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Improving the Food and Agriculture Sector Tehran Stock Exchange by using Artificial Intelligence

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Abstract

Agriculture plays a significant role in the economic sector. The automation in agriculture is the main concern and the emerging subject across the world. The population is increasing tremendously and with this increase the demand of food and employment is also increasing. The traditional methods which were used by the farmers, were not sufficient enough to fulfill these requirements. Thus, new automated methods were introduced. These new methods satisfied the food requirements and also provided employment opportunities to billions of people. Artificial Intelligence in agriculture has brought an agriculture revolution. This technology has protected the crop yield from various factors like the climate changes, population growth, employment issues and the food security problems. This main concern of this paper is to audit the various applications of Artificial intelligence in agriculture such as for irrigation, weeding, spraying with the help of sensors and other means embedded in robots and drones. These technologies save the excess use of water, pesticides, herbicides, maintains the fertility of the soil, also helps in the efficient use of man power and elevate the productivity and improve the quality. This paper surveys the work of many researchers to get a brief overview about the current implementation of automation in agriculture, the weeding systems through the robots and drones. The various soil water sensing methods are discussed along with two automated weeding techniques. The implementation of drones is discussed, the various methods used by drones for spraying and crop-monitoring is also discussed in this paper.

Keywords: Artificial Intelligence, Agricultural Companies, Tehran Stock, improve the food and agriculture sector.

Introduction

The estimation of the global food production must be increased by 60–110% to feed 9-10 billion of the population (Rockström et al., 2017) and (Krishna, 2016).
Thus, the sustainability of agriculture field is the key to guarantee food security and hunger eradication for the ever-growing population. In addition, due to the appearance of several food safety scandals and incidents in the food sector such as bovine spongiform encephalopathy and dioxin in poultry (Ben-Ayed et al., 2013), a well-documented traceability system has become a requirement for quality control in the food chain. Moreover, weather and climate change conditions, together with the sustainable water management due to water scarcity, are crucial challenges in the next years. For these

reasons, urgently, the establishment of a strategic shift from the current paradigm of enhanced agricultural productivity to agricultural sustainability is needed. To anticipate efficient solutions, helping farmers and stakeholders to enhance their decision by adopting sustainable agriculture practices is a crucial choice, especially the use of digital technologies including Internet of things (Iot), Artificial Intelligence (AI), and cloud computing. Additionally, the subsets of AI (machine and deep learning algorithms) combined with location intelligence technologies are extensively used. The goal of our review is to present the main applications of artificial intelligence and machine learning techniques in the agro-food sector.

The world's population is assumed to be nearly 10 billion by 2050, boosting agricultural order-in a situation of humble financial development by somewhere in the range of 50% contrasted with 2013 (Tripoli & Schmidhuber, 2018).

At present, about 37.7% of total land surface is used for crop production. From employment generation to contribution to National Income, agriculture is important. It is contributing a significant portion in the economic prosperity of the developed nations and is playing an active part in the economy of the developing countries as well. The augmentation of agriculture has resulted in a significant increase in the per-capita income of the rural community. Thus, placing a greater emphasis on agricultural sector will be rational and apposite. For countries, like India, the agricultural sector accounts for 18% of GDP and provides employment to 50% of the country's workforce. Development in the agricultural sector will boost the rural development, further leading toward rural transformation and eventually resulting in the structural transformation (Mohri & Rostamizadeh, 2018).

Literature Review

With the advent of technology, there has been observed a dramatic transformation in many of the industries across the globe. Surprisingly, agriculture, though being the least digitized, has seen momentum for the development and commercialization of agricultural technologies. Artificial Intelligence (AI) has begun to play a major role in daily lives, extending our perceptions and ability to modify the environment around us (Ahir et al., 2020).

(Patelli & Mandrioli, 2020), gave a method for harvest planning based on the coupling of crop assignment with vehicle routing is presented. With this emerging technologies the workforce which were restricted to only a minimal industrial sectors are now contributing to numerous sectors. AI is based on the vast domains like Biology, Linguistics, Computer Science, Mathematics, Psychology and engineering.

(Jha et al., 2019), a brief overview of the current implementation of agricultural automation. The paper also addresses a proposed system for flower and leaf identification and watering using IOT to be implemented in the botanical farm.

The basic concept of AI to develop a technology which functions like a human brain This technology is perpetrated by studying how human brain thinks, how humans learn, make decisions, and work while solving a problem, and on this ground intelligent software and systems are developed. These software's are fed with training data and further these intelligent devices provide us with desired output for every valid input, just like the human brain. Vast domains including Machine Learning and Deep learning are core part of AI (Patelli & Mandrioli, 2020). While AI is the science of making intelligent machines and programs, ML is the ability to learn something without being explicitly programmed and DL is the learning of deep neural networks. The main subjective of AI is to make problem solving facile which may include the use of ANN (Gao et al., 2020).

ANN is a processing algorithm or a hardware whose functioning is inspired by the design and functioning of a human brain (Gao et al., 2020). Neural networks have a remarkable ability of self-organization, and adaptive learning. It has replaced many traditional methods in numerous fields like Computer Science, Mathematics, Physics, Engineering image/signal processing, Economic/ Finance, Philosophy, Linguistics, Neurology. ANN undergoes the process of learning. Learning is the process of adapting the change in itself as and when there is a change in environment. There are two learning techniques, supervised learning and unsupervised learning. The work of, encloses the connected relations between the various embedded systems and the AI technology coherent with the agricultural field, it gave a brief about the various applications of neural networks, ML in this sector for precision farming (Jha et al., 2019). Is an emerging technology in the field of agriculture? AI-based equipment and machines, has taken today's agriculture system to a different level. This technology has enhanced crop production and improved real-time monitoring, harvesting, processing and marketing. The latest technologies of automated systems using agricultural robots and drones have made a tremendous contribution in the agro-based sector. Various hi-tech computer based systems are designed to determine various important parameters like weed detection, yield detection and crop quality and many other techniques. This paper encompasses the technologies used for the automated irrigation, weeding and spraying to enhance the productivity and reduce the work load on the farmers. Various automated soil sensing techniques are discussed (Liakos et al., 2018).

(Sujatha et al., 2021), brought together temperature and moisture sensors to close the loop holes of the vehicle predictions. The robots used in sensing were localized by GPS modules and the location of these robots was tracked using the google maps. The data from the robots was fetched through Zigbee wireless protocol. The readings were displayed on the 16 × 2 LCD display which was integrated to the LPC2148 microcontroller. The latest automated weeding techniques are discussed and the implementation of drones for the purpose of spraying in the fields is discussed followed by the types of sprayers utilized on UAVs. Further speaking about drones, yield mapping and monitoring is discussed beginning with an outline of the yield mapping processes followed by the programming of the software and briefing about the calculation as well as calibration process. Finally the processing of these yield maps is illuminated.

Artificial Intelligence and Machine Learning Approach

The artificial intelligence (AI) is a creative tool that simulates the human intelligence and ability processes by machines, principally computer systems, robotics, and digital equipment (Patelli & Mandrioli, 2020).

Several applications of the AI include natural language processing (NLP) to comprehend human verbal communication as it is spoken, computer vision to see an analog-to-digital conversion such as video, and speech recognition and expert systems to simulate the judgment. The AI encoding is based on learning (acquire data and then create algorithms to turn them into actionable information), reasoning (choose the right algorithm to reach a preferred result), and self-correction (continually adjust designed algorithms and ensure that they provide the most accurate results) as three cognitive skills (Gharaei et al., 2019).

The AI technique is being used in several sectors which are seeing the fastest growth in the recent years such as finance, healthcare, retail, pharmaceutical research, intelligent process automation, and marketing. Machine learning (ML) is one of the central themes of AI and helps people to work more creatively and efficiently. In ML, statistical and mathematical methods are used to learn from datasets to make data-driven predictions/decisions. Several different methods exist for this. General distinction can be made by two systems; the first one is the symbolic approaches (the induced rules and the examples are explicitly represented) and the second one is the sub symbolic approaches (artificial neuronal networks: ANN). The ML approach is classified into three major tasks: supervised, unsupervised, and reinforcement learning. According to the supervised learning, the aim of this approach is to map the variables to the preferred output variable (Traore et al., 2017). The predictive model is created using the labeled data with the prior knowledge of the input and the desired output variables. Algorithms used under supervised learning techniques are numerous, particularly, decision trees, Bayesian networks, and regression analysis. Concerning the unsupervised learning, it includes algorithms such as Artificial Neural Networks (ANNs), clustering, genetic algorithm, and deep learning and uses unlabeled datasets without prior knowledge of the input and output variables. In fact, and as mentioned by (Jordan & Mitchell, 2015), this case of unsupervised machine learning method establishes the hidden patterns by using the unlabeled dataset and is primarily used for dimensionality reduction and exploratory data analysis. According to the third category of ML task named the reinforcement learning, numerous algorithms are used for machine skill acquisition, robot navigation, and real-time decision making such as Q-learning and deep Q-learning. In this case of ML task, the learner interacts with the environment to collect information and the two steps of training and testing datasets are combined.

The learner gets awarded for his actions with the environment leading to an exploration versus exploitation dilemma. The learner must explore new unknown actions to gain more information as compared to exploiting the information already collected. Recently, AI technology has opened the doors of its implementation in the agro-food sector. In fact, AI approaches offer significant contributions and assistances to understanding a model's identification, service creation, and the decision-making processes as support to the different agro-food 's applications and supply chain stages. The principal goal of AI in agriculture is to provide precision and forecasting decision in order to improve the productivity with resource preservation (Patelli & Mandrioli, 2020); through this, AI tools propose algorithms to evaluate performance, classify patterns, and to predict unexpected problems or phenomena in order to solve comprehension problems in the agricultural field and for the identification of pests and its suitable method of treatment, as well as the management of the irrigation process and water consumption by setting up smart irrigation systems.

Abiotic and biotic factors are being assessed through remote sensing and sensors in order to optimize crop and livestock management.

In addition, the AI implementation and applications have enormous advantages which could revolutionize the agro-food sector and its related business. Firstly, AI provides more efficient ways to produce, harvest, and sell crops products as well as emphasis on checking defective crops and improving the potential for healthy crop production and also AI is being used in applications such as automated machine adjustments for weather forecasting and disease or pest identification with 98% accuracy. In fact, recently, (Sujatha et al., 2021), compared the performance of machine learning (ML) and deep learning (DL) methods to detect and identify the citrus plant leaf disease. They showed that the VGG-16 deep learning method gave the best result in terms of disease classification accuracy. Secondly, the progression in the AI technique has reinforced agro-based businesses to run more proficiently by improving crop management practices, thus helping many tech businesses invest in algorithms that are becoming useful in agriculture as well as by solving the contrasts farmers face such as climate variation and an infestation of pests and weeds that decreases yields.

Indeed, (Crane-Droesch, 2018), developed a novel modeling approach for augmenting parametric statistical models with deep neural networks, which we term semi parametric neural networks (SNNs), and by using data on corn yield from the US Midwest, they showed the outperformance of this approach in predicting yields of years withheld during model training compared to classical statistical methods and fully nonparametric neural networks. Thirdly, by using AI tools, farmers could be able to remain updated with the data related to weather forecasting and, therefore, predicted weather data help farmers to increase yields and profits without risking the crop, and as a result, after analyzing the generated data, AI allows the farmers to better understand and learn and then to take the precaution by implementing practices in order to make a punctual smart decision. In fact, (Fente & Singh, 2018), collected different weather parameters (temperature, precipitation, wind speed, pressure, dew point visibility, and humidity) from the Indian climate data center and implemented a weather forecasting model by using a recurrent neural network (RNN) with the long-short-term memory (LSTM) technique. They concluded that the used technique gave high-accuracy results compared to other weather forecasting approaches. Fourthly, AI approaches are capable of monitoring soil health and management by conducting and identifying the possible defects and nutrient deficiencies in the soil either by image captured with the camera recognition tool or by deep learning based tool to analyse flora patterns in farms and to simultaneously understand soil defects, plant pests, and diseases. In fact, (Suchithra & Pai, 2020), classified and predicted the soil fertility indices and pH levels of Kerala north central laterite Indian region soil by using the Extreme Learning Machine (ELM) technique with different activation functions such as hard limit, sine-squared, triangular basis, hyperbolic tangent, and Gaussian radial basis. They revealed that the maximum performance (80% of the accuracy rate calculations in every problem) for four out of five problems was obtained with the Gaussian radical basis function followed by hyperbolic tangent.

However, the best performance (90%) of the pH classification problem was given by the hyperbolic tangent, whereas the moderate values were given by the gaussian radial basis. Fifthly, an important functional benefit of the AI technology employment is the environmental protection by decreasing pesticide usage.

For example, and in order to manage weeds faster and with greater accuracy, AI techniques by implementing robotics, computer vision, and machine learning could help farmers to spray chemicals only where the weeds are; thus, this directly reduced the use of the chemical substance spraying on the whole field. Consequently, AI tools are helping farmers find more efficient actions to protect their crops from weeds. Finally, the practice of the advanced AI-based technologies has other advantages on the agro-food supply chain such as reducing employee training costs, reducing the time needed to solve problems, reducing the amount of human errors, reducing human intervention, and offering an automated good, accurate, and robust decision-making on the right time with low cost (Kamilaris & Prenafeta-Boldú, 2018).

The technologies which are AI-based help to improve efficiency in all the fields and also manage the challenges faced by various industries including the various fields in the agricultural sector like the crop yield, irrigation, soil content sensing, crop-monitoring, weeding, crop establishment (Suprem et al., 2013).

Agricultural robots are built in order to deliver high valued application of AI in the mentioned sector. With the global population soaring, the agricultural sector is facing a crisis, but AI has the potential to deliver much-needed solution. AI- based technological solutions has enabled the farmers to produce more output with less input and even improved the quality of output, also ensuring faster go-to- market for the yielded crops. By 2020, farmers will be using 75 million connected devices. By 2050, the average farm is expected to generate an average of 4.1 million data points every day. The various ways in which AI has contributed in the agricultural sector are as follows:

Image recognition and perception

(O'Grady, 2019), said that in recent years, an increasing interest has been seen in autonomous UAVs and their applications including recognition and surveillance, human body detection and geo localization, search and rescue, forest fire detection. Because of their versatility as well as amazing imaging technology which covers from delivery to photography, the ability to be piloted with a remote controller and the devices being dexterous in air which enables us to do a lot with these devices, drones or UAVs are becoming increasingly popular to reach great heights and distances and carrying out several applications.

Skills and workforce

(Morellos et al., 2018), said that artificial intelligence makes it possible for farmers to assemble large amount of data from government as well as public websites, analyze all of it and provide farmers with solutions to many ambiguous issues as well as it provides us with a smarter way of irrigation which results in higher yield to the farmers. Due to artificial intelligence, farming will be found to be a mix of technological as well as biological skills in the near future which will not only serve as a better outcome in the matter of quality for all the farmers but also minimize their losses and workloads. UN states that, by 2050, 2/3rd of world's population will be living in urban areas which arises a need to lessen the burden on the farmers. AI in agriculture can be applied which would automate several processes, reduce risks and provide farmers with a comparatively easy and efficient farming.

Maximize the output

(Zhang, 2018), said in his wok that Variety selection and seed quality set the maximum performance level for all plants. The emerging technologies have helped the best selection of the crops and even have improved the selection of hybrid seed choices which are best suited for farmer's needs. It has implemented by understanding how the seeds react to various weather conditions, different soil types. By collecting this information, the chances of plant diseases are reduced. Now we are able to meet the market trends, yearly outcomes, consumer needs, thus farmers are efficiently able to maximize the return on crops.

Chatbots for farmers

Chatbots are nothing but the conversational virtual assistants who automate interactions with end users. Artificial intelligence powered catboats, along with machine learning techniques has enabled us to understand natural language and interact with users in away more personalized way. They are mainly equipped for retail, travel, media, and agriculture has used this facility by assisting the farmers to receive answers to their unanswered questions, for giving advice to them and providing various recommendations also.

Artificial Intelligence Technology and Application to Improve Agriculture and Food Industries

Currently, the use of ML algorithms in the main four clusters (preproduction, production, processing, and distribution) of the agriculture supply chain is becoming more and more important (Ahumada & Villalobos, 2009).
In fact, in the preproduction step, the ML technologies are used, especially for the prediction of crop yield, soil properties, and irrigation requirements. In the next stage of the production phase, the ML could be used for disease detection and weather prediction. Concerning the third cluster of the processing phase, utilization of ML approaches is applied, especially to estimate of the production planning to reach a high and safe quality of the product. ML algorithms could be used also to the distribution cluster, especially in storage, transportation, and consumer analysis. The preproduction cluster is the initial step in the agriculture supply chain. It mainly concerns the prediction of crop yield, soil properties, and irrigation requirement.
Many researchers report the importance of the crop yield production in order to better support plant management. In fact, by using as an input data (equipment requirements, nutrients, and fertilizers) in predicting efficient models based on ML algorithms, these precision agriculture tools aim to make stakeholders and farmers support ideal decision in crop yield forecasting and improve the smart farming practices. Recently, different ML algorithms are used for crop yield prediction such as the Bayesian network, regression, decision tree, clustering, deep learning, and ANN (Zhang, 2018).
According to the prediction of soil management properties, several ML algorithms are used in learning soil properties. Among them, the LS-SVM (least-squares support vector machine) method was used by (Morellos et al., 2018), to study 140 soil samples.
(Nahvi et al., 2016), used the SaE (self-adaptive evolutionary) ML algorithm to boost the performance of the extreme learning machine (ELM) architecture to estimate daily soil temperature. Additionally, (Kumar et al., 2019) proposed a novel method named the CSM (Crop Selection Method) to resolve crop selection problems and help improve net yield rate of crops over the season. In addition, Ben (Elavarasan et al., 2018) analyzed 18 worldwide table olive cultivars by using morphological, biological, and physicochemical parameters and the Bayesian network to study the influence of these parameters in tolerance, productivity, and oil content. They revealed that oil content was highly influenced by the tolerance of the crop. Another important parameter in the preproduction cluster is the irrigation management that plays a crucial role in affecting the quality and quantity of the crops. In fact, to achieve an effective irrigation system (better decision in when, where, and how much to irrigate), researchers used soil moisture data, precipitation data, evaporation data, and weather forecasts as input data for simulation and optimization of predicted models based on ML adequate algorithms (Goap et al., 2018).

Methodology

Neural networks for unsupervised clustering
Self-organizing maps

The self-organizing map (SOM) is composed of neural units ordered on a (usually 2-D) fixed lattice, where each unit has an associated weight vector with the same dimensionality of the data space. The weight vectors of the SOM units are adapted to become quantization prototypes of the data samples, by an iterative learning process composed of three steps: competition, cooperation, and adaptation. For a D-dimensional dataset M and an SOM grid G (most frequently a 2D rectangular grid) with N neural units, where w_i is the D-dimensional weight vector associated with the neural unit i, the sequential SOM learning can be summarized as follows:

A. (competition) randomly select a data sample $v \in M$ and find its best matching unit (BMU) i whose w_i satisfies $\|v-w_i\| \leq \|v-w_j\| \forall j \in G$ (cooperation) excite the grid neighbors j of the BMU i determined by a neighborhood function $h_{i,j}(t)$ (usually defined as a Gaussian around the BMU i, based on the grid distance between neural units i and j),

B. (adaptation) adapt w_i and its grid neighbors using $w_j(t+1) = w_j(t) + \alpha(t) h_{i,j}(t)(v - w_j(t))$

C. where $\alpha(t)$ is a learning parameter decreasing with time.

These steps are repeated until either a predefined error criterion or a maximum number of iterations is reached. After learning, adapted weight vectors of neural units (the SOM prototypes) produce a Voronoi tessellation of the data space, where each prototype is the geometric center of its Voronoi polyhedron (receptive field) where it is the BMU for the data samples. Thanks to the SOM rigid grid and cooperative adaptation, the SOM produces a topology preserving mapping of the data space onto a (lower-dimensional) fixed grid on the prototype level. Namely, the prototypes neighbors on the grid are ideally neighbors in the data space (their Voronoi polyhedrons share an edge) and vice versa. The SOM learning also provides a faithful representation of the data distribution on the prototype level, which can be controlled by a magnification parameter with slight changes in the learning algorithm.

Topology preserving mapping onto a lower-dimensional grid enables interactive cluster extraction using various informative SOM visualization schemes. Despite the success of the interactive process, practiced knowledge is usually necessary to evaluate visualized SOM information, which in turn makes it difficult for inexperienced users, and time consuming even for the experienced users. This necessitates automated methods for fast and effective SOM segmentation, especially for applications that require processing many large datasets, such as monitoring environmental and agricultural resources, relying on remotely-sensed data acquired on a yearly basis. Automated methods, described in Section "Automated SOM clustering for LPIS assessment", exploit how the SOM prototypes quantize the dataset by determining prototype similarities (such as distances, neighborhood relations, density distribution) with respect to data space. Due to the rare consideration of the SOM grid in automated methods, a neural network paradigm with no rigid grid, neural gas, described in the following section, is also used to obtain prototypes for comparison in terms of clustering accuracies. Even though the neural gas is not a topology-preserving mapping (contrary to the SOM), it is shown to reach relatively small quantization errors.

Results

Neural gas

The neural gas has also a learning algorithm based on finding the BMU unit w_i and adaptation of w_i and its neighbors. Contrary to the SOM which forces a grid layout of the neural units, the neural gas defines the neighbors using distance ranks (ρw_js) of neural units (w_js) to the presented data sample v, which are calculated at each learning step. Noting that $\rho w_i=0$ for the BMU w_i, the neighborhood function $h_\lambda(w_j)$ is constructed by ρw_j and a characteristic decay λ as $h_\lambda(w_j)=\exp(-\rho w_j/\lambda)$

Then adaptation rule for neural gas is:

$w_j(t+1) = w_j(t) + \alpha(t) h_\lambda(w_j)(v - w_j(t))$

with $\alpha(t) \in [0,1]$ decreasing with time t.

Automated SOM clustering for LPIS assessment

Hierarchical agglomerative clustering for SOMs

Due to the fact that hierarchical agglomerative clustering (HAC) can find arbitrary cluster shapes with appropriate criterion for cluster similarity, and can suit high-dimensional data which are often hard to describe with parametric models, it is often preferred for SOM clustering. Each SOM prototype is considered as a singleton cluster and two clusters that are the most similar according to a predefined (dis)similarity criterion are merged iteratively until a predetermined number of clusters is obtained. A common approach is to use a criterion based on (Euclidean) distances between SOM prototypes, such as centroid linkage in and Ward's measure in Since any similarity measure solely based on the distances between SOM prototypes underutilizes available SOM knowledge such as data topology and data distribution, recent studies merges distance and density information.

A recent study proposes CONN linkage, which is average linkage with CONN similarity based on detailed local density distribution, instead of traditional distance based similarity. CONN, originally proposed in for informative SOM visualization, is a symmetric matrix, showing pairwise similarities of the SOM prototypes. Each pairwise similarity, CONN (i, j), is

$CONN(i,j)=|RFij|+|RFji|$

with RF $_{ij}$ is that portion of RF $_i$ (receptive field of w_i) where w_j is the second BMU, and |. | is the cardinality of the set. Therefore, CONN (i, j), not only indicates neighborhood relations of prototypes with respect to the dataset but also indicates how data samples are distributed within their receptive fields with respect to the neighboring prototypes, providing a density information more detailed than on the prototype level. Consequently, CONN linkage is shown to outperform distance-based linkages for several real datasets including a remote sensing image in addition, since CONN does not depend on SOM grid structure, it can be used as a similarity measure for prototypes obtained by any other quantization method (such as neural gas, *k*-means).

Spectral clustering for SOMs

Similarly, to HAC, spectral clustering (SC) can extract arbitrary shapes and can be easily implemented with high accuracies, as supported by empirical studies Contrary to HAC, SC is principally a manifold learning based on Eigen decomposition of a similarity matrix, aiming at changing data representation to easily capture sub manifolds (i.e., clusters). Being associated with relaxed optimization of graph-cut problems, by a graph *Laplacian* matrix, *L*, various methods exist for SC; however no clear advantage exists among them as long as a normalized *L* is considered. Referring to for detailed overview on different methods, we briefly explain the method in utilized for this study.

Let $G = (V\ S)$ be a weighted, undirected graph, nodes (*V*) represent *N* samples (prototypes in this study) W= {*w*1, *w*2, …, *wN*}
to be clustered, and *S*, a $N \times N$similarity matrix, defines edges. A common way to construct edges is to define pairwise similarities based on the (Euclidean) distances,

$s(i,j)=e-||||wi-wj||||2\sigma2$

with a decaying parameter $\sigma$to be determined properly, either by experimentally finding the optimum σ value or by an automated setting of σ (different σ_i for each prototype $w_{i,}$ changing the denominator to 2 $\sigma_i\,\sigma_{j)}$. The latter is done by definingσ_i as the distance to the *k* th nearest neighbor ofw_i, introducing another parameter (*k*) to be set by the user.

Let *D* be the diagonal matrix denoting the degree of *N* nodes where $d_i = \sum_j s\ (i\ j)$. Then the *Laplacian* matrix, *L*, is constructed in various ways depending on the approach for graph-cut optimization. Ng et al. define a normalized Laplacian matrix, L_{norm}, based on *S* and *D*,

$L\text{norm}=D-1/2SD-1/2.$

Then, K clusters are extracted using K eigenvectors associated with the K greatest eigenvalues, by the following algorithm:

Calculate the similarity matrix S, its degree matrix D, and normalized Laplacian, L_{norm}

Find the K eigenvectors $\{e_1, e_2\ldots, e_K\}$ of L_{norm}, associated with the K greatest eigenvalues $\{\lambda_1, \lambda_3\ldots, \lambda_K\}$

Construct the $N \times K$ matrix $E = [e_1 e_2 \ldots e_K]$ and obtain $N \times K$ matrix U by normalizing the rows of E to have unit norm, i.e., $u$ij=$e$ij∑ke2ik√

Cluster the N rows of U with the k-means algorithm into K clusters.

Recently, we utilize this algorithm as an SOM clustering method, using similarity matrices calculated either by σ or local σ_i. This approach often outperforms HAC with the distance-based linkages or with CONN linkage, for synthetic and real datasets. However, a σ or k value (to determine local σ_i), specific to the dataset, is required to be set optimally. Contrary to the distance-based similarity requiring user-set parameters, CONN similarity can be advantageous for SC due to its construction using intrinsic data details without any parameter, its sparse nature by definition, and previous studies showing its outperformance. Therefore, we modify the algorithm above by replacing S with CONN.

Proposed method for the LPIS assessment

The proposed method aims to find the anomalies in the LPIS. Based on the SOM based spectral clustering described in previous section and the current LPIS, the method first finds a land cover mapping (with a predetermined number of clusters) in an unsupervised manner, then constructs an eligibility mask by checking whether clusters are eligible or ineligible according to the current LPIS. The difference between the resulting eligibility mask and the LPIS indicates possible anomalies in the system. A step-by-step explanation of the proposed method for the LPIS assessment is below:

The proposed method is automated, given that N and k are known a priori. Since the SOM is used as an intermediate quantization of the remote sensing images, and k can be determined from the LPIS, setting of N and k is not a limitation for this study.

Study area and images

For automated LPIS assessment with the proposed method, we use study areas in Hungary. According to the rules related to the direct support schemes for farmers under the Common Agricultural Policy (CAP) Hungary applies the Single Area Payment (SAPS) scheme. For SAPS the eligibility criteria are defined in Council Regulation (EC) No. 73/2009 of 19 January 2009, Article 124: the eligible agricultural area under the single area payment scheme shall be part of the total area taken up by arable land, permanent grassland, permanent crops and kitchen gardens. We select three test zones from the northern central part of Hungary (Figure 1).

Zone1 is a transition area between the Hungarian Great Plain and the hilly area of the Northern Hungarian low mountain range, while Zone2 is between the two hills (Mátra and Bükk) of the Northern Hungarian low mountain range. Zone3 covers the geographic area called Cserhát. These zones are selected due to the availability of new airborne very high resolution (VHR) orthophotos with 50 cm ground sampling distance, acquired in 2010 for the same regions. The synergy between the RapidEye data and the new VHR orthophotos makes it possible to compare the clustering results with the VHR orthophotos of the same year. The systematic update of the LPIS using the new VHR orthophotos is carried out by the Hungarian administration parallel to the current project so the results of the “manual” update can also be used to evaluate the results obtained by the proposed method.

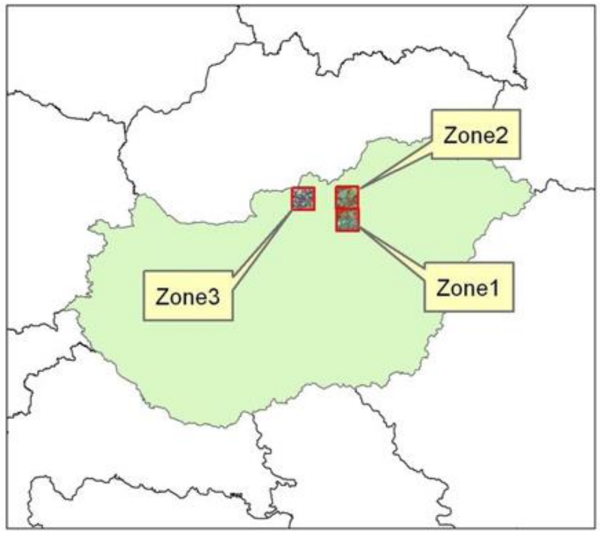

Figure 1. Location of the test zones in Hungary. Each test zone is a 24 *km* × 24 *km* square region. For each zone, a 5-band (blue, green, red, red-edge and near-infrared) 4800×4800pixel Rapid Eye image is used for LPIS assessment with the proposed method.

The first zone, Zone1, is dominantly agricultural (64%eligible), with mostly arable lands but with an intensive presence of vineyards. The zone covers partly two wine-growing regions: Mátraalja and Eger. The north-west corner of the zone partially covers the forests of Mátra Hills. The mid-west part of the zone is dominated by the outcrop lignite mines that are partially recultivated (covered by soils to be able to grow some vegetation). (Figure 2) shows a false color composite of the RapidEye image for this zone acquired on 10 July 2010. Contrary to Zone1, the second zone, Zone2, is dominantly non-agriculture (35%eligible). The zone partially covers Mátra Hills (West), Bükk Hills (East), and Heves-Borsod Hills (North). The agricultural land is represented mainly by pastures and fodder crops with a limited number of arable parcels. A false color composite of the Rapid Eye image for the zone acquired on 10 July 2010 is shown in (Figure 3). The third zone, Zone3, is balanced between agriculture and non-agriculture (45%eligible). The non-agricultural land cover is mainly forest stretching west, south and north-east from the center of the zone. The RapidEye image for the zone was acquired very early in the vegetation season, on 3 April 2010. As the false color composite on (Figure 4) shows, the forests are still leafless. The areas appearing as yellow, orange and light brown are winter crops (winter wheat, rapeseed), pastures and alfalfa. Coniferous woods appearing as dark brown on the false color composite are very distinct on the early spring image. Zone3 was selected to test whether the proposed method can be applied to images acquired very early in the vegetation season.

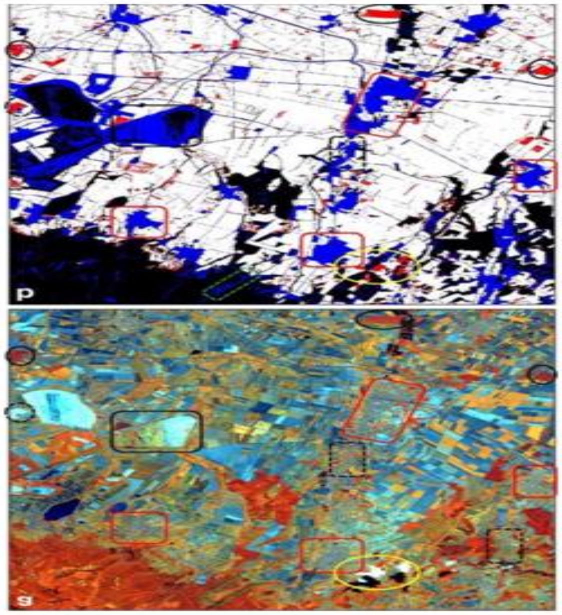

Figure 2. Zone1: (a) False color composite (RGB bands correspond to near-infrared, red-edge, and red bands, respectively), (b) Resulting LPIS mask obtained by spectral clustering with CONN similarity (SC_CONN) and k=30 clusters. White: eligible lands detected as eligible; Blue: ineligible lands detected as eligible; Red: eligible lands detected as ineligible; Black: ineligible lands detected as ineligible. Blue and red indicate possible anomalies in the LPIS according to the automated assessment. The outlined regions are discussed in the text

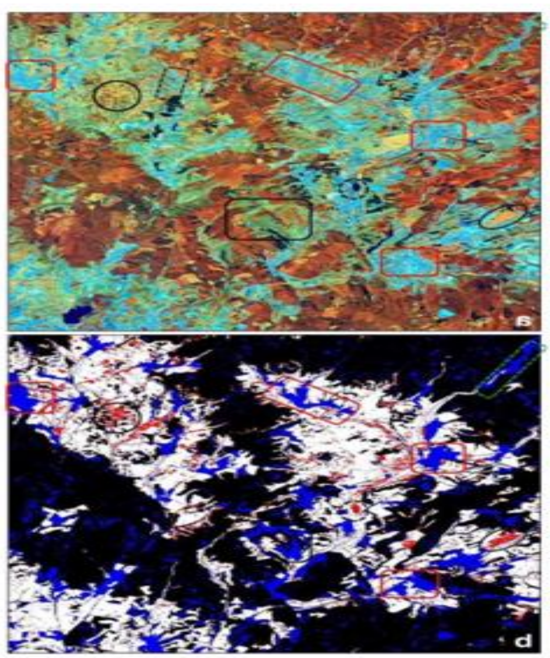

Figure 3. Zone2: (a) False color composite (RGB bands correspond to near-infrared, red-edge, and red bands, respectively), (b) Resulting LPIS mask obtained by SC_CONN and k=30, for LPIS assessment. White indicates eligible lands detected as eligible, blue stands for ineligible lands detected as eligible, red indicates eligible lands detected as ineligible, and black is for ineligible lands detected as ineligible. The outlined regions are discussed in the text.

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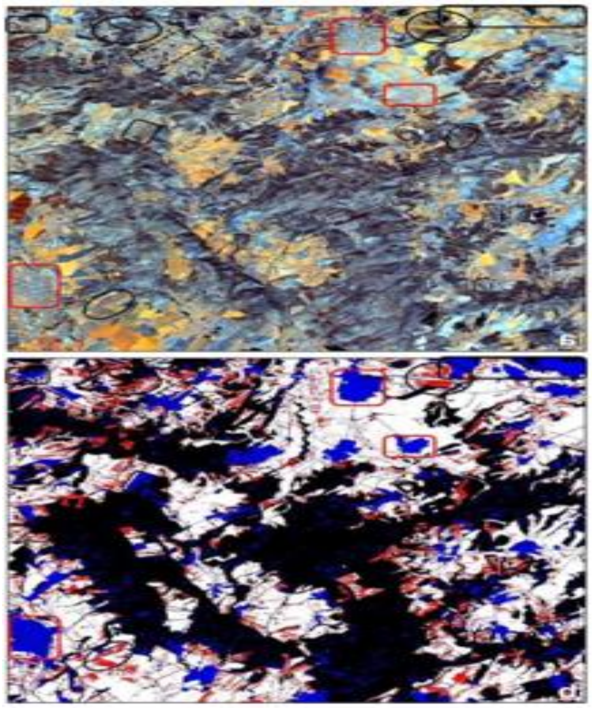

Figure 4. Zone3: (a) False color composite (RGB bands correspond to near-infrared, red-edge, and red bands, respectively). This image is acquired in early spring, before vegetation growth. (b) Resulting LPIS mask. White: eligible lands; blue: ineligible lands detected as eligible; red: eligible lands detected as eligible; black: ineligible lands.

Rapid Eye images are used in this study, based on their successful applications in previous studies: shows that they can help effectively determine land parcels which are in good agricultural condition (GAC) and are potentially applicable for payments in Bulgaria in the frame of the Common Agricultural Policy of the European Union (EU); shows their use in agricultural applications, especially during the controls of agricultural subsidies. In addition, with its background mission, Rapid Eye aims at covering Europe at least once a year cloud free at 5 m resolution during the vegetation season. Thanks to its spectral resolution (including red-edge band) at a spatial resolution of 5 m, and its large area coverage, Rapid Eye can provide a huge opportunity to detect LPIS anomalies at the EU level, if an automated method robust enough to be applicable from the Mediterranean to Northern continental regions of the EU and using images acquired on different dates throughout the vegetation season can be developed.

The agriculture sector consumes 85% of the available freshwater resources across the world. And this percentage is increasing rapidly with the population growth and with the increase in food demand. This leaves us with the need to come up with more efficient technologies in order to ensure proper use of water resources in irrigation. The manual irrigation which was based on soil water measurement was replaced by automatic irrigation scheduling techniques. The plant evapotranspiration which was dependent on various atmospheric parameters such as humidity, the wind speed, solar radiations and even the crop factors such as the stage of growth, plant density, the soil properties, and pest was taken into consideration while implementing autonomous irrigation machines.

Kumar et al., (2019), discusses about the different irrigation methods with the primary motive of developing a system with reduced resource usage and increased efficiency. Devices like fertility meter and PH meter are set up on the field to determine the fertility of the soil by detecting the percentage of the primary ingredients of the soil like potassium, phosphorous, nitrogen. Automatic plant irrigators are planted on the field through wireless technology for drip irrigation. This method ensures the fertility of the soil and ensures the effective use of water resource.

The technology of smart irrigation is developed to increase the production without the involvement of large number of man power by detecting the level of water, temperature of the soil, nutrient content and weather forecasting. The actuation is performed according to the microcontroller by turning ON/OF the irrigator pump. The M2M that is, Machine to Machine technology is been developed to ease the communication and data sharing among each other and to the server or the cloud through the main network between all the nodes of the agricultural field. They developed an automated robotic model for the detection of the moisture content and temperature of the Arduino and Raspberry pi3. The data is sensed at regular intervals and is sent to the microcontroller of Arduino (which has an edge level hardware connected to it), it further converts the input analog to digital. The signal is sent to the Raspberry pi3 (embedded with KNN algorithm) and it sends the signal to Arduino to start the water source for irrigation. The water will be supplied by the resource according to the requirement and it will also update and store the sensor values. (Jha et al., 2019), also developed an automated irrigation system with the technology of Arduino for reducing the man power and time consumption in the process of irrigation.

Suchithra & Pai, (2020), also developed the idea of efficient and automated irrigation system by developing remote sensors using the technology of Arduino which can increase the production up to 40%.

Another system for automated irrigation was given by (Fente & Singh, 2018). In this approach different sensors were built for different purposes like the soil moisture sensor to detect the moisture content in the soil, the temperature sensor to detect the temperature, the pressure regulator sensor to maintain pressure and the molecular sensor for better crop growth. The installation of digital cameras. The output of all these devices is converted to digital signal and it is sent to the multiplexer through wireless network such as Zigbee and hotspot.

The first technique was the subsurface drip irrigation process, which minimized the amount of water loss due to evaporation and runoff as it is directly buried beneath the crop. Later researchers came with different sensors which were used to detect the need of water supply to the fields as soil moisture sensor and rain drop sensor, which were instructed through wireless broadband network and powered by solar panels. The rain drop sensor and soil moisture sensor informs the farmer about the moisture content in the soil through SMS in their cell phone using GSM module. Accordingly, the farmer can give commands using SMS to ON and OFF the water supply. Thus we can consider that this system will detect part or area in the fields which required more water and could hold off the farmer from watering when it's raining.

Soil moisture sensors use one of the several technologies used to measure the soil moisture content. It is buried near the root zones of the crops. The sensors help in accurately determining the moisture level and transmit this reading to the controller for

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irrigation. Soil moisture sensors also help in significantly conserving water. One technique of moisture sensors is the water on demand irrigation in which we set the threshold according to the soil's field capacity and these sensors permits your controller to water only when required. When the scheduled time arrives, the sensor reads the moisture content or level for that particular zone, and watering will be allowed in that zone only if the moisture content is below the threshold. The other was the suspended cycle irrigation which requires irrigation duration unlike the water on demand irrigation. It requires the start time and the duration for each zone.

Dielectric method

The moisture in the soil is calculated by the sensors which basically evaluate the moisture content in the soil based on the dielectric constant (soil mass permittivity) of the soil. The amount of irrigation needed can also be determined on the basis of the dielectric constant.

Suchithra & Pai, (2020), proposes an automated system that uses dielectric soil moisture sensors for real time irrigation control. The measurement method based on the dielectric properties is considered to be the most potential one. gave the information regarding how soil types affect the accuracy to dielectric moisture sensors. The dielectric steady is only the capacity of soil to transfer power or electricity. The soil is comprised of various parts like minerals, air and water, subsequently the estimation of its dielectric consistent is determined by the general commitment of every one of these segments. Since the estimation of the dielectric value of water (Kaw = 81) is a lot bigger than the estimation of this consistent for the other soil parts, the estimated value of permittivity is primarily represented by the nearness of moisture in the soil. One method to calculate the relationship between the dielectric constant (Ka_b) and volumetric soil moisture (VWC) is the equation of Topp et al.:

$$VWC=-5.3\times10-2+2.29\times10-2Kab-5.5\times10-4Kab2+4.3\times10-6Kab3$$

The other method used for determining the dielectric constant is the by the Time Domain Reflectometry (TDR). It is determined on the basis of the time taken by an electromagnetic wave to propagate along a transmission line that is surrounded by the soil. As we probably are aware, the propagation velocity (V) is an element of the dielectric constant (Kab), therefore it is legitimately corresponding to the square of the transmission time (t in a flash) down and back along the transmission line:(2) Kab=c/v2=ct/2L2where c is the speed of electromagnetic waves in a vacuum (3·108 m/s or 186,282 mile/s) and L is the length of the TL in the soil (in m or ft).

Neutron moderation

This is another technique for deciding the moisture content in the soil. In this strategy fast neutrons are launched out from a decomposing radio dynamic source like 241Am/9Be and when these neutrons slam into particles having a similar mass as theirs (protons, H+), they drastically slow down, making a "cloud" of "thermalized" neutrons. As we already know that water is the primary wellspring of hydrogen in soil, the thickness of thermalized neutrons around the test is about corresponding to the division of water present in the soil. The arrangement of the test is as a long and limited chamber, comprising of a source and a finder. The estimations are taken in this test by bringing the test into an entrance tube, which is as of now presented in the soil. One can decide soil amount of moisture in the soil at various profundities by balancing the test in the cylinder at various profundities. The moisture substance is gotten with the assistance of this gadget dependent on a direct alignment between the check pace of thermalized neutrons read from the test, and the soil moisture substance got from adjacent field tests.

The installation of sensors plays an important role in the efficient implementation of irrigation robotics. One can use a single sensor to control the irrigation of multiple zones in the fields. And one can also set multiple sensors to irrigate individual zones. In the first case where one sensor is utilized for irrigating multiple zones, the sensor is places in the zone which is the driest of all or we can say the zone which requires maximum irrigation in order to ensure adequate irrigation in the whole field. The placement of the sensors should be in the root zone of the crops (ensuring that there are no air gaps around the sensor) from where the crops extract water. This will ensure the adequate supply of water to the crops. Later, we need to connect the SMS controller with the sensor. The controller will control the working after the sensor responds. After making this connection the soil water threshold needs to be selected. Then water is applied to the area where the sensor is buried and it is left as it is for a day. The water content now is the threshold for the sensor for scheduled irrigation as described earlier.

After fetching the data through the sensors the microcontrollers come into work. It is the major component of the entire automated irrigation process. The whole circuit is supplied with power up to 5 V with the help of transformer, a bridge rectifier circuit (which is a part of electronic power supplies which rectifies AC input to DC output) and voltage regulator. Then the microcontroller is programmed. The microcontroller receives the signals from the sensors. The OP-AMP acts as an interface between the sensors and the microcontroller for transferring the sensed soil conditions. The irrigator pumps thus operate on the information of the soil properties at run time (Figure 5).

The irrigation process can therefore be automated with the help of moisture sensors and microcontrollers (Table 1).

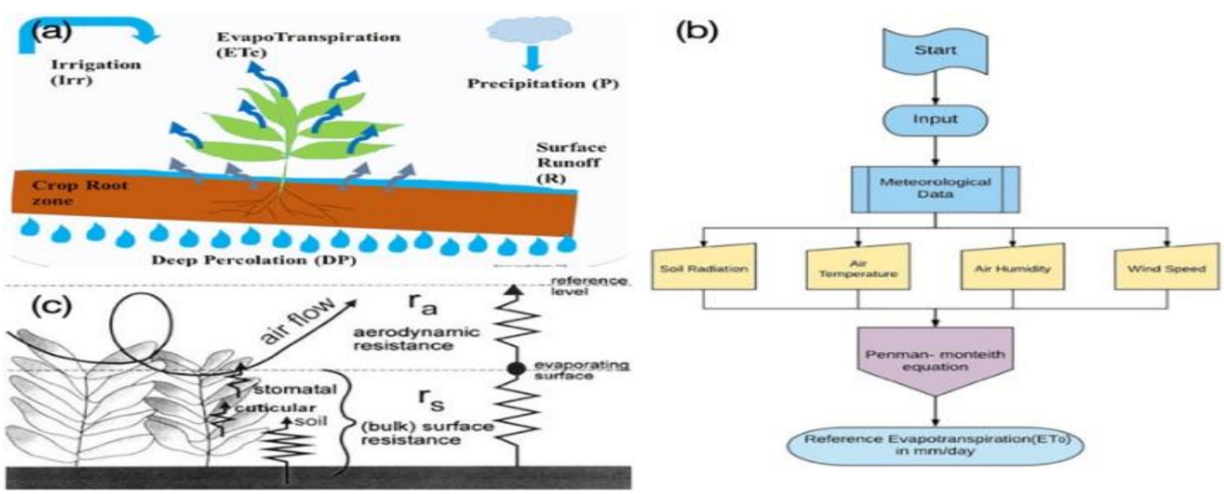

Figure 5. (a) Soil Water Balance Components for Evapotranspiration Model Source: University of Minnesota (b) Flowchart for Evapotranspiration Reference, (c) FAO Penman-Monteith method.

Table 1. Summary of Irrigation Automation Using Various Artificial Intelligence Technologies

No.	Algorithms	Method of evapotranspiration / desired calculation	Other Technologies	Advantages/Results
1.	PLSR and other regression Algorithms	Evapotranspiration model	Sensors for data collection, IOT Hardware Implementation	Increased efficiency and economic feasibility
2.	Artificial Neural Network based control system	Evapotranspiration model	Sensors for measurement of soil,temperature,wind speed, etc.	Automation
3.	Fuzzy Logic	FAO Penman-Monteith method	–	Optimization
4.	ANN (multilayer neural model), Levenberg Marquardt, Backpropagation	Penman–Monteith method	–	Evaporation decreased due to schedule and savings observed in water and electrical energy
5.	Fuzzy Logic	–	WSN, Zigbee	Experimental results verification. Can be applied to home gardens and grass
6.	ANN Feed Forward, Backpropagation	–	–	Optimization of water resources in a smart farm.
7.	Fuzzy Logic Controller	Penman–Monteith method	Wireless sensors	Drip irrigation prevents wastage of water and evaporation
8.	Machine Learning algorithm	–	Sensors, Zigbee, Arduino microcontroller	Prediction and tackles drought situations

Weeding

In his report on “A History of Weed Science in the United States” stated about Thomas K. Pavlychenko, a pioneer weed experimentalist, who did a study on the competition among plants. After his detailed research on the same, he came concluded that the competition among the plants for water begins when their roots in the soil overlap to absorb water and nutrients and weeds were the strongest competitors for water. The water requirement for the aerial parts of the plant is the number of pounds of water used to produce a pound of dry matter. The wild mustard plant (*Brassica kaber* var. *pinnatifida*) requires four times as much water as a well-developed oat plant, and the common ragweed plant (Ambrosia artemisiifolia) requires three times as much water as a corn plant to reach maturity. One can calculate the water requirement per acre is determined by multiplying the production of the plant in pounds of dry matter per acre times the plant's water requirement. Light is also an essential component for the growth of the plants. Weeds which grow tall, generally blocks the way of light to the plants. Sometimes weeds like green foxtail and redroot pigweed are intolerant of shade but may times weeds like field bindweed, common milkweed spotted spuroe, and Arkansas rose are shade tolerant. According to a study by researchers of the Indian Council for Agricultural Research, the country India, loses agricultural produce worth over $11 billion — more than the Centre's budgetary allocation for agriculture for 2017–18 annually due to weeds. So to remove these weeds from the fields is of great importance otherwise it will not only occupy the land space but will also adversely affect the growth of other plants.

brought up a vision based weed detection technology in natural lighting. It was created utilizing hereditary calculation distinguishing a locale in Hue-Saturation-Intensity (HSI) shading space (GAHSI) for open air field weed detecting. It utilizes outrageous conditions like radiant and shady and these lightning conditions were mosaicked to discover the likelihood of utilizing GAHSI to find the locale or zones in the field in shading space when these two boundaries are displayed at the same time. They came about given by the GAHSI gave proof to the presence and severability of such a locale. The GAHSI execution was estimated by contrasting the GAHSI-portioned picture and a comparing hand sectioned reference picture. In this, the GAHSI achieved equivalent performance.

Before developing a weed control automated system, we need to differentiate between the crop seedlings and the weeds. A method was applied for recognition of carrot seedlings from those of ryegrass. implemented this method by the simple morphological characteristic measurement of leaf shape. This method has varying effectiveness mostly between 52 and 75% for discriminating between the plants and weeds, by determining the variation in size of the leaf. Another method for weeding was implemented using digital imaging. This idea involved a self-organizing neural network. But this method did not give appropriate results which were expected for commercial purposes, it was found that a NN based technology already existed which allows one to find the differences between species with an accuracy exceeding 75%.

In the contemporary world many automated systems are developed, but earlier various physical methods were used which relied on the physical interaction with the weeds. proposed that weeding depends on the position and the number of weeds. Classical spring or duck foot tines were used to perform intra row weeding by breaking the soil and the interface of roots by tillage and thus promote the witling of the weeds. But this is not advisable method as tillage can destruct the interface between the crop and the soil. Thus, further no contact methods like the laser treatments and micro spraying, which do not affect the contact between the roots and the soil was developed. explained the method of the use of agricultural robots for the suppression of weeds and developing methods of controlling the postures of robots in case of uneven fields in the rice cultivation. It used the method of Laser Range Fielder (LRF) for suppressing the weeds and controlling robot's posture.

Presented a robotic weed control system. The robot was embedded with different vision systems. One was the gray- level vision which was used in developing a row structure in order to guide the robot along the rows and the other vision was color-based which was most important and used to differentiate a single among the weeds. The row recognition system was developed with a novel algorithm with an accuracy of ±2 cm. The first trial of this system was implemented in a greenhouse for weed control within a row of crops. The same technology was mentioned in the research done by (Zhang, 2018).

example, showing in-field fluctuation, and the soil moisture content of the yield giving a

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benchmarking apparatus, when the yield is being harvested. In combination with soil examining data, yield maps empowers the arrangement of variable compost maps which considers soil supplement levels just as the supplement which was expelled in the collected harvest. Last result of yield mapping is typically a tonal or shaded guide showing scopes of yield inside a field. Fundamental segments of grain yield mapping framework incorporate grain fow sensor (determines grain volume gathered), grain moisture content sensor (remunerates for grain moisture variability), GPS antenna (receives satellite sign), Yield screen show with a GPS receiver (geo-reference and records information), header position sensor(distinguishes estimations logged during turns), travel speed sensor (determines the separation the join goes during a specific logging interim) (Figure 6).

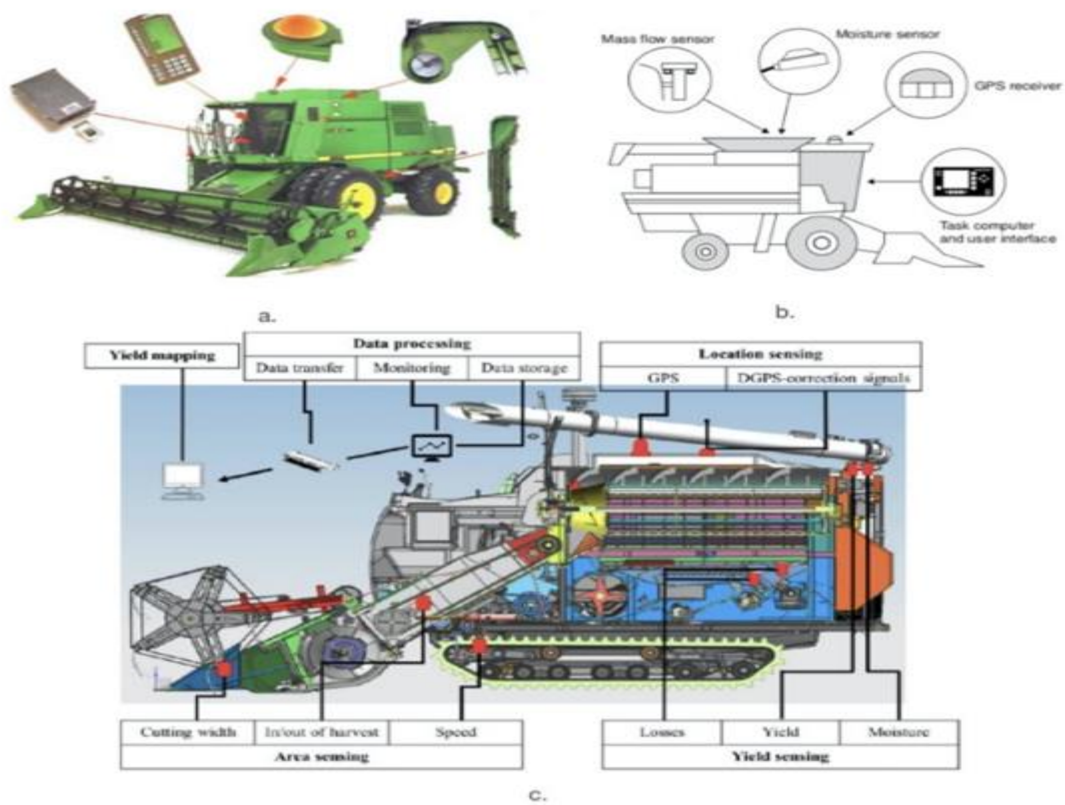

Figure 6. (a)Yield mapping, (b)devices - diagram, (c)yield mapping harvester equipped to do both tasks

Programming of the software

For yield mapping, there are basically 5 errands which are to be managed; information procurement, information preparing, LCD displaying < contact screen info and information sparing. The details of each one of them can be alluded from the (Figure 7).

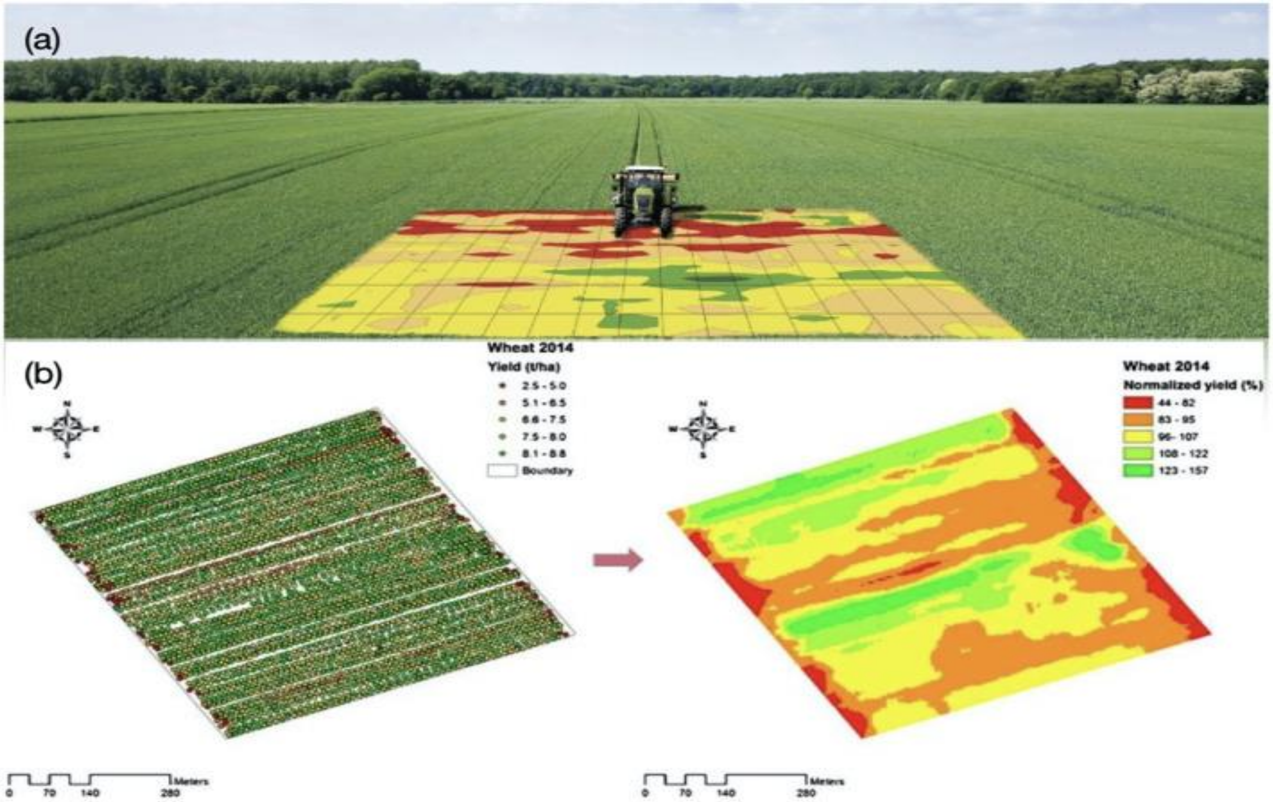

Figure 7. Yield Mapping (a) Sensing for yield (Source: Utah State University) and (b) example of raw yield map versus interpolated yield map using GIS

These 5 undertakings inside and out, structures in performing various tasks sometimes bring about clashes. Predominantly these contentions are identified with the time arrangement. To conquer these contentions and to mull over every one of the undertakings we utilize four interfere with wellsprings of P80C592 in the framework, which are the clock intrude on source, the outer intrude on source, the ADC end-of-transformation intrude on source and the UART sequential I/O port intrude on source.

Yield calculation and calibration

Yield is characterized as harvest weight (lbs for cotton) or volume (bu for grains) reaped per unit region, which is in a roundabout way estimated by the yield sensor stream rate/(speed x swath width). Yield stream rate is commonly determined each 1–2 s during collecting. The begin and end times for each line pass are balanced relying upon the measure of time the harvest takes to travel through sifting, isolating, and cleaning to the area of the yield sensor. The deferrals for beginning of-pass and end-of-pass will rely upon the yield and speed of the consolidate. Scientific interjection systems have been utilized to expel commotion because of blunders and regular spikes in the crude sensor and area information.

Yield is by implication estimated as a mass power or volume estimation by the yield sensors. Presently the yield count needs to join an adjustment factor because of the way that the yield figuring that changes over to weight relies upon the harvest. To acquire an exact yield information a legitimate sensor alignment is imperative. Contrasting the scale loads of four with five burdens with the determined yield decides an alignment bend. Yield sensors ought to be recalibrated as factors change, for example, dampness substance or half breed. However, utilizing the Yield Sense screen evacuates the requirement for recalibration after the underlying alignment toward the start of the period (Precision Planting).

Processing yield maps

With the utilization of a Geographic Information System (GIS) programming, the yield determined at each field area can be shown. The raw log document, contains focuses which are recorded during turns and as the grain move through a consolidate is a deferred process (unless ongoing amendment is connected), the sensor estimations neglect to compare to the careful gather areas. To dispense with these conspicuous mistakes, the crude information is moved to make up for the joining delay. Increasingly finished, the focuses which compare to the header up position are evacuated. Settings for grain stream postponement are join and some of the time even harvest explicit, yet run of the mill esteems for grain yields extend from around 10 to 12 s.

Typically a couple of focuses toward the start and toward the finish of a pass ought to be expelled too. These focuses are alluded to as begin and end-pass delays. Begin pass postponements happen when the grain stream has not balanced out in light of the fact that the lift is bit by bit topping off yet the consolidate begins gathering the yield. Thus, end-pass deferrals happen when the join moves out of the yield and grain stream progressively decreases to zero when the lift is totally exhausted. Moving of raw information to address for grain stream postponement and exclusion of focuses that speak to header status up and begin and end-pass deferrals is the essential information separating method incorporated with programming provided with yield mapping frameworks.

Discussion

The agriculture and food industries are one of the most vital fields for humanity. The first products of agriculture are used as inputs in several multifactor distributed supply chains, including four clusters or stages of the agriculture supply chain (preproduction, production, processing, and distribution) in order to reach the end user or consumer. Due to several challenges in the future for the agriculture and food sector and various factors such as climate change, population growth, technological progress, and the

Agriculture has been tackling significant difficulties like absence of irrigation system, change in temperature, density of groundwater, food scarcity and wastage and substantially more. The fate of cultivating depends to a great extent on reception of various cognitive solutions. While large scale research is still in progress and some applications are already available in the market, the industry is still highly underserved. When it comes to handling realistic challenges faced by farmers and using autonomous decision making and predictive solutions to solve them, farming is still at a nascent stage. In order to explore the enormous scope of AI in agriculture, applications need to be more robust. Only then will it be able to handle frequent changes in external conditions, facilitate real-time decision making and make use of appropriate framework/platform for collecting contextual data in an efficient manner. Another important aspect is the exorbitant cost of different cognitive solutions available in the market for farming. The solutions need to become more affordable to ensure that the technology reaches the masses. An open source platform would make the solutions more affordable, resulting in rapid adoption and higher penetration among the farmers. The technology will be useful in helping farmers in high yielding and having a better seasonal crop at regular interval. Many countries, including India, the farmers are dependent on monsoon for their cultivation. They mainly depend on the predictions from various departments over the weather conditions, especially for rain-fed cultivation. The AI technology will be useful to predict the weather and other conditions related to agriculture like land quality, groundwater, crop cycle, and pest attack, etc. The accurate projection or prediction with the help of the AI technology will reduce most of the concerns of the farmers. AI-driven sensors are very useful to extract important data related to agriculture. The data will be useful in enhancing production. In agriculture, there is a huge scope for these sensors. Agriculture scientist can derive data like quality of the soil, weather and groundwater level, etc.; these will be useful to improve the cultivation process. AI empowered sensors can also be installed in the robotic harvesting equipment in order to get the data. It is speculated that AI-based advisories would be useful to increase production by 30%. The biggest challenge to farming is the crop damage due to any kind of disasters including the pest attack. Most of the time due to lack of the proper information farmers lose their crops. In this cyber age, the technology would be useful for the farmers to protect their cultivation from any kind of attacks. AI-enabled image recognition will be useful in this direction. Many companies have implemented drones to monitor the production and to identify any kind of pest attacks. Such activities have been successful many times, which gives the inspiration to have a system to monitor and protect crops. A robotic lens zooms in on the yellow flower of a tomato seedling. Images of the plant flow into an artificial intelligence algorithm that predicts precisely how long it will take for the blossom to become a ripe tomato ready for picking, packing, and the produce section of a grocery store. The technology is being developed and researched at Nature Fresh Farms, a 20-year-old company growing vegetables on 185 acres between Ontario and Ohio. Knowing exactly how many tomatoes will be available to sell in the future makes the job of the sales team easier and directly benefits the bottom line, said Keith Bradley, IT Manager for Nature Fresh Farms. It's only one example of AI transforming agriculture, an emerging trend that will help spur an agricultural revolution. From detecting pests to predicting what crops will deliver the best returns, artificial intelligence can help humanity confront one of its biggest challenges: feeding an additional 2 billion people by 2050, even as climate change disrupts growing seasons, turns arable land into deserts, and floods once-fertile deltas with seawater. The United Nations estimates we will need to increase food production 50% by the middle of the century. Agricultural production tripled between 1960 and 2015 as the world's population grew from 3 billion people to 7 billion. While technology played a role in the form of pesticides, fertilizers, and machines, much of the gains can be attributed to simply plowing more land—cutting forests and diverting fresh water to fields, orchards, and rice paddies. We will have to be more resourceful this time around. AI is likely to transform agriculture and the market in the next few years. The technology has been useful for the farmers to understand various types of hybrid cultivations which would yield them more income within the limited time frame. The proper implementation of AI in agriculture will help the cultivation process and to create an ambiance for the market. As per the data with leading institutions, there is a huge wastage of the food across the world and using the right algorithms, this problem can also be addressed which will not only save the time and money but it will lead to sustainable development. There are better prospects for digital transformation in agriculture backed by leveraging technologies like AI. But, it all depends on the huge data which is quite difficult to gather because of the production process which happens once or twice in a year. However, the farmers cope up with changing scenario to bring digital transformation in the agriculture by implementing AI. It's only one example of AI transforming agriculture, an emerging trend that will help spur an agricultural revolution. We will have to be more resourceful this time around.

Conclusion

The agricultural industry faces various challenges such as lack of effective irrigation systems, weeds, issues with plant monitoring due to crop height and extreme weather conditions. But the performance can be increased with the aid of technology and thus these problems can be solved. It can be improved with different AI driven techniques like remote sensors for soil moisture content detection and automated irrigation with the help of GPS. The problem faced by farmers was that precision weeding techniques overcome the large amount of crops being lost during the weeding process. Not only do these autonomous robots improve efficiency, they also reduce the need for unnecessary pesticides and herbicides. Besides this, farmers can spray pesticides and herbicides effectively in their farms with the aid of drones, and plant monitoring is also no longer a burden. For starters, shortages of resources and jobs can be understood with the aid of man-made brain power in agribusiness issues. In conventional strategies huge amount of labor was required for getting crop characteristics like plant height, soil texture and content, in this manner manual testing occurred which was tedious. With the assistance of various systems examined, quick and non-damaging high throughput phenotyping would occur with the upside of adaptable and advantageous activity, on-request access to information and spatial goals.

For the LPIS assessment with the SOM based clustering, first we obtain the SOM prototypes by Matlab SOM toolbox (developed by Helsinki University of Technology) using a 50×50rectangular lattice with sequential learning and Gaussian neighborhood. We also train a neural gas with 2500 prototypes using default learning parameters in the SOM toolbox. We select the number of prototypes (2500) to be of O(n−−√) where n is the number of data samples (pixels in the 4800×4800 image of each zone, covering an area of 24km×24km). Then we cluster these prototypes by spectral clustering with CONN similarity (SC_CONN). For comparison, we also use spectral clustering with distance-based similarity (SC) and hierarchical agglomerative clustering (HAC) with average and CONN linkages. We set the maximum number of clusters, k = 30, according to the different land use and vegetation types declared in the zones, whereas we also choose two smaller values (k = 10 and k = 20). Based on our experiments, we also experience that using a k value greater than the number of existing natural clusters in the zone (number of declared vegetation types in the LPIS) would not help achieve higher accuracies. Since the expected number of clusters (k) is determined from the LPIS information a priori, setting k in advance does not represent a limitation here. Then we assign the clusters as eligible/ineligible using LPIS, based on the assumption that LPIS has to be (mostly) correct even though it may have anomalies due to changes in land cover or land use.

state of natural resources (water, etc.), it is urgent to use the digital technologies at different stages of agriculture supply chain such as automation of farm machinery, use of sensors and remote satellite data, artificial intelligence, machine learning for improved monitoring of crops, and water, for agriculture food product traceability. In the present study, we demonstrate the main applications of the AI and ML algorithms in different clusters of the agriculture supply chain and the unquestionable growing tendency in the adoption of these algorithms to improve food industries.

For agriculture management (at large cartographic scale) by mono-temporal multi-spectral remote sensing images, we develop a method using self-organizing maps (SOM) based spectral clustering (SC). By providing two consecutive mapping (SOM: a topology-preserving mapping together with an adaptive vector quantization; SC: a manifold learning based on eigendecomposition) and local density-based similarity, the proposed method outperforms both other SOM based and neural gas based clustering methods, for three test zones in this study. It can be an effective tool to reduce the extensive time required for interactive computer-aided photointerpretation for precise delineation of eligible/ineligible agricultural regions. However, in addition to mono-temporal multi-spectral image, other ancillary data—which can be exploited by decision rules—may be necessary for fine tuning of the resulting eligibility mask

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

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