In the digital era, financial systems serve as the backbone of global economic activity, facilitating transactions that underpin individual, corporate, and governmental functions. As these systems evolve, they are increasingly digitized, integrating advanced technologies to streamline operations and provide efficient services. However, this evolution also brings new vulnerabilities, particularly in the domains of data privacy and security. With financial institutions handling massive volumes of sensitive data—including personal details, transaction records, and payment credentials—ensuring secure and privacy-aware systems has become paramount.

The urgency for secure financial systems stems from the rising number of cyber threats targeting the financial sector. Financial services consistently rank among the most targeted sectors for cyberattacks, including data breaches, phishing schemes, and ransomware (Kumar et al., 2021). Such incidents not only lead to financial losses but also erode consumer trust and invite stringent regulatory scrutiny. Governments and regulatory bodies worldwide, including the General Data Protection Regulation (GDPR) in Europe and the California Consumer Privacy Act (CCPA) in the United States, now mandate robust measures to protect consumer data and ensure compliance with privacy standards (Smith & Brown, 2020). Consequently, financial institutions face the dual challenge of safeguarding data against breaches while maintaining compliance with these regulations.

In recent years, federated learning (FL) has emerged as a transformative approach to address these challenges. As a decentralized machine learning paradigm, FL enables multiple entities to collaboratively train models without sharing their raw data (McMahan et al., 2017). In the context of financial systems, this capability is invaluable. Banks, payment processors, and other financial organizations can leverage FL to build powerful predictive models for tasks like fraud detection, credit scoring, and risk assessment, all while preserving the privacy of their data. Unlike traditional centralized approaches, which require aggregating data into a single repository, FL keeps sensitive information localized to its source. Only model updates—not the data itself—are shared, significantly reducing the risk of data exposure.

Several studies have explored the application of FL in privacy-sensitive domains. For example, FL has been used to create robust fraud detection models across financial institutions (Yang et al., 2019). Similarly, FL has demonstrated its utility in healthcare, enabling collaborative predictive modeling while adhering to stringent privacy laws (Li et al., 2020). These efforts underscore the potential of FL in addressing privacy and security concerns across diverse industries.

To overcome the computational and communication inefficiencies often associated with FL, optimization techniques are increasingly being integrated into FL frameworks. Among these, bio-inspired algorithms have gained prominence for their adaptability and efficiency. For instance, Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) have been employed to enhance the convergence and accuracy of FL models (Wang et al., 2020). However, these methods often require extensive computational resources and fine-tuning. This study introduces a novel Slime Mold Algorithm (SMA)-based optimization technique to address these challenges. Inspired by the adaptive foraging behavior of slime molds, SMA mimics the process of creating efficient pathways between food sources to identify optimal solutions. Its unique ability to balance exploration and exploitation makes SMA highly suitable for improving the convergence and accuracy of FL models.

By incorporating SMA, this research aims to enhance the robustness and efficiency of secure financial transactions. The privacy-preserving nature of FL, combined with SMA's adaptive capabilities, aligns seamlessly with regulatory requirements, providing a pathway for institutions to innovate without compromising compliance. Additionally, SMA minimizes communication overheads by dynamically optimizing model updates. This approach ensures that even if one node is compromised, the overall system remains resilient and maintains its operational integrity.

Despite its promise, the adoption of FL with SMA optimization in financial systems requires addressing specific challenges. These include fine-tuning SMA parameters to reduce computational costs, ensuring robustness against adversarial attacks, and improving the scalability of FL frameworks. This manuscript explores the application of FL with SMA in financial systems, detailing its methodologies, benefits, and transformative potential for secure financial transactions.

Literature Review

Federated Learning in Financial Systems

Financial systems are a cornerstone of global economic stability, and their security and privacy challenges have been exacerbated by increasing digitalization. The financial sector has always been a prime target for cyberattacks due to the sensitivity of financial data, such as account details, credit scores, and transaction records.

Traditional machine learning models rely heavily on centralized data collection, making them susceptible to data breaches and regulatory non-compliance.

Federated Learning (FL) has emerged as a transformative approach to address privacy and data security challenges in financial systems. Initially introduced by McMahan et al. (2017), FL allows multiple entities to collaboratively train machine learning models without sharing raw data. This is particularly beneficial for financial institutions handling sensitive data, such as personal details and transaction records. Banks and payment processors, for example, have utilized FL for tasks like fraud detection and credit scoring (Yang et al., 2019).

Enhanced privacy mechanisms, such as differential privacy and secure multi-party computation, have further strengthened the applicability of FL in financial domains (Smith et al., 2020).

The horizontal and vertical FL paradigms, as categorized by Yang et al. (2019), enable effective collaboration between financial entities. Horizontal FL, focusing on entities with similar data types, has been utilized for fraud detection, while vertical FL allows collaboration between entities with complementary datasets, as shown in credit scoring models by Liu et al. (2021). These paradigms showcase the flexibility of FL in adapting to diverse financial use cases.

The adoption of FL is driven by increasing regulatory scrutiny under frameworks like the General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA) (Smith & Brown, 2020). These regulations emphasize the importance of data privacy, encouraging financial institutions to explore decentralized learning models like FL to achieve compliance while enabling innovation. Studies, such as Liu et al. (2020), highlight FL's

effectiveness in enabling cross-institution collaboration without exposing sensitive data. However, challenges remain, including computational inefficiencies and communication overheads in large-scale FL deployments (Li et al., 2020).

Financial systems consistently rank among the most targeted sectors for cyberattacks due to the sensitive nature of the data involved. Attackers exploit weaknesses in centralized data storage systems, resulting in significant financial and reputational losses for institutions (Kumar et al., 2021). FL addresses these vulnerabilities by decentralizing the training process, thus reducing the risk of large-scale data breaches. Furthermore, FL's privacy-preserving nature enables institutions to comply with regulations while innovating collaboratively. Recent studies demonstrate the effectiveness of FL in fraud detection and credit scoring (Zhang et al., 2021; Liu et al., 2021).

Optimization in Federated Learning

Optimization techniques are crucial for enhancing the performance and scalability of FL systems in financial applications. The traditional Federated Averaging (FedAvg) algorithm proposed by McMahan et al. (2017) has become a foundational technique, focusing on averaging local model updates to create a global model. While effective, FedAvg faces limitations in environments with heterogeneous data distributions, often leading to slow convergence and suboptimal model performance (Wang et al., 2020).

Recent advancements incorporate metaheuristic and heuristic optimization techniques to address these limitations. For instance, Particle Swarm Optimization (PSO) has been integrated with FL to improve convergence rates and reduce communication costs (Chen et al., 2022). Genetic Algorithms (GA) have also been explored for their ability to optimize FL's hyperparameters and ensure robust performance across diverse datasets (Zhang et al., 2021). These approaches demonstrate significant improvements in model accuracy and efficiency but often require substantial computational resources, limiting their applicability in resource-constrained environments. Hybrid algorithms, such as PSO combined with Gradient Clipping, address issues in imbalanced datasets, improving model performance in fraud detection scenarios (Zhou et al., 2022). Furthermore, Adaptive Optimization methods such as Adaptive Moment Estimation (Adam) have been successfully employed to fine-tune local learning rates, improving model accuracy and reducing convergence time (Zhou et al., 2022).

Bio-Inspired Algorithms for Optimization

Bio-inspired algorithms have gained attention for their adaptability and efficiency in solving complex optimization problems. Inspired by the adaptive foraging behavior of slime molds, SMA dynamically adjusts its search strategies based on environmental stimuli (Li et al., 2021).SMA has been employed in FL to optimize model aggregation and reduce communication costs, demonstrating superior performance in handling high-dimensional data (Zhou et al., 20 21). Modeled after competitive survival strategies in nature, HGS excels in balancing exploration and exploitation, making it suitable for large-scale optimization tasks (Chen et al., 2022). Its integration with FL has resulted in improved convergence rates and robustness against adversarial attacks (Yang et al., 2021). Other bio-inspired algorithms, such as Ant Colony Optimization (ACO), Monarch Butterfly Optimization (MBO), and Firefly Algorithm (FA), have also been explored for FL applications, each offering unique advantages in specific scenarios (Wang et al., 2022; Gupta et al., 2021).

Technique	Inspiration	Key Features	Advantages	Limitations	Applications in FL
Particle Swarm Optimization (PSO) [1][2]	Swarming behaviour of birds and fish	Local and global best positions search	Simple implementation, effective in low-dimensional spaces	Premature convergence in high-dimensional or non-convex problems	Hyperparameter optimization, enhancing convergence in FL
Genetic Algorithm (GA) [3][4]	Evolutionary principles of selection, mutation, and crossover	Generates diverse solutions	Finds global optima, effective for large search spaces	Slow convergence, computationally intensive	Federated hyperparameter tuning
Ant Colony Optimization (ACO) [5] [6]	Foraging behaviour of ants	Constructs shortest paths using pheromone trails	Suitable for combinatorial problems, adaptive to dynamic environments	Limited effectiveness in continuous search spaces	Optimizing communication routes, adaptive learning rate adjustment in FL
Artificial Bee Colony (ABC) [7] [8]	Foraging behaviour of honeybees	Balances exploration and exploitation phases	Lightweight computation, efficient resource utilization	Struggles with high-dimensional problems	Optimizing resource allocation, reducing communication overhead in FL
Slime Mold Algorithm (SMA) [9] [10]	Adaptive foraging of slime molds	Balances exploration and exploitation	Handles high-dimensional data effectively, reduces communication costs	Sensitive to parameter tuning, limited large-scale FL applications	Model aggregation optimization
Hunger Games Search (HGS) [11] [12]	Competitive survival in the wild	Adaptive survival strategies for exploration and exploitation	Robust against adversarial attacks, suitable for large-scale optimization	High computational complexity, potential need for hybridization	Enhancing convergence rates, securing decentralized collaborative learning
Firefly Algorithm (FA) [13] [14]	Attraction among fireflies	Exploits light intensity for search guidance	Robust in noisy environments, effective for multimodal optimization	Requires fine-tuning, convergence rate depends on complexity	Improving model accuracy, minimizing computational overhead in FL
Monarch Butterfly Optimization (MBO) [15]	Migration behaviour of monarch butterflies	Balances global and local search via	Efficient exploration, effective for multimodal problems	Limited research in FL-specific use cases	Assisting model convergence in decentralized FL

		migration patterns			
Bat Algorithm (BA) [2] [6]	Echolocation behaviour of bats	Utilizes sound waves for navigation in search spaces	Adaptive step sizes, effective for continuous optimization	Limited performance with discrete problems	Enhancing aggregation efficiency, balancing accuracy and communication

Novel Optimization Algorithm for Federated Learning in Financial Fraud Detection

To introduce novelty beyond using the standard **Slime Mold Algorithm (SMA)**, we can design a **Hybrid Adaptive Slime Mold Algorithm (HASMA)** that combines SMA with other strategies like **gradient-based local refinement** and **momentum-enhanced pheromone adjustment**. Below is the detailed design of this novel algorithm:

1. Initialization

Define the search space and initialize parameters:

- Population size N
- Maximum iterations T
- Slime mold positions (solutions): $X=\{X_1,X_2,\ldots,X_N\}$
- Fitness function F(X)
- Learning rate η
- Momentum coefficient μ

2. Fitness Evaluation

Evaluate the fitness of each slime mold position:

$$\mathrm{F}(Xi) = f(Xi), for\ i = 1,2, \ldots, N$$

Where $f(X_i)$ is the objective function to optimize.

3. Adaptive Pheromone Adjustment with Momentum

For each slime mold, adjust pheromone concentration using momentum to balance exploration and exploitation:

$$P_i^{t+1} = \mu P_i^t + (1-\mu) \cdot normalize(F(X_i))$$

where:

- P_i^t:pheromone level for slime mold *i* at iteration *t*
- Normalize ($F(X_i)$): normalized fitness values across all slime molds.

4. Movement Mechanism

The positions are updated using the slime mold foraging strategy and a gradient-based local refinement.

4.1 Foraging Strategy (Exploration and Exploitation)

$X_i^{t+1} = X_i^t + r \cdot sign(P_i^{t+1} - P_j^{t+1}) \cdot (X_j^t - X_k^t)$

where:

- $r \sim U(0,1)$: random number for stochastic exploration
- X_j^t, X_k^t : random positions in the population
- $P_i^{t+1} - P_j^{t+1}$: pheromone concentration difference

4.2 Gradient-Based Local Refinement

For each slime mold, refine the position using gradient descent:

$$X_i^{t+1} = X_i^{t+1} - \eta \,.\nabla \mathrm{F}(X_i^{t+1})$$

where:

$\nabla \mathrm{F}(X_i^{t+1})$: gradient of the fitness function at X_i^{t+1}

η: learning rate for refinement

5. Fitness-Based Selection

Select the top-performing positions based on fitness:

$$X_{best} = argmin_i \, F(X_i)$$

Retain X_{best} as the global best for this iteration.

6. Dynamic Parameter Adaptation

Adapt parameters dynamically based on iteration progress:

$$\boldsymbol{\eta = \eta_0 . \left(1 - \frac{t}{T}\right)}$$

$\mu = \boldsymbol{\mu_0} + (\boldsymbol{(\mu_{max} - \mu_0) . \frac{t}{T}})$

where:

- $\boldsymbol{\eta_0}$: initial learning rate

- μ_0, μ_{max}: initial and maximum momentum coefficients
- t: current iteration
- T: maximum iterations

7. Termination

Terminate the algorithm when the maximum iterations T are reached or the improvement in fitness falls below a predefined threshold:

$$\textbf{Stop if } \left|F\left(X_{best}^{t+1}\right) - F(X_{best}^{t})\right| < \in$$

where ∈ is the convergence tolerance.

Here's the simplified version of the algorithm with simple sentences:

1. Initialize the positions X_i^0, pheromones P_i^0, and global model W_g^0,
2. Set hyperparameters: alpha, beta, gamma, rho, lambda_max, and lambda_min.
3. For each iteration *t* from 1 to R:
    - For each client *i* in parallel:
        1. Compute fitness Fi(ΔW_i^t),
        2. Update position:
            - $X_i^{t+1} = X_i^t + \lambda_t \times$weighted pheromone influence
            - $X_i^{t+1} -= \eta \times$ gradient loss (W_i^t)
            - $X_i^{t+1} += \epsilon \times$random noise
        3. Update pheromones with momentum:
            - $P_i^{t+1} = \rho \times P_i^t + (1-\rho) \times F_i(\Delta W_i^t)$
        4. Normalize pheromones:
            - $P_i^{t+1} /= \sum_j P_j^{t+1}$ for all *j*
    - Aggregate global model:
        1. W_g^{t+1}=weighted average of ΔW_t^{t+1}
    - Adjust λ_t dynamically.
    - Check for convergence. If criteria are met, break.
4. Broadcast W_g^{t+1}= to clients.

Advantages of HASMA

1. **Improved Convergence**:
    - Gradient refinement ensures better exploitation of high-fitness regions.
2. **Robustness**:
    - Dynamic balancing prevents premature convergence.
3. **Adaptability**:

- Client-specific adaptation improves performance on heterogeneous datasets.

4. **Scalability**:
   - Momentum-enhanced pheromone adjustment reduces the sensitivity to initial conditions.

Pseudo-Code for HASMA

Input:

N ← Number of slime molds

T ← Max iterations

f(X) ← Fitness function

Output:

X_{best} ← Best solution found

Step 1: Initialize

X ← Random positions of slime molds

P ← Random pheromone levels

X_{best} ← Best solution in X

Step 2: Main Loop (for t = 1 to T)

1. Evaluate fitness for each slime mold: $F(X_i) = f(X_i)$
2. Update pheromone levels: P_i ← Pheromone update based on fitness
3. Update positions for each slime mold:
   - Move based on pheromone: X_i ← Move towards better solutions
   - Refine position using fitness gradient: X_i ← Adjust position based on gradient
4. Update global best if needed: If $F(X_i) < F(X_{best})$, set $X_{best} = X_i$
5. Check convergence: If no significant improvement, stop early

End Loop

Return X_{best}

This **Hybrid Adaptive Slime Mold Algorithm (HASMA)** offers novelty by combining SMA principles with gradient-based refinement, dynamic control, and momentum-enhanced pheromone updates, tailored for financial fraud detection in Federated Learning systems.

Pseudo Code for Hybrid Adaptive Slime Mold Algorithm (HASMA)

Here is a structured pseudo code for the Hybrid Adaptive Slime Mold Algorithm (HASMA) designed for Federated Learning in Financial Fraud Detection:

```
Initialize parameters:
   - Population size (N)
   - Maximum iterations (MaxIter)
   - Learning rate (alpha)
   - Momentum factor (beta)
   - Local models (M) for each participant
   - Pheromone levels (P) initialized randomly

For each iteration t from 1 to MaxIter do:
   For each participant i from 1 to N do:
      // Local model training
      Train local model Mi using HASMA:
         1. Initialize slime mold positions (X[i]) randomly
         2. Evaluate fitness of each position using local data
         3. Update pheromone levels based on fitness:
            P[i] = (1 - beta) * P[i] + beta * fitness(X[i])
         4. Apply gradient-based local refinement:
            Compute gradient (G[i]) of loss function for Mi
            Update position: X[i] = X[i] - alpha * G[i]
         5. Apply momentum-enhanced pheromone adjustment:
            P[i] = P[i] + momentum(P[i], previousP[i])
            previousP[i] = P[i]

      // Update global model
      Aggregate local models:
         Global model G = Aggregate(M1, M2, ..., MN)

      // Adaptive learning rate adjustment
      If improvement in fitness is small then:
         alpha = alpha * decrease_factor
      Else:
         alpha = alpha * increase_factor

   // Check for convergence
   If convergence criteria met then:
      Break
```

Return global model G

Explanation of Key Components:

- **Initialization**: Set up the population size, maximum iterations, learning rate, momentum factor, and initialize pheromone levels.
- **Local Model Training**: Each participant trains their local model using the HASMA approach, which includes evaluating fitness, updating pheromones, and refining positions based on gradients.
- **Pheromone Update**: The pheromone levels are adjusted using a momentum factor to stabilize the search process.
- **Adaptive Learning Rate**: The learning rate is adjusted based on the observed improvements in fitness, allowing for dynamic optimization.
- **Convergence Check**: The algorithm checks for convergence to determine if it should terminate early.

This pseudo code outlines the essential steps of the HASMA, integrating the unique features of gradient-based refinement and momentum-enhanced pheromone adjustment to optimize federated learning for financial fraud detection.

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Applications of Federated Learning in Security and Privacy

FL's utility extends beyond financial systems to other privacy-sensitive domains. In healthcare, FL has enabled collaborative disease prediction while maintaining patient privacy (Liu et al., 2020). For instance, FL has been used to train predictive models for heart disease diagnosis using distributed patient data (Chen et al., 2021). Similarly, FL has been applied in smart cities for traffic prediction and energy management, ensuring data security while leveraging insights from distributed sources (Zhang et al., 2021).

FL's integration with blockchain technology has further enhanced its security capabilities. Blockchain provides a tamper-proof ledger for tracking model updates, ensuring transparency and integrity in FL systems (Kumar et al., 2021). Additionally, privacy-preserving techniques like differential privacy and secure multi-party computation have been incorporated into FL frameworks to safeguard against data breaches and adversarial attacks (Smith et al., 2020).

Challenges and Future Directions

Despite its potential, FL faces several challenges that require further research:

1. **Communication Bottlenecks:** Large-scale FL systems often encounter significant communication overheads, particularly in environments with limited network bandwidth (Li et al., 2020).
2. **Adversarial Attacks:** FL systems are vulnerable to attacks like data poisoning and model inversion, necessitating robust defense mechanisms (Wang et al., 2022).
3. **Optimization Efficiency:** Existing optimization techniques often struggle with scalability and computational efficiency, particularly in heterogeneous environments (Chen et al., 2022).

Future research should focus on integrating advanced optimization algorithms like SMA and HGS with FL to address these challenges. Additionally, exploring hybrid approaches that combine multiple bio-inspired algorithms may offer a pathway to develop more resilient and efficient FL systems.

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