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A Study on Smart Agriculture Monitoring Systems Using IoT and Machine Learning Technology

Shilpa K Assistant Professor[1], Dr. V Ganesh Babu Assistant Professor[2]
Department of Computer Science, Government Science College, Bangalore 560001[1]
Department of Computer Science, Government College for women, Maddur 571428[2]

Abstract- Although restricted technology hindered the use of old farming methods, agricultural technology in India has had a tremendous impact on living things. The purpose of this study is to investigate how agricultural practices have changed over time in ancient India. Real-time monitoring and adjustment of system settings to maximize plant growth and support farmers in their job is now possible with smart farming. The current agricultural practices in India have an impact on several Machine Learning (ML) techniques that forecast soil moisture by evaluating unprocessed field data together with variables like humidity and air temperature. These ML models predict soil moisture requirements with accuracy. The study's main objectives are to evaluate variables such soil moisture, temperature, humidity, and rainfall as well as to discover plant diseases at various phases. With its sophisticated features, machine learning (ML) is a state-of-the-art technology for image analysis and data extraction, improving classification, segmentation, detection, and error-reduction accuracy. This research shows how machine learning (ML) models assist farmers in analyzing massive datasets, enhancing soil quality, and increasing crop yields by using Convolutional Neural Networks (CNN) for model performance evaluation.

Keywords- Ancient Farming methods, Smart Farming methods, Machine Learning, Convolutional Neural Networks.

I. INTRODUCTION

Indian agriculture dates back to 9000 BC, and the Mehrgarh excavations, which date between 8000 and 6000 BC, have revealed some amazing insights into this history. On the Indian subcontinent, both plants and animals had already been domesticated by that point. Goats and sheep were among the first animals to be domesticated, while the earliest crops to be produced were jujube, wheat, and barley. During this time, elephant domestication also started. India quickly saw the emergence of a settled way of life as agricultural methods and implements advanced. The double monsoon system allowed for the practice of harvesting two harvests in one year, which was essential to the development of settled agricultural output.

While agriculture was not every community's main means of subsistence during the Neolithic era (c. 8000–5000 BC), those who did thrived. Threshing, row-cropping (either in pairs or groups of six), and granary storage were among the Indian agro-pastoralism techniques that were passed down to the next generations. The basis for the agricultural sector's continuous progress in India was established by this transfer of knowledge. The Kashmir Valley was home to agricultural settlements by 5000 BC, and cotton cultivation is thought to have begun there as early as 5000–4000 BC. Between 4530 and 5440 BC, wild oryza rice initially developed in the Belan and Ganges basins of northern India. Around this time, hemp was also domesticated and utilized to make medicines, oil, and fiber [2].

South Indian Agriclture in past

- Agriculture in ancient South India was equally vibrant and diverse. The Tamil people cultivated a wide range of crops, including rice, sugarcane, millets, black pepper, various cereals, coconuts, beans, cotton, plantains, tamarind, and sandalwood, along with trees like jackfruit, coconut, palm, areca, and plantain.
- Sustainable agriculture in the region was achieved through systematic practices such as weeding, irrigation, manuring, and crop protection. Water storage systems were also developed during this time. Notably, the Kallanai Dam, built on the Kaveri River in the 1st and 2nd centuries AD, is one of the earliest water-regulation structures in the world still in use today.

Agriculture in ancient India during the Chola period:

- During the Chola Empire (875–1279), South India's agrarian society saw a shift from communal land ownership to individual plots, each equipped with its own irrigation system.
- The Cholas also appointed officials responsible for overseeing water distribution, particularly to drier regions, utilizing tank-and-channel networks. As individual landholdings became more common, dry farming practices in these areas likely decreased.

Today, over 80% of people on the planet have access to the internet, which has revolutionized modern life by enabling services like VoIP, social networking, mobile communication, instant messaging, phone conversations, two-way immersive video chats, and e-commerce platforms. The next generation of communication platforms is represented by the Internet of Things (IoT), which makes it easier for technical and environmental systems to interact. IoT is a safe and economical technology that has the potential to change many industries, including agriculture, where IoT-based solutions are being created to manage and monitor farms on their own without the need for human intervention. As urbanization pushes young people toward cities and decreases the amount of farmland available, IoT can help address the issues faced by a declining agricultural workforce by enabling smart devices and equipment to interact with minimal human intervention.

Because smart farming may assist farmers in making decisions regarding their fields and crops in real time, it has attracted a lot of attention from researchers. The quality of agricultural goods and farmers' lives could be significantly improved by the incorporation of new information and communication technologies. Only approximately 24% of farmers in Europe have implemented smart agricultural technologies, compared to about 80% of farmers in the US. Smart farming makes it possible to automate, optimize, and enhance conventional farming practices, which boosts agricultural productivity and makes cultivation easier. Agricultural gear and IoT sensor utilization in smart farming work together to produce a synergistic impact that increases crop yields and improves farming efficiency [3].

IoT components like DeviceHive, Arduino, and Raspberry Pi, cellular networks (3G/4G/5G), ZigBee, Wi-Fi, and microcontrollers used as gateways are the basic parts needed for smart farming. While sensors collect vital information on numerous agricultural factors, such as soil moisture, water levels, and fertilizer levels, to enable precision farming, GPS is used for location tracking. A typical smart farming technique consists of four basic processes, as shown in Figure 1.

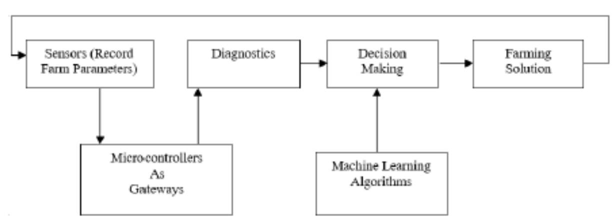

Figure 1: Fundamentals of smart farming architecture

A variety of agricultural characteristics, including soil type, moisture content, and nutrient availability—all crucial for a given crop—are measured using sensors. The specific requirements or shortfalls of the crop are determined by comparing these sensor results to predetermined parameters. Following data analysis, machine learning algorithms generate insights that can be used to develop practical agricultural solutions. The smart farming cycle's ongoing operation is guaranteed by this procedure.

II. IOT AND MACHINE LEARNING-BASED SOLUTIONS FOR SMART FARMING

An innovative IoT-based smart farming technology has been developed, utilizing a wrapper feature selection method known as WPART to enhance crop production. Their methodology incorporates a powerful decision-making tool called PART, which does not require global optimization for its results. The performance of the classifier is improved through the wrapper algorithm. However, a limitation of their approach is that it only analyses time series data and does not make future predictions. The model achieved an accuracy rate of 92.51%. Additionally, an expert methodology was created for assessing the suitability of agricultural land using sensor networks. The IoT sensors employed to develop the agricultural dataset included pH sensors, soil moisture sensors, salinity sensors, and electromagnetic sensors. Their evaluation and analysis process is based on a Multi-layer Perceptron (MLP). Data collected from various IoT devices is stored on a cloud platform, with the effectiveness of this research model influenced by network architecture, weight correction, and activation features.

A simple and cost-effective Internet of Things (IoT) system for real-time monitoring of various crops has been proposed. This system integrates machine learning and IoT technology to create an affordable smart agriculture module. All monitored agricultural datasets are uploaded to the cloud (Amazon AWS). The developed dataset is trained using logistic regression (LR) and support vector machines (SVM) to predict future crop conditions based on historical data. A unique model was created to evaluate soil quality and determine the most suitable crop for cultivation in that soil. The methodology utilizes the Node MCU ESP8266 microcontroller and employs three main sensors—a temperature sensor, a rain sensor, and a humidity sensor—to collect essential soil data for assessing its fertility and quality. The model also outlines the process for gathering environmental data, which can be used to forecast conditions and aid farmers in their decision-making. The data is stored on an open cloud server called Thing Speak. To identify the best crop for cultivation in the soil, a hybrid approach combining Multiple Linear Regression (MLR) and K-Means clustering is used. Additionally, an innovative smart irrigation system merges a decision tree method with various regression and classification techniques to predict a crop's water requirements. This model, capable of tracking temperature, moisture, and humidity, utilizes a range of agricultural sensors. The collected data is sent to a cloud-based IoT system, employing the DHT11 soil moisture sensor alongside the Raspberry Pi. [6].

An IoT framework has been developed that incorporates sensors, an LTE HUA8372 Wi-Fi internet module, and a microcontroller. This methodology allows for the immediate collection of environmental data, which is then transmitted to a cloud storage platform. The framework employs a support vector machine regression (SVMr) approach to detect fungal infections in various scenarios. Additionally, a strategy has been devised for predicting and disseminating information about harmful fungal diseases, with SVMr serving as a popular tool for delivering intelligent solutions [7].

An open-source method has also been established to determine field-based irrigation needs by monitoring soil moisture, soil temperature, and weather conditions. This method uses support vector regression (SVR) and K-means clustering to estimate soil moisture differences (SMD) during rapid fluctuations in meteorological conditions, improving accuracy while reducing mean square errors (MSE). This innovative algorithm demonstrates superior accuracy (R=96%) and lower MSE compared to traditional SVR methods for predicting soil moisture. The hybrid learning approach combining SVR and K-Means is employed for irrigation planning due to its enhanced accuracy and reduced MSE.

Based on agronomic knowledge, the best regression model for smart irrigation guidance was identified as gradient boosted regression trees (GBRT), achieving an accuracy of 93% [8]. This model allows agronomists to manage irrigation effectively.

Additionally, a thermal imaging-based intelligent monitoring system was proposed, which involves using a drone equipped with a thermal imaging sensor. The images produced by the sensor are analyzed to assess critical irrigation parameters such as water consumption, leaf quality, and fertilizer requirements.

Soil moisture on the surface was predicted using an extreme learning machine (ELM) built on a regression model, utilizing data collected from the field. A novel validation approach called "leave-one-out" cross-validation was employed. The experimental setup was evaluated using the sine kernel function, yielding a root-mean-square error (RMSE) of approximately 2.19%.

To enhance irrigation efficiency, a technique was proposed to analyze soil nutrient concentration. This method utilized soft sensors based on ELM to determine the amount of nutrient solution required.

The technique effectively monitors variations in pH, temperature, and concentration throughout the nutrient solution synthesis process [9]. Park et al. employed soil moisture forecasting methods and MODIS data, utilizing cubist and Random Forest (RF) approaches to reduce moisture content. Data on soil humidity was collected using a combination of several techniques, and the findings of their research were compared to those obtained through the least-squares method [10].

Various methods have been explored to assess total nitrogen (TN) and soil organic carbon (SOC) using machine learning algorithms. For their study, researchers collected soil samples from four agricultural regions in Morocco, India. Instead of relying on traditional chemical soil analysis techniques, they utilized near-infrared (NIR) spectroscopy to gather data. This approach reduces both time and computational overhead. The methodology predicts SOC and TN through ensemble learning modeling (ELM). Visible and near-infrared (NIR) spectroscopy were employed to measure total nitrogen, soil carbon, and moisture levels in the agricultural fields [11].

The spectroscopic dataset was then used to estimate these three soil characteristics, and machine learning models were developed based on this data. The analysis employed Cubist methods and least squares support vector machines (LS-SVMs), with the results indicating that the LS-SVM approach outperformed linear multivariate methods for estimating soil properties.

The study also examined machine learning algorithms for calculating and predicting soil carbon concentration. In addition to SVM, KNN, Cubist, and extreme gradient boosting (XGBoost), it was found that Random Forest (RF) accurately predicted SOC on simulated data, achieving an R^2 of 0.60 and an RMSE of 0.30%. The research revealed that SOC is influenced by factors such as air temperature, annual precipitation, valley depth, and terrain roughness [12].

Furthermore, deep learning architectures, specifically Convolutional Neural Networks (CNN) and conditional restricted Boltzmann machines, were investigated to predict soil attributes using infrared spectroscopy data.

An SVR model was proposed to forecast soil moisture levels in remotely sensed hyperspectral images, accounting for seasonal climate variations in the area.

To estimate daily water droplets and temperature across various regions in Iran, an extreme learning machine model was employed. Table 1 from the study demonstrates that extreme learning machine models outperformed SVM and ANN algorithms in terms of accuracy [13].

Table 1: Comparison of smart farming algorithms

Sl. No.	Smart farming approach	Attributes	Algorithms/approach
1.	Conducted a comparison of a novel approach and other machine learning algorithms for the prediction of soil organic carbon and total nitrogen using near infrared spectroscopy [14]	Soil organic carbon (SOC) and total nitrogen (TN)	Ensemble-learning algorithm
2.	measuring the composition of nutrient solutions for soilless culture using a soft sensor model based on DBN-ELM [15]	pH value, temperature, and flow rate	ELM
3.	Developed an Internet of Things-based smart irrigation management system that uses open source software and machine learning [16].	Soil moisture - temperature - climate conditions	SVR and K-Means clustering
4.	Developed a regression model based on machine learning for the prediction of soil surface humidity over fields with modest vegetation [17].	Soil surface moisture	Extreme learning machine regression (ELM-R)
5.	Described AMSR2 soil moisture downscaling using multiple sensor products [18].	Soil moisture	RF and Cubist algorithms
6.	Described a system for detecting soil moisture and atmosphere components using IoT and machine learning.	Humidity-temperature-moisture-rainfall	Hybrid approach MLR method and K-Means clustering
7.	Used VIS-NIR spectroscopy to predict soil total nitrogen organic carbon and moisture content using machine learning.	TN, SOC, and moisture content (MC)	LS-SVM and Cubist ML algorithms
8.	Using machine learning on sensor data to recommend irrigation: exposing the agronomist's hidden knowledge.	Temperature - solar radiation - relative air humidity	GBRT, regression tree model (RTM), and boosted trees classifiers (BTC)
9.	the use of machine learning in IoT-based smart agriculture.	Moisture, temperature and humidity	Decision tree
10.	Spatial prediction of soil organic carbon using machine learning algorithms.	Temperature, yearly rainfall	Cubist, XGBoost, RF, SVM, and KNN.
11.	Support vector regression was used to estimate soil moisture from airborne hyperspectral data.	Soil moisture	SVR
12.	Using an Internet of Things (IoT) environmental data collection system.	Soil moisture – temperature - air humidity - wind speed - wind direction - sunlight intensity	SVMr
13.	Describe deep learning architectures for soil attribute prediction.	Soil characteristics	Deep learning and CNN
14.	Weather forecasting has improved crop productivity using a recommender system.	Daily water droplet point - temperature	ELM, SVM, and ANN
15.	IoT and Machine Learning for Affordably Smart Farming.	Soil, temperature, moisture	Linear regression (LR), SVM

III. THE MAIN PILLARS AND METHODS OF SMART FARMING

To explore scientific approaches related to smart farming, the current study examined a diverse array of research topics. Consequently, our work encompasses various aspects of agricultural practices, decisions, and technologies. We utilized numerous sources from different scientific publishers, including Springer, Elsevier, Wiley, and MDPI. In addition to research project reports, our sources included books, book chapters, conference proceedings, and journal articles. Thus, this study is grounded in publicly available documents, primarily published within the last three years, authored by contributors from various countries worldwide. Notably, particular attention was given to smart agriculture practices on the African continent. The assessment subsequently addresses key components of smart farming, including the Internet of Things (IoT), the role of internet connectivity, and smart sensing technologies.

IV. IOT IN SMART AGRICULTURE

According to Fig. 2, the Internet of Things (IoT) is a clever and innovative technology that provides novel and useful solutions in a variety of fields, including smart cities, smart homes, traffic management, healthcare, smart agriculture, etc. The use of IoT technology in agriculture has significantly improved farm management. With the help of this technology, all agricultural machinery and tools can be connected in order to make informed decisions regarding fertiliser and irrigation supply [29].

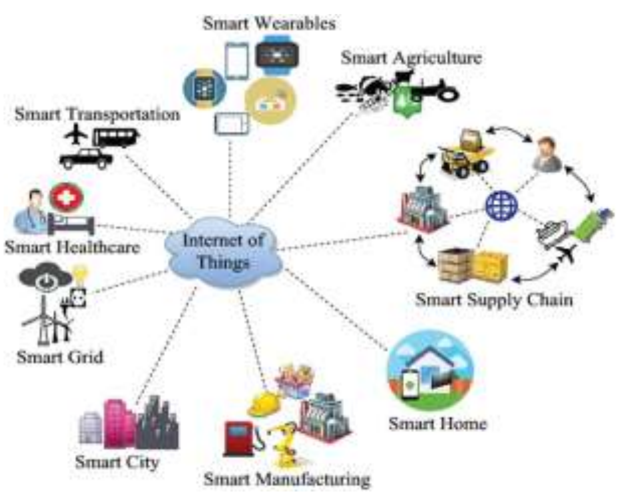

Fig. 2. IoT applications in several fields [18].

The precision and effectiveness of machinery used to track animal productivity and plant growth are improved by smart systems. Wireless sensor networks are used to gather data from a variety of sensing devices (WSNs). It is imperative to link cloud services with the Internet of Things (IoT) in order to assess and analyze this remote data, which streamlines decision-making and allows for optimal judgments. Information and communication technology (ICT), ground sensors, and control systems installed on robots, self-driving cars, and other automated equipment are needed for smart farm management. Satellite technology, cutting-edge mobile devices, and high-speed internet are also essential for the efficient operation of smart systems, which includes image capturing and placement.

Using a variety of satellite photos and sensors placed in fields, the Internet of Things (IoT) has been effectively used in real-time to monitor and detect leaf diseases that hamper crop growth (such as paddy and banana crops). Through the use of a web server, this technology helps with data analysis and expedites decision-making, which is then conveyed to farmers.

Pests, illnesses, and poor agricultural monitoring cause 20–40% of crops to be lost each year, according to estimates from the Food and Agriculture Organization. As a result, the use of sensors and intelligent systems enables the tracking of weather patterns, soil fertility, and the precise amounts of fertilizers needed for the best possible crop growth. Soil fertility can be negatively impacted by overuse of fertilizers.

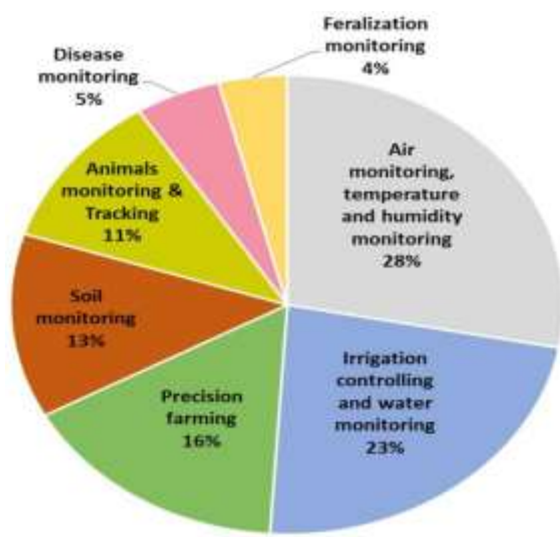

Fig. 3. IoT implementation in smart agriculture

An analysis of fifty research papers on Internet of Things applications in agriculture published between 2011 and 2018 revealed that roughly sixteen percent of the publications dealt with irrigation monitoring, and sixteen percent with precision agriculture. Water monitoring (7%), air and disease monitoring (5%), animal monitoring (11%), temperature monitoring (12%), soil monitoring (13%), and humidity monitoring (11%), were additional areas of focus. Monitoring of fertilizers was covered in just 4% of the research studies.

V. SMART SENSING FOR AGRICULTURE

Sensors measure and keep an eye on a number of factors in a smart system. For instance, sensors used in soil health evaluation monitor variables like soil moisture, compaction, phosphate concentrations, and nutrient levels. Several sensors are integrated by the smart irrigation system to track water levels, irrigation effectiveness, and weather. In addition to other variables, these sensors are able to measure and monitor changes in soil properties, yield quality, and weather conditions on farms.

As a result, they gather a variety of information that may be examined to evaluate farm circumstances and support well-informed decision-making. By keeping an eye on the condition of the soil, crops, and livestock, these cutting-edge sensors help to improve the amount and caliber of agricultural output.

Soil moisture sensors, soil temperature sensors, air temperature sensors, soil pH sensors, humidity sensors, and sensors for nitrogen (N), phosphorus (P), and potassium (K) are frequently utilized in smart agricultural networks.

These devices are crucial for tracking changes in the moisture and temperature of the soil. Smart irrigation, leaf disease detection, crop yield enhancement, and smart animal husbandry are only a few of the sensor-based applications for smart agricultural management that are shown in Figures 4 and 5. Every application has pertinent causes and effects.

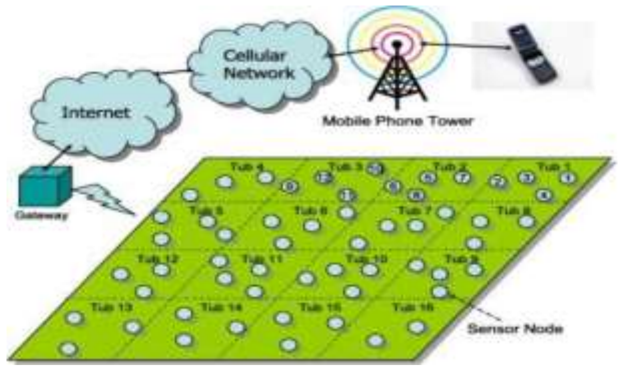

Fig. 4. Automated Wireless smart Sensors [35].

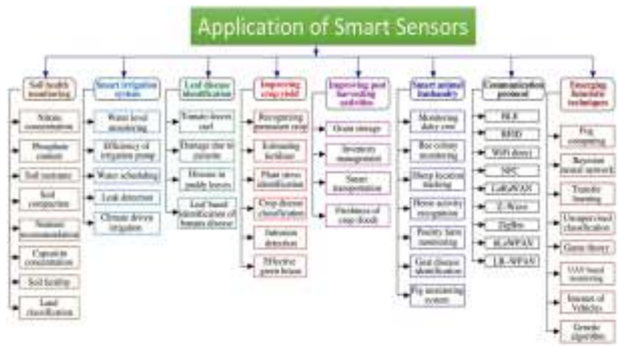

Fig. 5. Use of intelligent sensors in agriculture [35].

VI. SWOC ANALYSIS

Strengths	Weaknesses
• Home market • Close to consumers • Fertile land • Good technical skills • World-class breeding	• Tight regulation • Much political influence • High land costs • High market awareness • Lack of co-operation • Lack of investment • Foot-and-mouth disease
Opportunities	**Threats**
• Co-operate through vertical and horizontal integration • Good understanding of market • Good understanding of 'value' • Investment in technical efficiency	• Variations in currency • Cheaper overseas land and labour • Export of technical skills • Various diseases

VII. CONCLUSION

A recent World Health Organization report estimates that 800 million people worldwide, or one in nine people, experience food insecurity as a result of poverty and food shortages. This problem is made worse by the world's population expanding so quickly. Climate change, groundwater depletion, a shrinking labor force in agriculture, pollution, and the loss of arable land brought on by urbanization and industrialization are all causes making the food problem worse. These difficulties underline the pressing need for improvements in farming and agricultural technology in order to produce and maintain high-quality agricultural goods.

A workable way to produce high-quality agricultural products with less waste and human intervention is through smart farming. This technology helps farmers at every stage of the process, from planting crops to harvesting them. It includes machine learning, data analytics, cloud computing, and agricultural robotics. This research performs an extensive analysis of different smart farming algorithms and architectures. It also highlights how crucial it is to create new technology to improve farming methods in order to satisfy future food demands as well as other requirements. It also promotes greater research into better farming techniques in order to guarantee that food of a good caliber is available for all living things, not just humans.

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