AI-driven Internet of Agro-Things Adaptive Farm Monitoring Systems for Future Agricultural Production and Food Systems in Africa

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Abstract

Emerging technologies like Machine Learning (ML) and the Internet of Things (IoT) assist farmers in addressing challenges and maximizing limited agricultural resources. Data-driven farming requires integrating various tools across the production chain, along with a System of Systems (SoS) approach for scalability, adaptability, and sustainability. Essential technologies include Artificial Intelligence (AI), Blockchain, big data analytics, remote sensing, and the Internet of Agro-Things (IoATs). This paper presents novel techniques for improving agricultural productivity among African small-holder farmers using ML and IoATs. It shares experiences in developing digital agriculture platforms, climate-smart farming, and a business-oriented approach. Key technologies covered are: (a) IoT-based agricultural systems, and (b) AI/ML for increasing productivity. The paper showcases real-time ML-driven IoATs implementation for farm-level crop monitoring and yield prediction. The paper outlines recommendations, trends, and research directions in digital and data-driven agriculture in Tanzania. By leveraging ML and IoT, this paper offers innovative techniques to transform agriculture and empower African small-holder farmers. Integration of advanced technologies and sustainable farming approaches contributes to addressing food security, resource efficiency, and economic development.

Key words: Artificial Intelligence, Machine Learning, IoTs, Remote Sensing, Digital Agriculture, Small-holder farmers

Introduction

Smallholder farmers employ about 70% of the world's population and produce 70% of the world's food (Giller *et al.,* 2021; Barakabitze *et al.,* 2015). Tanzania's agriculture sector accounts for 26.7% of GDP and employs more than 80% of the population, with women accounting for 60% of the farm workforce. Apart from the sector being the main source of food security and nutrition, agriculture contributes to poverty alleviation and countries' economic growth (Lyatuu *et al.,* 2015). The role of small scale agriculture on economic growth is vivid as it leads to growth of product within the sector itself.

Agriculture is undoubtedly the largest and most important sector of the Tanzanian economy, with the country benefitting from a diverse production base that includes staple food crops (e.g., maize and sorghum), and a variety of cash crops. Smallholder farmers and emerging farmers 9 women and youths) as well as other sector stakeholders face considerable challenges in modernizing the industry to increase yields. This is because smallholder farmers are struggling to access economically viable technology.

Farm-scale crop monitoring and management as well as crop yields prediction for maize and sorghum in Tanzania is very challenging due to many factors involved, such as crop and variety, soil type, management practices, pests and diseases, and climate and weather patterns during the season. Most small and medium-sized farmers in Tanzania, on the other hand, cannot afford to embrace advanced equipment for improving their prodcivity and achieve sustainable agriculture, which goes against the UN Sustainable Development Goals (SDG) tenet of "leaving no one behind." Soil degradation and water stress are the outcome of unsustainable farming methods. There is a lack of data at the farm, farmer, and sector levels, resulting in greater service costs. Food waste in the country is increasing due to a lack of food processing, logistics, and warehousing infrastructure near farm gates. Smallholder farmers face lots of financial and digital inclusion challenges as well as huge gaps in market linkages, difficulties in price discovery and market price volatility. Additionally, farm mechanization is inadequate due to financial constraints (Simbakalia *et al.,* 2012; Kingu, 2021, Sanka *et al.,* 2021).

Emerging technologies such as the Internet of things (IoT) (Dahane *et al.,* 2015), artificial intelligence (AI), machine learning (ML), remote sensing, and blockchain, which are being pushed by the fourth industrial revolution, are disrupting many industries and delivering quick and large-scale change. Agriculture has been slow in Tanzania to take advantage of the potential of these emerging technologies. Low levels of adoption of emerging technologies in agriculture in Tanzania is caused by the sector's complexity, which includes small farm sizes, a lack of telecoms infrastructure in rural areas, high regulatory burdens that drive up costs, and farmers' limited ability and willingness to pay.

Machine learning techniques take a data-driven or empirical modeling approach to learn useful patterns and relationships from input data and provide a promising avenue for improving crop monitoring, farm management and yield predictions for smallholder farmers.

The study bridges this technological gap and develop an intelligent ML-based IoTs smart adaptive farming system for improving the agricultural productivity in Tanzania. The developed AI/ML-IoT based solution can monitor in real-time crop performance and provide decision support tools for SSFs. The contributions of this paper are three fold:

- Development of a ML-driven IoT-based cloud computing farm monitoring and management architecture to monitor in real-time crop performance and provide recommendations and decision support tools for SSFs.
- Showcase a real-time implementation of ML –driven IoATs for monitoring, management and predicting crop yields for farmers at a farm –level based on a soild moisture parameter.
- Illustrate a deployment of a small-scale smart farming system using low-cost Internet of Agro Things (IoAT) sensors and interactive cloud-based big data analytics to monitor and evaluate crops' performance in real-time.
- Develops measures and recommendations that that will support decision making in terms of policy and AI intervention strategies for data and digital agriculture in the context of agriculture productivity and food security in Tanzania.

Therefore this investigates the importance of multisource data (weather, and climate patterns, remote sensing data, crop type, soil type, etc.) in monitoring, managing and predicting crop yield for different crops across different regions in the country. The paper show how the low-cost agricultural IoT sensors which are installed in different agricultural zones can facilitate the collection of farm-level datasets. The developed ML –driven IoT –based dashboard can collect considerable big data and stream the results using a big data analytics platform.

The beneficiaries of this study will be small farmers to receive various recommendations of crop performance in real –time based on the collected agricultural big IoT data from various sources. Researchers in the country will able to utilize the collected dataset in the development of novel agricultural approaches for enhancing productivity.

The rest of this paper is organised as follows. Section two provides related work and Section three presents the proposed architecture of an ML-driven IoT-based cloud computing farm monitoring and management architecture for SSFs. Section four provides initial implementation outputs/findings and discussion. Section five provides future challenges and research directions and Section six concludes the paper.

Material and methods

Study area

This study was carried out in Morogoro at SUA farming sites. The study area was selected based on climate-related conditions and easy monitoring of study implementation. The study employs various IoT sensors such as temperature, weather, soil and environmental sensor nodes located at different locations in the farms/plots to communicate with the gateway over local telecommunication systems to collect big data and measure the growth and performance of root activity of crops in the farms in real-time (Fig. 1).

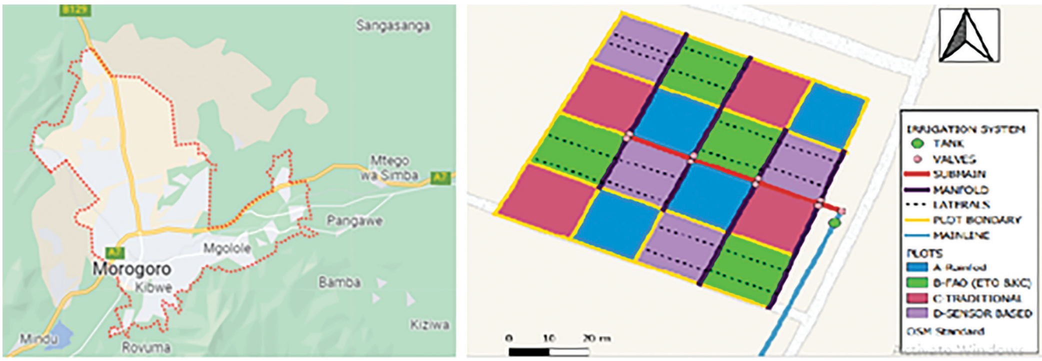

Figure. 1: Study area and experimental design

The Morogoro Region has a tropical climate with regular rainfall. In lowlands, the annual average temperature ranges from 18°C to 30°C. Nearly the entire year, Morogoro receives moderate temperatures of about 25°C. Typically, the cooler season lasts from July to September. The Region experiences a bi-modal rainfall pattern, with long rains from March to May and short rains from November to January. The yearly rainfall ranges from 600 to 1800 millimeters.

ML–driven IoT based smart monitoring, management and crop yield prediction system for farmers

Various IoT sensors were employed such as temperature, weather, soil and environmental sensor nodes located at different locations in the farms/plots to communicate with the gateway over local telecommunication systems to collect data and measure the growth and performance of root activity of crops in the farms in real-time.

Fig. 2 indicates the proposed architecture for performing crop performance monitoring and yield prediction using ML and agriculture IoT technologies in Tanzania. The ML –driven IoT based architecture consists of sensors (soil moisture, temperature, and humidity), gateway, solar panel, monitoring tools to monitor crops performance in real-time, smartphone Apps for farmers, cloud storage and crop yield prediction modules. The description of these modules are

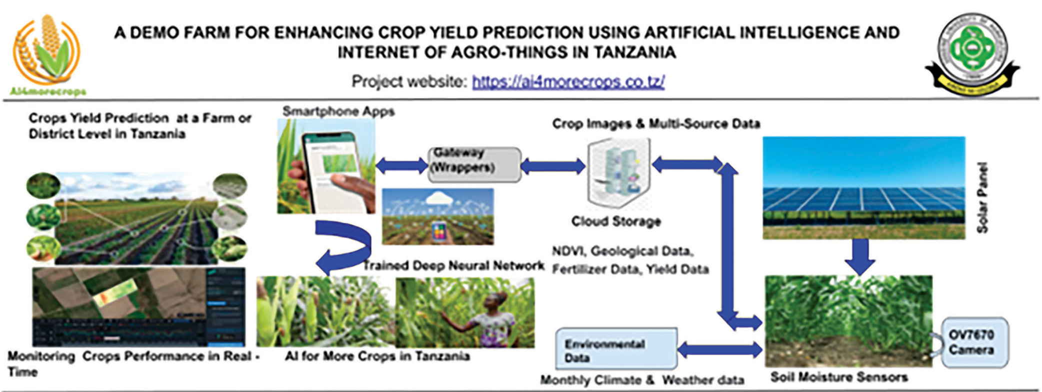

Figure 2: ML –driven IoT based smart monitoring and crop yield prediction system for farmers

provided below.

Agriculture IoT sensors

We utilize a group of weather, soil moisture, temperature and environmental sensor nodes located at different positions in the farms that communicate with the gateway over local telecommunication systems to collect various environmental data and measure the growth and performance of root activity of crops in the farms (Wang *et al.,* 2015). Soil moisture sensors measure the moisture content in the soil, helping farmers optimize irrigation practices and avoid over or under-watering. By providing data on soil moisture levels, these sensors assist in efficient water management and prevent water stress in crops. Weather sensors monitor environmental conditions such as temperature, humidity, rainfall, wind speed, and solar radiation. This data is essential for making informed decisions regarding crop management, pest control, and disease prevention. Nutrient sensors measure the concentration of essential nutrients in the soil, such as nitrogen, phosphorus, and potassium. This information enables farmers to apply fertilizers more precisely, reducing nutrient wastage and environmental pollution. Crop health sensors are used to assess various aspects of crop health, including leaf temperature, chlorophyll levels, and disease detection. Monitoring crop health in real-time, would help farmers to identify early signs of stress or disease and take timely action to mitigate potential losses.

Gateway

The Gateway (Fig. 1) that is connected to the Internet stores the collected data and process them in the cloud, specifically using cloud computing servers such as Microsoft Azure, Amazon Web Services or Google Cloud. An agriculture gateway provides connectivity options to connect and communicate with different IoT devices and sensors on the farm. It supports various communication protocols such as Wi-Fi, Bluetooth, Zigbee, LoRaWAN, or cellular networks, depending on the specific requirements and availability of infrastructure in the agricultural area.

The gateway collects data from multiple sensors and devices deployed across the farm. It acts as a central hub, aggregating the data

Figure 3: Implementation of the proposed ML –driven IoT –based crop monitoring and yield prediction system

Figure 4: Collection of weather data and forecast and image pictures in real time

and preparing it for transmission to the central data management system. This ensures that data from different sources can be processed and analyzed effectively. The gateway establishes a connection with the central data management system, a cloud-based platform or a local server. This facilitates the seamless transfer of data from the farm to the central system, allowing for further analysis, visualization, and decision support at a broader scale.

Fig. 3 and 4 show the implementation of the architecture and the process of data collection from IoT sensors and precision agriculture weather data and forecast. The implementation process started in November 2022 and the data collection was performed as soon as the crops emerged from the soil using various IoT sensors installed in the farm field.

Cloud –storage infrastructure

Cloud platforms provide ample storage space for agricultural data, including sensor data, satellite imagery, weather information, and historical records. It also offers powerful computational capabilities that can be leveraged for data processing and analytics. Farmers can utilize cloud-based tools and algorithms to analyze large datasets, perform predictive modeling, and gain insights into crop performance, weather patterns, market trends, and other relevant factors. In addition, cloud-based applications and platforms enable remote monitoring and control of agricultural systems.

Integrating IoT devices, sensors, and actuators with cloud infrastructure, enable smallholder farmers to remotely monitor and manage irrigation systems, greenhouse environments, and other aspects of their farms, improving efficiency and reducing costs. Moreover, the cloud-based decision support systems provide farmers with real-time access to agricultural knowledge, best practices, and recommendations. It is worth noting that by leveraging cloud infrastructure, agricultural experts can develop and deploy decision support tools that consider local conditions, crop-specific requirements, and market dynamics, helping farmers make informed decisions for improved productivity and profitability.

Cloud platforms facilitate collaboration and knowledge sharing among farmers, researchers, and agricultural stakeholders. We use ThingSpeak (https://thingspeak.com/) shown in Fig. 1 to store and manage the data that are generated by sensors. ThingSpeak allows you to aggregate, visualize, and analyze live data streams in the cloud (Varshney and Richardson (2017)). ThingSpeak provides instant visualizations of data posted by your devices or equipment.

Smartphone apps for agriculture productivity

Smartphone apps have become powerful tools for agriculture, providing farmers with access to information, resources, and tools right at their fingertips. Our implementation focuses on five categories of smartphone apps: (a) crop management apps, (b) farm management apps, (c) weather and climate apps, and (d) irrigation control apps, and (e) training and knowledge sharing mobile apps. Crop management apps provide guidance and information on crop selection, planting schedules, fertilization, irrigation, and pest management. They offer features such as pest and disease identification, nutrient calculators, and growth tracking, helping farmers optimize their crop management practices.

Farm management apps are designed to assist farmers in managing their farms more efficiently by offering features such as task scheduling, record-keeping, inventory management, and expense tracking. These apps help farmers to streamline agricultural operations, improve productivity, and keep better track of their resources. Weather and climate apps provide farmers with accurate and localized weather forecasts, including temperature, rainfall, wind speed, and humidity (Ghanshala *et al.,* 2018). This app also provides information on climate patterns, historical data, and early warning systems for extreme weather events.

Farmers can use these apps to plan their activities and make weather-informed decisions. Irrigation control apps allow farmers to remotely monitor and control their irrigation systems. They provide features like scheduling, flow monitoring, and water usage analytics. These apps help farmers optimize water usage, reduce costs, and ensure efficient irrigation practices. Finally, we also provide the training and knowledge sharing apps to provide farmers with educational content, videos, tutorials, and best practices in agriculture. They offer information on various topics, including crop cultivation techniques, pest management strategies, and sustainable farming practices, empowering farmers with valuable knowledge and skills (Barakabitze *et al.,* 2017); Juma *et al.,* 2017).

Crops yield prediction models

Accurate yield prediction is valuable for farmers, agricultural planners, and policymakers as it helps in decision-making related to resource allocation, marketing strategies, and overall crop management. As indicated in Fig. 2, historical crop yield data, including yield records from previous years, can be analyzed to identify patterns and trends. By considering factors such as weather conditions, crop management practices, and field characteristics, statistical models can be developed to predict future yields based on past data. Weather and climate play a crucial role in crop growth and development. Incorporating historical and forecasted weather data, including temperature, rainfall, humidity, and satellite imagery can help predictive models to assess the impact of weather on crop yield and provide yield forecasts for stallholder farmers.

It is important to note that crop yield prediction models integrate inputs such as weather data, soil characteristics, crop variety, and management practices to estimate crop yield under different scenarios. They can be used for yield prediction and to explore the effects of various management strategies. AI/ML algorithms can then analyze large datasets, including weather data, soil data, and crop management data, to identify patterns and relationships that affect crop yield and provide recommendations to farmers. The developed IoT-based ML agriculture solution will help to measure soil variability and micro-climate data in the agricultural field. AI/ML and big data analytics tools are applied to give relevant information that will help SSFs and emerging farmers in analyzing the data patterns, insights, correlation, and predictions and help them in good decision making (e.g., where to cultivate –which crop, when to plant, irrigate, supply fertilizers, spray chemicals, and harvest) (Ahmed *et al.,* 2018).

The IoT-ML-based solution provides a detailed picture using the local understanding context of microclimate SSFs' agricultural farms/plots and soil variability across a range of conditions. It delivers these insights and patterns to the SSFs' as current management agricultural practices and future predictions for monitoring crop productivity in Tanzania using a real-time agriculture ML–driven IoT crop monitoring dashboard.

Preliminary Results

Figure 5 shows a real time prototype implementation of a ML-driven IoAT–based architecture for monitoring and management of crops as well as prediction of crops yield. As shown in Figure 5, we developed a web-based application that can be accessed in laptop or smartphone devices that is connected to the Internet. We have also configured the hardware IoT sensor devices and programmed them so as to connect them with the web–based applications and smartphone applications.

The sensors used include the soil moisture, humidity, temperature and camera sensors. The data is collected from the IoT sensors and stored in the cloud–storage and displayed on the web application for the smallholder to view on various parameters and growth performance of a crop. The data is collected after every 1 minute, which is a threshold that is set for IoT sensors to upload the data to the cloud storage. The IoT-data pushed to the cloud storage can be also available to the smartphone for a farmer to visualize and take the necessary actions of performing irrigation/fertilize applications in the farm.

The data was collected in 2022 consisting of temperature, humidity and soil moisture data. We employ ML and big data analytics tools to analyse the data patterns, insights, correlation, and predictions and help famers in good decision making (where to cultivate–which crop, when to plant, irrigate, supply fertilizers, spray chemicals, and harvest).

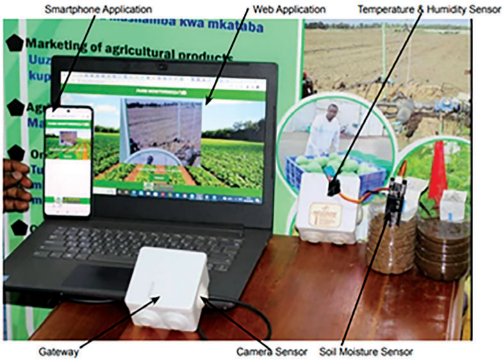

Figure 5: A Real-time prototype implementation of a ML–driven IoAT architecture

Date	Time	Temperature	Humidity	Soil moisture
9/5/2022	22:06:16	26.7	69	26
9/5/2022	22:06:18	26.7	69	26
9/5/2022	22:06:21	26.7	69	26
9/5/2022	22:06:24	26.7	69	26
9/5/2022	22:06:26	26.7	69	26
9/5/2022	22:06:29	26.7	69	26
9/5/2022	22:06:32	26.7	69	26
9/5/2022	22:06:35	26.7	69	26
9/5/2022	22:06:38	26.7	69	26
9/5/2022	22:06:41	26.7	69	26

Figure 6: Real-time flow of data in the cloud from IoT sensors

We also developed a ML-driven IoT system dashboard indicated in Figure. 7. A dashboard for an ML-driven IoT system in agriculture provides a visual interface to monitor and manage the various components and data of the system. It allows users, such as farmers, agronomists, or agricultural managers, to access real-time information, track performance, and make data-driven decisions. Key features and components of a dashboard shown in Fig. 6 for an ML-driven IoT system in agriculture:

Data Visualization: The dashboard presents data collected from IoT devices, sensors, and other sources in a visual format, such as graphs, charts, maps, or tables. It provides an overview of the system's performance and allows users to quickly interpret and understand the data.

Real-time Monitoring: The dashboard displays real-time data on different parameters, such as temperature, humidity, soil moisture and crop growth performance. Farmers and agriculture extension officers can monitor these variables to detect anomalies, trends, or critical events that require immediate attention.

Predictive Analytics: The dashboard incorporates ML models for predictive analytics which display forecasts, predictions, or recommendations based on the data collected. It helps farmers anticipate potential issues, plan actions, and optimize resource allocation (irrigation plans and nutrients treatment to the farm).

Alerts and Notifications: The dashboard can generate alerts and notifications based on predefined thresholds or triggers. For example, it can notify farmers and agriculture extension officers when certain environmental conditions are outside the desired range, or when anomalies are detected in the data. This feature enables timely response and intervention. For example, the red color in the irrigation dashboard

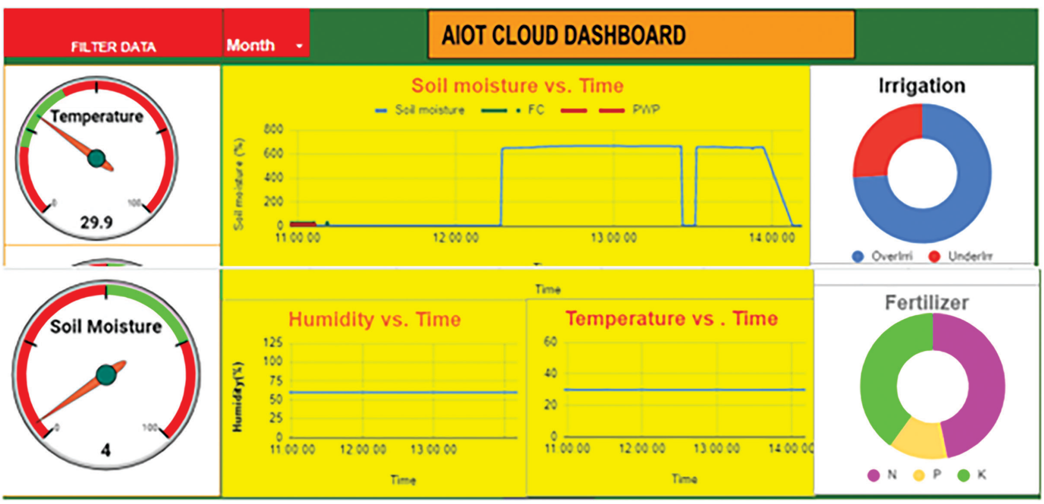

Figure 7: A ML-driven IoT dashboard for real –time data visualization

indicates that the water is below level and needs to be irrigated.

Historical Data Analysis: The dashboard allows farmers to access and analyze historical data collected by the ML- driven IoT system. It enables farmers to review trends, patterns, and performance over time, facilitating retrospective analysis and informed decision-making.

Configuration and Control: The dashboard can also provide options for configuring and controlling the ML- driven IoT system. Farmers can set parameters, adjust thresholds, schedule actions, or change settings related to the connected devices and sensors through the dashboard interface.

Integration with External Data: The dashboard can integrate external data sources, such as weather forecasts, market prices, or satellite imagery, to provide additional context and insights. This integration enables users to make more comprehensive and informed decisions.

User Management and Access Control: The dashboard may support user management functionalities, allowing administrators to assign roles, permissions, and access levels to different users or user groups. It ensures that appropriate users have access to the relevant data and functionalities.

Mobile Compatibility: To enhance accessibility and usability, the dashboard is compatible with mobile smart devices. Mobile apps or responsive web design can enable users to access and interact with the dashboard from smartphones or tablets while on the go.

Data Export and Reporting: The dashboard allows users to export data or generate reports for further analysis, documentation, or sharing purposes. This feature enables users to communicate insights, track progress, and comply with reporting requirements. It is worth noting that the design and layout of the dashboard is intuitive, user-friendly, and customizable, considering the specific needs and preferences of the target users. It also present actionable information and empower users to optimize their agricultural practices based on the ML-driven insights provided by the IoT system.

Discussion and Related Work

This study has indicated that farmers have a turning to the IoT and ML technologies to improve production capabilities and analytics. The IoT sensors are placed all over the field for data collection, allowing farmers to use a smartphone and the Internet to get extensive information about different soil, plant, weather characteristics. Farmers can be given complete information using IoT sensors at several levels of smart farming, including soil analysis and mapping, irrigation, fertilizers and pesticides, disease detection, harvesting, and production forecast and monitoring (Adamchuk *et al.,* 2004).

Accurate and timely crop monitoring and yield prediction is critical for the agricultural supply chain and food security in the country. Previous research in Tanzania relied on monitoring and crop yield prediction either based on climate or satellite data to develop empirical or statistical models for decades. Laudien *et al.* (2020) provide a monitoring and forecasting approach for maize yields in Tanzania based on climatic predictors at the sub-national scale about 6 weeks before the harvest. The authors perform monitoring and predictions of absolute anomalies and yield anomalies at the sub-national about six weeks before harvesting.

However, this study is based on a statistical yield forecast covering the time period from 2009 to 2019 only and cannot be extrapolated to other spatial and temporal contexts. It is also only focused on within-seasonal predictions for the entire country and is limited to one crop (maize). Liu and Basso (2020) provide a monitoring and prediction of yields for three case studies in Tanzania based on a process-model for the lead time of 14-77 days. However, this study is limited to the survey data at a large scale farm.

Volk *et al.* (2021) provide a simulation study from the Singida region that investigates the adaptation measures to prevent future maize yield decline in Tanzania for the baseline period 1980 - 2012. However, this study does not use climate and satellite data to perform monitoring and prediction of maize yields (Ghanshala). Again, this method involves only one crop while machine learning (ML) - based modular models that are suited for many crops are required in Tanzania. Any previous statistical relationships between yields and climate indices may no longer hold true in light of the current climate change and variability as well as climate teleconnections between a region of interest and other regions of the world, as the future will be characterized by climate regimes (variability) not previously observed.

The Government of Tanzania has recently established the Agricultural Routine Data System (ARDS), a district's convenient tool for agricultural data management, analyses, report writing and planning. ARDS is a system whereby agricultural performance information is collected, managed, and transmitted from LGAs to the ASLMs through regions.

The ARDS is composed of: (1) the Village/ Ward Agricultural Extension Officer (VAEO/ WAEO); (2) the Integrated Data Collection Format (District format); and (3) an Integrated ARDS Local Government Monitoring Database 2, a computer software which transmits data from LGAs to ASLMs via Regions. The data collected by ARDS includes: weather conditions, crop (planted area, yield production and prices), plant health services, extension services, biological control measures, irrigation (planted area, production, etc.), soil erosion, area cultivated and means of cultivation. However, the data collected by the ARDS is inaccurate and untrustworthy because it involves manual tallying.

As indicated in this study crop performance monitoring and yield prediction using IoT sensors in real-time can provide accurate and timely information for farmers and policy makers to take necessary actions. Different fro preious works, this paper introduces a ML –driven smart farming system for small-holder farmers based on low-cost IoT sensors and popular data storage services and data analytics services on the cloud for farm-scale crop monitoring and prediction in real-time.

Conclusion and Recommendations

Conclusion

The proposed management architecture offers real-time monitoring of crop performance and provides valuable recommendations and decision support tools for small-scale farmers (SSFs). The deployment of a small-scale smart farming system, powered by low-cost Internet of Agro Things (IoAT) sensors and interactive cloud-based big data analytics, enables continuous monitoring and evaluation of crop performance. The development of effective measures and recommendations will contribute to data-driven decision-making for policy and intervention strategies, thereby enhancing agriculture productivity and food security in Tanzania. The results demonstrate that the ML-driven IoT system in agriculture offers a user-friendly visual interface to efficiently monitor and manage various components and data within the system.

Recommendation

To supporting decision-making in the context of digital and data-driven agriculture productivity and food security in Tanzania, there are several measures and recommendations that can be considered to leverage technology and data to improve agricultural practices, enhance productivity, and ensure food security in Tanzania. These are some key measures and recommendations:

i. Improve data collection and analysis: Enhance the collection, quality, and accessibility of agricultural data, including crop yields, weather patterns, soil health, and market prices. Establish mechanisms to analyze and interpret data effectively, such as utilizing data analytics, ML tools, and remote sensing technologies.
ii. Strengthen digital infrastructure: Invest in improving digital infrastructure, including internet connectivity and mobile networks, particularly in rural areas. This will enable farmers to access and utilize digital tools and platforms effectively for agricultural decision-making.
iii. Promote farmer education and digital literacy: Provide training and capacity-building programs to enhance farmers' digital literacy and knowledge of data-driven agricultural practices. This can include workshops, demonstrations, and online resources to educate farmers about the benefits and effective use of digital tools

and technologies (Barakabitze *et al.,* 2017).

iv. Facilitate access to digital tools and platforms: Promote the availability and affordability of digital tools, such as mobile apps, sensor technologies, and drones, that can assist farmers in monitoring and managing their crops effectively. Encourage the development of user-friendly applications tailored to the needs and contexts of Tanzanian farmers.

v. Foster public-private partnerships: Encourage collaboration between government agencies, private sector entities, and research institutions to develop and deploy digital and data-driven solutions for agriculture. Public-private partnerships can help leverage expertise, resources, and technological innovations to address challenges in the sector effectively.

vi. Support innovation and research: Allocate resources and funding to support research and development initiatives focused on digital and data-driven agriculture in Tanzania. Encourage innovation in areas such as precision agriculture, remote sensing, and data analytics to identify and implement effective strategies for boosting productivity and ensuring food security.

vii. Establish robust data governance frameworks: Develop and implement appropriate data governance frameworks to address issues related to data ownership, privacy, security, and sharing. These frameworks should ensure that farmers have control over their data and that data is used ethically and responsibly to benefit the agricultural sector as a whole.

viii. Encourage market linkages and access to information: Promote the use of digital platforms to connect farmers with markets, buyers, and agricultural extension services. Facilitate the dissemination of market information, pricing trends, and best practices to empower farmers in making informed decisions about crop selection, production techniques, and marketing strategies.

ix. Monitor and evaluate interventions: Establish mechanisms to monitor and evaluate the impact of digital and data-driven interventions in agriculture. Regularly assess the effectiveness and outcomes of implemented strategies to identify areas of improvement and inform future decision-making processes.

x. Policy and regulatory support: Develop and enforce supportive policies and regulations that facilitate the adoption and integration of digital and data-driven technologies in agriculture. This includes addressing issues related to data privacy, intellectual property rights, and standardization of digital platforms. By implementing these measures and recommendations, Tanzania can harness the potential of digital and data-driven agriculture to improve productivity, enhance food security, and ensure sustainable agricultural practices.

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