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INTELLIGENT LAND SUITABILITY ANALYSIS UTILIZING MULTILAYER PERCEPTRON AND IOT SENSORS

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ABSTRACT

In contemporary agriculture, intelligent computational models are becoming increasingly popular in analysing land suitability to achieve greater precision and scale. The paper is a comparison of hybrid and advanced Multilayer Perceptron (MLP) architectures with rich Internet of Things (IoT) sensor data on a large, real-world data set (10,000+ samples, 50. The purpose is to rigorously test the robustness, accuracy, and computational speed of both MLP-based IoT systems in a practical agricultural environment. In high-dimensional, information-rich settings, the advanced MLP coupled with advanced IoT sensors (which comprises drone-acquired Normalised Difference Vegetation Index (NDVI)) achieves 92.4% accuracy, a 0.91 F1 score, and a 0.88 Matthews Correlation Coefficient (MCC), surpassing the hybrid model. The Hybrid MLP + Hybrid IoT Sensor, on the other hand, has a robustness score of 0.9 and operates well in handling noisy circumstances, real-time inference, and quick deployment. Both models facilitate practical and context-sensitive benchmarking so that the appropriate system can be chosen by the stakeholders. The study contributes to methodological practices in land suitability assessment and provides recommendations to scale to additional crops, areas, and sensors to promote data-informed and robust agricultural decision support.

Keywords: *Land suitability, Multilayer Perceptron, IoT sensors, Agriculture, Normalised Difference Vegetation Index (NDVI)*

1. INTRODUCTION

Land suitability analysis has advanced beyond mere agronomic surveys and resource management policies to modern contemporary demands of food insecurity and scarcity of resources and climate change impacts [1], [2]. Traditionally, the process of identifying optimal land use in agriculture involved manual field inspection and human expertise, but they have been unable to keep up with the requirements of fast-moving environments, vast amounts of data, and the need to be able to provide accurate, location-editable recommendations.

The proven ability of MLPs combined with advanced IoT sensors to model nonlinear interactions in complex, multidimensional agricultural data drives the adoption of intelligent techniques. While IoT platforms, such as ground-based and aerial (drone) systems, supply the detailed, real-time data needed for comprehensive land assessment, MLPs are powerful tools for identifying subtle patterns from various sensor inputs [3], [4]. The integration of these computational and sensing technologies presents a way to automate, scale, and conduct context-specific land suitability analyses, providing actionable recommendations that may not be achievable with manual or conventional methods.

Particularly, this research identifies the extent to which integrating hybrid and advanced MLP models with IoT sensors can enhance the accuracy of a land suitability analysis, its efficiency, and its relevance to the performance of ground operations. The

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problem addressed is developing and comparatively benchmarking such intelligent model-sensor pairings to create robust, situationally-adaptive classification of over a variety of agricultural conditions and data conditions [5].

Whether advanced MLPs, given deep and varied sensor data, can excel over hybrid MLP variants, both in terms of overall accuracy and in critical real-world circumstances like noisy or information-rich contexts, is the main research question driving this work. The main hypothesis is that intelligent, data-driven, MLP and sensor combinations will lead to substantial increases in the quality of classification, robustness and deployment predisposition of land suitability analysis [6].

This study is important as it advances the methodological horizon for intelligent land suitability modelling with realistic, useful benchmarks employing hybrid and advanced MLPs, rather than comparing with old or legacy systems. With visible, actionable output from massive, complicated datasets, the results directly address significant problems in contemporary agriculture, including optimising resource efficiency and facilitating scaled, site-specific planning [7].

The novelty of this study is its systematic comparison of hybrid and advanced MLP architectures that are trained and gauged on a synchronised, high-volume IoT sensor data, including multispectral drone data and on an extraordinarily large and diverse agricultural dataset. The primary objectives are to evaluate and compare the predictive strength, computational efficiency, and operational robustness of these model-sensor systems, provide a holistic framework for risk-aware, context-driven deployment and derive practical deployment recommendations and empirical insights based on comparative performance and robustness findings of hybrid and advanced MLP-IoT land suitability systems [8].

The primary objectives are to assess and compare predictive power, calculational efficiency, and operational robustness of these model-sensor systems, offer a holistic framework to formulate risk-aware and context-specific deployment, and draw actionable recommendations and empirical understanding on the deployment of these MLP-IoT land suitability systems through comparative performance and robustness finding of hybridised and advanced models. The paper's structure includes the following sections: survey of literature, materials and techniques, model construction, results with comparative analysis, discussion considering existing literature and practical implications and a conclusion that offers important insights and directions for further study.

2. LITERATURE SURVEY

The advent of digital agriculture has led to land suitability analysis becoming a rapidly developing field, as it uses machine learning (ML) and IoT sensors to address issues of efficiency, robustness, and scale of data [9]. Early approaches involved expert-centred and geospatial mapping, although more recently, an apparent transition to data-driven frameworks that combine sensor time-series, satellite imaging, and multi-criteria evaluation has become apparent [10]. In practical applications, although parametric and rule-based methods remain an essential element in crop and agro-climatic classification, ML approaches (such as Random Forests, Support Vector Machines, and neural networks) still show better accuracies, adaptations, and generalisations [11].

IoT-enabled smart agriculture platforms have become the providers of abundant environmental data streams of soils, climates, and crops. The existing studies prove the idea that a strategic combination of IoT and ML wires real-time decision making, risk management, and optimised resource use in the field [12]. In agricultural datasets, hybrid models combining deep learning, such as MLPs, with a variety of sensor inputs are particularly effective at inducing nonlinear phenomena, improving classification performance and scaling strength. NDVI-based remote sensing using drones builds further on these methods by offering high-resolution data, which directly increases land suitability forecasting and precision agriculture management [13]. Nevertheless, the literature still has critical constraints, even after the advances. Several studies have been made that use small or local data, which have the negative effects of limiting generalisation and the danger of overfitting. Noise recording, missing values, and ambiguous data toleration, although repeatedly described as an essential requirement it remain rarely tested in active, real-world conditions [14].

In some cases, robustness-aware modelling methods (e.g. drop-out, batch normalisation) are introduced, though they are often tested on artificially clean data, which do not reflect real-world complexities [15]. Comparative analyses on various model-sensor combinations specific to applications are still not common, although their importance in real-world implementation is well-known. Finally, deep neural models may lack interpretability, which reduces user trust and the ability to receive regulatory and stakeholder approval [16].

Overall, the latest research highlights several important points: the efficacy of machine learning and IoT sensing in determining land suitability, the power of multi-layer perceptrons and hybrid neural networks in managing intricate agro-environmental interactions, the value of integrating sensors from both drones and the ground to improve spatial and temporal analytics, and the ongoing requirement for broader and more varied datasets, practical benchmarking, and evaluation frameworks that take context into account [17], [18]. This research comprehensively compares hybrid and advanced MLP-IoT systems on a large, complex dataset, utilising robust and practical assessment methodologies that are in line with the newest best practices. It explicitly tackles these suggestions and shortcomings.

3. METHODOLOGY

3.1. Research Design and Study Area Description

The study design is in the form of a comparative, cross-sectional experiment over an area that is diverse enough in soil type, topography, and crop diversity. The approach facilitates the assessment of sensor and model-specific performance in multi-crop land suitability prediction. The distribution of field plots ensures the robustness and generalizability of the findings by reflecting all significant environmental gradients in the research region. To manage massive, varied data more accurately and efficiently, recent developments have lifted land suitability analysis above traditional methods by emphasising the combination of high-resolution sensing technologies with advanced MLP models.

3.2. Data Collection Using IoT Sensors

The foundation of this work is multi-parametric, high-resolution, and accurate data, which allows for a direct and comprehensive comparison of advanced and hybrid models and sensors.

3.2.1. Hybrid IoT Sensor

Long Range (LoRa) probes based on the Raspberry Pi and Arable Mark are used to gather important agricultural data, including temperature, pH, electrical conductivity, and soil moisture. The Raspberry Pi system offers a versatile, affordable option with customisable sensor integration, while Arable Mark offers an integrated, solar-powered solution with integrated wireless data transfer. Both systems transmit their data remotely using different methods (Arable using cellular connection and Raspberry Pi through the LoRa technology), which provides a possibility to continuously track data and conduct analysis. The combination of the two makes them very robust, scalable and flexible to collect data on precision agriculture usage and for classical MLP and fuzzy logic analyses. The proposed system of architecture of land suitability, which combines hybrid and advanced models of MLP with multi-source IoT sensors information, is shown in Figure 1.

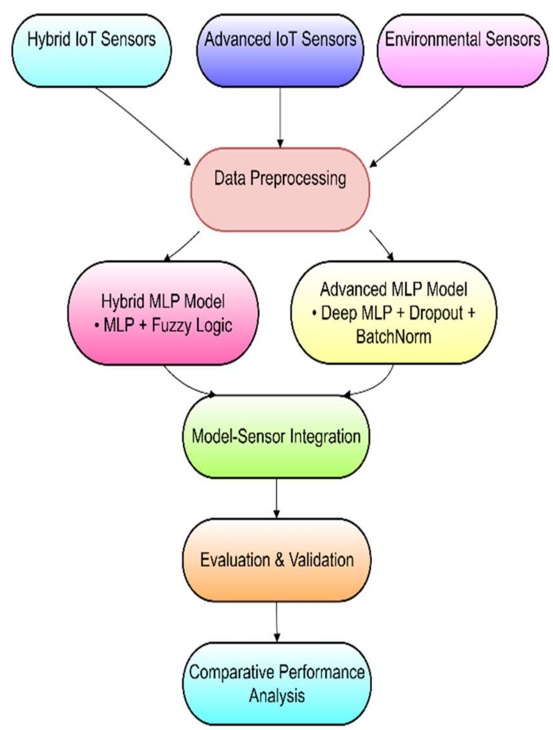

Figure 1 Proposed Architecture for MLP-Based Land Suitability Analysis

3.2.2. IoT Sensor: NDVI via Multispectral Drone

Agricultural plots are routinely surveyed by drones fitted with multispectral sensors, such as the Parrot Sequoia, which record the NDVI and other important spectral bands. These sensors provide information on crop vigour and health changes across space, canopy temperature, extra vegetation indicators, and NDVI. High-resolution, field-scale information that is harder to get with ground-based sensors alone are provided by such aerial sensing. This information improves predicted accuracy in deep MLP-based studies and is essential for geographically specific crop suitability modelling. It enables high-dimensional data applications and precision agriculture by supporting large-scale monitoring.

SHT31 Sensor, Tipping Bucket Rain Gauge and Apogee SQ-110 are the additional sensors used to record ambient temperature, humidity, rainfall, and light intensity throughout the year.

3.2.3. Data sources and sample size

Primary Dataset: Over 10,000 distinct, time-stamped observations matched to both model types were obtained using time-series sensor and drone data acquired in situ from 50 geo-tagged field plots, sampled at least twice a week for a minimum of 12 months.

Public Supplementary Data: With complete alignment to in-field observed variables (such as soil pH, EC, NDVI, and rainfall), data from the Open Soil Data Portal (https://www.data.gov.in/keywords/soil) and comparable sources provide history and validation information while guaranteeing cross-compatibility with all model and sensor inputs.

3.3. Data Preprocessing and Feature Selection

The data is combined, synchronised with time, and georeferenced from all sources, including probes, drones, and public databases. The following is the preprocessing protocol:

- Outlier Detection: Sensor abnormalities are eliminated, and missing data are filled in using appropriate statistical interpolation.
- Normalisation: To guarantee constant amplitude for neural network inputs, input elements are subjected to min-max normalisation.
- Feature Selection: All model pipelines employ a combination of L1 regularisation, recursive feature elimination (RFE), and correlation analysis. By balancing the complexity of the model with the informativeness of the data, this process ensures that only the most predictive variables for land suitability are retained.

3.4. Multilayer Perceptron Model Design and Training

This section covers each of the mathematical modelling procedures used in the implementation of the Deep MLP+Dropout+BatchNorm and Hybrid MLP+Fuzzy Logic models:

3.4.1. Hybrid MLP model: MLP + Fuzzy logic

The study uses hybrid MLP+Fuzzy Logic, as MLP offers classification based on nonlinear interactions, and fuzzy rules are employed to handle ambiguity in soil and environment characteristics.

Input to Hidden Layer Transformation: This process aggregates weighted, normalised input features like sensor variables and fuzzified inputs as per the hidden neuron. It is used to combine all input feature effects for subsequent nonlinear transformation.

$$z_j^{(1)} = \sum_{i=1}^{n} w_{ji}^{(1)} x_i + b_j^{(1)} \tag{1}$$

Where, $w_{ji}^{(1)}$ Is the weight, x_i Is the feature, $b_j^{(1)}$Is the bias for the neuron j.

Activation Function: This function introduces nonlinearity via Rectified Linear Unit (ReLU) to model complex soil-crop-climate relationships. It enables the detection of nonlinear interactions between environmental variables.

$$a_j^{(1)} = \phi\left(z_j^{(1)}\right) \tag{2}$$

Where, ϕ Is the activation function, $z_j^{(1)}$ Is the input to the neuron.

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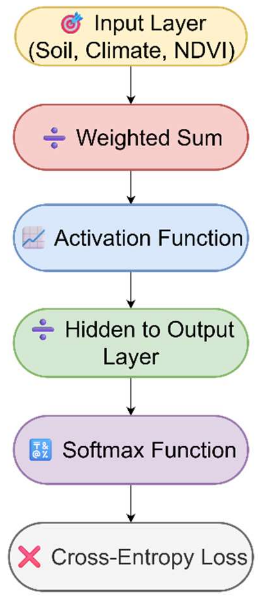

Figure 2 Hybrid MLP Model Architecture

Figure 2 shows the architecture of the hybrid MLP model of land suitability classification, which depicts the major steps in classification from the entry of sensor data to output prediction.

Hidden Layer to Output Transformation: It is used to aggregate abstracted hidden layer information to the output layer for crop suitability classification. This transformation also integrates information across hidden neurons into class scores for final predictions.

$$z_k^{(2)} = \sum_{j=1}^{m} w_{kj}^{(2)} a_j^{(1)} + b_k^{(2)} \qquad (3)$$

Where, $w_{kj}^{(2)}$ is the hidden-output weight; $a_j^{(1)}$ is the activation; $b_k^{(2)}$ Is the bias.

Softmax Probability Output: Employed to convert raw scores into probabilities for each suitability class. It ensures outputs lie in probability space summing to 1, supporting multiclass classification.

$$y_k = \frac{e^{z_k^{(2)}}}{\sum_{l=1}^{K} e^{z_l^{(2)}}} \qquad (4)$$

Where$z_k^{(2)}$Is the class k activation, and K is the number of classes.

Cross-Entropy Loss: This function measures the difference between predicted and true suitability classes, guiding model training. It is used to properly penalise prediction errors, leading to optimal class separation.

$$L = -\sum_{k=1}^{K} y_k^{(true)} \log(y_k^{(pred)}) \qquad (5)$$

Where, $y_k^{(true)}$ Is the ground truth? $y_k^{(pred)}$ Is the predicted probability.

Fuzzy Logic Overlay: For parameters with ambiguous or unclear limits, such as soil pH or rainfall, this module works in conjunction with the MLP to apply rule-based categorisation.

3.4.2. Advanced MLP model: deep MLP with dropout and batch normalisation

This advanced model is designed for high-dimensional, fused multispectral and IoT data to learn complex nonlinear relationships. In this architecture, all five steps of hybrid MLP are used, with batch normalisation added before the activation function and dropout added after the activation function. Both models (Hybrid and Deep MLP) are trained on the identical preprocessed and feature-selected data for fair comparison. Key layers from input to output are shown in the architecture of the advanced MLP used for classifying land suitability (Figure 3).

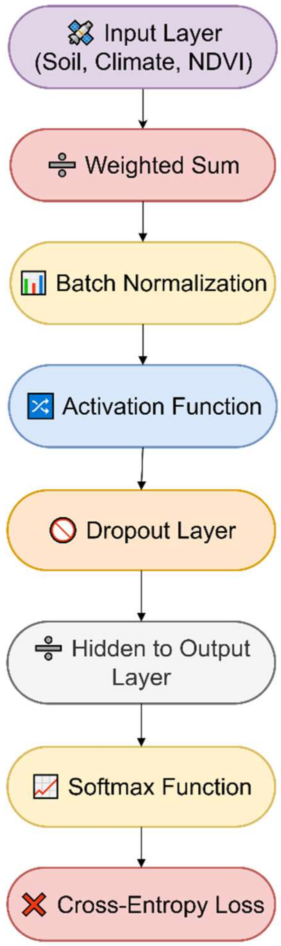

Figure 3: Advanced MLP Architecture for Land Suitability Classification

Batch Normalisation: Normalises layer outputs during training, supporting faster, more stable learning with varied inputs.

$$\hat{z}_j^{(1)} = BN\left(z_j^{(1)}\right) = \frac{z_j^{(1)} - \mu}{\sqrt{\sigma^2 + \epsilon}} \cdot \gamma + \beta \quad (6)$$

Where, μ is the batch mean, σ^2 Is the batch variance, ϵ is the small constant (prevents division by 0), and γ, β There are learnable parameters to scale and shift.

Dropout Layers: This layer randomly deactivates neurons during training to prevent overfitting from correlated or redundant inputs.

$$\tilde{a}_j^{(1)} = a_j^{(1)} \cdot r_j, r_j \sim Bernoulli(p) \quad (7)$$

Where, $a_j^{(1)}$ Is the activated output from the hidden neuron j, r_j Is the random mask (0 or 1) drawn from a Bernoulli distribution with probability p and $\tilde{a}_j^{(1)}$ Is the output after dropout, with some neurons set to 0?

3.5. Application Context Performance Metrics

Application context metrics provide composite ratings based on weighted and averaged normalised base metrics, as well as qualitative variables, to summarise the suitability of model-sensor pairs for practical usage. High-dimensional data handling is evaluated by improvements in accuracy and F1 on fused, high-dimensional inputs; interpretability is based on expert evaluation of decision logic clarity and model transparency; speed is measured by inference and training time; and robustness is represented by the approximate minimum class F1 under added noise or ambiguity. When combined, these metrics enhance conventional assessment techniques and provide a more useful viewpoint on the suitability of the model in various operational contexts.

3.6. Model-Sensor Integration & Comparative Protocol

Two main combinations are used to structure model-sensor integration: Hybrid MLP in conjunction with a Hybrid IoT sensor and advanced MLP in conjunction with an advanced IoT sensor. Every pair conforms to the same experimental methodology and is assessed using the same time-synchronised datasets. K-fold cross-validation is used for all combinations to provide fair and dependable benchmarking, enabling performance comparison under consistent settings.

3.7. Validation Protocol and Evaluation Metrics

The metrics in Table 1 serve as the main quantitative assessment criteria, carefully measuring model resilience and classification quality.

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Table 1. Metrics Mapped To Key Application Attributes For Model Evaluation

Evaluation Metric	Attribute Measured
Accuracy	General model correctness
F1 Score	Robustness under class imbalance and noise
Matthews Correlation Coefficient (MCC)	Balanced performance across all classes
Cohen's Kappa	Agreement and interpretability
ROC-AUC	Sensitivity to class discrimination (binary/multiclass) supports robustness and high-dimensional input evaluation.

The comparative findings of hybrid and advanced MLP systems across several performance aspects are shown in the next part, which is based on the suggested models, sensors, and testing methodologies.

4. RESULTS

4.1. Data Overview and Quality Assessment

The primary data attributes gathered for land suitability modelling are compiled in Table 2 below.

Table 2: Dataset Overview For Model Evaluation

Metric	Value
Total samples	10,000+
Number of plots	50
Duration	12 months
Missing values	<2% (handled)
Features kept	70%

This table presents the 10,000+ data points collected from 50 field plots over one year. There was minimal missing data, and the critical aspects like soil, climatic, and vegetation properties were retained by careful feature selection. The robust and fair evaluation of both advanced and hybrid models is guaranteed by the dataset's size and thorough preprocessing.

4.2. Performance Metrics: Hybrid vs Advanced Model-Sensor Pairs

Table 3 shows that the advanced MLP with an advanced IoT sensor produces an accuracy of 92.4%, an F1 score of 0.91 and a Matthews correlation coefficient of 0.88. Comparatively, the Hybrid MLP model, with Hybrid IoT Sensor, yields the results with 88.3% accuracy, F1 score of 0.86 and Matthews correlation of 0.82. These statistics indicate that the advanced model-sensor system is more competent than the hybrid one in all aspects, in that it is better at modelling complex and multi-modal data as well as providing better land suitability classification.

Table 3 Model-Sensor Fusion Performance Metrics

Metric	Hybrid MLP + Hybrid IoT Sensor	Advanced MLP + Advanced IoT Sensor
Accuracy (%)	88.3	92.4
F1 Score	0.86	0.91
MCC	0.82	0.88

In contrast to the Hybrid MLP + Hybrid IoT Sensor, which attains an AUC of 0.91, the Advanced MLP + Advanced IoT Sensor provides better discrimination between appropriate and inappropriate land classes with an AUC of 0.95. The advanced system's ROC curve continuously remains above the hybrid system, demonstrating a greater true positive rate at every false positive level, making this distinction visually apparent (Figure 4).

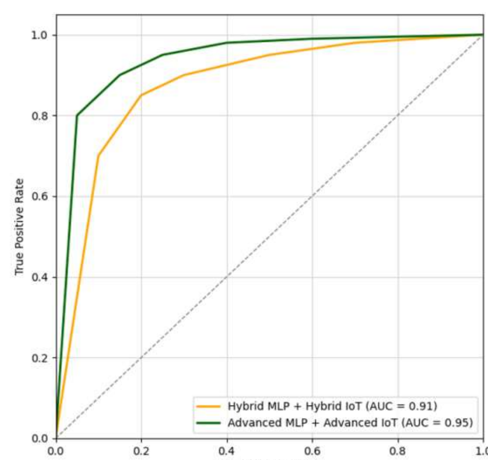

Figure 4: ROC Curve Comparison of Model-Sensor Performance

With Advanced MLP and Advanced IoT Sensor, there is a better, precise land suitability classification. It has superior ROC-AUC, which illustrates a consistent, acceptable performance in determining the right areas of interest on land in diverse threshold settings. As a result, when maximal classification quality is essential, the advanced system is the better option.

4.3. Confusion Matrix and Class-Wise Analysis

Featuring fewer misclassifications of just 25 and 15 errors for Highly Suitable and 20 and 10 for Not Suitable, the Advanced MLP + Advanced IoT Sensor matrix shows a greater count of true positives for all classes: 450 (Highly Suitable), 430 (Moderately Suitable), and 470 (Not Suitable). (Figure 5).

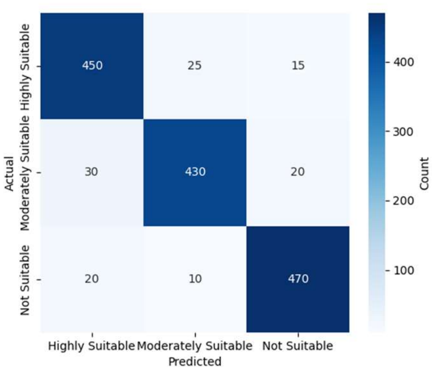

Figure 5: Confusion Matrix: Advanced MLP + Advanced IoT Sensor

The Hybrid MLP + Hybrid IoT Sensor, by contrast, returns 420, 410 and 440 true positives and a far larger volume of off-diagonal errors, particularly to the categories of Highly Suitable and Moderately Suitable (40 and 30, and 45 and 35, respectively) (Figure 6).

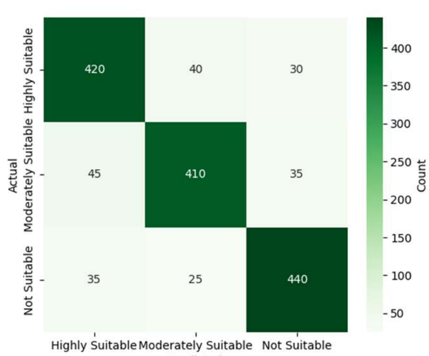

Figure 6: Confusion Matrix: Hybrid MLP + Hybrid IoT Sensor

The advanced model minimises misclassifications, particularly in crucial land suitability groups, by achieving more accurate and consistent class predictions. With greater rates of predicting neighbouring classes, the hybrid method is more likely to confuse borderline situations. When reducing false positives and negatives and achieving high individual class accuracy are critical for decision-making, the advanced model is the better option from an operational standpoint.

4.4. Computational Efficiency

The quickest training scenario is represented by the Hybrid MLP + Hybrid IoT Sensor, which is used as the baseline with a relative training time of 1.0x. In order to adequately represent the higher level of model complexity and depth, the Advanced MLP + Advanced IoT Sensor takes 1.3 times as long to train as the hybrid system. Both methods are effective for real-time applications since their inference times are less than one second. Robustness scores (0.70 advanced, 0.90 hybrid) measure performance in the presence of unclear or noisy data (Table 4).

Table 4. Computational Efficiency Comparison of Model-Sensor Systems

Model-Sensor Combo	Relative Training Time	Inference Time (sec)	Robustness (Noise/Ambiguity)
Hybrid MLP + Hybrid IoT Sensor	1.0x (Baseline)	< 1	0.9
Advanced MLP + Advanced IoT Sensor	1.3x (Baseline	< 1	0.7

The hybrid system works well in settings where robustness is crucial and for quick deployment. When more classification accuracy is required and longer training durations are permitted, the advanced system is the better choice.

4.5. Application Contexts Performance Comparison

Each model-sensor combination's performance under certain, realistic circumstances is described in depth in Figure 7. The Hybrid MLP + Hybrid IoT Sensor performs very well in low-resource or real-

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time scenarios (0.95 versus 0.60) and excels at managing noisy or unclear data (0.90 vs 0.70). The Advanced MLP + Advanced IoT Sensor, on the other hand, performs better in precision agriculture (0.92 vs. 0.80) and leads in high-dimensional data contexts (0.95 vs. 0.75).

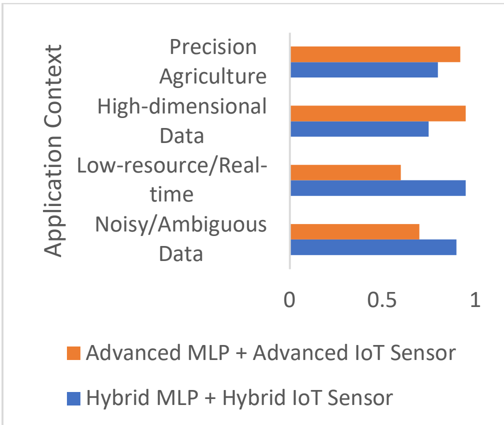

Figure 7 Model-Sensor Performance in Diverse Operational Scenarios

The hybrid system is the better option for situations that demand resilience to noisy inputs or require fast, reliable operation in resource-constrained settings. The advanced system excels in analytical, data-intensive applications and precision agricultural activities because of its capacity to analyse complicated, information-rich data and provide very accurate outputs.

Key trade-offs comparing the two systems are revealed by the observed outcomes, and they are further interpreted in the discussion that follows to comprehend their practical consequences.

5. DISCUSSION

This paper developed and benchmarked intelligent land suitability models through a rich and mixed set of data based on a hybrid Multilayer Perceptron (MLP) with fuzzy logic (and classic sensors), of a more complex Multilayer Perceptron (MLP) with deep sensing capabilities, such as drone NDVI. With 92.4% accuracy, 0.91 F1 score, and 0.88 MCC, the advanced MLP + Advanced IoT Sensor continuously outperformed its competitors in key classification parameters. It performed well in high-dimensional, complicated scenarios like precision agriculture. The hybrid model, on the other hand, showed distinct benefits in terms of training speed (baseline 1.0x), resistance to ambiguity or noise (score: 0.90), and low-resource or real-time circumstances (score: 0.95) [19]. These results reflect well with the research objectives that aimed to explain the trade-offs that exist between the predictive power, computational efficiency and operational robustness [20] [21].

This work used more than 10,000 samples, 50 field plots, and extensive preprocessing—including normalisation and feature selection—to assure reliability and comparability, addressing previous problems of small sample numbers and limited sensor/model variation. To guarantee equitable benchmarking, the method made advantage of robust k-fold cross-validation and synchronised, multi-source data [22]. Significant advancements over earlier research include the use of NDVI drone data to improve feature richness, the inclusion of specific application context criteria (such as interpretability and computational efficiency), and the clear reporting of useful operational metrics rather than just important accuracy [23].

Its major downsides are its geographic and crop-specific orientation, limited to two relevant model-sensor pairs, and the practicality of itself simply always assuming constant label and hardware quality [24]. The sensor types, machine learning models and wider deployment considered in this study could be expanded upon to provide further insight in future studies; however, the current options represent resource limitations considering physical location and current agricultural technology norms [25].

6. CONCLUSION

The article shows that the Advanced MLP + Advanced IoT Sensor combination has the highest level of accuracy and is a successful solution in complicated, data-rich scenarios, and thus, is effective in environments where the classification accuracy and precision agriculture are the main goals. The hybrid MLP + hybrid IoT sensor, on the other hand, continues to be particularly useful for real-time applications, quick deployment, and situations where resistance to noise or ambiguity is crucial. It offers strong benefits in terms of resilience and operating speed.

This study gives stakeholders the tools to choose the appropriate technology for their unique objectives by offering a useful, context-aware assessment process for intelligent land suitability models. Future developments in model architectures and the extension to larger areas, crops, and sensor kinds will assist in optimising these systems' utility and dependability for a range of real-world agricultural problems.

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REFERENCES:

[1] A. Wongchai, S. K. Shukla, M. A. Ahmed, U. Sakthi, and M. Jagdish, "Artificial intelligence-enabled soft sensor and internet of things for sustainable agriculture using ensemble deep learning architecture," Comput. Electr. Eng., vol. 102, p. 108128, 2022.

[2] M. K. Senapaty, A. Ray, and N. Padhy, "IoT-enabled soil nutrient analysis and crop recommendation model for precision agriculture," Computers, vol. 12, no. 3, p. 61, 2023.

[3] P. K. Priya and N. Yuvaraj, "An IoT-based gradient descent approach for precision crop suggestion using MLP," in Journal of Physics: Conference Series, IOP Publishing, 2019, p. 012038. Accessed: Aug. 07, 2025. [Online]. Available: https://iopscience.iop.org/article/10.1088/1742-6596/1362/1/012038/meta

[4] K. Hussain et al., "Analysing LULC transformations using remote sensing data: insights from a multilayer perceptron neural network approach," Ann. GIS, pp. 1–28, May 2024, doi: 10.1080/19475683.2024.2343399.

[5] B. M. Mohammad El-Basioni and S. M. Abd El-Kader, "Designing and modelling an IoT-based software system for land suitability assessment use case," Environ. Monit. Assess., vol. 196, no. 4, p. 380, Apr. 2024, doi: 10.1007/s10661-024-12483-8.

[6] S. Bouarourou, A. Boulalaam, and A. Zannou, "A predictive model for abnormal conditions in smart farming using IoT sensors," Procedia Comput. Sci., vol. 230, pp. 248–256, 2023.

[7] A. A. S. Aliar, J. Yesudhasan, M. Alagarsamy, K. Anbalagan, J. Sakkarai, and K. Suriyan, "A comprehensive analysis on IoT-based smart farming solutions using machine learning algorithms," Bull. Electr. Eng. Inform., vol. 11, no. 3, pp. 1550–1557, 2022.

[8] S. Mewada et al., "Smart Diagnostic Expert System for Defect in Forging Process by Using Machine Learning Process," J. Nanomater., vol. 2022, no. 1, p. 2567194, Jan. 2022, doi: 10.1155/2022/2567194.

[9] B. A. Ganati and T. M. Sitote, "Predicting land suitability for wheat and barley crops using machine learning techniques," Sci. Rep., vol. 15, no. 1, p. 15879, May 2025, doi: 10.1038/s41598-025-99070-0.

[10] M. Mehmood, A. Shahzad, B. Zafar, A. Shabbir, and N. Ali, "Remote Sensing Image Classification: A Comprehensive Review and Applications," Math. Probl. Eng., vol. 2022, pp. 1–24, Aug. 2022, doi: 10.1155/2022/5880959.

[11] A. Li et al., "Spatial suitability evaluation based on multisource data and random forest algorithm: a case study of Yulin, China," Front. Environ. Sci., vol. 12, p. 1338931, Feb. 2024, doi: 10.3389/fenvs 2024.1338931.

[12] Y. P. Arul Teen, R. Bharathi, C. Justin Dhanaraj, and B. S. Anchana, "Soil Analysis and Nutrient Recommendation System Using IoT and Multilayer Perceptron (MLP) Model," in Predictive Analytics in Smart Agriculture, 1st ed., Boca Raton: CRC Press, 2023, pp. 80–106. doi: 10.1201/9781003391302-5.

[13] S. Harsh, D. Singh, and S. Pathak, "Efficient and Cost-effective Drone – NDVI system for Precision Farming," Int. J. New Pract. Manag. Eng., vol.. 10, no. 04, pp. 14–19, Jan. 2022, doi: 10.17762/ijnpme.v10i04.126.

[14] G. Saha, F. Shahrin, F. H. Khan, M. M. Meshkat, and A. A. M. Azad, "Smart IoT-driven precision agriculture: Land mapping, crop prediction, and irrigation system," PLOS ONE, vol. 20, no. 3, p. e0319268, Mar. 2025, doi: 10.1371/journal.pone.0319268.

[15] "Land Suitability Analysis to Assess the Potential of Public Open Spaces For Urban Agriculture Activities - ProQuest." Accessed: Aug. 07, 2025. [Online]. Available: https://www.proquest.com/openview/36e165f78be9ec6002811b29182a6bc3/1?pq-origsite=gscholar&cbl=2026366&diss=y

[16] A. Mamatha and P. S. Sandeep, "Climate Change Impact on Agricultural Land Suitability," vol. 8, no. 3, 2025.

[17] Y. T. Pratama, S. Sukemi, and B. Tutuko, "Utilising IoT-Enhanced Multilayer Perceptron and Run Length Encoding for Classifying Plant Suitability Based on pH and Soil Humidity Parameters," J. Inf. Syst. Inform., vol. 6, no. 3, pp. 2022–2036, Sep. 2024, doi: 10.51519/journalisi.v6i3.811.

[18] H. Yang, W. Ma, T. Liu, and W. Li, "Assessing farmland suitability for agricultural machinery in land consolidation schemes in hilly terrain in China: A machine learning approach," Front. Plant Sci., vol. 14, p. 1084886, Mar. 2023, doi: 10.3389/fpls 2023.1084886.

[19] D. R. Vincent, N. Deepa, D. Elavarasan, K. Srinivasan, S. H. Chauhdary, and C. Iwendi, "Sensors Driven AI-Based Agriculture Recommendation Model for Assessing Land Suitability," Sensors, vol. 19, no. 17, p. 3667, Aug. 2019, doi: 10.3390/s19173667.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[20] L. G.S., A. R. Devidas, R. Pushpalatha, B. Gangadharan, and H. K.M., “Enhancing coconut yield potential: A climate-smart land suitability analysis using machine learning,” Smart Agric. Technol., vol. 12, p. 101087, Dec. 2025, doi: 10.1016/j.atech.2025.101087.

[21] Y. Cao and L. Jiang, “Machine Learning based Suggestion Method for Land Suitability Assessment and Production Sustainability,” Nat. Eng. Sci., vol. 9, no. 2, pp. 55–72, Oct. 2024, doi: 10.28978/nesciences 1569166.

[22] A. B. Rashid, A. K. Kausik, A. Khandoker, and S. N. Siddque, “Integration of Artificial Intelligence and IoT with UAVs for Precision Agriculture,” Hybrid Adv., vol. 10, p. 100458, Sep. 2025, doi: 10.1016/j.hybadv.2025.100458.

[23] S. Mansoor, S. Iqbal, S. M. Popescu, S. L. Kim, Y. S. Chung, and J.-H. Baek, “Integration of smart sensors and IOT in precision agriculture: trends, challenges and prospects,” Front. Plant Sci., vol. 16, p. 1587869, May 2025, doi: 10.3389/fpls 2025.1587869.

[24] P. Dhir and J. Gill, “Analysis of Neural Network and Hybrid Techniques for Plant Classification,” vol. 10, no. 1, 2021.

[25] S. Castillo-Girones, S. Munera, M. Martínez-Sober, J. Blasco, S. Cubero, and J. Gómez-Sanchis, “Artificial Neural Networks in Agriculture, the core of artificial intelligence: What, When, and Why,” Comput. Electron. Agric., vol. 230, p. 109938, Mar. 2025, doi: 10.1016/j.compag.2025.109938.