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Wastewater Management Using a Neural Network-Assisted Novel Paradigm for Waste Prediction from Vermicomposting

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Abstract: Vermicomposting is one of the most important waste management techniques in the process of vermiculture. In this study, a neural network-assisted novel paradigm is proposed to predict waste from vermicomposting. The proposed neural network skeleton is based on a gallium arsenide processing schema, which is used to separate wastes. By comparing the proposed system with existing methods, it was found that the proposed approach had the highest average prediction ratio of 91.32%, outperforming other techniques like the encoder-recurrent decoder (ERD) network, recurrent neural network (RNN), and deep long short-term memory (deep LSTM) network. The separation ratio analysis also demonstrated the effectiveness of the proposed method, with a range of 45–94%. Furthermore, the study emphasizes the importance of chemical equilibrium and the effectiveness of our proposed gallium arsenide processing schema in achieving high prediction and separation accuracies, showcasing its potential for practical application in waste management processes. Lastly, the prediction of the process evolution stages is detailed, indicating the efficiency of the proposed system in achieving various levels of waste separation. Overall, the study provides valuable insights into the potential of the proposed methods in optimizing wastewater management processes, paving the way for more effective and sustainable vermicomposting practices.

Keywords: gallium arsenide processing schema; separation accuracy; waste management; neural network; vermicomposting

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1. Introduction

Wastewater management is a critical challenge in modern societies, particularly in the context of urban areas and industrialized regions, with the increasing volume and complexity of waste generation posing a threat to the environment and human health. The effective management of wastewater is essential for maintaining environmental health, conserving water resources, and mitigating the impact of pollutants. Understanding waste streams and their composition is key to optimising wastewater management strategies. In this context, the accurate prediction of waste stream composition is crucial for the development of targeted interventions to divert materials from landfill disposal [1].

Conventional waste management techniques have proven inadequate, leading researchers to explore innovative solutions to address this pressing issue.

In the quest to address the global challenge of food waste and its environmental impact, researchers have increasingly turned to AI-based approaches to automate and optimize waste management processes.

Previous studies have explored the application of artificial intelligence and machine learning techniques in the context of waste and wastewater management.

Researchers have demonstrated the ability of neural networks to assess the reuse potential of wastewater [2–4], highlighting the ability of these models to capture the nonlinear, uncertain, and time-varying nature of wastewater treatment systems [5–7]. Furthermore, comparative studies have revealed the superior performance of decision tree algorithms and gradient boosting machines in predicting total nitrogen levels in wastewater, a critical parameter in nutrient removal and treatment plant optimization [8].

The application of machine learning algorithms, including neural networks, has shown promise in improving municipal solid waste management [9]. Furthermore, the use of advanced sensing and monitoring technologies, such as wireless sensor networks, can provide valuable data for optimizing waste management strategies [10]. Additionally, efforts are being made to improve the robot's structure, sensors, waste classification algorithms, and robotic arms to make them more effective and efficient. Sensor-based waste monitoring is a technology that utilizes sensors to track the amount of waste generated, identify the sources of waste, and measure the effectiveness of waste management strategies in a specific area. Sensor-based waste monitoring and classification systems have been developed to enhance the efficiency of waste management in smart cities [10]. Recent studies have explored the use of deep learning and neural networks for various waste management applications, including waste segregation, classification [11], and prediction [4].

Deep learning techniques have also been employed to classify and quantify food waste, a significant component of municipal solid waste [12]. Several models were proposed and assessed for their high accuracy and precision rates in waste classification, including RWNet [13], Garbage Classification Net [14], the faster region-based convolutional neural network [15], and ConvoWaste [16]. Some studies also incorporate IoT [17] and waste grid segmentation mechanisms [18] to classify and segregate waste in real-time.

In this context, vermicomposting, a process that utilizes earthworms to convert organic waste into a nutrient-rich compost, has gained increasing attention as an eco-friendly and viable solution for managing municipal solid waste and wastewater sludge, but also as an extensive approach for restoring the environment, producing nutrient-rich bio-fertilizers, and growing crops in a sustainable manner [19].

The potential of vermicomposting as a solution for sustainable waste management has been well-documented [20,21]. Vermicomposting utilizes earthworms as a natural bioreactor to transform organic waste, such as household and kitchen waste, into a valuable soil amendment [21]. Feeding, stocking density, pH, C/N ratio, temperature, and moisture are critical factors that influence the vermicomposting process [22]. To enhance the efficiency of vermicomposting, it is essential to accurately predict the optimal time for harvesting the vermicompost. The chromatographic analysis of vermicompost can indicate the mature condition of the compost materials [20]. However, the complex interactions between the various environmental factors make it challenging to precisely determine the optimal harvesting time [23].

Neural networks, with their ability to model nonlinear relationships, have the potential to address this challenge. Recent advancements in artificial intelligence and machine learning have opened up new possibilities to assist in predicting waste generation from vermicomposting processes and to enhance its efficiency [24]. While advanced ANN models that can handle nonlinear patterns well include the Elman, functional link, and radial basis function neural networks, the chosen model prioritizes interpretability and simplicity, which are appropriate for the vermicomposting data. In comparison to dynamic time-dependent systems, the suggested model, which has been improved by gallium arsenide processing, fits the precise waste prediction and separation criteria well, particularly since the nonlinearities are less extreme.

The first step in developing the neural network model is to establish a robust dataset for training and validation. The work of Abdulmahmood and Grammenos [11] on improving the deployment of recycling classification through efficient hyper-parameter analysis provides a valuable benchmark for the model's performance.

According to Sim and Wu [21], the study of the neural network structure within vermicomposted waste can provide valuable insights into the decomposition and transformation processes occurring during this sustainable waste treatment method.

Senthil Kumar et al. [20] integrated deep learning algorithms and scanning electron microscopy analysis to investigate the structural changes and compositional dynamics of vermicomposted waste. The learning algorithm uses a backpropagation technique, in which the neural network propagates the error back through the network layers and modifies its parameters to minimize prediction error. This is accomplished by iteratively improving the model by computing gradients and updating weights using a gradient descent technique. In terms of mathematics, this reduces the loss function, $L(\theta) = \sum_{i=1}^{n} \|f(X_i, \theta) - Y_i\|^2$, that effectively captures intricate nonlinear patterns. The robustness of this method guarantees accurate forecasts that are appropriate to the waste composition during the vermicomposting process.

Embalzado et al. [25] developed an Automated Vermicomposting System (of Proper Waste Ratio + MCU Vermicomposting Bed) and concluded that the produced vermicompost had a high content of nitrogen, medium content of phosphorus, and sufficient content of potassium, and that the prototype has a faster processing duration for vermicomposting due to the Waste Ratio input.

To address the issue of accurately predicting the optimal time for harvesting the vermicompost, the primary objective of this study is to develop a robust and accurate model for predicting waste generation and composition in the vermicomposting process, thereby enhancing the overall efficiency and sustainability of this waste management technique.

In this paper, a novel paradigm is proposed for waste prediction in the vermicomposting process, leveraging the power of neural networks and a unique processing schema based on gallium arsenide technology. The proposed approach combines the benefits of neural network-assisted waste prediction with the advantages of the gallium arsenide processing schema. The neural network skeleton is used to predict the composition of waste, with a particular focus on fine separation and destructive processes. Gallium arsenide is a semiconductor material known for its high efficiency and performance, making it an attractive choice for various applications, including waste management systems. The gallium arsenide (GaAs) processing schema is selected for waste composition prediction because of its stability in processing a variety of waste materials and great efficiency in managing intricate separations. GaAs is especially useful in the vermicomposting process for separating organic and inorganic compounds because of its exceptional chemical qualities, which enable accurate waste component separation. This schema helps the neural network detect minute changes in waste composition, which further improves the model's forecast accuracy. GaAs's distinct properties collectively make it an effective instrument for improving compost quality and resource recovery, as well as for obtaining more precise and dependable waste forecast results.

By leveraging the power of neural networks, this study seeks to contribute to the understanding of the intricate relationships between the microstructural changes, decomposition patterns, and overall effectiveness of the vermicomposting process; it also aims to accurately predict the composition of the waste stream, enabling more efficient resource recovery and reducing the environmental impact of the process.

The main contributions of this study are as follows.

1. A neural network-assisted novel paradigm is proposed to predict waste from vermicomposting. The proposed neural network skeleton is based on a gallium arsenide processing schema, which is used to separate wastes.
2. Classification and separation processes are performed based on chemical liability reactions.

In summary, this comprehensive analysis provides valuable insights for the advancement of efficient and sustainable waste management practices in the context of vermicomposting and beyond.

2. Materials and Methods

2.1. Vermicomposting Process and Its Relative Components

Vermicomposting is a special process that uses the combined activity of earthworms and microorganisms in their stomach to turn organic wastes into vermicompost or organic fertilizer. Vermicompost is a nutrient, microbe, and plant-growth-promoting rich organic substance that enhances crop yield and maintains soil heath [26]. Similar to traditional composting, vermicomposting necessitates the presence of oxygen, as it is an aerobic process [27].

Decomposable organic wastes such as animal excreta, kitchen waste, farm residues, and forest litter are commonly used as composting materials. In general, animal dung, mostly cow dung, and dried chopped crop residues are the key raw materials. A mixture of leguminous and non-leguminous crop residues enriches the quality of vermicompost. Raw materials are utilized by earthworms to aid in their decomposition, where they can only be consumed under conditions of prolonged moisture. The moisture content during the bio-conversion process must be maintained between 45 and 75% for the optimal reproduction and activity of the earthworms [28]. The optimal temperature for suitable earthworm species used in vermicomposting ranges from 15 to 30 °C. At temperatures below 10 °C, feeding and other developmental activities are reduced, and below 4 °C, the cocoon production and growth rate of earthworm stops [29]. When raw material is completely decomposed, it appears black and granular. Watering should be stopped as compost becomes ready. The compost shout be kept over a heap of partially decomposed cow dung so that earthworms can migrate to the cow dung from the compost. After two days, the compost can be separated and sieved for use.

A flow chart for the vermicomposting procedure, depicted in Figure 1, was developed for this study.

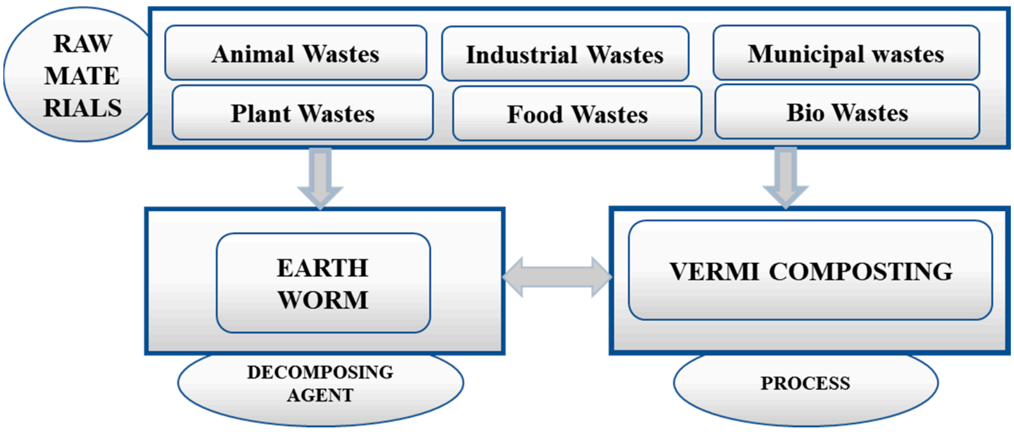

Figure 1. Vermicomposting process and its relative components.

2.2. Vermicomposting Layers

In addition, different methods of soil extraction for soil composting are also studied, culminating in the determination of effective organic layers of the soil composting form for the vermiculture bed or vermi bed.

A layer of fine sand (3 cm) should be spread over the culture bed, followed by a layer of garden soil (3 cm). All layers must be moistened with water. Shredded paper or cardboard, straw, and leaves makes an excellent bedding, particularly when combined with typical on-farm organic resources such as straw and hay.

This makes an ideal environment for earthworms to live in and complete their composting tasks. A first layer of sawdust, newspaper, straw, coir waste, sugarcane trash, etc., can be placed at the bottom of the tub or container to prepare the vermi bed. Newspaper is one bedding material with a high absorbency level, while sawdust has a poor to medium absorbency level.

The vermi beds may have several layers. Earthworms can use this to break down waste. Layer 1 can be processed using rapidly decomposing materials like wood shavings, coconut shells, and shed leaves. The next layer of decomposing leaves, layer 2, is made up of particles with rice straw and cow dung, as well as any other materials from layer 1 of the vermicomposting process.

Layers can be filled with solid cow dung, and materials that can be partially moisturized can be covered with layers of vermi beds that can be moistened over a period and can be used with vermi beds [30]. For earthworms, layers can be used in moist environments. Waste materials can be slowly decayed by covering them with jute fibres for a period of 60 to 70 days.

The leachate derived from vermicomposting units is called vermiwash. It is a naturally occurring product with a brown colour that is rich in plant nutrients and can be used as a liquid fertilizer. Furthermore, the composition of its humic acid aids in the development of plants. Earthworms can be very effective in digestion and waste excretion and aid in the vegetable compost process. This process is used in the neural network approach to predict waste layers and determine which specific waste materials to use as bedding for an effective waste management procedure.

Figure 2 illustrates how vermi bed layers are used in the vermicomposting process. These layers are primarily made up of organic wastes, which have a significant impact on the entire soil during the vermicomposting process [31]. Waste in the layers can be transformed by earthworm digestion components, nutrients, and mineral-enriched soil.

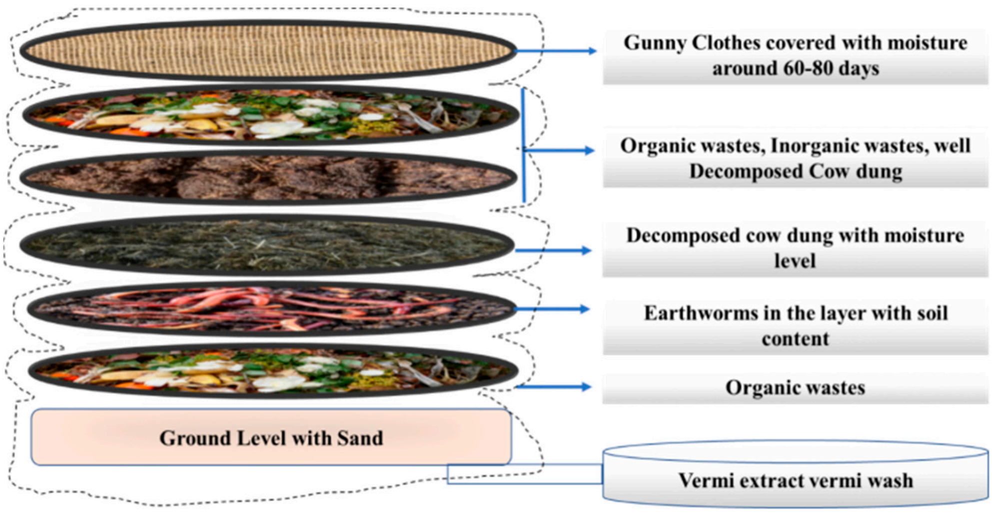

Figure 2. Vermicomposting layers.

Jutes and gunny sack components help keep the soil balanced and moist, allowing these layers to be preserved in a closed environment [32].

2.3. Prediction of Wastes on Vermi Bed Layers

Neural networks are used for the prediction of wastes in vermi beds by using the processed layer illustrated in Figure 3.

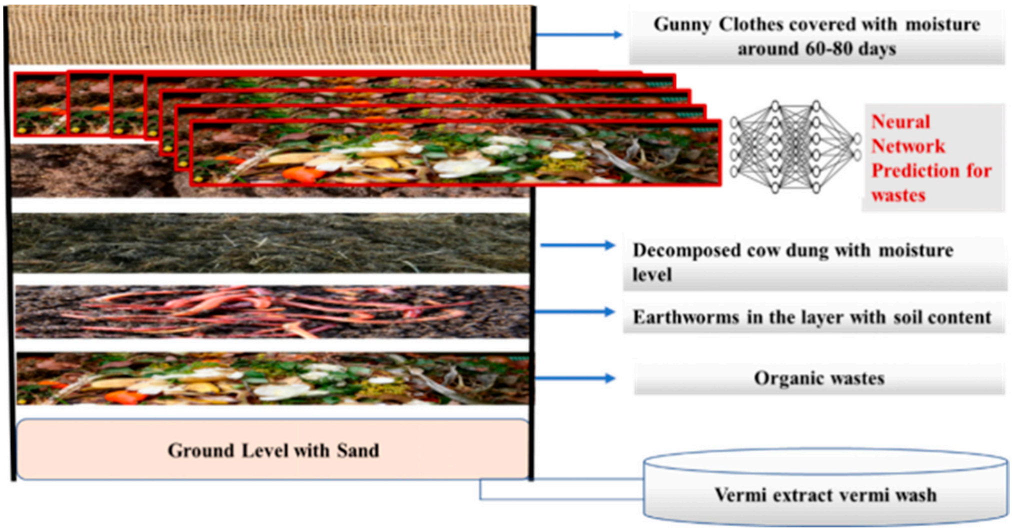

Figure 3. Prediction of wastes on vermi bed layers.

Earthworms can use these layers very effectively for the digestion and excretion of waste during the vermicomposting process.

The processes described in the previous paragraph are used in the neural network approach to predict waste layers and determine which specific waste materials to use as bedding for an effective waste management procedure.

Figure 4 shows the types of digestive particles of earthworms with biodegradable, not non-biodegradable, and plastic wastes. Thus, they can be separated using a neural network approach [33].

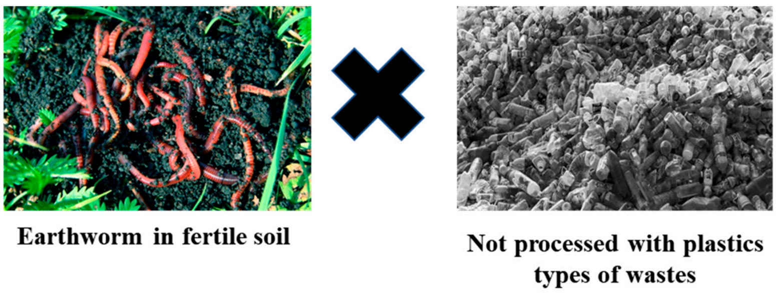

Figure 4. Types of digestive particles of earthworms.

As different forms of waste can be processed with neural network processes to the pool, Figure 5 demonstrates how the process of vermicomposting to layers can be defined by the neural network processing of input layers. In order to specify a way of removing waste particles for various gallium arsenide separation schemes for chemical processing with a balanced waste management process, hidden layers can be used in conjunction with the output process [34]. The prediction algorithm can be applied to the time series of bio- and non-bio-waste prediction using a shallow neural network (SNN). To optimize model performance, specific hyperparameter tuning was carried out for the ANN model, including the number of hidden layers, neurons per layer, and learning rate. Considering the intricacy of the model and the diversity of waste kinds, these parameters were selected via testing and cross-validation. The number of neurons in the model were usually proportionate to the complexity of the data, and generally, two to three hidden layers were used. In an effort to balance convergence speed and prediction accuracy as well as make sure the model adapts adequately to a variety of inputs without overfitting, learning rates ranging from 0.01 to 0.001 have proven to be useful.

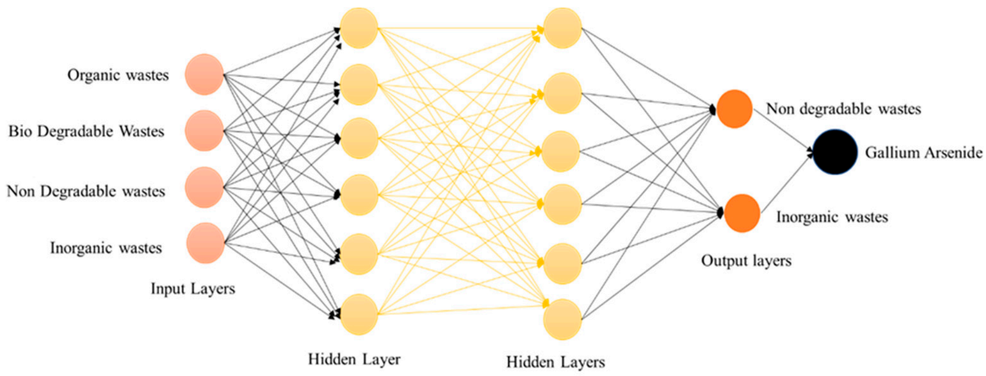

Figure 5. Neural architecture over prediction of wastes.

2.4. Gallium Arsenide Processing Schema from GaAs Wastewater Separation

Gallium is a material composed of metals, which can be soft, and silvery-white metals like aluminium and silicon-like arsenide can be mixed with it. It is useful as a replacement for items made by the electronic industry, such as integrated circuit chips and radio and microwave particles, which are mostly employed in the production of electronic devices and gadgets for the electronic industry.

Neural networks can be used to separate gallium arsenide, and different solid waste management systems can be used to process it. Only biodegradable wastes that are primarily used for vermicomposting earthworm digestive tracts can be categorized as waste products. Only bioproducts that are suitable for vermicomposting are secreted by these earthworms [35]. In addition to affecting earthworm fertility toward vermicomposting, this approach cannot replicate the proper digestion and excretion of waste to the vermicomposting process if waste particles are to be implemented for the operation of the entire vermicomposting ecosystem. Using techniques like gas chromatography (GC), high-performance liquid chromatography (HPLC), and Fourier-transform infrared spectroscopy (FTIR), waste components in earthworm composting can be identified by identifying chemical changes and phases of breakdown. Nutrient levels are monitored by elemental analysis (such as AAS or ICP-MS), and compost maturity is indicated by the carbon-to-nitrogen (C/N) ratio, pH, and moisture content. Effective vermicomposting monitoring is made possible by chemical equilibrium analysis, which helps with accurate waste separation for sophisticated processes like those utilizing gallium arsenide.

Figure 6 illustrates the approach used to extract waste products for non-biodegradable waste materials. The process of using non-biodegradable waste materials for the careful separation of the pyrolysis method—which can be used to find pyrolysis residues—for the study's conclusion is covered in [36]. It can be applied as a vaporization method for managing wastewater as well as a chemical separation method for removing gallium and arsenide materials from the wastewater management system. The Balz–Schiemann reaction can be used to process the finalized by-products of resultants with chemical balancing, as well as proof of chemical equilibrium, in order to move to the technological implementation.

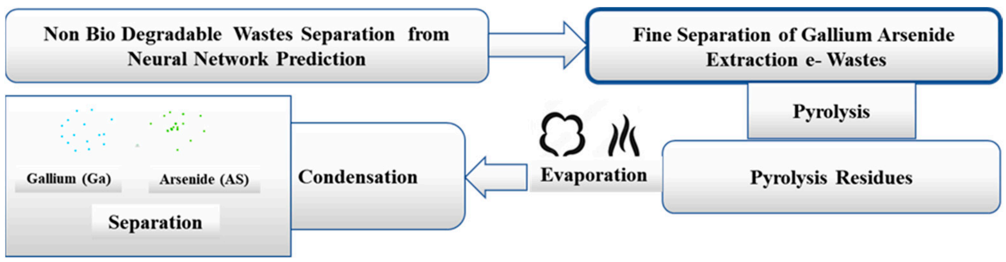

Figure 6. Gallium arsenide separation process.

Pseudocode: Neural network training for waste prediction.
Initialize neural network parameters;
For each batch of input data, the following actions are taken:

Feed input through network layers to produce output;
Calculate error by comparing predicted output with actual target;
Backpropagate error to adjust weights;
Update weights based on gradients and learning rate.

Repeat until convergence criteria are met;
Output final model parameters and predictions.

This pseudocode describes the neural network model's process flow, emphasizing crucial phases from initialization to weight adjustment and error calculation, guaranteeing effective learning and adaptability for precise waste prediction.

This study addresses the challenging problem of forecasting waste output in the vermicomposting process, which entails complicated interactions between the various components of organic waste. In this field, traditional models have had trouble making accurate predictions. To improve waste output prediction and separation, a neural network model and a gallium arsenide processing schema are created.

In mathematics, let $X = \{x_1, x_2, \ldots, x_n\}$ stand for the input parameters, which include temperature, moisture, and nutrition content, and let Y stand for the desired waste products. In order to achieve accurate and effective predictions for sustainable waste management, the neural network function $f(X, \theta)$ is trained to predict Y. During training, θ is tuned to minimize the error $E = \|Y - \widehat{Y}\|^2$, consisting of model weights and biases.

Chemical formulas for this approach can be expressed as follows: benzene diazonium chloride or diazonium salt with fluoric acid can be balanced, and aryl fluoride and diazonium fluoroborate can be precipitated with the heat precipitation of -N2 and -BF3 [37]. The hybrid method of gallium arsenide (GaAs) and the Balz–Schiemann reaction can be used to apply the Balz–Schiemann reaction mechanism in chemical formulas. Gallium can be used in conjunction with wastewater separation to observe a reaction that will allow states to use it for the chemical equilibrium of liability in the process:

$$C_6H_5N_2Cl + HBF_4 \rightarrow C_6H_5N_2\ BF_4 \rightarrow C_6H_5F + Ga\ As$$

For chemical processing, we can make use of the above equation for the gallium arsenide process with the N2 and BF4 sediment. Therefore, waste and chemical processing can be separated from the vermicomposting layers, and (GaAs) wastewater can be separated according to processed wastewater types. When combined with an artificial neural network, the system can be utilized for effective waste management. On the other hand, pyrolysis waste management techniques can be used to separate waste materials that are not used for vermicomposting [38].

Therefore, waste management and wastewater separation through chemical processing are possible with the recently developed (GaAs) method.

3. Results and Discussion

A neural network skeleton is used to estimate the suggested chemical processing for waste management in vermicomposting. This study uses a dataset of 24,705 solid household wastes that have been divided into two classes: recyclable (10,825) and organic (13,880). The initial dataset was created by Sashaank Sekar and is accessible via this link: https://www.kaggle.com/techsash/waste-classification-data (accessed on 1 November 2024).

Then, based on a number of parameters, a performance comparison analysis was carried out between the proposed methods and the existing ones, such as the recurrent neural network (RNN), deep long short-term memory (deep LSTM) network, and encoder-recurrent decoder (ERD) network. The prediction ratio, separation ratio, prediction accuracy, and separation accuracy are estimated.

Table 1 shows the percentage prediction ratio of the suggested method compared to our current procedure. Compared to ERD, RNN, and deep LSTM, which have average prediction ratios of 73.4%, 79.7%, and 80.8, respectively, our suggested method has the highest average prediction ratio of 91.32%.

Table 1. Comparison of concentration curves for prediction using a neural network skeleton.

Evolution	Prediction Ratio (%)			
	ERD	RNN	Deep LSTM	Proposed Neural Network Skeleton
1	65	74	78	87
2	64	78	79	89
3	73	75	82	92
4	76	73	79	86
5	75	75	80	89
6	79	77	82	92
7	68	89	82	93
8	75	83	84	94
9	79	85	80	96
10	80	88	82	95

Figure 7 shows the prediction ratio of various classification techniques in vermicomposting based on an increasing evolution count.

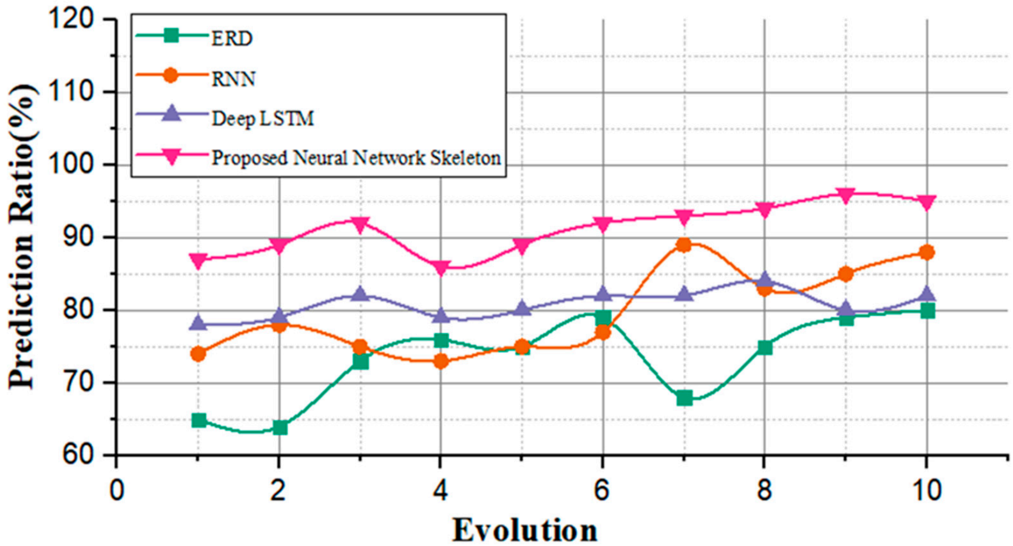

Figure 7. Prediction ratio of various classification techniques.

The neural network's number of neurons and hidden layers largely determines its computational complexity. The complexity of the model, which includes both forward and backward propagation phases, is roughly $O(L \cdot N^2)$, with L hidden layers and N neurons per layer. This intricacy was balanced between prediction accuracy and computational economy, resulting in a scalable and efficient model for vermicomposting applications involving enormous datasets. As the prediction ratio increased in percentage terms, the evolution counts also increased. Prediction ratios for the ERD network, RNN, deep LSTM network, and proposed neural network skeleton approaches were 65%, 74%, 78%, and 87% for the first evolution, respectively. Our proposed neural network skeleton achieves a prediction ratio of 92% after more than five evolutions, which is 13% better than the ERD network, 15% better than the RNN, and 10% more efficient than the deep LSTM method. Compared to the other approaches, our suggested system produced a 95% prediction ratio of waste in the tenth and final evolution process. According to the aforementioned assertion, our suggested approach is more efficient than the other methods in terms of prediction ratios. After this, the proposed gallium arsenide processing methods are used to separate wastes.

The separation ratio is the amount of material reduction that shows how the removed materials impact the measurement precision in percentages. Table 2 compares the suggested approach with current techniques for the separation of waste.

Table 2. Comparison of concentration curves for separation using a neural network skeleton.

Evolution	Separation Ratio (%)			
	ERD	RNN	Deep LSTM	Proposed Neural Network Skeleton
1	34	38	40	45
2	39	43	46	53
3	45	49	54	59
4	51	53	60	64
5	58	58	67	72
6	64	64	72	78
7	70	69	76	83
8	74	74	81	89
9	78	79	86	92
10	81	84	89	94

Figure 8 illustrates the separation ratio of wastes during vermicomposting using four different methods.

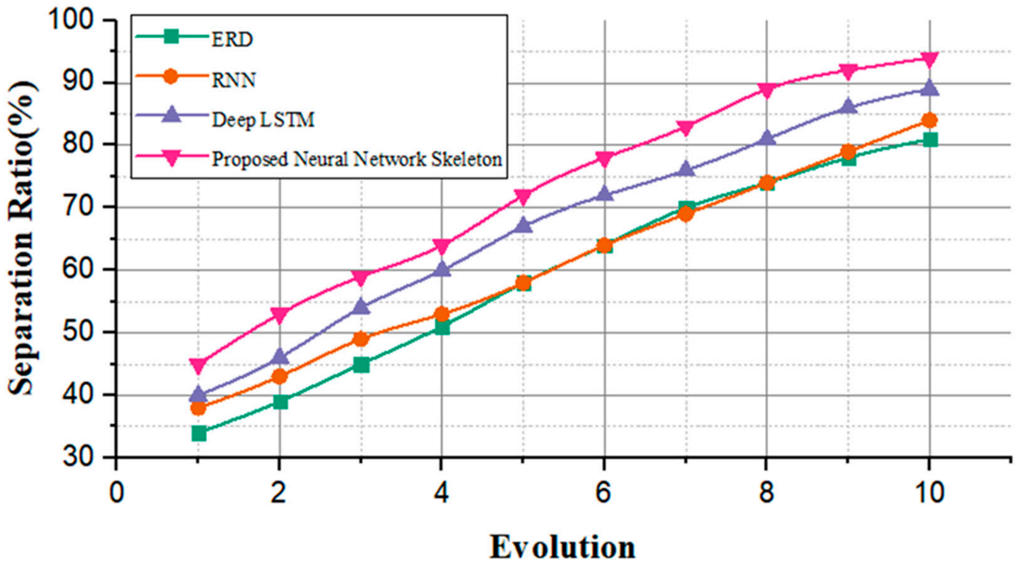

Figure 8. Separation ratio of various classification techniques.

The RNN spans from 38% to 845, while the ERD network ranges from 34% to 81%. The deep LSTM network's accuracy varied from 40% to 89%. On the other hand, the separation ratio of our proposed method was 45–94%. As can be seen from the graph, separation ratios are derived by increasing the count evaluation from 10 to 100. A higher separation ratio denotes better system performance, and a lower value denotes lower performance and operation to reach the optimum value. Therefore, for each evolution, the suggested method offers a wider range of separation ratios for waste from vermicomposting.

Also, the chemical processing of waste management was analysed. When reactants and products are present in a chemical reaction at concentrations that do not seem to change over time, the system's properties remain unchanged. This is known as chemical equilibrium. The prediction accuracy can be defined as the difference between the observed value and the predicted value:

$$\text{Prediction accuracy} = \text{observed value} - \text{predicted value}$$

The prediction accuracy for waste was determined by subtracting the observed and predicted values. Table 3 shows the prediction accuracy of our proposed gallium arsenide processing scheme using the existing methods.

Table 3. Prediction accuracy of waste management against any chemical equilibrium vs. proposed gallium arsenide processing schema.

Time	Prediction Accuracy of Waste Management (%)	
	Chemical Equilibrium	Proposed Gallium Arsenide Processing Schema
10	53.4	58
20	60.2	62
30	68.8	67
40	74.3	78
50	79.1	82
60	84.4	85
70	85.6	89
80	85.3	90
90	85.5	92
100	85.7	95

Figure 9 illustrates the waste management prediction accuracy based on time(s) increases of up to 100 (s).

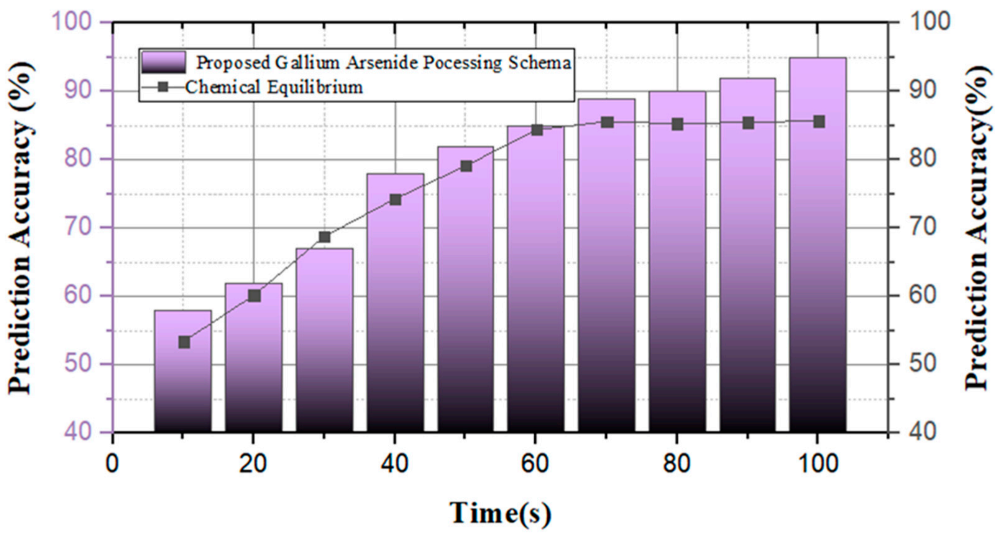

Figure 9. Prediction accuracy of various separation techniques.

In a GaAs waste management system, the technique of interrupting the operation is utilized to preserve chemical equilibrium throughout a chemical reaction. After a period of time, the chemical equilibrium of this chemical reaction and forward action is reached at 70s with an 85% prediction accuracy, starting at 53% at 10 s. Our suggested method's chemical equilibrium keeps an accuracy of 85–85.9%. According to Figure 10, the suggested gallium arsenide processing schema has a prediction observance that rises linearly with time. Using the suggested gallium arsenide processing schema, the waste management prediction accuracy begins at 58% at 10 s.

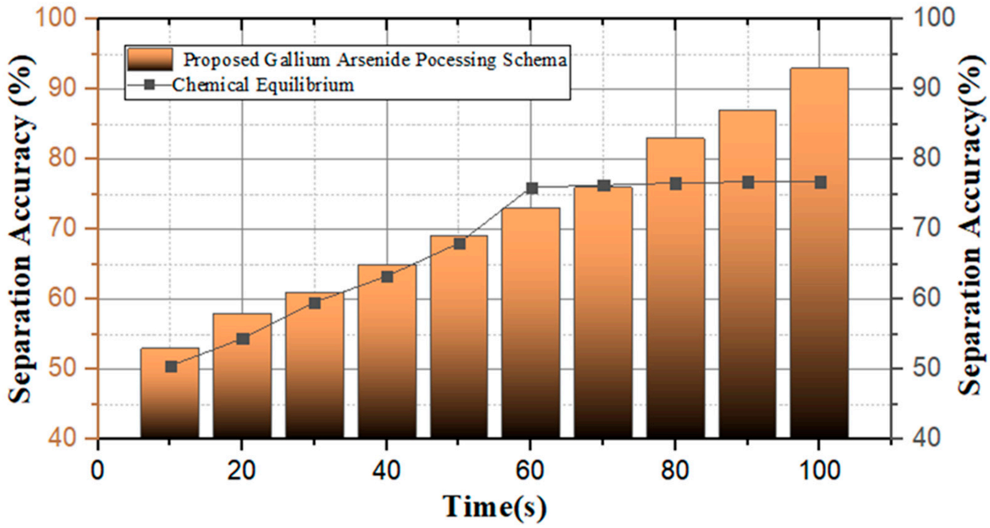

Figure 10. Separation accuracy of various separation techniques.

At 100 s, it grows and reaches a 95% prediction accuracy. The chemical equilibrium and gallium arsenide processing schematic of our suggested method are more accurately predicted in Figure 10. Consequently, an analysis of the suggested system method's separation accuracy is performed.

Table 4 compares the separation accuracy of our proposed gallium arsenide processing schema with existing methods.

Table 4. Separation accuracy of any chemical equilibrium vs. proposed gallium arsenide processing schema.

Time	Separation Accuracy of Waste Management (%)	
	Chemical Equilibrium	**Proposed Gallium Arsenide Processing Schema**
10	50.5	53
20	54.4	58
30	59.6	61
40	63.3	65
50	68.04	69
60	76.02	73
70	76.31	76
80	76.65	83
90	76.79	87
100	76.84	93

Figure 10 illustrates how the waste management's separation accuracy varies with time, expressed in seconds. Waste prediction is important, but waste separation plays a more important role. In order to achieve a satisfactory level of waste separation, the froth flotation technique is applied in the GaAs wastewater separation method. Then, chemical equilibrium is followed by operation cessation, and the Balz–Schiemann reaction is used to support chemical liability. Chemical compensation for waste management separation accuracy increases linearly and is maintained at a particular time, with an approximate separation accuracy of 76%. This study demonstrates that the analysis of wastewater separation using our suggested gallium arsenide processing schema increases with time.

The waste separation accuracy was 53% at the beginning and rises to 93% at the end of the 10 s time interval. This leads us to the conclusion that our method provides a significant separation accuracy percentage.

The relationship between the separation accuracy and classification accuracy of the proposed method and the methods currently used will be further investigated in this study.

Table 5 shows the separation accuracy of wastes based on a classification accuracy range of 60–100.

Table 5. Classification accuracy vs. separation accuracy against neural network for waste prediction.

Classification Accuracy Range	Separation Accuracy					
	ERD with Balz–Schiemann Reaction	ERD Without Balz–Schiemann Reaction	Proposed Classification Techniques with Balz–Schiemann Reaction	FLOTAC with Balz–Schiemann Reaction	FLOTAC Without Balz–Schiemann Reaction	Proposed Froth Flotation Techniques with Balz–Schiemann Reaction
40–50	40	43	47	38	40	45
50–60	52	52	58	46	49	54
60–70	59	61	69	53	57	67
70–80	65	73	76	60	69	74
80–90	71	82	88	67	74	83
90–100	76	87	94	71	79	91

The separation accuracy in percentage of our proposed classification techniques with the Balz–Schiemann reaction and existing methods with or without the Balz–Schiemann reaction is also calculated. A comparison between the separation accuracy value and the classification accuracy range is presented in Figure 11. The accuracy of the current separation method is shown in Figure 11 both with and without the Balz–Schiemann reaction. Our proposed separation and classification techniques using the Balz–Schiemann reaction continue to rank highest, as shown in Figure 11.

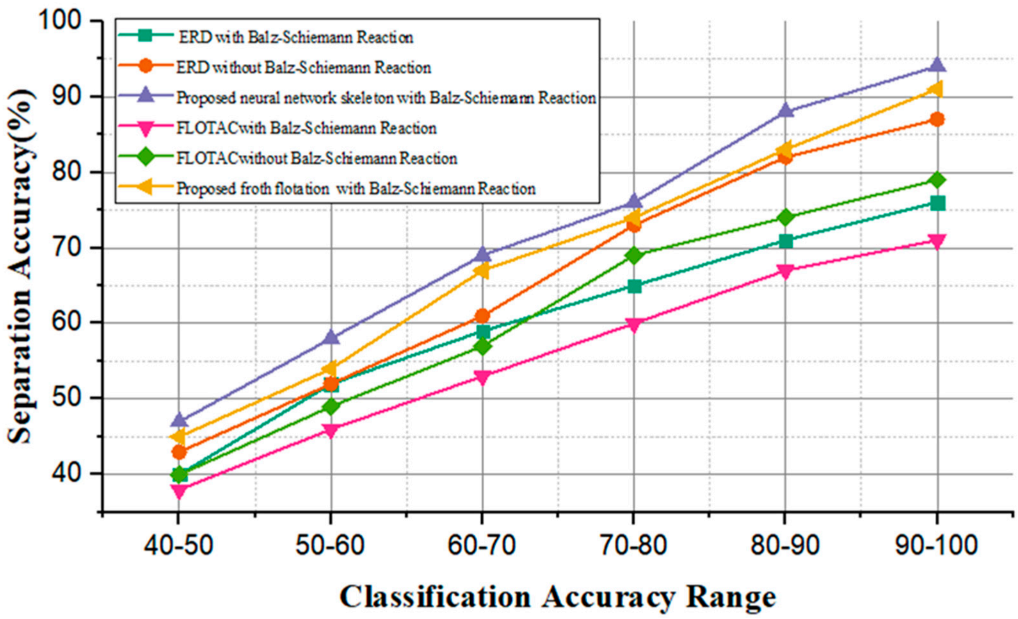

Figure 11. Relationship between classification accuracy and separation accuracy of existing and the proposed method.

Table 6 illustrates the percentage of waste management that is separated using an exemplary separation mechanism. It also shows the separation level and its approximate percentage.

Table 6. Pie chart for predicting process evolution stages.

Evaluation Measure	Separation Percentage
More Separation	12%
Moderate Separation	45%
High Separation	25%
Higher Separation	40%
Extensive Separation	15%
Extraordinary Separation	28%

Finally, the percentage-based prediction of the process evolution stages is analysed. A pie chart representing the separation percentage during stages of the prediction process is presented in Figure 12 [19]. The evaluation process of the waste separation is based on six levels: more separation, moderate separation, high separation, higher separation, extensive separation, and extraordinary separation.

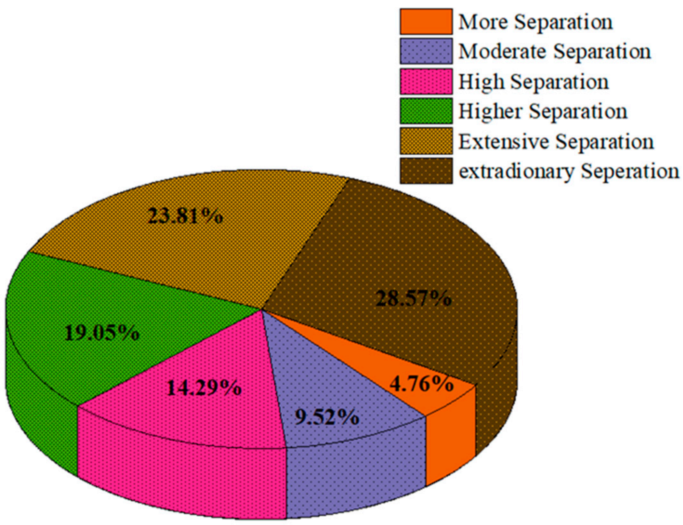

Figure 12. Pie chart for predicting process evolution stages with their percentages.

Each parameter has an estimated value that is expressed as a percentage. At level 1, this research mentions more separation of waste at 12%. Similarly, level 2 had a moderate separation of 45%, a high separation of 25% at level 3, 40% at level 4, and an extensive separation of 15% at level 5. Finally, a great separation occurs at level 6 at 28%.

The model's specific function in the study is to optimize the composting process by precisely predicting and separating waste components during vermicomposting. The model outperforms conventional models by combining a neural network skeleton with the gallium arsenide processing schema to obtain high prediction accuracy and efficient waste separation. By effectively assessing the stages of decomposition, enhancing resource recovery, and facilitating more environmentally friendly waste processing techniques, it improves waste management. A precise, scalable solution for vermicomposting applications is made possible by this model's advanced separation and prediction capabilities.

4. Conclusions

Wastewater management is a critical challenge faced by municipalities and industrial facilities worldwide. The increasing volume and complexity of wastewater streams, coupled with the need to minimize environmental impact and maximize resource recovery, have necessitated the development of advanced treatment technologies. One promising approach is the integration of neural network-based models with traditional wastewater management practices, such as vermicomposting.

Vermicomposting, the process of using earthworms to convert organic waste into nutrient-rich compost, known as vermicompost, has gained significant attention as a sustainable waste management solution. The potential to utilize biodegradable municipal solid waste as feedstocks in vermicomposting offers an attractive alternative to conventional disposal methods, which often result in environmental degradation. However, the inherent complexity of the vermicomposting process, including the sensitivity of earthworms to environmental factors, has presented challenges in predicting the waste output and optimizing the system's performance.

Neural network models have shown promise in addressing these challenges. By leveraging neural network-based models, researchers can develop more accurate predictions of waste generation from vermicomposting, enabling more effective planning and the optimization of waste management systems.

This study focused on the estimation of a proposed chemical processing method for waste management in vermicomposting using a neural network skeleton. An in-depth analysis was performed, comparing the proposed system with existing methods based on various parameters such as the prediction ratio, separation ratio, prediction accuracy, and separation accuracy.

The proposed neural network skeleton demonstrated superior performance over existing methods, achieving an average prediction ratio of 91.32%, compared to the average prediction ratios of 73.4%, 79.7%, and 80.8% for the ERD network, RNN, and deep LSTM network, respectively. This superiority was further evident in the separation ratio and prediction accuracy, highlighting the efficiency and effectiveness of the proposed method.

Furthermore, the study delved into the chemical equilibrium and separation accuracy of waste, emphasizing the linear increase and maintenance of prediction accuracy and separation accuracy over time.

The findings showcased the significant potential of the proposed gallium arsenide processing schema, which shows high prediction and separation accuracy, underscoring its ability to optimize waste management and vermicomposting processes.

Lastly, the prediction of the process evolution stages was presented, indicating the efficiency of the proposed system in achieving various levels of waste separation.

The findings of this study underscore the potential of the proposed neural network skeleton and gallium-As-based processing schema in optimizing waste management strategies, improving the quality of vermicompost, and developing more efficient waste segregation systems.

These results highlight the need for further exploration and the eventual implementation of these advanced techniques in real-world waste management scenarios. Further research and the implementation of these methods could significantly contribute to environmental conservation and sustainable waste management practices.

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