Review on Application of Big Data Analytics in Agriculture

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Abstract

Vegetables and other row-crops represent a large share of agricultural production. There is a large variation in crop species and limited availability in specialized herbicides.

In such circumstances, more efficient farming practices can be attained using the recent technological advancements and solutions to current bottlenecks in farming. A direct application of Big Data Analytics across the farming sector could act to be an epitome of a shift in how farming is practiced today. The current paper throws a vision of how the diverse sectors of agriculture can be fueled using Big Data Analytics. It also investigates the new technological ideas for the future and the challenges anticipated in the future.

Key Words **:- Agriculture, Big Data Analytics, Data Mining, Remote sensing, Smart Farming**

I. INTRODUCTION

Nowadays, a large amount of the agricultural fieldwork is accomplished with human-driven machines in high scale farming. Due to high demanding farming methods in mechanized agriculture, most farmers deficit the hands-on expertise with judging the state of the farm [1].

Interesting relation between data of the database can be known through Association rules which is a method of Data mining. Applying Data Mining in the field of agriculture can become very fruitful [2]. It is helpful to assess and discover concealed liaison between the entities of agricultural data and also support scientific decision-making [3]. So, this performed agriculture data analysis by association rules using the Apriori algorithm in the general rules acquisition, whereas linear regression was applied to show the relationships between several input variables and an outcome variable. Moreover, this work was aimed to design and implement a WSN system for sensors in the crop field, along with data management interfaced with the user via a smartphone and a web application. With the help of connectivity with the system, this suggested system can assist varied crop farming and aid farmers [2].

This article is organized as follows: Section 2 discusses related work, Section 3 presents the proposed diagnostic system, Section 4 shows the agricultural data analysis, Section 5 has results and discussion, and finally, Section 6 concludes the article.

II. METHODOLOGY

The bibliographic analysis in the domain under study involved three steps: (a) collection of related work, (b) filtering of relevant work, and (c) detailed review and analysis of state of the art-related work. In the first step, a keyword-based search for conference papers and articles was performed from the scientific databases IEEE Xplore and ScienceDirect, as well as from the web scientific indexing services Web of Science [4]and Google Scholar. As search keywords, we used the following query: “Big Data” AND [“Precision Agriculture” OR “Smart Farming” OR “Agriculture“] In this way we examined numbers of papers and journals related to agriculture, And analyzed the use of Big Data Technology in precision farming. The number of citations was recorded based on Google Scholar. Use of big data analysis was quantified as satisfying some of its five “V” characteristics [5]. We primarily targeted the first three “V”s (i.e. volume, velocity and variety), since dimensions V4 and V5 (i.e. veracity and valorization) were more difficult to quantify.

Similarly, we have gathered information about the applications of Big Data in the field of agriculture in the terms of yield prediction, food safety and spoilage prevention, operation management and farm management. Then using various architecture and tools we have created models. We have also focused on the problems which Big Data include in the field of agriculture for instance: funding, serendipity, and data science, data quality and so on..

III. BIG DATA IN AGRICULTURE

[6] characterize big data according to the following five dimensions:

- **Volume (V1)**: The size of data collected for analysis.
- **Velocity (V2)**: The time window in which data is useful and relevant. For example, some data should be analyzed in a reasonable time to achieve a given task, e.g. to identify pests and animal diseases.
- **Variety (V3)**: Multi-source (e.g. images, videos, remote and field-based sensing data), multi-temporal (e.g. collected on different dates/times), and multi-resolution (e.g. different spatial resolution images) as well as data having different formats, from various sources and disciplines, and several application domains.
- **Veracity (V4)**: The quality, reliability and potential of the data, as well as its accuracy, reliability and overall confidence.
- **Valorization (V5)**: The ability to propagate knowledge, appreciation and innovation.

Although these five “V”s can describe big data, big data analysis does not need to satisfy all five dimensions. Big data is generally notorious for being less accurate and stable, usually compromising V4 (veracity) [5]. According to the above, big data is less a matter of data volume than the capacity to search, aggregate, visualize and cross-reference large datasets in a reasonable time. It is about the capability to extract information and insights where previously it was economically or technically not feasible to do so [7].

3.1. Applications of big data analysis in agriculture:

Big data has no shortage of uses within farming. Some of the more prominent include:

- **Yield prediction**

Yield prediction sees the use of mathematical models to analyze data around yield, weather, chemicals, leaf and biomass index among others, with machine learning used to crunch the stats and power the making of decisions. Prediction yields in this way can allow a farmer to extract insight on what to plant as well as where and when to plant it. The use of sensors for collecting data means that only a small amount of manual work is required to hand each business an instruction manual on how to guarantee the best return from their crops. According to the International Journal of Computer & Mathematical Sciences, predicting yields in this way should improve the production of crops in countries like India, where population increases represent a very real concern [36].

- **Risk management**

One area that is becoming all the more influenced by connected devices and algorithms is risk management. It's now possible for farmers to leverage a web of big data to evaluate the chances of events like crop failure, and even improve feed efficiency within the production of livestock. The area of risk management created headlines in 2014 as advice from data scientists to Colombian rice farmers was said to have saved millions in damages caused by shifting weather patterns [36].

- **Food safety and spoilage prevention**

A critical aspect of modern-day farming - allowing instant detection of microbes and incidents of contamination. The collection of data around things like humidity, temperature, and chemicals will paint a picture of health around smart agricultural businesses. That level of insight should be of interest to organic farmers in the US, whose issues with GMO contamination between 2011-2014 was said to have caused damages of $66,395 per affected business. Perhaps an earlier detection may have lowered the repair bill, or at least reduced some of the wastage [36]?

- **Operation/equipment management**

Finally, we cannot underestimate the role of big data in aiding various aspects of the everyday running of an agricultural business. Equipment manufacturers like John Deere have already made a good start with their fitting of sensors around vehicles to aid their providing of data. Farmers can then log into special portals to manage their fleet and maintenance of equipment to reduce downtime and keep everything productive. As more companies provide solutions to aid areas of equipment management and supply chain optimization, we can expect a much smoother delivery of crops to the market[36].

- **Farm Management**

Management or control processes ensure that the business process objectives are achieved, even if disturbances occur. The basic idea of control is the introduction of a controller that measures system behavior and corrects if measurements are not compliant with system objectives. This implies that they must have a feedback loop in which a norm, sensor, discriminatory, decision-maker, and effector are. As a consequence, the basic management functions are[9]

- Sensing and monitoring: measurement of the actual performance of the farm processes. This can be done manually by a human observer or automated by using sensing technologies such as sensors or satellites. Also, external data can be acquired to complement direct observations.

- Analysis and decision making: compares measurements with the norms that specify the desired performance (system objectives concerning e.g. quantity, quality and lead time aspects), signals deviations and decides on the appropriate intervention to remove the signaled disturbances.

- Intervention: plans and implements the chosen intervention to correct the farm processes' performance.

Table-1: Source of big data and techniques for big data analysis per agriculture area

No.	Agricultural Area	Big Data sources	Techniques for Big Data Analysis	Ref
1	Weather and climate change	Weather stations, surveys, static historical information (weather and climate data, earth observation data),remote sensing (satellites), geospatial data	Machine learning (scalable vector machines), statistical analysis, modeling, cloud platforms, MapReduce analytics, GIS geospatial analysis	[27]
2	Land	Remote sensing (satellites, synthetic aperture radar, airplanes), geospatial data, historical datasets (land characterization and crop phenology, rainfall and temperature, elevation, global tree cover maps), camera sensors (multispectral imaging), weather stations	Machine learning (scalable vector machines, K-means clustering, random forest, extremely randomized trees), NDVI vegetation indices, Wavelet based filtering, image processing, statistical analysis, spectral matching techniques, reflectance and surface temperature calculations	[24]
3	Animals research	Historical information about soil and animals (physiological characteristics), ground sensors (grazing activity, feed intake, weight, heat, milk production of individual cows, sound), camera sensors (multispectral and optical)	Machine learning (decision tree, neural networks, scalable vector machines)	[34]
4	Crops	Ground sensors (metabolites), remote sensing (satellites), historical datasets (land use, nation land information, statistical data on yields)	Machine learning (scalable vector machines, K-means clustering), Wavelet based filtering, Fourier transform,), NDVI vegetation indices	[35]
5	Soil	Ground sensors (salinity, electrical conductivity, moisture), cameras (optical), historical datasets (e.g. AGRIC soil)	Machine learning (K-means clustering, Farthest First clustering algorithm)	[29]
6	Weeds	Remote sensing (airplanes, drones), historical information (digital library of images of plants and weeds, plant-specific data)	Machine learning (neural network, logistic regression), image processing, NDVI vegetation indices	[23]
7	Food availability and security	Surveys. historical information and databases (e.g. CIA•CA, MAR, rice crop growth datasets, GIS geospatial data, statistical data, remote sensing (synthetic aperture radar)	Machine learning (neural networks), statistical analysis, modeling, simulation, network based analysis, GIS geospatial analysis, image processing	[8]
8	Biodiversity	GIS geospatial data, historical information and databases (SER databases of wildlife species)	Statistics (Bayesian belief network)	[21]
9	Farmers' decision making	Static historical information and databases (e.g. US government survey data), remote sensing (satellite, drones), weather station, humans as sensors, web-based data, GIS geospatial data, feeds from social media	Cloud platforms, web services, mobile applications, statistical analysis, modeling, simulation, benchmarking, Big data storage, massage-oriented middleware	[25]
10	Farmers insurance and finance	Web-based data, historical information, weather station, human as sensors (crops, yields), financial transactions data	Cloud platforms, web services, mobile applications	[39]
11	Remote sensing	Remote sensing (satellite, drones, airplanes), historical information and datasets (e.g. MODIS surface reflectance datasets), earth and land surface datasets of images, WMO weather datasets, reservoir heights derived from radar altimetry	Cloud platforms, statistical analysis, GIS geospatial analysis, image processing, NDVI vegetation indices, decision support system, big data storage, web and community portals	[32]

3.2 Available architectures, database and tools:

There exist various successful and popular architectures, which researchers may use to start building their models instead of starting from scratch. These include AlexNet [10], CaffeNet [12] , VGG [12], GoogleNet [14] and Inception ResNet [13] among others. Each architecture has different advantages and scenarios where it is more appropriate to be used It is also worth noting that almost all of the aforementioned models come along with their weights pretrained, which means that their network had been already trained by some dataset and has thus learned to provide accurate classification for some particular problem domain [5]. Common datasets used for pre-training DL architectures include ImageNet [15] and PASCAL VOC [16].

Moreover, there exist various tools and platforms allowing researchers to experiment with DL [17]. The most popular ones are Theano, TensorFlow, Keras, Caffe, Py-Torch, TFLearn, Pylearn2 and the Deep Learning Matlab Toolbox. Some of these tools (i.e. Theano, Caffe) incorporate popular architectures such as the ones mentioned above (i.e. AlexNet, VGG, GoogleNet), either as libraries or classes. For a more elaborate description of the DL concept and its applications, the reader could refer to existing bibliography [18].

3.3 Techniques of Big Data Analysis

Table-1[5] presents the proper approaches and techniques (column 4) used in the different agricultural sector which are considered in the papers under review (column 2). As Table 1 shows, machine learning, cloud-based platforms (9), image processing (8), modeling and simulation (7), statistical analysis (6) and NDVI vegetation indices (6) are the most commonly used techniques, while some approaches employ online services (e.g. publish/subscribe messaging, online portals, decision support) (5) and geographical information systems (GIS) (4).

Machine learning tools [26] are used in [27] clustering [28] and classification problems [29] while image processing is used when data originates from images and remote sensing. Cloud platforms (together with MapReduce) offer possibilities for large-scale storing [31], preprocessing, analysis and visualization of data [32], while GIS [33] are used in geospatial problems [24]. Big datasets are appropriate for the storing of large volumes of heterogeneous information, using database management systems (DBMS) that implement the array data model and NoSQL database management platform. NoSQL platforms store and manage large unstructured data.
Array DBMS are built specifically for serving big raster datasets.

IV. DISCUSSION

As Section 3 illustrated, a recent practice is to approximate agricultural problems by employing image analysis, using images originating from remote sensing, either from airborne or satellites [5]. Remote sensing has several advantages when applied to agriculture [19], being a well-known, non-destructive method to collect information systematically over very large geographical areas. A modern application of remote sensing in agriculture, as observed from the surveyed papers, is on the delivery of operational insurance products such as insurance from crop damage [20] flood and fire risk assessment or from drought and excess rain [37].

From the surveyed papers, relevant agricultural applications include yield prediction and characterization/mapping of crops, risk management, food safety and spoilage prevention, farm management are fulfilled up to certain instances. On the other hand data from high spatial resolution satellites like Landsat and SPOT have been used in support of local- and regional-scale applications requiring increased spatial detail [22], such as farmers' decision making support. Finally, some papers use airplanes and drones to achieve their goals, focusing on weeds' identification [23], or grassland inventories [24]. Combining remote sensing with ancillary data (e.g. GIS data, historical data, field sensors, etc.) significantly improves the analysis performed, especially when it includes some form of prediction, i.e. crop identification or accuracy of distinguishing grasslands [5].

4.1 Problems of Big Data in agriculture

The application of big data analysis in agriculture has not been beneficial in all cases, as it has created some problems too. We list below some of the problems,

- **Funding**

Collecting and managing Big Data is expensive due to the volume, and variability of the data. Big Data for biomedical research was funded through sustained investment from government agencies, which led to the creation of the NCBI. Investments from the private sector could enable the development of Big Data systems for agriculture, which could also increase the efficiency of applying these data tools across the industry. To comply with public funding, however, the private sector must address issues such as data ownership to ensure the integrity of these data system [38].

- **Serendipity and Data Science**

Investments in Big Data are not immediately guaranteed to result in far-reaching discoveries. On many occasions, discoveries in the biomedical sector have occurred by chance. Due to the serendipitous nature of scientific discoveries, there is a need for Big Data in agriculture to be given enough time and space to develop before the players have to be ready for massive, long-term investments to facilitate growth. In the meantime, such investments can lead to small wins and incremental developments that will make Big Data more useful for farming applications [38].

- **Data Quality**

The quality of data can be objective and suggests that Big Data in agriculture uses similar standards as those utilized by NCBI. This calls for the primacy of data observations over interpretation. There might be challenges with doing so especially with the fact that demand for such data is becoming increasingly in demand in the non-scientific community. Standards that facilitate a balance between technically sound and easily consumable data, therefore, have to be utilized [38].

- **Interoperability Standards**

Interoperability of data is one of the most important issues that have to be addressed in order to make a Big Data system widely useful. Big Data Convention is to strengthen data ontologies for agricultural research [38].

- **Tensions in Data Ecosystems**

Various tensions exist in the Big Data ecosystem for agricultural players to effectively leverage. These tensions include competing commercial interests, data ethics, user privacy, academic credit systems, and data security issues. All of these tensions have to be countered because they impede the ability of industry players to take advantage of data at their disposal. More importantly, these tensions hamper the sharing of data and limit the ability of data scientists and farmers to utilize Big Data in agriculture to improve their operations [38].

V. CONCLUSION

This paper reviewed big data analysis in agriculture, mostly from a technical perspective. More than twenty papers were identified and analyzed, examining the problem they addressed, the solution proposed, tools/techniques employed as well as data used. Based on these projects, the reader can be informed about which types of agricultural applications currently use big data analysis, which characteristics of big data are being used in these different scenarios, as well as which are the common sources of big data and the general methods and techniques being employed for big data analysis.

Every farmer has a goal for their operation. Some of the more commonly cited are around improving profitability and efficiency, reducing the cost of an operation, or increasing product value. To achieve each goal, farmers must make better decisions and move beyond the use of general knowledge from research experiments, which can only carry them so far. No business is the same, and there is now an increasing need for information generated in a location-specific manner, providing a solution which fits in line with what each farmer needs. Through big data and connected devices, every one of the goals around profitability, efficiency and cost management are not only achievable but completely realistic.

VI. REFERENCES

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