

AgriSarthi – A Digital Twin for Smart Agriculture

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Abstract - Farming depends on weather, crop choice, water needs, plant health and costs all at once. To pick the right move, a farmer has to juggle these pieces together. Recent breakthroughs in AI, machine learning, deep learning and Digital Twin tech now make it possible to offer digital helpers for planning. We introduce AgriSarthi, a Digital Twin-based framework that gives growers the data they need to decide wisely. It pulls weather data from the Open-Meteo API, runs crop-prediction models, spots plant diseases, estimates how much water each crop will need, projects revenue and profit, and even lets users run “what-if” scenarios. The disease-detection part leans on a MobileNetV2 deep-learning model trained with the PlantVillage dataset. By nesting all these tools in a single virtual farm, AgriSarthi lets users explore conditions, compare outcomes, and see how different choices might play out. Instead of wiring up a field full of sensors, this version leans on API-driven weather feeds, predictive algorithms, image-based disease checks and scenario simulation. We survey the most relevant work, lay out the framework, discuss its strengths and limits, and point to future upgrades. In short, the approach offers a foundation for linking a suite of decision-support tools through a farm-scale Digital Twin.

Key Words: Smart Agriculture, Digital Twin, Machine Learning, Deep Learning, Crop Prediction, Disease Detection, Water Requirement Estimation, Precision Agriculture

1. INTRODUCTION

Agriculture feeds people and fuels economies, yet farmers must constantly balance shifting weather, crop suitability, water supply, plant health and costs. A single misstep can dent yields, waste resources, and slash income.

Old-school methods rely on gut feeling, observation and local lore. Those still matter, but digital tools can add a layer of insight. Smart agriculture brings AI, machine learning, deep learning and data analytics into the field to help interpret conditions and sharpen decisions [1]–[3].

Researchers have already used machine learning to suggest crops and forecast yields, while deep-learning networks can identify diseases from leaf photos [4]–[13]. Weather forecasts, too, give growers a heads-up on what the environment will do.

A Digital Twin acts like a virtual copy of a real system. In farming, it can gather all the farm’s data and let users play out different what-ifs [14]–[19].

AgriSarthi takes that idea and bundles several decision-support tools together. Right now it pulls weather from Open-Meteo, predicts crops, detects diseases, estimates water needs, forecasts revenue and profit, and runs scenario simulations.

The goal is a single platform where farmers can explore information and weigh options. Rather than depending on a mesh of IoT sensors, this first release leans on readily available digital data, predictive models and image analysis.

2. REVIEW METHODOLOGY

We scanned the literature on agricultural Digital Twins, machine-learning crop forecasts, deep-learning disease spotting and digital decision-support systems. Topics ranged from crop choice and yield estimation to water management, image-based plant classification, weather-driven planning and the role of Digital Twins on farms. Those studies form the backdrop for the technologies woven into AgriSarthi.

The review is organized by the agricultural challenges each method tackles and how each technology could fit into an integrated support framework.

What follows is a thematic overview and a description of the AgriSarthi system. We’re not presenting new experimental data or claiming measurable yield gains. Real-world performance will have to be proven with proper testing and field trials.

3. TECHNOLOGIES USED IN AGRISARTHI

3.1 Digital Twin Technology in Agriculture

A Digital Twin is a virtual copy of a real-world object, process or system. It gathers data about the thing it mirrors and lets users examine how conditions evolve.

In farming, people have tried Digital Twins for everything from crop production and irrigation control to aquaponics, vertical farms and decision-support tools [14]–[19].

At the farm level, a Digital Twin can act as a common hub for many kinds of information. Weather forecasts, crop growth predictions, disease alerts and water-need estimates can all be tied to the same field or scenario.

In AgriSarathi, the Twin idea links the various decision-support modules inside a single digital environment. Its value hinges on how good the data are and how reliable the underlying prediction models happen to be.

3.2 Machine Learning for Crop Prediction

Machine learning sifts through agricultural data, spots patterns and spits out forecasts. Studies have applied it to crop choice, yield forecasting and overall farm planning [4]–[9], [21], [23].

A crop-prediction tool can suggest which plants might thrive given the inputs you feed it weather trends, soil traits, and other agronomic factors.

Within AgriSarathi, crop prediction is a core decision-support feature. Its output lets users weigh different planting options before committing to a field.

But remember, predictions only reflect the data and assumptions fed into the model. Treat the advice as guidance, not a promise of harvest performance.

3.3 Deep Learning for Plant Disease Detection

Diseases can cripple growth, lower quality and cut yields. Spotting symptoms early gives farmers a chance to act before damage spreads.

Deep-learning networks, especially convolutional neural networks (CNNs), have shown promise for spotting diseases from leaf photos [10]–[13].

AgriSarathi's disease-detection module runs on MobileNetV2 trained with the PlantVillage dataset. You upload a plant image, and the system returns the most likely disease category based on what it has learned.

The tool can flag potential health issues, yet its accuracy depends on lighting, image clarity, background clutter, crop variety and disease stage.

So, treat the model's output cautiously, especially when your photos differ from the conditions seen during training.

3.4 Weather Information Using Open-Meteo

Weather drives crop growth, water demand and overall farm scheduling. Knowing temperature, rainfall and other

climate variables helps frame the environment in which plants develop.

AgriSarathi pulls weather data from the Open-Meteo API for the user-selected location. This feed adds environmental context to the platform's decision-support calculations.

Having up-to-date forecasts can steer users toward better crop choices and irrigation plans.

The feature's usefulness, however, rests on correct location input, API uptime, forecast uncertainty and how closely the retrieved data match the actual farm conditions.

3.5 Water Requirement Estimation

Water is a linchpin of successful farming. Too little stresses plants; too much wastes a precious resource.

AgriSarathi offers a water-need estimator to give users a ballpark figure of how much irrigation a crop might require. Weather data feed into the calculation, adding another layer of realism.

The numbers are meant to aid planning, not replace on-site measurements or expert irrigation advice. Real water use will vary with soil type, growth stage, local climate and field specifics.

Because the current version lacks live IoT sensors, the system can't claim to measure soil moisture in real time or automatically control irrigation hardware.

3.6 Revenue and Profit Estimation

Farmers need to gauge the economic side of their choices. Revenue and profit projections give extra insight when comparing crops or different farming scenarios.

AgriSarathi includes a revenue-and-profit estimation tool that helps with this kind of planning. Those numbers can give users a rough sense of the financial impact of a chosen farming option.

But real income hinges on a lot of uncertain factors crop yield, market prices, input costs, transport fees, and shifting weather conditions all play a role.

So treat the financial figures as ball-park planning data, not guaranteed returns.

4. PROPOSED AGRISARTHI FRAMEWORK

AgriSarathi is built as a digital decision-support framework that ties several functions together in one environment. It pulls weather data, runs predictive analytics, spots plant diseases, estimates water needs, calculates financial

outlooks, and runs scenario-based simulations all under one roof.

4.1 System Architecture

The system breaks down into these functional blocks:

1. **Input Layer:** Users pick a location, enter needed farm details, or upload a plant photo for disease checking.
2. **Weather Information Layer:** The platform fetches weather data from the Open-Meteo API for the chosen spot.
3. **Prediction Layer:** Based on the inputs, this part spits out crop forecasts, water-requirement estimates, and revenue or profit projections using the appropriate models.
4. **Disease Detection Layer:** A MobileNetV2 model scans plant images, leveraging patterns learned from the PlantVillage dataset.
5. **Digital Twin Layer:** This virtual farm stitches together all the agricultural data and analytical outputs for a specific field or scenario.
6. **Simulation Layer:** The “what-if” engine lets users tweak parameters and compare possible outcomes.
7. **Output Layer:** Finally, the system shows predictions, estimates, image-classification results, and scenario reports to the user.

The focus is on software-driven data gathering and predictive modeling; IoT sensors or automated field gear aren't part of the current version.

4.2 Crop Prediction and Decision Support

Crop prediction lets users explore viable crop choices using the system's data. By displaying these forecasts in a single digital space, AgriSarathi aims to make planning feel more organized. Users can weigh crop outputs alongside weather info and other estimates.

How useful the results are depends on the model's quality, the input data, and how well the model reflects real-world conditions.

4.3 What-If Simulation

The what-if simulator is a key piece of the framework. It lets users see how tweaking certain parameters might shift predicted results.

For instance, a farmer could compare scenarios with different weather assumptions or alternative input levels, helping weigh options before committing.

Remember, the simulation offers model-derived outcomes, not direct glimpses of future fields. Its trustworthiness hinges on the underlying models, assumptions, and input values.

4.4 Integration of Agricultural Functions

AgriSarathi's main goal is to fuse multiple decision-support tools rather than run them as separate apps. Weather data sets the environmental stage; crop prediction guides planting plans; disease detection adds image-based health insights; water and financial estimates round out the decision matrix.

All these pieces live in the Digital Twin, giving users a single place to view outputs and test scenarios.

This integrated view can help farmers juggle several planning aspects at once. Its real-world value will depend on each component's accuracy and the overall system's ease of use.

5. RESEARCH GAPS AND CHALLENGES

5.1 Dependence on Data Quality

Prediction quality rides on the data fed into the system and the datasets that trained its models. Missing inputs, wrong location tags, or gaps between training conditions and field reality can all erode reliability.

Thus, AgriSarathi needs solid data-validation steps and clear communication about what the predictions can—and cannot promise.

5.2 Generalisation of Disease Detection

Disease-detection models often stumble when faced with images taken under different lighting, backgrounds, resolutions, or disease presentations. Those variations can sway classification results, so the system must account for them.

Testing the model with a diverse set of real-world plant images would give a clearer picture of how well it works in everyday farming.

5.3 Limitations of Water and Financial Estimates

Water needs and financial results hinge on many factors that a simple prediction model can't capture fully. For instance, irrigation demand shifts with soil texture and the crop's growth stage, while profitability swings with market prices and surprise expenses. Because of these gaps, any numbers we provide should be framed as estimates, not guarantees.

5.4 Absence of Real-Time Sensor Integration

AgriSarathi's current release doesn't include IoT-based sensor monitoring. So it can't pull live soil-moisture readings from connected devices, nor can it automatically drive irrigation hardware. Future versions might add sensor hooks, but that would mean extra hardware, new data pipelines, and thorough testing.

5.5 Reliability of External Weather Data

We pull weather data from an external API, which ties the feature to that service's uptime and data quality. Forecasts always carry uncertainty and may not match conditions in a specific field. Later work could tighten validation, handle API outages gracefully, and bring in additional agricultural data sources.

6. FUTURE SCOPE

There are plenty of ways to push AgriSarathi forward. One path is to benchmark crop prediction, disease detection, water-use estimation, and financial forecasting against solid datasets and realistic test cases; that would show how dependable each module really is. Another angle is to sharpen the Digital Twin environment so users can more easily compare scenarios and see the assumptions behind each output.

We could also improve how we treat weather data, broaden the range of crop-disease datasets, and add richer agronomic information. If real-time field measurements become a requirement, IoT integration think soil-moisture probes or other environmental sensors might be added, though it isn't part of today's system.

Further tweaks might make the interface more intuitive, explain model predictions more clearly, and accommodate users with varying technical backgrounds. Any new feature should be vetted before being marketed as reliable for actual farms.

7. CONCLUSION

This paper introduced AgriSarathi, a Digital Twin-based framework aimed at smart agriculture. We surveyed relevant tech Digital Twins, machine learning, deep learning, and weather-driven decision support. The prototype stitches together Open-Meteo weather data, crop forecasting, MobileNetV2 disease detection (trained on PlantVillage), water-need estimates, revenue and profit calculations, and "what-if" simulations.

By housing these tools in a single digital space, AgriSarathi lets users explore farm data and compare possible scenarios. Right now the system leans on API-sourced weather, prediction models, and image analysis; it does not

include IoT field monitoring. Its real-world value hinges on input data quality, model reliability, and how well the outputs map to actual farm conditions.

Future work should emphasize rigorous model testing, field validation, clearer communication of uncertainties, and expanding the Digital Twin's capabilities. IoT-based monitoring may appear in later releases, but it isn't part of the current version.

In short, AgriSarathi lays a groundwork for linking several agricultural decision-support tools within a farm-focused digital framework.

ACKNOWLEDGMENT

The authors thank the Department of Computer Engineering, Indala College of Engineering, Bapsai, Kalyan, for its academic support during the preparation of this review paper.

REFERENCES

- [1] X. Yang et al., "A survey on smart agriculture: Development modes, technologies, and security and privacy challenges," *IEEE/CAA Journal of Automatica Sinica*, vol. 8, no. 2, pp. 273–302, Feb. 2021.
- [2] S. I. Hassan et al., "A systematic review on monitoring and advanced control strategies in smart agriculture," *IEEE Access*, vol. 9, pp. 32517–32548, 2021.
- [3] R. P. Sishodia, R. L. Ray, and S. K. Singh, "Applications of remote sensing in precision agriculture: A review," *Remote Sensing*.

BIOGRAPHIES



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