Artificial Intelligence in Agriculture: Enhancing Productivity and Efficiency

Abstract—The application of Artificial Intelligence (AI) has been evident in the agricultural sector recently. The sector faces numerous challenges in order to maximize its yield including improper soil treatment, disease and pest infestation, big data requirements, low output, and knowledge gap between farmers and technology. The main concept of AI in agriculture is its flexibility, high performance, accuracy, and cost-effectiveness. This paper presents a review of the applications of AI in soil management, crop management, weed management and disease management. A special focus is laid on the strength and limitations of the application and the way in utilizing expert systems for higher productivity.

Keywords-artificial intelligence; agriculture; soil management; crop management; disease management; weed management; yield

I. INTRODUCTION

Agriculture is the bedrock of sustainability of any economy [1]. It plays a key part in long term economic growth and structural transformation [2-4], though, may vary by countries [5]. In the past, agricultural activities were limited to food and crop production [6]. But in the last two decades, it has evolved to processing, production, marketing, and distribution of crops and livestock products. Currently, agricultural activities serve as the basic source of livelihood, improving GDP [7], being a source of national trade, reducing unemployment, providing raw materials for production in other industries, and overall develop the economy [8-10]. With the global geometric population rise it becomes imperative that agricultural practices are reviewed with the aim of proffering innovative approaches to sustaining and improving agricultural activities. The introduction of AI to agriculture will be enabled by other technological advances, including big data analytics, robotics, the internet of things, the availability of cheap sensors and cameras, drone technology, and even wide-scale internet coverage on geographically dispersed fields. By analyzing soil management data sources such as temperature, weather, soil analysis, moisture, and historic crop performance, AI systems will be able to provide predictive insights into which crop to plant in a given year and when the optimal dates to sow and harvest are in a specific area, thus improving crop yields and decrease the use of water, fertilizers, and pesticides. Via the application of AI technologies the impact on natural ecosystems can be reduced, and worker safety may increase, which in turn will keep food prices down and ensure that the food production will keep pace with the increasing population.

II. CONSIDERATION OVERVIEW

Farming entails a great deal of choices and uncertainties. From season to season the weather varies, the prices of farming materials fluctuate, soil degrades, crops are not viable, weeds suffocate crops, pests damage crops, and the climate changes. Farmers must cope with these uncertainties. Although agricultural practice is broad, this research considers soil, crop, disease and weeds as major contributors to agricultural production. It is paramount to review the application of AI to agriculture in respect to soil, crop, diseases and pest management.

- Soil is a critical part of successful agriculture and is the original source of the nutrients used to grow crops. Soil is the basis of all production systems in agriculture, forestry and fishery. Soil stores water, nutrients and proteins in order to make them available for proper crop growth and development.
- Crop production plays a crucial role in Nepal's economy. It does provide food, raw materials, and employment. In modern times, marketing, processing, distribution and after-sales service are also accepted as parts of crop production. In places where the real income per capital is low, emphasis is being laid on crop production and other primary industries. It is seen that increased crop production output and productivity tend to contribute substantially to the overall economic development of a country. It will hence be appropriate to place greater emphasis on further crop production development.
- As agriculture struggles to support the rapidly growing population, plant diseases reduce crop production quantity and quality. Agricultural losses due to post-harvest diseases can be disastrous.
- Weeds consist one of the major threats to all agricultural activities. Weeds reduce farm and forest productivity, invade crops, smother pastures, and in some cases harm livestock. They aggressively compete with the crops for water, nutrients and sunlight, resulting in reduced crop yield and poor crop quality.

III. SOIL MANAGEMENT

Soil management is an integral part of agricultural activities. A sound knowledge of various soil types and conditions will enhance crop yield and conserve soil resources. It is the use of operations, practices and treatments to improve soil performance. Urban soils may contain pollutants which can be investigated with a traditional soil survey approach [11]. The application of compost and manure improve soil porosity and aggregation. A better aggregation indicates the addition of organic materials that play an important role in preventing soil crust formation. It is possible to adopt alternative tillage systems to prevent soil physical degradation. The application of organic materials is essential to improve soil quality [12]. Production of vegetables and other edible crops is often significantly affected by several soil-borne pathogens that require control through soil management [13]. Sensitivity to soil degradation is implicit in the assessment of the sustainability of land management practices, with recognition of the fact that soils vary in their ability to resist change and recover [14].

A summary in AI soil management techniques is shown in Table I. Management-oriented modeling (MOM) minimizes nitrate leaching as it consists of a set of generated plausible management alternatives, a simulator that evaluates each alternative, and an evaluator that determines which alternative meets the user-weighted multiple criteria. MOM uses "hill-climbing" as a strategic search method that uses "best-first| as a tactical search method to find the shortest path from start nodes to goals [15]. Knowledge of engineering for constructing the Soil Risk Characterization Decision Support System (SRC-DSS) involves three stages: knowledge acquisition, conceptual design and system implementation [16]. An artificial neural network (ANN) model predicts soil texture (sand, clay and silt contents) based on attributes obtained from existing coarse resolution soil maps combined with hydrographic parameters derived from a digital elevation model (DEM) [21]. The dynamics of soil moisture are characterized and estimated by a remote sensing device embedded in a higher-order neural network (HONN) [22].

IV. CROP MANAGEMENT

The crop management techniques are summarized in Table II. Crop management starts with sowing, and continues with monitoring growth, harvesting, and crop storage and distribution. It is summarized as the activities that improve the growth and yield of agricultural products. In-depth understanding of class of crops according to their timing and thriving soil type will certainly increase crop yield. Precision crop management (PCM) is an agricultural management system designed to target crop and soil inputs according to field requirements to optimize profitability and protect the environment. PCM has been hampered by lack of timely, distributed information on crop and soil conditions [26]. Farmers must combine various crop management strategies to cope with water deficit resulting from soil, weather or limited irrigation. Flexible crop management systems based on decision rules should be preferred. Timing, intensity, and predictability of drought are important features for choosing among cropping alternatives [27].

TABLE I. AI IN SOIL MANAGEMENT SUMMARY

Application	Technique	Strength	Limitation
[15]	MOM	Minimizes nitrate leaching, maximizes production.	Takes time. Limited only to nitrogen.
[16]	Fuzzy Logic: SRC-DSS	Can classify soil according to associated risks.	Needs big data. Only a few cases were studied.
[17]	DSS	Reduces erosion and sedimentary yield.	Requires big data for training.
[18]	ANN	Can predict soil enzyme activity. Accurately predicts and classifies soil structure.	Only measures a few soil enzymes. It considers more classification than improving the performance of the soil.
[19]	ANN	Can predict monthly mean soil temperature	Considers only temperature as a factor for soil performance.
[20]	ANN	It predicts soil texture	Requires big data for training. Has restriction in areas of implementation.
[21]	ANN	Able to predict soil moisture.	The prediction will fail with time as weather conditions are hardly predictable.
[22]	ANN	Successfully reports soil texture.	It does not improve soil texture or proffers solution to bad soil texture.
[23]	ANN	Cost-effective, saves time, has 92% accuracy	Requires big data.
[24]	ANN	Can estimate soil nutrients after erosion.	Its estimate is restricted to only NH_4 .

Proper understanding of weather patterns helps in the decision-making process that will result in high and quality crop yield [28]. PROLOG utilizes weather data, machinery capacities, labor availability, and information on permissible and prioritized operators, tractors, and implements for evaluating the operational behavior of a farm system. It also estimates crop production, gross revenue, and net profit for individual fields and for the whole farm [30]. Crop prediction methodology is used to predict the suitable crop by sensing various soil parameters and parameter related to the atmosphere. Parameters like soil type, PH, nitrogen, phosphate, potassium, organic carbon, calcium, magnesium, sulfur, manganese, copper, iron, depth, temperature, rainfall, humidity [31]. Demeter is a computer-controlled speed-rowing machine, equipped with a pair of video cameras and a global positioning sensor for navigation. It is capable of planning harvesting operations for an entire field, and then executing its plan by cutting crop rows, turning to cut successive rows, repositioning itself in the field, and detecting unexpected obstacles [32]. The use of AI in harvesting cucumber comprises of the individual hardware and software components of the robot including the autonomous vehicle, the manipulator, the end-effector, the two computer vision systems for detection and 3D imaging of the fruit and the environment and, finally, a control scheme that generates

collision-free motions for the manipulator during harvesting [33]. Field-specific rainfall data and weather variables can be used for each location. Adjusting ANN parameters affects the accuracy of rice yield predictions. Smaller data sets required fewer hidden nodes and lower learning rates in model optimization [38].

TABLE II. AI IN CROP MANAGEMENT SUMMARY

Application	Technique	Strength	Limitation
[29]	CALEX	Can formulate scheduling guidelines for crop management activities.	Takes time.
[30]	PROLOG	Removes less used farm tools from the farm.	Location-specific.
[31]	ANN	Predicts crop yeild.	Only captures weather as a factor for crop yeild.
[32]	ROBOTICS-Demeter	Can harvest up to 40 hectares of crop	Expensive: Uses a lot of fuel.
[33]	ROBOTICS	Has 80% success rate in harvesting crops	Slow picking speed and accuracy.
[34]	ANN	Above 90% success rate in detecting crop nutrition disorder.	A little number of symptoms were considered.
[35]	FUZZY Cognitive Map	Predict cotton yield and improve crop for decision management.	It is relatively slow.
[36]	ANN	Can predict the response of crops to soil moisture and salinity.	Considers only soil temperature and texture as factors.
[37]	ANN and Fuzzy Logic	Reduces insects that attack crops.	Shows inability to differentiate between crop and weed.
[38]	ANN	Can accurately predict rice yield.	Time-consuming, limited to a particular climate.

V. DISEASE MANAGEMENT

To have an optimal yield in agricultural harvest, disease control is necessary. Plant and animal diseases are a major limiting factor regarding the increase of yield. Several factors play role in the incubation of these diseases which attack plants and animals, which include genetic, soil type, rain, dry weather, wind, temperature, etc. Due to these factors and the unsteady nature of some diseases causative influence, managing the effects is a big challenge, especially in large scale farming. Table III lists the AI applications in disease management available in the literature. To effectively control diseases and minimize losses, a farmer should adopt an integrated disease control and management model that includes physical, chemical and biological measure [39]. To achieve these is time consuming and not at all that cost effective [40], hence the need for application of AI approach for disease control and management. Explanation block (EB) gives a clear view of the logic followed by the kernel of the expert system [42]. A novel approach of rule promotion based on fuzzy logic is used in the system for drawing intelligent inferences for crop disease management. A text-to-speech (TTS) converter is used for providing capability of text-to-talking user interface. It provides highly-effective interactive user interface on web for live interactions [45]. A rule based and forward chaining inference engine has been used for the development of the system that helps in detecting the diseases and provide treatment suggestion in [46].

TABLE III. AI IN DISEASE MANAGEMENT SUMMARY

Application	Technique	Strength	Limitation
[42]	Computer vision system (CVS), genetic algorithm (GA), ANN	Works at a high speed. Can multi-task.	Dimension-based detection which may affect good species.
[42]	Rule-Based Expert, Data Base (DB)	Accurate results in the tested environment.	Inefficacy of DB when implementing in large scale.
[43]	Fuzzy Logic (FL), Web GIS	Cost effective, eco friendly.	Inefficiency due to scattered distribution. Takes time to locate and disperse data. The location of the data is determined by a mobile browser.
[44]	FL Web-Based, Web-Based Intelligent Disease Diagnosis System (WIDDS)	Good accuracy. Responds swiftly to the nature of crop diseases.	Limited usage as it requires internet service. Its potency cannot be ascertained as only 4 seed crops were considered.
[45]	FL & TTS converter	Resolves plant pathological problems quickly.	Requires high speed internet. Uses a voice service as its multimedia interface.
[46]	Expert system using rule-base in disease detection	Faster treatment as diseases are diagnosed faster. Cost effective based on its preventive approach.	Time consuming. Needs constant monitoring to check if pest has built immunity to the preventive measure.
[47]	ANN, GIS	95% accuracy	Internet-based. Some rural farmers will not have access.
[48]	FuzzyXpest provides pest information for farmers. It is also supported by internet services.	High precision in forecast.	Internet dependent.
[49]	Web-Based Expert System	High performance.	Internet and web based.
[50]	ANN	Has above than 90% prediction rate.	The ANN does not kill infections or reduces its effect.

VI. WEED MANAGEMENT

Weed consistently reduces the farmers' expected profit and yield [51]. A report confirms a 50% reduction in yield for dried beans and corn crops if weed infestations are not controlled [51]. There is about 48% loss in wheat yield due to weed competition [52, 53]. These losses may at times rise up to 60% [54]. A study on the impact of weed on Soybean showed about 8%-55% reduction in yield [55]. A study on yield losses in

sesame crops accounts them to about 50%-75% [56]. The fluctuation in yield losses may be attributed to the length of exposure of the crops to the weeds [57, 58] and spatial heterogeneity of weeds [59]. Beyond these, weed has both positive and negative effects to the ecosystem. According to the relative Weed Science Society of America (WSSA) report, weed effects include flooding during hurricane, some species of weeds can pave their way during rampant fire, some cause irreparable liver damage if consumed, and they muscle out plants or crops by competing for water, nutrients and sunlight. Some weeds are poisonous and cause allergic reactions or even may threat public health. Table IV lists a summary of the AI in weed managements uses.

TABLE IV. AI IN WEED MANAGEMENT SUMMARY

Application	Technique	Strength	Limitation
[61]	ANN, GA	High performance. Reduces trial and error.	Requires big data.
[62]	Optimization using invasive weed optimization (IVO), ANN	Cost effective, enhanced performance.	Adaptation challenge with new data.
[63].	Mechanical Control of Weeds. ROBOTICS. Sensor machine learning	Saves time and removes resistant weeds.	Expensive. Constant use of heavy machine will reduce soil productivity.
[64]	UAV, GA	Can quickly and efficiently monitor weeds.	Has little or no control on weeds. Expensive.
[65]	Saloma expert system for evaluation, prediction & weed management.	High adaptation rate and prediction level.	Requires big data and usage expertise.
[66]	Support Vector Machine (SVM), ANN	Quickly detects stress in crop that will prompt timely site–specific remedies.	Only detects low levels of nitrogen.
[67]	Digital Image Analysis (DIA), GPS	Has above 60% accuracy and success rate.	Its success was achieved after 4 years and as such, it is really time consuming.
[68]	UAV	High rate of weed detection within a short period of time.	It is really expensive and requires vast human expertise.
[69]	Learning Vector Quantization (LVQ), ANN	High weed recognition rate with short processing time.	The method of data input used affected the AI's perfromance.

An intensive management with herbicides has been deployed over the past decades to reduce its effect on crops. However, even with this management pattern, it was predicted that crop losses due to weed in western Canada field crops are estimated to exceed $500 million annually [60], hence the need for a more expert weed management technique to compensate for this loss emerges [51]. A system can utilize an unmanned aerial vehicle (UAV) -imagery to divide image, compute and convert to binary the vegetation indexes, detect crop rows, optimize parameters and learn a classification model. Since crops are usually organized in rows, the use of a crop row detection algorithm helps to separate properly weed and crop pixels, which is a common handicap given the spectral similitude of both [64]. Weed control in sugar-beet, maize, winter wheat, and winter barley, can be done by applying online weed detection using digital image analysis taken by an UAV (drone), computer-based decision making and global positioning system (GPS)-controlled patch spraying [67]. The drone in [68] travelled at a speed of 1.2km/h, with 58.10ms and 37.44ms execution time to find the tomato and weed locations to the spray controller respectively

VII. CURTAILING CHALLENGES OF AI IN AGRICULTURE

Expert systems are tools for agricultural management since they can provide site-specific, integrated, and interpreted advices. However, the development of expert systems for agriculture is fairly recent, and the use of these systems in commercial agriculture is rare to date [70]. Although AI has made some remarkable improvement in the agricultural sector, it still has a below the average impact on the agricultural activities when compared to its potentials and impacts in other sectors. More still need to be done to improve agricultural activities using AI as there are many limitations to its implementation.

A. Limitation: Response Time and Accuracy

A major attribute of an intelligent or expert system is its ability to execute tasks accurately in very short time. Most of the systems fall short either in response time or accuracy, or even both. A system delay affects a user's selection of task strategy. Strategy selection is hypothesized to be based on a cost function combining two factors: (1) the effort required to synchronize input system availability, and (2) the accuracy level afforded. People seeking to minimize effort and maximize accuracy, choose among three strategies: automatic performance, pacing, and monitoring [71].

B. Limitation 2: Big Data Required

The strength of an intelligent agent is also measured on the volume of input data. A real-time AI system needs to monitor an immense volume of data. The system must filter out much of the incoming data. However, it must remain responsive to important or unexpected events [72]. An in-depth knowledge of the task of the system is required from a field expert and only very relevant data should be used improving the system's speed and accuracy. The development of an agricultural expert system requires the combined efforts of specialists from many fields of agriculture, and must be developed with the cooperation of the growers who will use them [70].

C. Limitation 3: Method of Implementation

The beauty of any expert system lies on its execution methodology. Since it uses big data, the method of looking-up and training should be properly defined for speed and accuracy.

D. Limitation 4: High Data Cost

Most AI systems are internet-based which in turn reduces or restricts their usage, particularly in remote or rural areas.

The government can support farmers by designing a web service enabling device with lower tariff to uniquely work with the AI systems for farmers. Also, a form of "how to use" orientation (training and re-training) will really help farmers adapt to the use of AI on the farm.

E. Limitation 5: Flexibility

Flexibility is a strong attribute of any sound AI system. It is perceived that much progress has been made in applying AI techniques to particular isolated tasks, but the important theme at the leading edge of the AI-based robotics technology seems to be the interfacing of the subsystems into an integrated environment. This requires flexibility of the subsystems themselves [73]. It should also have expansive capabilities to accommodate more user data from the field expert.

VIII. THE FUTURE OF AI IN AGRICULTURE

Global population is expected to reach more than nine billions by 2050 which will require an increase in agricultural production by 70% in order to fulfil the demand. Only about 10% of this increased production may come from unused lands and the rest should be fulfilled by current production intensification. In this context, the use of latest technological solutions to make farming more efficient remains one great necessity. Present strategies to intensify agricultural production require high energy inputs and market demands high quality food. [74]. Robotics and autonomous systems (RAS) are set to transform global industries. These technologies will have great impact on large sectors of the economy with relatively low productivity such as agro-food (food production from the farm to the retail shelf). The UK agro-food chain generates over £108bn p.a., with 3.7m employees in a truly international industry yielding £20bn of exports in 2016 [75].

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