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Supervised Machine Learning in Precision Agriculture

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Abstract

Computer-based technologies have had a significant influence on the techniques employed in a wide range of real-world domains. Many fields, such as medicine and agriculture, rely heavily on computers for data gathering and analysis in order to provide useful information. Precision agriculture, a modern agricultural paradigm, analyzes the entire farm as a collection of tiny units and identifies anomalies in output and demand for those units. The ultimate objective of precision agriculture is to minimize the cost of farming in order to maximize profit. Innovative agricultural methods are being used by smart farmers. ICT, automation, and WSN technologies can be utilized to reduce the negative impacts of experience-based irrigation techniques. ICT has the ability to boost crop growth and production in the agricultural sector. The application of wireless sensor technology in micro irrigation projects can increase production per unit of water, reduce water and energy consumption, and reduce the usage of human labor in agriculture fields. WSN technology may be utilized in a number of applications, however there are several problems and restrictions in large-scale sensor network implementation. Massive size, restricted access, and dynamic monitoring are examples of systemic problems. The combination of actuation methods with wireless sensor networking may be employed in a variety of applications. In vast spatiotemporal settings, mobile ad-hoc networks may be utilized to produce and evaluate many parameters. Object detection and grading is emerging area in precision agriculture. It is vital in production estimation.

Index Terms - Smart farming, Machine learning, Soft computing, Sensor technology, Object detection

INTRODUCTION

Precision Agriculture (PA) is a well-known and enhanced agricultural method above traditional farm management strategies in modern agriculture. Precision agriculture is the use of agricultural and information technology to monitor crop health and production by measuring field crop condition and associated factors [1]–[5]. The objective of PA is to reduce agricultural input costs while maintaining end product quality. Traditionally, fertilizers and chemicals have been given to crops in bulk and at a flat rate, with the entire field treated as a single unit. As a result of such even application, certain units of land may receive an excessive quantity of dosage, while others may go without essentials owing to strong demand. In contrast, PA views the entire field as a collection of tiny units with varying requirements that generate varying amounts of the same product owing to poor management. PA seeks to analyze the geographical variability of production within a field and produces recommendations for applying requirements in accordance with demand. This method not only decreases the total cost of inputs, but it also aids in the uniformity and rise in production from all across the field. There are several phases involved in implementing PA, which may be divided into three categories: data gathering, data interpretation, and application. Figure 1 is an example of a precision agriculture cycle [6]. Alternatively, new technology such as remote sensing has made it feasible to do production estimation and mapping on extremely large open areas; but, due to operational restrictions, this approach is not practicable for small farms or areas. Computer vision object recognition and classification algorithms have been proven to be highly efficient in obtaining real-time information regarding production, not just during harvest but also at various phases of crop development. Computer vision has given inexpensive and dependable solutions for job automation in various domains such as industries, surveillance, and quality control. Some of the most notable characteristics of computer vision include accurate, consistent, and quicker automatic data gathering and analysis. The same technologies are now being utilized in PA for the purpose of production estimate. Several research have been done in the past in the vineyard, wheat, and fruit industries to automate the production estimation process. The majority of these research make use of computer vision and other related technologies. The availability of real-time information is regarded as the most important aspect of PA. Prior to crop harvesting, production estimate generates a highly valuable production database [7]–[13].

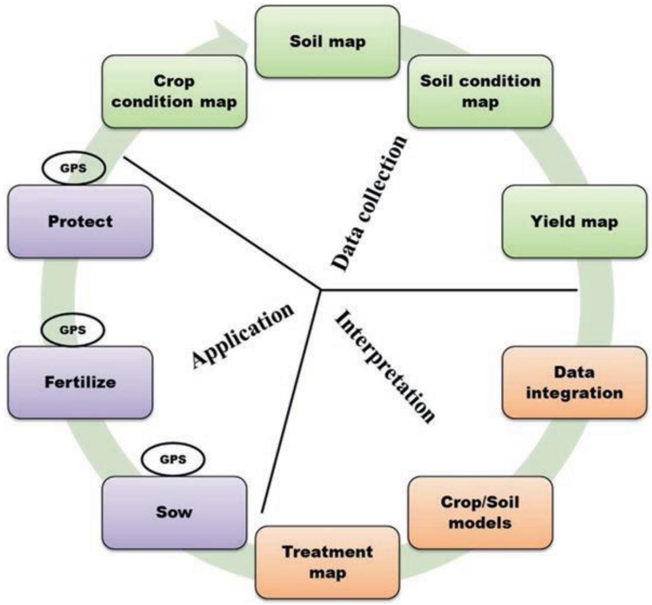

FIGURE 1
PRECISION AGRICULTURE CYCLE

Such a database enables PA to be expanded beyond its core aims to include resource management, harvesting workforce estimation, harvesting time, postharvest problems, storage, and transportation. Production counts have also been shown to be beneficial in financial decisions such as calculating selling price, timing of sales, and estimating profit or loss.

SOFT COMPUTING

Soft computing has been widely employed in a variety of applications in recent years, including medical diagnosis, character recognition, biometric applications, time series analysis, and many more. Soft computing methods have grown in favor for handling real-world issues in which the computer must operate with human intelligence while simultaneously dealing with imprecision and ambiguity in the problem area. The opposite of soft computing is the traditional, well-established “hard computing” paradigm, which necessitates a clearly defined solution approach and necessitates a long computational time.

Hard computing, such as statistical techniques, need reliable and exact data. These computational approaches are appropriate for relatively basic systems that exhibit exactness and complete truth. More complicated issue domains, such as health, artificial intelligence, and agriculture, which involve ambiguity or nonlinear mapping, find hard computing problematic.

These difficulties with traditional computing in problem solving led to the development of a new set of calculation techniques known as "Soft Computing," which produces outcomes that are comparable to human capabilities. Soft computing is based on a variety of techniques found in a wide range of biological systems and is classified as Computational Intelligence.

Humans have strong control over reasoning tasks such as object recognition, categorization, estimate, and planning because to the sophisticated biological information processing system. Human information processing includes both logical and intuitive reasoning. To mimic human processing paradigms in computing systems, it must be able to adapt to changes in the actual world; moreover, most traditional automated systems fail because they are not consistent and tolerant with partial or imprecise inputs.

Soft computing, which operates on the same principles as its three primary branches, Artificial Neural Network (ANN), Fuzzy Logic (FL), and Genetic Algorithm (GA), has produced solutions that may be reasonably applied in real-world systems. Complex issues in natural language processing, picture classification, and handwritten text summarization have been solved utilizing a mix of these soft computing approaches. Because it is connected with unpredictable behavior concerning inputs and outcomes, soft computing can be an effective technique in tackling Agricultural domain challenges.

One cannot be certain of the crop requirements and time, as well as the amount of requirements; moreover, environmental elements represent ambiguity, resulting in challenges in modeling it with a specific theory or formula. Agriculture systems require continual updates to inputs and learning from prior experiences (data); they cannot be inflexible or consistent every time, for example. The estimating technique is based on continual crop monitoring and previous production experiences for the same field and variety. Because food supplements, temperature, and humidity are not consistent, systems must prepare appropriately.

Soft computing may play an important role not just in input management but also in post-harvesting procedures such as advanced production estimation and quality inspections. Production estimation deals with labor, transportation, and storage management, as well as market analysis.

OBJECT DETECTION AND CLASSIFICATION

ANNs have been utilized as a strong tool in scientific research and engineering applications to solve issues. The ANN approach has been widely used as a replacement for older methods. Classification, regression, pattern recognition, time series analysis, and function approximation are common ANN applications. With the advancement of computer power over the next decade or two, ANNs will continue to find new applications in agricultural and biological engineering as a strong alternative to traditional approaches.

Artificial neural networks performed well in experiments [14] for identifying weed from cultivated crop in field pictures. The characteristics of corn plant and weed were extracted in intensity form from digital pictures in the first phase, and a back propagation based neural network was trained to identify the images as weed and corn plant. The fully learned neural network was then utilized to distinguish the weed plant from the maize plant. In the trial, the maximum success rate of 100 percent was attained.

In a study [15] to estimate soybean and corn production in Maryland, an artificial neural network using a back propagation algorithm was constructed with a configurable learning rate and number of neurons in the hidden layer. The study compared the performance of the ANN model to that of the regression model and discovered that the ANN model was superior and more accurate than the regression model in forecasting soybean and corn production.

A review [16] of many uses and research of soft computing technology in agriculture. They cited research in crop management, irrigation techniques, soil analysis, chemical applications, and precision agriculture that used artificial neural networks, fuzzy logic systems, and genetic algorithms. Another research [17] investigated the use of several characteristics on pictures of horticultural items to recognize and categorize the products. To achieve the goal, a neural network classifier based on back propagation was created. The BPNN classifier based on color, texture, and morphological characteristics produced good results in the investigation.

For cereal grains, mango, and jasmine flowers, the average recognition and classification accuracies using color characteristics are 87.5 percent, 78.4 percent, and 75.7 percent, respectively. The study emphasized the effectiveness and accuracy of machine vision systems for item identification and classification. According to a study [17], paddy rice disease is a serious economic concern in Sri Lanka's agriculture industry. They performed studies to classify and identify the paddy rice illness. The study's main purpose is to build a method for detecting paddy illnesses.

Around 50 paddy rice pictures were segmented using color and other characteristics to extract illness spots on leaf, and the disease spots were classified to one of three categories of diseases using the membership function. The study's findings revealed a success rate of more than 70% in classification accuracy with 50 sample pictures. In [18], a study was done to identify the maturity of bananas into three categories: underripe, ripe, and overripe. The color histogram of the RGB values of the source picture was utilized as an input to the artificial neural network in the study. In all, 60 sample source pictures were collected in the study using a camera with a resolution of 2 mega pixels.

For artificial neural network learning, a 32-image training data set was employed. Following successful training, ANN was tested on 28 pictures, with final findings indicating a success rate of about 89 percent.

GRADING AND SORTING

The product grading process is an essential stage in the quality evaluation system. It not only marks the grades, but it also determines the relevance of the provided output in terms of money and labor. Grading necessitates professional knowledge and close examination of the provided output. The ultimate quality is established by evaluating the many grading factors. A high-quality product has a high demand as well as a high return rate. Quality assurance is the final but most critical step that must be followed by every production unit in industry or agriculture in order to fulfill industry or market standards.

In order to earn more money from agricultural goods, the agriculture industry must also meet quality requirements. The laws and regulations governing the import and export of agricultural goods are becoming more stringent. Countries conduct thorough product inspections while passing agricultural items. Traditionally manual inspection systems are now outfitted with cutting-edge soft computing techniques such as neural networks and fuzzy logic, as well as technologies such as computer vision and x-rays. Many studies have been conducted to demonstrate the efficiency and correctness of the automated grading or inspection process using these technologies. The following section discusses computer vision-based grading and inspection systems. Online fruit grading was tried [19] to categorize apple fruit within four quality levels. The investigation examined the quality of the apple based on exterior characteristics, and around 90% of the categorization was right. The fruit market is a significant shareholder in horticultural products. This section contains more studies on quality rating. According to the literature, machine vision has been largely and effectively utilized in several fruit grading systems in the past.

Author [20] did a research for apple fruit grading and deciding on one of four apple categories for approval as per European standards: 'I,' 'II,' 'Extra,' and 'Reject.' External characteristics of the apple, such as flaws, color, and size, were assessed for categorization. Using classification methods on two apple types, the study found a success rate of up to 78 percent and 72 percent for two selected kinds: Golden Delicious and Jonagold apples. Another study was carried out to grade apples using a fuzzy logic system [21].

The study [22] draws attention to the difficulties of high cost, time consumption, and inconsistency that arise with the human technique of sorting, resulting in the need for automated grading and sorting system fruits. A fuzzy inference system was built to evaluate apples using fuzzy sets specifying size, color, and faults of the source apples. When compared to the grading results of human experts, the automated grading system achieved a score of 89 percent.

CONCLUSION

This review focuses on several applications of computer vision in agriculture. Several research have been conducted to examine the application of computer vision and soft computing approaches for fruit detection, harvesting, and grading, according to the literature. Object identification or sorting methods are commonly used to conduct studies on fruit items. It has also been noticed that less research on flowers have been done in the past. There is relatively little information available for flower production estimate. During a survey of the literature, no studies involving computer vision or soft computing were discovered to be connected to floricultural production. Secondary data also highlight the importance of an automated production system in floriculture for improved information compilation and communication.

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