Advances in Modern Agriculture (2023) Volume 4 Issue 2
doi: 10.54517/ama.v4i2.2374

Original Research Article

Applications of artificial intelligence in precision agriculture to ameliorate production and distribution

Garimella Bhaskar Narasimha Rao

Deputy General Manager, IDBI Bank Ltd, IDBI Training College, Gachibowli 500032, India; bhaskargnr@yahoo.com

ABSTRACT

Automated intelligence platforms, i.e., machine learning, big data, and Internet of Things (IoT), provide new deployment opportunities within the agricultural marketing paradigm. This study attempts to derive a framework of predictive models to ameliorate crop yield and assists in understanding various features that affect crop yield. On the one hand, it investigates the impact of allied technologies, including networks with memory and generative models, and on the other, it quantitatively analyzes different agri-factors, including the management of plant growth, its quality, crop disease, inorganic fertilizer and pesticide deployment, weed management, irrigation, and field-level phenotyping. Further, the study analyzes the utilization of smart farming and the monitoring of highly dependent variables across the spectrum of precision agriculture. The conclusion is to manifest the importance of networks with memory and generative models and emphasize the vital role of artificial intelligence in transforming farm methods into a novel methodology of smart information communication technology (ICT) in fidelity agriculture. Apart from increased productivity, this study seeks to contribute to the ongoing efforts to reduce the incidence of malnutrition associated with limited access and lower production of food grains.

Keywords: artificial intelligence; machine learning; networks with memory; generative models; smart farming; agri marketing

1. Introduction

Production and consumption of food play a prominent role in leading human life. Agriculture has been around for more than 12,000 years, and it's a reality today that, with the world population projected to touch 8.37 billion by 2025 and surpass 9.61 billion by 2050, the need to improve farming methodology and ameliorate agricultural production is pivotal. It makes an important case to explore portable technologies to make farming more efficient and improve sustainability.

With the invention of chip-based drip irrigation, this research, on the one hand, believes that AI-powered machinery can harness the human workforce in more productive functions, ameliorate crop quality, and enable hope for the economic sustainability of smaller farming operations, atypical of India, where 87.23% of land is owned in fragments of less than 1.02 hectares per piece and where 57.64% of the population are into farming for a livelihood and contribute to 14.27% of the gross domestic product (GDP). Using AI, if this data is put up in the cloud and interlinked with big data, the output can serve the farming community on a wider scale[1]. It is a technological milestone that Israel, as a nation, recycles over 85.59% of its waste water, the highest by far

ARTICLE INFO
Received: 1 November 2023 | Accepted: 6 December 2023 | Available online: 15 December 2023

CITATION
Rao GBN. Applications of artificial intelligence in precision agriculture to ameliorate production and distribution. *Advances in Modern Agriculture* 2023; 4(2): 2374. doi: 10.54517/ama.v4i2.2374

across the globe. Nicknamed "shotgun", it absorbs raw sewage through AI-enabled filters, employs microorganisms for cleaning, and repeats the process[2]. This enhances the purity of the liquid to attain stringent parameters for drinking water.

This study explores the establishment of an inter-dependent network of remote sensing, data analysis, image rendering, and predictive analytics to perform regular farm activities by being able to identify pests and insects down to a dimension of 0.1 mm per pixel on a leaf, and then the platform can train a computer to analyze and identify these insects of disease or weeds and give a farmer a report with advice on the recommended spraying pattern in the field with accuracy in place of spraying the insecticide all over the field.

The platform can also monitor and deploy bio-pesticides, viz., predatory wasps, to rationalize the employment of chemical pesticides. Intelligent farm mechanics deploy big data, and receptors advise the farmer on the quantity of nutrients and water as and when required[3,4]. This is the next agriculture revolution, and this study is one of the first to try and understand the process of AI deployment in an analytical manner. The process of food production includes regular cycles of agriculture, proper management of food production, and adding technology to the function of cultivation to give efficient and precise outputs. An important factor in agriculture is crop management and productivity. Integration of information and technologies can help in good resource management in the field of agronomics. Agriculture operations and management need to be done in a more efficient, safer, profitable, and environmentally friendly manner. Smart agriculture with technology support can make farming more reliable and logical. This helps in monitoring agricultural practices to improve crop yield with fewer costs and optimize inputs like decreased use of water, organic fertilizers, less usage of pesticides, weed management, and environmental conditions.

Implementation of predictive analysis with generative models and networks with memory plays a prominent role in the field of agriculture management. These models[5,6] are used to enhance the capacity coverage and energy efficiency of networks as a means of improving crop scouting, analyzing data, and detecting problems at a rapid pace to help solve and promote crop health. For example, monitoring crop health issues such as infections, deficiency in growth, and loss of nutrients can improve productivity and avoid low crop yields.

2. Data description

The research need is to manifest data collected for the period of 10 years (from 2010 to 2020) about the yield of major field crops in the agri-intensive state of Andhra Pradesh, India (maize, cotton, paddy, soyabean, sweet beet, cereals) from the university database (2010–2019) and collect primary data for 2019–2020[7]. **Table 1** specifies the data sets with variability in attributes as observed on three primary types of crop yield that help in the implementation of predictive models to retrieve possible benefits. The study mainly focuses on the evaluation of attributes that are minimal (V_{min}), maximal (V_{max}), and average (V_{avg}) of features: (a) monthly perception of weather data; (b) air temperatures; (c) water cycle; (d) soil moisture; (e) water evaporation from the plants; (f) chemical applications; (g) spraying decisions; and (h) irrigation scheduling[8].

Table 1. Analysis of data sets with attributes variability—implementation of predictive models for possible benefits.

Data sets	**Attributes – Yield [kg/ha]**			
	Min	**Mean**	**Max**	**Std.**
Cotton	2543	5049	6969	1241.72
Paddy	1003	2153	3040	591.46
Cereals	16,172	38,571	52,023	9244.51

Source: Author compiled.

2.1. Networks with memory

Memory networks (MN) provide the inference capability of neural networks, apart from the inclusion of components into a cycle of AI. This method overcomes the limitations of a multitude of machine learning algorithms that have limited memory for handling low-level tasks like object recognition. Networks with memory are capable of multi-tasking, i.e., recall and inform; viz., memory networks comprise of two parameters that are strongly supervised.

MN exhibited robust performance and indicated the selection of this model[9]. Derived an amended structure of the MN proposed by Yu et al.[10]. Layered MN (single and triple 3-hops) is depicted in **Figure 1**.

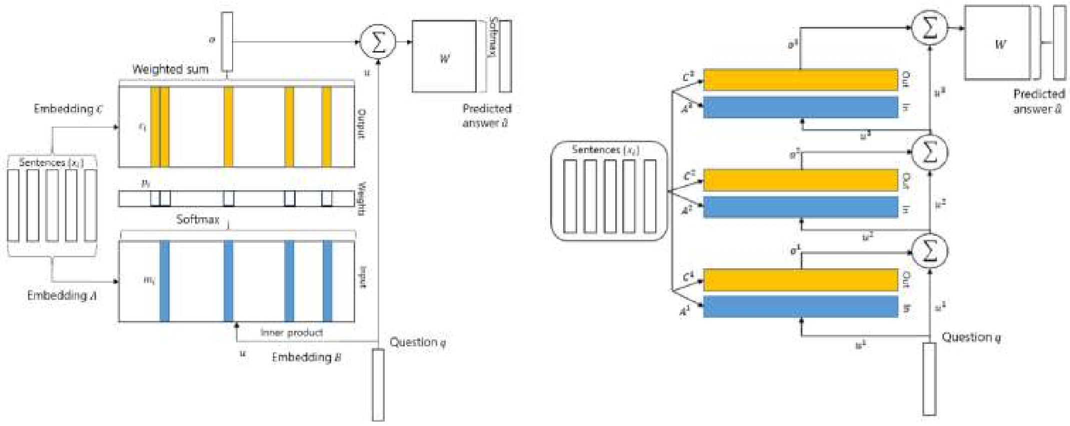


Figure 1. MN models, depicted as from (Source: Sukhbaatar et al.[11]), **(a)** single layer memory model; **(b)** triple-layer memory network model.

Here, x_i represents a string of words (clause) in a dialogue. Here, question q would be the last sentence of the entire conversation. Symmetrically, the answer would be the answer word, and a sentence is the summation of a vector of words. The embedment of words is a representational vector. Referring to the triple-layer network, duly weighted and embedded word(s) matrices B^1, B^2, and B^3 are networked. Along the same lines, embedded word matrices A^1, A^2, A^3 are also networked. This MN renders the desired output for most QA problems[12] apart from functioning as a complete language model.

In agricultural applications, a primary difference between MN and supervised memory networks (SMN) is that strongly supervised networks have embedded labels, and when programmers train the model, the output can signify and derive the expected response stimuli along categorized lines. Whereas, in the case of an MN model, programmers iterate, and the expected outcome is not trained[13]. With regard to the robustness of MN and SMN, the response lies in the designated plane rather than the model having to figure out the required output. The architecture of MN has four components. Input "x", which transforms the arrived data-like sentences to the inner feature map like raw text or word embedding's; Generalization is responsible for the maintenance of memory updates, i.e., storing the obtained function (I(x); converted text) into a memory slot of the newly arrived inputs; Output (I(x), m) generates a new output that has a scoring function that takes the question, matches it with each of the memory components, and tabulates a score.

The higher the score, the better the match is. "Hops" is an extension of RNNsearch with multiple computation steps. (Once a sentence or a memory score is achieved, the same is taken again to obtain a memory sentence and another score.) "Hops" are also used when two supporting facts based on labels are analyzed based on the given memories; responses transform new outputs into an appropriate sequence that can take the form of "one word" or a "complete sentence" or it can be "action" which can be decoded by the end users.

2.2. Predictive modeling by expert learning machine

Predictive analytics fits into the spectrum of analytics, which cleans, summarizes, and visualizes collected data and performs diagnostics to determine why desired or undesirable output is emanating, what's leading the increase or decrease, and how variables or features are related. Predictive analytics can derive robust methods to assist decision-making in real time, apart from indicating future trends in chosen variables. One chosen employment method of predictive analytics is by regression methods. Expert learning machine (ELM) algorithms, which are superior to support vector machines (SVM), are categorically administered for regression problems. It can perform predictive analytics across multiple domains of medicine, pharmacy, mechatronics, aviation, marketing, and tech deployment in agriculture.

Regression algorithms aim to identify a quantifiable association between input and prediction variables as a linear function, as shown below in Equations (1) and (2):

$$f(x) = (v, b) + r \tag{1}$$

where v, $b \in D^n$, linear regression as a methodology is employed in lieu of its simplicity[8]. Non-linear deployments are spearheaded by ELM and comprise their functionality to initially classify and subsequently apply to prediction and regression problems. Regression can be associated with ELM using kernel functions. This study deploys linear regression and is tabulated as a feature engineering variable from "R-Package". Along with a Gaussian radial basis equation, ELM can yield plausible results[14].

$$L(a, b) = exp\left(\frac{\|a - b^2\|}{2\Omega^2}\right) \tag{2}$$

Finally, regression function can be expressed as in Equation (3):

$$f(a) = \sum_{i=1}^{l} (\beta_i - \beta_i^*) L(a, a_i) + x \tag{3}$$

where β_i, β^*_i are Lagrange multipliers and i and * are support vectors. The study employs a predictive model and parameter selection procedure by way of Equation (4):

$$\Omega \; and \; \lambda = \frac{1_r}{2\Omega^2} \tag{4}$$

The final model is built and evaluated using two methods of error measurement: root mean square error (RMSE) and mean absolute error (MAE). The resulting predictive model reflects non-variable sets among input and output variables. This acts as an impediment for ELM deployment or any other predictive model, including black boxes. Hence, feature contribution plays a major role[6].

2.3. Instance explanation

To explore the prediction of crop yield obtained from one input vector and the value predicted, this method asserts an improved contribution from the complex structure of interactions. Hence, an approximation is adopted. A pre-identified feature vector output regression method with K as the desired output and N as the resultant feature subset vector of population M functions "a" is the dependent relationship. This can be derived as a function in Equations (5)–(8):

$$K \; \varepsilon \; K_1 \times K_2 \times K_3 \times \ldots \ldots K_n \tag{5}$$

$$M = \{k_1 \ldots\ldots k_n\} \; with \; subset \; of \; N \subseteq M \tag{6}$$

Predicted regression model can yield feature values by

$$\triangle N(a) = E[f) and\ N\ for\ all\ E[(f) \tag{7}$$

Prediction result for i[th] feature the study tabulates $\triangle N(a)$ for every $N \subseteq M$ and for correlated analysis, Game Theory provides

$$\gamma(a) = \sum\nolimits_{N \subseteq M \setminus \{i\}} \frac{|N|!\,(|M| - |N| - 1)!}{|M|!} \big(\triangle (N \cup \{i\})\big)(a) - \triangle (N)(a) \tag{8}$$

To address extrapolated time complexity, the study deploys a two-process randomization method. For "a", can include the i[th] feature with 'b' for inputs by way of a regression method. The contribution for the i[th] feature can be tabulated as a scalable model of regression analysis.

The derived model at Equation (8) can estimate the analysis of features selected and predicted values. Regression models yield more robust results against parametric variables[15].

2.4. Model explanation and results

Table 2 presents the results obtained on the cotton, paddy, and cereal data sets. The study reports on the results obtained from training and testing. The model explanation results are presented in **Table 2** for cotton, paddy, and cereal yields, respectively.

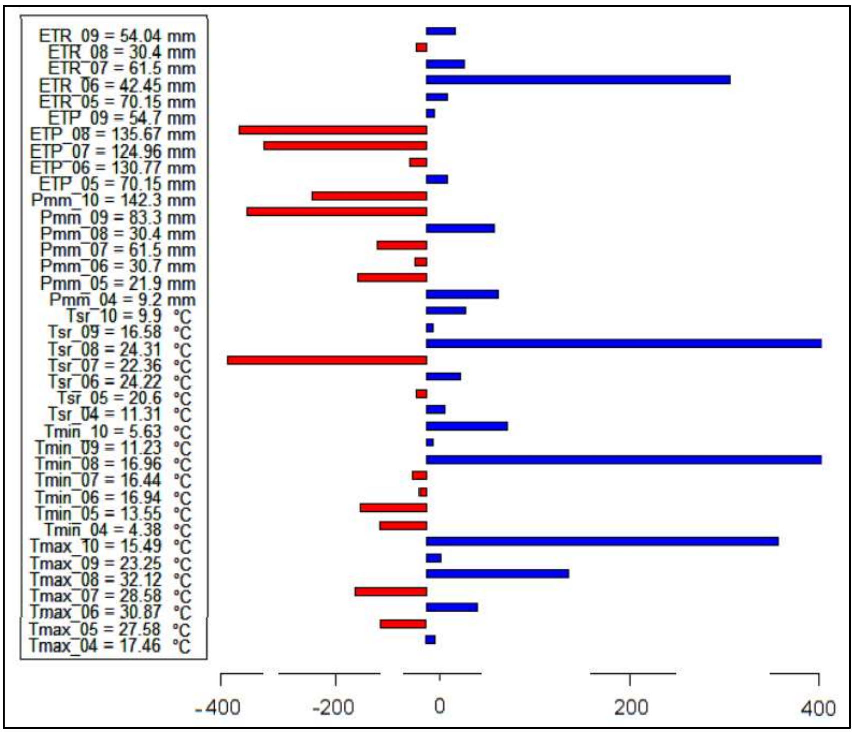
Table 2. Cotton, paddy and cereals analysis metrics.

Cotton	Performance		
	Correlation co-efficient	**MAE**	**RMSE**
SVM (Training Set)	0.9418	203.07	312.04
SVM (Test Set)	0.9327	412.92	507.29
Mt (Cross Validation)	0.8617	431.11	510.29
Paddy	**Performance**		
	Correlation co-efficient	**MAE**	**RMSE**
SVM (Training Set)	0.9431	211.34	320.31
SVM (Test Set)	0.9115	421.19	515.56
Mt (Cross Validation)	0.8782	439.38	518.56
Cereals	**Performance**		
	Correlation co-efficient	**MAE**	**RMSE**
SVM (Training Set)	0.856	205.9	316.86
SVM (Test Set)	0.8244	415.75	512.11
Mt (Cross Validation)	0.7911	433.94	515.11

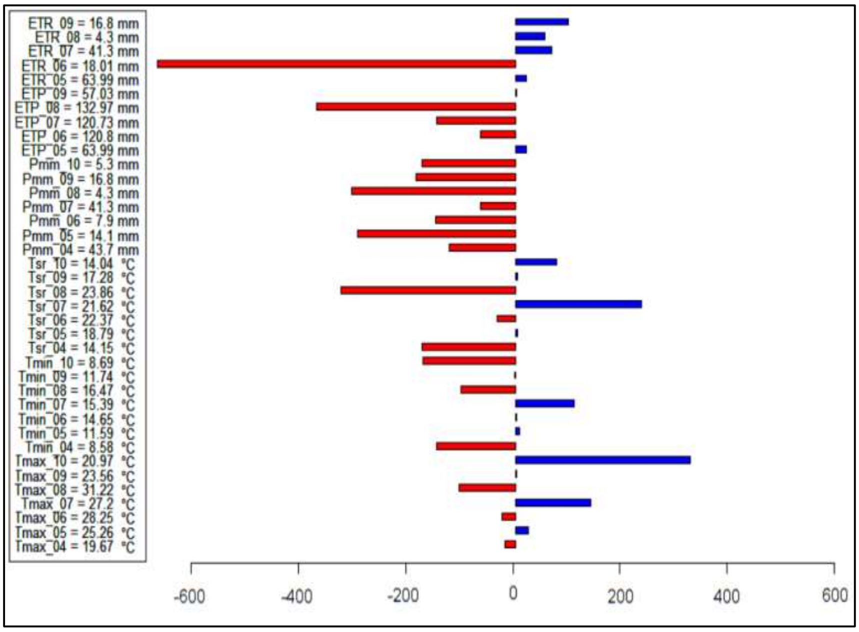
Source: Author compiled.

For all the data sets about 2/3rd of the data is deployed for training and the remainder is allocated for testing activity and displayed as a grid. Estimation of the error is set and deployed for algorithm comparison with different parameters C and γ_a.

The best parameters were C = 50 and = 0.001. Additionally, results from the study with model tree analysis, as presented in the instance explanation, are shown in **Figure 2** below.



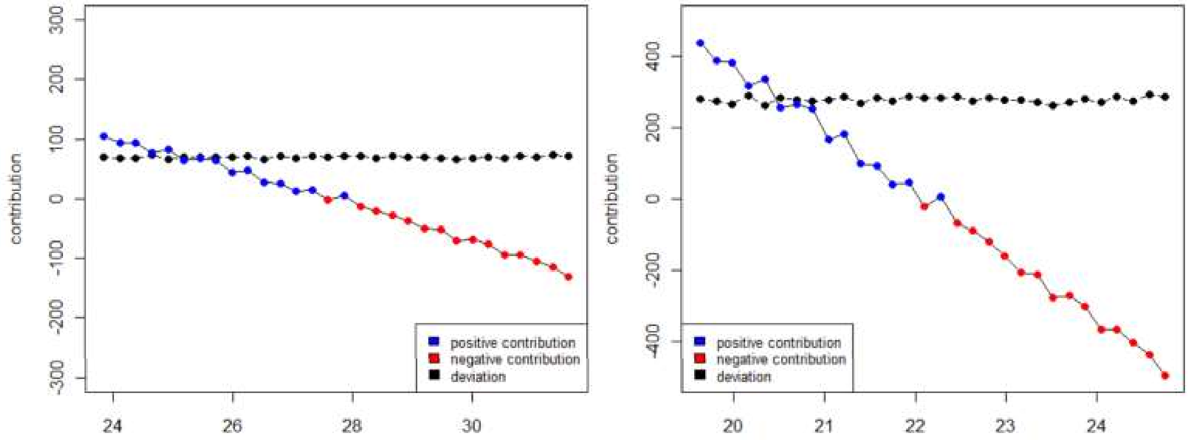
(a)



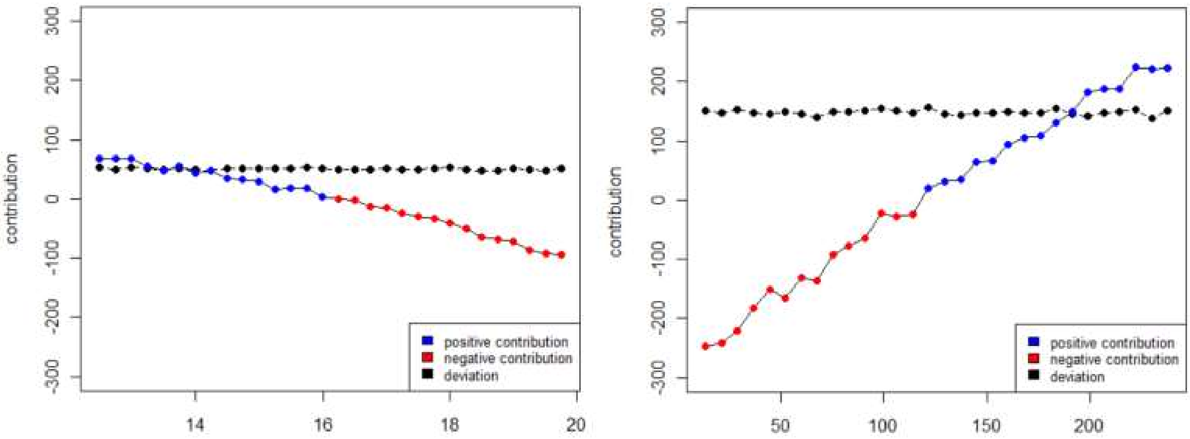
(b)

Figure 2. Model tree analysis and explanations, **(a)** Cotton yield—instance explanation results; **(b)** Paddy yield—instance explanation results.
Source: (a) Lab Exp - Matlab 9.5 Screen Capture; (b) Lab Exp - Matlab 9.5 Screen Capture; (Actual Value – 2743.7 Qu/Ha, Predicted Value – 2731.09); (Actual Value – 5247.6 Qu/Ha, Predicted Value – 5207.41).

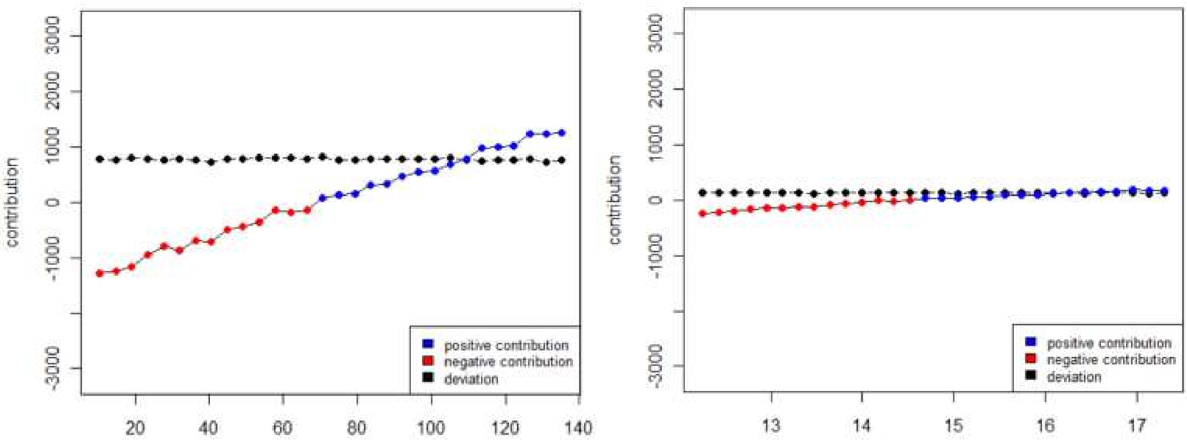
Figure 3 depicts six explanation graphs, i.e., two for each sampled crop. These graphs may technically be generated for all the identified features. Given the wide spectrum of chosen features, only these six are represented.



(a)



(b)



(c)

Figure 3. (a) Comparative Analysis Cotton Yield, Attribute Vmax_04n Attribute Cw_5br, Contribution to Cotton yield; **(b)** Comparative Paddy Beet, Attribute Vmin_1Fr Attribute Cw_7d Contribution to Paddy yield; **(c)** Comparative Cereal yield, Attribute Vavg_7tr Attribute Cw_04n Contribution to Cereal yield.

Figure 3(a) depicts the impact of high temperatures on cotton crops across the coastal Andhra Region in April–May. **Figure 3(b)** details how paddy crop yield is impacted by coastal evapotranspiration in May, with attribute Cw_7d inclusive of the monsoon onset month of June. **Figure 3(c)** reflects real-time evapotranspiration in July and minimal temperature in August. The color code is Blue dots indicate "+ve" and red dots indicate “-ve” association of corresponding feature on yield of the chosen crop. Black dots are indicative of the standard deviation of the tabulated Σ contribution.

On one hand, values in the upper circuit denote that the chosen feature is dependent on other corresponding feature variables; on the other hand, low-circuit values denote improved independence.

3. Discussion: Generative models

As enterprises shift to AI-first, the study’s approach is not to replace human intelligence with AI but to augment capability and intelligence more than artificial intelligence itself. The idea is to determine a probability density model of data analysis from which a researcher can draw new samples for a given data density or training dataset. Given data X with N data points (I = 1 to N) where X_i are given, this could be an approximation to get an empirical density, i.e., P_{data} (x)[16]. With the available data, a program can be written given the empirical density estimates of the said data and derive a model that can determine and sample data points. “Word"-generated models and new samples can be drawn, which are similar to the training data.

Training data is representative of the problem that the study attempts to solve. The need for generative models is to generate new images or relevant outlines that can be used for image translation[17]. Giving labels or outlines to generate new data, for instance, transforms black and white to color and can yield the virtual aerial map of an entire city; it can differentiate between day and night; and if labels are given with outlines and apriori training, the model can give an output with a new design of the object that was modeled.

The scoring function in a generalized model’s (GM) depicts the way of providing answers to a given input by matching different sentences through word embedding. The word embedding is used to map different words in a low-dimensional vector space for tabulating the distance between word vectors. It helps in finding the maximum score between sentences to understand the high correlation with a question[18].

For example, question stem: “What is the water level for the paddy crop?" A scoring function will take the question and answer from memory mentioned as “water level for rice crop is 6 mm–10 mm”[19].

GM’s examines the correlation between these two sentences. The word embedding’s uses “q” transpose and “U” transpose Ud (qTUTUd), where “q” is the question, “d” is the answer, and U is the matrix by which the word embedding’s is the output. The pareto representation of the training set with model likelihood is presented for both data and the model in **Figure 4** below.

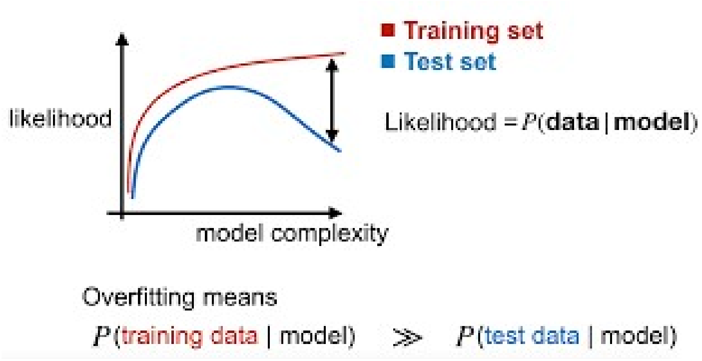


Figure 4. Pareto analysis of likelihood and complexity of the model.

Weight tying is a method of multiplying the weight matrix with the input and output functions; there are two types of weight tying, i.e., the first is “adjacent”, whose functioning is similar to that of a stack. In this, the program passes output weights to one layer as an input layer to another layer, which represents a hierarchical structure.

The second one is “layer-wise", in which the program passes the same weights to every layer. Functional aspects of the selected model employ unique smart methods to draw responses from the “hub of words” Smart[9].

AI methodology analyzes each variable for its mediation and moderating capabilities and helps to qualify the resulting vectors without word association. The other is position encoding (PE). This is more powerful than the “bag of words” model as it considers the context of the sentence. When modeling words, PE considers the preceding and successive words of a sentence and maps them to the low-dimensional vector space. Implementation can be derived using symmetric tensor flow methods (34) and (40). An illustration of this method is presented in **Table 3** below**.** Question: Is the yellow square to the left of the blue? Answer = ‘no’ - Confidence score = 93.77% correct.

Table 3. Data analysis for generative models.

Text	Memory hope 1 (multiple lookups 1)	Memory hope 2	Memory hope 3
The blue square is above the pink rectangle	0.00	0.04	0.36
The yellow square is to the right of the pink rectangle	0.37	0.59	0.64

Source: Author design.

Generative models can also be used for deeper applications, such as generating speech or raw audio from the stored text in the form of digital format (Kosovic et al.[20] generating a sequence of text similar to the auto-complete of the sentences while we are writing a mail or a message and generating the images with super-resolution, i.e., given low-resolution data and ideally the code to generate high-resolution data of the same, we can think of an image in a painting as having some holes or damage areas that can be rectified by generative models to figure out the missing data or data imputation methods. In the context of analyzing static, high-resolution images of agricultural fields, auto-regressive GM’s (learning models) can be deployed to a high degree of suitability[21].

Two algorithms are presented in **Tables 4** and **5** below that can complete the task of GM’s and auto regression to capture the missing links and variables. Both are homogeneous learning models.

Table 4. Learning model M1.

Algorithm 1: Learning in model M1
while $generativeTraining()$**do** $D \leftarrow getRandomMiniBatch()$ $z_i \sim q_{\emptyset}(z_i\|x_i) \quad \forall x_i \in D$ $J \leftarrow \sum_n J(x_i)$ $(g_\theta, g_\emptyset) \leftarrow \left(\frac{\partial J}{\partial \theta}, \frac{\partial J}{\partial \emptyset}\right)$ $(\theta, \emptyset) \leftarrow (\theta, \emptyset) + \Gamma(g_\theta, g_\emptyset)$ **end while** **while** $discri\,min\,a\,tiveTraining()$**do** $D \leftarrow getLabeledRandomMiniBatch()$ $z_i \sim q_{\emptyset}(z_i\|x_i)\ \forall\{x_i, y_i\} \in D$ $trainClassifier(\{z_i, y_i\})$ **end while**

Source: Author derived.

Table 5. Learning model M2.

Algorithm 2: Learning in model M2
while $training()$**do**
$D \leftarrow getRandomMiniBatch()$
$y_i \sim q_\phi(y_i \vert x_i) \quad \forall\{x_i, y_i\} \notin O$
$z_i \sim q_\phi(z_i \vert y_i, x_i)$
$J^\alpha \leftarrow \sum_n J(x_i)$
$(g_\theta, g_\phi) \leftarrow \left(\frac{\partial l^\alpha}{\partial \theta}, \frac{\partial l^\alpha}{\partial \phi}\right)$
$(\theta, \emptyset) \leftarrow (\theta, \emptyset) + \Gamma(g_\theta, g_\emptyset)$
end while

Source: Author derived.

In the context of agriculture images (remote sensing), GM's have powerful usage when it's hard to label identified differences by screening pixels. Images can be diagnosed by a generative algorithm for generating images of the anomaly (weed, insect, rock, etc.) or a regular plant anatomy that helps in doing anatomical level segmentation. Till recently, GM's were applied only as applications of image-to-image translation for medical imaging where doctors have a lot of data for a particular modality, like CT images of the liver, which are easily available. In both instances, researchers can train a model to perform the diagnostic task of transforming the images of the same anatomy, such as (a) classifying remote sensing agri-field images and (b) transforming MR images to CT images and using the trained model for diagnosis and decision-making.

The types of generative models that are used for generating the data (images) are Anastasi et al.[22] and Varela et al.[23]. (a) Auto-regressive models: PixelRNN and PixelCNN are highly cited models based on auto-regression methods and are explicit. It determines the probabilistic or probability density of the data and generates a desired set (predicted) of images based on the collected and captured pixels. This method is an auto-regressive model and gives explicit density images, which are representations of a deep neural network, or (b) a latent variable model—variational auto-encoder (VAE). This is another class of GM that also explicitly determines density based on the variation auto-encoder and includes an approximate way of determining the density function. So, it is called a latent variable model because of the algorithms that are implemented in it. A third model (c) is the implicit density model, which is a generative adversarial network (GAN). This method does not explicitly model the density with the probability density; rather, it is sampled directly from a neural network output. The sample and its output have primarily been used for generating images, mostly human faces, that look very realistic.

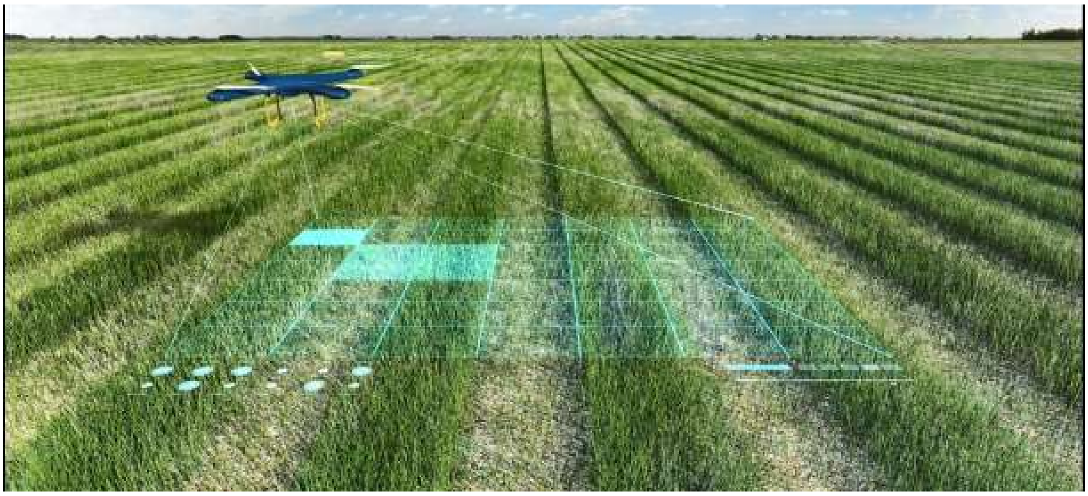
This same method[24] can be designed to derive the expert system identification of insect types, weed pattern, color of crop (health attribute), and other aspects that require human intervention.

GM's try to model underlying training data distributions, and users desire to figure out (x), where x is the set or a sub-set of the training data. A researcher can draw samples from the probability distribution that resemble training data and can endorse improved interpretation of GM's. This pattern has a multitude of possible applications. GM's can also be used as classifiers, of course, but when working with labeled data, it is much more straightforward to train the classifiers by directly using deep neural networks.

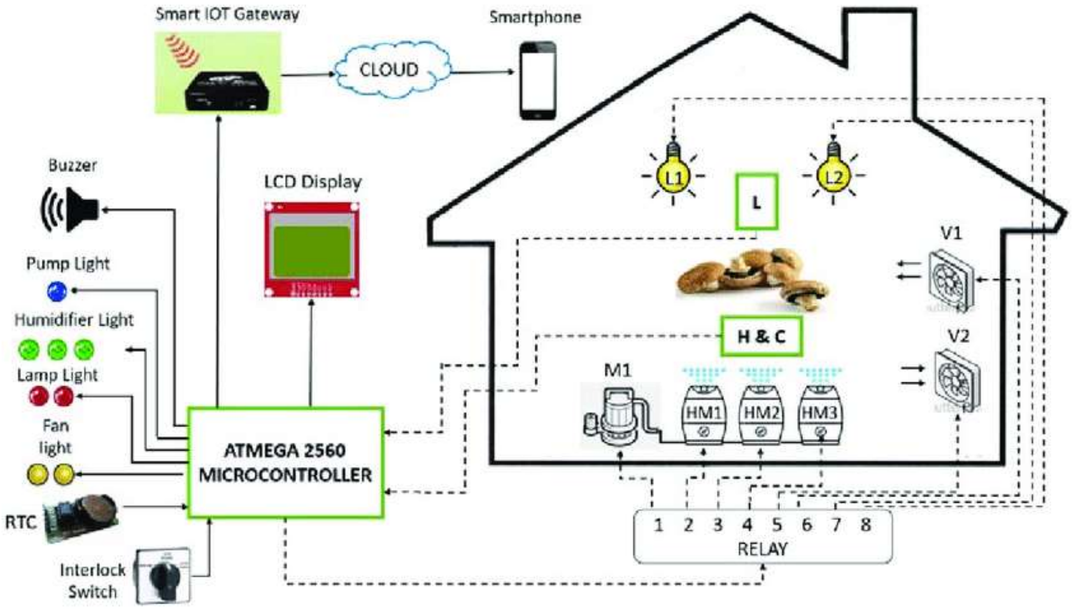
3.1. Application of networks with memory

Digital technology Networks with memory are driving change in agriculture for analyzing and decision-making; they can measure and transmit data via a network. On agri-farms, strongly "supervised networks" in "networks with memory" allow better output.

Information generated by supervised learning algorithms (SLA) can be enabled to predict using labeled datasets, i.e., questions for which a possible "bag of answers" is server-driven. For instance, (illustrated in **Figure 5** as below), capturing data from soil about its moisture and levels of topsoil provides for variances with the pre-stored value of desired levels of moisture. It can also predict crop yield per hectare based on features such as land wetness, pH levels of soil, minerals left in soil, crop efficiency, and rate of growth on the farm field.



(a)



(b)

Figure 5. AI powered supervised learning algorithm, **(a)** field model using ai powered (atmega 2560-microcontroller) drones; **(b)** block diagram of supervised learning algorithm (SLA) employed for smart agriculture.
Source: Author design.

SLA's are powerful algorithms and can teach a model to learn from the labeled example that is provided in **Figure 5(b)** above[25,26].

Supervised learning can be further divided into classification and regression. In classification, the output label is categorized into two or more classes, such as true/false, red/blue, yes/no, and crop has disease/no disease. Whereas in regression problems, the output variable is real or continuous, viz., insecticide quantum per square inch of tractable land or water required for plant growth, etc.

Regression methods create a predictive model that provides trends in vital data, such as crop health and yield quality. When researchers build an algorithm for the collation of single-point data referring to crop behavior, its growth, its health, its yield, fertilizers, etc., by reviewing the data about the crop, false data can be identified through some keywords, i.e., growth levels, yield data, soil moisture level, etc. These data points help in predicting crop quality and yield with a high degree of accuracy. So, in regression, let's say there are two labels, "temperature" and "humidity", where humidity is dependent on temperature, such that as the temperature increases, humidity decreases. When this data is fed to a regression model, SLA's can guide to improve understanding and derive a correlation amongst dependencies for a better crop yield.

3.2. Applications of generative models

Generative models deployed with the assistance of agricultural farmers can make farming a simpler task by providing real-time data (through labeled images) and improving efficiency by way of identifying water management requirements. It also lessens the amount of fertilizer runoff, spot spray fertilizer based on the snapshot of crops taken, which helps in scouting the field by finding the exact problem and its precise location in the field.

Using auto-regressive models (PixelRNN), PixelCNN users can recover lost data in the images and try to find the probability density of the data, which helps in the improvement of overall metrics of cultivation, better profits, and reduced input cost[13]. Auto-regressive models play a prominent role in identifying and guiding steps to improve plant growth through the extraction of various vegetation indices and supporting farmers' decision-making by rendering an estimate of crop yield, apart from addressing 24 × 7 crop monitoring, reduced field visits, limited human exposure to harmful pesticides, scouting wide and vast tracts of agri-fields, quantity, and quality improvement of crops.

4. Conclusion

The emerging technologies of artificial intelligence, machine learning, and deep learning models are changing the perspective of traditional practices in the agriculture system drastically, including SVM as a revolutionary approach in traditional farming that helps to lead farmers to implement modern practices by managing and monitoring the cultivation field. The implementation of ICT improves crop yield, diagnoses crop disease, applies fertilizer and pesticides, monitors crop growth, manages water resources, manages weeds, and requires less maintenance. Agrarian inter-linkages using smart farming remain to be addressed, which include efficient management of crop disease, pollution management, rational fertilization, and accurate yield predictions. However, scientific contributions towards the agri-food industry can be ameliorated by machine learning algorithms, generative models, and networks with memory where auto-encoders are employed as an integral part of GM's, which can improve deep learning, i.e., when encoders map data to a low-dimensional latent space and decoders map latent space back to reconstructed data, dynamically assisting remote sensing abilities. This aspect attests that deep generative models are useful for tasks where the underlying structure of the data is important for decision-making and the generated data can be treated and iterated as a virtual sensory information flow to augment improved decision-making. On the other hand, deep generative models are atypically harder to learn than discriminative models and foster interpretable results.

Generally, applications of AI, especially ELM's, are also employed for mediating and moderating features not limited to speech recognition, sensitivity analysis, optical character recognition, remote sensing, and translation of languages. This study scoping GM's and applications does not encompass these applications and can be taken as a future study direction.

Conflict of interest

The sole author of the manuscript declares that there is no conflict of interest whatsoever.

References

1. Talaviya T, Shah D, Patel N, et al. Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides. *Artificial Intelligence in Agriculture* 2020; 4: 58–73. doi: 10.1016/j.aiia.2020.04.002
2. Elmoulat M, Debauche O, Mahmoudi S, et al. Edge computing and artificial intelligence for landslides monitoring. *Procedia Computer Science* 2020; 177: 480–487. doi: 10.1016/j.procs.2020.10.066
3. Ampatzidis Y, Partel V, Costa L. Agroview: Cloud-based application to process, analyze and visualize UAV-collected data for precision agriculture applications utilizing artificial intelligence. *Computers and Electronics in Agriculture* 2020; 174: 105457. doi: 10.1016/j.compag.2020.105457
4. Su WH. Crop plant signaling for real-time plant identification in smart farm: A systematic review and new concept in artificial intelligence for automated weed control. *Artificial Intelligence in Agriculture* 2020, 4: 262–271. doi: 10.1016/j.aiia.2020.11.001
5. Heiden B, Alieksieiev V, Volk M, et al. Framing artificial intelligence (AI) additive manufacturing (AM). *Procedia Computer Science* 2021; 186: 387–394. doi: 10.1016/j.procs.2021.04.161
6. Talukdar S, Pal S, Singha P. Proposing artificial intelligence based livelihood vulnerability index in river islands. *Journal of Cleaner Production* 2021; 284: 124707. doi: 10.1016/j.jclepro.2020.124707
7. Singh H, Kumar Y. Hybrid artificial chemical reaction optimization algorithm for cluster analysis. *Procedia Computer Science* 2020; 167: 531–540. doi: 10.1016/j.procs.2020.03.312
8. Aghelpour P, Bahrami-Pichaghchi H, Kisi O. Comparison of three different bio-inspired algorithms to improve ability of neuro fuzzy approach in prediction of agricultural drought, based on three different indexes. *Computers and Electronics in Agriculture* 2020; 170: 105279. doi: 10.1016/j.compag.2020.105279
9. Riahi Y, Saikouk T, Gunasekaran A, et al. Artificial intelligence applications in supply chain: A descriptive bibliometric analysis and future research directions. *Expert Systems with Applications* 2021; 173: 114702. doi: 10.1016/j.eswa.2021.114702
10. Yu H, Wen X, Li B, et al. Uncertainty analysis of artificial intelligence modeling daily reference evapotranspiration in the northwest end of China. *Computers and Electronics in Agriculture* 2020; 176: 105653. doi: 10.1016/j.compag.2020.105653
11. Sukhbaatar S, Szlam A, Weston J, Fergus R. End-to-end memory networks. In: Cortes C, Lawrence N, Lee D, et al. (editors). *Advances in Neural Information Processing Systems 28*, Proceedings of the Annual Conference on Neural Information Processing Systems; 7–12 December 2015; Montreal, Quebec, Canada. pp. 2440–2448.
12. Weston P, Hong R, Kaboré C, Kull CA. Farmer-managed natural regeneration enhances rural livelihoods in dryland West Africa. *Environmental Management* 2015; 55(6): 1402–1417. doi: 10.1007/s00267-015-0469-1
13. Soni N, Sharma EK, Singh N, et al. Artificial intelligence in business: From research and innovation to market deployment. *Procedia Computer Science* 2020; 167: 2200–2210. doi: 10.1016/j.procs.2020.03.272
14. Ahmadi F, Mehdizadeh S, Mohammadi B, et al. Application of an artificial intelligence technique enhanced with intelligent water drops for monthly reference evapotranspiration estimation. *Agricultural Water Management* 2021; 244: 106622. doi: 10.1016/j.agwat.2020.106622
15. Seyedzadeh A, Maroufpoor S, Maroufpoor E, et al. Artificial intelligence approach to estimate discharge of drip tape irrigation based on temperature and pressure. *Agricultural Water Management* 2020; 228: 105905. doi: 10.1016/j.agwat.2019.105905
16. Li X, Liu J, Liu D, et al. Measurement and analysis of regional agricultural water and soil resource composite system harmony with an improved random forest model based on a dragonfly algorithm. *Journal of Cleaner Production* 2021, 305: 127217. doi: 10.1016/j.jclepro.2021.127217
17. Debauche O, Mahmoudi S, Mahmoudi SA, et al. Edge computing and artificial intelligence for real-time poultry monitoring. *Procedia Computer Science* 2020; 175: 534–541. doi: 10.1016/j.procs.2020.07.076
18. Bhagat SK, Tung TM, Yaseen ZM. Development of artificial intelligence for modeling wastewater heavy metal removal: State of the art, application assessment and possible future research. *Journal of Cleaner Production* 2020; 250: 119473. doi: 10.1016/j.jclepro.2019.119473
19. Liu T, Sun Y, Wang C, et al. Unmanned aerial vehicle and artificial intelligence revolutionizing efficient and precision sustainable forest management. *Journal of Cleaner Production* 2021; 311: 127546. doi: 10.1016/j.jclepro.2021.127546

20. Kosovic IN, Mastelic T, Ivankovic D. Using Artificial Intelligence on environmental data from Internet of Things for estimating solar radiation: Comprehensive analysis. *Journal of Cleaner Production* 2020; 266: 121489. doi: 10.1016/j.jclepro.2020.121489
21. Maruthi SP, Panigrahi T, Jagannath RPK. Distributed version of hybrid swarm intelligence-Nelder Mead algorithm for DOA estimation in WSN. *Expert Systems with Applications* 2020; 144: 113112. doi: 10.1016/j.eswa.2019.113112
22. Anastasi S, Madonna M, Monica L. Implications of embedded artificial intelligence—Machine learning on safety of machinery. *Procedia Computer Science* 2021; 180: 338–343. doi: 10.1016/j.procs.2021.01.171
23. Varela N, Silva J, Pineda OB, et al. Prediction of the corn grains yield through artificial intelligence. *Procedia Computer Science* 2020; 170: 1017–1022. doi: 10.1016/j.procs.2020.03.080
24. Pathan M, Patel N, Yagnik H, et al. Artificial cognition for applications in smart agriculture: A comprehensive review. *Artificial Intelligence in Agriculture* 2020; 4: 81–95. doi: 10.1016/j.aiia.2020.06.001
25. Lu Y, Young S. A survey of public datasets for computer vision tasks in precision agriculture. *Computers and Electronics in Agriculture* 2020; 178: 105760. doi: 10.1016/j.compag.2020.105760
26. Zougagh N, Charkaoui A, Echchatbi A. Artificial intelligence hybrid models for improving forecasting accuracy. *Procedia Computer Science* 2021; 184: 817–822. doi: 10.1016/j.procs.2021.04.013