

A Human-Centered Machine Learning Dashboard for Real-Time Smart Farming Decision Support

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Article Info

Article history:

Submission July 27, 2026

Revised August 14, 2026

Accepted September 7, 2026

Published September 30, 2026

Keywords:

Artificial Intelligence

Human-Centered Design

Internet of Things (IoT)

Machine Learning

Precision Agriculture



ABSTRACT

The integration of Machine Learning (ML) into precision agriculture has advanced predictive accuracy for tasks such as crop monitoring, irrigation scheduling, and yield estimation. However, many existing IoT-based smart farming systems remain technically driven, offering limited attention to how farmers and field operators actually interact with and interpret model outputs. This gap often results in low adoption rates, as complex predictions fail to translate into actionable, trustworthy decisions for end users. This study proposes a human-centered machine learning dashboard designed to bridge predictive modeling with real-time, farmer-friendly decision support. The system integrates IoT sensor data streams with ML-based prediction modules, presented through an interactive, usability-tested interface that emphasizes clarity, accessibility, and interpretability over raw technical complexity. A working prototype was developed and evaluated using both quantitative usability metrics (e.g., task completion time, System Usability Scale scores) and qualitative feedback from target users to assess the dashboard's effectiveness in supporting field-level decisions. The proposed system architecture, dashboard interface, and underlying ML pipeline are implemented as open and reproducible source code, enabling replication and adaptation across similar smart farming contexts. Results indicate that the human-centered design significantly improves users' comprehension of model outputs and their confidence in acting on system recommendations, without compromising predictive performance. This research contributes a practical framework for designing machine intelligence systems that prioritize end-user experience alongside technical accuracy, offering implications for the broader development of human-centered AI in agricultural and IoT-driven decision support environments.

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DOI: <https://doi.org/10.68012/shem.v2i2.302>

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1. INTRODUCTION

The convergence of the Internet of Things (IoT) and Machine Learning (ML) has fundamentally reshaped the landscape of modern agriculture, giving rise to what is broadly termed precision or smart farming. Networks of low-cost sensors now continuously capture granular data on soil moisture, ambient temperature, humidity, light exposure, and, in livestock contexts, physiological and behavioral indicators of animal health

Journal homepage: <https://journal.sundarapublishing.com/shem>

[1]. When paired with ML algorithms, this data stream enables predictive capabilities that were previously unattainable at scale, including early disease detection, optimized irrigation scheduling, yield forecasting, and automated anomaly detection in livestock environments [2]. Despite this technical promise, the actual adoption of such systems in real-world farming operations particularly among smallholder farmers and field technicians in developing agricultural economies remains disproportionately low relative to the sophistication of the underlying algorithms [3]. This adoption gap is rarely attributable to insufficient model accuracy rather, it stems from a structural mismatch between how these systems are designed and how their intended users actually think, work, and make decisions in the field [4]. Dashboards cluttered with raw statistical outputs, probability scores, or opaque model confidence intervals offer little practical value to a farmer who needs a clear, immediate, and actionable recommendation. Consequently, the success of smart farming technology depends not merely on predictive performance but equally on the accessibility, clarity, and contextual relevance of the interface through which that intelligence is delivered [5].

The technical feasibility of ML and DL based agricultural prediction has been well established across a diverse range of applications. Convolutional neural networks have been applied extensively to image-based crop and pest classification tasks, achieving high accuracy in distinguishing disease symptoms from healthy foliage [6]. Ensemble methods such as random forest and gradient boosting have similarly demonstrated strong performance in structured, sensor-derived datasets for yield prediction and soil quality assessment [7]. In parallel, a separate stream of research has focused on improving model transparency through explainable AI (XAI) techniques most notably SHAP and LIME allowing researchers and, to a lesser extent, practitioners to inspect which environmental variables most heavily influence a given prediction [8]. A third and increasingly active research direction concerns the engineering of IoT-based monitoring platforms themselves: architectures for sensor data ingestion, edge-to-cloud pipelines, and real-time visualization dashboards have been proposed to support continuous farm monitoring at scale [9, 10]. Collectively, these three streams of literature predictive modeling, explainability, and system architecture have each independently matured to a considerable degree, laying substantial technical groundwork for integrated smart farming solutions.

Notwithstanding this progress, a close reading of the literature reveals that these three research streams have largely evolved in isolation from one another, with limited cross-pollination toward a unified, user-facing system [11]. Studies on predictive modeling tend to report accuracy, precision, recall, and F1-scores as the primary often sole measures of success, with no accompanying assessment of whether the resulting predictions are comprehensible or actionable to a non-technical end user [12]. Explainability research, while conceptually oriented toward human understanding, is frequently validated only through researcher-side interpretation of SHAP or LIME plots rather than through empirical testing with actual target users such as farmers or agricultural extension workers. System architecture papers, for their part, tend to emphasize throughput, latency, and scalability of the IoT pipeline, treating the dashboard interface as an implementation detail rather than a design object subject to rigorous usability evaluation [13, 14]. The consequence of this fragmentation is a body of literature rich in individually validated components but conspicuously lacking in end-to-end systems whose usability has been empirically measured using established human-computer interaction (HCI) instruments. Moreover, very few of these studies release open, reproducible source code that integrates the full pipeline from raw sensor ingestion through model inference to interface rendering thereby limiting both academic reproducibility and practical adaptation by other researchers or agricultural technology developers [15].

This study addresses the identified gap by proposing and empirically evaluating a human-centered machine learning dashboard that treats usability as a first-class design constraint rather than a downstream afterthought. The system architecture integrates a real-time IoT sensor data pipeline with an ML-based inference module, and critically wraps this technical core in an interface whose design decisions are informed by iterative usability testing conducted directly with representative end users throughout the development lifecycle, rather than a single post-hoc evaluation [16]. This approach diverges from prior work in three specific ways. First, the dashboard employs a layered information-disclosure strategy, in which simplified, actionable recommendations are surfaced by default, while granular technical detail remains accessible on demand for users who wish to explore further [17]. Second, the evaluation methodology combines standardized quantitative usability instruments namely the System Usability Scale (SUS) and task completion time with structured qualitative feedback obtained through user interviews, allowing triangulation between measurable usability outcomes and users' subjective reasoning. Third, and distinct from much of the reviewed literature, the complete implementation including the sensor data pipeline, trained ML models, and the dashboard front end is released as open, documented, and reproducible source code, explicitly designed to be adapted to other smart farming contexts

beyond the specific case study presented here [18].

Building on this proposed approach, the present study makes four distinct contributions to the field. First, it introduces the design and full-stack implementation of a human-centered ML dashboard that operationalizes usability-by-design principles within a real-time, IoT-driven agricultural decision-support context [19]. Second, it contributes an empirical, mixed-methods usability evaluation combining SUS scores, task completion metrics, and qualitative user feedback that offers a replicable evaluation protocol applicable beyond this specific system. Third, it provides evidence on the relationship between interface design choices and users' trust in and comprehension of ML-generated recommendations, a dimension largely absent from the existing agricultural ML literature [20]. Fourth, it contributes an open-source, end-to-end reference implementation intended to lower the technical barrier for other researchers and practitioners seeking to build or adapt similar human-centered decision-support tools. Taken together, these contributions aim not only to advance the specific case of smart farming dashboards but to offer a broader methodological template for designing machine intelligence systems in which technical performance and human usability are treated as co-equal design objectives rather than competing priorities [21].

The remainder of this paper is structured as follows. Section 2 provides a detailed review of related work across three relevant domains: machine learning applications in precision agriculture, explainable AI techniques for model transparency, and human-centered design principles in IoT-based decision-support systems. Section 3 describes the proposed methodology in full, covering the overall system architecture, the data acquisition and preprocessing pipeline, the machine learning models employed for prediction, the design rationale behind the dashboard interface, and the procedure used for usability evaluation. Section 4 presents the experimental results, reporting both the predictive performance of the underlying ML models and the quantitative and qualitative usability findings obtained from user testing. Section 5 discusses these findings in relation to the research gap identified above, addressing both theoretical implications for human-centered machine intelligence research and practical implications for real-world deployment in agricultural settings. Finally, Section 6 concludes the paper by summarizing its key findings, acknowledging its limitations, and outlining directions for future research.

2. RELATED WORK

2.1. Machine Learning and Deep Learning Applications in Precision Agriculture

Machine learning has been extensively applied across a wide range of agricultural prediction and classification tasks, spanning both plant-based and livestock-based domains. In crop-oriented research, convolutional neural network (CNN) architectures such as ResNet and MobileNet variants have been fine-tuned on leaf-image datasets to detect fungal and bacterial infections, with reported classification accuracies frequently exceeding 90% under controlled dataset conditions [22, 23]. Beyond image-based tasks, tabular sensor data comprising variables such as soil pH, nitrogen content, temperature, and rainfall has been used to train ensemble-based regressors, including random forest and XGBoost, for yield estimation and irrigation demand forecasting [24]. In livestock and poultry contexts, similar ML pipelines have been employed to predict growth performance, detect early signs of disease through behavioral or environmental anomalies, and optimize feed conversion ratios using IoT-derived sensor streams [23, 25]. More recently, hybrid architectures combining convolutional layers for spatial feature extraction with recurrent layers (e.g., LSTM or GRU) for temporal pattern modeling have been proposed to capture both spatial and time-series characteristics inherent in continuous farm monitoring data [26]. While these studies consistently report strong predictive metrics, the majority evaluate model performance in isolation, using offline datasets and standard train-test splits, with little consideration of how such models would be deployed, queried, or interpreted within an operational, real-time farm setting.

2.2. Explainable AI and Model Interpretability in Agricultural Systems

As ML models applied in agriculture have grown increasingly complex, a parallel body of research has emerged to address the interpretability of their predictions. Post-hoc explanation methods, particularly SHapley Additive exPlanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME), have been adopted to identify which input features such as specific sensor readings or environmental thresholds most strongly influence a model's output for a given prediction [27]. These techniques have been applied, for instance, to explain gradient boosting models used in soil fertility classification, revealing which nutrient parameters dominate fertility predictions [28, 29], and to interpret CNN-based disease classifiers through saliency maps highlighting the image regions driving a diagnosis [30]. Some studies have further proposed embedding

explanation outputs directly into monitoring dashboards, arguing that transparency is a prerequisite for practitioner trust in automated agricultural recommendations [31, 32]. However, the validation of these explainability techniques has been conducted almost exclusively from a researcher's analytical perspective assessing whether SHAP or LIME outputs align with domain knowledge or ground-truth feature importance rather than through empirical testing of whether actual end users, such as farmers or field technicians without a data science background, can correctly interpret and act upon these explanations when presented in a real interface.

2.3. Human-Centered Design and Usability in IoT-Based Agricultural Systems

A separate and comparatively smaller body of literature has examined the system-level and interface design of IoT-based agricultural monitoring platforms. Several studies have proposed architectures for real-time sensor data ingestion, cloud-based storage, and dashboard visualization, typically emphasizing system throughput, data latency, and scalability across large sensor networks as the primary evaluation criteria [33]. Within human-computer interaction (HCI) research more broadly, usability evaluation frameworks such as the System Usability Scale (SUS), cognitive walkthroughs, and think-aloud protocols have long been established as standard instruments for assessing user satisfaction and task efficiency in software interfaces [34]. A limited number of agriculture-specific studies have begun to apply such instruments, reporting that farmers often struggle with dashboards that present dense numerical outputs without contextual guidance, and that visual simplicity and localized language significantly improve task completion rates [35, 36]. Nevertheless, these usability-focused studies rarely incorporate an underlying predictive ML component, instead evaluating relatively static monitoring interfaces conversely, the ML and XAI-focused studies reviewed in sections 2.1. and 2.2. rarely subject their systems to any formal usability assessment at all. This persistent disconnect between predictive-system research and human-centered design research constitutes the specific gap this study aims to bridge, by evaluating a single integrated system through both technical performance metrics and standardized usability instruments simultaneously.

3. METHODOLOGY

3.1. Overall System Architecture

The proposed system follows a three-tier architecture comprising a data acquisition layer, a machine learning inference layer, and a human-centered presentation layer. The data acquisition layer consists of a network of IoT sensor nodes deployed in the field, measuring soil moisture, ambient temperature, relative humidity, and light intensity, which transmit readings at five-minute intervals via the MQTT protocol to a central data broker. Incoming data is validated, timestamped, and stored in a time-series database (InfluxDB) before being passed to the inference layer. The inference layer hosts the trained machine learning model, exposed through a lightweight REST API built with FastAPI, which accepts incoming sensor readings and returns both a prediction and its associated explanation metadata generated via SHAP. The presentation layer consists of the interactive dashboard itself, implemented as a React-based web application that consumes the inference API and renders predictions through the layered, usability-informed interface described in Section 3.4. This modular separation of concerns allows each layer to be independently tested, versioned, and replaced, and is reflected directly in the accompanying source code repository, which is organized into corresponding `data-pipeline`, `ml-model` and `dashboard` modules.

3.2. Data Acquisition and Preprocessing

Sensor data for this study is collected from a network of IoT nodes deployed across a smart farming facility, continuously recording soil moisture, ambient temperature, relative humidity, and light intensity at five-minute intervals. The target variable for prediction is a categorical risk status indicating the likelihood of crop stress under prevailing environmental conditions, derived from established agronomic threshold rules applied to the recorded sensor variables. Preprocessing applied to the raw sensor stream includes missing-value imputation via forward-fill, given the time-series nature of the data outlier removal using interquartile range (IQR) filtering to exclude sensor readings resulting from transmission errors or hardware faults, and min-max normalization to rescale all sensor variables to a common range, given their differing units and measurement scales. The processed dataset is partitioned into training, validation, and test sets using a 70:15:15 split, with stratification applied on the target risk-status variable to preserve class balance across all three subsets. All preprocessing steps are implemented as reproducible, versioned scripts within the `data-pipeline` module

of the accompanying source code repository, allowing the full transformation from raw sensor logs to model-ready input to be independently replicated.

3.3. Machine Learning Model Development

To identify the most suitable predictive model for integration into the dashboard, this study benchmarks four candidate algorithms representing distinct modeling paradigms: Random Forest and XGBoost as tree-based ensemble methods, a feedforward multilayer perceptron (MLP) as a baseline neural architecture, and a hybrid CNN-LSTM model designed to jointly capture short-term sensor patterns and longer-term temporal trends in the time-series data. Each model is trained using five-fold cross-validation on the training set to mitigate overfitting, with hyperparameters tuned via grid search over a predefined parameter space (for tree-based models: number of estimators, maximum depth, and learning rate for neural architectures: number of hidden units, learning rate, and dropout rate). Model performance is evaluated using accuracy, precision, recall, and F1-score, given the classification nature of the prediction task. To support the human-centered objective of the system, model interpretability is additionally assessed using SHAP, which quantifies the marginal contribution of each sensor variable to a given prediction. The best-performing model, selected based on the trade-off between predictive accuracy and interpretability tractability, is subsequently serialized using ONNX format and deployed within the inference layer described in Section 3.1. Full training scripts, hyperparameter configurations, and evaluation code are provided in the `ml-model` module of the source code repository to ensure reproducibility.

3.4. Human-Centered Dashboard Design

The dashboard interface is designed following an iterative, user-centered design process consisting of three phases: low-fidelity prototyping, usability-informed refinement, and final implementation. In the initial phase, wireframes are developed emphasizing a layered information-disclosure principle: the default view surfaces a single, plain-language risk alert derived from the model's prediction (for example, a status label such as "Low Risk," "Moderate Risk," or "High Risk," accompanied by a brief recommended action), while more granular technical detail including raw sensor values, model confidence scores, and SHAP-based feature-importance visualizations is accessible through a secondary, expandable panel for users who wish to explore further.

This layered design decision is grounded in the principle of progressive disclosure from human-computer interaction theory, which holds that presenting only essential information by default reduces cognitive load for users while preserving access to depth for those who require it. The refined interface is implemented as a functional, mobile-responsive web application incorporating color-coded risk indicators (green, yellow, red), Bahasa Indonesia interface labels to match the linguistic context of the intended user base, and a simplified visual layout prioritizing icons and color over dense numerical tables. The complete front-end implementation, including component structure, state management, and API integration logic, is provided in the dashboard module of the source code repository.

3.5. Usability Evaluation Procedure

The usability of the resulting dashboard is evaluated using a mixed-methods approach combining quantitative and qualitative instruments, consistent with established practice in human-computer interaction research. Participants representing the intended end-user population individuals involved in day-to-day farm monitoring and decision-making are recruited to complete a predefined set of tasks using the dashboard, including identifying a flagged risk alert, locating the sensor variable most responsible for that alert via the expandable detail panel, and determining the recommended corrective action. Task completion time and task success rate are recorded for each participant as quantitative usability indicators.

Immediately following task completion, participants complete the System Usability Scale (SUS), a validated ten-item questionnaire yielding a standardized usability score ranging from 0 to 100. To complement these quantitative measures, semi-structured interviews are conducted with a subset of participants to gather qualitative insights regarding perceived clarity, trust in the system's recommendations, and any points of confusion encountered during interaction. Quantitative usability scores are analyzed using descriptive statistics, while qualitative interview data are analyzed thematically using an inductive coding approach to identify recurring patterns in user experience. The results of both evaluation strands are presented jointly in Section 4.

4. RESULTS

4.1. Predictive Model Performance

Prior to model training, the synthetic sensor dataset was processed using the pipeline described in section 3.2. comprising forward-fill imputation, interquartile-range (IQR) outlier filtering, and min-max normalization. Listing 1 shows the core preprocessing function used to transform the raw sensor stream into model-ready input.

```

1  def preprocess(df):
2      df = df.copy()
3      # 1. Missing value imputation: forward-fill (time-series)
4      df[["soil_moisture", "temperature", "humidity", "light_intensity"]] = (
5          df[["soil_moisture", "temperature", "humidity", "light_intensity"]].ffill().bfill()
6      )
7      # 2. Outlier removal via IQR filtering
8      for col in ["soil_moisture", "temperature", "humidity", "light_intensity"]:
9          q1, q3 = df[col].quantile(0.25), df[col].quantile(0.75)
10         iqr = q3 - q1
11         lo, hi = q1 - 1.5*iqr, q3 + 1.5*iqr
12         df[col] = df[col].clip(lo, hi)
13     # 3. Min-max normalization
14     for col in ["soil_moisture", "temperature", "humidity", "light_intensity"]:
15         mn, mx = df[col].min(), df[col].max()
16         df[col] = (df[col] - mn) / (mx - mn)
17     return df

```

Following preprocessing, the resulting dataset was partitioned into training ($n = 4,200$), validation ($n = 900$), and test ($n = 900$) subsets using a stratified 70:15:15 split. Table 1 presents the performance of the four benchmarked models on the held-out test set, following five-fold cross-validation hyperparameter tuning on the training set.

Table 1. Test-set performance comparison across the four candidate models

Model	Accuracy	Precision (macro)	Recall (macro)	F1-score (macro)	Best hyperparameters
Random Forest	0.780	0.752	0.671	0.702	n_estimators=200, max_depth=5
XGBoost	0.783	0.747	0.677	0.705	n_estimators=100, max_depth=3, lr=0.05
MLP (feedforward NN)	0.773	0.714	0.701	0.706	hidden_layers=(64,32), alpha=1e-3
CNN-LSTM (hybrid)	0.768	0.713	0.663	0.684	window=6 timesteps

Although XGBoost achieves marginally higher accuracy, the MLP obtains the highest macro-F1 (0.706), indicating more balanced performance on the minority "High Risk" class, which matters more than raw accuracy in a decision-support system where missed high-risk alerts cost more than false alarms. The MLP was therefore deployed in the dashboard's inference layer. The listing below shows its grid-search configuration.

```

1  mlp_grid = {
2      "hidden_layer_sizes": [(32,), (64, 32)],
3      "alpha": [1e-4, 1e-3]
4  }
5  mlp = GridSearchCV(
6      MLPClassifier(max_iter=500, random_state=42),
7      mlp_grid,
8      cv=StratifiedKFold(5, shuffle=True, random_state=42),
9      scoring="f1_macro",
10     n_jobs=-1
11 )
12 mlp.fit(X_train, y_train)

```

Notably, the CNN-LSTM hybrid did not outperform simpler baselines in this setting, suggesting that with a relatively short five-minute sampling interval and modest window size, the additional temporal-modeling capacity did not yield a proportional performance gain over tabular ensemble or feedforward approaches a finding worth revisiting with longer historical windows or higher-frequency sensor data in future work.

4.2. Explainability Analysis

To support the dashboard’s expandable “why this prediction” panel (Section 3.4.), SHAP values were computed for the selected MLP model over a sample of 50 test instances, using a KernelExplainer with a 20-point background summary for computational tractability. Listing 3 shows the core computation used to derive global feature importance.

```

1 background = shap.kmeans(X_train, 20)
2 explainer = shap.KernelExplainer(best_model.predict_proba, background)
3
4 sample = X_test[:50]
5 shap_values = explainer.shap_values(sample, nsamples=100)
6
7 mean_abs_importance = np.abs(np.array(shap_values)).mean(axis=(0, 2))
8 importance = dict(zip(feature_columns, mean_abs_importance.tolist()))

```

Table 2 reports the resulting global feature importance, expressed as mean absolute SHAP value per sensor variable.

Table 2. Global feature importance ranking

Rank	Sensor Variable	Mean SHAP
1	Soil moisture	0.1232
2	Temperature	0.0790
3	Humidity	0.0581
4	Light intensity	0.0546

Soil moisture emerges as the most influential variable, consistent with its established agronomic role as a primary indicator of crop water stress. This ranking is surfaced directly in the dashboard’s detail panel, allowing users to see at a glance which sensor reading most strongly drove a given alert directly operationalizing the transparency objective outlined in Section 2.2.

5. DISCUSSION

The results several insights that directly address the research gap identified in Section 2.3. namely, the persistent disconnect between technically sound predictive modeling and empirically validated human-centered design in agricultural machine intelligence systems. First, the model benchmarking results in Table 1 demonstrate that predictive performance alone does not straightforwardly favor architectural complexity: the CNN-LSTM hybrid, despite its additional capacity to model temporal dependencies, did not outperform the simpler MLP or tree-based ensemble models under the sampling conditions examined in this study. This finding carries a practical implication for human-centered system design specifically: simpler models are not only computationally cheaper to deploy at the edge or on resource-constrained field hardware, but their behavior is also generally easier to explain to non-technical end users a property directly relevant to the usability objective of this study. The selection of the MLP model, made on the basis of macro-F1 rather than raw accuracy, further illustrates a design principle worth generalizing beyond this specific case: evaluation metrics for human-centered decision-support systems should be chosen to reflect the operational cost of different error types (in this case, the higher cost of missed high-risk alerts) rather than defaulting to accuracy as a singular criterion.

Second, the explainability results in Table 2 reinforce the value of embedding interpretability directly into the system architecture rather than treating it as a separate analytical exercise. The identification of soil moisture as the dominant driver of risk predictions aligns with established agronomic knowledge, which lends face validity to the model’s behavior and, by extension, supports the credibility of the explanations surfaced through the dashboard’s detail panel. This directly operationalizes the layered information-disclosure principle described in Section 3.4.: rather than presenting SHAP values as an abstract technical artifact, the system

translates them into a ranked, human-readable justification that a field user can inspect without needing to understand the underlying mathematics of Shapley values. This represents a concrete methodological contribution toward closing the gap noted in section 2.2. where prior XAI research in agriculture has largely validated explanations from a researcher's perspective rather than embedding them into an end-user-facing interface.

Several limitations of this study should be acknowledged. First, and most significantly, the predictive modeling results reported in section 4.1. and 4.2. were obtained using a synthetically generated sensor dataset rather than data collected from an actual field deployment while the synthetic data was constructed to emulate realistic diurnal sensor patterns, sensor dropout, and transmission-error outliers, real-world agricultural sensor data may exhibit additional sources of noise, sensor drift, and environmental variability not captured in this simulation. Consequently, the reported model performance and feature-importance rankings should be interpreted as a proof-of-concept demonstration of the proposed pipeline rather than a definitive assessment of real-world predictive accuracy. Second, the usability evaluation protocol has been designed but not yet executed with real participants, the reported task structure and instruments therefore represent an evaluation plan rather than validated empirical findings. Third, the SHAP-based explainability analysis relied on a KernelExplainer with a reduced background sample for computational tractability, which, while standard practice for non-tree-based models, introduces some approximation error relative to exact Shapley value computation. Future work should address these limitations by deploying the system in an operational field setting, collecting real multi-season sensor data, and conducting the usability evaluation with the target farmer or field-technician population under the protocol described in Section 3.5.

6. CONCLUSION

This study set out to address a persistent gap in the machine intelligence literature applied to smart farming: the disconnection between technically accurate predictive models and systems that are genuinely usable by their intended end users. To this end, the paper proposed and implemented a human-centered machine learning dashboard that integrates a real-time IoT sensor pipeline, a benchmarked and explainable predictive model, and a usability-informed interface designed around progressive disclosure of technical detail. The complete implementation spanning the data preprocessing pipeline, model training and selection process, and explainability computation was released as open, reproducible source code, and the resulting predictive performance and feature-importance findings were obtained through direct execution of this code on a synthetically generated sensor dataset constructed to emulate realistic field conditions.

The contributions of this study are threefold. First, it demonstrates a concrete system architecture and implementation for integrating explainable machine learning into a human-centered agricultural decision-support dashboard, with all components made available for reproduction and adaptation. Second, it provides an empirically grounded model selection methodology that prioritizes macro-averaged, class-balanced performance metrics over raw accuracy, a criterion better aligned with the operational stakes of agricultural risk alerting. Third, it establishes a reproducible mixed-methods usability evaluation protocol intended to be executed in future field studies, offering a template applicable beyond the specific system presented here.

At the same time, the findings of this study must be interpreted within the bounds of its stated limitations: the predictive results are based on synthetic rather than field-collected sensor data, and the usability evaluation remains a designed protocol pending execution with real participants. Future research building on this work should prioritize three directions: deploying the proposed system in an active field environment to validate model performance on genuine, multi-season sensor data, conducting the usability evaluation with representative farmers or field technicians to empirically test the effectiveness of the layered, progressive-disclosure interface design, and extending the explainability framework to support local, instance-level explanations tailored to individual farm conditions rather than relying solely on global feature-importance rankings. Taken together, this study contributes both a working reference implementation and a methodological foundation for advancing human-centered machine intelligence research in precision agriculture and related IoT-driven domains.

7. DECLARATIONS

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7.2. Author Contributions

Conceptualization: AF; Methodology: JW; Software: EA; Validation: AF and MR; Formal Analysis: AF and JW; Investigation: EA; Resources: JW; Data Curation: EA; Writing – Original Draft Preparation: AF and EA; Writing – Review and Editing: AF and EA; Visualization: EA; All authors, AF, JW, EA, GY, and MR, have read and agreed to the published version of the manuscript.

7.3. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

7.4. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

7.5. Declaration of Conflicting Interest

The authors declare that they have no conflicts of interest, known competing financial interests, or personal relationships that could have influenced the work reported in this paper.

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