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Current Trends and Gaps in Machine-Based Predictive Analysis in Agriculture for Better Agricultural Output Management – A Systematic Review

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***Abstract*-The use of Artificial Intelligence in agriculture is a novel approach that promises many benefits. Notable is the emphasis by nations of the world to end hunger by 2030 as enshrined in Sustainable Development Goal number 2. To end world hunger, the fundamental ways of doing things in and around the agricultural space will have to change by adopting much more sustainable models and relooking at the supply chain systems within the space. For example, it is noted that more food goes to waste through spoilage than is required to feed all the hungry on earth. However, in other parts of the globe, the food supply would be sufficient were it not for the stock that spoils due to pests and diseases. It the goal of this paper to provide a possible solution for the second scenario on spoilage due to pests and diseases by adopting Artificial Intelligence approaches such as Machine Learning and tweaking existing methods by improving the overall prediction score. We provide areas of interest that may be considered and show that further research in the subject may yield positive results in the field of Predictive Analysis as applied to agriculture. A Systematic Review is done on over 100 pieces of literature around the field of Predictive analysis with a selected 20 papers that are used in the final analysis. Notable gaps are highlighted while areas of possible improvement are also indicated. It is against this backdrop that the highlighted areas of improvement may later be tested in subsequent work.**

Keywords: Predictive Analysis, Artificial Intelligence, Machine Learning, Agriculture, Systematic Review

I. INTRODUCTION

Artificial intelligence will assist the world have better agricultural output[1], improve agricultural forecasts and assist in achieving part of the 2030 sustainable development goals[2] by incorporating technology in the space. As an accepted standard, there are four pillars necessary to achieve food security and these are food availability at a national level, food access at a household level, sustainable food utilization at an individual level and the stability of the 3 previous pillars viewed over time[3], an important question to ask would be what is needed to ensure that those pillars of food security are attainable? The UN SDG number 9 talks about industries, innovation, and infrastructure. This naturally leads into the quest for smart methods and ways of agriculture and it has been shown that there are synergies between SDG 2 and SDG 9[4]. While methods of agriculture have improved over the years and since the start of the industrial revolution, there remains key areas that have been untouched such as the Predictive Analysis of pest outbreaks and diseases which can better prepare farmers to either plant certain crops, stock up on certain chemicals to prepare for the outbreak and potentially, change environmental conditions to completely stop a suspected outbreak from even taking off. Predictive analysis has long been used by man to better manage yield expectations for crops since the advent of agriculture. With better tools at the disposal of man came large scale commercial farming which was made better by the development of artificial means for farming such as large-scale irrigation, the use of pesticides and fungicides to control diseases and artificial ecosystems such as greenhouses to deliberately manipulate and control environments so that specific conditions are mimicked for the efficient growth of certain crops. With the widescale use of computing technology in agriculture, which is usually abbreviated as Agritech [5], scientists must realise that better decisions may be made by using Machine Learning and Predictive Analysis to make decisions such as whether there may be need for specific pesticides and what disease may have suddenly affected crops. This is usually done by analyzing existing data, running the data through artificial intelligence models for a decision and then applying recommendations based on the current situation. In this paper, we note that there are several gaps in the current methods that are used in agriculture, and we show how we may improve the methods by considering various other variables and new sources of data that have traditionally been left out. We argue that an ecosystem-wide approach to predictive analysis may enable decisions to be made for events that may occur in the future as opposed to a reactive approach, we consider how proactive approaches may be taken using the same tools that are used today.

II. LITERATURE REVIEW

In this section, various literature relevant to the research was reviewed ranging from an understanding of Predictive Analysis to looking into multivariate analysis[6], the importance of ecological considerations in agricultural forecasting and how we propose to improve Predictive analysis in agriculture.

A. AGRICULTURAL PREDICTION METHODS

Several methods on improving agricultural prediction methods have been proposed and many of them focus on the monitoring of a singular variable. We note issues with the current models due to a general lack of the inclusion of multivariate data. Before a model is even proposed, it is important to look at how manual predictive models may be enhanced and then we can address how to formulate machine models. Typical methods used in traditional agricultural prediction include the monitoring of nutrient in the soil, a review of past rainfall patterns to forecast subsequent rainfall[7], an analysis of the types of seeds used and their historical yield[8] and examination and analysis of typical pests and diseases that may affect a certain geographical area[9]. What can be noted in what has been discussed above is a question as to why a certain event that would require measurement happens. As an example, a question could be asked such as "What could suddenly cause a certain pest to proliferate?". The answer might not be so clear, but we note that Ecology[10] and Chaos Theory[11] may have significant implications as to the turnout of future events. It therefore becomes important to not only analyse a variable, but to also consider factors that may affect that variable. In the next section, we look at a brief history of Predictive Analysis and how it is used.

B. PREDICTIVE ANALYSIS

It can be argued that Predictive Analysis is as old as man. People would look at the night sky, record the position of stars and create a map that would tell them what the weather expectations would be based on certain alignments of the heavenly bodies. The effects of Luminaries on weather on earth is a well-documented occurrence. For example, the moon, depending on its relative position in the sky affects the wave of the sea and weather rain will fall or not[12]. Over a period of a few 100 years and even Millenia, enough data was gathered such that trends could be observed by correlating one set of data to another. This is the overall basis of Predictive Analysis in Computer Science today.

Much more relevance has been placed in the science since the advent of Big Data. With the sprawling number of sensers and digital records capturing information to the Cloud, so much data became available for computers to crunch and predict patterns. The typical method used in the analysis is to collect a significantly large sample of data and to divide that data into two sets, one set is used to analyze trends while the other data set is to test the accuracy of the prediction model. It is against the method that an assumption can be made about future correlations for uncaptured data or for events that are yet to happen.

C. ISSUES WITH PREDICTIVE ANALYSIS

The major issue that can be noted in Predictive Analysis is that many of the currently available methods to not make use of a multivariate approach as concerns the different factors within a system. Typical applications used in Agritech are based on image recognition such as identifying a type of pest using trained data. Once the pest or disease is identified, the user can then be prompted to select the appropriate remedy. Some great applications that can be noted are AgriPredict which is an application that has been created by a Zambian tech startup to assist farmers in determining pests or diseases that are affecting their plants and can also reportedly predict the possibility of their being adverse weather conditions such as drought, floods and cold fronts.[13]. The exact mechanism of how the application does this and whether there has been success in predicting adverse weather conditions is unknown as there have been no reproducible or predicated and validated results.

Another noteworthy application is OneSoil[14] [15] by a Swiss Company which is used to determine the chemical composition of soil from satellite imagery based on a vegetation index which can predict possible soil mineral content by analyzing whether crop rotation is practiced. The company has successfully assisted farmers in yield enhancement using their trained data from images captured across the globe. What is notable about the application OneSoil is that the company says it can increase productivity, reduce waste and protect the environment.

D. IMPROVING PREDICTIVE ANALYSIS

We start by defining two key terms that were used in this research and these are *multivariable* and *multifactor.* Factors of prediction are holistic systems such as rain and the occurrence of pests. The multi variable approach towards this research is to identify those variables that affect a specific important factor in agriculture such as what variables affect the rainfall factor which are known to be variables such as temperature, humidity, pressure etc. Hence different factors would have different variables hence we use the term a *Multi-Variable, Multi-Factor* approach, the factor being the parent to the variable. We note through research and experiments that have been conducted that chaotic systems such as those we wish to study in this research can be predicted with an accuracy that is based on how well such variables and factors can be abstracted in the form of data[11]. While current predictive methods tend to focus on one variable, the world is inherently chaotic in nature hence we want to determine if multivariate or multivariable and multifactor approaches have been used in existing prediction models which would enhance the overall accuracy of the models[16].

III. METHODOLOGY

We used the Systematic Review method to assess the question, define the gaps and offer possible solutions. The search for text used simple phrases such as “Predictive Analysis in Agriculture” or “Trends in Agricultural Technology” or “Pest and Disease Management in Agriculture using Artificial Intelligence”. These searches were conducted on Google Scholar which has been shown to better index and find relevant papers[17] where the citation count plays a key factor in the ranking of papers[18]. There were no specific journals of interest as this study covers multiple disciplines. This approach towards research can better help us understand what is and what is not known about a specific research question[19]. In this regard, we ask the question whether current methods in Predictive Analysis within the agricultural space can be improved by considering multivariable and multifactor approaches to machine learning.

A. INCLUSION CRITERIA

The inclusion criteria define how the papers that were addressed are scoped. We have the following inclusion criteria discussed below and summarized in Table 3 below. We analysed the top 100 papers that have been written within the last 2 years about Predictive Analysis in agriculture and we do not restrict the language to English. The selection criteria were based on overall search ranking for each of the searched phrases and synonyms. For each search, we picked the top 2 most relevant articles based on a review of the abstract. Other Systematic Review studies may also be concluded, and we also looked at multidisciplinary fields such as Computing and a combination of one or either of Ecology, Biology, Meteorology and Crop Science. We selected 2 years deliberately because according to a well-accepted trend in the field of computing, significant changes take place in a space of 18 months as defined by Moores Law[20]. We then built a synthesis table to summarize the key points in those papers, how the problem in Predicative Analysis was solved, where we believe the gaps are and how we can address those gaps. Two researchers scored 100 papers initially using the paper abstract to rule out 80% of the papers and finally a detailed full paper analysis of the balance 20% of the papers. The principal to pick only 20% was based on the Pareto Principal which has been used in computing[21] [22] to optimize the search space where large amounts of data need to be considered.

Table 1 - Inclusion Criteria

Main question	1. What are the current trends and gaps in the last 2 years in Predictive Analysis within the Agricultural Space? 2. Can these methods identified in (1) be improved using multivariable and multifactor approaches?
Goal	To determine gaps in the Predictive Analysis of agricultural produce and to provide possible solutions.
Inclusion Criteria	1. Papers written within the last 2 years 2. Books published in the last 2 years 3. Papers concerned with Predictive Analysis in Agriculture 4. Papers dealing with terms such as Agritech, Machine Learning in Agriculture 5. Papers with a multidisciplinary approach that combine Computer Science and fields such as Ecology, Biology, Metrology and Crop Science
Exclusion Criteria	Papers written over 2 years ago

B. RELEVANT QUESTIONS FOR THE SYSTEMATIC REVIEW

Below we list the questions that were asked for each of the top 20% of selected papers that underwent thorough reading and assigned a normalized weighted score with a value of between 0 and 1 with 0 representing no positive answer to the question, 0.5 indicating partial compliance and 1 indicating full evidence with a positive yes answer. Two researchers analysed the various papers and gave each paper a score of between 0 and 10 which were interpreted as percentages of compliance to the specified questions indicated below. The scores were further normalized with the values indicated in Table 2 below. Therefore, we eventually only have 3 scores after normalization for each of the questions indicated below. The summary is shown in the modified Interpretation Table[23].

Table 2 - Normalization of Interpretation Table

Score	Level of Agreement	Normalization
>0.8	Almost Perfect	1
>0.6	Substantial	
>0.4	Moderate	0.5
>0.2	Fair	
>0	Slight	0
<0	No Agreement	

We then selected the 10 highest scoring papers to form our conclusions and suggestions on areas for improvements. The questions indicated below are suggested by Computer Science researcher Kofod-Petersen[24] and they are chosen as they are relevant to this research study and have been used in other Computer Science Systematic Literature Review papers[25].

1. "Is there is a clear statement of the aim of the research?"
2. "Is the study put into context of other studies and research?"
3. "Are system or algorithmic design decisions justified?"
4. "Is the test data set reproducible?"
5. "Is the study algorithm reproducible?"
6. "Is the experimental procedure thoroughly explained and reproducible?"
7. "Is it clearly stated in the study which other algorithms the study's algorithm(s) have been compared with?"
8. "Are the performance metrics used in the study explained and justified?"
9. "Are the test results thoroughly analyzed?"
10. "Does the test evidence support the findings presented?"

Table 3 below lists the quality criteria of the papers that were selected by analysing each to see if it addresses all the 10 questions that were asked for each paper and scoring each paper on each question as previously discussed above. The total score was then obtained for each paper and highest grossing papers selected for the final review process.

Table 3- Quality Criteria

SN	Article Title	1	2	3	4	5	6	7	8	9	10	Total
1	A Deep Learning and Social IoT Approach for Plants Disease Prediction Toward a Sustainable Agriculture[26]	1	0	1	0.5	0.5	1	0.5	0.5	0.5	1	**6.5**
2	A Systematic Review of Current Trends in Artificial Intelligence for Smart Farming to Enhance Crop Yield[27]	1	1	1	1	0	0.5	1	1	1	1	**8.5**
3	Agricultural decision system based on advanced machine learning models for yield prediction: Case of East African countries[28]	1	1	0.5	0.5	0.5	0.5	1	0.5	1	1	**7**
4	Smart IoT Monitoring System for Agriculture with Predictive Analysis[29]	1	0.5	0.5	0.5	0	0	0	0	0	0.5	**3**
5	Automated predictive analytics tool for rainfall forecasting	1	0	0.5	1	1	1	0.5	1	1	1	**8**
6	Comparison of Artificial Intelligence Algorithms in Plant Disease Prediction[30]	1	1	1	1	1	1	1	1	1	1	**10**
7	Disruptive technologies in agricultural operations: a systematic review of AI-driven AgriTech research[5]	1	1	1	1	1	1	1	1	1	1	**10**
8	Emerging technologies revolutionise insect ecology and monitoring	1	1	0	0	1	1	1	1	1	1	**8**
9	Evolving Concepts of Integrated Pest Management[9]	1	1	1	0	0	1	0	0	0	0	**4**
10	Field pest monitoring and forecasting system for pest control[31]	1	0	0.5	0	1	0.5	0	0.5	0	0.5	**3.5**
11	Humidity and high temperature are important for predicting fungal disease outbreaks worldwide[32]	1	0	0	0	0.5	0.5	0	1	0	1	**4**
12	Identifying critical research gaps that limit control options for invertebrate pests in Australian grain production systems: Research gaps for grain pest management[33]	1	1	1	1	1	1	1	1	1	1	**10**
13	Integrating Neighborhood Effect and Supervised Machine Learning Techniques to Model and Simulate Forest Insect Outbreaks in British Columbia, Canada[34]	1	1	1	1	1	1	1	1	1	1	**10**
14	Rainfall prediction: A comparative analysis of modern machine learning algorithms for time-series forecasting[35]	1	1	1	1	1	1	1	1	1	1	**10**
15	sCrop: A Novel Device for Sustainable Automatic Disease Prediction, Crop Selection, and Irrigation in Internet-of-Agro-Things for Smart Agriculture[36]	1	1	1	0.5	1	1	1	0.5	1	1	**9**
16	Tomato plant disease detection using transfer learning with C-GAN synthetic images[37]	1	1	1	1	1	1	1	1	1	1	**10**
17	Enabling smart agriculture by implementing artificial intelligence and embedded sensing[38]	1	0	1	1	1	1	0	0.5	0.5	0.5	**6.5**
18	A deep neural network-based decision support system for intelligent geospatial data analysis in intelligent agriculture system[39]	0.5	0	1	0.5	1	1	0	0.5	0.5	0.5	**5.5**
19	Data Mining Analysis for Precision Agriculture: A Comprehensive Survey	1	0	0.5	0	1	1	1	0.5	0.5	0.5	**6**
20	Prediction of environment variables in precision agriculture using a sparse model as data fusion strategy[40]	1	1	1	1	1	1	1	0.5	0.5	0.5	**8.5**

IV. RESULTS

We selected 10 papers with the highest total score in the Quality Criteria presented in Table 3 above. The selected papers are numbered 6, 7, 12, 13, 14, 16, 15, 2, 20, 5. We then carefully analyzed each of the 10 papers using another decision table that asks whether a multivariable and multifactor approach is used and what the gaps are as indicated in Table 4 below. Of particular interest to our approach is to consider whether ecological and/or biological data is used as it has been shown that considering these points is a novel approach in Integrated Pest Management[41] and we extend this ecological viewpoint to plant disease management too.

Table 4 – Gap Analysis

Paper Title	Key Thematic Area	MV[1]	MF[2]	Gaps
Comparison of Artificial Intelligence Algorithms in Plant Disease Prediction[30]	This paper looks at several algorithms and compares their accuracy as compared to each other	Yes	No	The paper gives details of various methods that can be used in Predictive Analysis but does not discuss how multivariable and multifactor may improve the overall accuracy of the available methods
Disruptive technologies in agricultural operations: a systematic review of AI-driven AgriTech research[5]	The article analyses research into AI driven applications in agriculture	No	No	While the author does well in presenting evidence that AI is agriculture is used in the context of Agritech, the do not address the details and methodology of what each of the cited works offer. This paper was however helpful in assisting with finding several other articles of interest as highlighted in the inclusion criteria.
Identifying critical research gaps that limit control options for invertebrate pests in Australian grain production systems: Research gaps for grain pest management[33]	Identifying the current gaps on the methods used in integrated pest management.	No	Yes	The author identifies and conclude that gaps do exist in current methods of pest management and suggest that more funding and research in the area may improve the overall applicability and usage adoption of integrated pest management. However, we note that while multifactor are considered, multivariable for those factors are not.
Integrating Neighborhood Effect and Supervised Machine Learning Techniques to Model and Simulate Forest Insect Outbreaks in	Determining the possibility of deforestation being caused by Mountain Pine Beetle using generalized linear regression and random forest models.	Yes	No	The author used mutli-variates but did not consider several other factors that could affect the propagation of the Mountain Pine Beetle.

[1] Multifactor considered in the article
[2] Multivariable considered in the article

British Columbia, Canada[34]				
Rainfall prediction: A comparative analysis of modern machine learning algorithms for time-series forecasting[35]	Predicting rainfall probability using the LSTM AI model	Yes	No	The author only considered those variables that are connected to the rain factor whereas our argument is that so many other factors could affect rain such as sea surface conditions for example.
Tomato plant disease detection using transfer learning with C-GAN synthetic images[37]	Determine the occurrence of plant disease by analysing pictorial data and training an AI model	No	No	Only images were used to train an AI model. However, several other factors could affect the proliferation of plant-based diseases such as ecological factors.
sCrop: A Novel Device for Sustainable Automatic Disease Prediction, Crop Selection, and Irrigation in Internet-of-Agro-Things for Smart Agriculture[36]	Determine the occurrence of plant disease by analysing pictorial data and training an AI model	No	No	Only images were used to train an AI model. However, several other factors could affect the proliferation of plant-based diseases such as ecological factors.
A Systematic Review of Current Trends in Artificial Intelligence for Smart Farming to Enhance Crop Yield[27]	Systematic literature review of the trends in Agritech	No	Yes	The study determined that several factors are usually considered separately in the field of predictive analysis. From 67 papers that were analyzed, none of them took a multifactor and multivariable approach.
Prediction of environment variables in precision agriculture using a sparse model as data fusion strategy[40]	Monitoring environmental variables to assist in the prediction	Yes	Yes	While it does appear that multifactor may have been at play, it is noted that all the mentioned variables are closely related to the rain factor though the author does not indicate what results those measured variables would have in agriculture and merely shows that they can be predicted or inferred. This paper does however present a much better diversion from the others that had been reviewed.
Automated predictive analytics tool for rainfall forecasting[42]	Develop a rain prediction model using neural networks.	Yes	No	Only considers those variables that affect the rain factor.

V. DISCUSSION AND CONCLUSION

We have noted that in all research methods used in Table 4, key factors such as looking into the chemical, ecological and other physical conditions which may best favor the proliferation of undesirable pests and plant diseases or indeed what the authors were trying to predict and suggesting methods to counteract outbreaks or mitigate risks are missing. All the papers but one employed both multifactor and multivariable. Scientists have long argued that any complex system may be modelled provided enough data is available, this is inherently how the world operates. So, if we can attempt to bring in more complex data within the realm of Predictive Analysis, we would certainly have much more accurate results[43].

VI. RECOMMENDATIONS

The field of Predictive Analysis may need to evolve to include more complex data sets such as those found in chaos theory. While current models do seem to work quite well, there will obviously be gaps if the processes that govern physical systems are not included as part of the variables or factors in machine learning models. As computers become more powerful, it becomes an easy task to process large amounts of data for better decision making.

VII. FUTURE WORK

We will proceed and attempt to model a complex chaotic system such as being able to determine the future occurrence of rain, plant disease or pests using models that incorporate multivariable and multifactor. This research did expose those gaps and it will also be important to determine why the suggested methods have not generally been in use.

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