2023 Annual International Conference on Emerging Research Areas: International Conference on Intelligent Systems (AICERA/ICIS) | 979-8-3503-0345-2/23/$31.00 ©2023 IEEE | DOI: 10.1109/AICERA/ICIS59538.2023.10420012

Research on Sustainable development of green energy and manufacturing in smart agriculture based on big data analysis

Maryam Ghassan Majeed
Technical Computer Engineering Department, Al-Kunooze University College,
Basrah, Iraq:
maryam.ghassanmajeed@kunoozu.edu.iq

Adnan allwi ftaiet
Department of Medical Devices Engineering Technologies, National University of Science and Technology,
Dhi Qar, Nasiriyah, Iraq:
adnan.alameri@nust.edu.iq

Laith Fouad
Medical instruments engineering techniques,
Al-farahidi University,
Baghdad, Iraq:
LaithFouad@uoalfarahidi.edu.iq

Naseer Ali Hussien
Information and Communication Technology Research Group, Scientific Research Center, Al-Ayen University,
Thi-Qar, Iraq
naseerali@alayen.edu.iq

Saad Qasim Abbas
Computer Technologies Engineering, Al-Turath University College,
Baghdad,Iraq:
saad.qasim@turath.edu.*iq*

***Abstract*— In response to global environmental changes, smart agriculture (SA) has emerged as a means of boosting agricultural output and the income of low-income communities. This article assesses the efficacy of SA strategies for advancing sustainable agriculture to ensure the availability of safe, nutritious food globally. It looks at how different aspects of SA work together to further the goals of sustainable agriculture. A deeper understanding of the intricate agricultural ecosystems is required to control the expanding issues in agricultural output. It's possible with today's digital technology, which can constantly monitor the physical surroundings and generate massive volumes of data at breakneck speeds. Farmers and companies might enhance output via the study of data. While big data analysis has been widely used in other sectors, it is still uncommon in agriculture. The study aims to examine current agricultural studies and research, which applies the newest big data analysis practices to deal with many important green energy challenges in smart agriculture by analyzing big data (GE-SABDA). Data analytics and the internet could boost safety and product quality while reducing production downtime. The experimental results show the proposed method achieves a rising green energy level ratio of 94.3%, overall accuracy of smart agriculture ratio of 90.7%, crop disease identification ratio of 98.1%, daily productivity ratio of 450, and production wastage ratio of 18.5% compared to other methods.**

Index Terms*— *Smart Agriculture, Big Data, Green Energy, Sustainable Growth, IoT

I. INTRODUCTION TO SMART AGRICULTURE

In agriculture, big data have great promise [1]. An appropriate understanding of big data can assist in solving farming difficulties and increase output and quality [2]. Farmers everywhere must use big data strategies to meet rising consumer demand for fresh produce [3]. Using big data, the agriculture and food industries can work together for the long haul [4]. Even though big data has been a driving force in agriculture, the relevant authorities, including policymakers, managers, researchers, and practitioners, have not paid enough attention to it [5]. Now is the moment to utilize sustainable agriculture's big data technology [6]. It offers a fresh vision for the study to preserve the link between big data and the practical application of agricultural data [7]. Rapid population expansion is currently a vital concern [8]. The issue of rapid population increase can only be met by expanding agricultural productivity [9]. Technology to enhance farm productivity [10] is the only key to quality and quantity. Big data technology can be an appropriate instrument for enhancing agricultural productivity and tackling future difficulties [11]. Additional challenges hinder increased output, such as slower productivity, arable scarcity, climate change, freshwater shortages, energy prices, and expanding urbanization [12]. Through clever technologies and devices like the IoT, cloud computing, and big data, these limits can help boost productivity [13]. Climate-smart, harvesting, postharvest, and marketing management for intercultural plant development are required. [14] Intelligent farming uses information and communication technology (ICT), modern machinery, the internet of things (IoT), cloud-based technologies, machine learning, and big-data analysis [15]. Modern technologies are trying to construct and promote robots and artificial information using IoT, cloud computing, and Big Data analysis [16]. Big data analytics, sensors, and global positioning system (GPS) services [17] are used in smart and accurate agriculture. Its financial gains, quality, and quantity use the most advanced technologies to optimize the penalty unit's sustainable return [18,19]. The main contribution of the paper is as follows. Designing the proposed GE-SABDA to focus on socio-economic elements in applying big data in farming, which considers practically all components of agriculture. The extensive data for sustainable agriculture are vital for planning and reducing obstacles to agricultural output. Green energy-smart big data agriculture (GE-SABD) has been proposed in this context to explore optimal and compatible techniques that can enhance productivity and quality for farmers at the field level. The experimental results show the proposed methods achieve rising green energy levels, overall accuracy of smart agriculture ratio, crop disease identification ratio, daily productivity, and production wastage compared to other methods. The remaining section of the document is structured as follows: The second section deals with the literature survey. The third section elaborates on the research methodology for smart green agriculture based on big data analytics on sustainable development. The next section discusses the experimental analysis results with significant discussions. The final section concludes the research with future scope.

II. BACKGROUND TO BIG DATA ANALYTICS

A quick study is carried out of various AI approaches used previously for adaptation in training. Fuzzy logic is an evolution of the standard probability theory since declarations may be incomplete realities that lie between ultimate fact and complete falsehood [20]. There's been a multi-agent participant classification scheme focused on fugitive logic. The application of fluid logic formally describes the subject model, the student version, and the required judgment. Neural networks consist of large sensory computers, analogous to artificial neural systems, which function together to process data [21]. It may be used for participant classification. Previous experiments showed the use of neural networks for study types. Each branching node makes a tree-based selection of options, and each binary tree makes a judgment. A decision tree algorithm was used to have customized pathways for learning [22]. A Network model is a generalized linear network wherein results indicate definitions, and borders signify dependences between theories on action and reaction .

III. PROPOSED SMART GREEN AGRICULTURE BASED ON BIG DATA ANALYTICS ON SUSTAINABLE DEVELOPMENT

Big data supplies farmers with precise rainfall pattern data, water cycles, requirements for fertilizer, and more. It allows them to make intelligent decisions like what crops to sow and when to harvest. Ultimately, the proper selections increase farm returns. Analytical tools can evaluate production potential based on weather, history, and farmers' information. These yield statistics allow farmers to enhance their crop management and boost yields. Farming data is highly significant since the content and the capacity to offer correct information and results for digital agricultural goods depend greatly on collecting various data sources. Agricultural data are pretty vital. Sustainable agriculture allows for the production of nutritious food without compromising the ability of future generations to do the same, according to updated statistics on the topic.

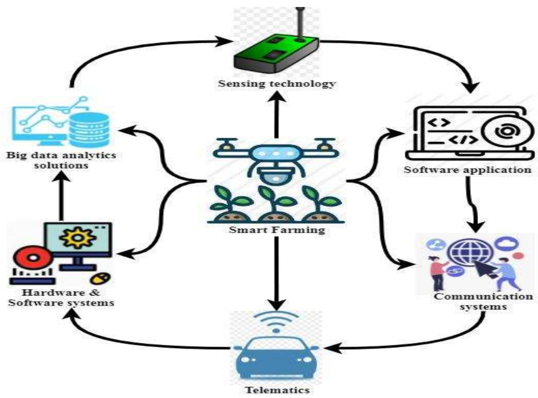

Fig. 1. Proposed Structure of smart agriculture

Figure 1 says smart farming is a concept of farm management that uses current ICT to optimize output quantity and quality. Modern farmers can access various sensing instruments, such as soil scanning, water, light, humidity, and temperature regulation. Software applications have specialized software solutions targeting specific types of farmers; cellular communication technology, positioning technologies, GPS; IoT solutions, robotics, and automation hardware and software systems; and data analysis underlying decision-making and prediction.

$$K = \left(-\int_{l=0}^{\infty} g(\emptyset) dl\right) * F_0 \tag{1}$$

As shown in equation (1) agriculture products have been calculated. Where K is agriculture products, l is some data, g is global information shared, $\emptyset$ as current product location, F_0 are food products. Intelligent farming is a development that focuses on using ICT in a cyber-physical farming cycle. New technologies like the Internet of Things and cloud computing can take advantage of the rise of agriculture, deploying additional robots and artificial intelligence.

$$J = \left(\iiint_{i=1}^{m} y_t * a_t * n_t\right) - \frac{25}{p} \tag{2}$$

As found in equation (2) agriculture product data has been evaluated. Equation 2 says J is a justification of product data, m is minimum devices used, i is several locations, y is power consumption, a is an area allocated, n is seeds feed, p is data permissible, t is period. Big data supplies farmers with precise data on precipitation patterns, water cycles, requirements for fertilizer, and more. It allows them to make intelligent decisions like which crops to sow and when to harvest.

Figure 2 shows that using intelligent sensors and devices on-field complements traditional agricultural operations. The architectural physical layer includes genuine sensors and gateways scattered over farms and greenhouse constructions. These systems include airborne drones, autonomous tractors, cattle-backed sensors, or implanted hub devices for communication between intelligent things or a central cloud. These tools are responsible for data sensing and help operate other devices to implement various cases of smart farming based on the data obtained. They collect data in real-time on things like weather, soil humidity, or bovine body temperature and then send that data to the cloud or the edge to aid AI-powered decision-making. The Edge computing layer is comprised of several different edge nodes.

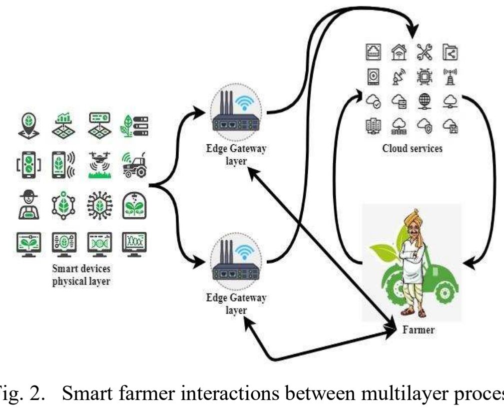

Fig. 2. Smart farmer interactions between multilayer process

Each node acts as a portal, providing access to various services such as information gathering, security monitoring, detection, prediction, and real-time decision-making aid. Services that gather, filter, encrypt, and encode data as it is being recorded are known as real-time streams. The cloud level is generally virtualized and communicates with lower levels online. These cloud layer platforms often follow the architecture paradigm PaaS where users can concentrate their activities on executing and importing applications. In an intelligent farming system, the network layer has two essential tasks. First of all, at every tier of a smart agricultural system, there are several heterogeneous instruments. The coating is essential for system-wide cyber communication, ranging from large data processing systems utilized to analyze the data gathered to individual sensors collecting information from the field.

$$E = (S * H) - \left(\frac{2\propto}{\theta}\right) ln\, ln\, (amp - N) * G \tag{3}$$

As expressed in equation (3), edge gateway product data has been explored. Where E shows edge gateway product data, S for several stocks, H for hybrid connectivity, θ if video surveillance $\propto$ is subnetworks, amp is amplitude to cloud services, N for a layer of networks, G is farmers gain. Intelligent research into agriculture aims to establish a decision-making system for farm management. Smart farming thinks it is essential to solving population increase and climate change and work, from planting and watering to health care and harvesting, which have received much technical attention.

$$A_w = \frac{s_o * d_o}{4} - \frac{r_o * (h_o - 2) * T_o}{3} + B_k \tag{4}$$

As obtained in equation (4), the average product growth weight has been deliberated. Where A is average product growths, w is weightage of product, s is a stage of development, o is outcome period, d is data, r is rainwater, h is harvesting time, T total product, B is body temperature, k is kelvin. It is a network of various devices that form a network for themselves. Smart farming's new advances with its usage of IoT alter old processes by optimizing them, lowering crop waste, and making them cost-effective.

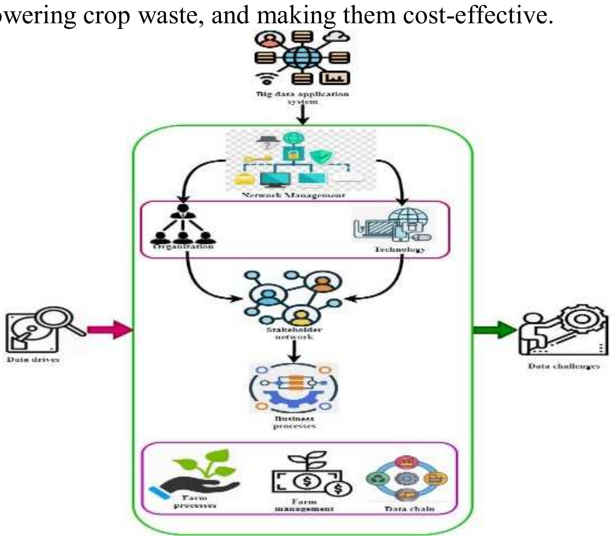

Fig. 3. Big data smart agriculture framework

Figure 3 denotes the proposed framework. Business processes are centered on generating and using big data in agricultural process management. This integration happens when the area is divided into the data chain, farming, and farming processes. Agricultural operations and farms interact with the data chain, which provides crucial information for multiple decision-making processes. The stakeholder network incorporates all parties involved in these processes, from end-users of big data to data management experts to policymakers and regulators. The next layer, network management, defines the network's organizational and technical frameworks, making it simple to coordinate and manage the activities of the many stakeholders involved in the network. The network management software section focuses on the information delivery network's data chain. Management of the data chain and the business model are the main concerns of the business section. Finally, several potential sources of development-related issues may be recognized as major drivers of big data development for smart farming.

$$D(C) = \frac{1}{j}\sum_{u=1}^{j}\left[P(Y^u) + \sigma P\big(\mu(W), \mu(C)\big)\right] \tag{5}$$

As demonstrated in equation (5), data drives challenges data has been examined. Where D is data drives, C is challenged in data, j for data chain, u is users, P for policymakers, W is stakeholders share, Y is a business frame, σ is standard deviation, μ is the mean value. In many ways, technology and IoT can change agriculture. There are five ways in which IoT might enhance farming: data acquired by intelligent farm sensors, masses of data, e.g., weather conditions, quality of the soil, progress in crop development, or the health of livestock.

$$\tau^{(v)} = exp\, exp\left(-\frac{\left(x^{(v)} - x\right)^2}{2q^2}\right) * \hat{\phi}(X^e RX)^{-1} X^e RX \tag{6}$$

Equation 6 refers to τ for farming process, v is organization value, x is several organizations, q is quality of the report, X is technological uses, R is reputed value in society, e is expected value, $\hat{\phi}$ is the variance of farms. A data-driven approach to crop control, maximizing production, optimizing the supply chain, and reducing food waste.

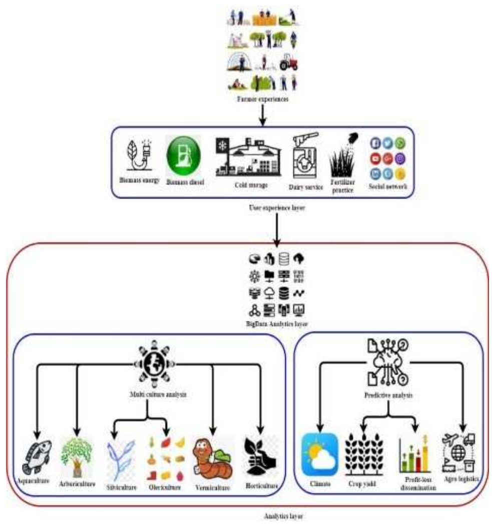

Fig. 4. Framework of farmer interactions in big data analytics

Figure 4 refers to the layer user experience as the highest layer intended entirely for the farmer's personal experience. Cold storage is utilized in several seasons to keep the crops for consumption. Comportement study and cold storage pattern analysis can raise farmers' profit-generating. Integrating the IoT framework with dairy services like milk production, dairy filtration, marketing, cow sickness management, etc., results in substantial financial and economic benefits. When intelligent grids can connect, regulate, and control power use, biopower production using an IoT framework may be implemented. Bio-diesel is a renewable fuel that natural processes may break down. Farmers may evaluate the quality of the rich soil to see whether it will support healthy plant growth. Farmers may participate in social network activities and communicate with neighbors on the politics and economics of agriculture.

$$Q_b = \sum_{j=0}^{m} \beta_j * \left(\frac{y_j - y_j^*}{f_j^*}\right), \quad b = 1,2, \ldots\ldots Q \tag{7}$$

Equation 7 specifies Q as crop quality, b as the base of seeds, m is milk quantity, β is fertile selection, y is economic value, f is farmer income. The primary purpose is to produce decent crops and healthy animals to help the population live and eat. All crops and cattle required to exist are the responsibility of farmers. The world would slowly perish without food, and farmers would work daily to maintain lots of crops and animal goods on the market to prevent it.Big data processing is done in the analytics layer to needs. Vermicomposting is an organic fertilizer produced during vermicomposting. The importance of forests to human survival cannot be overstated. The careful management of forest planting, growth, composition, health, and quality may meet the needs of a diverse population. The forestry process may be boosted by utilizing environmental data analysis with big data. Plants that live for many growing seasons are the focus of arboriculture. Predicting the growth rates of vegetable plants using human civilization's food consumption data.

$$a = \frac{1}{(u^M r + c)} - \sum_{n \in r}(z_n) + k_n \tag{8}$$

Equation 8 refers to a is the analytics of products, u is vehicles used, M is the cultivation process, c is stricture, r is Vermiculture value, z is earthworms production, n is many cultivations, k for food consumption. A farmer can cultivate crops for the consumer market, medical usage, production of animal feeds, and the developing herbal sector. A farmer can carry out crop planting, fertilization, and harvesting and transport them to the correct production lifts for sale during harvest.

Figure 5 says the service layer supported by the IoT cloud plays a significant role in offering cloud storage and SaaS apps for agriculture challenges. Data and equipment identification of sensors is collected, information on agricultural illnesses is stored, and statistical analysis is provided to simplify disease detection, action, and identification. The aim is to provide value from farm data, including livestock management, crop planting management, pesticide control, and autonomous bovine gaze monitoring.

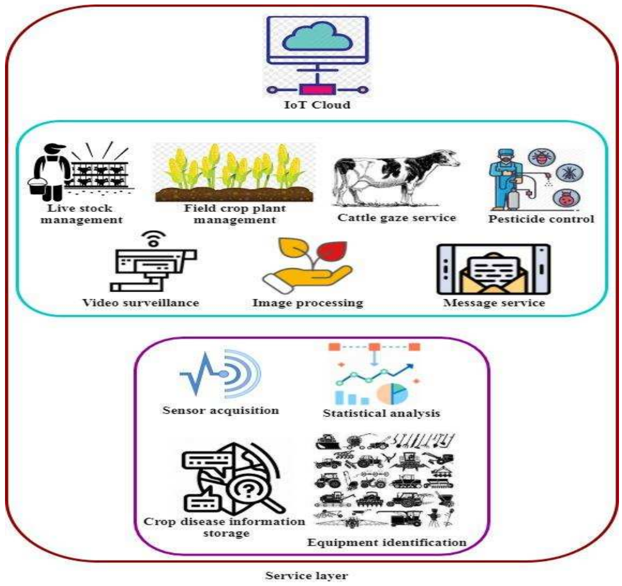

Fig. 5. Structure of IoT services in smart agriculture – stage 1

Agricultural companies can obtain information through online, messaging, and specialized services. The data provided in the real-time tracking of on-demand services is an image and video analysis. For example, farmers want the cattle on the field, virtual imaging on the soil and bug penetration in the area, etc., to know about. The web-based control panel uses the farmers' requirements to solve various services. Web-based control systems

$$C_b = (\textstyle\sum_V O_V) * \gamma\delta + (1-\gamma)n_p \tag{9}$$

Equation 9 shows C as crop plantation, b as a battlefield, O as pesticide control, V as message services, γ as sensing products, δ as virtual image store, n as a panel, p is equipment count. In smart IoT agriculture, sensors are constructed to monitor the agricultural field. It enables farmers to monitor the conditions in the area from anywhere. In comparison to the conventional methodology, IoT-based smart farming is very efficient. The major factors of irrigation in agriculture are unpredictable and variable monsoon rainfall.

$$h = \frac{d_c}{3} + (U * M_7^l) + \left(\sum \; md_\vartheta\right) \tag{10}$$

Equation 10 is mentioned as $h$is image of products analysis, d is detecting crop, c is crop disease, U is unknown plants, M is soil value, m is the mean value of soil, ϑ is sensor acquisition. Data can be used for real-time monitoring and performance tracking. High output can therefore be reached. Strategies for practical water usage, including technological, agronomic management, and institutionally enhanced technology, must be established urgently. The implementation requires employing a microcontroller-based board to employ a water management system. PC-specific software interfaces the board and regulates the engine on/off times. The data from the controller is sent at a fast speed.

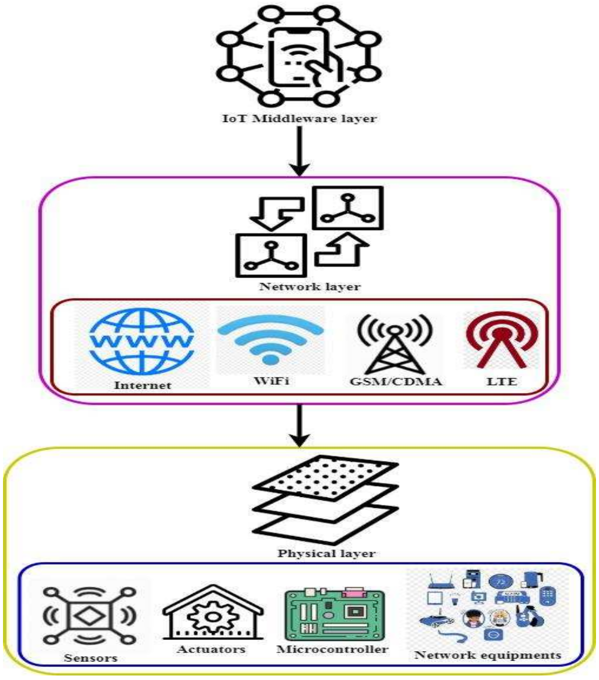

Fig. 6. Structure of IoT services in smart agriculture – stage 2

Figure 6 mentions the structure of IoT services in smart agriculture – stage 2. It comprises many sensors, actuators, Microscope modules, and other network devices like gateways, routers, switches, etc. It is a physical layer. These are the environmental conditions, activity by the set tasks, and the overall terrain. Microcontrollers are key elements of a network and another functionally controlled layer (done by sensors and actuators). The main aim of the layer is to transport the processed root-level data to higher layers of abstraction. The network layer includes the internet and other communications technologies. The most widely utilized agricultural applications are Wi-Fi, GSM, CDMA, and LTE (4G). Without GSM/CDMA/LTE services, ZigBee is one of the best solutions to communicate vast distances. The HTTP, WWW, and SMTP protocols are suitable for agricultural use. The IoT-based middleware layer performs device management, context-sensitivity, interoperability, portability of platforms, and related security duties. The ideal ways to incorporate security and user privacy in architecture are several types of software, such as HYDRA, UBIWARE, UBI ROAD, or SMEPP. In addition, SOCRATES, GSN, SIRENA, and so on.

IV. PERFORMANCE EVALUATION

In short, the portfolio based on Big Data analytics has grown over the last decade to implement and scale up SA on scientific and analytical tools for supporting strategic and tactical decisions in individual farms. Initially, developments occurred separately across climate change, genomics/phenomics, and agricultural decision support systems. The paper investigates the potential of big data analytics to quicken SA's research and development processes. Farmer field-level insights and practical information for the practice of SA may be improved with the use of big data. Increased productivity, climate change adaptation, and mitigation can be achieved through (i) accelerating plant breeding for greater climate resilience, (ii) providing individualized and prescriptive real-time farm knowledge, and (iii) developing a predictive capability to factor climate change effects to scales relevant to farming practice

A. Identifying the crop disease in agricultural land:

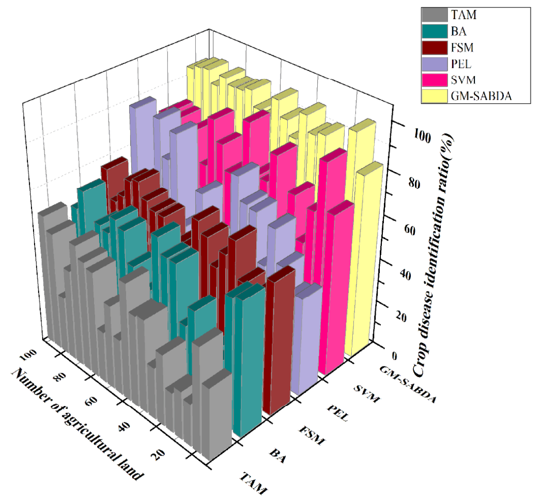

Fig. 7. Crop disease identification ratio

Figure 7 identifies the crop disease and explains that plant diseases represent a major yield and a quality limit for farmers of broadacre crops. Fungal, bacterial, viral, or nematode plant diseases can damage a plant above or below the earth. Identifying symptoms and determining when and how illnesses might be controlled efficiently is a continuing struggle. The crop conditions can be recognized by the black, water-soaking lesions of trees, leaves, or fruit that grow from diseased plants. Advanced disease detection and prevention in crops is necessary to limit the harm caused to crops through growth, harvest, and postharvest and enhance productive activity while ensuring agricultural sustainability.

B. Reducing the production wastage

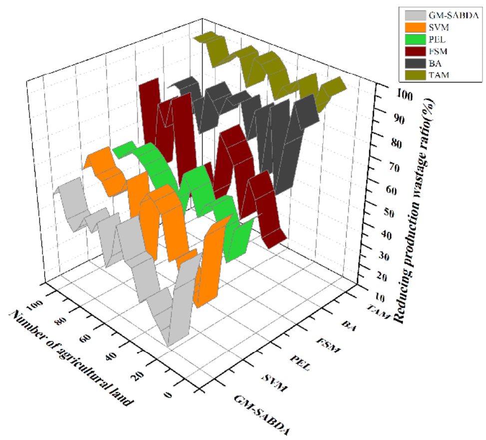

Fig. 8. Production wastage ratio

Figure 8 shows the reduced production wastage. The decrease in waste begins with knowing what is purchased and how items are used. It is then used to develop strategies for removing, reducing, reusing, and recycling materials. Essential elements in the waste stream and the initial straightforward reduction procedures must be targeted as a solid approach. Buy things using recycled or renovated components.

V. Conclusion and Findings

Increased agricultural production compels farmers to rely more and more on different types of energy to improve productivity. Agriculture can only increase energy usage. Due to current climate-change worries, energy efficiency-enhancing technique like intelligent farms is becoming popular. During growing, the crop is monitored continually by sensors. Here, the sensing model as in fertilization is adopted. In the case of estimated returns not reaching the objective, intervention through fertilization and irrigation might be done. The yield estimate can be generated by connecting the historical metrics using biomass estimations using reflectance measures. However, a national big data innovation ecosystem has to be created that integrates diverse, dynamic, and dispersed data sets and analytical tools, which improve the finding of the information to apply SA. Finally, digital and smart climate agriculture is possible with the latest approaches to data science, technology, and integrated agricultural systems, to be linked, data-driven, and customized (to farmers/farmers).

References

[1] Wang, F., Gong, Z., & Shao, Y. (2022). Incomplete Complex Intuitionistic Fuzzy System: Preference Relations, Expert Weight Determination, Group Decision-Making and Their Calculation Algorithms. Axioms, 11(8), 418.

[2] Sekaran, K., Meqdad, M. N., Kumar, P., Rajan, S., & Kadry, S. (2020). Smart agriculture management system using internet of things. Telkomnika, 18(3), 1275-1284.

[3] Andronie, M., Lăzăroiu, G., Iatagan, M., Hurloiu, I., & Dijmărescu, I. (2021). Sustainable Cyber-Physical Production Systems in Big Data-Driven Smart Urban Economy: A Systematic Literature Review. Sustainability, 13(2), 751.

[4] Al-Turjman, F., & Alturjman, S. (2018). Intelligent Positioning for Precision Agriculture (PA) in Smart-cities. Intelligence in IoT-enabled Smart Cities, 189.

[5] Jamwal, A., Agrawal, R., Sharma, M., Kumar, A., Kumar, V., & Garza-Reyes, J. A. A. (2021). Machine learning applications for sustainable manufacturing: a bibliometric-based review for future research. Journal of Enterprise Information Management.

[6] Hemalatha, P., Dhanalakshmi, K., Matilda, S., & Anand, M. B. (2018). Farmbot-a smart agriculture assistor using internet of things. International Journal of Pure and Applied Mathematics, Special Issue, 119(10), 557-566.

[7] Islam, N., Rashid, M. M., Pasandideh, F., Ray, B., Moore, S., & Kadel, R. (2021). A Review of Applications and Communication Technologies for Internet of Things (IoT) and Unmanned Aerial Vehicle (UAV) Based Sustainable Smart Farming. Sustainability, 13(4), 1821.

[8] Vangala, A., Das, A. K., Kumar, N., & Alazab, M. (2020). Smart secure sensing for IoT-based agriculture: Blockchain perspective. IEEE Sensors Journal.

[9] Kumar, M. S. (2021). Design and development of automatic robotic system for vertical hydroponic farming using IoT and big data analysis. Turkish Journal of Computer and Mathematics Education (TURCOMAT), 12(11), 1597-1607.

[10] Saravanan, V., Santhi, R., Kumar, P., Kalaiselvi, T., & Vennila, S. (2013). Effect of forest fire on microbial diversity of the degraded shola forest ecosystem of Nilgiris Eastern Slope Range. Research Journal of Agriculture and Forestry Sciences, 1(5), 5-8.

[11] Zhang, Y., Mao, Y., Jiao, L., Shuai, C., & Zhang, H. (2021). Eco-efficiency, eco-technology innovation and eco-well-being performance to improve global sustainable development. Environmental Impact Assessment Review, 89, 106580.

[12] Więckowski, J., Kizielewicz, B., & Sałabun, W. (2023). Handling decision-making in Intuitionistic Fuzzy environment: PyIFDM package. SoftwareX, 22, 101344.

[13] Feroz, A. K., Zo, H., & Chiravuri, A. (2021). Digital transformation and environmental sustainability: A review and research agenda. Sustainability, 13(3), 1530.

[14] Nasir, I. M., Bibi, A., Shah, J. H., Khan, M. A., Sharif, M., Iqbal, K., ... & Kadry, S. (2021). Deep Learning-Based Classification of Fruit Diseases: An Application for Precision Agriculture. CMC-COMPUTERS MATERIALS & CONTINUA, 66(2), 1949-1962.

[15] Ullah, A., Pinglu, C., Ullah, S., Abbas, H. S. M., & Khan, S. (2021). The role of e-governance in combating COVID-19 and promoting sustainable development: a comparative study of China and Pakistan. Chinese Political Science Review, 6(1), 86-118.

[16] Hsu, T. C., Yang, H., Chung, Y. C., & Hsu, C. H. (2018). A Creative IoT agriculture platform for cloud fog computing. Sustainable Computing: Informatics and Systems, 100285.

[17] Sheron, P. F., Sridhar, K. P., Baskar, S., & Shakeel, P. M. (2019). A decentralized scalable security framework for end - to - end authentication of future IoT communication. Transactions on Emerging Telecommunications Technologies, e3815. https://doi.org/10.1002/ett.3815

[18] SANCHEZ, JM, RODRIGUEZ, JP, & MONTENEGRO, CE (2020). The relevance of climate variability in the formulation of agricultural public policies in tropical countries. ESPACIOS Magazine, 41 (08).

[19] Production. Indian Journal of Science and Technology, 9, 28.

[20] Maddikunta, P. K. R., Hakak, S., Alazab, M., Bhattacharya, S., Gadekallu, T. R., Khan, W. Z., & Pham, Q. V. (2021). Unmanned aerial vehicles in smart agriculture: Applications, requirements, and challenges. IEEE Sensors Journal.

[21] Riley, C., Vrbka, J., & Rowland, Z. (2021). Internet of Things-enabled Sustainability, Big Data-driven Decision-Making Processes, and Digitized Mass Production in Industry 4.0-based Manufacturing Systems. J. Self Gov. Manag. Econ, 9, 42-52.

[22] Orjuela, K. G., Gaona-García, P. A., & Marin, C. E. M. (2020). Towards an agriculture solution for product supply chain using blockchain: case study Agro-chain with BigchainDB. Acta Agriculturae Scandinavica, Section B—Soil & Plant Science, 1-16.