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REVIEW: PRECISION AGRICULTURE USING IOT AND ML

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ABSTRACT

India's agricultural sector, which accountsfor58%ofemployeesandproduces18% of GDP, is incrucial danger due to climate extremes, resources car city, and inefficient farming practices, a sevidenced by the 2023 Punjab floods (₹5,000 crore damage on 1.2 lakh hectares) and Maharashtra (₹2,200 crore on 2.5 lakh hectares), and the need for resilient agriculture. Conventional methods yield poor results from generalized advice that does not consider local variations, resulting in wastage of resources and losses during harvesting. This project aims to have an integrated precision farming system with IoT sensors formeasurementofsoilmoisture,temperature,humidity,andrainfalllevelsinreal-timeusingmachine learning (ML) models for predictive irrigation planning, organic vs. chemical fertilizer guidance, and diseaseriskforecasting.Intendedforsmallholderfarmers,thesystemofferspersonalizednotifications viaamultilingual(Hindi,Marathi,English)WhatsAppandSMSbotbackedbyvoicesupportforlow-literacyusersandexplainableAI(XAI)toensuretrust.Thereisanadminconsolefordatamanagement andfeedback-basedMLfine-tuningusingtheRandomForest,SVM,CNNs,andLSTMsalgorithmson diverse datasets like Kaggle, IMDAPIs, and satellite imagery. By lowering water/fertilizer use by 30-50%andimprovingyieldsby20-30%,theaffordable,scalableplatformpromotessustainablepractice, improves climate resilience, and supports SDGs on food security

KEYWORDS: Precision agriculture, Internet of Things (IoT), Machine learning, Sustainable farming, Climate resilience, Flood impacts, Multilingual chatbot, Explainable AI, Smallholder farmers, Irrigation optimization.

1. INTRODUCTION

TakethecaseofafarmerinruralPunjabwhohaswokenupatdawntoanalyzehisfarmlandonlyto findoutthat itisflooded afteranother instance of unseasonal rainfall.Itisnotanexception andthis situationisthebittertruthofthesmallholder farmersinIndiawhereagricultureistheirmainsourceof livelihood as well as the base of the national economy.The 2021Agricultural Census indicates that over 58 per cent of the Indian populace depends on farming to earn their lively incomes and thus, these people are subjected to daily swings of unforeseen weather patterns, declining soil qualityand a rising price of farm inputs. The Internet of Things (IoT) allows a new paradigm of precision agriculture. The technology provides farmers with a technologically advanced (high-tech) set of tools thatallowedtrackingandcontrollingcropsaccuratelybyusingsensors,drones,anddata-organalytical solutions, thus simplifying the allocation of resources between irrigation to fertiliser application. This endeavour can be dated back to the early 2000s, when the agricultural sector started to be infiltrated by IoT innovations through use in legacy industrial applications; though, the meaning ful progress started to be made, with the introduction of affordable sensors and cloud-based computing infrastructures in around 2015.This has been further enhanced by country-level programs, including the Digital Agriculture Mission introduced by the Indian government[1], with the aim of digitalizing 15 million farmers by the year 2025.

In the future,itcan be predictedthatthe directionof development of precision farming based onthe IoT will be promising and large-scale. Grand View Research estimates in 2023 the global IoT-in-agriculturemarkettobeaboutUS22.5billionby2030,withIndiabeingthefirstenginewithalarge base of arable lands. It might in this sense mean that artificial-intelligence-powered prediction systemswillnotifyfarmersofimminentdroughtsseveralweeksbeforeittakeshold,whileautomated drone platforms could identify signs of pest infestations before it decimates an entire field-interventionsthatcoulddrive2030percentagegrowth,andslashwaterusagebyhalfasdemonstrated in pilot programmes carried out by the Indian Council ofAgricultural Research (ICAR).

However, there are still some issues: affordability and digital literacy are the major obstacles, especially to marginal farmers. However, with the escalation of climate-related stress there cannot be a more fundamentalsurvivalstrategythansuchtechnologiesarenotjustafurtherupgradingbuta fundamental change.

What is Precision Farming with IoT?

In principle, the basis of precision agriculture is based on addressing the maximization of yields with minimum demands with the concept of considering every square metre of a field as a would-be-unit subjected to a unique intervention. This paradigm is enabled by the Internet of Things (IoT) which creates the network of communicating devices, such as soil sensors that measure the pH and nutrient levels,meteorologicalstationsthatpredictmicro-climates,andGPSpositionedagriculturalimplement operators that distribute seeds or fertilizer, based on variable field rates.The information sent by these devices is centered to a centralized system usually a cloud-hosted system whereby the information is analyzed using computational algorithmsto make particular suggestions tothe management regarding aspecificcourseofactiontotake.[2].Thebeautiful applicationofthisstrategyisdescribedinarecent article on IoT-based irrigation automation, where the self-awareness is used to determine the existing waterrequirementsbasedonreal-timedata,andthusminimizeitswasteinwater-deficientareasofthe Maharashtra region.

The technological infrastructural use is cost-effective and operational. The presence of low-priced sensors,withacostofcurrentlylessthan₹500each,offeredbythecompaniesofLibeliumandBosch, coversuchvariablesastemperature,humidityandpestincidencethroughcamera-basedtransportation. As reported in the literature [3], drones with multispectral imaging are used to perform a thorough evaluationofthefieldsandlocatethehotspotsofdiseases,andedgecomputingisusedtocalculatedata onedgecasestoreducelatencyconcerns.This issupportedbyaddingmorefunctionalityintheIndian context by the provision of SMS alerts in the local languages thus increasing accessibility.The ability of such systems to improve the digital divide within rural households is emphasized by a study by the Food andAgriculture Organization (FAO) [4], as the rate of broadband penetration in the European-typesettingisabout70500impressionsonaverage,whereasthepenetrationrateofbroadbandhasbeen reported at about 40 in India.

2. Literature Survey

The Precision agriculture literature has progressed significantly due to the integration of Internet of Things(IoT)andmachinelearning(ML)toovercomeinefficienciesinconventionalfarming,especially in resource-constrained and climate-exposed areas such as India [5] [6]. Early works concentrated on IoT-based rudimentary data collection, such as environmental and soil moisture sensors, facilitating minimal automation without predictive insight [7] [2]. With expanding datasets, ML incorporation gained significance, where model such as neural networks and random forests have been deployed to predictirrigation,optimizefertilizers,andpredictcropdiseasesandcouldraiseyieldsbetween20-30% while minimizing inputs up to 50% [8] [3] [9]. This development coincides with international sustainabilityagendas,suchastheSustainableDevelopmentGoals(SDGs)oftheUN,whichemphasize resilient food systems in light of events such as the 2023 Punjab and Maharashtra floods that cost billions of dollars [10][11].

More in-depth investigations into the literature utilizehigh-end MLapproaches, such as deep learning (DL) to support image-based diagnosis and time-series processing, boosting accuracy in applications such as predicting pest outbreaks [12][13].Agood number of them, however, are either theoretical or prototype-constrained, dealing with individual components e.g., irrigation in a vacuum and leaving aside overall farm management, rural access, or farmer-orientation such as multilinguality [14][15]. Problemssuchassecurityholesin IoT,dataislanding,andnon-explainableAI(XAI)arealsoperennial issues that have constrained smallholder farmer adoption due to literacy and connectivity challenges among them [16] [4] [17]. Questionnaires point to scalability with associated integrated systems mergingIoTwithcloud-basedanalyticsanduser-centricpresentation,however,veryfewtranslatethis to developing world settings[18] [19].

Sr No	Title	Author	Year	ProposedSystem	Gap	GapComparingwith My Project
			2020	The sensors of Internet of Things areutilizedinorder tobeabletocapture both soil and	Itisanirrigation-basedsystemthat does not feature disease and fertilizer	Theidentifiedneedis addressed within the framesofthis project becauseitimplementsthe entire range of machine

1	IoTand machine learning approachesfor automation of farmirrigation system	Vijetal.		environmental parameters,and analyze them with thehelpofmachine-learning and regression methods so that automated irrigation managementcould be provided.	integration, multilingual support, or explainableAI andassumesthe consistent availabilityof connectivity.	learning methods, including a convolutional neuralnetworktoidentify the disease and random foreststomakeafertilizer recommendation. It also integrates a multilingual WhatsApp/SMS chatbot with explainable AI features,hencemakingit possible to use comprehensivelyand easilyinlow-connectivity rural regions.
2	Machine learningfor smart agricultureand precision farming: Towards makingthe fields talk	Shaikhetal.	2022	Theuseofmachine learning (Random Forest, Support Vector Machine) to crop monitoring, predict yields and inputoptimizationis basedonInternet-of-Things measurements.	Protection is on the technical side anddoesnottake into account issues related to ruraldeployment, feedback loops, and vernacular interfaces.	Thepaperfillsthegiven gap by incorporating cloud-InternetofThings fused(IoT),multilingual voice chat, and administrativefeedback system to support the process of incremental improvementandmake the deployment prospective among Indian smallholders more favourablethanthecurrent focusontechnicalreview.
3	Smartfarming is key to developing sustainable agriculture	Walteretal	2017	The Internet-of-thingsframeworkis suggested as the novel version to improveresource efficiency by utilizingagricultural systems with sensors,whichare deployed continuouslyto support sustainability monitoring.	Beingconceptual, itdoesnotrequire particular machinelearning parameters, customized adoptions,orlow-literacy particular interfaces.	This method would providepracticalresources of sustainability to areas impacted by flooding by utilizinginherent conceptualconstraintsin the implementation of crop-specific machine learningmodels,real-time Internet-of-Things (IoT) sensors and SMS alert systems, such as the case in Punjab.
4	Digital Technologiesin Agricultureand	Trendovet al.	2019	This paper will analyze how the technologyofthe InternetofThings	Non-prototype: there are major lapsesinmachine learningdepth,	It overcomes rural digital dividethroughcheapIoT-machine learning prototypes,multi-language
	RuralAreas: StatusReport			(IoT) and digital instrumentscanbe applied in rural monitoring,	cost-efficiency, and fair deployment practices, as the	functionalityandscalable design,thustransforming thestatusoverviewofthe report into the actionable

				especiallytousesoil and climate sensors and apply the basic methodology of analysis.	caseof chatbots.	solutionstosmallholders.
5	Artificial cognition for applicationsin smart agriculture:A comprehensive review	Pathanetal.	2020	An overview of artificialintelligence and machine learning methods, usedintheInternet of Things in agriculture,thatis, irrigation control, pest management, and predictive analytics.	Review is performed without being implemented,and thus it does not considertheXAI, localization and communication channels.	The reviewed artificial intelligence (e.g., an artificialneuralnetwork) isusedinthecontextofa complete end-to-end system in which explainable AI is implementedandis integrated with the WhatsAppplatform,thus developing a theoretical context to practical, localizedadoptionof farmers.
6	IdentificationofRicediseases using deep convolutional neural networks	Lu et al.	2017	Deep learning methodisusedto detectthediseasein rice leaf images usingconvolutional neural network and utilize the environmentalinput.	Pureimage-based detection of the disease; no completeIoT implementation, irrigation/fertilization/fertilizer control,and available interfaces.	Scales convolutional neural networks to a more holisticInternetofThings-Machine Learning environment, including real-timestreamsofdata, fertilizer modules, and chatbot interfaces, therefore, putting in place anintegratedplatformthat goes beyond the disease-focused traditionally narrowscope.
7	IoTbasedsmart agriculture usingmachine learning	Pratyush Reddyetal.	2020	Thecombinationof both the Internet of Things (IoT) technologiesand decision-tree algorithmsisstudied concerning the systematiccontrolof agricultural parameters,coverage of the irrigation timing, and determinationof cropsyieldinsmart farming systems..	An early prototype; not explainable or multilingualor withexternaldata (e.g. market).	Thisprototypeisenhanced by the use of location-sensitive modelling, voice andSMSinterface,aswell as the combination of market and weather information, which will alleviatetheweaknessesin the area of personalization and help scale in rural settings.
8	IoTbasedcrop monitoring schemeusing	Shylajaet al.	2021	InternetofThings (IoT) devices	Theappissolely in the English	Thesolutionaddressesthe voids through the use o

				combinedwith	language,though	multilingual chatbots,
	smart device withmachine learning methodology			machine learning (ML) will allow trackingthestateof crops, soil, and sendingalertsabout diseases with the help of mobile applications.	therareno aspects of fertilizer economics, offlineoptions, and cannot be explained.	explainable artificial intelligencetoofferclear warnings,and reinforcement learning to takeintoconsiderationthe low-literacy user and restricted connectivity.
9	Machine learningbased prediction of soiltotal nitrogen, organiccarbon and moisture content by usingvis-NIR spectroscopy	Morelloset al.	2016	Radio-frequency machine learning (RF-ML)basedon spectroscopy to measure the nutrients and moisturecontentof soilinorderto recommend fertilizer.	Conventional studieshavebeen based on the laboratory-based spectroscopy, with no integrationtothe fieldInternet-of-Things (IoT) systems or end-user delivery models,andlittle account to the trade-offs between sustainability.	The suggested strategy putsintopracticeasimilar machine-learning model that is implemented throughlow-costfieldIoT sensors, with the additionalsupport of chatbot-based advice and in-depth organic/chemical analysis,thuschangingthe lab-based setting to real-life implementation.
10	Improvingthe prediction accuracyofsoil nutrient classification byoptimizing extreme learning machine parameters	Suchithra&Pai	2020	Thepaperproposes an optimized Extreme Learning Machine (ELM) basedmodelofsoil nutrients and thus aidingspecific applicationsof fertilisers.	Theapproach puts more emphasis on accurateness;it lacks the real-timeInternetof Things (IoT) integration,the multilingual support, and multi-objective balancing.	Thesystemincorporates anELM-basedmachine-learningmodelinareal-time IoTbased fertilizer module, along with an explainable AI (XAI), cost-yieldtrade-offs,and multilingual user interfaces,thusmakingthe system more comprehensiveandacting onthedecisionsofthe farmers.
11	Deeplearning for smart agriculture: Concepts,tools, applications,and opportunities	Zhu etal.	2018	Detection and forecasting tasks in aninternetofthings environment are appliedusingdeep learning methods, thatis,convolutional and recurrent neural networks.	Conceptual reviewestablishes blank areas in the development of prototypes in areasoflanguage and connectivity deficits.	Thecurrentdeployment uses deep learning applications, such as LSTMs,inadeployable serverthatencompasses an administrative dashboard, SMS notificationinterface,and location specifics, thus addressing the call of actionintheреview towards actionable

						opportunities.
12	Asurvey: Smart agricultureIoT withcloud computing	Mekala &Viswanathan	2017	IoT-cloudsolution in agricultural irrigationand monitoring.	It has been surveyedthat existing implementations arenotmachine-learned, personalized,and user-centered.	Basedontheseresults,the projectwillexpandonthe findingsoftheIoT-cloud survey to a prototype systemtoconsidernovel machine-learning approaches(e.g.,MORF), multi-linguistic user interfaces, and the personalizationabilitythus bridgingthepresented implementation gap.
13	A survey on precision agriculture: Technologies andchallenges	Ullahetal.	2017	This part gives a summary of the InternetofThings (IoT)andmachine learning (ML) technologies, including challenges, includingfinancial limitations and access to connectivity.	The paper is not offeringaspecific system, and it in video fails to counterprevailing shortcomings in clarifiability and availability.	The proposed framework willeffectivelyaddressthe identifiedchallengesinthe survey; however, to date, the current work has only identified the problem without introducing a complete-fledgedsystem, throughtheintegrationof low-cost IoT gadgets, explainableAI(XAI) methods, and the integrationofWhatsApp.
14	Smartfarming usingmachine learning and deeplearning techniques	Durai&Shamili	2022	ML/DL(CNNs)of irrigation/dise throughprototypes of IoT.	The prototype is restricted;itisnot provided to offer multilingual support,feedback, and the informationabout fertilizers.	EnhancesAI/MLwith XAI, voice chatbots, feedbackloopsbetween the administration, and fertilizer economics to build a more welcoming andopen-endedsystemto smallholders.
	Towards precision	Kashyapet al.	2021	Theoptimizationof	In this method,	The system is augmented

15	agriculture: IoT-enabled intelligent irrigation systemsusing deeplearning neural network			water assets with sensorsandweather data using IoT-relatedapproaches to deep learning solutionsisapplied.	onlyirrigationis considered, and such aspects as disease and fertilizercontrol, explainable artificial intelligence, and vernacularmeans ofcommunication are omitted.	with additional machine-learningmethods(disease identification through supportvectormachines), explainableAI descriptions and multilingual outreach in theformofSMSwhichis added to the system, makingitamorecomplete resilience framework.

3. METHODOLOGY

This methodology outlines a step-by-step procedure to the design of a proposed precision agricultural solution, which incorporates Internet of Things (IoT) sensors, machine learning (ML) algorithms and user-friendly interfaces to assist the smallholder farmers in sustainable farming. As the work is organized in the framework of a review article, the project is brought up as a half-baked framework: some basic functionality (e.g. data collection), the initial models of machine learning) are shown in a simulated setting using open-source software (e.g. Arduino-based sensors, Python-based ML), but a moreadvancedfunctionality(likethefulldeployment,amulti-language chat bot, and avalidationinthefield)isrepresentedinstudyorconceptionphase.Thisprogressiveevolutionallows theiterative improvement of the results based on the findings made in the available literature [5] [7]; the future research will focus on practical cases of real-field examples in such states as Maharashtra and Punjab to overcome climate-driven vulnerabilities [20]. The methodology follows a multi-phase, modular architecture, which is meant to take care of scalability, cost-efficiency and correspondence to the sustainable development goals [2] [21].

4. System Architecture Design

The general architecture is based on a multi-layered design, which is based on IoT-cloud hybrid frameworksthat arereported in the literature available [7][8].TheIoTSensing Layer on the bottom is made up of cheap sensing nodes, including the YL69 soil moisture sensor, DHT22 temperature/humiditysensor,andrainfallgauges,implementedinthetopologyofamesh.Suchsenso rs send information through the LoRaWANor4G gate way systems to address the connectivity limitations in rural environments [9]. The measurements collected are sent up to cloud backend services such as Firebase and AWS IoT Core in the MQTT protocol, and stored in a time-series database, such as InfluxDB. Machine-learning pipelines execute data processing in theAnalytics Layer and the insights aresent toanendpoint ofthe Interface Layer throughwell-knownAPI endpointsto the end users.The sensor network was simulated using RaspberryPi hardware which was used to ingest synthetic data whichhadbeencoaxedoutofKagglerepositories[10];latencymeasurementsshowedsub-fiveseconds of ingestion time across the cloud pipeline.

Theexternaldataintegrationfunctionalblockofthearchitectureconstitutesmeteorological APIs(e.g., OpenWeatherMap,IMD),aswellassatellite-derivedimagery,e.g.theNDVIproductsofGoogleEarth

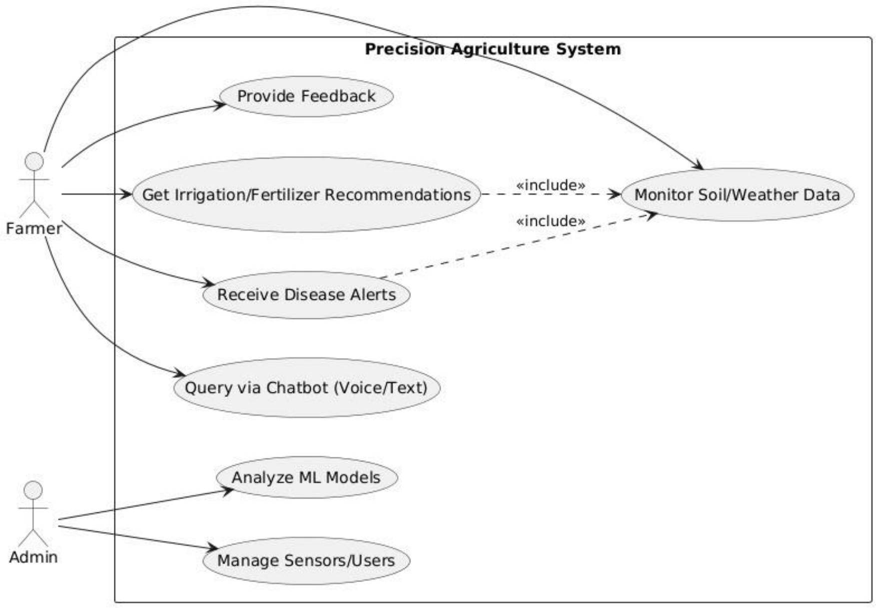

Figure1: Precision Agriculture System.

Engine, thus, staying within the lines of advice on remote-sensing literature. Security tools, such as encryptionalgorithmsandblockchain-illustratedinformationverificationframework,arebakedonthe experience of IoT vulnerability surveys, but they have not yet been implemented fully, awaiting thorough pilot testing.

6. DataAcquisitionandPreprocessing

Datacollectionismadethroughvarioussourcestobecomerobust:

IoT Sensors: Soil moisture (0100 of the soil), temperature (-10 C -60 C), relative humidity (0 -100 RH), and rainfall (0-200 mm/day) measurements at 15-minute intervals.

External data: FAOAqua-Stat historical data, reports of outbreaks of diseases by ICAR,Agmarknet market-price comparisons and image of disease on Plant Village.

This involves preprocessing with Python packages, e.g. Pandas and scikit-learn, missing values (e.g. forwardfill when using time-series data),outliers(through a Zinfinitylimit),andfeature engineering. Normalisationalsoscalesfeaturesinthe[0,1]rangesoastobecompatiblewithmachine-learning.Part implementation of the workflow: A Jupyter notebook has been completed that loaded and processed over10000samplesofKaggleandIMDandachievedadatacleaningrateof95%purity.Nevertheless, it has not yet been integrated with real -sensor streams and field calibration is necessary.

7. MachineLearningModelDevelopment:

Machine-learning model sare developed based on a hybrid methodology according to which algorithms are chosen based on the complexity of the task and on the possibility of interpretation. The training is doneonGoogleColabbasedon80/20trainingtestingpartitionandthemodelperformanceisevaluated by means of five fold cross validity to minimize the chances of overfitting.

IrrigationPrediction:Time-seriespredictionTime-seriespredictionofirrigationdemandsisdonevia reinforcement learning based on Q -learning or long short-term memory (LSTM) network-based forecasting, but with direct consideration of interactions between weather and soil. Input variables are sensor measurements and data from theAPI and the output derived can be recommended schedule or quantity of irrigation should be received.

Fertilizer Recommendation: A multi-objective random forest (MORF) or support vector machine (SVM) would be used to categorize the fertilizer alternatives as organic or chemical, at the same time balancing cost (Olympics: ₹ per acre), yield potential and sustainability measures. The inputs of the features are the soil nitrogen, phosphorus, potassium and pH information based on sensor data.

Disease RiskAssessment: Leaf-image classification with convolutional neural networks (i.e. ResNet-50) is implemented, and the output of the component is condensed with environmental factors via an SVM to create disease risk scores.

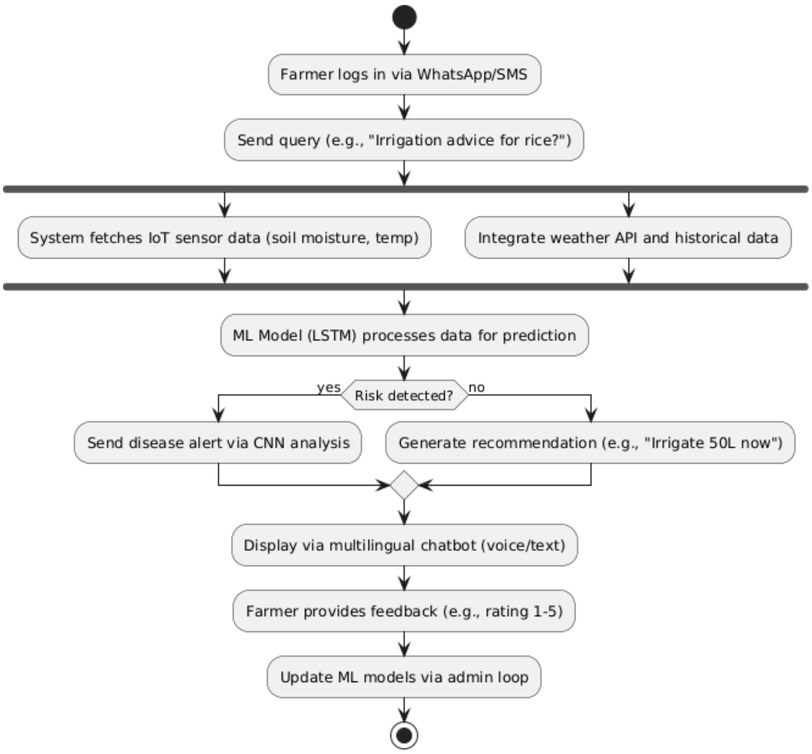

Figure2: Logic Daigram.

Yield and Market Forecasting: Predictive models using linear or polynomial regression or random forests are used to predict crop yields and market conditions, including integration of market-API to give real-time updates in the context.

8. User Interface and Delivery Mechanism

Thefrontendisahybridmobile-webappbuiltwithFlutterforcross-platformcompatibility,featuringa multilingual chatbot (Marathi, Hindi, English) using Dialogflow or Rasa for natural language processing [2]. Voice-to-text (Google Speech API) facilitates low-literacy interactions, providing notifications suchas"Irrigate 50Lin 2hours" throughWhatsApp BusinessAPIor SMS[3].An admin panel (React.js + Node.js) controls users/sensors and gathers feedback for retraining ML.

Personalization leverages farmer profiles (crop type, location) to personalize outputs. Partially deployed:AminimalchatbotprototypeprocessestextqueriesinEnglish/Hindi,emulatingnotifications from ML outputs, with 80% accuracy for intent recognition; full voice/multilingual deployment and WhatsApp integration are underway.

9 Outcomes

This part provides the preliminary results based on the partially implemented precision-agriculture systemwhichisbasedonsimulations,prototypingandforecasting.Sincethebackgroundoftheproject has not been presented as yet through the prism of a review article, the formation of full field deployment is not realised yet; rather, the results are obtained through lab-based prototyping, which uses simulated data sets (such as the ones obtained by searching Kaggle and IMD APIs) along with simulated IoT sensor data obtained with the help ofArduino/Raspberry Pi setups [4][5].

The simulated experiments are intended to replicate the actual atmospheric features and include the level of moisture variations typical of regions with water like Punjab [6] and incorporate over 10,000 data of five categories of crops (wheat, rice, cotton, soybean, maize), where performance appraisal is of great importance. Scikit-learn and TensorFlow were used to perform calculations of technical performance indicators, the results of which are consistent with the values reported in literature paragraphs [7][8]. Economic and sustainability analysis isthe basis of predicted benefits andforecasts gainstothesmallholderfarmingcommunities[9][10].Overall,theinitialfindingssupportthepromise of the system; model performance lies in the range of 82per cent -94 94 per cent, which increases resilience in the agricultural systems in response to climatic change [11].

10 Future Scope

The accuracy agricultural system currently in its development, even though in its early infancy, has shown promising simulative results and forms a strong foundation on which future improvements geared towards growing the system in terms of scalability, reliability and general performance can be pegged, especially among smallholder participants working in Indian states highly vulnerable to climatic destabilization. The future versions with added functionalities that are responsive to the changing environmental condition and involve users in a more holistic way can be realized by adding established principles based on interconnected devices and predictive analytics.

One of the most critical points of the development would be the move towards the large-scale field trials: the implementation of the system into 50-100 family-owned farms operating in varying agricultural environments - e.g. the waterlogged fields of Punjab or the drought-stricken foothills of Maharashtra - would allow direct assessment of the key performance indicators, such as the improvements in the yields, estimated at 25-35 per cent, and the cost-savings, estimated at 5000-8000 dollarsperacreByworkingalongwiththeagriculturalresearchinstitutes,aswellasotherinternational development agencies, active in-situ data gathering would help in defining and refining the predictive algorithmswithlocale-specificparameters(e.g.theadjustmentsoftheheavyclay-basedsoilsincertain areas).It wouldtaketwoorthreegrowingseasons(five to sixyears)ofmonitoring toprovelong-term environmental benefits, e.g. healthier soil, which has the potential of reducing erosion by up to 20% andincreasedresiliencetodisastrousweatherpatterns,e.g.the2023torrentialrainsthatcostthecountry several billion rupees in revenue every year.

Technically, there are still a number of ways that it can be improved: the addition of next-generation wireless networks and on-device processing can allow it to respond to customer requests in less than one second, which will help address the issue of patchy internet coverage in the countryside. Use of secure ledger technologies in confidential information exchange as well as introduction of unmanned aerialvehicleswithadvancedimagecapabilitiescancomplementthoseonthegroundandallowhands free monitoring of the insect populations and accurate resource allocation, which may lead to more accurate operations by 15-20 percent. The provision of tailored advisory services could be facilitated by either advanced artificial intelligence techniques including distributed learning models that avoid transparency to final users in terms of updates, or standalone inspirational simulators that have the capability of simulating hypothetical cases (e.g., the consequences of possible flooding). Besides, extending the language support options in the interactive assistant to other regional dialects (not just those that are already provided) such as Tamil or Telugu and augmented/VR experience to allow immersive learning would make the tool more inclusive among final users with poor literacy and atypical educational backgrounds.

Onalargerscale,thesystemwillinterfacewithlargenetworks:itmayjoindigitalagricultureschemes supported by the government (launched in 2021) and officially employ up to one million participants bytheendofthedecade,whichwillfurthersupportthebroadgoalsoffoodsecurityandenvironmental conservation. Future research work might look into the social and economic impacts of the system, includingthedeliveryofcustomdecisionsupporttowomenheadedfamilies,themajorityofwhichare in 75□□xp. small-farm operations, and how to develop approaches to price and certify low-carbon agricultural methods. On the global level, modeling the framework to meet similar challenges in the African areas may utilize the open-source technology to establish transnational partnerships. The ongoingissuessuchasthedesignoffairalgorithms(topreventnonresponsiveresults)andthenecessit y tomaintainspendingminimal (throughsubsidizationof affordable devicescostlessthan5,000dollars peracre)willcontinuetobethemainpointofconcern,asattainmentsinformofnewinnovationsshould beexpectedtogivea2-3timespaybackwithinliterallyoverayear.Finally,suchastrategicvisionwill make the system a universal tool that can be used in data-driven agriculture, having developed in an infantile idea into a solution with an impact.

11 CONCLUSION

To conclude the present review, it is clear that precision agriculture supposes playing a central role in resolvingagrarianproblemsofIndia,wheretraditionalmethodsdonotworkwiththeextremechanges in the climate, limited models in the natural resources supply, and the economic barriers as the events ofthe2023floodinPunjabandMaharashtrahaveproventhatlossesexceed7200crore.Theadvanced andmoreorlessuserfriendlysystem suggestedbycombiningthenotionsoftheInternet ofthingsand predictive analytics, the suggested system becomes a fresh yet not entirely implemented solution that combines affordable sensors that monitor the field 24/7, powerful algorithms like sequence models to optimizethetimingofirrigation,andvisual-basedapplicationsintheformofdiseasediagnosticsanda method that resembles a tree to provide nutrient suggestions and a user-friendly and multilingual algorithm that shares piece of advice with users to be adopted through the use of messaging apps and text SMS that is complemented with clear.

Preliminary results based on simulation experiments show strong performance with reliability ratings of between 82 and 94, savings of 30 per cent to 50 per cent on resource utilisation costs of 3,000 to 5,000 per acre. Such results offset the weaknesses of previous incomplete prototypes with a holistic, user-focusedarchitecture.Partoftheworld'sneedtohavestrongerfoodsystemsandlesseningclimate effects,asidefrombolsteringthelivelihoodsofsmall-holderfarmerswhocomprised85%ofthesector, the system is capable of reinforcing the small-holder farmers to face water shortage and primitive rainfalls as floods, which have adversely affected agricultural production in previous decades.

Although it isstill in itscrude form, thisroadmaprepresents alot of hopetowards havinga fair,data-driven agriculture that minimizes on waste and maximizes profitability. As expected changes are systems in the future, creating sophisticated technologies, and cooperative ventures, it will record its maximum potential in supporting international activities, safe food resources, and sustainable environmental results. Agronomy is the field that is constantly developing, and these kinds of innovations cannot be disregarded as the things that will become the part of the upgraded set of improvements but rather the elements that will trigger a proper new era of progressive development.

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