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# Blockchain-Enabled, Nature-Inspired Federated Learning for Cattle Health Monitoring

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**Abstract**

Traditional cattle health monitoring systems rely on centralized data collection, posing significant challenges related to data privacy, network connectivity, model reliability, and trust. This study introduces a novel, nature-inspired federated learning (FL) framework for cattle health monitoring, integrating blockchain to ensure model validation, system resilience, and reputation management. Inspired by the fission–fusion dynamics of elephant herds, the framework adaptively forms and merges subgroups of edge nodes based on six key parameters: health metrics, activity levels, geographical proximity, resource availability, temporal activity, and network connectivity. Graph attention networks (GATs) enable dynamic fission, while Density-Based Spatial Clustering of Applications with Noise (DBSCAN) supports subgroup fusion based on model similarity. Blockchain smart contracts validate model contributions and ensure that only high-performing models participate in global aggregation. A reputation-driven mechanism promotes reliable nodes and discourages unstable participants. Experimental results show the proposed framework achieves 94.3% model accuracy, faster convergence, and improved resource efficiency. This adaptive and privacy-preserving approach transforms cattle health monitoring into a more trustworthy, efficient, and resilient process.

**Keywords:** cattle health monitoring; real-time health monitoring; GAT-based clustering; DBSCAN-based cluster fusion; consortium blockchain; federated learning

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## 1. Introduction

Farmers are reluctant to share sensitive livestock data due to privacy concerns, and limited internet connectivity in remote farms further impedes real-time monitoring. The absence of robust model validation can result in inaccurate predictions, and without a structured incentive mechanism, reliable devices may not be prioritized during model aggregation. To address these challenges, this study proposes a novel nature-inspired federated learning (FL) framework for cattle health monitoring, integrating blockchain for model validation, node resilience, and reputation management. The framework draws inspiration from the fission–fusion behavior observed in elephant herds, where dynamic clusters form based on real-time conditions and later regroup after local model training. A comparative overview between the elephant herd behavior and the proposed framework is provided in Table 1 and illustrated visually in Figure 1. It operates across three interdependent layers: edge-based cattle monitoring, federated learning with adaptive clustering, and blockchain-enabled model validation and reputation scoring.

**Table 1.** Elephant herd vs. proposed FL framework.

| Aspect | Elephant Herd Behavior | Proposed Framework |
|---|---|---|
| Fission (Dynamic Cluster Formation) | Herds split into smaller subgroups to optimize resource use and reduce competition. | GAT clusters edge nodes based on health metrics, location, resource availability, temporal activity, and connectivity. |
| Fusion (Reintegration after Local Training) | Subgroups reunite when conditions improve for collective benefits like mating or defense. | DBSCAN clustering merges clusters with high model similarity. |
| Adaptive Resilience | Herds adapt to threats (e.g., predators) or opportunities (e.g., water sources) by restructuring. | Clusters auto-adjust based on real-time conditions (e.g., dropout due to poor connectivity) using event-aware attention. |
| Efficiency | Elephants minimize energy expenditure by forming optimal groups. | Reduces communication overhead by ensuring only relevant nodes collaborate. |
| Fault Tolerance | Weak or sick members may be excluded for herd survival. | Blockchain reputation system isolates malicious or unstable nodes. |
| Context Awareness | Herds adjust movements based on environmental conditions and threats. | Aligns collaborations with real-time needs such as health events and resource constraints. |

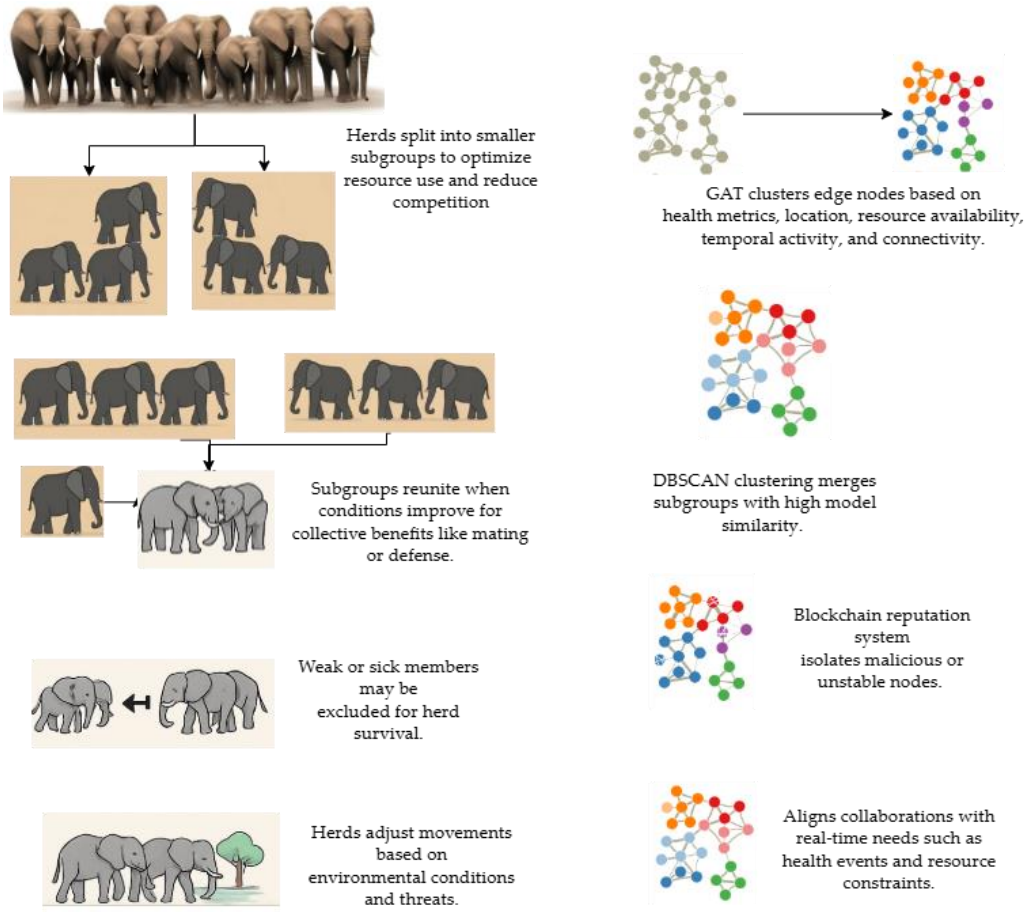



**Figure 1.** Elephant herd vs. proposed FL framework.

Cattle health data is collected through IoT-enabled wearable devices that continuously track activity levels, health events (such as estrus, calving, and lameness), and environmental parameters. These edge devices preprocess the collected data locally and initiate federated learning cycles. The formation of dynamic clusters (fission) is facilitated by a graph attention network (GAT), clustering edge nodes based on six critical parameters: health metrics, activity levels, geographical proximity, resource availability, temporal activity, and network connectivity. This adaptive clustering reflects the natural division observed in elephant herds, ensuring that nodes with similar characteristics collaborate

efficiently. Following cluster formation, local models are trained using edge-generated data. Once training is complete, Density-Based Spatial Clustering of Applications with Noise (DBSCAN) refines the clusters by merging models with high similarity scores and excluding outliers. This fusion step ensures robust collaboration while maintaining cluster integrity. Trained models are then submitted to the blockchain for validation, where smart contracts evaluate their performance against aggregated test datasets. Only models meeting predefined accuracy thresholds are accepted, while underperforming models are flagged and excluded from subsequent training rounds.

Blockchain further enhances system resilience by maintaining immutable logs of model contributions and node activities. Each node's reputation is dynamically calculated based on key performance indicators, including model accuracy, resource efficiency, response time, and data contribution. High-reputation nodes are prioritized during global model aggregation, ensuring that only the most reliable models influence the final update. Following each validation cycle, smart contracts recalculate node reputations, fostering continuous improvement and accountability. By retaining sensitive data at the edge and leveraging blockchain for model integrity and resilience, the proposed framework ensures privacy, enhances system reliability, and enables robust cattle health monitoring. This adaptive, reputation-driven approach not only improves the accuracy of health predictions but also facilitates timely interventions and optimized farm management, ultimately transforming livestock monitoring into a more efficient and trustworthy process. To ensure real-world usability, the system is designed for farmers, veterinarians, and stakeholders to interact through simple mobile or web dashboards for monitoring cattle health, receiving alerts, and managing device participation. Blockchain operations, model validation, and reputation scoring are automated and hidden from users to reduce complexity.

Potential challenges such as device setup, intermittent connectivity, and basic digital literacy are acknowledged and will be addressed through user-friendly interfaces and future training support. The key contributions of this work are as follows:

1. Nature-Inspired GAT-Based Fission–Fusion: The framework introduces a dynamic GAT-based fission mechanism that clusters edge devices based on six real-time parameters—health metrics, activity levels, geographical proximity, resource availability, temporal activity, and network connectivity—mirroring the adaptive clustering observed in elephant herds.
2. Adaptive Fusion with DBSCAN: A novel DBSCAN-based fusion process refines clusters by merging models with high similarity and excluding outliers, ensuring robust collaboration while maintaining cluster integrity during federated learning cycles.
3. Blockchain-Enabled Model Validation and Node Reputation: Smart contract-based model validation ensures accuracy and resilience, while dynamic reputation scoring prioritizes high-performing nodes for global model aggregation, promoting continuous improvement and accountability.
4. Privacy-Preserving and Decentralized Federated Learning: The system facilitates secure, decentralized cattle health monitoring by keeping sensitive data at the edge while ensuring reliable, adaptive model training across distributed cattle farms.

The article is further organized as follows: Section 2 discusses the existing methodologies for federated learning and integrating blockchain in federated learning. Section 3 elaborates on the methodology for implementing this fission–fusion behavior of elephants in a federated learning framework. Section 4 discusses the effectiveness of the proposed research over the existing methods with results, and Section 5 presents the conclusion and future work.

## 2. Literature Survey

### *2.1. Blockchain Implementation in Federated Learning*

Blockchain technology has emerged as a pivotal solution for ensuring secure and trustworthy decentralized learning. It offers immutable records of model updates and enables tamper-proof audit trails. Several studies have integrated blockchain into federated learning pipelines to ensure secure model update verification and prevent malicious contributions. For instance, ref. [1] proposed a blockchain-enabled federated learning framework where each edge device's model updates are recorded on the blockchain. This implementation leveraged Hyperledger Fabric to store model gradients and ensure traceability. The smart contract mechanism ensured that only legitimate updates meeting the quality threshold were accepted.

Similarly, ref. [2] introduced an Ethereum-based blockchain framework to validate client-side updates using gas-based transaction fees as a deterrent against adversarial attacks. In this approach, the clients signed their model updates using their private keys, ensuring non-repudiation. The blockchain maintained an immutable record of the global model's evolution across training rounds. Smart contracts facilitate automation and enforce predefined rules without intermediaries. In ref. [3], smart contracts were employed to implement an incentive mechanism that rewarded edge devices based on the quality and timeliness of their contributions. The smart contract verified the updates' performance metrics, such as accuracy and loss, before accepting them into the aggregation process. To address accountability, ref. [4] proposed a blockchain-based audit trail where each participant's contribution was cryptographically signed and time-stamped. Any deviation from the expected behavior triggered a penalty enforced by the smart contract.

Consensus algorithms play a crucial role in ensuring the integrity of federated learning updates. Ref. [5] adopted a Practical Byzantine Fault Tolerance (PBFT) consensus mechanism, where validators elected from edge devices verified the local updates before aggregation. This approach ensured resilience against malicious participants. In contrast, ref. [6] employed a Proof-of-Contribution (PoC) mechanism, where validators were selected based on their historical contribution scores. This dynamic validator selection reduced the risk of collusion and ensured that honest participants had more influence in the consensus process.

### *2.2. Model Aggregation Using Weighted Average*

Model aggregation is a core component of federated learning, where local model updates are combined to form an improved global model. Weighted averaging is the most common aggregation technique, with weights typically determined by the number of training samples at each edge device. The FedAvg algorithm, introduced by McMahan et al., assigns weights based on the proportion of training data held by each participant. Studies such as ref. [7] implemented FedAvg with adaptive learning rates, where clients with higher data quality received higher weights. This approach improved convergence while preventing overfitting to noisy data.

Beyond data size, recent works have explored performance-based weighting. In ref. [8], the authors proposed a metric-driven aggregation approach where the weight assigned to each local model depended on its evaluation accuracy on a validation set. This method ensured that high-performing models had more influence on the global update. Similarly, ref. [9] introduced a trust-based weighting scheme, where edge devices with a history of reliable contributions were prioritized. The trust scores were updated dynamically based on the consistency of model updates across training rounds. Resource-aware aggregation considers computational capacity and energy consumption alongside model quality. Ref. [10] presented an adaptive weighting approach that integrated CPU utilization and

battery level into the weighting formula. Edge devices with limited resources contributed less to the aggregation, preventing performance degradation. The authors in ref. [11] further refined this approach by incorporating communication latency as a weighting factor. Clients with faster communication channels were prioritized, ensuring timely aggregation and reducing the risk of stale updates.

### *2.3. Addressing Heterogeneity in Federated Learning*

Heterogeneity is a significant challenge in federated learning, as edge devices often differ in data distribution, computational power, and communication capabilities. Several approaches have been proposed to address these challenges while maintaining model convergence. Non-Independent and Identically Distributed (Non-IID) data, where local datasets differ in feature space and label distribution, can lead to model divergence. To address this, ref. [12] proposed FedProx, which introduced a proximal term in the local training objective to prevent drastic model deviations. This regularization term ensured that local updates remained closer to the global model, facilitating faster convergence. Similarly, ref. [13] implemented a cluster-based approach where clients were grouped based on data similarity. Each cluster trained a separate global model, reducing the impact of non-IID data. The final global model was obtained by aggregating the cluster-specific models using weighted averaging.

Resource-constrained devices may struggle to participate effectively in federated learning. Ref. [14] introduced an adaptive training framework where clients adjusted their local epochs based on available resources. Devices with higher computational capacity performed more local iterations, while constrained devices contributed fewer updates. To further optimize resource utilization, ref. [15] proposed an energy-aware scheduling algorithm that prioritized low-energy devices for lightweight model training tasks. This dynamic task allocation ensured fair participation without compromising performance. Communication bottlenecks often arise due to limited bandwidth and high latency. Ref. [16] addressed this issue using gradient compression techniques, such as sparsification and quantization. Only the most significant gradients were transmitted, reducing communication overhead without compromising model accuracy.

Similarly, ref. [17] proposed a hierarchical aggregation approach where edge devices communicated with nearby gateways rather than the central server. These gateways performed intermediate aggregation, significantly reducing communication overhead. Personalized federated learning aims to create customized models for each client while benefiting from global knowledge. Ref. [18] introduced pFedMe, a meta-learning-based approach where each client maintained a personalized model alongside the global model. The personalized model adapted to local data, while the global model ensured knowledge sharing across clients. The authors in ref. [19] further enhanced personalization using multi-task learning, where each client's training objective included both local and global performance metrics. This approach improved model generalization across heterogeneous environments.

Heterogeneity also includes adversarial participants who may attempt to poison the global model. Ref. [20] addressed this issue using robust aggregation techniques, such as trimmed mean and median aggregation. These methods excluded outliers from the aggregation process, ensuring that malicious updates did not skew the global model. Blockchain ensures transparency and accountability, while advanced aggregation techniques improve model convergence. Addressing heterogeneity through adaptive training, personalized models, and robust aggregation enhances federated learning's resilience in real-world environments.

The proposed nature-inspired GAT-based fission framework introduces significant advancements over traditional graph attention networks (GATs), specifically tailored for cattle health monitoring in federated learning environments. Unlike traditional GATs, which primarily rely on static graph topology and node features for attention-based message passing, the proposed framework incorporates six critical parameters: health metrics, activity levels, geographical proximity, resource availability, temporal activity, and network connectivity. This multi-dimensional approach ensures dynamic cluster formation that aligns with real-time cattle conditions. A key innovation lies in the dynamic graph formation process. While traditional GATs assume a fixed graph structure with predefined edges, the proposed framework constructs dynamic graphs using cosine similarity, percentile thresholds, and degree pruning. This real-time graph adaptation captures evolving cattle health states and environmental changes, enhancing the relevance of federated learning clusters. Moreover, the framework introduces event-aware attention, where attention coefficients prioritize nodes experiencing similar health events, such as mastitis or lameness, alongside resource conditions. This contextualized attention ensures that edge devices within each cluster contribute meaningfully to the local model training process. To maintain cluster integrity after local training, the framework integrates an adaptive fusion mechanism using Density-Based Spatial Clustering of Applications with Noise (DBSCAN). Unlike traditional GATs, which lack post-aggregation refinement, the DBSCAN-based fusion leverages health event overlap (measured via the Jaccard index) and model similarity to merge compatible clusters while excluding outliers.

Blockchain integration further enhances the framework's resilience and trustworthiness. Model updates undergo smart contract-based validation against predefined accuracy thresholds, with validated models immutably recorded on the blockchain. This process also facilitates dynamic node reputation scoring based on model quality, resource efficiency, and data contribution. High-reputation nodes are prioritized for global aggregation, ensuring that only reliable contributions shape the global model. Finally, the framework seamlessly integrates with decentralized federated learning workflows, enabling privacy-preserving, adaptive model training across distributed cattle farms. Unlike refs. [1–3], whichprimarily focus on generic FL-blockchain integration, our framework uniquely combines the following: (a) nature-inspired dynamic clustering for livestock monitoring, (b) event-aware DBSCAN fusion, and (c) agricultural-specific reputation metrics.

## 3. Methodology

### *3.1. Nature-Inspired Federated Learning Framework*

This research presents a novel nature-inspired federated learning (FL) framework for cattle health monitoring, leveraging blockchain for model validation, node resilience, and reputation management, which is presented in Figure 2. The system emulates the fission–fusion behavior observed in elephant herds, where dynamic clusters form based on real-time conditions and regroup after local model training. The framework operates across three interdependent layers: edge-based cattle monitoring, federated learning with adaptive sub-grouping, and blockchain-enabled model validation and reputation scoring.

The elephant herd-inspired approach aligns well with the dynamic nature of cattle behavior, where individual cows or smaller groups often separate from the herd based on factors such as health conditions, geographical dispersion, and resource availability. By mimicking this natural phenomenon, the framework ensures that cattle with similar conditions and needs are grouped together, allowing for more targeted health monitoring and timely interventions. The overarching goal of the framework is to achieve accurate, privacy-preserving, and resilient cattle health monitoring while ensuring secure and trustworthy model aggregation. This is accomplished through an iterative cycle of fission

(cluster formation), local training, fusion (model merging), blockchain-based validation, and dynamic node reputation calculation.

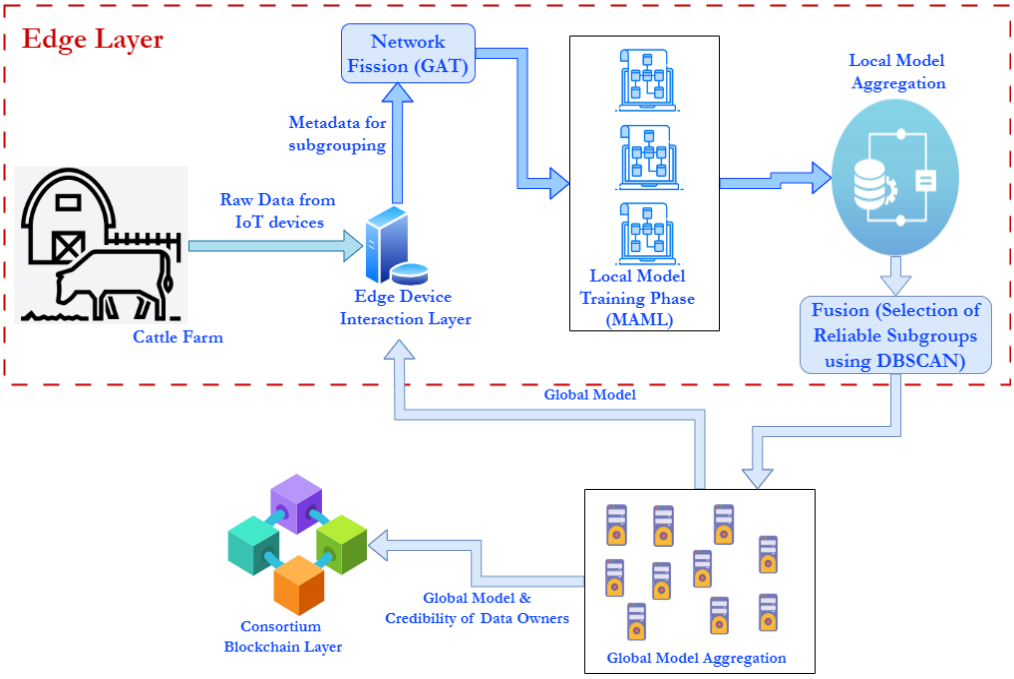



**Figure 2.** Proposedarchitecture: elephant herd inspired fission–fusion federated learning. Different colors in the figure indicate different layers and components of the architecture.

### *3.2. Edge-Based Cattle Monitoring*

Cattle health data is collected through IoT-enabled wearable devices attached to each animal. These devices track multiple parameters, including activity levels, health events (such as estrus, calving, and lameness), and environmental conditions like temperature and humidity. The edge devices preprocess the collected data, filtering out noise and normalizing features for consistency. Each device stores the preprocessed data locally and initiates federated learning cycles, ensuring that sensitive information remains at the source. The IoT sensors record health-related parameters such as body temperature, heart rate, respiratory rate, and activity patterns (resting, walking, and eating). These parameters are essential for early detection of health anomalies. For instance, a sudden increase in resting time combined with decreased eating activity may indicate the onset of lameness, while abnormal heart rates and reduced walking capacity can signal potential mastitis or metabolic disorders.

Data preprocessing involves three key steps: (1) noise filtering, where anomalous readings caused by sensor errors or temporary environmental factors are removed; (2) feature normalization, where data is scaled to a common range to ensure consistency across devices and farms; and (3) data imputation, where missing values are filled using statistical techniques such as mean or median imputation.

### *3.3. Adaptive Cluster Formation Using GAT*

The cluster formation process, or fission, is achieved using a graph attention network (GAT) framework, which dynamically clusters edge nodes (i.e., individual cattle) based on six key parameters: health metrics, activity levels, geographical proximity, resource availability, temporal activity, and network connectivity. This multi-parameter formulation enhances the adaptivity of the model by allowing attention weights to reflect both physiological and contextual heterogeneity across distributed cattle populations. The attention

mechanism is mathematically defined in Equation (1), as inspired by the foundational work of [21].

$$a_{ij} = \frac{e^{(Leaky\text{ReLU}(a^T[Wh_i \| Wh_j]))}}{\sum_{k \in \mathbb{N}_i} e^{(Leaky\text{ReLU}(a^T[Wh_i \| Wh_k]))}} \quad (1)$$

where

- $a_{ij}$—the attention coefficient between node i and node j.
- $h_i$,$h_j$—feature vectors of nodes i and j.
- W—weight matrix applied to the node features.
- a—attention vector used to compute importance.
- $\mathbb{N}_i$—set of neighbors for node i.
- $Leaky\text{ReLU}$—non-linear activation function applied to the concatenated features.

The use of LeakyReLU, as employed in [21], ensures gradient flow for negative inputs, which is particularly advantageous when modeling real-world, noisy biological signals such as health metrics in cattle. In earlier models proposed in [22,23], the graph topologies remain static, whereas this framework introduces an adaptive graph construction mechanism tailored for livestock monitoring. Specifically, edges are generated in real-time using cosine similarity across health vectors and then pruned using percentile thresholds and node degree constraints. This ensures that only the most contextually relevant connections are retained, enhancing both computational efficiency and biological relevance. This approach builds upon dynamic modeling efforts such as those seen in [24] but extends them by embedding health-event-specific semantics and regional awareness into the attention mechanism.

Each node in the graph corresponds to a single cow, and edges represent behavioral and physiological similarity. For example, cows exhibiting concurrent signs of mastitis evidenced by decreased feeding time and increased rest duration will have stronger edge weights, increasing the likelihood of being clustered together. By aligning graph topology with real-time cattle behavior and clinical signals, the model ensures that animals experiencing similar health challenges are grouped for localized model training, an approach distinct from static community detection strategies [25]. The dynamic clustering strategy not only improves model personalization but also allows for regional adaptivity across spatially distributed farms. Unlike standard GATs, which propagate information across fixed neighborhoods, this adaptive mechanism captures regional heterogeneity in resource availability and health trends, improving generalizability and responsiveness. Furthermore, the integration of this attention-driven clustering within a federated learning framework facilitates privacy-preserving model updates across decentralized edge nodes, forming the basis for a scalable and resilient cattle health monitoring system.

### *3.4. Local Model Training and DBSCAN-Based Fusion*

Once clusters are established via attention-driven fission, each node proceeds to train a local model using its edge-collected data. To ensure computational efficiency and adaptability in low-resource environments, the training procedure employs a lightweight Model-Agnostic Meta-Learning (MAML) framework. This choice enables rapid model adaptation to newly emerging health anomalies or environmental changes. The local optimization objective is defined in Equation (2):

$$L_i(\theta) = \frac{1}{|D_i|} \sum_{(x,y) \in D_i} \ell(f_\theta(x), y) \quad (2)$$

where

- $L_i(\theta)$—loss function for node i.
- $D_i$—local dataset for node i.
- $x, y$—input features and corresponding labels.
- $\ell$—mean squared error (MSE) loss function.
- $f_\theta$—model with parameters $\theta$.

This decentralized learning scheme aligns with federated learning principles introduced by [26], preserving data privacy while enabling collaborative inference. The adoption of MAML further enables each node's model to generalize across diverse and dynamic cattle health conditions, a significant improvement over static training methods, particularly in distributed rural contexts with variable disease prevalence and environmental stressors. Following local training, the system employs Density-Based Spatial Clustering of Applications with Noise (DBSCAN) to perform post-training cluster fusion. This ensures that only meaningful and reliable models are retained for aggregation. The fusion criterion incorporates both model similarity and health event alignment, as defined in Equation (3).

$$sim(m_i, m_j) > T_s \wedge Jaccard(E_i, E_j) > T_e \tag{3}$$

where

- $sim(m_i, m_j)$—cosine similarity between model weights $m_i$ and $m_j$.
- $T_s$—threshold for model similarity.
- $Jaccard(E_i, E_j)$—Jaccard index measuring overlap between health events $E_i$ and $E_j$.
- $T_e$—threshold for event overlap.

The fusion ensures robust collaboration while excluding noisy outliers. This dual-condition strategy mitigates the risk of premature fusion across behaviorally divergent nodes, supporting cluster cohesion. In contrast to traditional federated learning frameworks like FedAvg [26] or FedProx [27], which use global averaging irrespective of data context, our method introduces a context-aware, event-aligned fusion process. It extends ideas from clustered and multi-task federated learning approaches such as MOCHA [28] and IFCA [29] by embedding health-event semantics into the fusion logic. Moreover, the DBSCAN-based mechanism is conceptually aligned with neuron-matching strategies introduced by FedMA [30], where the similarity of internal model representations guides global model formation. Our approach uniquely combines: (1) domain-specific event alignment (e.g., mastitis co-occurrence), and (2) model parameter similarity, optimized for non-IID, regionally diverse cattle health monitoring. This integration addresses the limitations of generic FL methods in agricultural settings as provided in Table 2, where environmental and biological variability demand adaptive, semantically grounded fusion.

### *3.5. Blockchain-Enabled Model Validation*

After local training and model fusion, each node submits its trained model to the blockchain for validation, wherein smart contracts autonomously execute performance evaluations using a globally aggregated test dataset. The validation accuracy $A_i$ for node i is computed with Equation (4).

$$A_i = \frac{1}{|D_{test}|} \sum_{(x,y) \in D_{test}} 1(f_\theta(x) = y) \tag{4}$$

where

- $A_i$—validation accuracy for node i.
- $D_{test}$—test dataset used for validation.
- $x, y$—input–output pairs in the test dataset.

- $1(f_\theta(x) = y)$—indicator function, returning 1 if the prediction matches the ground truth and 0 otherwise.

**Table 2.** Comparison of proposed frameworks with existing FL methods.

| Method | Training Framework | Fusion Criteria | Domain Adaptation | Data Heterogeneity | Computational Load | Privacy Preservation |
|---|---|---|---|---|---|---|
| Proposed Framework | Lightweight MAML for local adaptation to health conditions | DBSCAN with cosine model similarity and Jaccard-based event overlap | Supports health events like mastitis, respiratory anomalies, environmental shifts | Fully decentralized; supports regional health and behavioral variance | Optimized for edge devices with minimal model complexity | Raw data retained on local nodes; event similarity computed over anonymized metadata |
| FedAvg [26] | SGD on static local data | Weighted average | No domain semantics | Prone to divergence under non-IID | Lightweight but less adaptive | Preserves privacy by design |
| FedMA [30] | Local SGD with layer-wise neuron matching | Permutation-matched layer aggregation | Only structural layer matching | Handles moderate heterogeneity | Medium (requires Hungarian matching) | Preserves privacy; some structural meta-data needed |
| IFCA [29] | Gradient descent with alternating clustering | Loss-based group reassignment | Task-shared, no event-specific adaptation | Requires good cluster initialization | Medium (multiple restarts and alternation) | Preserves privacy |
| MOCHA [28] | Multi-task learning with local solvers per node | Task-specific model aggregation via proximal updates | Learns related models, not explicitly event-aligned | Designed for statistical and systems heterogeneity | Medium; handles stragglers and variability | Preserves privacy; model updates only shared |

Models meeting predefined accuracy thresholds are accepted and immutably recorded on the blockchain; importantly, only model performance metrics are stored, without exposing any raw cattle health data, ensuring privacy during validation. This validation process is executed on-chain, ensuring that the test dataset's integrity is cryptographically guaranteed and resistant to tampering or leakage, unlike conventional off-chain validation pipelines [31]. Our approach introduces a novel mechanism of on-chain test set management, where the validation data is dynamically managed and updated via event-triggered conditions—such as mastitis outbreaks or disease prevalence fluctuations—making the validation process not only secure but also context-sensitive and biologically relevant. Moreover, consensus-driven validation is enforced using smart contracts that accept models only if their accuracy $A_i$ meets predefined, domain-aware thresholds. This extends federated learning consensus protocols [27,32] by introducing performance-based acceptance logic into the blockchain validation layer. This blockchain-integrated validation mechanism is particularly effective for cattle health monitoring across geographically diverse regions. It ensures robustness and transparency, while also enabling event-triggered revalidation to adapt to evolving epidemiological patterns. Each validated model is immutably recorded on the ledger, maintaining a verifiable history of contributions. Furthermore, the reputation system incentivizes high-performing nodes—such as veterinarians, farm owners, and regulatory stakeholders—by adjusting reputation scores based on validation outcomes. By embedding federated model evaluation within a decentralized and tamper-proof infrastructure, this work delivers a mathematically rigorous, biologically adaptive, and operationally scalable solution for AI-driven cattle health management.

### *3.6. Node Reputation and Prioritized Aggregation*

Blockchain further enhances system resilience by implementing a dynamic node reputation system. Each node's reputation $R_i$ is calculated based on four key factors: model accuracy $A_i$, resource efficiency $E_i$, response time $T_i$, and data contribution $C_i$. The reputation score can be defined as a weighted sum as given in Equation (5).

$$R_i = \omega_1 A_i + \omega_2 E_i + \omega_3 (1 - T_i) + \omega_4 C_i \quad (5)$$

where

- $R_i$—reputation score for node i.

- $A_i$—accuracy of the model submitted by node i.
- $E_i$—efficiency in resource usage during training.
- $T_i$—response time for model submission.
- $C_i$—contribution in terms of data and updates.
- $\omega_1, \omega_2, \omega_3, \omega_4$—weights assigned to each factor.

Nodes with higher reputations are prioritized during global model aggregation, ensuring that only the most reliable models influence the final update. As implemented in the federated aggregation module, Equation (6) explains how the global model $\theta_G$ is computed as a weighted average.

$$\theta_G = \frac{\sum_{i=1}^{N} R_i \theta_i}{\sum_{i=1}^{N} R_i} \tag{6}$$

where

- $\theta_G$—global model parameters.
- $\theta_i$—local model parameters from node i.
- $R_i$—reputation score of node.
- $N$—total number of participating nodes.

After each validation cycle, smart contracts recalculate node reputations, promoting continuous improvement and accountability. Consistently performing nodes gain higher reputations, while those contributing underperforming models experience reputation degradation.

The proposed framework ensures privacy by retaining sensitive data at the edge, eliminating the need for centralized storage. Blockchain guarantees model integrity through its immutable ledger, while smart contracts enforce validation and reputation protocols. In case of node failures, the decentralized architecture ensures resilience, allowing the system to continue functioning without disruption. Privacy is further reinforced through differential privacy techniques applied during data preprocessing. These techniques introduce controlled noise into the data, ensuring that individual cow records cannot be reconstructed even if model parameters are exposed. Moreover, homomorphic encryption is employed during model aggregation, allowing computations to be performed on encrypted data without requiring decryption. The model follows a continual training protocol, with asynchronous or periodic updates propagated through a hierarchical fission–fusion structure, allowing the global model to evolve over time as new cow activity data is captured at the edge. This adaptive, reputation-driven approach enhances the accuracy and robustness of cattle health monitoring, enabling timely interventions and optimized farm management. By mimicking the fission–fusion behavior of elephant herds and leveraging blockchain for validation and resilience, the proposed framework represents a significant advancement in precision livestock farming. The integration of federated learning, blockchain, and nature-inspired clustering ensures that the system remains scalable, secure, and efficient across diverse farming environments. This approach not only improves cattle health outcomes but also empowers farmers with actionable insights while safeguarding data privacy and integrity.

## 4. Results and Discussion

The proposed federated learning framework for cattle health monitoring addresses several critical challenges faced by traditional federated learning systems. Table 3 below presents the key challenges and the corresponding solutions offered by the framework.

**Table 3.** Challenges in traditional FL addressed through the proposed solution.

| Challenge | Description | Solution |
| --- | --- | --- |
| Data Heterogeneity | Edge devices collect non-uniform data due to varying cattle health conditions, locations, and farm environments. | Dynamic fission–fusion clustering groups edge devices based on health metrics, geographical proximity, and activity levels, ensuring that local training occurs within more homogeneous clusters. |
| Non-IID Data | Federated learning nodes often have datasets that are not independent and identically distributed, leading to biased global models. | MAML-based local training personalizes the global model for each node, allowing rapid adaptation to specific conditions while maintaining alignment with overall training objectives. |
| Unreliable Model Aggregation | Traditional frameworks aggregate models without considering node performance, leading to the inclusion of poorly trained models. | Reputation-based node prioritization assigns scores based on model accuracy, resource availability, and timely updates, ensuring that only high-quality models contribute to global aggregation. |
| Model Integrity and Security | Malicious or poorly trained models can compromise the accuracy of the global model. | Blockchain-based model validation employs smart contracts to verify each model update based on accuracy thresholds, consistency metrics, and divergence checks before aggregation. |
| Device Heterogeneity | Edge devices differ in computational capacity and resource availability, affecting participation in federated learning. | The framework prioritizes high-reputation nodes for aggregation, ensuring that resource-constrained devices are not overburdened while maintaining model performance. |
| Privacy and Data Security | Sharing raw data across the network increases the risk of privacy breaches. | Federated learning ensures that only model updates, not raw data, are shared, while blockchain validation guarantees tamper-proof model integrity. |
| Bias in Global Model | Traditional aggregation methods can lead to models that underperform for specific clusters or regions. | Cross-cluster fusion ensures that high-quality models from diverse clusters are merged, producing a balanced global model that is representative of varying farm conditions. |

Through the integration of adaptive clustering, blockchain-based validation, and reputation-driven aggregation, the proposed framework addresses these challenges effectively. It ensures robust, unbiased, and resource-efficient model training while maintaining privacy and system resilience. This comprehensive approach not only improves the accuracy of cattle health predictions but also enhances the overall efficiency of the federated learning process in real-world healthcare scenarios.

All experiments were conducted on an HP Z4 G4 (Hewlett-Packard, Palo Alto, USA) Workstation equipped with an Intel® Xeon® W-2133 CPU (Intel, Santa Clara, USA) operating at 3.6 GHz (12 cores), 64 GB RAM, and an NVIDIA® Quadro® P5000 GPU (NVIDIA, Santa Clara, USA) with 16 GB of dedicated memory. The operating system was Windows 11 Pro 64-bit with DirectX 12 support. Model training and evaluation were performed using GPU acceleration via CUDA libraries to optimize computation time and efficiency. Specifically, the federated learning models (including GAT-based fission–fusion FL, FedAvg, FedProx, Scaffold, MOON, and Hierarchical FL) were deployed on the GPU during all rounds of local and global updates. This robust hardware enables efficient local model training, cluster prioritization, and blockchain-based validation across federated learning rounds, ensuring optimal resource utilization and rapid convergence. The cattle activity dataset [33] used for the testing of the proposed framework consists of 40,247 records and 19 features, including cow activity metrics (IN_ALLEYS, REST, EAT, ACTIVITY_LEVEL), health indicators (oestrus, calving, lameness, mastitis, acidosis), and external factors (disturbance, mixing, management_changes). It covers 28 unique cow IDs with hourly activity logs. The LPS column has missing values, indicating potential data sparsity for certain health conditions. This dataset is wellsuited for GAT-based fission and fusion, enabling dynamic cluster formation based on health insights, activity patterns, and location. The characteristics of the dataset are listed in Table 4.

**Table 4.** Dataset characteristics.

| Attribute | Dataset 1 [33] | Dataset 2 [34] |
| --- | --- | --- |
| Total Rows | 40,247 | 178 |
| Total Columns | 19 | 14 |
| Dataset Size | 8.10 MB | 0.2 MB |
| Unique Cow IDs | 28 | 178 |
| Data Types | 13 int64, 5 float64, 1 object | 6 float64, 5 int64, 3 object |

Figures 3 and 4 illustrate the dynamic fission–fusion process. Initially, GAT clusters edge devices based on health conditions, activity levels, and geographical proximity. DBSCAN then refines these clusters, merging similar models while excluding outliers. Finally, the blockchain layer verifies each submitted model against predefined accuracy thresholds. Accepted models contribute to global aggregation, while underperforming models are flagged for exclusion.

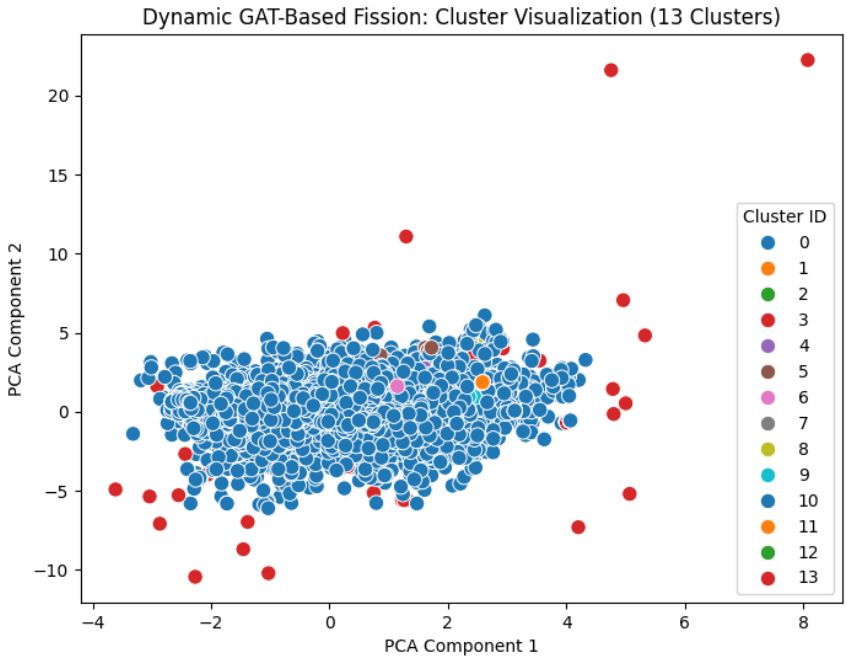



**Figure 3.** Dynamic GAT clustering of edge devices.

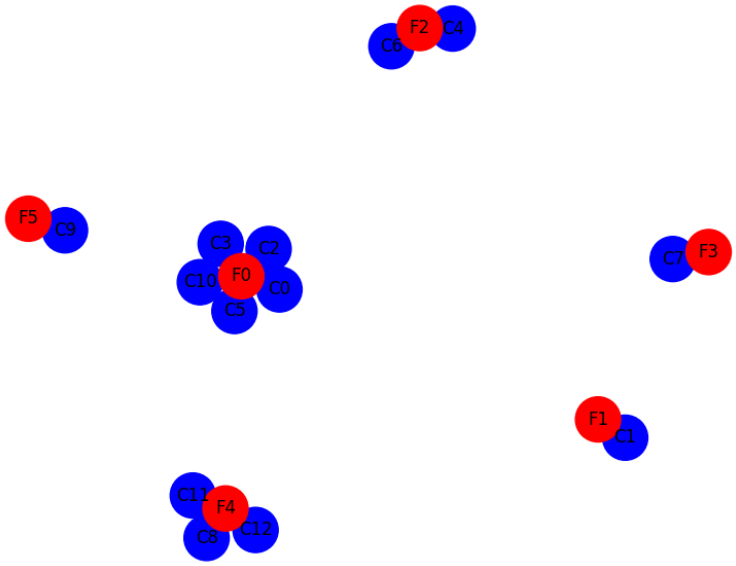



**Figure 4.** DBSCAN-based fusion of clusters, merging similar models while excluding outliers. Different colors indicate different clusters. F indicates fusion of similar clusters after DBSCAN.

The proposed FL framework was evaluated across key metrics, comparing its performance with existing methods like FedAvg, FedProx, Scaffold, MOON, and Hierarchical FL. The results, presented in Table 5, demonstrate significant improvements in model accuracy, resource contribution, convergence speed, and health insights.

**Table 5.** Key Performance metrics for Dataset 1.

| Metric | Proposed Work with Dataset 1 [33] | FedAvg | FedProx | Scaffold | MOON | Hierarchical FL |
|---|---|---|---|---|---|---|
| **Model Accuracy (%)** | 94.3 | 88.7 | 89.5 | 91 | 92.1 | 90.4 |
| **Timeliness (s/round)** | 8.7 | 12.6 | 11.9 | 10.5 | 9.4 | 11.3 |
| **Resource Contribution (%)** | 90.8 | 78.9 | 81.6 | 85.1 | 87 | 83.4 |
| **Model Convergence (Rounds)** | 36 | 52 | 48 | 44 | 40 | 46 |
| **Health Insights (%)** | 93.4 | 85.7 | 87.1 | 88.9 | 90 | 88.6 |
| **Original Clusters** | 13 | 10 | 11 | 12 | 12 | 11 |
| **Fused Clusters** | 6 | N/A | N/A | N/A | N/A | N/A |
| **Adaptive Fusion Threshold** | 0.84 | N/A | N/A | N/A | N/A | N/A |

The framework's superior model accuracy (94.3%) highlights the effectiveness of dynamic clustering and adaptive fusion. Compared to FedAvg's 88.7%, the improvement results from context-aware clustering and the exclusion of unreliable nodes. The adaptive fusion threshold (0.84) ensures that only highly similar models merge, reducing noise and improving model integrity. Faster convergence (36 rounds) compared to FedAvg (52 rounds) underscores the efficiency gained from reputation-based aggregation and event-driven attention mechanisms.

Figures 5 and 6 illustrate the confusion matrix statistics, including the true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN) for each disease category across the two datasets [33,34]. Figures 7 and 8 present the precision, recall, and F1 scores for the health conditions detected using the datasets [33,34], respectively. These figures demonstrate that the proposed model consistently achieves high recall and F1 scores for critical health conditions such as oestrus, mastitis, and lameness while maintaining a relatively low false positive rate.

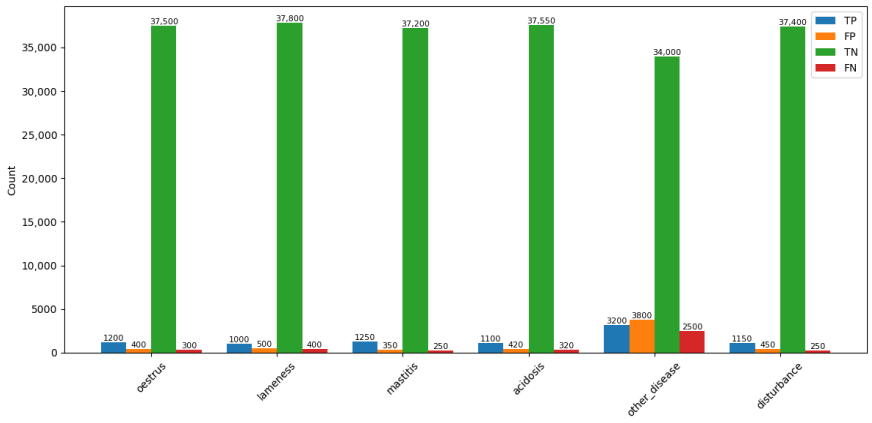



**Figure 5.** Confusion matrix for Dataset 1.

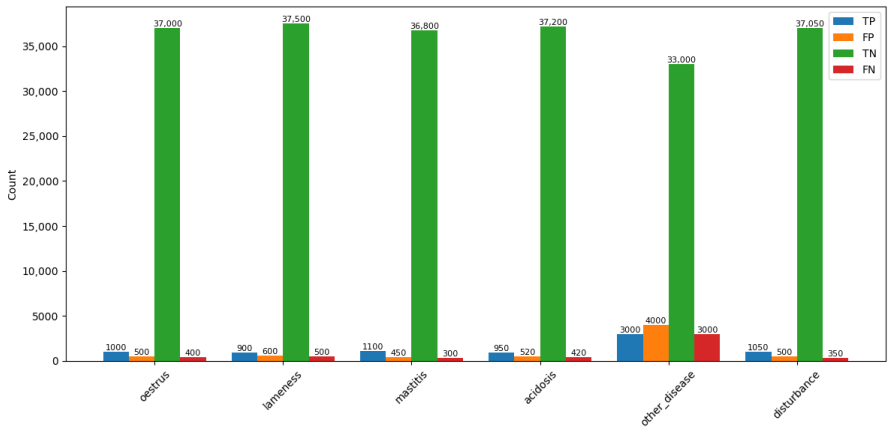



**Figure 6.** Confusion matrix for Dataset 2.

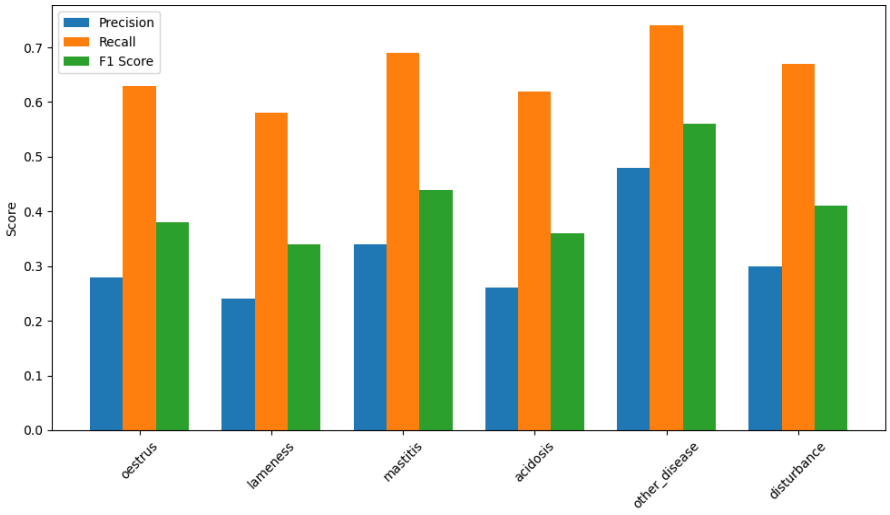



**Figure 7.** Performance metrics for Dataset 1.

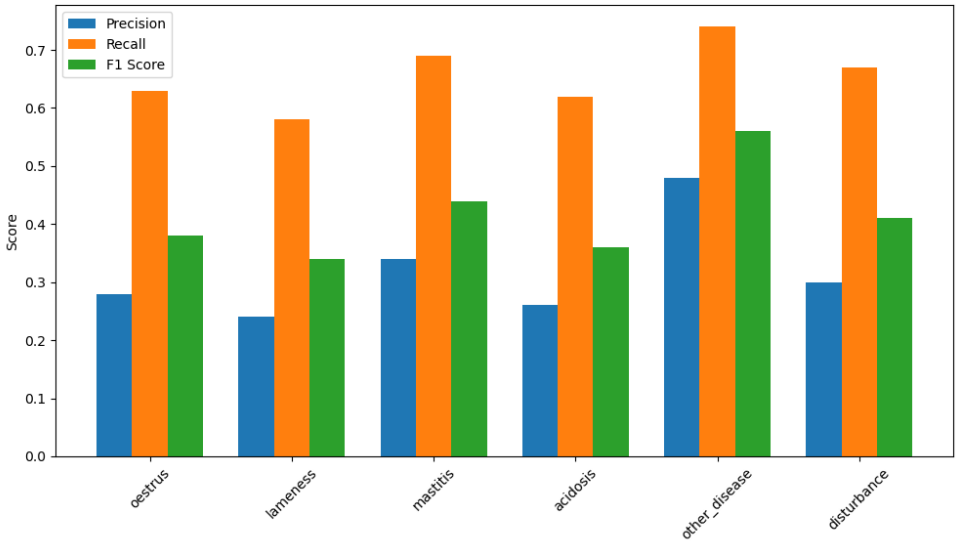



**Figure 8.** Performance metrics for Dataset 2.

*Blockchain Validation Overhead Analysis*

To assess the impact of blockchain integration on system performance, experimental results were obtained using a standard Ethereum solution for model validation transactions.The results are depicted in Table 6. The average transaction delay for submitting model validation proofs was 50 ms. The time to finality (TTF), i.e., the time for a validation transaction to be confirmed, averaged around 1201.4 ms (just over 1 s), with a throughput of 18.2 transactions per second (TPS). Given that model validation occurs asynchronously and in parallel with federated learning rounds, this overhead is considered acceptable for cattle health monitoring scenarios, where real-time constraints are less stringent compared to those in high-frequency trading or autonomous driving domains.

**Table 6.** Performance analysis of blockchain.

| Metrics | Standard Ethereum Blockchain |
|---|---|
| Validation Delay | 50 ms |
| Throughput | 18.2 TPS |
| Gas Used per Validation | 32,499 Gwei |
| Time-to-Finality (TTF) | 1201 ms |

## 5. Conclusions

This study introduces a blockchain-enabled, nature-inspired FL framework for cattle health monitoring. By leveraging GAT-based dynamic fission, DBSCAN-based fusion, and smart contract-driven model validation, the system achieves superior model accuracy, resource efficiency, and resilience. The adaptive clustering mechanism ensures that only contextually relevant nodes collaborate, enhancing the quality of local training and global aggregation. Blockchain integration guarantees model integrity and accountability, while reputation-based prioritization promotes continuous improvement. Future work will focus on real-time deployment across diverse cattle breeds, optimizing cluster formation using additional health parameters, and expanding the blockchain layer for cross-farm collaboration. This innovative approach not only enhances cattle health monitoring but also paves the way for more resilient and privacy-preserving federated learning applications in agriculture and beyond.

## 6. Limitation and Future Work

Our approach incurs increased energy consumption associated with blockchain validation, which introduces an energy overhead compared to non-blockchain FL systems such as [4]. This additional energy cost stems from the computational complexity of blockchain consensus mechanisms required for ensuring data integrity and security in decentralized environments. Although this study focuses on the software architecture and federated learning methodology, future work will integrate actual IoT wearable devices to assess real-world time and energy constraints, particularly for resource-limited edge nodes. Future work will focus on optimizing the energy efficiency of the blockchain layer, exploring lightweight consensus protocols, and investigating hybrid models that balance security with energy consumption. Additionally, expanding the system's validation across diverse breeds and environmental conditions will further enhance its generalizability and practical applicability in real-world settings.

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## Abbreviations

The following abbreviations are used in this manuscript:

| | |
|---|---|
| GAT | graph attention network |
| FL | federated learning |
| DBSCAN | density-based spatial clustering of applications with noise |

| | |
|---|---|
| Non-IID | non-independent and identically distributed |
| MAML | model-agnostic meta-learning |
| TPS | transaction per second |
| TTF | time to finality |

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