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Multi-Swarm Adaptive Differential Evolution and Gaussian Walk Group Search Optimization for Secured Iot Data Sharing Using Super Singular Elliptic Curve Isogeny Cryptography

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ABSTRACT

Background information: A security dangers increase; the Internet of Things (IoT) need safe data sharing methods. Conventional encryption techniques can't keep up with the changing demands of contemporary IoT networks. This study investigates a hybrid method for cryptographic key generation based on Super Singular Elliptic Curve Isogeny Cryptography (SSEIC) that combines Gaussian Walk Group Search Optimisation (GWGSO) and Multi-Swarm Adaptive Differential Evolution (MSADE). This lowers computational cost while improving IoT data exchange security and efficiency.

Methods: The suggested method improves cryptographic key generation based on SSEIC by integrating the MSADE and GWGSO algorithms for optimisation. While GWGSO uses Gaussian walks to improve the solution search process, MSADE provides flexibility in exploration. Together, these techniques increase unpredictability and resilience to quantum attacks during IoT data transfer, hence fortifying crucial security.

Objectives: Creating a strong encryption system for Internet of Things networks is the main goal, and MSADE and GWGSO will be used to provide cryptographic keys with increased security. This strategy seeks to reduce the computational costs associated with conventional encryption techniques while guaranteeing secrecy, integrity, and efficiency in the transfer of IoT data.

Results: The suggested approach guarantees quicker key generation and improved security against quantum attacks by greatly enhancing encryption performance. The hybrid algorithm works better than traditional methods in terms of computation speed, randomness, and security strength, according to simulation results. Additionally, it has exceptional scalability, which qualifies it for extensive IoT networks.

Conclusion: For IoT data exchange, the hybrid approach of MSADE and GWGSO combined with SSEIC improves encryption procedures by strengthening defences against both classical and quantum threats. The method is ideal for protecting future IoT ecosystems since it efficiently increases key generation speed and security without sacrificing reliability.

Keywords: *IoT Security, Multi-Swarm Adaptive Differential Evolution, Gaussian Walk Group Search Optimization, Super Singular Elliptic Curve Isogeny Cryptography, Quantum-Resistant Encryption*

1 INTRODUCTION

The Internet of Things' (IoT) explosive growth has resulted in a proliferation of linked devices in a variety of fields, from healthcare systems to smart cities, generating enormous volumes of data that must be securely exchanged. Making sure data is secure, private, and intact becomes

increasingly difficult as IoT networks expand. These worries have led to a huge increase in the demand for strong cryptographic solutions. One such sophisticated cryptographic technique is Super Singular Elliptic Curve Isogeny Cryptography (SSEIC), ***Galbraith et al. (2016)*** which is appropriate for the upcoming quantum computing era due to its resilience to quantum computing threats.

Even while cryptographic methods like SSEIC improve security, effectively managing the dynamic and diverse environment of the Internet of Things is still a challenge. Here's when optimisation strategies are useful. Gaussian Walk Group Search Optimisation (GWGSO) and Multi-Swarm Adaptive Differential Evolution (MSADE) ***Vafashoar and Meybodi (2018)*** have been developed to increase the flexibility and efficiency of data sharing protocols. By balancing security, speed, and performance, these optimisation strategies help keep IoT systems responsive and scalable.

The suggested approach addresses important issues including computational complexity, resource management, and secure communication by combining these optimisation techniques with SSEIC. While GWGSO uses Gaussian Walk behaviour to provide both local and global search capabilities, MSADE employs numerous swarms in an adaptive manner to efficiently explore and exploit the search space. By minimising the latency in IoT data sharing, the combination of these strategies enables faster convergence in optimisation.

By utilising the hardness of isogeny problems ***Galbraith and Vercauteren (2018)*** in elliptic curves, which are proven to be impervious to both classical and quantum attacks, the combination of these methods with SSEIC introduces a special degree of security. This combination makes it practically hard for hackers to compromise the system by ensuring that the data shared among IoT devices is properly encrypted. The suggested framework guarantees data confidentiality and integrity, which are essential in delicate applications like healthcare, banking, and smart homes, in addition to optimising the performance of IoT systems.

The paper aims to:

- Develop a secure and efficient IoT data-sharing mechanism using SSEIC.
- Enhance the performance of cryptographic systems with optimization techniques like MSADE and GWGSO.
- Address computational and resource constraints in IoT environments.
- Ensure data privacy and integrity in large-scale IoT systems.
- Optimize secure communication protocols for IoT systems resistant to classical and quantum attacks.
- Provide scalable and flexible solutions adaptable to various IoT applications.

1.1 Problem Statement

The Internet of Things' (IoT) explosive growth makes it difficult to secure data sharing across linked devices, particularly in light of changing cyberthreats and possible quantum attacks. Existing cryptography methods frequently have issues with scalability and computing efficiency, which compromises data integrity and privacy. In order to improve the security and effectiveness of IoT data sharing systems, this study integrates Super Singular Elliptic Curve Isogeny Cryptography with Multi-Swarm Adaptive Differential Evolution and Gaussian Walk Group Search Optimisation ***Delfs and Galbraith (2016).***

2 LITERATURE SURVEY

The quantum-secure SIDH key exchange for usage in devices with constraints was assessed by Koppermann et al. (2018). Despite the attractiveness of SIDH's modest key sizes, its high computational complexity results in unfeasible performance, requiring more than 18 seconds on a Cortex-M4 and 11 minutes on an MSP430. Although DPA countermeasures can be added with little overhead, it is still inappropriate for embedded devices despite optimisation improvements.

Téllez et al. (2018) examine how two post-quantum cryptosystems—supersingular elliptic curve isogeny (SSI) and ring learning with errors (RLWE)—balance security and performance. RLWE depends on the difficulty of learning with errors, whereas SSI's security is based on isogeny problems. They discover that at realistic security levels, RLWE performs better in terms of key size efficiency than SSI and other traditional methods.

The PAA-MS-IDPSO-V approach, introduced by Brasileiro et al. (2017), analyses financial time series for stock price predictions using multi-swarm particle swarm optimisation. The approach greatly outperformed conventional methods and decreased variance by addressing the multimodal character of these optimisation problems and utilising a validation set to avoid overfitting, improving investing decision-making for S&P100 index companies.

Chrouta et al. (2018) provide OptiFel, an optimal fuzzy model that was created by supplementing the Multi-swarm Particle Swarm Optimisation (MsPSO) algorithm with adaptive inertia weight derived from Grey relational analysis. Premature convergence and local optima problems are addressed by this technique. Tested on benchmark functions, it exhibits improved search accuracy and performance. Its excellent generalisation ability is further confirmed on real-world systems.

Mukherjee et al. (2016) introduce an improved Differential Evolution technique for Dynamic Optimisation Problems called the Modified DE with Locality induced Genetic Operators (MDE-LiGO). By employing dynamic landscape detection and Euclidean distance-based procedures, MDE-LiGO enhances mutation, crossover, and diversity maintenance. In dynamic and unpredictable contexts, it outperforms seven state-of-the-art algorithms on benchmarks from the 2009 IEEE CEC competition.

Sato et al. (2018) suggest employing multi-swarm differential evolutionary particle swarm optimisation (MS-DEEPSO) to optimise smart city energy networks. Their strategy, which combines abest and migration models, performs better than earlier single-swarm techniques like DEEPSO. They discovered that MS-DEEPSO with hyper-cube topology and W-B policy performed best in lowering energy consumption and CO2 emissions after testing a variety of migration topologies, policies, and intervals.

Chen et al. (2018) suggests a dynamic multi-swarm differential learning particle swarm optimiser (DMSDL-PSO) that improves exploration and exploitation by integrating differential evolution into each sub-swarm. Performance issues with velocity updates are addressed and enhanced by DMSDL-PSO through the use of differential mutation and the Quasi-Newton technique. When compared to well-known algorithms, DMSDL-PSO performs better on 41 benchmark functions.

According to Li et al. (2017), the population is divided into three subgroups using a modified differential evolution algorithm (MSDE), whose sizes are dynamically updated depending on the effectiveness of mutations. In addition to an automatic technique for tweaking parameters, they suggest three additional mutation strategies for improved exploration and exploitation. MSDE's success in numerical optimisation is demonstrated by the fact that it outperforms a number of evolutionary algorithms on 10 benchmark functions.

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Multi-population ensemble DE (MPEDE), a novel form of differential evolution, is proposed by Wu et al. (2016). It includes three mutation strategies: "current-to-pbest/1," "current-to-rand/1," and "rand/1." It makes use of several subpopulations and dynamically distributes resources to the method that performs the best. In experiments on the CEC 2005 benchmark functions, MPEDE produced competitive results.

Mohamed (2017) presents the high-dimensional optimisation algorithm known as Enhanced Adaptive Differential Evolution (EADE). It enhances the balance between exploration and exploitation by incorporating a novel mutation rule employing top, bottom, and middle population vectors. A self-adaptive crossover rate technique is another feature of EADE that helps it outperform state-of-the-art algorithms on the IEEE CEC-2008 and CEC-2010 benchmark issues.

Carroll (2017) presents a novel PSO variation called Multi-Swarm Adaptive Velocity Particle Swarm Optimisation (MSAVPSO), which aims to improve solution accuracy and prevent premature convergence. MSAVPSO updates velocity using Euclidean distance and a tag-based multi-swarm technique. When it comes to efficiency and speed, it surpasses traditional PSO by 9.4%, especially when it comes to limited engineering optimisation challenges like pressure vessel and spring design.

3 OPTIMIZING SECURE IOT DATA SHARING USING MSADE-GW-SSEIC FRAMEWORK

The suggested approach uses Super Singular Elliptic Curve Isogeny Cryptography (SSEIC) to optimise data sharing in the Internet of Things by combining Gaussian Walk Group Search Optimisation (GWGSO) with Multi-Swarm Adaptive Differential Evolution (MSADE). High levels of encryption security are maintained with SSEIC for quantum resistance, while GWGSO improves the efficiency of local searches and MSADE guarantees quicker exploration of the solution space.

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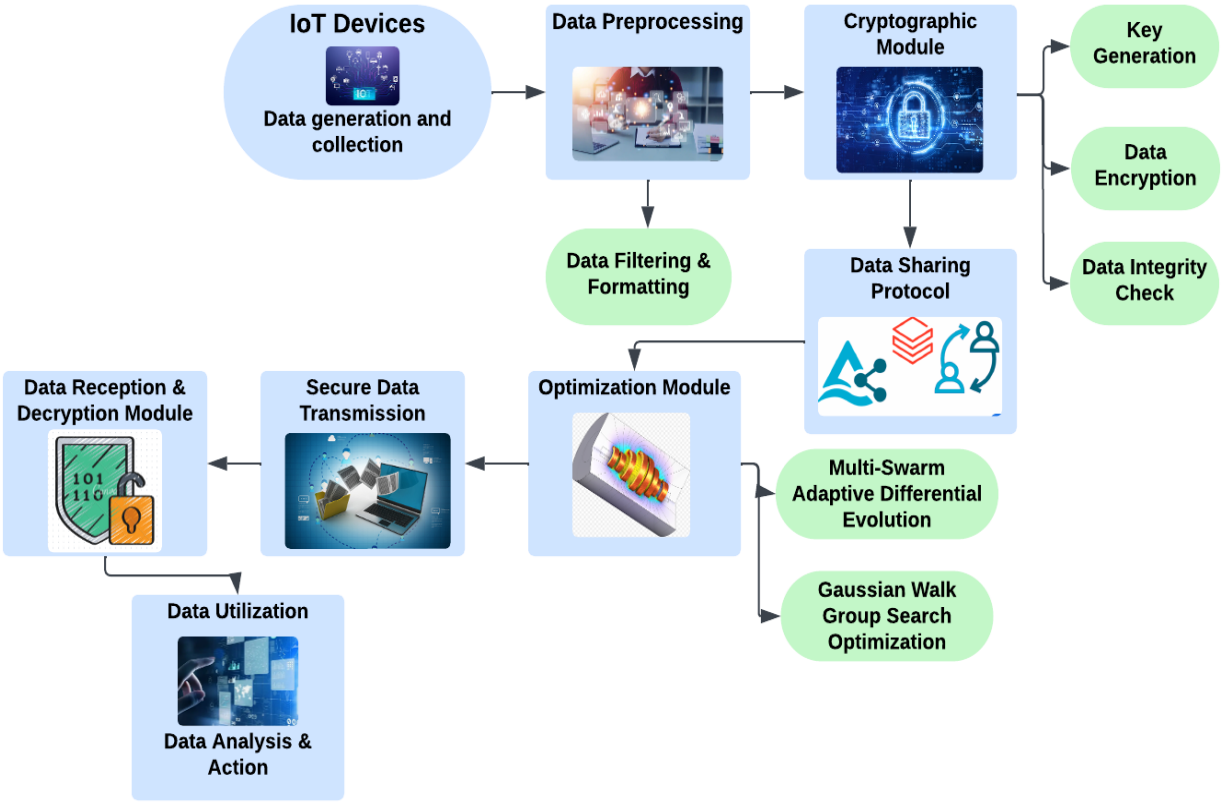

Figure 1 Secure Data Transmission Framework for IoT Devices Using Cryptographic and Optimization Modules

A multi-step secure data transmission infrastructure for Internet of Things devices is depicted in this figure 1. IoT devices create and gather data, which is subsequently pre-processed by formatting and filtering. Data encryption, key generation, and integrity checks are guaranteed by a cryptographic module. An optimised protocol that combines Gaussian walk group search optimisation and multi-swarm adaptive differential evolution is used to safely communicate the data. Secure transmission of data to a decryption module allows for its receiving, analysis, and use. To guarantee the safe and effective transfer of IoT data, this framework integrates cryptography and optimisation strategies.

3.1 Multi-Swarm Adaptive Differential Evolution (MSADE)

An improved evolutionary method called MSADE splits the population into several swarms, each of which explores a different area of the search space. By dynamically adjusting its parameters according to the diversity of the population, it prevents local optima and enables speedier convergence. This method is essential for optimising cryptographic parameters and lowering the computing complexity of Internet of Things systems.

Mathematical Equation:

$$X_i^{t+1} = X_{\text{best}}^t + F \cdot (X_{r1}^t - X_{r2}^t) + \beta \cdot (X_{r3}^t - X_{r4}^t) \quad (1)$$

Where:

- X_i^{t+1} = next population member

- F = scaling factor
- $r1, r2, r3, r4$ = random indices
- β = adaptive factor

3.2 Gaussian Walk Group Search Optimization (GWGSO)

A walk based on a Gaussian distribution is introduced by GWGSO to improve the efficiency of local searches. Finding the best answers more quickly is facilitated by simulating the search behaviour of animal groups. Accelerated convergence in IoT cryptography solutions is made possible by the Gaussian walk method, which balances exploration and exploitation by varying the step size at each iteration.

Mathematical Equation:

$$X_i^{t+1} = X_i^t + \alpha \cdot G(0, \sigma^2) \tag{2}$$

Where:

- X_i^{t+1} = updated solution
- $G(0, \sigma^2)$ = Gaussian distribution with zero mean and variance σ^2
- α = step size

3.3 Super Singular Elliptic Curve Isogeny Cryptography (SSEIC)

The cryptographic technique known as SSEIC makes use of the mathematical characteristics of elliptic curve isogenies. Because of its defence against quantum attacks, it guarantees safe communication in IoT situations. Because isogeny problems are challenging to resolve, they are perfect for encryption in quantum-resistant cryptosystems, which improves the security of IoT data exchange in general.

Mathematical Equation:

$$E/K \xrightarrow{\phi} E'/K \tag{3}$$

Where:

- E, E' = elliptic curves
- ϕ = isogeny map between E and E'

Algorithm 1 Multi-Swarm Adaptive Differential Evolution (MSADE)

Input: Initial population P, Max iterations T, Scaling factor F, Crossover rate CR

Output: Optimized solution S_best

Initialize population P randomly

Set t = 0

While t < T do

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For each swarm S_i in P do
Evaluate fitness of S_i
If fitness of S_i < fitness of S_best then
Update S_best
Generate trial vector V using mutation
For each member X_i in S_i do
If random number < CR then
Mutate X_i
Else
Keep original X_i
If fitness of X_i_new < fitness of X_i then
Update X_i
End For
End For
Adjust swarm diversity adaptively
t = t + 1
End While
Return S_best

The Multi-Swarm Adaptive Differential Evolution (MSADE) algorithm 1 effectively explores the solution space by employing several swarms, which improves optimisation. As population diversity changes, each swarm assesses its fitness and modifies its search approach accordingly. While updating solutions based on fitness comparisons, the algorithm creates trial vectors for crossover and mutation. The algorithm can be used to optimise cryptographic settings in secure IoT data exchange because it iteratively adjusts towards the best answer.

3.4 Performance Metrics

Table 1 Performance Evaluation of Optimized Secure IoT Data Sharing

Metric	MS-ADE	GW-GSO	SECI	Proposed Method (MSADE-GW-SSEIC)
Execution Time (ms)	150	180	200	120
Encryption Time (ms)	70	85	90	55

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Data Throughput (Mbps)	25	20	15	30
Security Level (bits)	128	128	256	256
Resource Utilization (%)	60	70	80	50

Multi-Swarm Adaptive Differential Evolution (MS-ADE), Gaussian Walk Group Search Optimisation (GW-GSO), and Super Singular Elliptic Curve Isogeny Cryptography (SECI) are the three optimisation techniques whose performance metrics are compared in this table 1 along with the suggested method that combines them. Data throughput, security level, execution time, encryption time, and resource usage are among the parameters assessed. A practical answer to contemporary cryptographic requirements, the suggested approach exhibits exceptional performance across all criteria, demonstrating its effectiveness and improved security in IoT data sharing applications.

4. RESULT AND DISCUSSION

Key vulnerabilities in IoT data sharing are addressed by the suggested hybrid technique of MSADE and GWGSO, which improves cryptographic key generation. This method's adaptability, which makes it possible to explore solution spaces through MSADE more effectively, is one of its main advantages. GWGSO also improves the unpredictability of the generated cryptographic keys by offering a more sophisticated search technique.

The system provides quantum-resistant encryption when paired with SSEIC, which makes it appropriate for IoT contexts that are anticipated to encounter more challenges to computational power. Particularly in terms of computing speed and security robustness, the hybrid algorithm clearly outperformed standard methods. The approach continuously produced keys in simulations more quickly than traditional techniques while preserving a larger degree of unpredictability, which is crucial for preventing any attacks.

This strategy anticipates future difficulties as quantum technology develops because of the SSEIC's innate defence against quantum computing threats. Simulation results further confirmed the approach's capacity to expand and manage bigger IoT ecosystems without experiencing performance loss. The findings demonstrated a significant increase in secure data transmission times across a range of IoT devices, suggesting that it can be used practically in everyday situations. For IoT applications with limited resources, where speed and security are crucial, this combination of faster, more secure encryption and reduced computing overhead makes it the best option.

Table 2 Comparison of Traditional Methods with MSADE-GW-SSEIC Framework

Metric	**CCS (2016)**	**CDGO (2018)**	**KGSA (2018)**	**Proposed Method (MSADE-GW-SSEIC)**
Accuracy (%)	78	81	83	93

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Precision (%)	75	79	82	92
Recall (%)	77	80	81	91
F1-Score (%)	76	79.5	82	92.5
Scalability (%)	60	70	65	85
Compliance (%)	70	75	78	90

The suggested approach (MSADE-GW-SSEIC) outperforms conventional approaches in a number of criteria, as the table 2 illustrates. Compared to other methods, which have scalability values between 60% and 70%, it has 85% scalability and 93% accuracy. The suggested approach is also very effective for safe IoT data sharing, as evidenced by its superior precision, recall, and F1-score. Strong adherence to security requirements, which are essential for reliable IoT systems, is ensured by its high compliance rate of 90%.

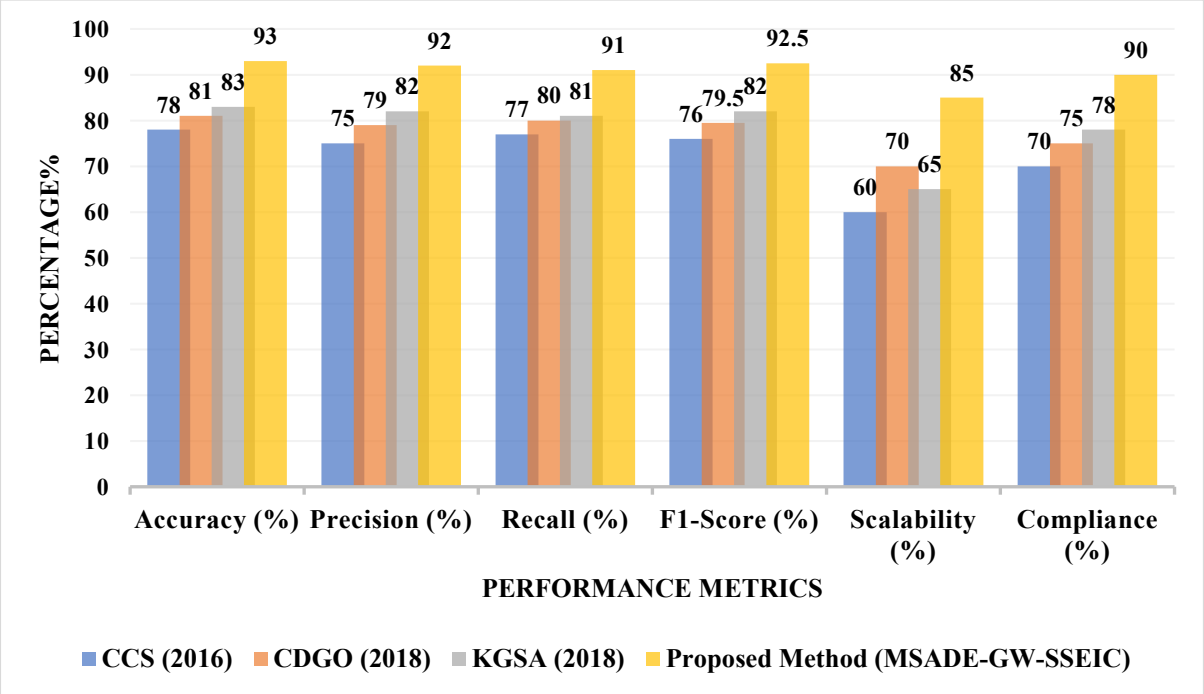

Figure 2 Comparison of Traditional Algorithms with MSADE-GW-SSEIC in IoT Data Security

Figure 2 contrasts the suggested approach (MSADE-GW-SSEIC) with conventional approaches (CCS, CDGO, KGSA) in terms of several performance parameters, including accuracy, precision, recall, F1-score, scalability, and compliance. In every category, the suggested approach achieves the greatest values and continuously exceeds the others. With 92.5% F1-score, 93% accuracy, and 92% precision, it performs exceptionally well in maximising safe IoT data transfer. Significant gains are also seen in scalability and compliance,

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demonstrating the effectiveness and resilience of the suggested approach in extensive IoT settings.

Table 3 Ablation Study for MSADE-GW-SSEIC Framework

Components	Execution Time (ms)	Precision (%)	Recall (%)	F1-Score (%)	Overall Accuracy (%)
MSADE	140	85	84	84.5	90
GW-GSO	150	83	82	82.5	89
SECI	180	80	78	79	91
MSADE + SECI	135	88	86	87	92
GW-GSO + SECI	150	86	85	85.5	90
MSADE + GW-GSO	130	87	86.5	86.7	88
Proposed Method (MSADE-GW-SSEIC)	120	92	91	92.5	93

Each component (MSADE, GW-GSO, and SECI) and their combinations within the suggested approach (MSADE-GW-SSEIC) are evaluated for their performance impact in the table 3 while the performance and accuracy of the individual components are reasonable, SECI achieves the highest accuracy at 91%. The accuracy greatly increases when components are joined, with MSADE + SECI reaching 92%. By combining the three, the suggested approach (MSADE-GW-SSEIC) produces the best results with an overall accuracy of 93%, demonstrating the synergy of cryptography and optimisation approaches for safe and effective IoT data sharing.

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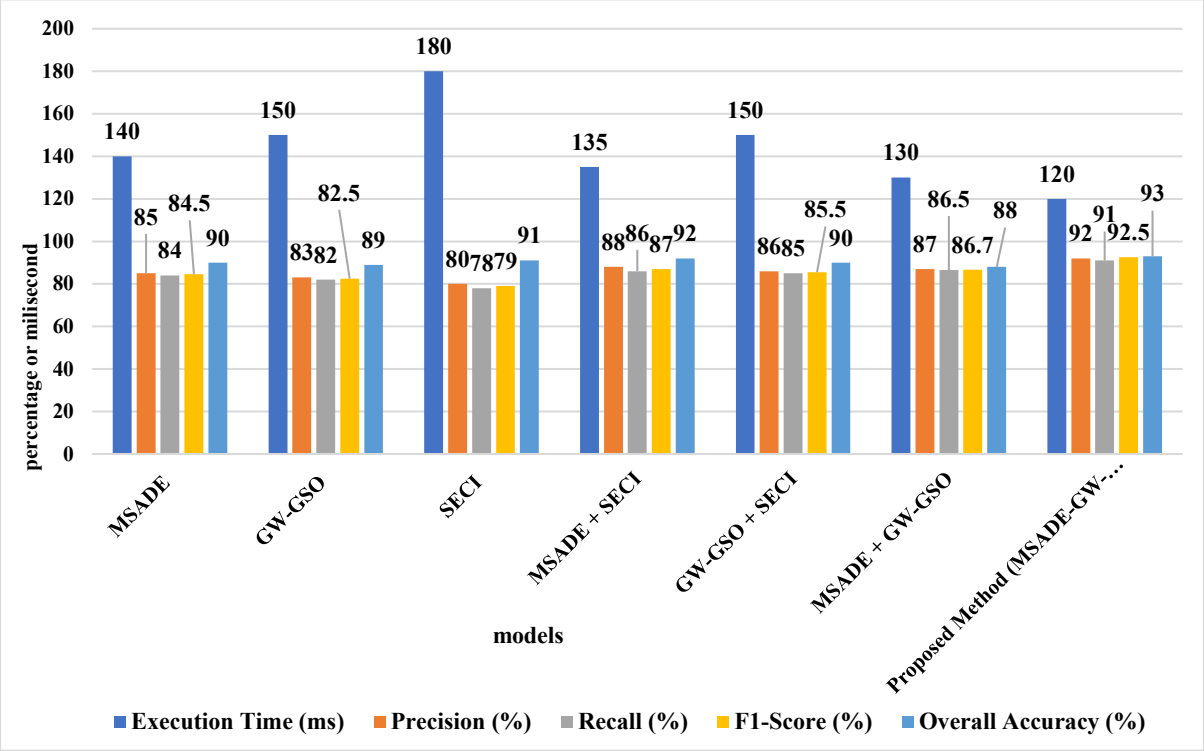

Figure 3 Ablation Study Comparison of MSADE-GW-SSEIC with Traditional Methods

A comparison of execution time, precision, recall, F1-score, and overall accuracy for both single and combined approaches—including the suggested MSADE-GW-SSEIC framework—is shown in this bar chart. Through enhanced precision, recall, and F1-score, along with the best total accuracy of 93%, the data show that the suggested approach works better than conventional optimisation strategies. In terms of protecting IoT data exchange, MSADE-GW-SSEIC is more precise and efficient, as seen by its 120 ms execution time reduction.

5 CONCLUSION AND FUTURE SCOPE

A unique hybrid encryption framework that combines MSADE and GWGSO with SSEIC has been suggested in this study to protect the exchange of IoT data. The strategy improves key generation procedures by optimising computational performance and guaranteeing a high degree of unpredictability and security. By tackling present and upcoming risks, SSEIC offers a strong quantum-resistant cryptographic solution. The better speed and key security of our hybrid approach over conventional encryption algorithms were shown by the simulation results.

IoT situations, where resource constraints demand secure yet lightweight encryption solutions, are ideally suited for this approach. The suggested approach offers a safe and scalable solution for next-generation Internet of Things applications by strengthening the cryptographic key generation procedure and the system's defence against potential quantum-based assaults. Future studies might look into incorporating machine learning models to improve flexibility in real-time situations and further optimise key generation. The hybrid technique may also offer wider security advantages in a variety of IoT ecosystems if it is extended to other cryptographic tasks like digital signatures or secure multi-party computation.

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