AIML and Remote Sensing System Developing the Marketing Strategy of Organic Food by Choosing Healthy Food

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Abstract: The growing demand for organic and healthy food products has prompted the need for innovative marketing strategies to educate consumers and help them make informed choices. This paper explores the integration of Artificial Intelligence and Machine Learning (AI/ML) technologies with remote sensing systems to develop a data-driven marketing strategy for organic food selection and promotion. By harnessing the power of AI/ML in analyzing remote sensing data, we aim to provide consumers with accurate information about the health benefits and quality of organic food products, ultimately contributing to healthier lifestyles and sustainable consumption. An emerging technology in agriculture is artificial intelligence. Tools and equipment powered by artificial intelligence have really raised the bar for the agriculture industry. This new technology has boosted immediate monitoring, processing, and collecting as well as crop yield. The most modern computerised systems that use drones and remote sensing have significantly improved the agricultural sector. Furthermore, by providing cyclic data on the state of the yield during the examined periods at various degrees and for various factors, remote sensing has the potential to promote the development of agricultural applications with the purpose of overcoming this major challenge. To determine many essential factors, such as plant detection, yield recognition, crop quality, and numerous other techniques, a variety of high-tech, computer-supported structures are developed. This study describes the methods used to analyse the data gathered in order to increase production, predict impending hazards, and lighten the strain on farmers.

Keywords: Food environment, obesity, food insecurity, food shopping, healthy food marketing.

I.INTRODUCTION

Finding efficient methods to encourage healthy eating and lower obesity rates is a top issue in the USA, especially for low-income and minority populations that frequently lack access to good food and have higher obesity rates. More stores are now present in low-income, ethnically diverse neighbourhoods as a result of efforts to increase food availability. However, this might not be sufficient on its own to lower food insecurity and enhance inhabitants' dietary quality and health. The design, procedures, first results, and supermarket in-store marketing plan compliance for a randomised experiment evaluating the effect of healthy food marketing on the purchase of healthier "target" food products are summarised in this report. On the basis of shop size and the percentage of sales from government food assistance programmes, 33 supermarkets in high-minority, low-income areas of the Philadelphia metropolitan region were matched and randomly allocated to the intervention or control group. Over 100 different food items were promoted using healthy marketing techniques for an 18-month period in 16 intervention stores, including increased availability of healthier "target" products, prominent shelf placement and call-out promotion signs, and decreased availability of regular "comparison" products. Bread, drinks from the checkout cooler, cheese, frozen meals, milk, and salty snacks were the six product categories examined. Weekly sales per store in each product category during the first year before the intervention and the subsequent 18 months of the intervention were the main outcome indicators.
Following the initial six months, compliance with the marketing strategy was evaluated once a month. Between the control and intervention stores, there were no discernible differences in the features of the store or the neighborhood.

The same six food categories were the subject of intercept surveys with customers to determine shopping preferences and analyses of the supermarket marketing environment to look at the food promotion environment. In intercept polls, 51.0% of customers admitted to being overweight and 60.6% said they desired to lose weight. Customers who frequently chose one meal type over another usually did so out of habit or because the product was on sale. According to the findings, there was no difference in preintervention sales of healthier "target" or regular "comparison" goods between intervention and control stores during the year before to the start of the intervention. In all 16 stores, compliance rates with the healthy marketing methods were strong, averaging 76.5% over the course of the first year. In community supermarkets, healthier in-store marketing initiatives should be implemented more widely if they prove successful in this scaled-up, longer-term research.

Various agricultural producers are actually trying to address the hazards and dangers associated with using pesticides in their crops to combat pests and other diseases. The farmers face a new problem as a result of the interaction of all these factors. Farmers are always under pressure due to a lack of available workers, the need to increase yields, and the dependence of agriculture on natural forces for the majority of its production and rain uncertainty [1]. This implies that in order for ranchers to succeed, agriculture must dramatically grow in the upcoming years, and agricultural productivity must almost double. Agriculture automation continues to be at the forefront of the world's pressing problems and worries. The population is growing rapidly, and with it, so is the demand for food and employment.

Currently, farmers' conventional practises cannot fulfil these objectives. Modern automated processes have been put in place as a result to make things easier and more effective [2]. Artificial intelligence is a technical advancement that can be used in agriculture. Consulting services for artificial intelligence, data analysis, the Internet, the use of cameras and other sensors, etc. are included in this category. The use of artificial intelligence in agriculture will advance to the point where it can analyse a variety of data sources, including weather, topography, crop yield, and temperature [3], and provide enhanced, anticipated insights. Such artificial intelligence-driven technology can help the agriculture industry produce more crops in the food supply chain and improve a wide range of agricultural tasks. These innovative methods have increased the world's food needs while creating employment possibilities for billions of people.

II. REMOTE SENSING IN AGRICULTURE

Physical approaches, empirical techniques, and a mix of both can be used as distant detection strategies for examining plant properties [3]. The radiative exchange theory serves as the foundation for most physical approaches, which use simulation designs to replicate plantlight linkages [4]. Empirical methods rely on the statistical relationship between data on plant reflectance and in-situ predicted vegetation parameters [5].

In general, combining the reflectance data of at least two distinct spectral wavebands to create the vegetation index (VI) is a common applied tool for establishing empirical relationships between plant features and spectral reflectance. For instance, the Normalised Difference Vegetation Index (NDVI) makes use of information from the red area with lower reflectance and the near infrared region with higher reflectance [6]. Since a long time ago, NDVI has been used to assess various vegetative characteristics, such as biomass and yield, to varying degrees [8]. The same is true for physically based vegetation indicators that are linked to vegetation biophysical properties [9]. The main remote sensing vegetation indicators for agricultural vegetation estimate are shown in Table 1.

Application	Symbol	Name	Formula
Assessment of the general state of vegetation	TVI	Triangular Vegetation Index	TVI = 0.5 × [120 × (R750 – R550) – 200 × (R670 – R550)]
	GNDVI	Green Normalized Difference Vegetation Index	GNDVI = (R860 – R550)/(R860 + R550)
Assessment of the amount of photosynthesis	REPI	Red Edge Position Index	REPI = 700 + 40 × {[(R670 + R780)/2 – R700]/(R740 – R700)}
	CTR2	Carter	CTR2 = R695/R760
Assessment of nitrogen content	NDNI	Normalized Difference Nitrogen Index	NDNI = [LOG(1/R1510) – LOG(1/R1680)]/[LOG(1/R1510) + LOG(1/R1680)]
Assessment of the amount of light used in photosynthesis	PRI	Photochemical Reflectance Index	PRI = (R531 – R570)/(R531 + R570)
	ZMI	Zarco-Tejada and Miller Index	ZMI = R750/R710
Assessment of the amount of dry biomass	PSRI	Plant Senescence Reflectance Index	PSRI = (R680 – R500)/R750
	NDLI	Normalized Difference Lignin Index	NDLI = [LOG(1/R1754) – LOG(1/R1680)]/[LOG(1/R1754) + LOG(1/R1680)]
	CAI	Cellulose Absorption Index	CAI = [0.5 × (R2000 + R2200)] – R2100
Assessment of water content	WBI	Water Band Index	WBI = R970/R900
	NDWI	Normalized Difference Water Index	NDWI = (R857 – R1241)/(R857 + R1241)
	DSWI	Disease water stress Index	DSWI = (R802 + R547)/(R1657 + R682)

Table 1. Remote estimation of crop fractional vegetation covers: the main remote sensing vegetation indicators.

The Enhanced Vegetation Index (EVI), one of these indices, is comparable to the Normalised Difference Vegetation Index (NDVI) and may be used to measure the greenness of vegetation [2]. EVI, however, compensates for some atmospheric factors, background noise from the canopy, and is more sensitive in densely vegetated regions. The Soil Adjusted Vegetation Index (SAVI) also has a structure that is comparable to the NDVI, but it also includes a soil brightness correction factor [4]. Additionally, the NDRE (Normalised

Difference Red Edge) index can only be created when a sensor has the Red edge band accessible. It is sensitive to variations in leaf area, soil background effects, and chlorophyll concentration in leaves (how green a leaf looks) [5].

Another way involves combining many spectral wavebands using multivariate statistical techniques to create a distinctive empirical prototype [7]. Additionally, empirical designs can be divided into linear (partial least squares regression, for instance) and nonlinear (support-vector machines, for instance) designs.

Although computationally quick and effective in recapitulating local knowledge, empirical approaches do have significant drawbacks [8]. These processes typically lack cause-and-effect connections, making it more challenging to relocate a design, research it at a different time, or even investigate it with a different spectrum detector without methodically recalibrating it. Physical approaches can be used to partially overcome the limitations of empirical methodologies [9]. Though computer-intensive, physical procedures occasionally require several input variables for calibration, and they require extensive parameterization before they can be used.

III.MACHINE LEARNING IN REMOTE SENSING

Remote sensing, the acquisition of information about the Earth's surface from a distance, has seen a significant transformation with the integration of machine learning techniques. This paper provides an overview of the applications of machine learning in remote sensing, including image classification, object detection, change detection, and more. We discuss the challenges faced in these applications and explore the potential for future advancements in this rapidly evolving field, where machine learning plays a pivotal role in unlocking valuable insights from remote sensing data.

First, in the 1990s, remote sensing used machine learning techniques. It was focused mostly on remote sensing as a way to computerise building that was based on cognition. Huang and Jensen's study described how a cognition-foundation was created with the least amount of user input, and how decision trees were then formed to comprehend the instructions from a single input for the specialised structure. They came to the conclusion that methods helped by machine learning offered more precision than conventional methods. As a result, similar advancements in machine learning were produced and were accepted as a crucial tool by professionals and scientists in remote sensing. It is now being used for a wide range of diverse tasks, including the organisation and the unsupervised satellite picture view classification. When using supervised prototypes, when the operator has created a preestablished marker with a set of attributes, there is a contrast between supervised and unsupervised learning.

Reinforcement learning is very different from the unsupervised method, which derives the data set by categorising the information into different groups based on the connections it has found between various pieces of data. The algorithm formulates options within the context provided by the operator, or setting. With each decision that is justified by the result of the preceding decision, it is always improving.

Artificial neural networks are used for remote sensing categorization because they are effective at handling large amounts of data and records from various sources [99, 100] and because scientific interpretations of this methodology may be useful for gathering and analysing image data. An Artificial Neural Network, when used for picture categorization, is a massively equally distributed processor made up of fundamental handling components that learns from its environment through a self-learning operation to adaptively build links between the input records, such as satellite imagery attributes, and the output records, such as target cover groups. The Multilayer Perceptron (MLP) [102], Kohonen's Self-Organizing Feature Map, and Fuzzy ARTMAP are prominent Artificial Neural Networks. Although the precise application of these approaches varies, it still requires organisation and training to distinguish critical information from remotely detected image data.

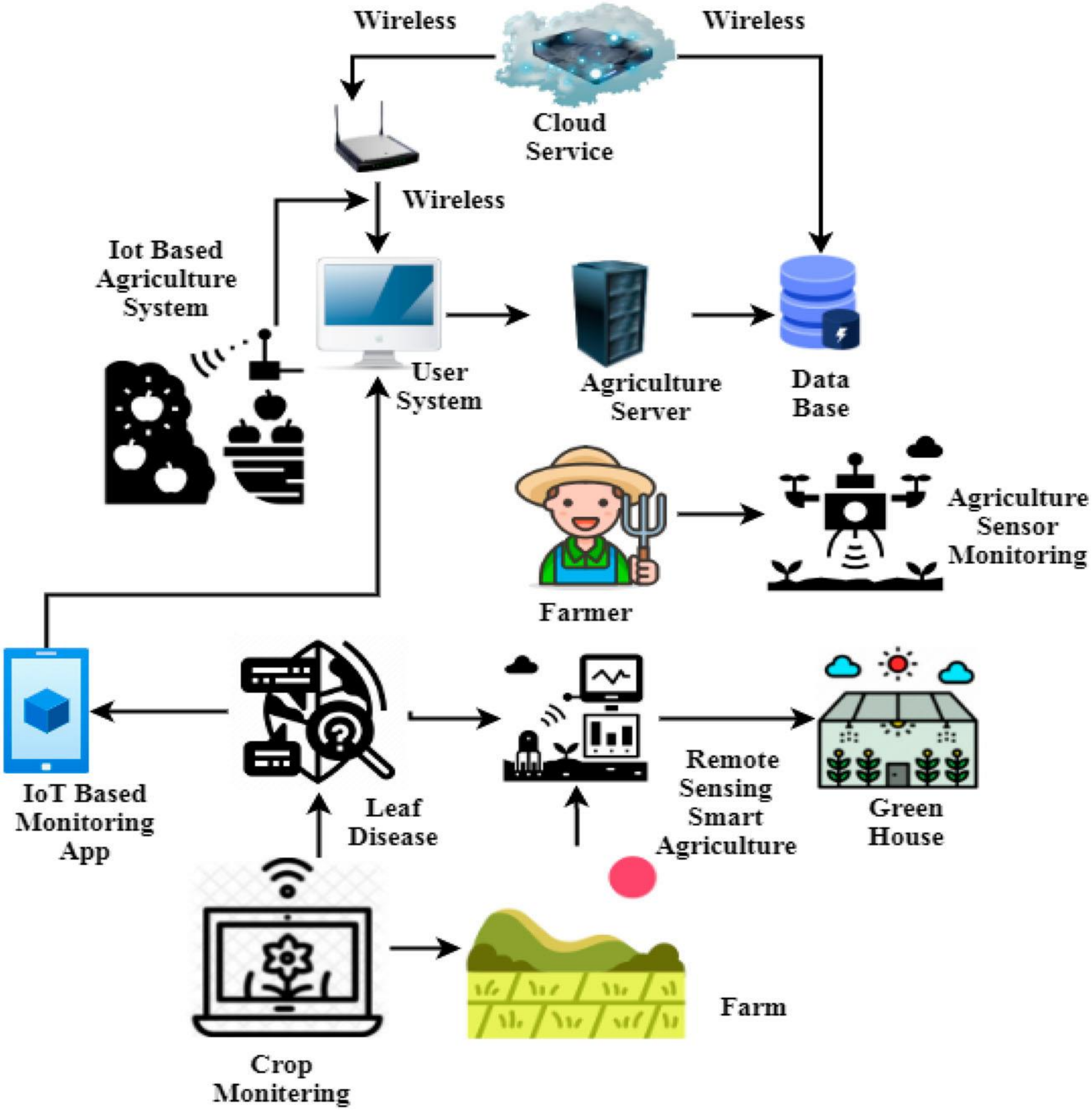

Figure 3. Remote Sensing in Smart Agriculture with IoT Technologies.

Remote sensing technology has revolutionized our ability to collect data about the Earth's surface and atmosphere using various sensors, including satellites, drones, and aerial platforms. With the increasing availability of high-resolution and multi-spectral data, machine learning has become an indispensable tool for extracting meaningful information and patterns from these vast datasets. Machine learning has significantly advanced the field of remote sensing, enabling the extraction of valuable information from vast and complex datasets. Despite challenges related to data availability, scalability, and interpretability, the future of machine learning in remote sensing looks promising. As technology continues to evolve, the integration of AI and remote sensing will play a pivotal role in addressing critical environmental, social, and economic challenges.

IV.MARKETING COMMUNICATION IN PROMOTING ORGANIC FOODS

Organic foods need a lot of advertising because they are a high-priced product category (Bezawada & Pauwels, 2013). In addition to this fundamental requirement, it has been noted that organic food brands must now be able to effectively differentiate their products beyond the organic label (Anisimova & Sultan, 2014). This observation is particularly pertinent for the processed organic sector, where most branding and packaging occurs and where the need for differentiation through marketing campaigns is greatest (Monteiro, 2009).

We were unable to find any studies on brand-driven communication strategies for processed organic foods despite this. In general, the amount of existing research on the use of marketing communication to promote processed organic foods is, at best, sparse and nonprogrammatic.
There have only been a few studies on this subject that have been published, and none of them have looked at how people's views of health are affected by advertising or any other type of mediated commercial communication.

Review of the organic food marketing literature by Hemmerling et al. (2015) demonstrates the extremely narrow focus of existing research on promotional communication for organic food items as well as how little actual analyses of messaging strategies exist. The number of publications is quite small when just papers that examine processed organic food are chosen from that body of knowledge. Hemmerling et al. (2015) discovered that the majority of research that were published in the organic food marketing literature concentrated on product labels. Only 30 articles regarding consumers' information and communication demands could be found. Of those, 14 focused on messaging techniques; none, however, addressed the influence of widely disseminated promotional communication, such as advertising, on consumers' views of the healthfulness of the products. There is obviously a need for more study on the marketing of processed organic foods.

V.CONCLUSION

These AI-based solutions are being employed to address a number of industrial goals, including those in finance, agriculture, medical, and transportation. The employment of artificial intelligence technologies has greatly improved the food production process. Artificial intelligence in agriculture supports producers in autonomous farming and culture in addition to enabling precision farming that improves crop production and quality while utilising scarce resources. Furthermore, remote sensing employs cutting-edge techniques that let ranchers keep an eye on their crops without having to personally monitor the land. Many businesses now anticipate the expansion of agriculture with AI support. Remote sensing and artificial intelligence reclassify the traditional farming paradigm by redefining common agricultural trends. The use of artificial intelligence in agriculture is rapidly developing with a wide range of sophisticated techniques thanks to thorough transformation. The integration of AI/ML technologies and remote sensing systems offers a powerful approach to develop a marketing strategy for organic food selection and promotion. By leveraging data-driven insights, consumers can make informed choices that prioritize health and sustainability. This approach not only benefits consumers but also supports the growth of the organic food industry and encourages more environmentally friendly agricultural practices. As technology continues to advance, the potential for enhancing food marketing strategies remains substantial.

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