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IoAT Enabled Smart Farming: Urdu Language-Based Solution for Low-Literate Farmers

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Abstract: The agriculture sector is the backbone of Pakistan's economy, reflecting 26% of its GPD and 43% of the entire labor force. Smart and precise agriculture is the key to producing the best crop yield. Moreover, emerging technologies are reducing energy consumption and cost-effectiveness for saving agricultural resources in control and monitoring systems, especially for those areas lacking these resources. Agricultural productivity is thwarted in many areas of Pakistan due to farmers' illiteracy, lack of a smart system for remote access to farmland, and an absence of proactive decision-making in all phases of the crop cycle available in their native language. This study proposes an internet of agricultural things (IoAT) based smart system armed with a set of economical, accessible devices and sensors to capture real-time parameters of farms such as soil moisture level, temperature, soil pH level, light intensity, and humidity on frequent intervals of time. The system analyzes the environmental parameters of specific farms and enables the farmers to understand soil and environmental factors, facilitating farmers in terms of soil fertility analysis, suitable crop cultivation, automated irrigation and guidelines, harvest schedule, pest and weed control, crop disease awareness, and fertilizer guidance. The system is integrated with an android application 'Kistan Pakistan' (prototype) designed in bilingual, i.e., 'Urdu' and 'English'. The mobile application is equipped with visual components, audio, voice, and iconic and textual menus to be used by diverse literary levels of farmers.

Keywords: smart farming; precision agriculture; IoT; sensor network; semi-literate farmers; interactive interface; User Interface (UI); Android apps

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1. Introduction

Agriculture is considered the base for human living because it is the primary food source and plays a crucial role in the global economy. Pakistan is 79.6 million km^2 and is home to a population of 192 million. The contribution of the agricultural sector to gross domestic product (GDP) in Pakistan gradually decreased to 19.3% in the year 2020–2021 from 22.04% previously recorded in 2019 and generating employment opportunities for 38.5% of Pakistan's labor force and valuable foreign exchange for the country [1–3]. It supports the manufacturing and services sectors of the economy by providing backward-forward linkages in inputs-outputs markets and the most significant consumer of household durables. Therefore, our agriculture sector can be considered an economic activity in the country [4]. Farmers are facing issues in the agriculture sector, so it's significant to research, develop of latest mechanisms, and adopt new practices to enhance production. Pressure on the agricultural system will increase with the continuing expansion of the human population.

Many areas of Pakistan are trailing in agricultural productivity due to a lack of farmers' awareness, timely access to crucial information, and proactive decision-making [5,6]. It is vital for human development in these underdeveloped areas to utilize information and communication technologies (ICTs), artificial intelligence techniques, machine learning (ML), and deep learning (DL) to make such information more readily accessible to farmers, significantly increasing crop production [7–13]. Climate change and shortage of agricultural resources are also significant concerns for the downfall of agricultural performance resulting in food insecurity [14–17]. This lets farmers hamper soil with intensified pesticides, which affect agricultural practices in a harmful manner. Finally, fields remain barren [18–22]. These are reasons for crop failure, lower production due to diseases, unpredictable climate change, and loss of soil fertility [23,24].

In this scenario, the traditional agriculture trends are insufficient to increase agricultural growth. Agriculture is also out of the reach of less conventional technologies. In this context, digital agriculture, automation, and precision farming, now termed smart farming, have arisen as new scientific fields that use intense techniques to drive agricultural productivity while minimizing its environmental impact [25–27]. Data generated by smart farming operations is provided by various sensors that enable a better understanding of the operational environment (interaction of dynamic conditions of the crop, soil, weather, and environmental factors) and the operation itself, leading to more accurate and timely decision-making [28,29]. Variability in climate and labor shortage is increasing continuously, providing better insights for agricultural machinery automation. Remote monitoring technologies facilitate farmers to access every inch of the farmlands by creating virtual fences to monitor, detect and protect crops in real-time [30–32]. IoT-based technologies allow farmers, among other things, to gather data on plants' environmental conditions like climate change, soil fertility level, humidity, temperature, and light intensity to monitor fields and farms remotely. These technologies assist farmers in having know-how and status of crops anywhere and anytime [33–36].

In Pakistan, most farmers have android phones [37–41] but are regrettably underutilized. Our preliminary literature study compelled us to work to facilitate farmers for agriculture automation, recommendations, and guidelines in their local language, i.e., Urdu, by using the internet of agricultural things (IoAT), also known as agricultural internet of things (Ag-IoT) and artificial intelligence technologies with transliteration and voice-speech support in the local language. IoAT is the network of complex and diverse agricultural objects that compute, process, and recommend solutions intelligently based on data generated from every connectable thing [42].

Previous research shows that using graphical cues, audio, speech, and video in mobile interfaces helps low-literates better adapt [43,44]. Field study experiences reflect that low-literates feel more challenged in understanding and interpreting textual information than their literate peers [45]. In our research, we try to accommodate such users by introducing audio, speech, Urdu language support, and an interactive graphical interface. Researchers also talked about the improvements in information dissemination systems for less literate farmers via different means [46–50]. However, none considered interface design and Urdu language-based real-time updates about agricultural guidelines using the android application and user preferences. Our choice of Urdu in this work was made by observing that 87% of farmers preferred Urdu as a medium of information dissemination [51]. Our research is an extended form of [52–54] and primarily focuses on developing an IoT-based and user-friendly system with these utilities.

1.1. Rationale

This section reflects the findings and an evaluation report on information found in the literature relevant to our research domain. It represents the overview of different approaches used by other researchers. Integrating the Internet of Things into the agricultural system has led to the internet of Agricultural things (IoAT) and advanced computing techniques. The researchers applied this to obtain maximum benefits and also to improve the production of agriculture, artificial intelligence, and IoT [55]. The agriculture domain is experiencing new evolution and revolution motivated by cloud technology, IoT, Edge and fog computing, sensors, IoT, and big data [56]. A proposal was presented for agriculture applications by investigating integrated platforms, including cloud computing, IoT, and data mining techniques [57]. An IoT-based smart agricultural system was developed using deep learning combined with a cloud environment comprised of four layers: data collection, edge computing, data transmission, and cloud computing layer [58]. A scalable network-based architecture was proposed to monitor and regulate agricultural farms in rural areas using IoT-based wifi, long-distance network, and fog computing [59]. Agricultural data analytics employed with IoT has transformed from specific crops to any kind of crop. The developed system could support various applications, from controlling and monitoring the crops to promoting them to market [60].

Literacy is the ability to read and write simple statements [61]. Illiteracy, low education, and computer illiteracy are significant concerns in developing countries like Pakistan. Studies indicate that user interface (UI) would be designed differently for literate, low-literate, and illiterate users. A user interface should also consider the cultural context, such as language and images. The non-textual interface is more user-friendly than the textual one for illiterate users [62].

The inability to read and write and the illiteracy of small farmers make them vulnerable to various workers and cause human health risks [63]. Previous research inferred that complex hierarchy and multi-screens become difficult for low-literates to understand helpful information, so the visuals, audio, video, speech, icons, and images are a better approach to passing complex data and information to mobile users [64]. The research findings shed light on some user interface (UI) design guidelines for illiterate and semi-literate users that can help take advantage of information and communication technologies ICT [51]. The most powerful design factors that should be incorporated into a user interface (UI) for low-literate users are localization and graphics [65]. An android application with audio, textual, and visual components was designed for farmers with diverse literacy levels. It could facilitate them regarding vital weather information [45]. Pakistani farmers typically rely on traditional sources of information, which could be a reason for their information deficiency. Data analysis indicated that farmers had diverse demographic conditions, but primary among them is the ordinary level of education (52.4% illiterate). A high level of information deficiency was observed among farmers regarding fertilizers application, seed rate, disease diagnosis, pests, and insects' identification, and a medium level of lack in information regarding the selection of varieties, harvesting, and pets' management was observed [66]. Providing information access to low-literate, linguistic minority, tech-shy, handicapped and marginalized users using speech-based services is a viable solution. These services were made the national weather hotline of Pakistan [50]. A survey data revealed that farmers in the Vehari district of Pakistan have a low literary rate and less technical knowledge. They are unable to read agricultural instructions, unaware of pesticides persistence and toxicity (73%), unable to diagnose cotton pests and diseases (86%), and unable to decide which crop to grow on cotton adjacent farms (100%) [67]. The research was conducted to study knowledge, attitude, and practices regarding pesticide usage by vegetable growers in three districts; Dadu, Larkana, and Shikarpur of Sindh, Pakistan. Results show that most vegetable growers (40.90%) have low primary education literacy, and 27.27% possess a middle pass. That's why most growers are unfamiliar with pest and insect damage indications and the safe handling of pesticides [68]. Pakistani farmers' awareness of the damaging effects of different pesticides can lead to integrated and smart pest control and management [69]. Research findings reflect farmers' behavior and a low tendency towards reading the labels of the pesticides due to low education, advanced age, usage of too technical language, illegible fonts, and unclear texts [70]. In [71], the authors developed a basic interactive voice response (IVR) system for agro-information dissemination, such as fertilizer, pesticide information, and weather forecast. In terms of usability and information extraction, their study reflected that simple menu-based navigation interfaces are relatively easy to use and understand.

A remote agricultural monitoring platform was proposed in [72] after a detailed literature study. Cyber security-based precision farming conceptual architecture was presented in [73] for the frost prediction in peach production by analyzing data captured by sensors implanted around an orchard. IoT-based precision farming comprises multiple control and monitoring applications like monitoring water needs according to climate conditions, analyzing soil patterns, monitoring crops disease and pest attacks, and assessing optimum time for planting, harvesting, and tracking [74,75].

AquaAgro offers IoT and Artificial Intelligence (AI) enabled solutions for precision farming. Using a software or app embedded hardware, the predictions will be made for the Irrigation scheduling, Fertilizer requirement, Pest attack prediction, and Plant disease detection. The essential four services that AquaAgro provides are irrigation scheduling, Fertilizer requirement, Pest attack prediction, and Plant disease detection. They have received an overwhelming response from the people [76]. An android mobile application named 'Mentha Mitra' was developed with an interactive interface with bilingual (Hindi and English) for menthol mint growers [77]. Android application provides scientific e-advisories on crop-related diseases, high-yield varieties, pests, insects, and improved distillation units.

An IoT-based wireless sensor network (WSN) framework was proposed to monitor crops smartly by analyzing environmental factors [78]. In [79], the authors utilized the benefits of IoT for the implementation of precision agriculture by sensing required parameters from the field and making suitable decisions such as activation and deactivation of irrigation valves. Parameters include soil moisture, temperature and light intensity, etc. Sensors could also send the gathered data to the cloud, and an Android application was developed to access these parameters. An expert IoT-based system relies on the stored knowledge base and real-time data for farmer recommendations [80]. This system will help in proactive and reactive tasks to a minimum the loss of water. Farooq et al. [81] performed a comprehensive literature study on state-of-the-art techniques in smart farming. They discussed agriculture networks, platforms, architecture, and topologies to help farmers to enhance the corps' productivity. This survey paper shows that Government and many other stakeholders are interested in deploying IoT in Pakistan's agriculture field. To increase agricultural productivity, the authors suggested that collaboration between allied and agriculture activities can be built by integrating big data into climate-smart agriculture with resource utilization [82].

In [83], the authors are more concerned about the water supply to the plants. They proposed a system in which a farmer can water the plants with a push of a button on his phone when he is out of the station. Machine learning algorithms and radio frequency identification (RFID) tags detect and measure moisture and humidity. Internationally, many studies [12,84–86] have been conducted to improve agricultural processes based on soil fertility level, crops, weather patterns, and fertilizers. These studies used IoT, Global Position Systems (GPS), Global information systems (GIS), Wireless Sensor Networks (WSN), and many machine learning techniques. The implementation of studies results in increased profitability and self-sufficiency. IoT enabled decision support systems based on real-time farm sensors data, improving the water consumption by crops [87–89]. Authors in [90] provided the real-time farm data, weather, and crops data to a Penman-Monteith and crop-coefficient model to produce recommendations about irrigation schedules. An intelligent approach for diagnosing crop disease was proposed in [91], capable of working with android devices equipped with fuzzy decision-making at the backend. The system interacts with farmers in their native language of Urdu for crop disease diagnosing. 'Padi2U' is an android application developed for farmers to manage paddy fields. It provides guidelines related to paddy varieties, planting schedule, pest, disease, weed, weather forecast, and yield information in their native language 'Malay' [92]. In [93], the authors developed an application named 'BLYNK' to control the IoT-based hardware remotely. The purpose of 'BLYNK' was to automate irrigation and fertilizer supply to farms. Their results reflect approximately 50% water saving and a 35% increase in yield. Irrigation monitoring and automatic control systems were developed using fuzzy decision support to generate a moisture content distribution map of soil and enhance affectivity [53,94–98].

Soil having an essential quantity of macro and micro-nutrients would be capable of cultivating different crops. The soil's lack of significant nutrients (Nitrogen, Phosphorus, and Potassium) declines crops' cultivation, growth, and yield. To increase crop production, the suitability of a specific crop to be planted can be recommended by exploiting the soil's macronutrients [99–103]. Soil pH level is the major parameter for measuring soil macronutrients (N, P, and K) and some of the micronutrients [104–108]. Smart agro farms [109] use solar power and a low-cost smart system, a perfect combination of IoT, data mining, and Android application. The system monitors and extracts a farm's environmental factors such as soil moisture, humidity, and weather and temperature parameters via data mining modules, and provides optimized guidance regarding crop cultivation, irrigation, and weather forecast in the English language.

1.2. Objectives and Hypotheses

The proposed system obtains agricultural data through implanted IoT sensors, such as pH, soil moisture, humidity, and temperature. The Internet plays a mediatory role in communication and data exchange. We integrated agricultural data acquired from implanted IoT devices with the cloud platform. Data is processed in a decision-making system based on learning prediction rules in conjunction with a rule-based engine. Generally, a farmer requires guidelines, even from the crop selection phase to the harvesting stage. As presented in Figure 1, to facilitate low literate farmers at each of these steps in their native language, we performed the following research objectives:

- Investigated traditional techniques and systems with different agricultural interfaces to find a research gap.
- Design and develop an interface in an easy-to-use format and Urdu for low-literate farmers to facilitate their awareness and guidelines in their native language.
- Design and develop a mechanism for measuring soil fertility of specific land to recommend suitable crops according to soil fertility using fuzzy logic.
- Provide crops cultivation schedule, crop harvest schedule, automated irrigation process, and watering guidelines to farmers.
- Facilitate farmers concerning guidelines for weeds and their eradication, pest attacks, and awareness of best pesticides, crop diseases, and suitable fertilizers.

Figure 1. Agriculture Cycle.

2. Materials and Methods

Previous studies indicate that most farmers are unfamiliar with the latest practices of agriculture as they are not facilitated with new technologies to access agricultural information and thus rely on traditional methods to grow their crops. Related studies indicate that there is no such smart system providing an interactive interface to a low literate or illiterate farmer and guidelines from the crop selection phase to the harvesting stage. Significant barriers to accessing modern information systems are the low literacy of farmers, the non-availability of local-language information systems, and systems with fewer features. Our research identified that it is essential to equip rural and semi-literate or illiterate farmers with updated information through ICT, IoT, Edge Computing, Cloud Computing, and Machine learning techniques, and provide them guidance in almost every phase of the crop cycle. It is necessary to develop Urdu-language-based information smart systems to enhance farmers' comprehension, crop production, and sustainable agriculture.

Proposed System Design and Architecture

The overall design and architecture of the solution proposed to cover smart agriculture are depicted in Figure 2. It comprises three layers: crop (edge) layer, fog computing layer, data analytics, and smart management at the cloud layer. The edge and cloud layers are designed to be deployed respectively at local crop premises and remote data servers. The intermediate fog computing layer comprises a set of virtualized control modules in the form of Network Function Virtualization (NFV) nodes that can be initiated along the network path from the farm facilities to the cloud layer. NFV is a way to virtualize network services, for example, firewalls, routers, and load balancers that have traditionally been run on proprietary hardware. The intermediate fog layer increases the versatility of deployed solutions and connectivity performances with the edge layer. At the crop premises, suitable sensors like humidity, temperature, soil moisture sensor, light intensity, pH sensor, and actuators like water pumps, valves, and activation of devices for smart farming automation are deployed and connected with wireless nodes as shown in Figure 2. Sensors' data is captured at the edge layer through wireless nodes and transmitted to the fog layer. This layered architecture lets atomic operations requiring high reliability and low latency between sensors and actuators to be processed at the fog layer, such as executing irrigation mandates for a specific time interval. The fog layer subsystem comprises the farm's operative control like irrigation, farm monitoring, energy management, etc. The fog layer is responsible for data fusion and aggregation to offload analytics functions that are usually performed. The fog layer control modules are virtualized through NFV techniques that communicate with edge nodes via IoT protocols like constrained application protocol (CoAP) and MQ telemetry transport (MQTT). As depicted in Figure 2 cloud layer serves as an interface between users and the core platform. At this layer, crops current status and configuration parameters are maintained. Any change in configuration parameters triggers the control actions to be managed at fog subsystems.

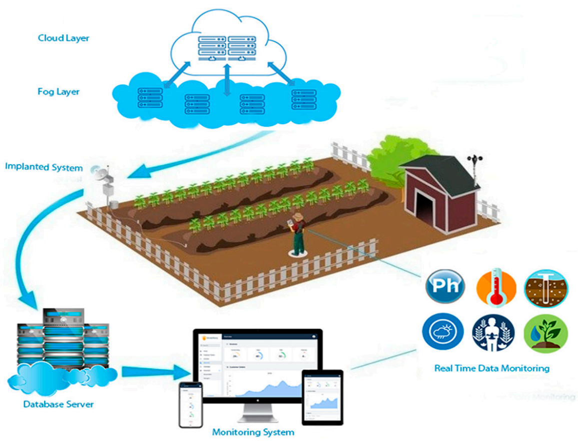

Figure 2. System Design and architecture.

3. Results and Discussion

3.1. System Components and Expected Outcomes

The proposed system gets real-time values from sensors implanted in farmland. The controller grabs data from sensors and transmits it to a cloud server, where data analysis is performed to match predefined conditions and the current state of crops. After mapping the requirements and data, the analysis system performs suitable actions via actuators. Our system provides access to an Android application for farmer facilitation with the following main features.

3.1.1. Soil Nutrient Analysis

With increased emphasis on precision agriculture, economics, and the environment, soil analysis is a tool to determine areas where adequate and excessive fertilization has occurred. Soil analysis is also used to monitor past fertility practices to changes in a field's nutrient status. Nutrient availability can be impacted by soil chemical and physical properties.

In determining soil nutrient contents, soil pH analysis is one parameter. Soil pH refers to the acidity and alkalinity of soil measured on a logarithmic scale; thus decrease in 1 unit of pH value causes an increase in acidity by a factor of 10. Small changes in pH values have significant consequences. Table 1 represents the range values defined for soil pH.

Table 1. Soil pH range values.

pH Level	Range Values
<3.5	Ultra-Acidic
3.6–3.9	Extremely Acidic
4–5.5	Strong acidic
5.6–6	Medium acidic
6.1–6.5	Slightly acidic
6.6–7	Very Slightly acidic
7.1–7.5	Very Slightly alkaline
7.6–8	Slightly alkaline
8.1–8.5	Medium alkaline
8.6–10	Strongly alkaline

Measuring the acidity and alkalinity of soil is essential for analyzing the number of macro-nutrients present in the soil, particularly nitrogen (N), potassium (K), and phosphorus (P). Crops need these macro-nutrients in their growth, thrive, and combat diseases. Removal of bases from the soil due to harvested crops, leaching, and acidic residual left in soil due to fertilizers causes an increase in acidity of the soil. Soil acidity affects crops and plants in many ways, such as whether the surface pH is very high or too low, when the efficacy of herbicides and chemical reactions may be affected. Soil analysis is the best way to check pH levels, and maintaining at least a pH of 6.0 is a realistic goal. When soil pH is very low (acidity is high) following conditions occur:

- Soluble metals, especially Manganese and Aluminum, may be toxic.
- The population of organisms and their activities accountable for transforming N, P, and S to plant-available forms may be reduced.
- Deficiency of Calcium. The soil's cation exchange capacity (CEC) is low.
- Symbiotic N fixation in legume crops is significantly impaired. The symbiotic association entails a narrower range of soil reactions than does the growth of plants not relying on 'N' fixation.
- Acidic soil with less organic matter is poorly aggregated and has poor tilt.

- The availability of mineral elements in soil may be affected. Association between soil pH and nutrient availability to plants can be depicted in Figure 3. The wider the blue bar, the greater the nutrient availability. For example, for a pH range of 5.5–7.5, the availability of P is highest and drops below 5.5. If the soil pH is 6, an amount of P applied to it will be more available than if the same amount is used in soil with a pH less than 5.5. Soil with high pH (>7.4) reduces several nutrients such as Fe, Mn, Zn, and P, which is not economical for growing agronomic crops.

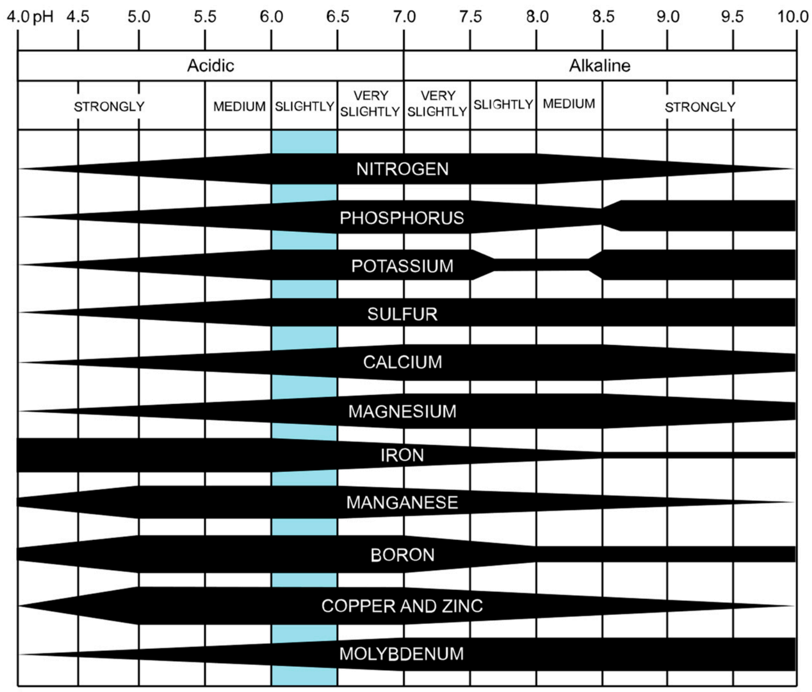

Figure 3. Chart representing availability of soil nutrients in terms of soil pH [110].

In relatively large amounts, soil provides nitrogen, potassium, phosphorus, calcium, magnesium, and sulfur. These are known as macronutrients. Soil supplies iron, boron, manganese, copper, molybdenum, and zinc in relatively small amounts, often called micronutrients. Plant nutrition is difficult to understand entirely because of the variation between different species of plants or individuals of a given clone.

Macronutrients are essential for plant growth and an excellent overall plant state. The primary macronutrients are nitrogen (N), phosphorus (P), and potassium (K). Nitrogen is a principal constituent of several essential plant substances necessary for plant development, energy metabolism, and protein synthesis. Phosphorus is involved in vital plant processes. Unlike other macronutrients, potassium is not included in the composition of essential metabolism components. Still, it substantially occurs in all plant parts for enzyme activities. Soil pH sensor and soil moisture sensor measure the soil characteristics frequently so that a farmer can monitor the status of crops in a healthy range in real-time and remotely. We can predict a specific value for nitrogen (N), phosphorus (P), and potassium (K), as Table 2. represents some ideas about these relations.

Table 2. Soil pH and corresponding estimation of N, P, and K.

pH Range	Nitrogen (N)	Phosphorus (P)	Potassium (K)
0–3.9	0%	0%	0%
4–4.5	2%	5%	2%
4.5–5	50%	20%	35%
5–5.5	100%	35%	50%
5.5–6	100%	45%	70%
6–6.5	100%	55%	100%
6.5–7.0	100%	100%	100%
7	100%	100%	100%
7–7.5	100%	100%	100%
7.5–8	100%	70%	2%
8–8.5	75%	20%	2%
8.5–9	65%	100%	100%
9–9.5	50%	100%	100%
9.5–10	2%	100%	100%

3.1.2. Crops Recommendation

The recommendation system proceeds based on a decree made by a fuzzy logic-based decision support system. Fuzzy logic is the key concept for decision-making systems and characterizes each object of a set by a degree of member functions from the interval [0,1]. The membership function defines the degree of similarity of an object to the fuzzy subset. Fuzzification is the method of allocating a system's numerical input to fuzzy sets with some degree of membership. The fuzzy system decides by considering predefined conditions and real-time data captured by sensors implanted on a specific farm. A fuzzy decision system is integrated with the controller to recommend suitable crops that can be cultivated on farmland based on available soil nutrients in the soil. Finally, real-time data is processed on the server, and a list of suitable crops is directed to the farmer's mobile app, as shown in Figure 4, where the farmer can select any crop to cultivate.

A fuzzy set S with parameters (U, i) where U is the universe of discourse and 'i' denotes the interval of U, i.e., i:U —> [0,1]. 'e' elements can signify a fuzzy set S ordered pairs. This universe of discourse is characterized by a membership function mS(e) that depicts the probability of belonging of 'e' to 'S' as shown in Equation (1):

$$S = \{(e, mS\ (e), e \in U)\} \tag{1}$$

The proposed fuzzy logic system design has four main components: fuzzifier, rule base, inference engine, and unfuzzified, represented in Figure 5. The fuzzifier converts crisp inputs to fuzzy sets. Rules are depicted as a group of if-then statements provided by an expert or acquired from data. The inference engine combines the rules and membership function to produce a fuzzy output.

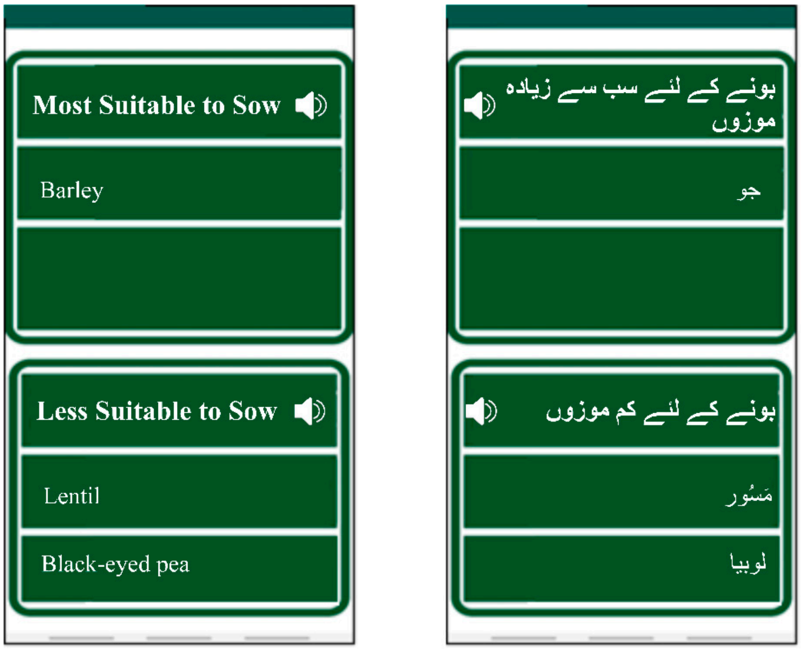

Figure 4. List of Recommended Crops.

The fuzzy logic system starts by fuzzing input variables. Later, the inference engine takes the decision based on if-then rules, membership functions, and fuzzy logic operators, i.e., "and", "or". The fuzzy inference maps input variables that are the pH level of soil, temperature, humidity, and season to fuzzy output by considering a fuzzy inference system that infers results based on fuzzy logic. Defuzzification evaluates the outcome from an input rule set provided as if-then statements. These rules are then stored in a knowledge base of the proposed system. Following is a brief description of the proposed algorithm.

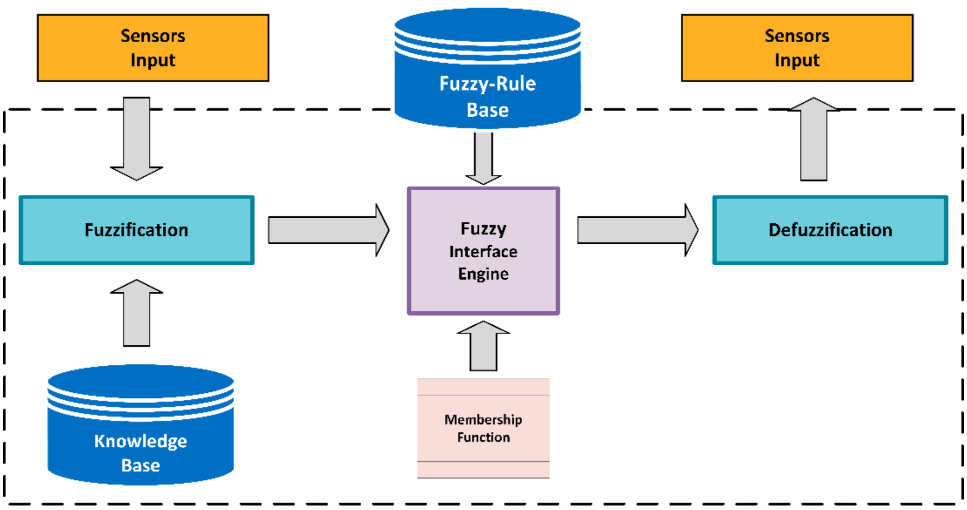

Figure 5. Fuzzy logic System for crop recommendation.

Algorithm 1: A Fuzzy Logic System

```
Input: RealTimePh, phMin, phMax, currentDate
Output: cropDetails [ ]
fetchSensorPh()
return RealTimePh
For row in TimeframOfCrop
If (CurrentDate > CultivationStartTime) && (CurrentDate < CultivationEndTime)
cropDetails [ ] = fetchCropDetail(CultivationStartTime, CultivationEndTime)
end
For row in ph Table
if (RealTimePh > phMin) && (RealTimePh < phMax)
cropDetails [ ] = showCropDetail (phMin, phMax)
end
Else
Print error
"No crop can be cultivated in these environmental conditions"
end
```

3.1.3. Land Preparation and Cultivation

A well-prepared land plays a vital role in providing the important nutrients to crops in weeds control and is suitable for sowing the seeds. A structured soil is required for ventilation and root penetration. The proposed system gets real-time data from the sensors implanted in the farms and recommends a list of crops most suitable for cultivating specific fields. From the suggested list, the farmers can choose any crop to sow. After the crop selection phase, systems provide guidelines for land preparation along with a list of appropriate fertilizers to prepare the soil for a specific crop. It also provides a cultivation schedule (suitable season) and cultivation method for each particular crop. All guidance is provided in text and voice to make the interface rural farmer-friendly, as shown in Figure 6.

Figure 6. Land Preparation and Cultivation.

3.1.4. Irrigation

The system transmits the input from deployed IoT devices in a specific farm to an underlying irrigation calculation algorithm (ICA) illustrated in Figure 7, which recommends the irrigation scheduling for a particular farm. An android application interface is presented to the farmer to monitor the farm parameters and to get feedback on the irrigation requirement. The whole process is controlled by an irrigation control module in the fog computing layer.

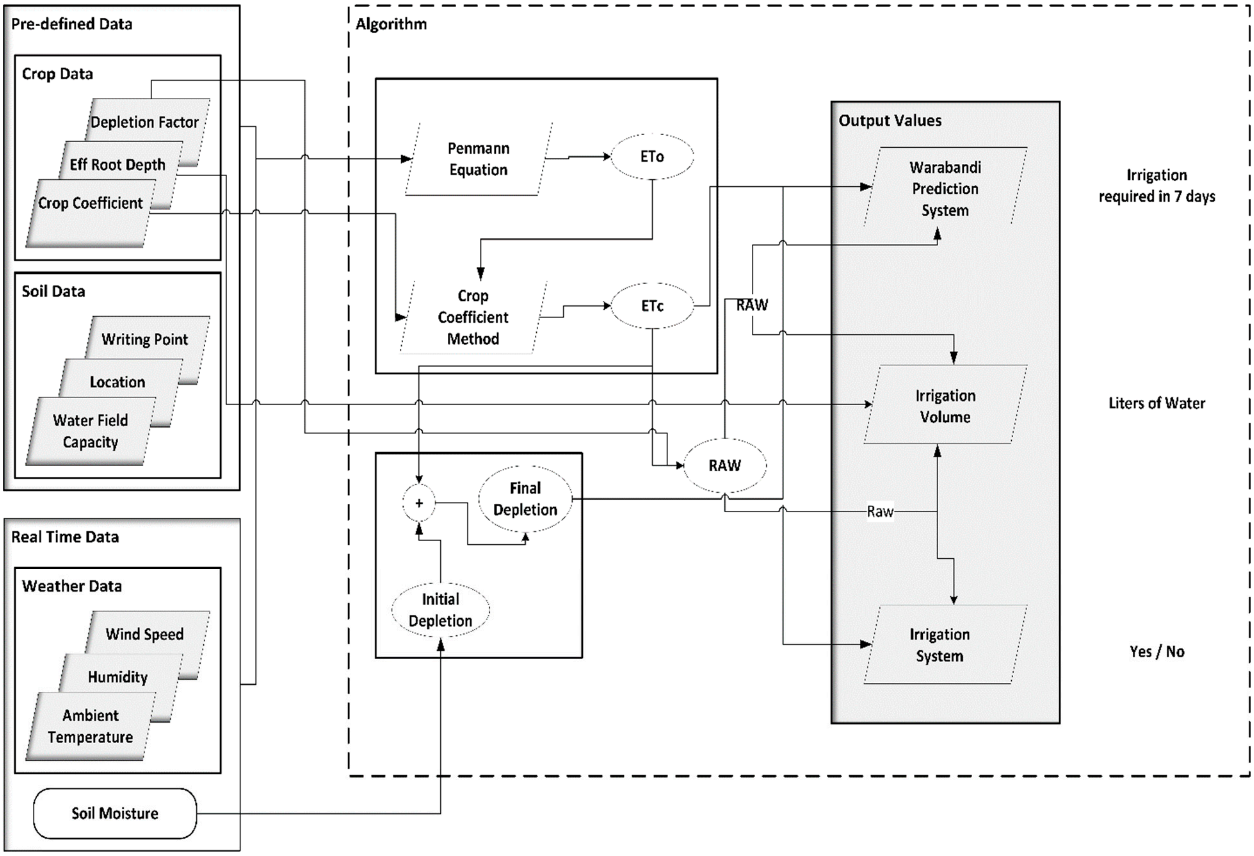

Figure 7. Irrigation Calculation Algorithm.

The irrigation calculation algorithm (ICA) determines whether irrigation is required or not and calculates the volume of irrigation needed. ICA operates on two types of data: real-time data collected by sensors and predetermined static data such as crop and soil data. Ambient temperature, humidity, and soil moisture measured by sensors are dynamic as they change hourly. Real-time data also incorporate average wind data (m/s) to calculate ET_0 from an online source [111]. Crop data comprises crop coefficient, depletion factor, and adequate root depth. Soil data contains soil category, water capacity, wilting point, and location. Location data further comprises the latitude and longitude of specific farms.

Food and Agriculture Organization (FAO) [112] recommends an essential condition that ICA evaluates daily to calculate irrigation decisions for a particular farm and crop. If $D_{r,\,i} \geq$ RAW, there is a need for irrigation, here $D_{r,\,i}$ is the root zone depletion or final depletion at the end of an i^{th} day, and RAW is readily available water or amount of water in the root zone measured in 'mm'. To ensure proper crop growth and avoid water stress, RAW must be maintained above final depletion ($D_{r,\,i}$). If the above condition is good, the RAW value and total farm area are used to compute the necessary irrigation volume. RAW is calculated using ET_c (depletion value) and predefined crop data. Every day depletion value increases due to crop evapotranspiration that cause an irrigation need if it increases than RAW. Depletion before evapotranspiration, called initial shortage, and lack after evapotranspiration, represented as the final deficit, are calculated using average soil moisture, water capacity, and adequate root depth daily. For optimistic irrigation, measuring the water amount a crop loses and requires for a specific duration is essential. Every crop type and soil has different water requirements; however, water loss occurs due to evaporation from the soil surface and plant transpiration. Evapotranspiration is a combination of evaporation and transpiration. Evapotranspiration 'ET_0' be determined by real-time and predefined variables such as humidity, wind speed, latitude, and altitude. ET_0 and ET_c can be computed using the Penman-Monteith model and crop coefficient, respectively.

Penman-Monteith Method:

The Penman-Monteith Equation (2) is an effective way to compute reference evapotranspiration (ET_0)

$$ET_0 = \frac{0.408\Delta(Rn - G) + Y\frac{900}{T+273}u_2(es - ea)}{\Delta + Y(1 + 0.34u_2)} \tag{2}$$

where Rn is net radiation at the surface and computed from publicly available libraries that apply an estimation formula named metabolic [113] and FAO [114], the values of maximum temperature, minimum temperature, longitude, and latitude are used to calculate Rn. 'G' is the soil heat flux, the amount of thermal energy that transfers through the soil surface per unit of time. As the ICA measures ET_0 every 24h, the value of soil heat flux is so tiny that it can be neglected; thus, $G \approx 0$. u_2 is the wind speed (m/s) measured by an anemometer placed at the height of 2 m above ground level. u_2 can be computed by Equation (3).

$$u_2 = u_z \frac{4.87}{\ln(67.8z - 5.42)} \tag{3}$$

where 'z' is the elevation (m) above sea level. Saturation vapor pressure (es) required in equation (1) is computed from Equation (4).

$$es = \frac{e0(Tmax) + e0(Tmin)}{2} \tag{4}$$

where 'T' is the temperature (°C) and $e0$ (T) is the saturation vapor pressure at air temperature T (kPa), represented in Equation (5).

$$e0\ (T) = 0.6108 \exp\left[\frac{17.27T}{T + 273.3}\right] \tag{5}$$

ea is the actual vapor pressure in Equation (1) is computed by Equation (6)

$$ea = \frac{e0(Tmax)\frac{RHmax}{100} + e0\left(Tmin\frac{RHmin}{100}\right)}{2} \tag{6}$$

where 'T' is the temperature (°C). 'Δ' in Equation (1) is the vapor pressure curve computed by Equation (7).

$$\Delta = \frac{4098\left[0.618\exp\left(\frac{17.27T}{T+237.3}\right)\right]}{(T + 237.3)2} \tag{7}$$

where 'T' is the temperature (°C). 'Υ' in Equation (1) is the psychometric constant represented in Equation (8)

$$\Upsilon = 0.665 \times 10^{-3}\text{P} \tag{8}$$

where 'P' is the atmospheric pressure (mb) computed by Equation (9).

$$\text{P} = 101.3\left(\frac{293 - 0.0065z}{293}\right)^{5.26} \tag{9}$$

where 'z' is the sea level (m) altitude.

Crop Coefficient:

The evapotranspiration (ET_0) calculated by the Penman-Monteith Equation (1) is used to compute reference evapotranspiration (ET_C). As every crop has different evapotranspiration, thus Penman-Monteith equation assigns 'ET_0' to every crop type. The 'ET_c' crop coefficient approach can be used as equation (10).

$$ET_c = K_c \, ET_0 \tag{10}$$

where 'K_c' is the crop coefficient which varies from crop to crop and their growth stages.

ICA Outputs:

The irrigation calculation algorithm (ICA) provides flexibility for the farmer with multiple options regarding irrigation parameters and user application interface in their native language. Some farmers need irrigation output in terms of volume, such as gallons or liters in acre per inch, whereas some need output in terms of time. ICA facilitates farmers with various output parameters as per their requirements. For example, if a crop in some specific farm needs 1000L of water, then the system transforms 1000L, whether the output in time, volume, and acre per inch. The system adjusts the output, calculates how much time or acre per inch equals 10L of water, and presents the correct output amount to the farmer. Therefore, our proposed solution can work on any farm in Pakistan with varying output parameter requirements.

3.1.5. Crops Disease Prevention and Cure

For ease of the user, the proposed system provides guidelines about diseases and prevention and cure methods for cultivated crops. This feature enables the farmer to take precautionary steps to avoid any illness before any disease occurs. Moreover, in case of any disease symptom found, the farmer can cure that disease with the help of disease cure methods provided by the proposed system, as shown on the app screen in Figure 8.

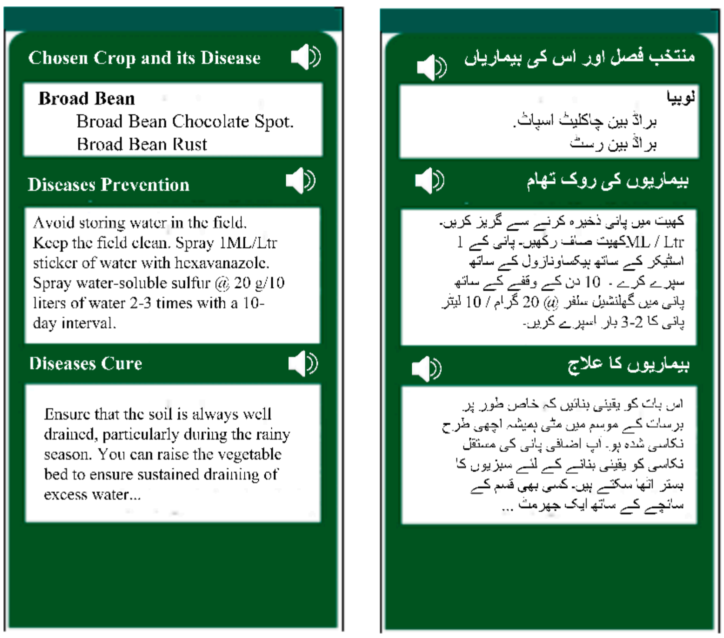

Figure 8. Crops' Disease Prevention and Cure.

3.1.6. Pest and Weed Control

Pests are harmful organisms that threaten crops' existence, spread diseases in crops, and cause destruction. On the other hand, weeds are plants that grow where and when they are not needed and compete with crops for nutrients, space, light, and water. Weeds and pests increase production costs, decrease the overall yield, and affect crop quality, so getting rid of them is important to maintain quality and yield. They become a big challenge if not controlled correctly at the right time because they cause severe damage to the crop. Our system aims to protect crops from economic damage by insects, plant pathogens, weeds, pests, and other harmful organisms while reducing reliance on hazardous pesticides. The system provides farmers with authoritative and up-to-date information about each crop's weeds and pests. It provides guidelines for controlling pest attacks and weed eradication methods, as shown in Figures 9 and 10, respectively.

Figure 9. Pests attack control guidelines.

Figure 10. Weeds eradication methods.

3.1.7. Fertilizing

Fertilizers have become a vital part of farming nowadays. Whether there is a need for weed eradication or to increase production, both farmers must use fertilizer. So, it is essential to choose a suitable fertilizer to fulfill the requirements. The concentration of macro and micronutrients varies season by season, so we cannot show the same crop every season. In the same way, we cannot use the same fertilizer every time. The selection of fertilizer depends upon the crops' requirements that the farmer may fulfill or the purpose they have to achieve. If the goal is to eradicate the weeds, the farmer should use some specific fertilizers for a particular weed. Suppose the requirement is to enhance crop growth and production. In that case, the fertilizer selection depends upon the nature of the crop as the native farmers are low-literate and less aware of choosing the right fertilizer. Thus, the proposed system "Kisan Pakistan" provides accurate guidance in terms of relevant fertilizers along with weed eradication support. The system suggests suitable fertilizers for different types of weeds and the crops' growth, along with usage guidance in the native and English languages, as shown in Figure 6. This makes it much easy for native and low-literate farmers to solve their issues without acquiring help from any external entity.

3.1.8. Harvesting and Storing

Harvesting and storing are critical phases in the agriculture cycle because if these are done correctly, they provide high-quality products resulting in high income. So right way of harvesting maximizes the yield and reduces crop fatalities. The proposed system makes it convenient for the farmer by providing the best harvesting schedule for each recommended crop and harvesting methods, as shown in Figure 11.

Figure 11. Harvesting and storing guidelines.

3.2. Discussion

This research was conducted on a small-scale farm of 2 acres in Sialkot, Pakistan. Of the two, one acre was controlled by the farmer (farm A), where they applied traditional farming techniques. The remaining one acre, farm B, was controlled by our proposed smart system integrated with sensors and IoT techniques. The system recommends different suitable crops to be cultivated according to the soil analysis, i.e., 6 pH level for farm B. Farms A and B were cultivated with the same crop. Regarding the irrigation module, we compared the water usage on both farm A and farm B. Farm A was irrigated by farmers who used conventional estimations for irrigation time and volume. Farm B was irrigated using decisions made by the Irrigation Calculation Method (ICA) as a function of real-time data supplied by IoT devices deployed on the farm. Table 3. highlights the total irrigation volume consumed in farms A and B. It can be depicted that farm A, using conventional farming methods, consumed 48,569 L of irrigation water, and farm B, using the proposed solution, utilized 22,779 L of irrigation water, which resulted in 25,790 L of water saved, approximately 53%. The data for the detailed irrigation schedule for both farms are also plotted in Figure 12 to illustrate the water usage efficiency in the proposed solution.

Table 3. Irrigation Statistics.

Water Consumption (Farm A)	Water Consumption (Farm B)	Water Saving (L)	Water Saving (%)
48,569	22,779	25,790	53

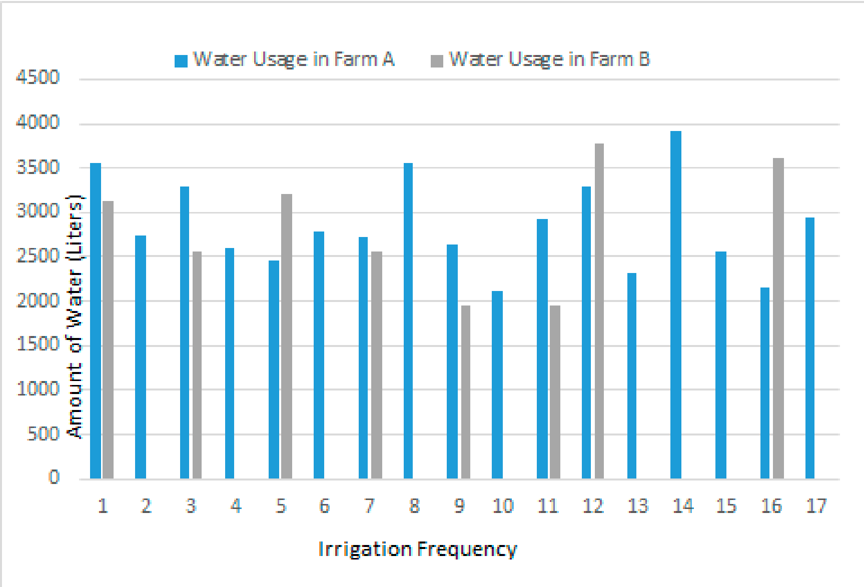

Figure 12. Irrigation frequency and water usage efficiency.

We implanted the proposed smart system on a small-scale farm. Results show that if we add more sensors and IoT devices, the proposed model has the flexibility to be implemented on medium to large farms. The system incorporates Edge, fog, and cloud computing with IoT devices which offers low latency, high bandwidth, less energy consumption, and real-time analytics that make it more efficient. Currently, the system incorporates data of major crops in Pakistan, but by involving more crop data from other global regions, the system could be implemented on farms with more crops.

Our research covered a wide range of previously proposed models, papers, and studies. All these researches and studies were thoroughly read and understood, their domain of interest, their architecture, the pros and cons, and the features added in their proposed studies. After critically evaluating many studies on smart agriculture, some crucial information about related studies is provided in Table 4. Readers can obtain an overview and comparison of the previous work done by researchers, practitioners, authors, and technologists related to our research contributions.

A few limitations are incorporated in this study. We could not conduct the yield analysis of crops cultivated on farm B. Concerning soil analysis, we could also involve more soil sensors, such as NPK sensors, for better fertility measurements. System recommendations address only major crops to be grown in Pakistan. In the future, we will incorporate more crop data for different global regions. This study was carried out when most regions were on lockdown, with restrictions on movements within Pakistan. We are intended to conduct the qualitative usability test of the android application 'Kisan Pakistan' among farmers in the future. We will perform experiments proposed system on large-scale farm lands to measure and improve its performance in the future.

Table 4. Comparison summary of related studies vs. proposed solution.

Study	Smart Solution	Interface for Semi-literate	Medium (Language)	Proposed Features and Guidelines								
				Soil Analysis	Crop Cultivation	Land Preparation	Irrigation	Crop Disease	Pest and Weed Control	Fertilizer	Harvest	Weather Forecast
[45]		Yes	Urdu	No	No	No	No	No	No	No	No	Yes
[53]	Yes	No	English	No	No	No	Yes	No	No	No	No	No
[54]	Yes	No	English	No	Yes	No	Yes	No	No	No	No	No
[111]	Yes	No	Urdu	No	No	No	No	Yes	No	No	No	No
[50]	No	Yes	N/A	No	No	No	No	No	No	No	No	Yes
[71]	No	Yes	N/A	No	No	No	No	No	Yes	Yes	No	Yes
[77]	Yes	No	Hindi, English	No	No	No	No	Yes	Yes	Yes	No	No
[109]	Yes	No	English	Yes	Yes	No	Yes	No	No	No	No	Yes
[92]	Yes	No	Malay	No	Yes	No	No	Yes	Yes	No	No	Yes
[93]	Yes	No	English	Yes	No	No	Yes	Yes	No	Yes	No	No
Proposed Solution	Yes	Yes	Urdu	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

4. Conclusion

Agriculture is the backbone of Pakistan. It is necessary to ensure its sustainable growth over the years. We studied traditional trends followed by farmers and investigated why productivity lags. The key barriers are information inadequacies, lack of information systems for illiterates or less-literates, and lack of a system that provides guidance at every stage of the crop cycle. This study was carried out to provide a smart advisory system for illiterate and semi-literate farmers of Pakistan that could provide them guidance from crop selection to the harvest stage phase. In this research work, we built a cost-effective smart system equipped with multiple sensors and devices related to the internet of things (IoT) technologies. We also developed an android application named 'Kistan Pakistan' that allows illiterate and low-literate farmers to manage their farms remotely. The interface of the android application is interactive due to its visual, audio, voice, and iconic components. The proposed solution is applicable globally as all information and guidelines are disseminated in both the 'Urdu' and 'English' languages. Edge-cloud computing delivers more accurate guidelines in less time and in almost every phase of the agricultural cycle, increasing productivity and making the agricultural ecosystem more robust. We experimented on a small-scale farm, but the results reflect that it will be efficient for medium to large-scale fields.

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