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Optimization of Agricultural Waste Biosorption in Textile Wastewater Using Artificial Intelligence

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Abstract

Wastewater from the textile sector contains many hazardous and non-biodegradable colors. This can be accomplished by using the biological absorption process, which is the passive removal of pollutants from agricultural waste. Therefore, it becomes extremely important for the environment to remove textile dye utilizing agricultural waste. This investigation low-cost agricultural waste such as Coco coir and paddy straw was utilized to create the ideal circumstances for removing Methylene Blue (MB) using Artificial intelligence (AI) techniques. The technique is Stochastic Gradient Decent Optimized-Improved Deep Neural Network (SGDO-IDNN). The experiment aimed to examine the effects of pH, temperature, amount of bio-sorbent and dye concentration. The highest MB dye removal when total substances submerged in fluid solutions are considered is 81.37% for coir and 70.99% for paddy straw. According to the models, biosorption could be predicted with excellent accuracy if the R2 value was greater than 0.99. Comparative statistical assessments of the SGDO-IDNN model were performed. Furthermore, using coconut coir at amount of biosorbent (1.43g), pH (5.42), dye MB concentration (29.99 mg/L) and paddy straw at amount of biosorbent (1.67g), pH (5.47), dye MB concentration (34.9mg/L), 26.8°C of MB solution, The models were set up to eradicate dyes as much as possible.

Keywords: Stochastic Gradient Decent Optimized-Improved Deep Neural Network (SGDO-IDNN), Methylene Blue (MB), Biosorption, Artificial Intelligence, Coir, Paddy straw)

Full-length article **Corresponding Author*, e-mail: ajay.chakravarty1@gmail.com

1. Introduction

One major problem that the processing of wastewater for fabrics pollutes the environment. Textile effluent can be treated with agricultural wastes, resulting in a large reduction in waste and an innocuous form before that is released into water bodies. Several therapy techniques have been used, such as chemical, physical and biological [1]. Most environmental pollutants arise from contaminants' discharge into air, water and other settings. The wastewater from the textile industries contains toxic substances, phenolic substances and colors [2]. Vital life-form water is a universal solvent with poisonous and non-toxic compounds. Urbanization and population growth have polluted water habitats with agricultural as well as industrial pollutants, producing health problems. Health problems result from non-degradable heavy metals. To treat wastewater, membrane filtration, reverse osmosis, chemical precipitation and biosorption. Biosorption is environmentally favorable [3].

The biosorption process in textile wastewater is a crucial aspect of agricultural waste management. It involves selecting suitable agricultural waste materials, optimizing bio-sorption and maximizing pollutant removal efficiency. This process is economically viable, environmentally friendly and contributes to water quality along with waste management, ensuring sustainable practices in textile industries [4]. Adsorption is a popular wastewater treatment process due to its cheap capital as well as operational costs, carbon footprint and environmental friendliness. Common sorbents include Molecular screens, polymer biological chemicals, silicon dioxide gel, zealous and alumina activated. Biochar from biomass waste is a popular adsorbent due to its high adsorption capacity and environmental friendliness. Effective wastewater cleanup requires electrochemical and adsorption methods [5]. Bio-sorption uses biomass as a sorbent material to remove hazardous pollutants from aqueous solutions to reduce levels. The initial use of absorption methods was for sewage and waste treatment. A biosorption technique was studied for repurposing chemical industry wastewater. Biomass, both living and dead, has many desirable qualities and it is a promising biotechnological technique for removing hazardous contaminants [6].

The study [7] decontaminated dye-polluted groundwater with Luffa cylindrica seed extracts by coagulation/flocculation. The bio-coagulants were described and predicted using Response Surface Methodology (RSM) and Artificial Neural Network (ANN) models. Fraser extracted functioned best, with the ANN algorithm estimating wastewater color/total suspended particles. The paper [8] investigated which native adsorbents best extract MB dye from industrial effluent. In experiments, the central composite design (CCD) and the one variable at a moment method were used to optimize the removal process parameters. Ash from banana leaves was discovered to have adsorption properties. The paper [9] used wheat stalk (T. aestivum) biomass to assess MB biosorption from wastewater effluent. Biosorption was enhanced through the application of Response Surface Methodology (RSM) and ANN modeling software. The study findings, which demonstrated the presence of functional components and the binding of fresh nanoparticles on the top layer. The study [10] used Peanuts shells and sugar cane bagasse is used as inexpensive leftovers from agriculture to maximize MB removal from wastewater from the textile sector utilizing RSM and ANN.

The paper [11] describes that textile wastewater has a high water demand and rice husk-based biomaterial (RHBB) can be employed as an inexpensive treatment material. Several methods have been used to deal with pollution problems, such as membrane separation, chemical combustion, oxygenation, the rate of blood coagulation and hydrolysis. Chemical modification is advised for improved efficacy in treating textile effluent.

The journal [12] presented the three absorbing substances for the coloring of textile effluent: Green-synthesized nanozerovalent iron (GT-nZVI), charcoal and nanozerovalent irons (nZVI). Many techniques, such as UV-V is absorption spectroscopy, EDX analysis, microscopy with scanning electrons and X-ray diffraction, among others, were used to characterize nano-materials. The analysis [13] utilized a dye removal from wastewater via biosorption, which is simple, effective and environmentally friendly. Due to their low cost, availability and pollutant removal, yeast cells and other biomaterials are used. This work discusses biosorption using living, dead and modified yeast cells, kinetic, equilibrium and analytical approaches.

The investigation [14] discusses sustainable textile wastewater treatment and residual biological agro-industrial waste management. It shows the promise of solid renewable biomass materials for sustainable development. An integrated, cross-disciplinary approach is reviewed for chemical-free and economically viable bioremediation of textile dye-contaminated water. The study [15] examines the integrated, cross-disciplinary strategy for textile dye-contaminated water remediation employing solid substrates are discussed. Soft computing models like ANN were utilized to extract cylindrical charcoal is used to remove contaminants from wastewater of textiles. Time, pH and adsorbent dosage affect the removal process, proving the reliability of the models for removing contaminants.

The research [16] used a mixed bacterial culture to decolorize and degrade Direct-Blue-71 (DB71) dye in textile dyeing industries. The microbiome includes Porphyromonadaceae, Pseudomonas, Acinetobacter, Comamonas, Aeromonadaceae, Flavobacterium, and Enterobacteriaceae. Response surface approach and ANN optimized de-colorization, with ANN model predicting as well as achieving more accuracy. In this research absorption testing of textile wastewater is carried out using agricultural waste materials such as coconut fibre and paddy straw. The artificial intelligence Stochastic Gradient Optimization-Improved Deep Neural Network (SGDO-IDNN) model is generated using these experimental result models.

The investigation's complying with sections is organized this way: Section 2: Methods; Section 3: Result as well as Discussion and Section 4: Conclusion.

2. Methodology

Coconut fibre and paddy straw, two agricultural waste products, are used in absorption tests of textile effluent. These models of experimental results are used to construct the artificial intelligence Stochastic Gradient Optimization-Improved Deep Neural Network (SGDO-IDNN) model. Fig 1 explains the working strategies in AI-based farming refuse biosorption in fabric sewage control. 60% of the data were used in training the SGDO-IDNN model, 20% in model validation and 20% in model testing. Using a trial-and-error method, the quantity of layers in the hidden layer was chosen to enhance the outcome forecasting according to the experimental results. Once the optimal number of synapses for the hidden layer has been established, the SGDO-IDNN model was trained for eight iterations.

2.1. Making bio-sorbents

The bio-sorbents employed in this investigation were coconut coir [17] and paddy straw [18]. India, Malaysia and Indonesia extract precious coir fiber from coconut husk waste as well as the paddy straw from the wheat, rye and barley grains comes from their seed heads. Hollow grass stems remain. Like hay, paddy straw or hollow stems are rolled into rectangular bales. The hygroscopic, compressible coconut husk makes up 35–40% of the coconut. Coir pith from separation is burned or discarded in roadside pits. Composting coir pith for land application has various limitations. Coir pith is studied for wastewater pollution reduction.

Inexpensive adsorbents can minimize waste volume and waste water contamination. They were rinsed using water to get rid of pigment and grime. The filtered water was used for the last cleans to get rid of any last bits of synthetic leftovers, especially acids and other substances that dissolve. They were sun-dried after that. Then they were maintained for 24 hours at 80°C in the hot air oven. Paddy straw and dried coconut coir was grounded independently. The particles that passed through a 600 µm sieve and remained on a 300 µm screen were collected for experimental investigations after they had been sieved using a sieve shaker.

2.2. Chemical Reactors

To prepare the dye mixture for empirical, the rate of an analytical grade MB (C16H18ClN3S) with a molecular weight of 320.16 Dalton and a dye-content of 70% was purchased. For the initial concentration of MB solution preparation, 10 to 50 mg/L of MB is the suitable amount. Table 1 was describing the dissolved in filtered water to create the MB dye solution. Design Expert, a program for statistical analysis, was used to process the experimental data. The variables (−α, −1, 0, 1, +α) are displayed in their Graded Sequences (See Table 1). The selection of α=1.683 was made to preserve rotatability.

2.3. Test-plan design

The study investigated the effects of heat, pH, quantity of bio-sorbent and the intensity of color on the adsorption process of paddy straw and coir as adsorbents for wastewater remediation. The starting amount of MB dye was set at 10–50 mg/L and the effects of the pigment's solution pH (4–8), warmth (20°C–40°C) and biosorbent material dosages (0.509 g–2.499 g) were investigated. The removal of color concentration is made feasible by this true wastewater treatment scenario.

2.4. Research Efforts on Biosorption

The experiment involved 250 mL conical flasks filled with 100 milliliters of MB dye solution at prescribed concentrations. A pH tester with calibration was utilized to change the solution's pH (Model: HQ40d) and variables were determined via runs. The % dye removal was determined using an equation by calculating the total amount of solids dissolved and dye-concentration. The contact period was two hours.

The solution's initial barnacle population can be identified as follows in Equation (1):

$$\boldsymbol{Dye\ Solvent}\ (\%)\ = \frac{\boldsymbol{R-S}}{\boldsymbol{R}} \times \mathbf{100} \quad (1)$$

Where $RandS$ are the very first and last normalization variables of TDS, and the quantity of dye is determined using Equation (2) and (3):

$$R = \frac{A1}{B1} \quad (2)$$

$$S = \frac{A2}{B2} \quad (3)$$

2.5. Optimization Techniques for Agricultural Waste Biosorption in Textile Wastewater

The Deep Neural Networks (DNN) is used to analyze current processes, design various approaches and predict system operations and behaviors. The Stochastic Gradient Descent (SGD) (back-propagation) method trains the multi-layer DNN model. On the other hand, stochastic gradient descent uses a single training event to update the model parameters more often.

2.5.1. Stochastic Gradient Decent Optimized Improved Deep Neural Network (SGDO-IDNN)

2.5.1.1. Improved Deep Neural Network

The DNN models (see Fig 2) utilized in this work were constructed with 10 hidden layer nodes, one output layer node and four input layer nodes that each indicated a different proportion of MB dye extracted from the paddy straw and coir, respectively. The input layer nodes stood for "temperature, pH, the amount of bio-sorbent and dye concentration." The MATLAB software's mean square error (MSE) was used to evaluate its performance. The plot of progression for the trained DNN design for paddy straw and coco coir is displayed in Fig 3 and 4, respectively. A higher correlation between the expected and actual results is demonstrated by an R-value closer to 1.

2.5.1.1. Stochastic Gradient Decent Optimization

An algorithm for optimization used to locate a differentiable function's local minimum is Stochastic Gradient Decent (SGD). Optimizing constants is a prominent use case in Machine Learning (ML). The majority of minimization problems in ML are able to be viewed as cost-functional minimizations. We refer to this type of function as the objective function. We can keep lowering the intended function's value by repeatedly adjusting the parameters in the gradient's opposite direction to get close to the neighborhood's minimum. We can keep reducing the intended function's weight to get close to the neighborhood's minimum. A machine learning algorithm's objective function breaks down into an expectation of the per-sample-loss function (such as the mean squared-error-loss (v)and cross-entropy-loss (u)). Total instruction sets.

$$K(u, v, \theta) = \frac{1}{q}\ k\ [u^{(j)}, v^{(j)}, \theta] \quad (4)$$

The instruction data ("temperature, pH, the amount of biosorbent, and dye concentration") is$\{[u^1, v^1], [u^2, v^2] \dots, [u^q, v^q]\}\theta$represents the instruction specifics, k is the pre-sample-loss, q is the data used for instruction size and K is the expectation of the loss function. To minimize the aforementioned objective function, gradient-descent requires calculating

$$\delta = \frac{1}{q}\sum_{j=1}^{q} \nabla_{f^k}\ [u^j, v^j, \theta] \quad (5)$$

Where k represents the gradients of each sample and$\nabla_{\theta^k}$is the mean angle of this total loss, Equation (5) has an P (q) computing cost. One calculation will require considerable time if the instruction set is huge. The computational cost was proposed to be solved by SGD. The basic principle behind SGD is utilized by a small-scale of training samples; one can predict the expected losses over the entire instruction set ($i.e., k[u, v, \theta]$in Equation (4)). The estimation of predicted loss and associated gradients is demonstrated by Algorithm 1. q, the size of the instruction set, does not affect n. Therefore, the SGD's processing expenses is*P (q)*, and the quantity of the instruction set (M) has no direct bearing on how much each variable update costs. Furthermore, approaches that employ more than one but not all of the training samples are referred to as simply stochastic methods. Previously, these methods were known as small-scale or small-scale stochastic techniques.

Algorithm 1: Stochastic-Gradient-Descent

Input: training rateη, epoch-s, initial variable, θ, neural-network, e, loss
Function, $\{[u^1, v^1], [u^2, v^2] \dots, [u^q, v^q]\}, K$, instruction set,
for $s = 1\ to\ S\ do$
Sample n samples from the instruction set as small-scale;
Estimate expectation:$K(v, s, \theta_s) = \frac{1}{m}\sum_{j=1}^{n} k\ [u^j, v^j, \theta_s]$;
Estimate gradient $h = \nabla_{f^K}(u, v, \theta_s)$;
Parameter update $\theta_{s+1} = \theta_s - \eta\delta$;
end

3. Result and Discussion

The study investigated farm waste biosorption in drainage from textiles prediction models; SGDO-IDNN performed better in accuracy and error metrics. To implement this model using MATLAB R2020b and later versions of Math Works offer advanced features for DNN, including optimization algorithms like SGD. The Deep Learning Toolbox in MATLAB provides detailed information and examples for implementing SGDO-IDNN. The system utilizes a Graphical Processing Unit (GPU) that excel in parallel computing, making it ideal for training larger DNNs faster than Central Processing Unit (CPU) on specialized gear like Intel Core i7 or i9.

3.1. Evaluation Matrix

This study used five additional factors to compare the performance of the suggested structure with various approaches. Determining model accuracy using the coefficient of determination (R). It is a statistical measure (see table 2) of how well the independent variable (PH, humidity, quantity of biosensor, and level of dye) explains the variability of the dependent variable in a correlation model's computation error matrices like "Root Mean Squared Error (RMSE), Mean Absolute Error (MAE)".

$$R^2 = 1 - \frac{Total\ Sum\ of\ Squares\ (SST)}{sum\ of\ Squared\ Residuals\ (SSR)} \quad (6)$$

$$SSR = \sum_{i=0}^{m}(y_i - \hat{y})2 \quad (7)$$

$$SST = \sum_{i=0}^{m}(y_i - \bar{y}_i)^2 \quad (8)$$

Where m is the quantity of its bio-sorbent, pH, humidity and percentage of dye are the number of data points. $y_i$is the experimental value and $\bar{y}_i$is the predicted value.

$$MAE = \frac{1}{M}\sum_{j=1}^{M}|c_j - \acute{c}_j| \quad (9)$$

$$RMSE = \sqrt{\frac{1}{M}\sum_{j=1}^{M}|c_j - \acute{c}_j|^2} \quad (10)$$

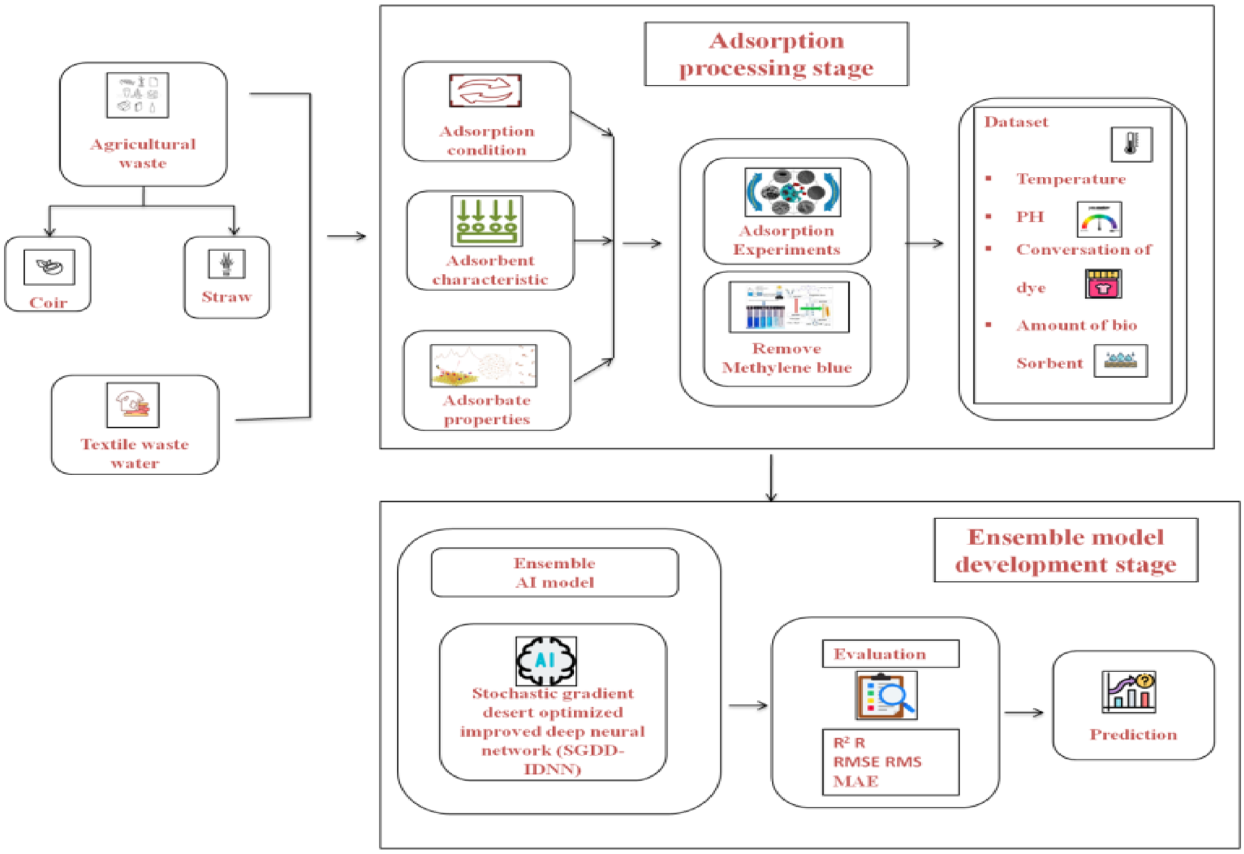


Figure 1. Workflow Model [Source: Author]

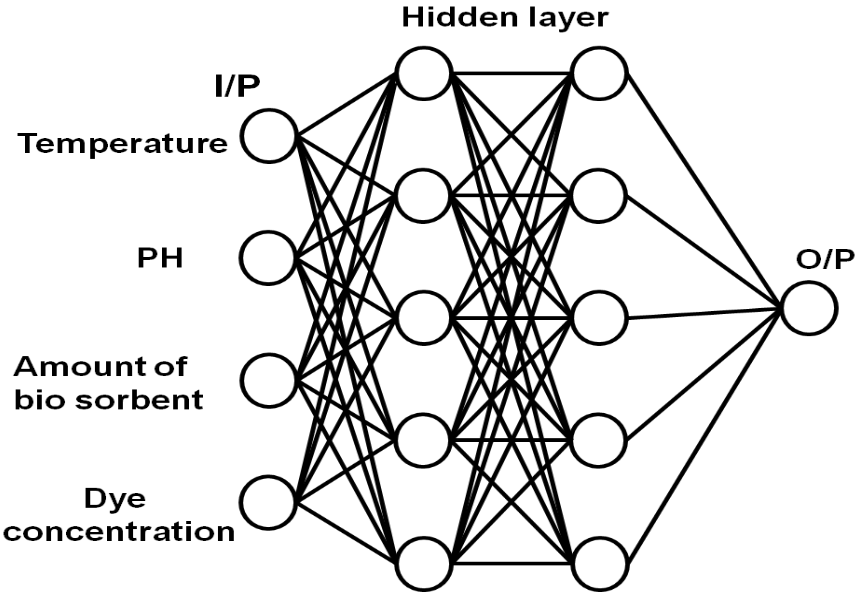
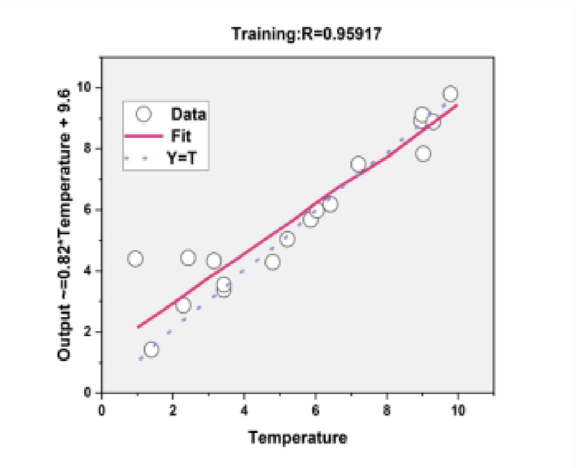
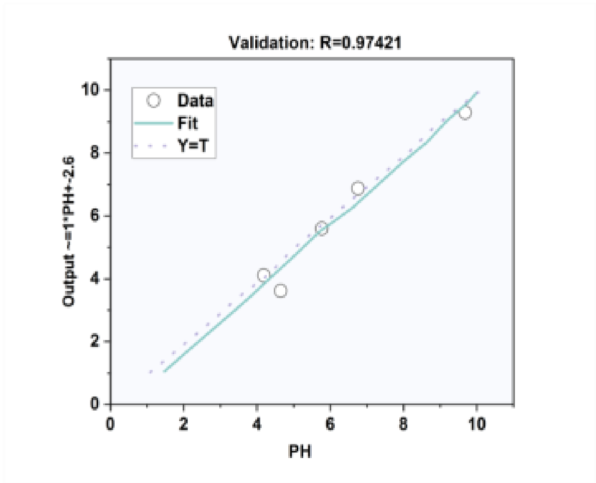


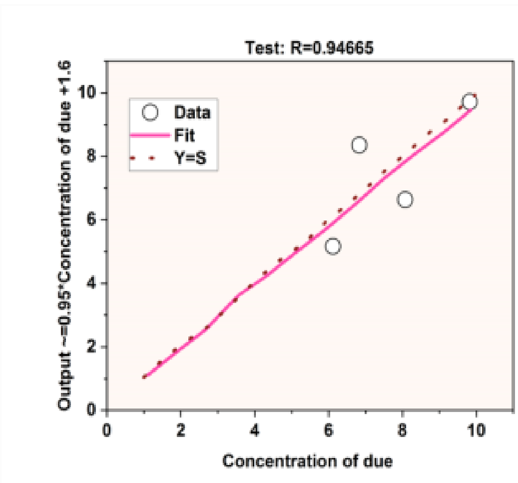
Figure 2. IDNN Architecture (Source: Author)



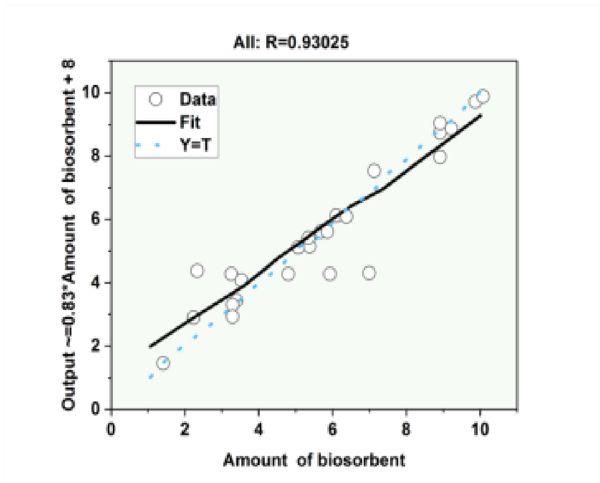
A. Temperature



B. pH



C. Concentration of Dye



D. Amount of Biosorbent

Figure 3. Paddy straw's IDNN prediction graphs for evaluation, development, verification, and total data (Source: Author)

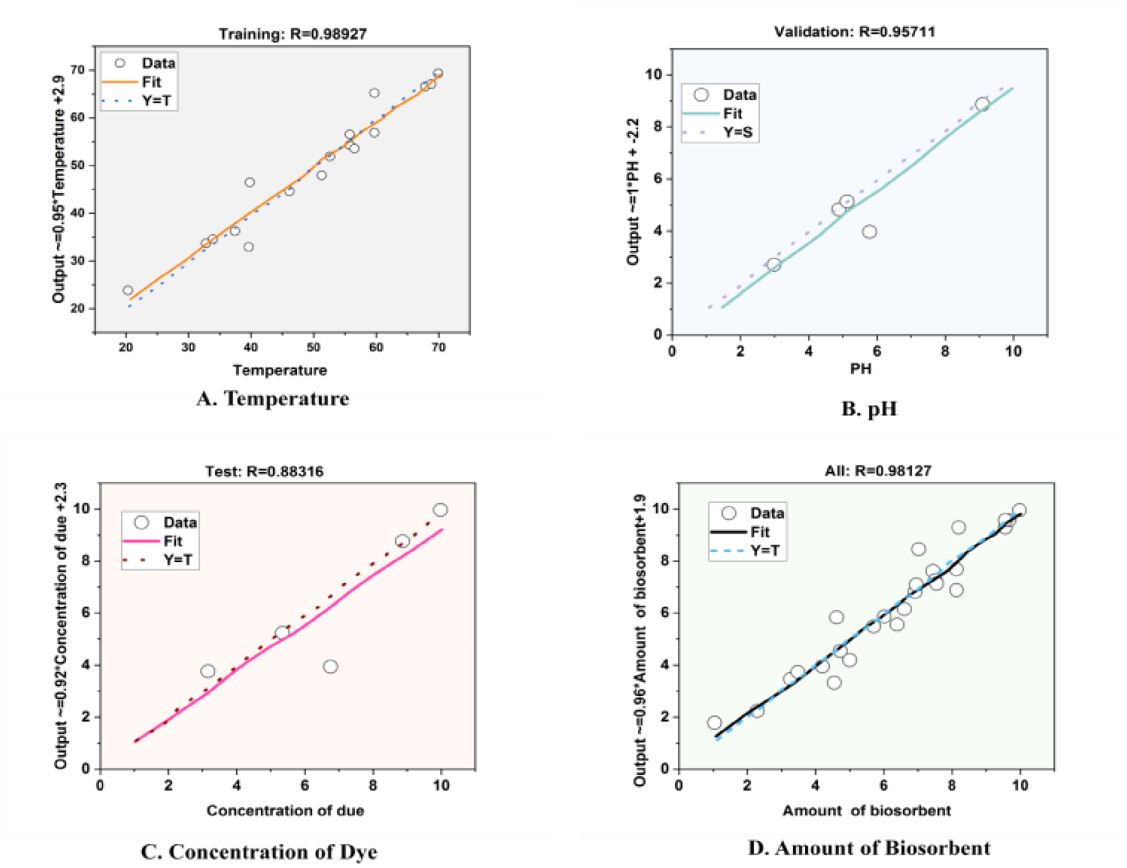


Figure 4. (A-D) Coir's IDNN prediction graphs for evaluation, development, verification, and total data (Source: Author)

Table 1. Result of precision and accuracy (Source: Author)

Variables	**Script**	**Graded Sequences**				
		−α	**-1**	**0**	**+1**	**+α**
Amount of Bio-sorbent (g)	P	0.492	0.99	1.489	1.99	2.46
pH	Q	5	6	7	8	9
Concentration of Dye (mg/Litter)	R	10	20	30	40	50
Temperature (°Celsius)	S	20	25	30	35	40

Table 2. Result of precision and accuracy (Source: Author)

Statistical Parameter	**SGDO-IDNN**	
	Coir	**Paddy straw**
R	0.999	0.9998
R2	0.987	0.9897
MAE	0.335	0.0721
MSE	0.007	0.0338
RMSE	0.008	0.1842

3.2. Discussion

Techniques from ML and deep learning (DL) are used to enhance the way agricultural waste biosorbs into textile effluent. These techniques include regression models like linear regression and polynomial regression, decision trees like Random Forests (RF), Support Vector Machines (SVM), K-Nearest Neighbors (KNN), clustering algorithms like K-Means and Hierarchical-Clustering, ANN, Auto-encoders, Gated Recurrent Units (GRU) and Long Short-Term Memory (LSTM) Networks. Transfer Learning is used to fine-tune pre-trained models for biosorption-related tasks. Hybrid approaches include Ensemble Learning, Feature Engineering, Hyperparameter Tuning, Explainable AI (XAI) and Optimization Algorithms. These techniques can be applied to predict biosorption efficiency, optimize process conditions and gain insights from complex datasets. Here, methods like SGT, an optimization technique along with regularization are applied to enhance its performance in deep neural network training on huge datasets from agricultural and environmental studies.

4. Conclusion

Using SGDO-IDNN models, the MB dye's adsorptive extraction from water solutions was assessed using paddy straw and coco coir. Numerical optimization was performed to maximize deduction by both biological sorbents. Using coconut coir (1.43g), pH (5.42), dye MB concentration (29.99 mg/L) and paddy straw at amount of bio-sorbent (1.67g), pH (5.47), dye MB concentration (34.9mg/L) as well as 28.6°C of MB treatment, the models were used to eliminate colors as much as feasible. As a result, our study has demonstrated that SGDO-IDNN can be utilized to simulate biosorption processes and identify the optimal environment for MB adsorptive removal. This model tends to have higher precision accuracy and less error rate.

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