Review on AI-Based Recognition of Earthworm Health and Vermicompost Quality Assessment

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Abstract—**Earthworms being one of the essential bioindicators of soil fertility and overall ecosystem health, have made a significant impact on the organic waste decomposition process and nutrient recycling through vermicomposting. The conventional methods for measuring earthworm vitality and compost quality are primarily based on manual observation and laboratory analysis, which are time-consuming, subjective, and inefficient for large-scale or real-time monitoring. To a large extent, the breakthroughs in Artificial Intelligence (AI) in computer vision, deep learning, and IoT-based sensing have facilitated the development of automated systems for health detection, movement pattern recognition, and vermicompost quality evaluation. This review presents a systematic assessment of AI-driven techniques for recognizing earthworm health and assessing vermicompost quality. It signifies the contribution of image-based classification, sensor data analytics, and predictive modeling to the monitoring of morphological, behavioral, and physicochemical parameters. This research also explores the availability of datasets, algorithmic frameworks, and hybrid models that integrate AI with the IoT and spectral analysis. Ultimately, it discusses issues such as data scarcity, model interpretability, and system scalability, in addition to outlining future research directions for sustainable, automated vermicomposting systems that utilize AI.**

Index Terms—**Earthworm health, vermicompost quality, Artificial Intelligence, Deep learning, computer vision, smart agriculture, Internet of Things**

I. INTRODUCTION

Earthworms are sometimes called "ecosystem engineers" due to their significant impact on soil structure, soil fertility, and nutrient cycling. Their burrowing and eating habits not only aid in soil aeration but also break down organic matter, thereby enhancing the reproduction of microbes and improving the physical and biological quality of the soil. Earthworms are indispensable in the ecological agricultural system, as they assist in producing humus, increase nitrogen mineralization, and enhance water retention. The condition and population changes of earthworms are universally accepted as major bioindicators of soil quality and general environmental health. Thus, examining their physiological and behavioral health can provide a clear picture of soil wear, pollution levels, and the overall functioning of land-based ecosystems.

Vermicomposting is a biotechnological method that utilizes earthworms to decompose organic waste, producing nutrient-rich compost through a biological process. The process reduces the volume of organic waste to zero. Still, in return, it yields a high-quality biofertilizer rich in essential macronutrients, containing beneficial microbes, and featuring plant growth-promoting hormones. From the perspective of a circular economy and sustainable agriculture, vermicomposting can be considered a cost-effective and environmentally friendly method for managing organic waste from urban, agricultural, and domestic sectors. Nevertheless, the quality of vermicompost is dependent on various factors, including substrate composition, environmental factors (such as temperature, moisture, and pH), and the physiological health of the earthworm species used (e.g., Eisenia fetida and Eudrilus eugeniae). Therefore, the condition of the earthworms and vermicompost parameters should be monitored appropriately to ensure the process is efficient and the product is of good quality.

The traditional methods used in determining the health of earthworms and the quality of vermicompost are heavily reliant on visual inspections, chemical assays, and laboratory tests. These methods require significant human labor, are subjective, and are not suitable for continuous or large-scale monitoring. As precision agriculture and smart farming gain more attention, the demand for automated systems that can provide real-time, data-driven evaluations is becoming more urgent. Artificial Intelligence (AI), specifically machine learning (ML) and deep learning (DL) techniques, offer excellent solutions for handling complex biological data, finding patterns in images or sensor data, and making accurate predictions with little human involvement. When AI is combined with imaging, spectroscopy, and Internet of Things-based sensor networks, the system can instantly identify unhealthy worms, recognize abnormal activity patterns, and even determine the maturity and nutrient content of the compost. This automation not only enhances the accuracy of the process but also enables scaling up, repeating the process, and maintaining sustainable operations.

While the use of AI in farming and environmental monitoring has been on the rise, the question of AI application for the health of earthworms and the quality of vermicompost has not received much attention in research. Most published research has focused on predicting soil parameters, assessing crop health, or determining compost maturity, without considering the biological health of the organisms involved in the process. The absence of standardized datasets, automated recognition systems, and AI models designed explicitly for vermiculture creates a bottleneck. Additionally, the health condition of the worms can be assessed by their body structure, changes in movement, color, and reaction to stimuli, thus requiring highly sophisticated image- and sensor-based modeling techniques capable of detecting minor differences under various environmental conditions. As such, a detailed overview of AI-powered methods that tackle both the biological (earthworm health) and material (vermicompost quality) sides is needed. The present report serves as a link by reviewing existing research trends, highlighting technological challenges, and providing hints of possible innovations in this new interdisciplinary field.

A. Paper Contributions and Organization

This paper presents a detailed review of Artificial Intelligence applications for recognizing earthworm health and assessing vermicompost quality. The significant contributions of this study are summarized as follows:

1. This review provides a scientific overview of earthworm physiology and vermicomposting mechanisms relevant to health and quality evaluation.
2. It categorizes and reviews existing AI, machine learning, and deep learning methods applied to image-based recognition, sensor data analysis, and quality prediction.
3. It compares various models and techniques in terms of performance metrics, datasets, and application domains.
4. It identifies key research gaps, such as limited data availability, model generalization issues, and a lack of integration between biological and physicochemical parameters.
5. Future research directions are proposed, including hybrid AI-IoT frameworks, multimodal data fusion, and edge AI deployment for real-time monitoring.

II. LITERATURE SURVEY

Sharma and Garg (2018) [1] studied the vermicomposting of rice straw and paper waste using Eisenia fetida, with cow dung serving as the bulking agent. Nine different feed ratios were tried for 105 days. The data revealed that the nutrient content (N, P, K) increased remarkably due to vermicomposting. At the same time, the total organic carbon was reduced (17–58%) along with the C: N ratio (19–102%), which is a clear indication of mineralization. The growth of the best worm (15.7 mg/worm/day) was recorded in a mixture of 90% cow dung and 10% rice straw; however, growth was hampered in the case of high rice straw content. The SEM results also supported that the material was more fragmented and stabilized. The research demonstrated that co-vermicomposting is an effective method for converting agro-waste and paper waste into nutritionally rich organic fertilizers.

Ramazanoglu (2024) [2] investigated the impact of varying vermicompost application rates on wheat growth, soil enzyme activity, and nutrient uptake using thermal imaging. Various treatments, ranging from 2 to 8 Mg ha^{-1}, significantly promoted the activities of β-glucosidase, urease, and catalase, which are strong indicators of improved soil biological health. Thermal imaging was used to confirm that leaves had lower temperatures, indicating the transpiration process was more efficient, and the plants received better growth.

The 6 mg ha^{-1} treatment resulted in maximum dry weight of the crop and nutrient accumulation, especially N, P, Zn, and Fe. The correlation and PCA analyses highlighted a strong connection between enzyme activity and plant performance. This research presents a compelling case for the use of vermicompost as a solution to soil infertility, thereby enhancing crop productivity while maintaining a balance with nature.

Pathma and Sakthivel (2012) [3] published a comprehensive review on microbial diversity in vermicompost, focusing on the key functional bacterial roles and their benefits for agriculture and the environment. The review sheds light on the mechanism by which earthworms and their associated microbes not only accelerate the degradation of organic waste but also enrich the soil and make it more fertile by suppressing pathogens. Several bacterial groups, including Bacillus, Pseudomonas, Rhizobium, and Actinobacteria, have been recognized as significant sources of plant growth through the production of hormones, enzymes, and antibiotics. Additionally, the research examines the role of vermicompost in controlling diseases, stabilizing metals, and managing biomedical waste. The review presents the process of vermicomposting as a biotechnological model driven by microbes, which is highly resource-efficient in waste recycling, improves soil health, and promotes clean crop production.

Alavi et al. (2019) [4] studied the destruction of tetracycline antibiotics-tetracycline (TCH), chlortetracycline (CTC), and oxytetracycline (OTC)-during the co-composting of chicken manure and bagasse. The research recorded removals of up to 99.5% in 56 days and found a 14% bagasse mixture as the best blend for both microbial activity and thermal stability. The degradation kinetics were well described by both the first-order and availability-adjusted kinetic models with corresponding half-lives of 8, 5, and 4 days for TCH, CTC, and OTC, respectively. An artificial neural network (ANN) is a suitable model for the degradation process, with signaling time identified as the most influential factor. This work proposes a cost-effective and environmentally friendly measure for reducing antibiotic residues.

Kumar et al. (2014) [5] conducted an assessment of the maturity of vermicompost produced from flower waste using Eisenia fetida and biofertilizer inoculants, employing SEM, paper chromatography, PCA, and cluster analysis. The research observed a decline in pH, total organic carbon, and the C: N ratio, along with an increase in nitrogen, phosphorus, potassium, and magnesium, thereby confirming nutrient enrichment and compost maturity. The scanning electron microscope revealed the porous, fragmented structures, while the chromatographic patterns signaled the presence of humus and mineralization. Principal Component Analysis distinguished the mature compost samples (E2 and E5) from the control ones, thus confirming the progression of the decomposition process. This research has convincingly demonstrated that SEM and chromatography are reliable tools for assessing the stability of vermicompost, nutrient transformation, and compost maturity during biodegradation.

Meghwanshi (2024) [6] focused on how artificial intelligence (AI) could transform vermicomposting through the integration of automation, predictive analytics, and intelligent optimization of the vermicomposting process. The research explains how AI-enabled sensors enable real-time monitoring of temperature, moisture, and pH, thereby ensuring optimal conditions for composting. Machine learning models can forecast the optimal feeding times and environmental conditions, while computer vision can be utilized for waste sorting and estimating compost quality. The AI-driven optimization of feedstock blends enhances nutrient balancing and accelerates the decomposition process. Continuous learning algorithms can further improve the process control. This research highlights AI as a powerful change agent that can increase productivity, reduce labor costs, and make organic waste management more sustainable and data-driven.

Oyege and Bhaskar (2023) [7] analyzed in detail the usage of earthworm excreta (VC) in the improvement of soil fertility, crop productivity, and keeping the environment clean. The primary benefit of VC, as depicted in the paper, is that it enhances nutrient availability, enzyme activity, and microbial diversity, while simultaneously reducing soil degradation and carbon dioxide emissions. The benefits of these crops have been evidenced in maize, wheat, rice, barley, and millet. Besides fertilizers, some products, such as humic substances and vermicompost tea, have also found their way into the market as the next generation of pest-free, drought-tolerant, and soil heavy metal clean-up agents. The paper also argued that it remains puzzling in large-scale farming how to optimize the use of VC, and how to get microbes to work in total harmony for sustainable and integrated crop management.

Kujawa et al. (2020) [8] proposed a machine learning method using a convolutional neural network (CNN) to spot the earliest maturity of compost made from sewage sludge and rapeseed straw. Their research involved 1312 images taken under visible, ultraviolet (UV), and mixed light conditions. They trained 25 different CNNs with various filter configurations. The model with 16 filters and mixed lighting was the most effective, resulting in a minimum classification error of 0.51. In this particular scenario, the CNN was capable of differentiating the maturity levels of compost in a non-invasive manner, thereby being more effective than traditional methods. The research serves as a proof of concept for CNNs as a fast and cost-effective means of evaluating compost quality, which in turn leads to improved waste management and a cleaner production process in the field of organic waste recycling.

Yılmaz et al. (2022) [9] experimented on the co-composting of tea waste (TW) and food waste (FW) by employing Radial Basis Function Neural Networks (RBFNN) and Genetic Algorithm (GA) for modeling and optimization. This paper focused on the losses of nitrogen, organic carbon, and moisture content resulting from varying the tea waste content from 0% to 40%. From the results, it is evident that the 25% tea waste mixture (TW) brought about the minimum nitrogen (26.8%) and organic carbon (40.1%) losses, making the compost more stable. The RBFNN models demonstrated better predictive capabilities than the other models used in this study (RSM, SVR, and FFNN), achieving high accuracy (MAPE less than 3%) in their predictions. The GA optimization identified a 24–25% range of tea waste as the optimal. This research provides evidence of the power of AI in optimizing the composting process for sustainable solid waste management.

Manley et al. (2022) [10] analyzed 56 studies in detail that applied machine learning (ML) and big data to solve issues raised in ecosystem service (ES) research. Specifically, these issues included data scarcity, uncertainty estimation, and socio-ecological modeling. The review showed significant growth in the application of ML and big data since 2017, primarily due to supervised algorithms such as Random Forests and Bayesian networks. Additionally, numerous useful cultural services mapping tools can be derived from analyzing social media and crowdsourced data. ML is a powerful ally in the fight against modeling uncertainty and in making predictions more accurate, whereas big data primarily focuses on filling information gaps. Moreover, the authors indicated that there is also a great need to bring these technologies to less developed areas, so that they can benefit from sustainable ES management as well.

Lyberatos and Lyberatos (2025) [11] experimented with four machine learning models (Decision Tree, Linear Regression, XGBoost, K-Nearest Neighbors Regressor) to predict composting results based on input variables, such as feed composition and ambient temperature, from 88 batches of composting. The K-Neighbors Regressor was the model that achieved the best performance, while the Decision Tree yielded the worst results due to overfitting. The study found that the source of the sawdust was the most significant factor influencing the results. The models accurately forecasted compost maturity, duration, and yield, confirming the potential of ML to optimize composting operations. This paper highlights the importance of expanding dataset sizes and utilizing more advanced models, such as recurrent neural networks, to both predict the variable nature of processes and optimize sustainable waste management.

Xia et al. (2022) [12] conducted a meta-analysis of more than 200 studies (published between 2000 and 2020) on the use of machine learning (ML) in municipal solid waste management (MSWM). The present research divides ML applications into waste generation prediction, collection optimization, classification, composting, incineration, and landfill management. The study highlights the application of algorithms such as ANN, SVM, RF, and CNN, emphasizing their predictive accuracy and potential for automation. ML has facilitated waste prediction, routing, and classification to become more efficient, while deep learning has demonstrated its effectiveness in image-based waste sorting. The authors identified data scarcity and the lack of real-world validations as the most significant issues. They suggested that large-scale datasets and hybrid models should be utilized to develop intelligent and sustainable waste management systems.

Kapila et al. (2024) [13] examined the vermicompost product resulting from the conversion of organic wastes, including wheat straw, bagasse, grass, neem leaves, and sawdust, by Eisenia fetida. The chemical analysis revealed a significant increase in nitrogen, phosphorus, potassium, and humic acid, accompanied by a decrease in C/N ratios, indicating nutrient stabilization. A compost of neem leaves and wheat straw showed the maximum nutrient content and promoted the growth of tomatoes, brinjals, and capsicums. The process of vermicomposting not only helps reduce pollution caused by organic waste but also contributes to increasing soil fertility and crop yield. The authors demonstrate how E. fetida serves as a valuable tool for converting agricultural waste into nutrient-rich manure, thereby facilitating the adoption of organic farming methods and promoting waste recycling at the local level.

Peng et al. (2024) [14] investigated the influence of biochar particle size variation on the performance of Eisenia fetida, microbial diversity, and compost quality during the sludge vermicomposting process. In this work, biochars with particle sizes of 1–2 mm, 25–75 μm, 200 nm, and 60 nm were compared. The biochar of millimeter and micron sizes resulted in improvements in the degradation of organic matter (12.6% and 8.8%, respectively) and the production of cocoons (a 94% increase with 25–75 μm biochar). On the other hand, nanoscale biochars (200 nm and 60 nm) led to worm deaths (24–33%) and a reduction in microbial activity. The authors confirmed through this research that excessive nanopowder biochar is detrimental to earthworms. At the same time, larger particles help increase the stability of compost, microbial diversity, and the mineralization of organic matter, thus providing valuable clues for biochar-assisted waste management.

Gręziak and Białowiec (2025) [15] surveyed the use of artificial neural networks (ANN) for the optimization of composting processes concerning municipal solid and organic waste. The work presented here outlines the cycling stages of composting, the factors that affect it, as well as the law-mandated quality standards. It then refers to the type of ANN used for predicting compost temperature, aeration, pH, C/N ratio, and maturity, including MLP, RBF, CNN, and ANFIS. The review, based on bibliometric and case studies, highlights that the advantages of ANN lie in nonlinear modeling, predictive control, and process automation. The findings authoritatively establish that ANN is superior to conventional regression models, while also highlighting the need for standardized data, hybrid integration, and cross-disciplinary validation to achieve optimal performance in large-scale composting systems.

Temel et al. (2023) [16] presented an exhaustive survey of the use of artificial intelligence (AI) and machine learning (ML) in modeling and improving the composting process. The paper inspected the most essential ML algorithms ANN, SVM, RF, ANFIS, and DNN—used for the prediction of variables like temperature, pH, moisture, and C/N ratio. Moreover, the review highlighted hybrid AI methods, such as genetic algorithms and particle swarm optimization, as means of enhancing prediction accuracy. The ML models demonstrated very high reliability in process control and compost maturity prediction; however, the writers identified data scarcity, poor model interpretability, and a lack of standardization as the primary obstacles to automating large-scale composting processes.

Goswami et al. (2024) [17] surveyed the role of artificial intelligence (AI) in vermicomposting as a solution for the problem of municipal solid waste (MSW) in Guwahati, India. The article highlights the role of AI in optimizing temperature, moisture, and pH control, thereby enhancing compost quality and reducing the need for manual work. It presents various machine learning models ANN, CNN, RF, and GA that can be utilized for compost maturity prediction, as well as the optimization of the composting process. Apart from this, the paper also highlights the role of vermicomposting as an eco-friendly waste management solution and a source of rural entrepreneurship in Northeast India. Finally, it states that AI-based automation can not only help increase efficacy, nutrient recovery, and environmental sustainability, but also promote local livelihoods and the organic agriculture sector.

Núñez et al. (2025) [18] developed an Edge AIoT-based agricultural recommendation system designed to enhance humus production in vermicomposting with Eisenia foetida. The system features bio-inspired algorithms—Genetic Algorithm, Ant Colony Optimization, and Simulated Annealing working together with LSTM and Gaussian Process models to predict both humus yield and worm population growth. Equipped with Raspberry Pi-based edge devices, the platform can work independently in areas with poor connectivity. The research conducted demonstrated that the system was able to significantly increase humus production (from 37.58% to 87.88%) and also the worm population (from 35.5% to 83%) in a corresponding way. This hybrid Edge AIoT framework fosters a sustainable approach to soil fertility, aligns with the SDGs, and facilitates the modernization of intelligent organic farming practices.

Thakur et al. (2021) [19] conducted a review on the process and value of vermicomposting as an environmentally friendly method of waste management and soil enrichment. The paper highlights the role of earthworms, particularly Eisenia fetida and Eudrilus eugeniae, in decomposing organic waste and converting it into nutrient-rich vermicast. It refers to the improvements in soil nitrogen, C: N ratio, and the reduction of heavy metals brought about by the activities of microbes. Additionally, the authors highlighted vermiwash and worm meal as beneficial fertilizers and pest repellents. The research concluded that the use of vermicompost leads to improved soil fertility and increased agricultural productivity. It is even more valuable than traditional compost, as it has a higher nutrient content and forms more humus. However, it takes longer to process and requires more material.

Dugassa and Worku (2025) [20] investigated how different materials common bean straw, maize stalk, coffee husk, and enset leaves with the addition of cow dung, altered the physicochemical and nutrient aspects of vermicompost made with the help of Eisenia fetida. The findings revealed significant differences in the feedstocks for organic carbon, nitrogen, and phosphorus. The combination of common bean straw, coffee husk, and cow dung was found to produce the highest quality vermicompost, with the highest nutrient content and the most significant yield (13.8 kg). Organic carbon was reduced by up to 100%, while total nitrogen increased by 59–157%. The authors argue that the use of mixed feedstocks not only promotes the maturity of the vermicompost, nutrient enrichment, and quality but also contributes to sustainable soil fertility in the long term.

Waghmode et al. (2021) [21] studied the vermicompost and vermiwash made from the leaf litter of jackfruit, coconut, arecanut, and sapota that was decomposed with Eudrilus eugeniae and Eisenia foetida. The outcome revealed that the vermicompost produced from jackfruit leaf litter was the best in terms of its nitrogen (1.42%), phosphorus (0.51%), and potassium (1.06%) content. The nutrient content of vermiwash was also the best from the same treatment (N: 114.57 ppm, P: 30.84 ppm, and K: 197.24 ppm). The paper claims that the process of vermicomposting serves not only as a means of horticultural waste disposal but also as a method of air pollution abatement and quality improvement of natural fertilizers, yielding the best results from jackfruit leaf litter to produce nutrient-rich vermicompost and vermiwash.

Bundele and Devaerakkam (2025) [22] take a deep dive into India's organic waste management (OWM) natural system and analyze the contribution of artificial intelligence (AI) toward a more sustainable OWM system in India. This work compares the efficiency of traditional waste management methods such as composting, anaerobic digestion, and vermicomposting, along with the effectiveness of new AI-driven waste segregation, monitoring, and forecasting techniques. By employing a PRISMA-based systematic review, the current investigation identifies obstacles to AI adoption, including public support and infrastructure for data, as well as the integration of policies. The co-authors envisage a hybrid model with decentralized features that would merge community-based composting activities with lightweight AI tools for decision support. The paper discusses the role of AI in bringing about efficiency and better resource utilization, thereby producing positive effects for the circular economy in India's urban waste sector.

Çelik and Uğuz (2022) [23] are the creators of the Cocoon Detection and Sorting System (CoDeSS), an intelligent, real-time deep learning framework for detecting and sorting earthworm cocoons in vermicompost. They used 1000 labeled images to train and test one-stage (YOLOv5 and SSD) and two-stage (Faster R-CNN) CNN architectures. The ResNet50-FPN-based Faster R-CNN yielded the most accurate detection results (AP = 0.89). The system, linked to a belt and a pneumatic separation tool driven by the NVIDIA Jetson TX2, thus achieved the goal of separating the cocoons from the compost. By introducing a pioneering vision-based automated approach, this report has the potential to enhance the efficiency, labor savings, and sustainability of the cocoon recovery process in vermicompost production.

Temel et al. (2023) [24] examined the application of Artificial Intelligence (AI) and Machine Learning (ML) in composting, focusing on modeling, monitoring, and optimization. This study highlighted the application of algorithms such as ANN, ANFIS, RF, SVM, and GA for predicting various parameters in composting, including temperature, moisture, pH, and maturity. Both ANN and ANFIS demonstrated perfect accuracy in nonlinear modeling, while the hybrid models (e.g., ANN–GA) further enhanced the predictive performance. Most of the works, however, depend on small datasets; the hyperparameters are tuned manually, and only a few validation metrics are used. The paper acknowledges that AI and ML can enhance process control when integrated; however, it suggests that future research should focus on developing hybrid frameworks, utilizing larger datasets, and implementing real-time optimization.

Ganguly et al. (2021)[25] studied the microbial roles involved in the maturation process of vermicompost, focusing on evaluating the nutrient transformations and decomposition rates of the microbial communities. They suggested that a significant challenge for large-scale bioprocessing, as well as the dynamic monitoring of bioprocesses, is an area that remains difficult to access, where AI-powered sensors and image-based techniques can deliver real-time data. Their work requires merging biological and computational methods to enhance the accuracy of compost quality evaluation.

Motamedi et al. (2021) [26] investigated the differences in nutrient content of five different vermicomposting products made from various horticultural residue materials and assessed the efficiency of composting. Their experiment provides an excellent source of information on nutrient sources, but it does not include any form of automation or prediction modeling. Additionally, the researchers suggested further development of AI-driven control systems to locate and balance nutrients in the compost precisely, as well as monitor the rate of breakdown.

Rosales et al. (2020) [27] evaluated the use of earthworms as bioindicators of soil health, examining their abundance, diversity, and behavioral parameters. They argued that the use of digital imaging, combined with AI-based detection technologies, can significantly improve not only precision but also repeatability and the scope of research in soil-biodiversity assessment. Their suggestion is quite consistent with the ultimate objective of implementing digital and AI technologies in ecological monitoring and soil quality evaluation processes.

Hosseinzadeh et al. (2020) [28] describe an experimental setup in which they compared Artificial Neural Network (ANN) and Multiple Linear Regression (MLR) models for predicting nutrient recovery (nitrogen and phosphorus) during vermicomposting of municipal solid waste. Their experiment involved inputting seven physicochemical parameters, and their findings showed that ANN models achieved higher prediction accuracies than MLR models ($R^2 = 0.9983$ for TN and 0.9991 for TP for ANN, and $R^2 = 0.834$ and 0.729 for MLR). These findings demonstrate the potential of ANN in accurately capturing the nonlinear nature of biological systems. However, the model's generalizability is limited by the dataset's size. This work uncovers various facets of AI-based nutrient recovery optimization.

Guo et al. (2021) [29] wrote a review paper presenting various Machine Learning (ML) strategies for the treatment and recycling of organic solid waste (OSW). One of the contributions of the review paper is that it categorizes research works on composting, anaerobic digestion, incineration, pyrolysis, and landfill management, while underscoring the fact that artificial neural networks (ANNs) are at the center of the field because they can model complex, nonlinear relationships more effectively than other methods. This survey paper highlights the benefits, drawbacks, and suitability of various ML techniques—ANN, SVM, GA, and While also providing insights into their future applications, and points to challenges such as data paucity and poor interpretability. Additionally, it casts a vision for the broad adoption of hybrid models and IoT integration. The research serves as a pioneering reference for AI-enabled approaches to green waste management.

Ayilara et al. (2020) [30] provide an extensive review of composting as a method of waste disposal, highlighting both its potential problems and benefits for sustainable agricultural development. The article explains in detail the various composting processes, including vermicomposting, windrow, in-vessel, and static composting, and their pros and cons. Among other things, a lengthy composting period, the release of offensive odors, nutrient imbalance, and the survival of pathogens in the compost were scrutinized. To increase the effectiveness of composting, the authors suggested various measures, including the use of biochar, odor-absorbing methods, and microbial activators. They further proposed that mono fertilizers could be extracted and that the resulting compost could be improved through the use of insect farming. This research exposes the potential of the composting process as a factor in environmental sustainability and food security.

Research on vermicomposting and composting has evolved significantly over the past two decades, transitioning from conventional biological waste stabilization methods to intelligent, data-driven frameworks for optimizing the process. The reviewed studies collectively illustrate a multidimensional progression from early investigations into feedstock composition, nutrient transformation, and microbial diversity to contemporary integrations of Artificial Intelligence (AI), Machine Learning (ML), and Internet of Things (IoT) technologies for real-time monitoring and predictive control. Traditional studies, such as those by Sharma and Garg (2018), Pathma and Sakthivel (2012), and Thakur et al. (2021), emphasize the biological and chemical mechanisms underlying organic matter mineralization and nutrient enhancement. More recent contributions, including those by Meghwanshi (2024), Aydın Temel et al. (2023), and Núñez et al. (2025), demonstrate the growing role of AI in automating composting operations, modeling nonlinear biodegradation dynamics, and improving compost quality prediction. The comprehensive literature summarized in the following table highlights the convergence of biological sciences and computational intelligence in promoting sustainable waste management, enhancing soil fertility, and developing environmentally resilient agricultural practices.

III. TABLE TYPE STYLES

Ref	Citation	Year	Study focus/objective	Methods / Approach	Key findings	Limitations
1	Sharma & Garg	2018	Evaluate vermicomposting of rice straw + paper waste using Eisenia fetida with cow dung.	Nine feedstock ratios, 105-day trials, SEM analysis, and worm growth measurement	Vermicomposting increased N,P,K; TOC reduced 17–58%; C:N reduced 19–102%; best worm growth at 90% cow dung + 10% rice straw; high rice straw slowed growth; SEM showed enhanced fragmentation.	Specific to tested feedstocks and E. fetida; limited scale; no economic analysis
2	Ramazanoglu	2024	Effect of vermicompost application rates on wheat growth, soil enzyme activity, nutrient uptake (with thermal imaging)	Field trials with 2–8 Mg ha^{-1} VC; enzyme assays; thermal imaging; PCA & correlation analysis	6 Mg ha^{-1} gave the highest dry weight and N, P, Zn, Fe uptake; increased β-glucosidase, urease, catalase; lower leaf temperature indicating improved transpiration; strong enzyme–plant performance links	Crop-specific (wheat); site-specific soil conditions; longer-term effects not reported
3	Pathma & Sakthivel	2012	Review microbial diversity and functional roles of bacteria in vermicompost.	Literature review: synthesis of microbial taxa and functions	Identified Bacillus, Pseudomonas, Rhizobium, and Actinobacteria as key PGP microbes; roles in degradation, pathogen suppression, and heavy metal stabilization	Review-level: dependent on reported studies; gaps in mechanistic/omics data at scale
4	Alavi et al.	2019	Degradation of tetracycline antibiotics during chicken manure + bagasse co-composting	Co-composting trials; kinetics modeling (first-order & availability-adjusted); ANN modeling	Up to 99.5% removal in 56 days; half-lives: TCH 8 d, CTC 5 d, OTC 4 d; 14% bagasse optimal; ANN captured kinetics with time as dominant variable	Focus on specific antibiotics and mixes; potential variability in environmental conditions.

5	Kumar et al.	2014	Assess the maturity of vermicompost from flower waste with biofertilizer inoculants.	SEM, paper chromatography, PCA, cluster analysis	Reduced pH, TOC, C: N; increased N, P, K, Mg; SEM showed porous structure; chromatograms indicated humus formation; PCA separated mature samples	Small-scale; specific waste type (flower waste); external validation limited
6	Meghwanshi	2024	Role of AI in vermicomposting — automation, predictive analytics, optimization	Conceptual/review: AI sensors, ML models, computer vision, optimization	AI enables real-time control of T/moisture/pH, predicts feed schedules, aids sorting and quality assessment, improves nutrient balance, and reduces labor	Mostly conceptual; limited field deployments and real-world validation reported
7	Oyege & Bhaskar	2023	Review the impact of vermicompost on soil fertility, crop productivity, and sustainability.	Systematic/critical review across cereals and VC derivatives	VC enhances nutrient availability, enzyme activity, microbial diversity, yield, pest suppression, heavy metal remediation, and drought tolerance benefits	Identified gaps in scale-up, rate optimization, and microbial enhancement strategies
8	Kujawa et al.	2020	Early maturity detection of compost (sewage sludge + rapeseed straw) using CNN	1312 images (visible, UV, mixed light); trained 25 CNN variants	Best model (16 filters, mixed light) achieved 0.51% classification error — rapid, non-destructive maturity assessment	Dataset specific to feedstock and lighting; transferability to other compost types needs testing
9	Yılmaz et al.	2022	Co-composting tea waste + food waste; model & optimize with RBFNN + GA	Experiments with 0–40% tea waste; monitored TN, TOC, MC; RBFNN modeling; GA optimization	25% TW minimized TN and TOC losses; RBFNN predicted parameters with MAPE <3%; GA found 24–25% TW optimal	Study limited to TW/FW mixes; long-term stability and field validation are limited
10	Manley et al.	2022	Systematic review of ML & big data in ecosystem services (ES) research	Review of 56 studies; bibliometric synthesis	Surge in ML use after 2017; RF & Bayesian networks common; crowdsourced data valid for cultural ES; ML reduces uncertainty and improves predictions	Geographic bias: underrepresented regions need more focus
11	Lyberatos & Lyberatos	2025	Predict composting outcomes using ML models (Decision Tree, LR, XGBoost, K-NN)	88 compost batches; models trained to predict maturity, duration, yield	K-NN best accuracy; sawdust feed most influential; Decision Tree overfitted	Dataset size is modest; recommends RNNs for dynamic modeling; needs more data diversity
12	Xia et al.	2022	Review of ML in municipal solid waste management (2000–2020)	Review of 200+ studies; categorized ML applications	ML is used across forecasting, routing, classification, and composting; ANN, SVM, RF, and CNN are effective; deep learning is suitable for image sorting	Data scarcity and limited real-world validation noted
13	Kapila et al.	2024	Chemical characterization	Vermicomposting of wheat straw, bagasse,	Enrichment of N, P, K, humic acid; reduced C/N;	Local-scale trials; composition-

			of VC from various organic wastes using E. fetida	grass, neem leaves, sawdust; chemical assays; plant growth tests	neem & wheat straw composts best for tomato/brinjal/capsicum growth	dependent results; longer-term soil effects not covered
14	Peng et al.	2024	Effect of biochar particle size on E. fetida, microbial diversity, and compost quality	Biochars: 1–2 mm, 25–75 µm, 200 nm, 60 nm; sludge vermicomposting experiments	Millimeter- and micron-scale biochars enhanced degradation and cocoon production, whereas nanoscale biochar resulted in 24–33% worm mortality and reduced microbial activity.	Highlights nanoparticle risks; needs broader ecological risk assessment
15	Gręziak & Białowiec	2025	Review ANN applications in optimizing composting processes	Bibliometric & case analyses covering ANN types (MLP, RBF, CNN, ANFIS)	ANN effective for predicting temp, aeration, pH, C/N, maturity; outperform regressions; need standardized datasets and hybrid models	Calls for standardization and cross-validation; dataset heterogeneity limits comparability
16	Aydın Temel et al.	2023	Review AI/ML in composting modeling & optimization	Review of algorithms (ANN, SVM, RF, ANFIS, DNN) and hybrid approaches	ML models are reliable for parameter prediction; hybrid methods (ANN–GA) improved accuracy	Small datasets, low interpretability, and limited standardization highlighted
17	Goswami et al.	2024	AI integration in vermicomposting for MSW in Guwahati, India	Review and local case discussion of ML models and IoT	AI helps optimize T/moisture/pH, predicts maturity, reduces manual labor, and supports entrepreneurship	Regional focus: calls for more deployments and pilot projects
18	Núñez et al.	2025	Edge AIoT recommendation system to enhance humus productivity (E. foetida)	Edge devices (Raspberry Pi), GA/ACO/SA, LSTM, Gaussian Process models; field experiments	Humus yield increased from 37.58% to 87.88%; worm population from 35.5% to 83%; effective in low-connectivity areas.	Early-stage; reproducibility across regions needs testing
19	Thakur et al.	2021	Review the vermicomposting process, earthworm roles, and by-products	Review of literature on species, nutrients, by-products (vermiwash, worm meal)	VC improves N, C: N, reduces heavy metals; VC is superior to conventional compost in nutrient/humus content	Notes slower processing and higher material inputs compared to some compost methods
20	Dugassa & Worku	2025	Impact of different feedstocks mixed with cow dung on VC properties (E. fetida)	Comparative vermicomposting with bean straw, maize stalk, coffee husk, enset leaves + cow dung.	Mixture bean straw+coffee husk+cow dung produced best quality; organic C decreased up to 100%; N increased 59–157%; yield 13.8 kg	Feedstock-specific; larger-scale operational studies needed
21	Waghmode et al.	2021	Evaluate VC & vermiwash from leaf litters (jackfruit, coconut, arecanut, sapota)	Vermicomposting with E. eugeniae & E. fetida; nutrient assays	Jackfruit litter produced highest N(1.42%), P(0.51%), K(1.06%); vermiwash rich in N,P,K; VC stabilizes horticultural waste	Limited crop trials; site-specific leaf chemistry affects outcomes

22	Bundele & Devaerakkam	2025	Analysis of India's OWM ecosystem and AI role for sustainability	PRISMA systematic review; policy & tech gap analysis	Proposes a hybrid decentralized model combining community composting with lightweight AI; identifies policy/data gaps	High-level policy focus; practical pilots and cost analyses required
23	Çelik & Uğuz	2022	CoDeSS: Deep learning system for cocoon detection & sorting in vermicompost	1000 labeled images; trained YOLOv5, SSD, Faster R-CNN; hardware integration with Jetson TX2 and conveyor + pneumatic sorter	Faster R-CNN (ResNet50-FPN) achieved AP=0.89; system automated cocoon recovery and separation	Hardware cost and conveyor integration constraints; dataset diversity may limit generalization
25	Ganguly et al.	2021	Microbial roles in vermicompost maturation: a call for AI-enabled monitoring	Experimental microbial analyses: review perspective	Documented nutrient transformations and decomposition dynamics; recommended AI sensors and image systems for monitoring	Implementation and large-scale monitoring are still underexplored
26	Motamedi et al.	2021	Compare VC products from diverse horticultural residues	Comparative compositional analyses	Showed substrate-specific nutrient variations; highlighted the need for automated/predictive control	Did not include AI/predictive modeling; limited automation discussion
27	Rosales et al.	2020	Earthworms as bioindicators of soil health: a review	Literature review on abundance, diversity, and behavior metrics	Advocated digital imaging and AI for scalable soil biodiversity assessment	Mostly conceptual; field-validated AI tools were scarce at the time of review
28	Hosseinzadeh et al.	2020	Compare ANN vs MLR for predicting nutrient recovery during vermicomposting.	Models using seven physicochemical inputs: performance comparison	ANN outperformed MLR (R^2 ~0.998 for TN, 0.999 for TP vs MLR 0.834/0.729), indicating strong nonlinear capture	Small dataset limits generalization; overfitting risk without cross-site validation
29	Guo et al.	2021	Review ML in the treatment & recycling of organic solid waste (OSW)	Review & categorization across treatment types	ANNs dominate; hybrid models and integration with IoT are promising; data scarcity & interpretability remain issues.	Broad review — calls for more standard datasets and real-world validation.
30	Ayilara et al.	2020	Review composting methods, challenges & potentials for sustainable agriculture	Comprehensive review across methods and innovations	Identified challenges: long duration, odors, nutrient imbalance; suggested biochar, microbial activators, odor control, insect-based composting	High-level needs empirical pilots for many proposed innovations

IV.RESEARCH GAP

Despite substantial progress in vermicomposting and composting research, several critical gaps remain that limit the full realization of intelligent, large-scale, and sustainable waste management systems. Most studies have focused on specific feedstocks, microbial interactions, or physicochemical transformations without integrating real-time monitoring or predictive modeling frameworks. Although recent innovations have integrated machine learning (ML) and artificial intelligence (AI) to optimize processes, the majority of models are still based on small-scale laboratory datasets and have only been slightly validated under various climatic and operational conditions. There are still significant obstacles to data standardization, model interpretability, and the scalability of AI models, particularly those using deep learning and hybrid metaheuristics. Moreover, only a handful of studies have connected microbial dynamics with computational predictions; thus, there is a biological understanding that is separated from the algorithmic modeling. The issues of economic viability, energy efficiency, and environmental impact have also been insufficiently addressed in the case of AI-assisted vermicomposting systems. Thus, the demand for integrated, data-rich, and explainable AI frameworks that utilize sensor-based IoT monitoring, bioinformatics, and adaptive control to improve the accuracy, scalability, and sustainability of composting is very high.

V. DISCUSSION

The surveyed literature indicates a marked evolution in composting and vermicomposting research, moving away from standard biological experiments towards the use of intelligent, automated, and data-driven systems. Initial studies primarily focused on optimizing the mixture of feedstock, selecting suitable earthworm species, enriching nutrients, and evaluating structural maturity and microbial diversity. The research of Sharma and Garg (2018), Kumar et al. (2014), and Waghmode et al. (2021) has demonstrated the biochemical advantages of co-vermicomposting and substrate selection, thereby confirming the increase in nitrogen, phosphorus, and potassium, as well as improvements in humification and stability.

With the advancement in computational intelligence, the research paradigm has shifted to utilizing Artificial Intelligence (AI) and Machine Learning (ML) techniques for predicting compost maturity, nutrient dynamics, and process efficiency. The research outcomes of Kujawa et al. (2020), Yılmaz et al. (2022), and Lyberatos and Lyberatos (2025) witness the effectiveness of AI-driven modeling with Convolutional Neural Networks (CNNs), Radial Basis Function Neural Networks (RBFNNs), and regression models for the non-destructive, real-time evaluation of composting parameters. Similarly, the findings of Temel et al. (2023) and Gręziak and Białowiec (2025) suggest that hybrid models, such as ANN-GA and ANFIS, exhibit higher predictive accuracy for temperature, pH, and moisture content compared to traditional methods.

Additionally, the articles written by Meghwanshi (2024), Goswami et al. (2024), and Núñez et al. (2025) emphasize the merger of IoT and Edge AI platforms for the automated sensing, optimization, and humus productivity improvement, thus pointing to the transition to novel composting systems. However, the long-talked advancements in the field still have limitations that these works converge on, such as small datasets, a lack of standardized evaluation metrics, and limited interpretability of AI models in biological contexts. Additionally, most AI applications are still in the simulation stage and have not been tested on an industrial scale.

The debate suggests that AI-powered composting represents a significant leap forward in terms of efficiency, accuracy, and environmental friendliness. However, research in this area should continue to focus on linking biological mechanisms with computational modeling, establishing standardized datasets, and verifying the presence of intelligent control systems in real life.

IV. CONCLUSION

A thorough examination of vermicomposting and composting-related research shows how the life sciences and AI are gradually merging and reshaping the management of organic waste. In essence, traditional research has outlined the necessary nutrient cycles, microbial activities, and optimization of substrates. In parallel, recent research has further developed these concepts by utilizing AI, ML, and IoT-based automation to enhance process control and efficiency. This technological infusion has enabled the performance of predictive modeling, process optimization, and real-time monitoring, resulting in a significant enhancement of compost quality and operational efficiency.

On the other hand, the review also highlights that most of the work is still in the trial stage, and there are issues with data availability, model interpretability, and large-scale deployment. Standardized datasets, hybrid AI frameworks, and explainable models that can connect biological dynamics with computational predictions are in demand. Moreover, sustainability indicators such as energy consumption, environmental impact, and cost-effectiveness must be incorporated into the system's future designs to facilitate comprehensive system evaluation.

Combining biotechnological and intelligent computational tools is a practical approach for implementing circular and sustainable waste management strategies. By linking experimental composting research with dependable data-driven automation, future systems will be capable of achieving higher precision, scalability, and environmental resilience, thereby contributing to the attainment of global goals for sustainable agriculture and resource recovery.

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