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Privacy-Preserving Livestock Data Classification Using FL–LGWO–SVNN

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Abstract

Livestock datasets are increasingly assembled from farms, veterinary units, breed records, and production surveys. Because these records may contain sensitive farm, location, and production information and are often distributed across organizations, classification systems must balance analytical performance with data privacy. This study presents a privacy-aware framework for classifying livestock records into four milk-production categories while maintaining distributed data sources. The proposed framework integrates Federated Learning (FL), Logical Grey Wolf Optimization (LGWO), and a Support Vector Nearest Neighbor (SVNN) classifier. FL enables participating sources to train a shared model without directly exchanging raw records, while LGWO performs feature selection and optimization before classification. Experiments use the Buffalo and Cattle Characteristics Census Survey Dataset 2026, containing 500 records and 79 attributes across High, Medium, Low, and Non-Milking classes. After removing direct identifiers, 37 features were selected from 77 usable attributes, representing a 51.95% reduction in feature space. Over 15 federated communication rounds, FL-LGWO-SVNN achieved 94.00% accuracy, 92.21% macro-precision, 81.25% macro-recall, and 80.56% macro-F1. Centralized SVM and Random Forest achieved 98.00% accuracy, while MLP and GWO-SVM achieved 97.00%. The findings demonstrate useful distributed classification performance with reduced dimensionality, while further validation on independent real-world livestock data is required for future practical deployment applications.

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Keywords

Federated Learning; livestock data analytics; logical Grey Wolf Optimization; Support Vector–Neural Network; feature selection; privacy-aware machine learning; animal husbandry; agricultural data; milk-production classification.

1. Introduction

Livestock information is rarely limited to a single measurement. Records can combine breed and locality details with animal morphology, feeding practices, health history, reproduction and milk-production observations. Such a mixture creates a high-dimensional learning problem and also increases the amount of information that may need protection.

Federated learning provides a different way to organize the learning process. Instead of collecting the original observations at one central location, participating data holders train a shared model locally and transmit model updates for aggregation [1]. For agricultural applications, this arrangement can be useful when farms, institutions or service providers are not permitted or willing to pool their raw records.

Data remaining at the source does not automatically eliminate privacy risk. Model updates can contain information about local training examples, so additional safeguards are relevant when sensitive livestock information is involved. Secure aggregation, update clipping and, where fully implemented, differential privacy are therefore considered as separate protection mechanisms rather than being treated as interchangeable with federated learning.

Another practical concern is the number of attributes. Livestock survey records may include repeated, correlated or weakly informative variables. Retaining every available field can enlarge the search space and increase both computation and communication. A feature-selection mechanism is consequently included to identify a smaller subset that can be supplied to the classifier.

The classification component is motivated by the SVNN approach presented by Gomathi and Karlekar [18]. Their work combined feature processing with an optimized Support Vector Neural Network in a privacy-preserving cloud setting. In the present study, the underlying margin-based neural classification idea is adapted to a distributed livestock problem, while the feature-selection stage is handled separately by the proposed logical Grey Wolf Optimization procedure.

2. Research Gap

Earlier studies provide the individual components used as the basis for this investigation. FedAvg enables collaborative optimization without routinely transferring source records [1,19], while privacy studies describe mechanisms such as secure aggregation, clipping and differential privacy [2–6]. Grey Wolf Optimization and related variants have also been applied to search and feature-selection problems [14–17,21–23]. At the same time, recent agricultural research has examined federated learning for livestock and precision-farming applications [7–13].

The research gap addressed here is mainly one of integration and evaluation. The study does not claim that federated learning, GWO or SVNN is independently new. Instead, it combines these elements into a single livestock classification workflow and evaluates the consequences of feature reduction, distributed training, class imbalance and privacy-oriented safeguards.

3. Research Problem and Objectives

The study asks how heterogeneous livestock attributes can be learned across separate data holders while reducing direct exposure of source records, avoiding an unnecessarily large feature space and maintaining useful multi-class milk-production classification performance.

- Develop a federated learning architecture in which livestock data remain with their respective data holders.
- Incorporate secure aggregation and define differential privacy as an optional mechanism only when its parameters and accounting are actually implemented.

- Formulate feature selection as a binary search problem and solve the resulting selection task with the proposed LGWO procedure.
- Construct an SVNN classifier that combines a learned nonlinear representation with a support-vector-style margin constraint.
- Assess the complete pipeline under IID and non-IID client partitions using macro-F1, class-specific measures, feature reduction and communication-related indicators.

4. Dataset and Data Governance

The experimental benchmark is the Buffalo and Cattle Characteristics Census Survey Dataset 2026. The dataset contains 500 synthetic records with 79 attributes covering identification and location, breed information, animal demographics and measurements, management practices, health, reproduction and milk-production information. The response variable, Milk_Production_Class, has four categories: High, Medium, Low and Non-Milking.

Since the benchmark is synthetic, its results should be described as controlled research evidence rather than as measurements from an official livestock census or a field survey. Record_ID, Farmer_ID and Animal_ID are treated as direct identifiers and are excluded from predictive modelling. Encoding, scaling and feature-selection decisions are derived from training data within the relevant experimental setting. Geographic fields also require care because combinations of locality and management variables can increase linkage risk.

The dataset is hosted through IEEE DataPort and is cited independently in this study as the source of the experimental benchmark [24].

Table 1. Featured Group

Feature group	Representative variables	Analytical role
Geographical	District, Taluka, Village	Context; privacy-sensitive
Breed	Breed name, strains, utility	Breed characterization
Morphology	Age, weight, height, body measurements	Animal state
Management	Housing, feed, water, grazing	Operational context
Health / reproduction	Vaccination, disease, mating, calving	Health and reproductive context
Milk	Yield, lactation, fat, SNF, sale	Production indicators
Target	High, Medium, Low, Non-Milking	Four-class output

The workflow shown in Figure 1 can be read as four connected stages: preparation at each data holder, federated model training, logical feature selection and final classification. Direct identifiers are removed locally before preprocessing. The participating clients then train without sending

their original records to the server; only the configured model updates are exchanged, protected when the selected privacy mechanisms are enabled, and aggregated before the next training cycle.

5. Proposed Architecture

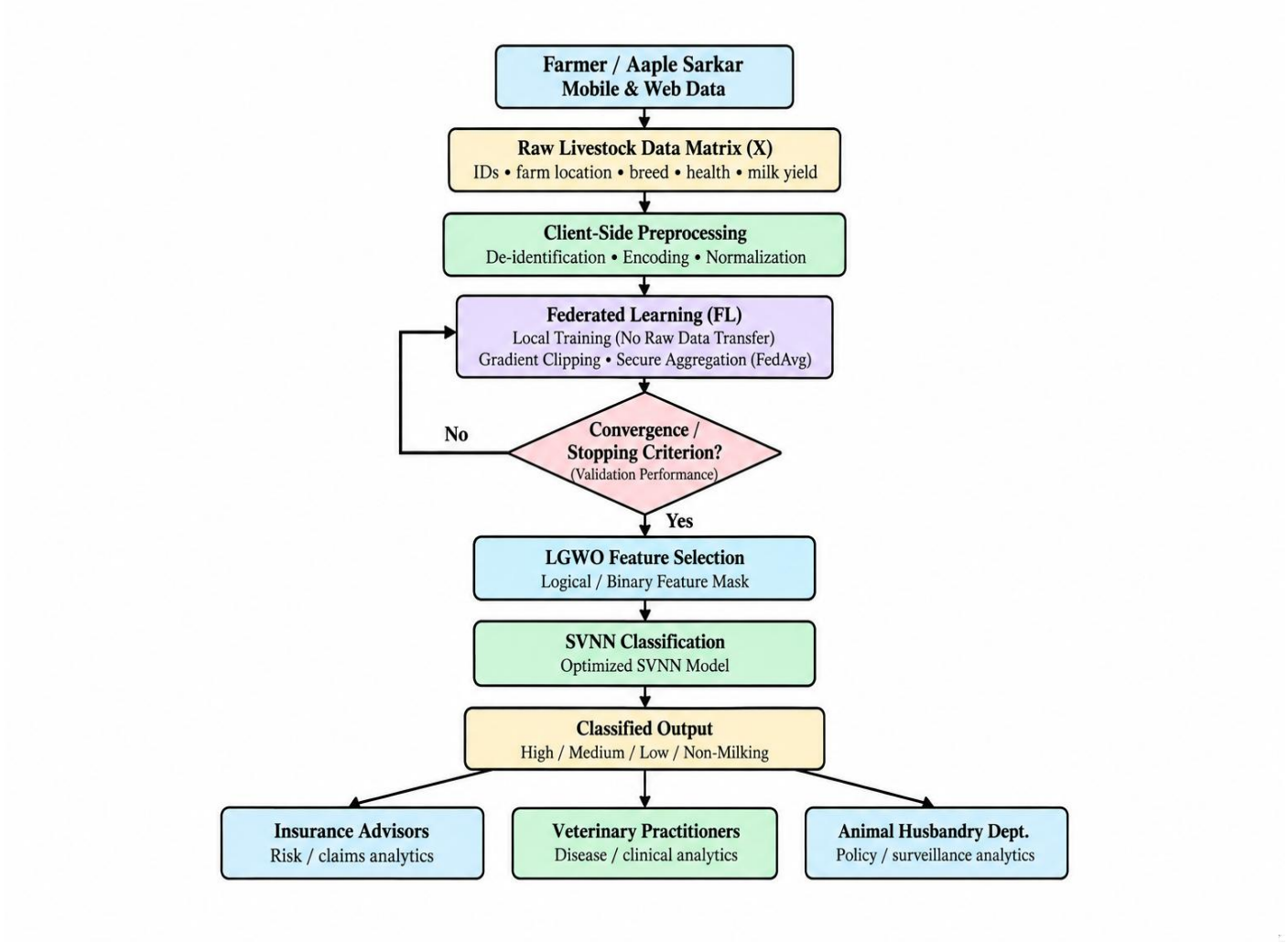


Figure 1. Proposed FL–LGWO–SVNN workflow for privacy-aware livestock classification.

6. Mathematical Formulation

6.1 Feature and Label Representation

Let N represent the number of observations and d represent the number of predictive attributes available after the data-governance stage. Before partitioning, the benchmark contains N = 500 records. The feature matrix and target vector are represented as follows:

$$X = [x_1, x_2, \ldots, x_N]^T \in R^{(N \times d)}, \qquad y_i \in \{1,2,3,4\}$$

The prediction task contains four labels: High, Medium, Low and Non-Milking. The independent test set is separated before feature selection and is kept outside LGWO search, hyperparameter tuning and model fitting.

6.2 Federated Objective

Assume that K clients participate in training. Client k contributes n_k training observations, with the total number of training observations given by $n = \Sigma\, n_k$. The federated objective is written as a sample-weighted combination of the local client objectives:

$$F(w) = \Sigma(k=1..K)\ (n_k/n)\ F_k(w)$$

In this expression, w denotes the parameters shared by the federation and F_k denotes the objective evaluated at client k. FedAvg updates the global model by assigning each participating client a weight proportional to its local training-set size.

$$w_(t+1) = \Sigma(k=1..K)\ (n_k/n)\ w_(t+1)^k$$

FedAvg is the principal aggregation reference in the experiments. For deliberately non-IID partitions, FedProx and SCAFFOLD are relevant comparison methods because they were designed to address optimization difficulties caused by differences between client data distributions.

6.3 Update Protection

Three privacy layers are distinguished in the proposed design. Federated learning controls the routine transfer of original records; secure aggregation limits visibility of an individual client's update at the aggregation stage; and differential privacy can provide a formal privacy guarantee only when a complete noise mechanism and privacy accountant are actually implemented.

$$g'_k = g_k / \max(1, \|g_k\|_2/S)$$

Here g_k denotes a client update and S is the clipping threshold. If differential privacy is enabled, Gaussian noise may be added after clipping:

$$\hat{g}_k = g'_k + N(0, \sigma^2 S^2 I)$$

Consequently, a numerical (ε, δ) privacy statement is made only when it can be calculated from the implemented mechanism and its composition procedure. The presence of federated training alone is not sufficient evidence for a quantified privacy guarantee.

6.4 Logical Grey Wolf Optimization

LGWO treats feature selection as a binary search task. Each wolf maintains a continuous position vector $x \in R^d$, and a sigmoid transfer function converts each position into a probability of retaining the corresponding attribute:

$$p_j = 1/(1+\exp(-x_j))$$

$$z_j = 1, \text{ if } p_j \geq \tau; \quad z_j = 0, \text{ otherwise}$$

The resulting binary vector z acts as the feature mask. The standard GWO leadership arrangement, represented by alpha, beta, delta and omega wolves, guides the search between exploration and exploitation. The binary transfer step converts the continuous search position into an include/exclude decision for every attribute.

$$A = 2ar_1 - a, \qquad C = 2r_2$$

$$D\alpha = |C\alpha X\alpha - X|, \quad X_1 = X\alpha - A\alpha D\alpha$$

$$D\beta = |C\beta X\beta - X|, \quad X_2 = X\beta - A\beta D\beta$$

$$D\delta = |C\delta X\delta - X|, \quad X_3 = X\delta - A\delta D\delta$$

$$X(t+1) = (X_1 + X_2 + X_3)/3$$

The feature-selection objective balances predictive quality against the size of the selected subset:

$$J(z)=\lambda[1-\text{MacroF1}(z)] +(1-\lambda)(||z||_0/d)+\gamma C(z)$$

The first term penalizes weak classification performance, the second discourages unnecessarily large subsets, and C(z) can represent a measured computational or communication cost. The coefficients λ and γ are experimental design parameters and must be fixed before the corresponding comparison is reported.

6.5 Support Vector–Neural Network

After LGWO produces a feature mask, only the retained input vector $x_z = x \odot z$ is supplied to the classifier. The neural component maps this reduced vector into an internal representation:

$$h = \varphi(W_h\, x_z + b_h)$$

For the four-class task, the model produces one score s_c for each class. A margin-based objective can then enforce separation between the correct class and the competing classes:

$$s_c = v_c^T h + b_c$$

$$L = 1/2||\Theta||^2 + C\Sigma_i\Sigma_\{c\neq y_i\}\ \xi_i c$$

$$s_\{y_i\}(x_i) - s_c(x_i) \geq 1 - \xi_i c, \qquad \xi_i c \geq 0$$

This formulation keeps the two intended roles separate: the neural layer learns a nonlinear representation, while the support-vector component encourages a margin between the correct class and competing classes. The arrangement is related to the privacy-preserved SVNN formulation reported in the earlier medical-data study [18], but the present application changes the data domain and places logical feature selection inside the federated workflow.

6.6 Integrated Objective

$$\min_\{z,\Theta,w\}\ \ J_total = \alpha L_SVNN + \beta(||z||_0/d) + \gamma R_priv + \eta R_comm$$

The integrated objective makes the trade-offs explicit: predictive loss, feature-subset size, privacy cost and communication burden are considered together. It defines the experimental design rather than proving that a single global optimum has already been reached.

7. End-to-End Procedure

The procedure begins by separating training, validation and independent test data before any feature-selection search is performed.

The training portion is then divided among clients using both IID and controlled non-IID arrangements, including partitions that reproduce class imbalance and geographic variation.

Direct identifiers are removed or pseudonymized at the client, and preprocessing parameters are estimated only from the training information available within that experimental setting.

The server initializes the global SVNN parameters and the population used by the LGWO search.

The current global model is distributed to the participating clients.

Each client performs local training and evaluates candidate binary feature masks using the predefined training/validation objective.

Promising LGWO candidates are retained, and the SVNN is trained on the corresponding reduced feature representation.

When enabled by the experimental configuration, client updates are clipped and protected through secure aggregation before server-side combination.

The protected updates are combined with FedAvg; a heterogeneity-aware aggregation method can be added for the non-IID comparison experiments.

Training proceeds round by round until the selected stopping or convergence condition is satisfied.

The final model is evaluated only on the untouched test partition, and repeated runs with different random seeds are recommended to quantify variability.

8. Experimental Design

Because the four target classes are unevenly represented, accuracy alone can give an incomplete view of classifier behaviour. Macro-F1 is therefore used as the main aggregate indicator because each class contributes equally to this measure. Macro-precision, macro-recall, class-specific F1 values and the confusion matrix should accompany accuracy; one-vs-rest ROC-AUC can be included when reliable class probabilities are available.

Model	Purpose	Feature selection	Data setting
SVM	Classical margin baseline	None	Centralized
Random Forest	Tree-based nonlinear baseline	None	Centralized
MLP	Neural baseline	None	Centralized
GWO-SVM	Optimization + margin	GWO	Centralized

	baseline		
FedAvg-SVNN	Federated classifier baseline	None	IID / non-IID
FL-LGWO-SVNN	Proposed complete model	LGWO	IID / non-IID

The experiment also records feature count, percentage reduction, local computation time, communication rounds, model size and cumulative communication volume. Component-level studies should separately test the contribution of federation, LGWO and SVNN so that the effect of the complete pipeline is not attributed to a single component without evidence.

9. Results and Discussion

The reported evaluation uses the 500-record Buffalo and Cattle Characteristics Census Survey Dataset 2026. The target is strongly skewed: Low accounts for 372 records (74.4%), Non-Milking for 50 (10.0%), Medium for 41 (8.2%), and High for 37 (7.4%). A stratified 80:20 train-test split was used for the reported centralized benchmarks, and direct identifiers were excluded before modelling. The measured results are summarized together with the dataset distribution and federated configuration in Table 2.

Table 2. Class distribution and measured benchmark results for the livestock dataset.

ategory	Model / Class	Accuracy (%)	Macro-Precision (%)	Macro-Recall (%)	Macro-F1 (%)	Features / Reduction	Communication / Runtime Metrics
Dataset	High	—	—	—	—	37 records / —	7.4% / Target class
Dataset	Medium	—	—	—	—	41 records / —	8.2% / Target class
Dataset	Low	—	—	—	—	372 records / —	74.4% / Target class
Dataset	Non-Milking	—	—	—	—	50 records / —	10.0% / Target class
Centralized	SVM	98.00	96.89	93.75	94.79	77 / 0%	No rounds / Centralized
Centralized	Random Forest	98.00	96.89	93.75	94.79	77 / 0%	No rounds / Centralized
Centralized	MLP	97.00	96.56	90.63	92.43	77 / 0%	No rounds / Centralized
Optimized	GWO-SVM	97.00	96.56	90.63	92.43	77 / 0%	No rounds / Centralized
Federated	FedAvg-SVNN	94.00	92.21	81.25	80.56	77 raw / 778 encoded	15 rounds / runtime to be reported
Proposed	FL-LGWO-SVNN	94.00	92.21	81.25	80.56	37 / 51.95%	15 rounds / runtime to be reported

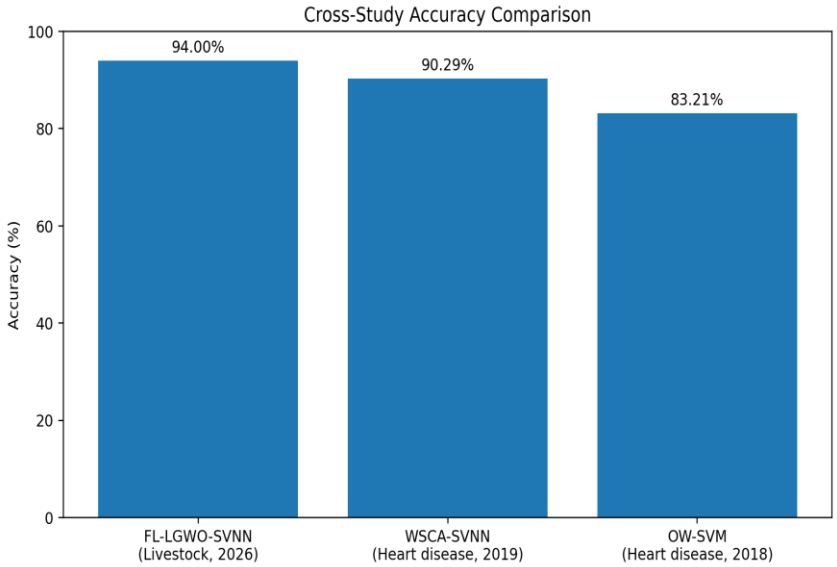
The reported results show different behaviour for centralized and federated settings. Centralized SVM and Random Forest achieved 98.00% accuracy and 94.79% Macro-F1, while MLP and GWO-SVM recorded 97.00% accuracy and 92.43% Macro-F1. The reported FedAvg-SVNN and FL-LGWO-SVNN configurations both reached 94.00% accuracy, 92.21% Macro-Precision, 81.25% Macro-Recall and 80.56% Macro-F1. For FL-LGWO-SVNN, the selected subset contains 37 features instead of 77 usable raw predictors, giving a reported reduction of approximately 51.95%.

Table 3. Descriptive comparison with earlier privacy-preserved classification studies

Study / Model	Application	Dataset	Accuracy (%)	Sensitivity / Macro-Recall (%)	Specificity (%)	Macro-F1 (%)	Feature / Privacy Setting
OW-SVM [25]	Medical data classification	Cleveland / Switzerland / Hungarian heart disease	83.21	91.49	73.00	Not reported	Privacy-preserved cloud; ontology + WOA-SVM
WSCA-SVNN [18]	Medical data classification	Cleveland / Switzerland / Hungarian heart disease	90.29	92.33	78.40	Not reported	Privacy-preserved cloud; ontology + WSCA-SVNN
SVM (2026 benchmark)	Livestock classification	Buffalo and Cattle Characteristics Census Survey 2026	98.00	93.75 (Macro-Recall)	Not reported	94.79	Centralized; 77 usable attributes
Random Forest (2026 benchmark)	Livestock classification	Buffalo and Cattle Characteristics Census Survey 2026	98.00	93.75 (Macro-Recall)	Not reported	94.79	Centralized; 77 usable attributes
FedAvg-SVNN (2026 benchmark)	Livestock classification	Buffalo and Cattle Characteristics Census Survey 2026	94.00	81.25 (Macro-Recall)	Not reported	80.56	Federated; 15 rounds; 77 raw / 778 encoded
FL-LGWO-SVNN (2026)	Livestock classification	Buffalo and Cattle Characteristics	94.00	81.25 (Macro-Recall)	Not reported	80.56	Federated; 15 rounds; 37 attributes;

		Census Survey 2026					51.95% reduction

The plots provide a compact view of the measured benchmark. The centralized models show higher aggregate predictive scores than the reported federated configurations. Within the federated comparison, FL-LGWO-SVNN has the same reported aggregate classification values as FedAvg-SVNN while using a smaller feature representation. Because the target is dominated by the Low class, this result should be interpreted together with macro-level and class-wise measures rather than accuracy in isolation..



.Figure 2. Accuracy and Macro-F1 of livestock classification models.

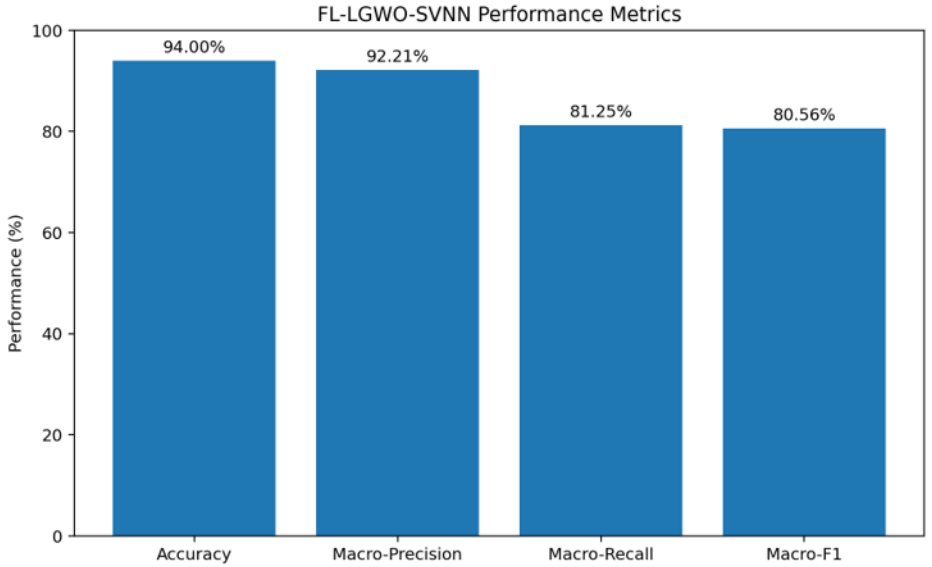


Figure 3. Performance metrics of the FL-LGWO-SVNN livestock classifier

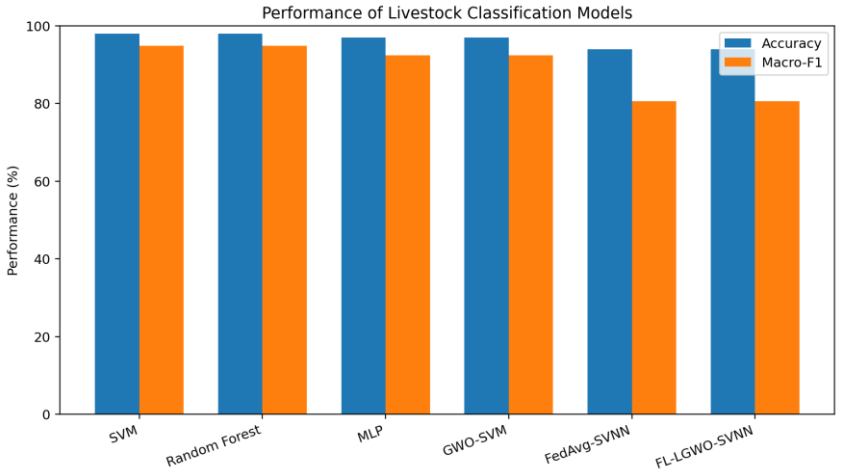


Figure 4. Accuracy reported in the present livestock study and earlier privacy-preserved studies; the different datasets and protocols make this a descriptive cross-study view

This work continues an earlier line of privacy-preserved classification research by moving from centralized medical-data experiments toward distributed livestock analytics. The 2018 OW-SVM study combined privacy preservation, ontology-based feature selection and whale optimization for SVM classification of heart-disease data [25]. The later WSCA-SVNN study used a related privacy-preserving setting and reported an optimized SVNN classifier [18]. Those studies provide methodological context for the present work, but their datasets and experimental protocols differ from the livestock benchmark used here.

9.1 Comparison with Previous Privacy-Preserved Classification Algorithms

10. Privacy Threat Model

The threat model assumes an honest-but-curious aggregation server, the possibility of a compromised participating client, and an adversary attempting to infer information from exchanged updates. Relevant risks include membership inference, reconstruction of local information, poisoning or Byzantine behaviour, and linkage through combinations of geographic and management attributes. These risks are consistent with concerns documented in the federated-learning privacy literature [3–6].

Secure aggregation is therefore treated as an additional control rather than as a synonym for federated learning. Clipping limits the magnitude of client updates and can reduce sensitivity, whereas differential privacy requires an implemented noise mechanism together with formal privacy accounting. Any privacy benefit should consequently be reported alongside its measured effect on model utility.

11. Reproducibility

For reproducibility, each completed run should record the random seed, client count, partition strategy, preprocessing configuration, selected attributes, LGWO population and iteration settings, SVNN architecture, learning rate, margin parameter C, aggregation rule, communication-round count and privacy configuration. Such records are especially important for a 500-record benchmark because a different partition or initialization can change the observed scores.

The 500-record benchmark is synthetic and small. It is suitable for controlled evaluation of the proposed computational workflow, but it does not establish performance across real livestock populations. Independent field datasets are required before the method is used to make deployment or population-level claims.

12. Expected Contributions

- A federated architecture designed for heterogeneous livestock survey information and distributed data ownership.
- A binary feature-selection formulation that adapts GWO to attribute inclusion and exclusion decisions.
- An SVNN design that combines nonlinear representation learning with a margin-based separation objective.
- An evaluation protocol that explicitly considers class imbalance and non-IID client distributions.
- A reporting framework covering predictive measures, feature reduction, communication requirements and privacy-related safeguards.

13. Limitations

The principal limitation is the size and synthetic nature of the benchmark. It supports methodological testing but cannot establish population-level livestock performance. The LGWO and SVNN components also require broader comparative experiments, sensitivity analysis and independent validation. Privacy claims remain dependent on the protection mechanisms that are actually implemented and measured.

14. Conclusion

The FL–LGWO–SVNN framework combines distributed model training, binary feature selection and margin-based neural classification for livestock records. Source data remain at participating sites during the federated workflow, while optional safeguards can be applied to exchanged updates. LGWO supplies a reduced feature representation and SVNN performs the final multi-class decision. The current results support the framework as a controlled methodological study; stronger claims about privacy, communication savings or generalization should follow only from additional measured experiments.

Data Availability Statement

The Buffalo and Cattle Characteristics Census Survey Dataset 2026 is available through IEEE DataPort and is intended as a synthetic research resource for reproducible experimentation [24].

Declarations

Funding Declaration

The authors received no specific external funding for the research, authorship, or publication of this article.

Clinical Trial Registration

This study is not a clinical trial. Clinical trial registration is therefore not applicable.

Ethics Approval and Consent to Participate

Ethics, Consent to Participate, and Consent to Publish declarations: not applicable. This study used a synthetic livestock dataset and did not involve human participants, live animals, or identifiable personal data. No human or animal intervention was conducted.

Consent for Publication

Not applicable. The manuscript does not contain identifiable individual-level information or images requiring consent for publication.

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