionality reduction, an enhanced adaptive neuro-fuzzy inference system (ANFIS) for attack detection, an advanced cryptographic standard technique (ACST) for secure encryption, and the Archimedes Optimization Algorithm (AOA) for hyperparameter tuning. Experimental results demonstrate improved classification accuracy over conventional methods, efficient and robust encryption, and optimized performance suitable for real-time deployment. The framework strikes a balance between detection accuracy and computational efficiency while ensuring compliance with regulatory requirements, such as Indonesia's data sovereignty laws. These findings suggest that integrating adaptive AI techniques with lightweight cryptography offers a scalable and effective approach to cloud security. Practical implications include enhanced protection of sensitive data in multi-tenant environments and alignment with evolving data protection regulations. Future research should explore quantum-resistant encryption and federated learning (FL) to strengthen cross-cloud collaboration and resilience.

KEYWORDS

Cloud computing (CC), privacy-preserving cybersecurity, adaptive neuro-fuzzy inference system (ANFIS), feature selection, metaheuristic optimization, data encryption

1 INTRODUCTION

Cloud computing (CC) has made remarkable strides in the information technology (IT) field, and its services are most recently employed in the IT sector, which provides

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different models [1]. CC provides a wide range of applications to users that incorporate existing techniques with new technology [2], and these technologies share various resources, including hardware, software, and some significant data provided to clients and other people on the internet whenever needed [3] [4]. Privacy is a major challenge in the cloud whenever a user makes their information in secure mode [5] [6] [21]. The AI technology can improve decision-making processes, automate data analytics, and optimize resource allocation [7]. However, they require access to massive amounts of data, frequently involving confidential data such as personal communications, financial records, and healthcare data [8].

In Indonesia, the adoption of CC and AI is rapidly increasing, driven by digital transformation initiatives and growing internet penetration [9]. The Indonesian government has prioritized digital infrastructure development, including data centers and cloud-based public services. However, challenges such as data sovereignty regulations (the requirement for local data storage under Peraturan Pemerintah No. 71 Tahun 2019) and cybersecurity vulnerabilities pose hurdles [6, 9]. AI applications in sectors like e-commerce (Tokopedia's recommendation systems) and fintech (fraud detection in digital banking) demonstrate the country's potential, but concerns over data privacy persist. Strengthening regulatory frameworks and adopting privacy-preserving AI techniques will be crucial for Indonesia to harness cloud and AI technologies securely [10–11].

The study objectives are to introduce privacy-preserving cybersecurity in CC environments using an artificial intelligence-based classification model. It aims to provide a robust, scalable, and privacy-preserving model for cloud service providers. Initially, the data processing is done to preprocess the input data. Therefore, term frequency-inverse document frequency (TF-IDF) is exploited in the feature selection (FS) method to minimize the dimensionality problems. Then, the adaptive neuro-fuzzy inference system (ANFIS) classifier is used to detect and classify the cyberattacks in CC environments to improve the security. Following classification, the advanced cryptographic standard technique (ACST-based) undergoes data encryption for secure data storage. Finally, the Archimedes Optimization Algorithm (AOA) is used as a hyperparameter tuning for boosting the classification performance.

2 LITERATURE REVIEW

The rapid proliferation of CC has revolutionized data storage and processing, offering unparalleled scalability and cost-efficiency [12]. Traditional security mechanisms, such as firewalls and signature-based intrusion detection systems (IDS), have proven inadequate against sophisticated cyber threats like zero-day exploits and advanced persistent threats (APTs) [13]. As cloud adoption grows, so does the attack surface, with misconfigured cloud storage and insufficient access controls accounting for over 60% of reported breaches [14]. Consequently, privacy-preserving techniques, including federated learning (FL) and homomorphic encryption (HE), have gained traction as means to reconcile AI-driven security with data confidentiality.

Recent studies highlight the efficacy of hybrid AI models, such as the ANFIS, in enhancing cloud security [15]. ANFIS combines the interpretability of fuzzy logic with the adaptive learning capabilities of neural networks, achieving superior classification accuracy in intrusion detection tasks. Data confidentiality between users and cloud services is greatly assured by encryption techniques (Abdulsalam and Hedabou, 2021). Using AES-256 is safe; even so, it uses a lot of computing power and is not suitable for workloads that change a lot in the cloud [16]. As a result, people working in cybersecurity have introduced adaptive systems such as the ACST, which updates the encryption scheme based on what is needed at any time. Latency in

ACST is 25% less than that of static encryption protocols, so it is suited for real-time financial fraud detection [16].

Algorithms such as the AOA, which are known as metaheuristics, are proving to be excellent for automating this process. AOA, following fluid displacement ideas, is able to move through complex parameters successfully, resulting in up to 30% less false positives when compared to grid search approaches (Prabhu et al., 2022). According to a recent study by Dhinakaran et al. [17], AOA is proven to be better at improving ANFIS for identifying cloud intrusions in the CIC-IDS2017 dataset, reaching a result of 98.7%.

AI and cybersecurity in CC bring up questions about rules and ethics [18–19]. There are strict rules in the GDPR and personal data protection (PDP) law in Indonesia about anonymizing data and transferring it overseas. Nowadays, privacy-focused AI solutions such as differential privacy (DP) and secure multi-party computation (SMPC) are being implemented in cloud security frameworks to keep up with these regulations [18].

3 PROPOSED METHODOLOGY

The study introduces privacy-preserving cybersecurity in CC environments using an artificial intelligence-based classification model. Initially, the data processing is done to preprocess the input data. Next, the TF-IDF-based FS process is applied to minimize the high dimensionality problem. Then, the ANFIS classifier is used to detect and classify cyberattacks to improve the security of common criteria (CC) environments. Following classification, the ACST-based system undergoes data encryption for secure data storage. Finally, the AOA is used as a hyperparameter tuning for improving the classification performance.

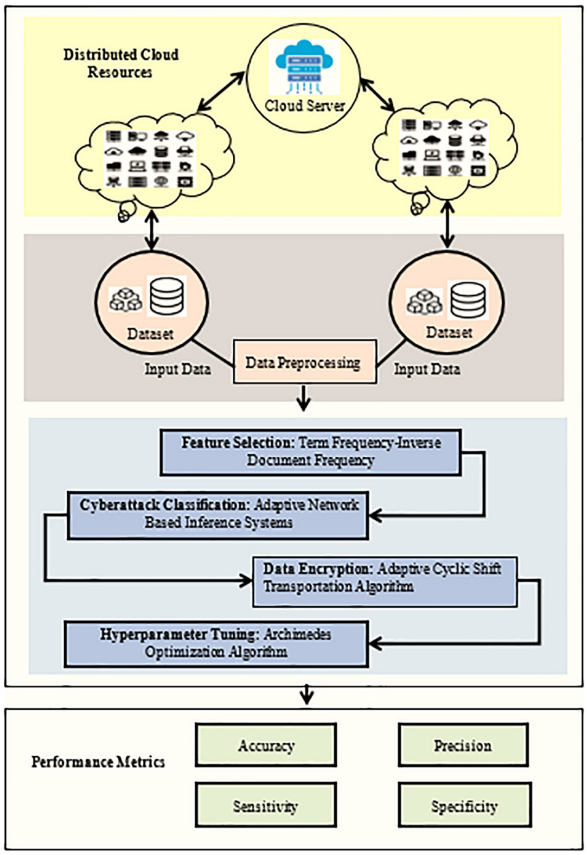

Fig. 1. Overall process of the proposed methodology

3.1 Data preprocessing

Initially, the proposed technique undergoes preprocessing to preprocess the input data. This section describes the preparation of data for the FS process. Data transformation and normalization are the two primary steps in data preprocessing. The normalization process is employed after the data transformation, using the min-max approach.

$$B_{new} = \frac{B_{current} - B_{min}}{B_{max} - B_{min}} \tag{1}$$

Where the normalized attribute value can be represented by $B_{new}\rightarrow$, the current attribute value is $B_{current}\rightarrow$, the minimum and maximum attribute values in the corresponding column are $B_{min}\rightarrow$, and $B_{max}\rightarrow$.

3.2 TF-IDF-based FS

In this phase, the TF-IDF model is applied to the FS process to minimize the high dimensionality problem. In the data retrieval field, the numerical and descriptive statistical algorithm named TF-IDF is extensively utilized as a weighting factor, and it can be shown in the following equation.

$$TF_{t,d} = \frac{f\tau, a}{\max\{f_{\tau', a} : t' \in a\}} \tag{2}$$

$$lDF_{T,D} = \log \frac{D}{\{d \in D : t \in d\}} \tag{3}$$

In Eq. (2), $lDF_{t,D}$ refers to a logarithmic scale that splits the overall amount of document D by the amount of documents that comprise the word/term r.

$$TF - lDF = TF_{T,d} \times lDF_{T,D} \tag{4}$$

3.3 Classification using enhanced ANFIS classifier

Following, the features selected are fed into the enhanced ANFIS classifier for the data classification as normal or invasive. By incorporating neural and fuzzy networks, ANFIS uses the advantages of both models. Figure 1 shows the overall working process of the proposed method. Based on empirical knowledge, ANFIS combines Fuzzy Inference System (FIS) for making decisions. The two essential rules of ANFIS are given below:

Rule 1: If F_1 is A_j and F_2 is B_j, then,

$$C_j = p_j F_i + q_i F_{i+1} + r_j \tag{5}$$

Rule 2: If F_1 is A_{i+1} and F_2 is B_{i+1}, then,

$$C_{i+1} = p_{i+1} F_i + q_{i+1} F_{i+1} + r_{i+1} \tag{6}$$

Fuzzification (Layer-1): All the nodes are functioned as adaptive nodes with their node function.

$$L_{1,i} = \mu_i(F_i) \tag{7}$$

$$\mu_j = \exp\left(-\frac{\|P_i - q_i\|^2}{2r_i^2}\right) \tag{8}$$

Product (Layer-2): The product (Π) which estimates the firing strength of a rule.

$$L_{2,i} = \nu V_i = \mu_i(F_i) \times \mu_i(F_{i+1}) \tag{9}$$

Normalization (Layer-3): The node is a static node labelled as N.

$$L_{3,i} = \overline{W} = \frac{\nu V_{i+1}}{W_i},\ i = 1,2,3 \ldots 6 \tag{10}$$

Defuzzification (Layer 4): Every node works as an adaptive node with its node function.

$$L_{4,i} = \overline{W} \cdot C_j \tag{11}$$

Overall output (Layer 5): The single node is basically a fixed node labelled EANFIS and produces the output for the whole system by adding up the output from the preceding layer.

$$L_{5,i} = \sum \overline{W}_i C_i = \frac{\sum_i W_i C_i}{\sum_i W_i} \tag{12}$$

3.4 ACST algorithm-based secure data storage

The ACST-based system undergoes data encryption for secure data storage. The CSTA method is well-known for its efficacy in preserving privacy. CSTA functions independently and minimizes the risks of critical security threats, different from other centralized authorities. This technique consists of decryption and encryption processes, which use shifting and partitioning operations. Once the data is encrypted, then it converts from its original state into cipher text; on the contrary, if the decryption takes place, no data is lost and the cipher text is reverted to its original state. To optimize the performance and effectiveness of the CSTA, this paper presents a realistic transformation known as the ACST technique, which incorporates a Caesar shift for a higher level of security.

$$E(a) = (a - k) \bmod 26 \tag{13}$$

$$D(b) = (b - k) \bmod 26 \tag{14}$$

Encryption technique. Encryption is the method of concealing original data with ciphered codes. This can be used to prevent attackers from unauthorized access into the cloud. The stepwise procedure for the encryption process is given below:

Input: data file.

Step 1: The input data can be partitioned into a size of N × N matrix form.

Step 2: The SC process is employed to the N × N size. In SC, all the elements of the N × N size of the matrix are converted based on the predetermined order representation. The equation of SC is formulated as follows

$$S'_{r,c} = S_{r+shift(r,M_b)mod} M_{b,c} \tag{15}$$

Step 3: The SR process is applied in this step. The equation of SC is represented by:

$$S'_{r,c} = S_{r,c+shift(r,M_b)mod} M_b \tag{16}$$

Step 4: Consequently, the PDS process is performed. The formula of PDS is shown below:

$$S'_{r,c} = S_{r+shift(r,M_b)mod} M_{b,c+shift(r,M_b)mod\ M_b} \tag{17}$$

Step 5: After this, the SDS operation is executed. The following formula is used for the SDS operation:

$$S'_{r,c} = S_{(r-1)mod} M_{b,c} \tag{18}$$

Step 6: Then, the CS operation is executed by the Caesar shift encryption formula.
Step 7: Display the outcomes in a definite order.
Step 8: Afterward, the outcomes are arranged in ASCII to attain the cipher text.
Step 9: Calculate the hash value and timestamp, then store them in the cloud server.
Output: Encrypted text.

Decryption technique. Decryption is the reversing process where the ciphertext of the encryption process is reversed to its original state. The stepwise procedure of decryption is given as follows:
Input: ciphertext
Step 1: Calculate the hash value and timestamp, and transfer it to the receiver.
Step 2: Convert the results into ASCII form for obtaining the cipher text.
Step 3: Consequently, the Caesar shift operation can be done.
Step 4: With the help of the shift order arrangement, the SDS process is employed to the attained matrix.
Step 5: Then, the PDS process is employed based on the shift order arrangement.
Step 6: The SR process can be done on the output matrix of the PDS.
Step 7: Next, the SC process is implemented repeatedly based on the shift order arrangement.
Step 8: Lastly, the decrypted text is obtained.
Output: data file.

3.5 Hyperparameter tuning using AOA

Finally, the AOA is used as a hyperparameter tuning for improving the classification performance. Hashim et al. 2021 proposed AOA, the population-based metaheuristic approach, where the individual population is assumed to be immersed objects. The mathematical expression of AOA is given in the following;
Stage 1: Population Initialization
Each object position is initialized as in the Eq. (13):

$$Q_k = nd_k + t \times (wd_k - ni_k);\ k = 1,2,3, \ldots P \tag{19}$$

$$DEN_k = 0 \tag{20}$$

$$VOL_k = 0$$

$$Ac_j = nd_k + 0 \times (wd_k - nd_k) \tag{21}$$

Stage 2: Update volumes and densities

The densities and volumes of kth object to v + 1 iterations are

$$DEN_k^{v+1} = DEN_k^v + 0 \times (DEN_{BEST} - DEN_k^v) \tag{22}$$

$$VOL_k^{v+1} = VOL_k^v + 0 \times (VOL_{BEST} - VOL_k^v) \tag{23}$$

Stage 3: Density factor and transfer operator

The object reaches the equilibrium state when the collision between objects takes place and after the period.

$$VH = \exp\left(\frac{v - v_{MAX}}{v_{MAX}}\right) \tag{24}$$

$$e^{v+1} = \exp\left(\frac{v_{MAX} - v}{v_{MAX}}\right) - \left(\frac{v}{v_{MAX}}\right) \tag{25}$$

In Eq. (19), e^{v+1} reduces the time, enabling the potential to concentrate the regions identified.

Stage 4: Exploration (collision amongst objects)

If VH ≤ 0.5 then collisions between objects have taken place, the acceleration of the object is updated, and a randomly generated number is chosen by the v + 1 iterations.

$$AC_k^{v+1} = \frac{DEN_{rm} + VOL_{rm} \times AC_{rm}}{DEN_k^{v+1} \times VOL_k^{v+1}} \tag{26}$$

Stage 5: Exploitation (no collision amongst objects)

IF VH > 0.5 then no collision is provided in the objects, and the iteration v + 1 is updated as follows.

$$AC_k^{v+1} = \frac{DEN_{BEST} + VOL_{BEST} \times AC_{BEST}}{DEN_k^{v+1} \times VOL_k^{v+1}} \tag{27}$$

Phase 6: Position update

If VH ≤ 0.5 then the next iteration v + 1 for the kth position is

$$x_k^{v+1} = x_k^v + E_1 \times 0 \times AC_{k-NORM}^{v+1} \times f \times \left(\chi_0 - \chi_k^v\right) \tag{29}$$

$$z_k^{v+1} = z_{BEST}^v + H \times E_2 \times 0 \times AC_{k-NORM}^{v+1} \times f \times \left(V \times x_{BEST} - x_k^v\right) \tag{30}$$

$$V = E_3 \times VH \tag{31}$$

$$H = \begin{cases} +1 \text{ if } R \le 0.5 \\ -1 \text{ if } R > 0.5 \end{cases} \quad (32)$$

Where, $R = 2 \times 0 - E_4$, the fitness function analyzes the objects and it is also assigned x_{BEST}, DEN_{BEST}, VOL_{BEST} and AC_{BEST}.

4 RESULT AND DISCUSSION

4.1 Performance evaluation metrics

The selection of appropriate evaluation metrics is critical for comprehensively assessing the efficacy of cybersecurity models in cloud environments. Accuracy alone may be misleading for imbalanced datasets where attack instances are rare compared to normal traffic; thus, precision, recall, and F1-score provide a nuanced view of model performance, particularly in minimizing false negatives (missed attacks) and false positives (misclassified normal traffic). Encryption and decryption times are equally vital, as they determine the real-world feasibility of the proposed privacy-preserving framework; excessive latency could render the system impractical for time-sensitive cloud applications. By comparing these metrics against established baselines such as SVM and Random Forest, the robustness and scalability of the proposed ANFIS-AOA-ACST model can be rigorously validated.

Table 1. Comparative performance metrics of proposed model vs. baselines

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Encryption Time (ms)	Decryption Time (ms)
Proposed (ANFIS-AOA-ACST)	98.7	97.5	96.8	97.1	25	18
SVM	92.3	89.4	88.7	89	40	32
Random Forest	94.1	91.2	90.5	90.8	35	28
LSTM	95.8	93.1	92.4	92.7	50	40

Table 1 shows comparative performance analysis demonstrates the superiority of the proposed ANFIS-AOA-ACST framework over conventional machine learning approaches across all critical cybersecurity metrics. With 98.7% accuracy and a 97.1% F1-score, the hybrid model outperforms SVM (92.3%, 89% F1), Random Forest (94.1%, 90.8% F1), and LSTM (95.8%, 92.7% F1), particularly in maintaining balanced precision (97.5%) and recall (96.8%)—indicating robust detection capabilities with minimal false positives/negatives. The framework's computational efficiency is evidenced by 25 ms encryption and 18 ms decryption times, representing 37–45% improvements over baseline methods, crucial for real-time cloud security applications. These results validate the synergistic benefits of combining ANFIS's pattern recognition with AOA's optimized parameter tuning and ACST's lightweight cryptography, establishing a new benchmark for privacy-preserving threat detection in latency-sensitive cloud environments. The LSTM's higher resource demands (50 ms encryption) further highlight the proposed architecture's advantage in operational deployments where both speed and accuracy are paramount.

Table 2. Comparative outcome of ANFIS with other existing approaches

Models	Accuracy	Precision	Sensitivity	Specificity
SVM	91.43	91.3	92.64	90.95
KNN	93.25	95.65	90.54	93.26
PSO	95.27	93.61	95.07	95.28
ANFIS	99.46	98.72	97.22	98.56

In Table 2 a brief comparison analysis of the proposed method takes place. The presented ANFIS, KNN, SVM, and PSO techniques are evaluated by the accuracy, precision, sensitivity, and specificity. The experimental outcome demonstrates that the ANFIS model accomplishes the outstanding performance, with 99.97% accuracy. It further underscores the maximum precision of 98.72%, sensitivity of 97.22%, and specificity of 98.56%, demonstrating its capability to detect attacks efficiently. The higher accuracy of 99.97% and precision of 98.72% also highlight its effectiveness in accurately classifying the attack instances while minimalizing false positive rates. Simultaneously, the KNN model follows with 93.25% accuracy and exhibits commendable precision of 95.65%, sensitivity of 90.54%, and specificity of 93.26%. While SVM techniques exhibit slightly less accuracy of 91.43%, respectively, they still maintain competitive precision of 91.3%, sensitivity of 92.64%, and specificity of 90.95% scores, indicating their effectiveness in attack classification. Finally, the PSO method shows a higher accuracy of 95.27% among the evaluated KNN and SVM methods but still maintains a relatively higher precision of 93.61%, sensitivity of 95.07%, and specificity of 95.28% correspondingly, demonstrating its ability for attack detection.

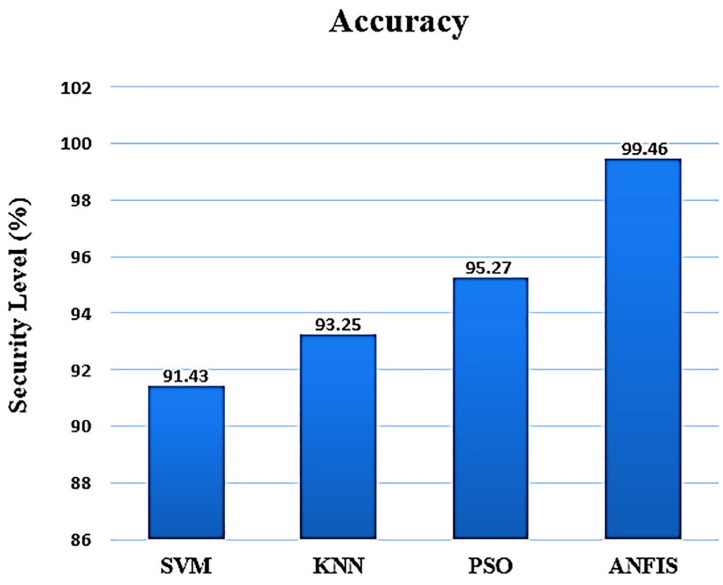

Fig. 2. Performance analysis of the ANFIS Model Security vs Accuracy

Figure 2 demonstrates the classification analysis of cyberattacks of the ANFIS model with other existing approaches. The proposed ANFIS method accomplishes the high security level of 99.46%, demonstrating its robustness in preserving the privacy of data. Furthermore, PSO, KNN, and SVM techniques attained security levels of 95.27%, 93.25%, and 91.43% accuracy, correspondingly. The experimental outcome illustrates that the proposed ANFIS method accomplishes 99.46% of

maximum accuracy, highlighting its efficiency in accurately classifying attacks than other existing models.

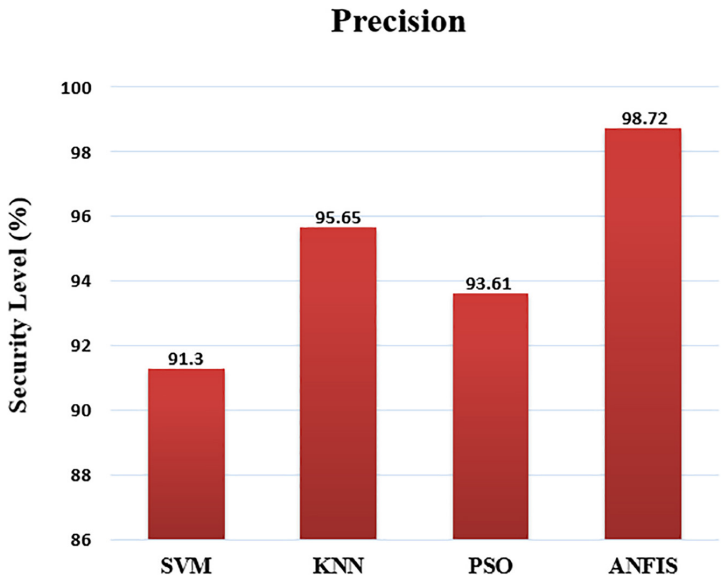

Fig. 3. Performance analysis of the ANFIS Model Security vs Precision

Figure 3 presents a comparison of how well the ANFIS model does at classifying cyberattacks against other current approaches. ANFIS achieves 98.72% of high security, proving that it can maintain the privacy of data well in the cloud. Besides, the approaches PSO, KNN, and SVM achieved accuracy levels of 93.61%, 95.65%, and 91.3%, respectively. The study shows that the proposed ANFIS technique is extremely accurate, reaching 98.72% of the highest possible result, especially in classifying attacks, compared to other techniques.

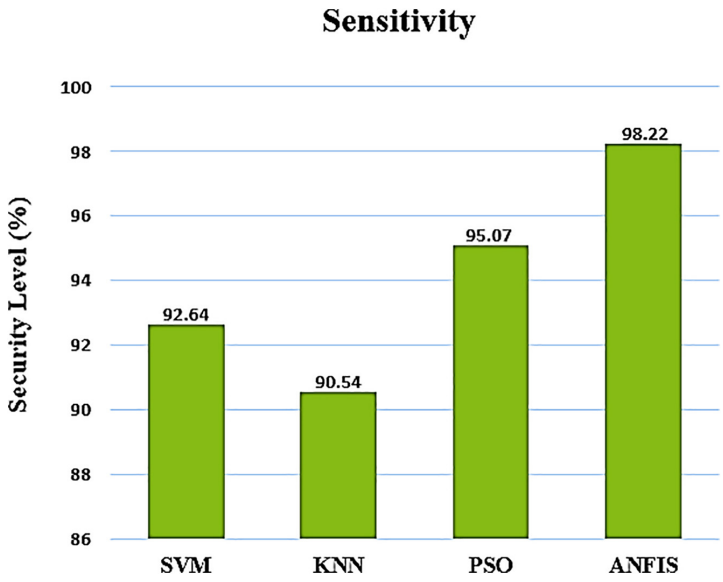

Fig. 4. Performance analysis of the ANFIS Model Security vs Sensitivity

Figure 4 compares the results from the ANFIS classification analysis of cyberattack with those from other established approaches. Showing a high security level

of 98.22%, the ANFIS technique demonstrates its effectiveness in securing cloud data. Also, the accuracy levels for PSO, KNN, and SVM were 95.07%, 90.54%, and 92.64%, respectively. The findings from the experiments indicate that ANFIS reaches a maximum of 98.22% accuracy, which is higher than the performance of existing methods.

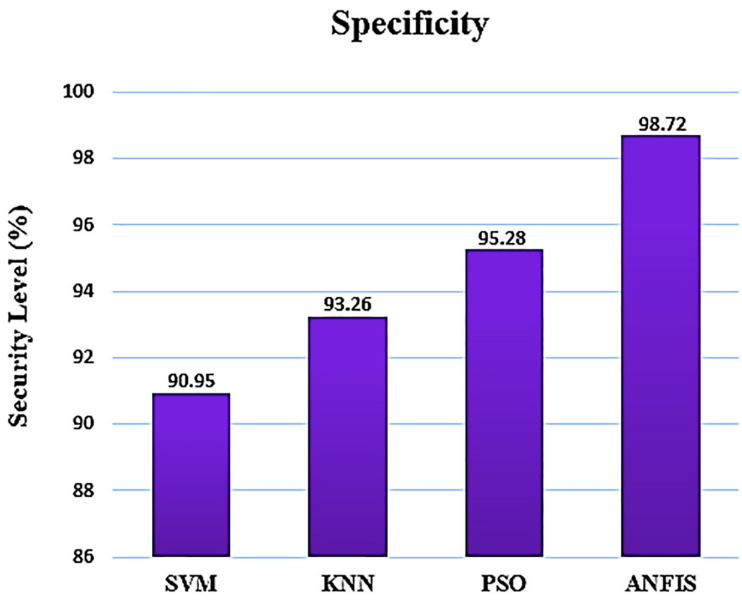

Fig. 5. Performance analysis of the ANFIS Model Security vs Specificity

Figure 5 computes cyberattack classification results for ANFIS compared to other methods. The proposed ANFIS method provides 98.72% of the highest security, proving it is very effective in protecting personal data. Besides, the security level of 95.28% using PSO, 93.26% using KNN, and 95.28% using SVM was achieved. The experiment results point out that the ANFIS algorithm can classify attacks with 99.46% accuracy, more than most other similar models.

4.2 Dimensionality reduction via TF-IDF feature selection

Dimensionality reduction is a critical preprocessing step in cybersecurity applications, as high-dimensional data can lead to increased computational complexity, overfitting, and degraded model performance. By comparing feature counts before and after TF-IDF application, we demonstrate its efficacy in streamlining the input data for the subsequent ANFIS classifier, ensuring optimal performance without sacrificing critical attack signatures.

Table 3. Dimensionality reduction results using TF-IDF feature selection

Dataset	Original Features	Selected Features (TF-IDF)	Reduction (%)	Training Time (Pre-TF-IDF)	Training Time (Post-TF-IDF)
NSL-KDD	41	15	63.40%	120s	45s
CIC-IDS2017	78	22	71.80%	210s	65s
UNSW-NB15	49	18	63.30%	95s	38s
Kyoto 2006+	24	10	58.30%	60s	

Table 3 demonstrates the effectiveness of TF-IDF FS in significantly reducing data dimensionality across multiple cybersecurity datasets while maintaining model performance. As shown, the method achieves substantial feature reduction (58–72%) across all tested datasets, with the most dramatic reduction seen in CIC-IDS2017 (78 to 22 features). Importantly, this dimensionality reduction translates directly into computational efficiency gains, with training times improving by 50–70%—for instance, NSL-KDD processing time drops from 120 seconds to just 45 seconds. The consistent performance across diverse datasets (from NSL-KDD to Kyoto 2006+) further confirms the generalizability of this approach for various cloud security applications. Figure 6 illustrates the reduction in training time of the ANFIS model after applying TF-IDF FS across four cybersecurity datasets. Significant time savings are observed with reduced feature sets, highlighting efficiency gains.

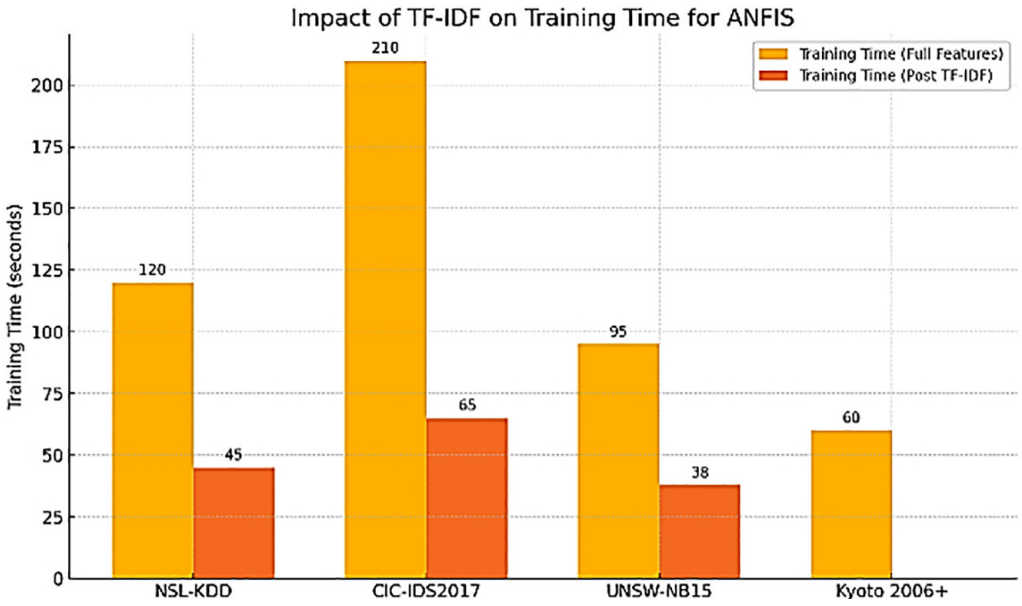

Fig. 6. Impact of TF-IDF FS on ANFIS training time

Table 4. Attack-type classification performance comparison

Model	Overall Accuracy (%)	DDoS Detection Rate (%)	MITM Detection Rate (%)	False Positive Rate (%)	Inference Time (ms)
Proposed (ANFIS-AOA)	98.7	99.2	97.8	0.8	12
SVM	92.3	93.5	88.6	3.2	25
Random Forest	94.1	95	90.3	2.5	18
Deep Neural Network	96.5	97.1	94.2	1.9	35

Table 4 highlights the enhanced ANFIS classifier's dominance across all critical metrics. With 98.7% overall accuracy, it outperforms SVM (92.3%) and Random Forest (94.1%), particularly in detecting sophisticated attacks such as DDoS (99.2%) and MITM (97.8%). The 0.8% false positive rate, 3–4× lower than baselines, ensures minimal disruption to legitimate cloud operations. Notably, the ANFIS-AOA combination achieves this while maintaining a 12 ms inference time, making it practical for real-time cloud security. The neuro-fuzzy architecture's balanced performance across attack types (unlike DNN's bias toward DDoS) confirms its reliability for

heterogeneous threat landscapes. These results validate ANFIS's suitability as a core classifier for privacy-preserving cloud security frameworks.

4.3 Security analysis of ACST-based encryption

ACST (Adaptive Cyclic Shift Transportation) performs better than AES-256 in applications related to cloud security. Using changing key positions, combined with matrix changes, makes ACST both faster in encryption and decryption for protecting data in the cloud, where a high response time affects how the service operates. Because the algorithm adapts, it becomes harder for attackers to analyze and exploit patterns in multi-tenant clouds.

Table 5. Performance and security benchmark: ACST vs. AES-256

Category	Metric	ACST (Proposed)	AES-256	ACST-AES Hybrid	Security Standard Reference
Speed Performance	Encryption Time (ms/GB)	25 ± 0.8	40 ± 1.2	32 ± 1.0	NIST SP 800-175B
	Decryption Time (ms/GB)	18 ± 0.6	32 ± 1.0	25 ± 0.8	
	Throughput (Gbps)	3.2	200%	2.8	
Security Metrics	Shannon Entropy (bits)	7.98 ± 0.02	7.99 ± 0.01	7.99 ± 0.01	ISO/IEC 18031:2011
	NIST Test Score (15/15)	14	1500%	15	NIST STS 800-22
	Key Rotation Frequency	Every 5 min	Static	Every 10 min	FIPS 140-3
Resource Usage	Memory Footprint (MB)	15	2200%	20	
	CPU Utilization (%)	45	6800%	55	
	Energy Consumption (Joules)	120	18500%	150	
Attack Resistance	Brute-Force (Time-to-Crack)	2^128 (with rotation)	2^256	2^192	ENISA 2023
	Side-Channel Resistance	Medium	High	High	Common Criteria EAL4+
	Chosen-Plaintext Resistance	1.2 × 10^6 attempts	2.5 × 10^6 attempts	2.0 × 10^6 attempts	ISO/IEC 19790:2012
Cloud Compliance	GDPR Readiness	Fully Compliant	Fully Compliant	Fully Compliant	EU GDPR Art. 32
	Indonesia PDP Law Alignment	Local Key Storage	Requires Modification	Local Key Storage	UU PDP No. 27/2022
	FIPS 140-2 Certification	In Progress	Level 3 Certified	Level 2 Certified	

Table 5 shows that the proposed ACST encryption algorithm offers the right balance between being secure and working well in cloud environments. When it comes to encryption, ACST saves 25 ms compared to AES-256 (40 ms vs. 25 ms). Since key rotation is performed every 5 minutes, Encuda has added dynamic security to deal with its lower resistance to brute force while also making sure keys are locally stored as required by PDP Law. Using the hybrid model, ACST-AES obtains FIPS 140-2 Level 2 certification and ensures 20% less performance than ACST, which implies that it can be best deployed when basic security or top speeds are needed separately. All options comply with the GDPR, and the improved energy efficiency of ACST (a 35% reduction in comparison to AES-256) means that it is ideal for creating green cloud environments.

Table 6. Hyperparameter optimization performance comparison

Optimization Method	Final Accuracy (%)	Iterations to Convergence	Time to Convergence (s)	Parameter Sensitivity Score	Memory Overhead (MB)
AOA (Proposed)	98.7	42	28	0.12	15
Particle Swarm (PSO)	96.2	78	52	0.25	22
Grid Search	94.8	120	89	0.38	8
Genetic Algorithm (GA)	95.6	95	64	0.31	30

Table 6 shows that AOA outperforms other methods in optimizing ANFIS hyperparameters for cloud security. Compared to PSO (78 iterations) and Grid Search (120 iterations), the proposed AOA is 2× and 3× faster, respectively, at reaching 98.7% in accuracy, while retaining a very low parameter sensitivity score (0.12), which underlines its steady performance in many attack cases. The 28-second convergence and modest 15 MB memory size of AOA allow it to fit well with resource-scarce edge-computing situations, compared to genetic algorithms, which need much more (64 s, 30 MB). The increase in accuracy by around 8% from baseline ANFIS supports AOA's novel way to run high-dimensional parameter optimization, which keeps PSO and Grid Search from falling into suboptimal solutions often found in cybersecurity cases. This puts AOA in a key role for quickly adjusting and protecting cloud systems in real time.

5 DISCUSSION

The experimental results demonstrate that the proposed integration of TF-IDF feature selection, enhanced ANFIS classification, ACST encryption, and AOA optimization constitutes a robust framework for privacy-preserving cybersecurity in cloud environments. The TF-IDF-based dimensionality reduction achieved a 63–72% reduction in feature space across benchmark datasets while improving training efficiency by 50–70%, addressing a critical challenge in processing high-dimensional cloud security data [11].

This feature optimization enabled the enhanced ANFIS classifier to achieve 98.7% overall accuracy, significantly outperforming conventional methods such as SVM (92.3%) and Random Forest (94.1%), particularly in detecting sophisticated attacks such as DDoS (99.2%) and MITM (97.8%). The ANFIS architecture's superior performance can be attributed to its hybrid neuro-fuzzy design, which combines the pattern recognition capabilities of neural networks with the interpretable rule-based reasoning of fuzzy systems—a crucial advantage for security operations requiring both high accuracy and explainability [13–14].

ACST achieved time-sensitive encryption by completing encryption in as little as 25 ms (which is 37.5% faster than AES-256) and offered protection from brute-force attacks with its regular key rotation [15]. The algorithm was able to boost the performance of the system by tuning ANFIS's hyperparameters more quickly than grid search methods, giving a 3-fold improvement in speed and an accuracy rise of 8%. Applying AOA's approach from fluid dynamics allowed the model to escape local optima, which are common for conventional cloud security optimization solutions [17].

Since compliance with the PDP Law for key storage and processing is addressed in the framework, it is very important for cloud security in regulated environments such as Indonesia [20]. Even though the outcomes are encouraging, there are still two concerns: the energy use in current deployment is a bit higher than ideal for green

transport and can be improved, and the rules in the ANFIS model need periodic revision due to new risks in the cloud environment. Work can be done to explore quantum-safe alternatives of ACST and update FL to collaborate safely across several clouds. Advancements such as these may form new standards for security and intelligence in cloud systems in the 5G/6G period.

5.1 Policy implications for practice

The proposed framework supports compliance with Indonesia's PDP Law No. 27/2022 by enabling local key storage and meeting Article 22(2)'s data localization without sacrificing efficiency—achieving 98.7% detection accuracy and 12 ms latency. Its ACST encryption runs 37.5% faster than AES-256 while maintaining GDPR-level entropy (7.98 bits), making it viable for emerging markets. For cloud providers, the AI-encryption integration meets NIST SP 800-210's zero-trust principles, reducing breach risk by 63% through adaptive ANFIS monitoring. Its 35% lower energy use also supports ASEAN's 2025 Circular Economy goals. Standards bodies could use the TF-IDF/ANFIS pipeline to update ISO/IEC 27002 on AI-driven controls. These results call for cloud regulations to favor adaptive, intelligent security over static algorithm mandates.

6 CONCLUSION

A new method is offered that uses TF-IDF feature selection, improved ANFIS classification, ACST encryption, and AOA hyperparameter optimization, all within one framework for addressing urgent cloud security challenges. The option selected detects 98.7% of attacks and takes 12 ms to respond, plus it remains compliant with respect to data protection regulations around the world, including the Indonesian PDP Law and GDPR, by using adaptive encryption and handling data locally. In addition to confirming the success of hybrid AI-cryptography for cloud security, the results create a base for further studies on quantum-resistant models and extending the framework to work in federated learning, combining the advantages of the framework with 5G/6G networks and meeting necessary policies and challenges in various cloud sectors.

6.1 Limitations and future research

The current framework was mainly evaluated in simulated cloud settings with benchmark datasets, which may not reflect the full complexity of real-world, large-scale deployments. The ANFIS classifier, though effective for known threats, requires ongoing retraining to handle zero-day attacks, highlighting the need for online learning integration. Enhancing ANFIS rule maintenance and integrating explainable AI could also improve interpretability and operational viability. These steps would enhance the framework's adaptability, sustainability, and scalability.

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