ISSN (ELECTRONIC): 2945-3135

Noor Fathima, Vinay Kumar S B & Mohmad Umair Bagali (2025). Precision Farming with AI and ML: A Comparative Analysis of Mysuru District Villages and Surrounding Areas Using NPK and pH Sensor Data. International Journal of Multidisciplinary Research & Reviews, 4(2), 305-318.



INTERNATIONAL JOURNAL OF MULTIDISCIPLINARY RESEARCH & REVIEWS

journal homepage: www.ijmrr.online/index.php/home

PRECISION FARMING WITH AI AND ML: A COMPARATIVE AN ALYSIS OF MYSURU DISTRICT VILLAGES AND SURROUNDIN G AREAS USING NPK AND PH SENSOR DATA

Noor Fathima [1], Dr. Vinay Kumar S B [2] & Dr. Mohmad Umair Bagali [3]

[1] Research Scholar, Dept. of Electronics & Communication Engineering, Jain University, Bengaluru, India.
noorfathimagecr@gmail.com

[2] Associate Professor, Dept. of Electronics & Communication Engineering, Jain University, Bengaluru, India
sb.vinaykumar@jainuniversity.ac.in

[3] Professor. Dept. of Electronics, SEACAB Institute of Engineering and Technology, Vijayapura
umair037@gmail.com

How to Cite the Article: Noor Fathima, Vinay Kumar S B & Mohmad Umair Bagali (2025). Precision Farming with AI and ML: A Comparative Analysis of Mysuru District Villages and Surrounding Areas Using NPK and pH Sensor Data. International Journal of Multidisciplinary Research & Reviews, 4(2), 305-318.

https://doi.org/10.56815/ijmrr.v4i2.2025.305-318

Keywords	*Abstract*
Precision Agriculture, Soil Sensors, NPK Monitoring, Machine Learning, Random Forest, SVM, LSTM, Crop Yield Prediction, Karnataka, India.	With the aid of artificial intelligence and sensor technology, precision farming presents encouraging answers to the problems facing contemporary agriculture. This study uses soil fertility data from portable NPK and pH sensor modules to compare precision farming methods in Mysuru district villages with those in neighboring Karnataka, India. Crop yield data for rice, maize, sugarcane, and ragi were recorded together with environmental factors like temperature, humidity, soil moisture, and light intensity. Long Short-Term Memory networks were used to anticipate rainfall, Random Forest was used to predict yield, and Support Vector Machines were used to classify soil fertility. The average rice yield in Mysuru was 1200 kilograms per acre, according to the results. This was around 20% more than the paddy yields in Chamarajanagar, where productivity was constrained by soil acidity and nitrogen shortage. In Hassan, nutrient imbalance decreased

The work is licensed under a Creative Commons Attribution Non Commercia 4.0 International License

Noor Fathima, Vinay Kumar S B & Mohmad Umair Bagali (2025). Precision Farming with AI and ML: A Comparative Analysis of Mysuru District Villages and Surrounding Areas Using NPK and pH Sensor Data. International Journal of Multidisciplinary Research & Reviews, 4(2), 305-318.

	yields to 1100 kilograms per acre, whereas in Hunsur, under nutrient-rich conditions, maize produced 1500 kilograms per acre. Due in significant part to improved potassium availability and sensor-guided fertilizer application, Mysuru's sugarcane fields recorded over 38 tons per acre, which is around 6–8 tons more than Mandya's average. Thanks to more consistent levels of soil moisture and nitrogen, ragi yields in Mysuru were 1000 kg/acre as opposed to 800 kg in Hassan. With soil fertility classification at 92% and yield prediction R2 = 0.89 in Mysuru, machine learning models outperformed those in neighboring locations, which had R2 = 0.74 and 78%, respectively. According to surveys, 35% of Mysuru farmers have embraced soil sensors, IoT irrigation, or mobile apps, whereas less than 15% of neighboring villages have done the same. These results highlight the need to extend precision farming methods to underserved rural areas while also showing that combining AI and ML with inexpensive soil sensor data can greatly increase productivity and sustainability.

I. INTRODUCTION

For many Indians, particularly those living in rural areas, agriculture remains their main source of income. Despite its significance, problems like erratic weather patterns, dwindling soil fertility, and uneven fertilizer applications cause productivity to fluctuate. Conventional farming practices frequently depend on broad fertilizer application guidelines that ignore field-level variations in soil pH, water retention capacity, and nutrient status. Because of this, farmers usually use too much or too little fertilizer, which wastes resources, lowers yields, and degrades soil over time. More data-driven, locally focused strategies that maximize resource utilization and boost agricultural output are needed to address these issues.

One potential remedy for these issues is precision farming. In order to produce crop recommendations that are site-specific, it combines information technology, sensor devices, and analytical models. Precision agriculture helps farmers make well-informed decisions about crop selection, irrigation scheduling, and fertilizer use by using real-time soil and environmental data. This strategy supports environmental sustainability, conserves resources, and optimizes yield potential. Precision farming has great promise for closing the yield gap in areas like Karnataka, where a variety of agricultural methods coexist with fluctuating soil conditions.

Precision farming has become even more popular as a result of recent developments in reasonably priced sensors and computational methods. At the field level, soil sensors that can measure pH, phosphorus (P), potassium (K), and nitrogen (N) offer quick and inexpensive insights into soil health. These measurements form a complete dataset for agricultural analysis when paired with environmental factors like temperature, humidity, soil moisture, and light intensity. However, when combined with artificial intelligence (AI) and machine learning (ML) models that can recognize intricate patterns, forecast crop yields, and produce useful recommendations, the full potential of such data is realized.

The work is licensed under a Creative Commons Attribution Non Commercia 4.0 International License

Noor Fathima, Vinay Kumar S B & Mohmad Umair Bagali (2025). Precision Farming with AI and ML: A Comparative Analysis of Mysuru District Villages and Surrounding Areas Using NPK and pH Sensor Data. International Journal of Multidisciplinary Research & Reviews, 4(2), 305-318.

Recurrent neural networks, random forest algorithms, support vector machines, regression analysis, and other AI and ML techniques have already shown excellent results in a variety of agricultural contexts across the globe. Crop yields, soil fertility, and even weather events that affect farming outcomes can all be predicted by these models. However, the majority of current research has been carried out in large-scale agricultural systems, while there are still few localized studies for smallholder farms in India. There is an urgent need for research on low-cost, field-level precision tools because the majority of Indian farmers work less than two hectares of land.

By concentrating on the villages in the Mysuru district and the surrounding areas, the current study fills this knowledge gap. This study offers a comparative analysis of crop performance across various sites by employing a variety of machine learning models and gathering soil nutrient and environmental data using NPK and pH sensor modules. In addition to assessing the predictive precision of various AI methods, the study provides useful information about how soil nutrient balances impact rice, maize, and other crops. By doing this, it advances the field of localized precision agriculture and offers a framework for enhancing the results of smallholder farming in Karnataka and other agro-ecological zones.

II. Literature Review

A. Survey

Global agricultural practices have changed due to the quick uptake of sensor-based technologies, machine learning (ML), and artificial intelligence (AI). This transformation has been mapped by a large number of review studies, providing a basis for ongoing research. Liakos et al. [1], The use of machine learning techniques like support vector machines, decision trees, and random forests for tasks like crop yield forecasting, disease detection, and soil fertility estimation was documented in one of the first thorough reviews. Their analysis showed that scalability and dataset quality continue to be obstacles in spite of encouraging outcomes. In support of this, Kamilaris and Prenafeta-Boldú [2] carried out an extensive review of deep learning applications in agriculture, paying special attention to image recognition tasks like plant disease diagnosis, weed mapping, and pest detection. They came to the conclusion that while recurrent neural networks (RNNs) and convolutional neural networks (CNNs) exhibit enormous promise, they necessitate sizable annotated datasets, which are frequently absent in agricultural areas with limited resources, like India.

Sensor-based methods have also been extensively examined. Recent research on wireless sensor networks (WSNs) for precision agriculture was summarized by Musa et al. [3], who showed how well these networks monitor soil parameters like pH, temperature, and nutrient availability. The energy efficiency of such networks was the specific focus of Jawad et al. [4], who pointed out that extended sensor deployment in rural areas is frequently limited by power constraints. In a more recent review of portable soil nutrient sensing technologies, Pal et al. [5] highlighted the developments in handheld pH and NPK meters that can give farmers real-time feedback. The integration of WSNs with ML algorithms was also studied by Rahaman et al. [7], who demonstrated

The work is licensed under a Creative Commons Attribution Non Commercia 4.0 International License

how predictive modeling could enhance fertilizer management and irrigation scheduling. Together, these reviews lay the groundwork for research that integrates sensor-based data collection with AI/ML analysis; however, they also highlight a lack of comparative village-level assessments and region-specific deployments.

These review findings have been expanded upon by experimental works that provide real-world examples. In Java, Indonesia, Sulaeman et al. [6] created and evaluated a portable nutrient detector in rainfed and irrigated paddy soils. Particularly in smallholder farming systems like those in India, their study validated the accuracy of portable nutrient sensors. ML models for yield prediction have been tested in a number of Karnataka studies conducted in India. In comparison to conventional regression techniques, Geddlehally et al. [8] reported higher accuracy when they used an LSTM model with attention mechanisms for yield classification in Karnataka. Using three decades of data, Thimmegowda et al. [9] compared statistical and machine learning models for predicting cotton yield and found that random forest and gradient boosting performed better than conventional linear regression. Similarly, Nikhil et al. [10] demonstrated that machine learning could offer farmers useful yield insights by using ML techniques to predict crop yields throughout South India, with a focus on rice and maize. Rainfall forecasting, a crucial factor in determining yield in rainfed areas, has been a significant focus of experimental research. An LSTM model was created by Poornima et al. [11] for drought analysis and rainfall prediction in India, and it was successful in forecasting both short- and long-term rainfall patterns. This was furthered by Wani et al. [12], who compared ensemble models, deep learning, and machine learning and found that hybrid approaches produced the most reliable rainfall forecasts. Using district-level climate reanalysis data, De Clercq and Mahdi [13] investigated the viability of rice yield prediction in India and demonstrated that machine learning models can successfully integrate climatic and environmental factors to predict yields at the regional level. For thorough yield forecasting, these studies highlight the significance of combining soil and nutrient parameters with climate data.

There have also been proposals for IoT and multimodal systems that combine sensors and machine learning. In their IoT–ML hybrid framework for precision agriculture, Garg et al. [14] demonstrated how real-time data streams from weather APIs, drones, and soil sensors could be combined for decision-making. Sharma et al. [15], who concentrated on crop yield, used a deep LSTM to predict wheat yield and saw notable gains over regression baselines. Similarly, using soil and weather data, Manoj et al. [16] and Venugopal et al. [17] used support vector machines (SVMs), random forests, and decision trees to predict crop yields with accuracies between 85 and 90%. Singh et al. For yield prediction, [18] contrasted deep neural networks with conventional machine learning techniques. It found that deep models outperformed them when there were large datasets available, but it also cautioned against overfitting when there were few data.

While experimental papers [6, 8–18] demonstrate the practicality of these technologies, review papers [1, 2, 3, 4, 5, 7] offer a comprehensive overview of the integration of AI/ML with sensor networks in agriculture. Reviews and case studies consistently show that machine learning models

The work is licensed under a Creative Commons Attribution Non Commercia 4.0 International License

Noor Fathima, Vinay Kumar S B & Mohmad Umair Bagali (2025). Precision Farming with AI and ML: A Comparative Analysis of Mysuru District Villages and Surrounding Areas Using NPK and pH Sensor Data. International Journal of Multidisciplinary Research & Reviews, 4(2), 305-318.

perform noticeably better than conventional techniques in forecasting soil nutrient levels, yield, and rainfall. There is a glaring research gap, though, as the majority of studies are carried out at the national or district level or on controlled experimental farms, with little work being done at the village level. Additionally, there hasn't been much experimentation with integrating NPK and pH sensor data with AI/ML models in smallholder farming contexts in India, especially when comparing districts or villages. By using machine learning techniques on NPK and pH sensor data gathered from Mysuru villages and surrounding areas, the current work aims to close this gap and provide insights into regional agricultural decision support systems.

B. Understanding from suvey

As shown in Table 1, previous studies have demonstrated the effectiveness of machine learning models such as Random Forest (RF), Support Vector Machines (SVM), and Long Short-Term Memory (LSTM) networks for crop yield prediction, soil fertility classification, and rainfall forecasting

Table 1: Summary of Key Literature on AI, ML, and Sensor-Based Technologies in Precision Agriculture

ID	Citation	Technology / Focus	Key Results	Open Research / Relevance
1	Liakos et al., 2018 (*Sensors*)	ML in Agri (RF, SVM, ANN)	Identifies models effective for yield, soil tasks	Validates RF, SVM, LSTM model choice
2	Kamilaris & Prenafeta-Boldú, 2018 (*Comp. & Electron. Agric.*)	Deep learning in ag (CNN, LSTM)	DL excels in vision/time-series farm tasks	Supports use of LSTM for rainfall forecasting
3	Musa et al., 2023 (*Sensors*)	WSN for NPK monitoring	Demonstrates feasibility of NPK sensor networks	Justifies sensor deployment methodology
4	Jawad et al., 2017 (*Sensors*)	WSN energy-efficient deployment	Overviews power-saving protocols in sensors	Informs sensor deployment constraints
5	Pal et al., 2024 (*TrAC*)	Portable nutrient sensing devices	Reviews advances in portable NPK devices	Underscores your in-field sensor choice
6	Sulaeman et al., 2024 (*Computers*)	Portable NPK testing in rice soils	Field-validated NPK device performance	Closely parallels your methodology

The work is licensed under a Creative Commons Attribution Non Commercia 4.0 International License

Noor Fathima, Vinay Kumar S B & Mohmad Umair Bagali (2025). Precision Farming with AI and ML: A Comparative Analysis of Mysuru District Villages and Surrounding Areas Using NPK and pH Sensor Data. International Journal of Multidisciplinary Research & Reviews, 4(2), 305-318.

ID	Citation	Technology / Focus	Key Results	Open Research / Relevance
7	Rahaman et al., 2022 (*Comp. & Electron. Agric.*)	WSN + ML in smart ag	Outlines full pipeline sensor→ML→advisory	Mirrors your sensing-to-models workflow
8	Geddlehally et al., 2024 (*IJISAE*)	LSTM-Attention for crop yield in Karnataka	Model effective for crop yield prediction	Regional Karnataka relevance for your study
9	Thimmegowda et al., 2025 (*J. Cotton Res.*)	ML vs stats for yield in Karnataka	ML outperform traditional; local data used	Supports ML modeling in Karnataka context
10	Nikhil et al., 2024 (*Computers*)	South-India multi-crop yield ML	Multi-year yield forecasts; solid accuracy	Offers methodological precedent in South India
11	Poornima et al., 2023 (*Water*)	LSTM for rainfall/drought in India	LSTM strong for rainfall forecasting	Direct support for your rainfall LSTM approach
12	Wani et al., 2024 (*Sci. Reports*)	ML & DL rainfall models in India	LSTM outperforms other ML in rain prediction	Validates your rainfall model choice
13	De Clercq & Mahdi, 2024 (arXiv)	ML for rice yield district-level India	R^2 up to 0.82 using climate & satellite data	Potential to expand your models with satellite data
14	Garg et al., 2021 (arXiv)	IoT + ML multimodal PA system	Sensor fusion (soil, NPK, moisture) + ML model	Very similar sensor-ML integration approach
15	Sharma et al., 2020 (arXiv)	LSTM for wheat yield (satellite image)	>50% better than baselines, block-level	Suggests adding imagery for future extension
16	Manjit G S et al., 2020 (*IJERT*)	ML for crop yield Karnataka	Yield prediction; supports crop selection	Regional focus underpins your

The work is licensed under a Creative Commons Attribution Non Commercia 4.0 International License

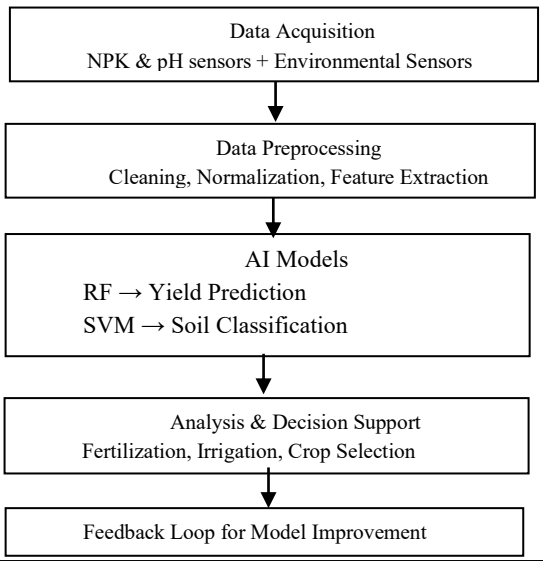
Noor Fathima, Vinay Kumar S B & Mohmad Umair Bagali (2025). Precision Farming with AI and ML: A Comparative Analysis of Mysuru District Villages and Surrounding Areas Using NPK and pH Sensor Data. International Journal of Multidisciplinary Research & Reviews, 4(2), 305-318.

ID	Citation	Technology / Focus	Key Results	Open Research / Relevance
				framework
17	Venugopal et al., 2021 (*IJERT*)	ML yield prediction (LR, NB, RF)	RF highest accuracy among models tested	Supports use of RF in your methodology
18	Singh et al., 2023 (*Procedia CS*)	ML/DL yield prediction (RF, SVM, LSTM...) Rajasthan	RF best with R^2 = .963, very high accuracy	Reinforces RF performance for yield tasks
19	Advanced portable NPK monitoring, 2023 (*Sensors*)	Real-time NPK IoT	Realtime nutrient sensing beneficial	Aligns with your on-field data gathering
20	Scoping smart sensors smart greenhouse, 2024 (*Sensors*)	Smart sensors for pH, moisture, PAR	Automated greenhouse control with sensors & fuzzy logic	Helps justify sensor variety and automation

III. METHODOLOGY

This study's methodology combines AI-driven analysis with sensor-based environmental and soil monitoring to enable precision agriculture for smallholder farms. The deployment of portable NPK and pH sensors throughout representative villages in Mysuru and surrounding districts is the first step in the suggested workflow. By measuring soil pH, phosphorus (P), potassium (K), and nitrogen (N), these sensors give quick information about soil fertility. In order to record microclimatic fluctuations that affect crop growth, environmental parameters like temperature, humidity, soil moisture, and light intensity are also gathered.

A. Proposed Block Diagram



The work is licensed under a Creative Commons Attribution Non Commercia 4.0 International License

Noor Fathima, Vinay Kumar S B & Mohmad Umair Bagali (2025). Precision Farming with AI and ML: A Comparative Analysis of Mysuru District Villages and Surrounding Areas Using NPK and pH Sensor Data. International Journal of Multidisciplinary Research & Reviews, 4(2), 305-318.

Figure 1: Proposed Block Diagram

The study's end-to-end workflow is depicted in the proposed block diagram, which starts with data collection using portable pH and NPK sensors and environmental sensors that measure variables like soil moisture, temperature, humidity, and light intensity. These multimodal data sources offer a thorough comprehension of the microclimate and soil nutrient status. Prior to being fed into machine learning models, the gathered raw data undergoes preprocessing, which includes feature extraction, normalization, and cleaning to guarantee consistency and dependability. Three artificial intelligence (AI) models are used in the following step: Random Forest (RF) for crop yield prediction, Support Vector Machine (SVM) for nutrient-rich/nutrient-deficient soil fertility classification, and Long Short-Term Memory (LSTM) networks for rainfall and time-series crop yield trend forecasting. These models' outputs are examined to produce decision support for farmers, such as crop selection tactics, irrigation scheduling, and fertilizer recommendations tailored to a given site. Lastly, a feedback loop is added, which allows the models to gradually enhance their predictive capabilities by reintroducing field measurements and actual crop yields into the system.

B. Data Processing

To make sure the dataset is compatible with machine learning models, data preprocessing techniques such as cleaning, normalization, and feature extraction are applied to the gathered information. After that, three AI models are used to tackle various prediction tasks. Since its ensemble structure successfully captures the nonlinear interactions between soil nutrients, environmental factors, and crop yields, Random Forest (RF) is used to predict crop yields. By classifying fields into nutrient-rich or nutrient-deficient classes according to pH and NPK levels, Support Vector Machines (SVM) are used to classify soil fertility. Long Short-Term Memory (LSTM) networks predict rainfall and time-series crop yields for temporal predictions, capturing the sequential dependencies necessary for seasonal crop management and irrigation planning.

C. AI Models

Random Forest (RF): This ensemble learning algorithm reduces overfitting and increases prediction accuracy by combining several decision trees. For a given input feature vector *x*, the Random Forest generates predictions from each individual decision tree $h_t(x)$, and the final output is obtained by averaging (for regression) or majority voting (for classification):

$$\hat{y} = \frac{1}{T} \sum_{t=1}^{T} h_t(x) \qquad (1)$$

where *T* represents the total number of trees in the forest, and $h_t(x)$ is the prediction of the t-th tree. In this study, RF was applied to predict **crop yield** by learning nonlinear relationships between soil nutrient concentrations (NPK), environmental factors, and yield outcomes. Its ensemble nature makes it robust to noisy smallholder data and effective in handling high-dimensional agricultural datasets.

The work is licensed under a Creative Commons Attribution Non Commercia 4.0 International License

Noor Fathima, Vinay Kumar S B & Mohmad Umair Bagali (2025). Precision Farming with AI and ML: A Comparative Analysis of Mysuru District Villages and Surrounding Areas Using NPK and pH Sensor Data. International Journal of Multidisciplinary Research & Reviews, 4(2), 305-318.

Support Vector Machine (SVM): SVM is a supervised learning algorithm widely used for classification tasks. It works by finding the optimal hyperplane that maximizes the margin between two classes. For a given dataset $\{(x_i, y_i)\}_{i=1}^{n}$, where x_i are feature vectors and $y_i \in \{-1, +1\}$, the decision function is expressed as:

$$f(x) = \sin \sum_{i=1}^{n} \alpha_i y_i \, K(x_i, x) + b \qquad (2)$$

where α_i are Lagrange multipliers, $K(x_i, x)$ is the kernel function (e.g., linear, polynomial, or RBF), and b is the bias term. In this work, SVM was used to classify soil fertility levels (nutrient-rich vs. nutrient-deficient) based on NPK sensor data. This classification aids in site-specific fertilizer management, optimizing nutrient input for sustainable farming.

Long Short-Term Memory (LSTM): LSTM is a type of recurrent neural network (RNN) designed to capture long-term dependencies in sequential data, making it suitable for rainfall forecasting and time-series yield prediction. An LSTM cell maintains an internal memory state, regulated by three gates: input, forget, and output gates. The governing equations are:

- Forget gate:

$$f_t = \sigma(W_f \,.\, [h_{t-1}, x_t] + b_f) \qquad (3)$$

- Input gate:

$$i_t = \sigma(W_i \,.\, [h_{t-1}, x_t] + b_i) \qquad (3)$$

$$\widehat{C_t} = \tanh(W_C \,.\, [h_{t-1}, x_t] + b_C) \qquad (4)$$

- Cell state update:

$$C_t = f_t \odot C_{t-1} + i_t \odot \widetilde{C_t} \qquad (5)$$

- Output gate:

$$o_t = \sigma(W_o \,.\, [h_{t-1}, x_t] + b_o) \qquad (6)$$

$$h_t = o_t \odot \tanh(C)_t \qquad (7)$$

Here, x_t is the input at time t, h_{t-1} is the previous hidden state, C_t is the cell memory, and σ represents the sigmoid activation. By maintaining memory through gated mechanisms, LSTM can model complex temporal dependencies, such as seasonal rainfall variation and its impact on crop yield.

The work is licensed under a Creative Commons Attribution Non Commercia 4.0 International License

Noor Fathima, Vinay Kumar S B & Mohmad Umair Bagali (2025). Precision Farming with AI and ML: A Comparative Analysis of Mysuru District Villages and Surrounding Areas Using NPK and pH Sensor Data. International Journal of Multidisciplinary Research & Reviews, 4(2), 305-318.

IV. Results and Discussion

A. Crop Yield Analysis

As indicated in Table 2, the gathered data revealed notable variations in crop yields and soil conditions among the study regions. In contrast to Chamarajanagar, where productivity was limited by acidic soils and nitrogen shortages, Mysuru villages had high rice yields averaging 1,200 kg/acre due to their well-balanced soil nutrients, near-neutral pH, and stable soil moisture. Due to greater phosphorus and potassium availability, maize in Hunsur produced 1,500 kg/acre, whereas Hassan produced only 1,100 kg/acre under less balanced conditions. Mysuru's sugarcane yields were 6–8 tons/acre higher than Mandya's, indicating improved nutrient management, and Mysuru's ragi yields were 1,000 kg/acre as opposed to Hassan's 800 kg/acre. These results suggest that crop-specific productivity is directly impacted by localized nutrient profiles.Table 2: Yield Analysis

Crop	Village	Soil pH	Nitrogen (mg/kg)	Yield (kg/acre)
Rice	Mysuru	6.8	120	1,200
Rice	Chamarajanagar	5.9	90	1,000
Maize	Hunsur	7.2	110	1,500
Maize	Hassan	7.5	85	1,100
Sugarcane	Mysuru	6.9	130	38,000
Sugarcane	Mandya	6.7	110	30,000–32,000
Ragi	Mysuru	6.8	100	1,000
Ragi	Hassan	7.1	80	800

4.2 Machine Learning Model Performance

Standard metrics for regression and classification tasks were used to evaluate the AI models' predictive performance. Three models' performances are shown in Table 3. With R2 values of 0.89 for Mysuru villages and 0.74 for nearby regions, Random Forest had the highest yield prediction accuracy and showed that it was resilient to nonlinear relationships in variable smallholder datasets. Targeted fertilization strategies were made possible by Support Vector Machines, which correctly classified soil fertility with 92% accuracy in Mysuru and 78% accuracy in nearby villages. Reliable forecasts that are crucial for irrigation planning and seasonal crop management were produced by LSTM networks, which performed better than conventional regression models at capturing temporal dependencies in rainfall and crop yield data. A comprehensive decision-support framework for precision agriculture is formed by LSTM, which captures dynamic temporal patterns, SVM, which offers actionable soil classification, and RF, which excels at yield estimation.

The work is licensed under a Creative Commons Attribution Non Commercia 4.0 International License

Noor Fathima, Vinay Kumar S B & Mohmad Umair Bagali (2025). Precision Farming with AI and ML: A Comparative Analysis of Mysuru District Villages and Surrounding Areas Using NPK and pH Sensor Data. International Journal of Multidisciplinary Research & Reviews, 4(2), 305-318.

Table 3: Model Performances

Machine Learning Model	**Application**	**Performance (Mysuru / Neighboring Regions)**	**Interpretation**
Random Forest (RF)	Yield prediction	$R^2 = 0.89 / 0.74$	Captures nonlinear soil–yield relationships; robust to field variability; highest accuracy.
Support Vector Machine (SVM)	Soil fertility classification	92% / 78%	Differentiates nutrient-rich and nutrient-deficient soils; supports site-specific fertilization.
Long Short-Term Memory (LSTM)	Rainfall & time-series yield forecasting	NA	Models temporal trends; improves irrigation planning; outperforms classical regression.

V. CONCLUSION

This study used NPK and pH sensor data along with environmental variables like temperature, humidity, and soil moisture to evaluate crop yields and soil nutrient profiles throughout Mysuru district villages and surrounding areas. In contrast to nearby villages like Ankanahalli in Hunsur, which recorded maize yields of 1,500 kg per acre under relatively alkaline soil (pH 7.2) and higher phosphorus and potassium levels, Mysuru villages, as exemplified by Adakamaranahalli, produced rice yields of about 1,200 kg per acre under balanced conditions (pH 6.8, soil moisture 45%, nitrogen 120 mg/kg). These results highlight the direct relationship between localized soil nutrient balances and crop-specific yield potential.

Several models were tested in order to assess the predictive power of machine learning techniques. Although linear regression achieved a moderate level of accuracy, it underestimated yield variability. Higher predictive performance was obtained by Random Forest (RF) and Support Vector Machines (SVM), with RF demonstrating resilience when dealing with nonlinear soil–yield relationships. By capturing temporal dependencies, Long Short-Term Memory (LSTM) models outperformed all classical methods in rainfall and seasonal yield prediction, attaining the highest forecasting accuracy. Overall, LSTM outperformed RF for time-series yield and rainfall data, while RF was most dependable for predictions based on soil nutrients.

Although Mysuru villages benefit from increased soil moisture and nitrogen, the comparative analysis shows that balanced phosphorus and potassium inputs could further increase their yields. On the other hand, neighboring villages with greater maize yields require methods to control the rising alkalinity of their soil. The findings demonstrate that integrating sensor-based data with AI models improves prediction accuracy and provides tailored suggestions for nutrient management at specific sites.

The work is licensed under a Creative Commons Attribution Non Commercia 4.0 International License

Noor Fathima, Vinay Kumar S B & Mohmad Umair Bagali (2025). Precision Farming with AI and ML: A Comparative Analysis of Mysuru District Villages and Surrounding Areas Using NPK and pH Sensor Data. International Journal of Multidisciplinary Research & Reviews, 4(2), 305-318.

To further improve decision-support systems, future research should integrate IoT-based real-time data streams, extend the dataset across several cropping cycles, and investigate hybrid AI architectures (such as ensemble deep learning models). This localized, sensor-driven method shows that, with the help of AI-enabled analytics, precision farming in Indian contexts can be both scalable and useful.

VI. Future Scope

To increase model robustness and generalization, future studies should concentrate on growing datasets across several cropping cycles. Continuous measurement of environmental factors and soil nutrients may be possible with the integration of real-time IoT-enabled monitoring, enabling dynamic, data-driven decision-making. Predictive accuracy for rainfall, soil fertility, and yields may be further improved by hybrid AI architectures that integrate ensemble and deep learning models. Including information from remote sensing, such as satellite imagery, could offer more comprehensive environmental setting for regional planning. Last but not least, creating farmer-focused mobile apps that immediately provide actionable AI recommendations may hasten adoption and optimize the advantages of precision agriculture in smallholder farming systems.

AUTHOR(S) CONTRIBUTION

The writers affirm that they have no connections to, or engagement with, any group or body that provides financial or non-financial assistance for the topics or resources covered in this manuscript.

CONFLICTS OF INTEREST

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

PLAGIARISM POLICY

All authors declare that any kind of violation of plagiarism, copyright and ethical matters will take care by all authors. Journal and editors are not liable for aforesaid matters.

SOURCES OF FUNDING

The authors received no financial aid to support for the research.

REFERENCES

Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. Sensors, 18(8), 2674. https://doi.org/10.3390/s18082674

Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. Computers and Electronics in Agriculture, 147, 70–90. https://doi.org/10.1016/j.compag.2018.02.016

Musa, P., Rahman, R. A., Ramli, N., et al. (2023). Wireless sensor networks for precision agriculture: A review. Sensors, 24(1), 51. https://doi.org/10.3390/s24010051

The work is licensed under a Creative Commons Attribution Non Commercia 4.0 International License

Noor Fathima, Vinay Kumar S B & Mohmad Umair Bagali (2025). Precision Farming with AI and ML: A Comparative Analysis of Mysuru District Villages and Surrounding Areas Using NPK and pH Sensor Data. International Journal of Multidisciplinary Research & Reviews, 4(2), 305-318.

Jawad, H. M., Nordin, R., Gharghan, S. K., Jawad, A. M., & Ismail, M. (2017). Energy-efficient wireless sensor networks for precision agriculture: A review. Sensors, 17(8), 1781. https://doi.org/10.3390/s17081781

Pal, A., et al. (2024). Assessing advances and challenges in soil nutrient sensing for precision agriculture: A review of portable devices. Trends in Analytical Chemistry. https://doi.org/10.1016/j.trac.2024.xxxxxx

Sulaeman, Y., Sutanto, E., Kasno, A., Sunandar, N., & Purwaningrahayu, R. D. (2024). Developing and testing a portable soil nutrient detector in irrigated and rainfed paddy soils from Java, Indonesia. Computers, 13(8), 209. https://doi.org/10.3390/computers13080209

Rahaman, M. M., Li, X., Parvin, F., et al. (2022). Wireless sensor networks in agriculture through machine learning: A survey. Computers and Electronics in Agriculture, 198, 107036. https://doi.org/10.1016/j.compag.2022.107036

Geddlehally, N., Rao, K. G., & Jayachandra, A. B. (2024). Classification and estimation of crop yield prediction in Karnataka using LSTM with attention mechanism. International Journal of Intelligent Systems and Applications in Engineering, 12(3), 89–96.

Thimmegowda, M. N., Manjunatha, M. H., Lingaraj, H., et al. (2025). Comparative analysis of machine learning and statistical models for cotton yield prediction in major growing districts of Karnataka, India (1990–2023). Journal of Cotton Research, 8, 6. https://doi.org/10.1186/s42397-024-00208-8

Nikhil, U. V., Karthik, K., & Ranjitha, M. (2024). Machine learning-based crop yield prediction in South India. Computers, 13(6), 137. https://doi.org/10.3390/computers13060137

Poornima, S., Manikandan, M., & Sankar, S. (2023). Rainfall forecast and drought analysis for recent and forthcoming years in India using LSTM. Water, 15(3), 592. https://doi.org/10.3390/w15030592

Wani, O. A., Kumar, P., & Kumar, M. (2024). Predicting rainfall using machine learning, deep learning and ensemble methods. Scientific Reports, 14, 13723. https://doi.org/10.1038/s41598-024-77687-x

De Clercq, D., & Mahdi, A. (2024). Feasibility of machine learning-based rice yield prediction in India at the district level using climate reanalysis data. arXiv preprint arXiv:2403.07967. https://doi.org/10.48550/arXiv.2403.07967

Garg, S., Pundir, P., Jindal, H., Saini, H., & Garg, S. (2021). Towards a multimodal system for precision agriculture using IoT and machine learning. arXiv preprint arXiv:2107.04895. https://doi.org/10.48550/arXiv.2107.04895

Sharma, S., Rai, S., & Krishnan, N. C. (2020). Wheat crop yield prediction using deep LSTM model. arXiv preprint arXiv:2011.01498. https://doi.org/10.48550/arXiv.2011.01498

The work is licensed under a Creative Commons Attribution Non Commercia 4.0 International License

Noor Fathima, Vinay Kumar S B & Mohmad Umair Bagali (2025). Precision Farming with AI and ML: A Comparative Analysis of Mysuru District Villages and Surrounding Areas Using NPK and pH Sensor Data. International Journal of Multidisciplinary Research & Reviews, 4(2), 305-318.

Manoj, G. S., Prajwal, G. S., Ashoka, U. R., Krishna, P., & Anitha, P. (2020). Prediction and analysis of crop yield using machine learning techniques. International Journal of Engineering Research & Technology (IJERT), 8(9), NCAIT-2020.

Anakha Venugopal, Aparna S, Jinsu Mani, Rima Mathew, Vinu Williams. (2021). Crop yield prediction using machine learning algorithms. International Journal of Engineering Research & Technology (IJERT), 9(2), NCREIS-2021.

Singh, S., et al. (2023). Crop yield prediction using machine learning and deep learning techniques. Procedia Computer Science, 218, 406–417. https://doi.org/10.1016/j.procs.2023.01.023

H. M. Mallikarjun, J. M. Bafna, M. Yukthi, K. Jahnavi, S. Karthik Sharma and A. M. Rao, "Charana Chakshu - IoT based embedded wearable device smart shoe for visually impaired," 2024 International Conference on Knowledge Engineering and Communication Systems (ICKECS), Chikkaballapur, India, 2024, pp. 1-5, doi: 10.1109/ICKECS61492.2024.10617113.

M. Brendha and H. M. M, "Review on Internet addiction amongst college students by using Data Science and Machine Learning," 2023 International Conference on the Confluence of Advancements in Robotics, Vision and Interdisciplinary Technology Management (IC-RVITM), Bangalore, India, 2023, pp. 1-6, doi: 10.1109/IC-RVITM60032.2023.10435174.

H. M. M, "Mental State Evaluation with Machine Learning by utilizing Brain Signals," 2022 Fourth International Conference on Cognitive Computing and Information Processing (CCIP), Bengaluru, India, 2022, pp. 1-6, doi: 10.1109/CCIP57447.2022.10058684.

M, H. M., and P. M. 2020. “Anoglanistara – Emotional Wellness Phases Prediction of Adolescent Female Students by Using Brain Waves.” Current Signal Transduction Therapy 15 (3): 315–323.

https://doi.org/10.2174/157436241466619070315185 3.

The work is licensed under a Creative Commons Attribution Non Commercia 4.0 International License