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AgriTwin : A Sensor Free Digital Twin System for Smart Farming Using APIs and Geo-Maps

[1]**GEETHA V**
ASSISTANT PROFESSOR,
DEPARTMENT OF COMPUTER SCIENCE AND NGINEERING.
KGiSL INSTITUTE OF TECHNOLOGY, COIMBATORE, TAMIL NADU, INDIA
Geetha.v@kgkite.ac.in
[2]**VIKASH J**
UG STUDENT, DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING. KGiSL INSTITUTE OF TECHNOLOGY. COIMBATORE, TAMIL NADU, INDIA vikashjai31@gmail.com
[3]**VAIDEESWARI A** UG STUDENT,
DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING.
KGISL INSTITUTE OF TECHNOLOGY, COIMBATORE, TAMIL NADU, INDIA vaideeayyappan@gmail.com
[4]**MOHAMMED IRFAN M** UG STUDENT,
DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING.
KGISL INSTITUTE OF TECHNOLOGY, COIMBATORE, TAMIL NADU, INDIA mohammedirfan24082004@gmail.com
[5]**RANJITH A**
UG STUDENT, DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING. KGISL INSTITUTE OF TECHNOLOGY. COIMBATORE, TAMIL NADU, INDIA
ranjithkumar994896@gmail.com

ABSTRACT
Farmers currently faces multiple challenges like fluctuating climatic conditions, reduced soil quality, excessive use of resources, and inconsistent market demands. In various regions, farmers still depends largely on direct observation and practical experience while making decisions about crop planning, irrigation, and fertilizer usage, which may lead to excessive resource utilization and reduced productivity. To overcome these disadvantages, this paper develops AgriTwin, a digital twin-based agricultural system that creates a digital representation of farmland for predictive analysis and decision support. The proposed system includes agricultural datasets, real time weather data collected through external APIs, and inputs provided by farmers to represent to soil condition, crop growth patterns, and environmental factors. By applying machine learning methods, the platform analyzes these data sources to generate insights such as crop suitability recommendations, yield estimation, irrigation scheduling, and market trend analysis. The digital twin environment enables farmer to stimulate different farming strategies before applying them in real fields, helping reduce risk and improve planning. In addition, that platform includes an interactive visualization dashboard that presents predictions and analytical insights in a simple and user-friendly format. By combining data- driven analysis with virtual farm modeling, AgriTwin aims to support informed decision-making, optimize resource utilization, and promote conventional agricultural practices.
KEYWORDS – Artificial Intelligence (AI), Machine Learning(ML), Decision Support System(DSS), Yield prediction Models, API-Based Data Integration, Precision Farming

I. INTRODUCTION

The agriculture sector plays an important role in sustaining global food security while strengthening the economic stability of various nations. In many agricultural areas, farming continues to support as an important source of livelihood for a significant share of the population. However, the agricultural system currently experiences several issues such as variable climate conditions, soil degradation, excessive resource consumption ,and fluctuating market conditions. Old agricultural methods depends on field observation and farmer experience while making decisions regarding crop planning, irrigation management, and fertilizer application. These methods provide knowledge, but may not always offer accurate informations for managing continuously changing farming environments. Hence, farmers can make immediate decisions instead of future based decisions, which can affect productivity and sustainability. Advanced developments in data analytics, artificial intelligence, and digital technologies have created new opportunities for improving agricultural decision making and agricultural management[1][2].

Recent technological developments such as Digital Twin have become a valuable tool for modeling and understanding real-world systems using virtual platforms. A digital twin forms a virtual model of a physical system and continuously updates it using data collected from multiple sources. In agriculture, this concept can be applied to represent farmland conditions, crop behaviour, and environmental factors in a virtual model. By connecting agricultural datasets, weather information, and analytical models, digital twin systems can support predictive analysis and scenario-based planning for farming activities. Researchers have studied the role of digital twin technology and artificial intelligence in agriculture for improving crop monitoring, resource efficiency,and agricultural productivity[3][4]. Using on these progress,the AgriTwin platform is designed as a digital twin-based smart farming system that supports data-driven agricultural decision-making through predictive analytics and simulation capabilities.

II. LITERATURE REVIEW A. Comprehensive Analysis of Research Papers

The Comprehensive analysis of 14 research papers related to digital twin technology in smart agriculture is presented in the table below. This comparative study focuses on key areas such as digital twin frameworks, smart farming systems, YOLO based smart farming, crop monitoring, sensor-based and sensor free agricultural technologies and AI- based agricultural decision support systems. This study examines the algorithms, tools and techniques used, combined with major challenges, key features, and research gaps identified in previous studies.

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TABLE I. Literature Review Summary of Related works

S.NO	TITLE	YEAR	METHODOLOGY	GAP(from conclusion/future work)
1.	Overview of the Application Progress of Digital Twins in Agriculture	2024	The study reviews the development of digital twin technology in agriculture and explains how virtual farm models can represent real farming environments.The methodology studies current research trends and explores their use in areas such as crop monitoring, farm management, and automated farming operations. It also explains how digital twins combine data from sensors, weather systems, and agricultural models.	The research shows that digital twin uses in agriculture are currently at an early stage. Most present systems focus on small-scale experiments rather than real farm deployment. Integration with large datasets and real-time monitoring systems remains limited. Future work suggests developing scalable digital twin platforms that can support multiple farms simultaneously. It also recommends improving data integration techniques and real-time simulation capabilities.
2.	Digital Twins in Agriculture: A Review of Recent Progress and Open Issues	2024	This paper presents a systematic review of digital twin research in agriculture by examining approximately seventy scientific publications. The methodology focuses on identifying the main technologies, architectures, and data sources used in agricultural digital twin systems.The research identifies multiple digital twin models designed for crop modelling, soil evaluation, and	The findings suggest that digital twin technology has considerable potential. Even so, practical implementation still faces several issues. Many agricultural digital twin systems lack standardized architectures and reliable data integration methods. Real-time data synchronization between
			farm management activities.	physical farms and digital models also remains challenging.Future work should focus on better improvement by connecting agricultural data systems and creating more effective simulation models.
3.	Digital Twin-Based Crop Yield Prediction in Agriculture.	2024	Systematic Literature Review was conducted using YOLO-based image analysis for crop monitoring with IOT sensor network to collect environmental data.	The limitations of this model, it tested on very small scale experimental studies and lack of large- scale datasets, real-time monitoring and integration. Future requirements, it needed real time data integration with large datasets.
4.	Digital Twins in Agriculture and Forestry: A Review	2024	This multimodal is an architecture that uses IOT sensors and digital twin modeling frameworks and simulation models which replicated forestry systems. Data analytics and monitoring platforms are used to analyze parameters.	The gaps in this model is continuous monitoring using sensors and high data acquisition and model accuracy. The limitation of the model is limited interoperability between different agricultural technologies. Future research should focus data quality and scalable deployment.
5.	Digital Twin-Based Applications in Crop Monitoring	2025	This study looks into digital twin models used for crop monitoring and farm management. The methodology studies different modeling techniques including data-driven models, spatial models, and hybrid simulation models. It explains how digital twins helps in simulating crop growth, environmental changes, and farm management strategies.	The paper explains that digital twin technology for crop monitoring is currently in its early development stage. Many present available models consider mainly on theoretical frameworks instead of real-world implementations. There is also limited research on long-term system performance and sustainability. Future research should focus on real-time field evaluation and integration with advanced AI analytics.
6.	A Comprehensive Review of Digital Twin Technology in Agriculture	2025	This research studies different digital twin architectures used in smart agriculture. The methodology reviews digital twin layers such as data acquisition, data processing, simulation modeling, and decision-making modules. It also evaluates the method by which these AI and IoT technologies are integrated with digital twins.	The review shows that many digital twin platforms lack uniform frameworks and unified datasets. Data privacy and security issues are also major issues when integrating large agricultural datasets. The study recommends in developing the open digital twin architectures and better data governance strategies in future agricultural research.
7.	Digital Twins in Precision Agriculture: Applications and Challenges	2024	This proposed system uses satellite remote sensing data, IOT based sensor networks, and agricultural simulation models and it also involves data analytics and monitoring system to analyze environmental and crop related parameters.	This system requires high deployment costs and technical complexity. Many farmers lack the digital infrastructure and technical resources. Future research is to work on lightweight and cost effective digital twin platforms, and improving accessibility
8.	Digital Twin Technology for Sustainable Agriculture	2025	This model integrates digital twin modeling with simulation based analytical techniques. The system integrates environmental data analysis, crop growth models, and soil condition to represent agricultural environments. The convolutional neural network (CNN) algorithm is employed to analyze data.	This study faces some limitations in data accuracy and simulation reliability. Future works recommends improving data integration, dataset quality, and adaptive simulation models.
9.	Digital Twin Technology for Real-Time farm simulation and Decision Support.	2025	This model is developed using advanced agricultural modeling methods that simulate crop growth , soil processe and water dynamics. Models such as Decision Support System for Agrotechnology Transfer(DSSAT) and the Agricultural Production Systems Simulator(APSIM) forms the basis of this system.	This study highlights several challenges related to data quality and integration. Many agricultural land lack consistent sensor infrastructure which limit its data availability. Future works recommends developing lightweight models.
10.	Smart Farm Digital Twin Model Based on Edge-Cloud Architecture	2025	This model integrates the advantage of both edge and cloud. Here, the hardware such as cameras and drones are used for data collection and this system uses edge computing services provided by edge devices(IOT sensors). The cloud layer extends the accessibility and remote sensing of agricultural lands. Modelling software is blender and object detection model is YOLOv8.	This model uses light weight model which is YOLOv8 and also the performance is analyzed by accuracy, latency and memory consumptions. Future development is to work on decision making functions such as automatic irrigation, automatic fertilization, and automatic harvesting. And to apply Generative Adversarial Network(GAN) for model training.
11.	Digital Twin-Driven Crop Monitoring and Modeling for Precison Agriculture.	2025	This work uses various models such as Agent-based models, Spatial models, Hybrid models combined physical-based and data- driven approaches, Theses models simulate crop behavior under various environmental conditions.	This study is not widely implemented in largescale farming environments. Future work should focus on multiple agricultural datasets and predictive modeling methods.
12.	Digital Twins in Sustainable and Climate-Aware Farming	2024	This study focuses on role of digital twin in sustainable agriculture. This model integrates climate models, monitoring systems and crop simulation techniques to analyze environmental changes in yield.	This work faces challenges in applying digital twin systems for climate aware agriculture. Lack of long term environmental data set is also a limitations. Future research is to work on better environmental modeling methods.
13.	Agricultural Digital Twin for Mandarin Crop Monitoring	2024	This System uses Open APIs from government and public data portals. The system uses statistical models, mixed-effects modeling, hierarchical clustering, and AutoML machine learning algorithms to analyze fruit quality. R Shiny-based digital twin dashboard is also developed.	This work relies mainly on observational datasets from a limited number of orchards. So that it restricts generalization of result of the crop. Future research should focus on automated sensor systems and expanding digital twin system to different types of crops.
14.	Smart Digital-Twin Hub for Rice yield Prediction Using Multivariate Time-Series Data	2023	This system uses digital twin hub that shows rice yield using time- series agricultural data. This system uses climate data, soil parameters, and crop growth indicators to represent crop development. Machine learning models analyze multivariate datasets to predict yield and crop performance.	This study have limitations in dataset availability and model adaptability. Future work is to explore scalable digital twin platforms.

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From the above table, it can be inferred that research on digital twin technology in agriculture is progressing rapidly with the use of technologies such as IOT, computer vision, machine learning, remote sensing, and geospatial data system. Although several advancements have been made many practical challenges still exist in real-world agricultural environments. Most current systems rely heavily on sensor-based infrastructures, which increases deployment cost and limit accessibility for small scale farmers. In addition to that, many models face difficulties in integrating large scale environmental data, real time monitoring, and accurate crop prediction across diverse farming conditions. Issues related to data availability, scalability, interoperability, and system complexity also restrict widespread adoption of digital twin systems in agriculture. While considerable progress has been made, the current system still lack the robustness and effectiveness required for practical deployment. Hence, future research aims to build hybrid multimodal and use of large and diverse datasets improving the model accuracy and prediction.

III. AGRITWIN : A SENSOR FREE DIGITAL TWIN SYSTEM FOR SMART FARMING USING APIS AND GEO-MAPS

A. System Overview

AgriTwin system is created as a digital twin-based smart farming system which supports data-driven agricultural decision-making. The system integrates agricultural datasets, weather information obtained through APIs, and machine learning models to develop a digital environment that represents land conditions. Crop data and soil nutrient data are used with real time weather parameters such as temperature, humidity, and rainfall. The data are processed in FastAPI backend server. Machine learning models analyze the data and generated predicted outputs related to crop selection, fertilizer usage , yield prediction and market price prediction. The AgriTwin system also shows real time dashboards that shows predictive outputs in chart, graphs and interfaces.

B. System Architecture

The architecture of AgriTwin system follows a structured multi-layer design ensuring different function oriented content and improve maintainability. Each function modules perform as specific function while interacting cohesively with other module to complete the analysis process.

Data Layer: The data layer creates a basic level of the system by giving agricultural datasets and data from APIs which are required for analysis. This layer includes data such as soil nutrient level, crop growth rate, pest attack, and other agricultural records collected from large datasets and open source APIs. These datasets helps system to understand relationship between soil properties, crop types, and yield patterns. These data are send to the machine learning model as a next step.

i) External API Layer: The API layer collects real time data from external data sources. Weather APIs gives climate and weather factors such as temperature, humidity, and rainfall that affects the crop growth and crop yield. Additionally, market price APIs provide updated commodity price and trend patterns. These external data sources helps system to continuously update to environmental conditions and help to make more accurate predictions.

ii) Backend Processing Layer: The backend processing layer works using FastAPI framework, which acts as a central communication component of the system. The backend server controls the data transfer between datasets, external APIs, and machine learning models. It manages request from user interface and process incoming data and send the processed data to machine learning models. The backend manages data flow and system coordination.

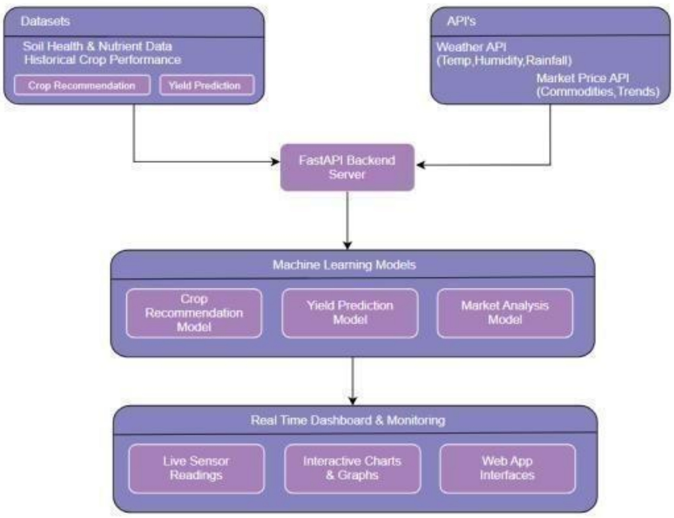
iii) Machine Learning Layer: The machine learning layer works on analytical processing and output prediction using trained models. This layer integrates multiple trained models which are designed for specific agricultural operation. The crop recommendation model analyzes soil and environmental conditions and suggest suitable crops. Similarly the yield prediction model and market analysis model works in the system. The Machine learning models used in the system are :

A. Crop Recommendation Model: The Crop recommendation model uses crop suggesting datasets which have 6000 records and the model and data is trained using Random Forest Classifier. The model is mainly trained on soil and climatic conditions. It shows predictive output of recommended crops based on the soil nutrient level such as Nitrogen(N), Potassium(K), Temperature, Humidity, Ph, and rainfall.

B. Yield Prediction Model: The yield prediction model uses yield prediction dataset which is a large dataset and the model is trained on Random Forest Regressor algorithm. The model is specifically trained on some environmental factors such as crop season, state, area, rainfall, fertilizer and pesticide usage. The expected output of this model is crop yield in tons per hectare. It also predicts total production which is total expected production in tons, The model is evaluated using mean squared error(MSE) and R2 score.

C. Market Analysis Model: This model uses market trend pattern framework and Government API for commodity pricing and market trend patterns. It predicts the price of destined crops particular to the specific region based on the updated price fixed in the market. The columns in the dataset includes id ,state, district, market commodity, variety, grade, arrival date, minimum price, maximum price, modal price.

v) Visualization and Monitoring Layer: This is the application layer or user layer of the system , where user communicates with the system through this dashboard. A real time dashboard shows analytical outputs using charts, graphs, and visual indicators from the predictions. The system also integrates a web application interface that helps farmers or users to interact with the system easily. It improves accessibility and understandable insights.



IV. CONCLUSION & FUTURE ENHANCEMENT

The AgriTwin system successfully illustrates that digital twin technology can be used in agriculture to facilitate predictive and data-driven farming practices. By integrating agricultural datasets, weather information obtained through APIs, and machine learning models, the system provides insights related to crop recommendation, yield prediction, and market analysis. By integrating the FastAPI backend with predictive analytics allows the system to process agricultural data efficiently and generate meaningful outputs. The visualization dashboard shows analytical results through charts and interactive interfaces, making the information easier to understand by the users. By this approach, the AgriTwin system analyzes farm conditions and help farmers in making informed agricultural decisions. In summary, the AgriTwin system shows the importance of digital technologies to improve agricultural productivity, resource management, and decision support in modern agricultural environments.

Future research is to work on real time datasets such as satellite imaging, remote sensing data, and advanced sensor network to increase system accuracy. More advanced machine learning and deep learning models can improve efficiency and prediction performance of the system. The agricultural system can be extended to support multiple farm lands. By combining these work, the AgriTwin system can be developed into a scalable and efficient platform.

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