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Artificial Neural Network Performance Modeling and Evaluation of Additive Manufacturing 3D Printed Parts

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ABSTRACT

This research article presents a comprehensive study on the performance modeling of 3D printed parts using Artificial Neural Networks (ANNs). The aim of this study is to optimize the mechanical properties of 3D printed components through accurate prediction and analysis. The study focuses on the widely employed Fused Deposition Modeling (FDM) technique. The ANN model is trained and validated using experimental data, incorporating input parameters such as temperature, speed, infill direction, and layer thickness to predict mechanical properties including yield stress, Young's modulus, ultimate tensile strength, flexural strength, and elongation at fracture. The results demonstrate the effectiveness of the ANN model with an average error below 10%. The study also reveals the significant impact of process

parameters on the mechanical properties of 3D printed parts and highlights the potential for optimizing these parameters to enhance the performance of printed components. The findings of this research contribute to the field of additive manufacturing by providing valuable insights into the optimization of 3D printing processes and facilitating the development of high-performance 3D printed components.

Keywords-3D printing; Artificial Neural Networks (ANNs); predictive modeling; Fused Deposition Modeling (FDM); mechanical properties

I. INTRODUCTION

3D printing methods have revolutionized various industries by enabling faster product production and the fabrication of complex geometries. Additive Manufacturing (AM), also known as 3D printing, is a manufacturing technique that involves the layer-by-layer addition of material [1]. One commonly used method is Fused Deposition Modeling (FDM), which utilizes a liquefier nozzle to deposit the filament material in the X-Y direction, creating three-dimensional polymer components [2]. However, FDM-produced parts often exhibit poor mechanical performance, limiting their potential applications. The mechanical properties of FDM parts can be improved by optimizing their manufacturing parameters [3]. The selection of suitable process parameters significantly affects the mechanical characteristics of FDM components. Compared to traditional manufacturing methods like machining and injection moulding, FDM exhibits lower material strength due to its layer-by-layer formation process [4]. Polylactic Acid (PLA) is a commonly used biodegradable material derived from cornflour in 3D printing. PLA is preferred for its environmental sustainability and extrusion stability [5]. However, the mechanical properties of PLA-based prints are influenced by the injection moulding technique parameter and fast cooling, resulting in reduced material strength [6]. The physical and mechanical properties of FDM parts primarily depend on the manufacturing parameters [7]. While some studies have investigated the mechanical properties of PLA, including tensile, compressive, flexural, and impact strength, more parameters need to be evaluated to enhance the application scope and control of FDM-produced components [8]. Furthermore, the mechanical properties and bonding strength of thermoplastic composites created through additive manufacturing must be comprehensively defined to ensure optimal functionality for product manufacturers [9].

Machine learning techniques, such as Artificial Neural Networks (ANNs), have demonstrated effectiveness in various applications [10, 11]. In the field of materials science, ANN models have been employed for the prediction and optimization of mechanical properties. These models have exhibited superior performance compared to conventional approaches like dimensional analysis [12, 13]. ANN models can help improve process parameters, reduce the need for extensive experimentation, and facilitate problem-solving in additive manufacturing [14]. Recent research has highlighted the potential of ANN modeling to predict and optimize the mechanical properties of 3D-printed parts. For instance, ANN models were used to predict the tensile strength of ABS P400 produced through FDM, demonstrating high accuracy in the majority of predictions [15]. Another study employed ANN techniques to create metamodels for optimizing the design parameters of hybrid components, showcasing their superior prediction capabilities compared to traditional methods like Design of Experiments (DOE) with RSM [16]. ANN models have the potential in optimizing 3D printing parameters such as layer height, thickness, fill density, temperature, and print speed for PLA materials [17]. ANNs have been also used to determine the optimal process parameters to improve creep compliance and recoverable compliance for the FDM parts [18]. However, most of the optimization techniques focus on experimental testing with the FDM parameters to investigate dimensions, tensile strength, flexural strength, and hardness [19-21]. In summary, ANN models have the potential in predicting additional mechanical properties with the process parameters for FDM 3D printing. Accurate mechanical properties predictions allow for a better understanding of the behavior and performance of 3D-printed materials. By predicting the mechanical properties, it becomes possible to optimize the 3D printing process parameters to achieve the desired material properties. Instead of relying solely on experimental testing, which can be time-consuming and expensive, using an ANN model for prediction allows quicker assessment of the mechanical properties, reducing development time and associated cost.

In this study, an ANN model is designed to model the relationship between process parameters and mechanical properties in 3D printing using the inputs of temperature, speed, infill direction, and layer thickness. The goal of the model is to predict the values of several mechanical properties, including Young modulus, ultimate tensile strength, yield stress, fracture elongation, and flexural strength, as the outputs.

II. EXPERIMENTAL METHOD

A. Experimental Parameter Determination

To assess the performance of 3D printing, experimental parameters were determined using a full factorial method. Two ranges, representing higher and lower values, were selected for each parameter. The specific conditions and corresponding levels used in the experiments are shown in Table I. The control parameters are temperature, speed, infill direction, and layer thickness. Temperature setting during the 3D printing process directly impacts the material's molecular structure and bonding, potentially affecting ultimate tensile strength, Young modulus, and mechanical performance. The printing speed affects the cooling rate and material deposition time. The infill direction determines the orientation of the internal structure of the printed part. Different infill patterns can affect the part's anisotropy, influencing properties such as yield stress, ultimate tensile strength, and flexural strength. The layer thickness directly impacts the resolution and structural integrity of the printed object, which potentially affects the mechanical properties due to the increased exposure to heat during the printing process. A two-level, full-factorial design of experiments was employed, requiring a total of 16 experimental runs. In this study, a feed-forward Neural Network (NN) utilizing the backpropagation (BP) algorithm was developed to construct multiple models for optimizing inputs and outputs. The process parameters used as inputs for the ANN model were temperature, speed, infill direction, and layer thickness. The ANN model aimed to predict the Young modulus, ultimate tensile strength, yield stress, fracture elongation, and flexural strength as the outputs. The operational parameters for 3D printing performance utilized in the ANN are summarized in Table II. Developing this ANN model with multiple inputs and outputs ultimately contributes to an adaptive system capable of continuously controlling various parameters.

TABLE I. CONTROL PARAMETERS AND THEIR LEVELS

Factor	Low	High
Temperature (°C)	210	225
Speed	40	90
Infill direction (°)	0	45
Layer thickness (mm)	0.1	0.3

B. Developing the ANN using Experimental Data

The development of the ANN system involved data collection, network configuration, weight and bias initialization, network testing, network validation, and data analysis. Specific algorithms for intelligent analysis, such as ANN architectures, facilitated the utilization of stored data available in software libraries. The research flow is illustrated in Figure 1. All collected data, including input (temperature, speed, infill direction, and layer thickness) and output (Young modulus, yield stress, fracture elongation, ultimate tensile strength, and flexural strength) parameters, were imported into MATLAB. Prior to that, the layout of the ANN was established, determining the number of neurons and layers. The ANN architecture for this study is depicted in Figure 2. During the implementation of the ANN structure using MATLAB, the data sets were divided into a 70% training set and a 30% testing set. The training set, consisting of randomly selected data points from the 16 experimental runs, comprised 11 data points. The subsequent step involved training the network using the training data. The programming involved propagating the information through the network, calculating the error, and adjusting the neural connections iteratively to minimize the error. Once the ANN was successfully trained, the trained output data were tested using the reserved testing data. The same code was employed to determine the performance of the NN based on the empirical requirements.

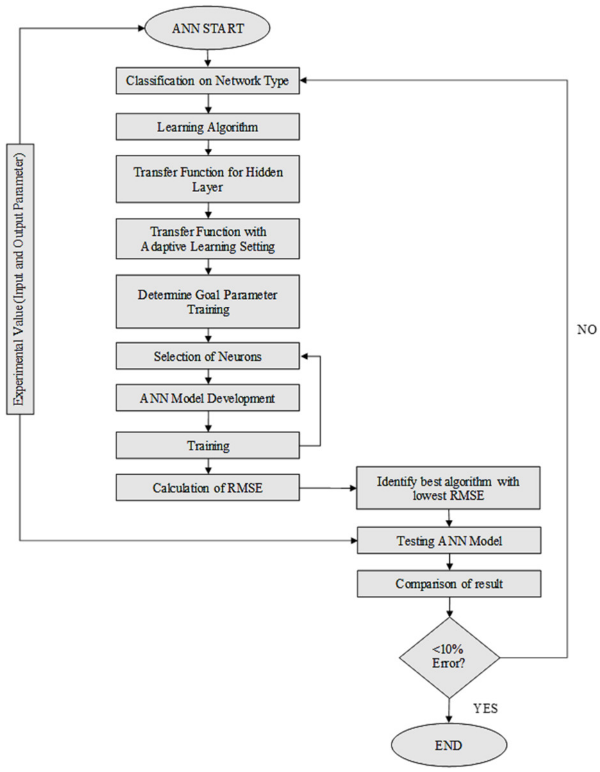

Fig. 1. Methodology flowchart of the ANN model development and validation.

TABLE II. PROCESS PARAMETERS

Exp. No	Controlled parameters				Responses				
	Temperature (°C)	Speed	Infill direction (°)	Layer thickness (mm)	Yield stress (MPa)	Ultimate tensile strength (MPa)	Young's modulus	Elongation at fracture (%)	Flexural strength (MPa)
1	210	40	0	0.1	40.25	45.43	3243.00	2.15	75.64
2	210	40	0	0.3	49.94	53.33	3209.67	2.71	92.03
3	210	40	45	0.1	44.45	47.93	2995.00	2.17	86.49
4	210	40	45	0.3	42.12	47.28	3338.67	2.29	95.23
5	210	90	0	0.1	32.73	37.52	2460.33	2.04	65.39
6	210	90	0	0.3	33.01	35.21	2648.67	1.86	76.96
7	210	90	45	0.1	28.85	31.21	2333.33	2.43	70.04
8	210	90	45	0.3	31.80	35.61	2566.67	2.91	73.46
9	225	40	0	0.1	28.16	32.47	2441.00	1.91	63.20
10	225	40	0	0.3	40.71	42.47	3351.33	1.94	79.10
11	225	40	45	0.1	32.05	35.24	2483.33	2.61	70.83
12	225	40	45	0.3	38.14	41.51	3043.67	2.35	74.10
13	225	90	0	0.1	33.33	36.25	2571.67	2.07	68.09
14	225	90	0	0.3	37.52	40.53	2815.67	2.06	75.09
15	225	90	45	0.1	46.15	50.00	3589.33	2.03	74.01
16	225	90	45	0.3	52.08	55.46	3307.67	2.13	93.30

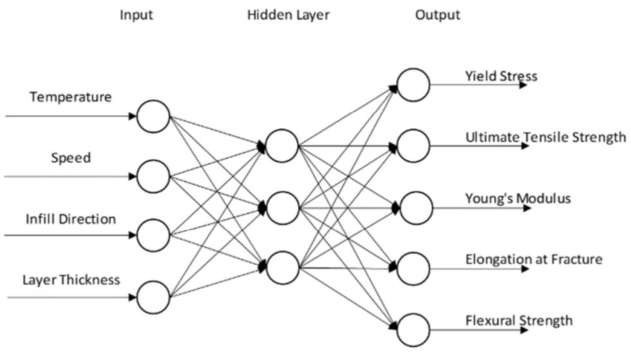

Fig. 2. The designed ANN architecture.

Finally, after the completion of the training process, the model was tested with additional experimental data. The evaluation of ANNs relies on the determination of errors, for which various error equations were employed. The Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and coefficient of determination (R^2) were calculated for performance evaluation.

C. ANN Optimization for Prediction

The MATLAB ANN toolbox offers a range of training and learning capabilities. In this analysis, the training functions TRAINLM and TRAINSG were utilized, with the architectural parameters specified in Table III. LEARNGDM was employed to adapt the network using the gradient descent momentum weight and bias learning function. The ANN model in this study was configured with 10 neurons and 2 layers. Network3 was identified as the best-performing network, as it achieved a percentage loss factor of 5.14%, which was below the threshold of 10%. The comparison between the experimental data and the predictions from the ANN and for mechanical properties such as yield stress, ultimate tensile stress, Young's modulus, elongation, and flexural strength are presented in Figure 3 and Tables IV-VI. In the study, the correlation between the predicted ultimate tensile stress and yield stress with the corresponding experimental stresses was found to be significant, as indicated in Figure 3. The error analysis revealed that the discrepancies between the experimental and the predicted results were below 10% for Young modulus and flexural strength data. Additionally, the error associated with elongation was found to be less than 2.53%. The data collectively demonstrate an average error below 10%, showcasing the effectiveness of the ANN model in accurately predicting the mechanical properties based on the input parameters.

III. RESULTS AND DISCUSSION

A. Performance Analysis of the ANN Predictions

The results obtained from the ANN predictions demonstrated a high level of accuracy in estimating the mechanical properties of the 3D-printed parts. The ANN model effectively captured the complex relationships between the input parameters (temperature, speed, infill direction, and layer thickness) and the output mechanical properties. This indicates the capability of the ANN to learn and generalize from the training data to provide accurate predictions for unseen data.

TABLE III. ANN TRAINING AND ARCHITECTURAL PARAMETERS

Network name	Network1	Network2	Network3
Network type	FeedForward	FeedForward	FeedForward
Training func	TRAINLM	TRAINLM	TRAINLM
Adaptive learning	LEARNGDM	LEARNGDM	LEARNGDM
No of neurons	8	9	10
Transfer func	TANSIG	TANSIG	TANSIG
Goal	0	0	0
min_grad	0.0001	0.0001	0.0001
Mu	0.0001	0.0001	0.0001

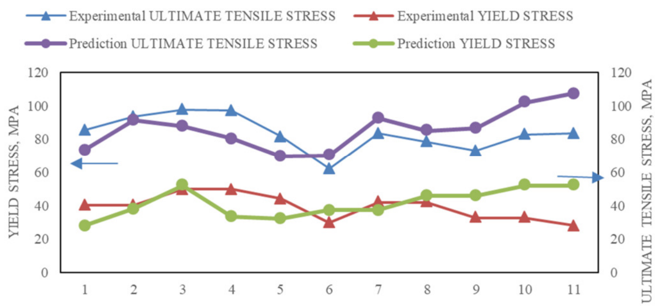

Fig. 3. Comparison between the experimental and ANN predicted results of training data for yield stress and ultimate tensile stress.

TABLE IV. COMPARISON BETWEEN EXPERIMENTAL AND ANN PREDICTED RESULT OF TRAINING DATA FOR YOUNG MODULUS

Exp. No.	Controlled parameters				Response		Error (%)
					Young modulus		
	Temperature (°C)	Speed	Infill direction (°)	Layer thickness (mm)	Experimental value	Predicted value	
1	210	40	0	0.1	3243.00	3242.96	0.00
2	210	40	0	0.3	3209.67	3209.76	0.00
3	210	40	45	0.1	2995.00	2969.53	0.85
4	210	40	45	0.3	3338.67	3339.04	0.01
5	210	90	0	0.1	2460.33	2460.43	0.00
6	225	40	45	0.1	2441.00	2441.43	0.02
7	225	90	45	0.3	3043.67	3307.67	8.67
8	225	90	0	0.1	2571.67	2500.21	2.78
9	225	90	0	0.3	2815.67	2815.69	0.00
10	225	90	45	0.1	3589.33	3589.27	0.00
11	225	90	45	0.3	3307.67	3307.67	0.00

TABLE V. COMPARISON BETWEEN EXPERIMENTAL AND ANN PREDICTED RESULT OF TRAINING DATA FOR ELONGATION

Exp. No.	Controlled parameters				Response		Error (%)
	Temperature (°C)	Speed	Infill direction (°)	Layer thickness (mm)	Flexural strength		
					Experimental value	Predicted value	
1	210	40	0	0.1	75.64	75.64	0.00
2	210	40	0	0.3	92.03	92.03	0.00
3	210	40	45	0.1	86.49	88.68	2.53
4	210	40	45	0.3	95.23	95.15	0.08
5	210	90	0	0.1	65.39	65.37	0.03
6	225	40	45	0.1	63.20	64.25	1.66
7	225	90	45	0.3	74.10	75.30	1.62
8	225	90	0	0.1	68.09	68.60	0.74
9	225	90	0	0.3	75.09	75.08	0.01
10	225	90	45	0.1	74.01	74.02	0.01
11	225	90	45	0.3	93.30	93.30	0.00

TABLE VI. COMPARISON BETWEEN EXPERIMENTAL AND ANN PREDICTED RESULT OF TRAINING DATA FOR FLEXURAL STRENGTH

Exp. No.	Controlled parameters				Response		Error (%)
	Temperature (°C)	Speed	Infill direction (°)	Layer thickness (mm)	Elongation (mm)		
					Experimental value	Predicted value	
1	210	40	0	0.1	2.15	1.97	8.32
2	210	40	0	0.3	2.71	2.69	0.73
3	210	40	45	0.1	2.17	2.33	7.59
4	210	40	45	0.3	2.29	2.27	0.78
5	210	90	0	0.1	2.04	2.13	4.31
6	225	40	45	0.1	1.91	2.02	5.76
7	225	90	45	0.3	2.35	2.38	1.28
8	225	90	0	0.1	2.07	2.09	0.89
9	225	90	0	0.3	2.06	2.07	0.60
10	225	90	45	0.1	2.03	2.03	0.15
11	225	90	45	0.3	2.13	2.08	2.33

The ANN model consistently exhibited lower error values, as indicated by the MAPE and RMSE metrics. The higher accuracy of the ANN model can be attributed to its ability to capture non-linear relationships and handle complex data patterns, which are often present in additive manufacturing processes. The ANN predictions align closely with the experimental data, demonstrating the reliability and effectiveness of the developed model. The R^2 values, which measure the goodness of fit, were consistently high for the ANN predictions, indicating a strong correlation between the predicted values and the experimental data. Overall, the results highlight the potential of ANN modeling in accurately predicting the mechanical properties of 3D-printed parts. The ANN model offers significant advantages over traditional statistical tools, enabling improved process optimization, reduced trial-and-error experimentation, and enhanced control over product quality.

B. ANN Optimization for Performance

The ANN model was optimized using a feed-forward process with a 4-10-5 architecture, consisting of 4 input neurons, 10 hidden neurons, and 5 output neurons. Out of the experimental results, 11 data points were utilized for training the ANN model, while the remaining data points were reserved for validation. The selection of training and evaluation data was performed randomly to ensure unbiased representation. The training process of the ANN model was monitored, and based on the validation error as shown in Figure 4, training was stopped at epoch 14. It was observed that the best validation performance, achieved at epoch 8, was 612.534. This indicates that the model was able to accurately capture the underlying patterns in the training data.

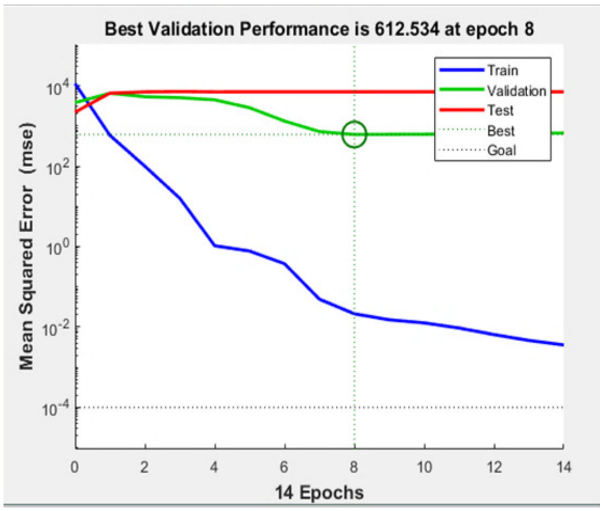

Fig. 4. Performance plot of mechanical properties.

The regression plots shown in Figure 5 demonstrate the performance of the trained ANN model. The regression values for training, validation, testing, and all data, which are 1, 0.99993, 0.99895, and 0.99954, respectively, indicate the goodness of fit between the predicted and the actual values of the target variable (mechanical properties in this case). A regression value, also known as the coefficient of determination (R^2), measures the proportion of the variance in the target variable that is explained by the model. It ranges from 0 to 1, where 1 signifies a perfect fit, indicating that the model's predictions align perfectly with the actual data. In other words, an R^2 value of 1 implies that the model can account for 100% of the variance in the target variable. For the validation and testing datasets, the acquired R^2 values of 0.99993 and 0.99895, respectively, indicate that the model's predictions are highly accurate and are very close to the actual values in those datasets. These high R^2 values suggest that the model's generalization capability is robust, as it performs exceptionally well on unseen data (validation and testing datasets).

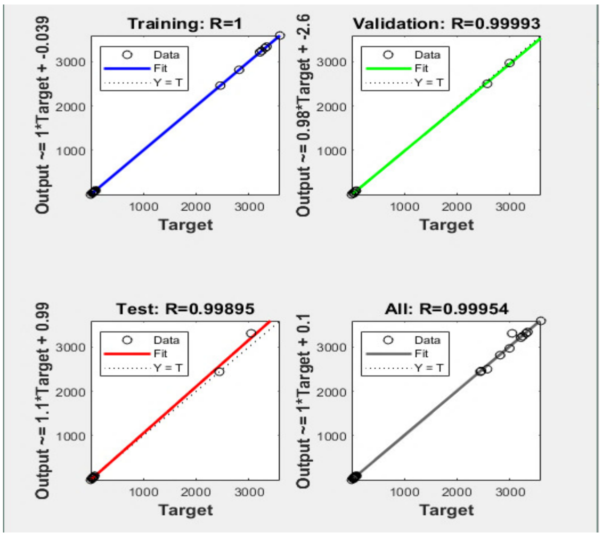

Fig. 5. Regression plot of mechanical properties.

Finally, the R^2 value for all data was 0.99954, which includes training, validation, and testing datasets, and indicates that the model's performance is consistent across the entire dataset. This means that the model's predictions are reliable and consistent across various scenarios and data points, providing further confidence in its accuracy and effectiveness. Overall, the high R^2 values demonstrate that the ANN model is capable of accurately predicting the mechanical properties based on the process parameters for 3D printing, and it offers a strong and reliable representation of the relationship between the input parameters and the target variable.

C. Validation of the Performance Model

The performance of the developed ANN model was validated by comparing its outputs with the experimental data. The regression coefficients, RMSE and MAPE were calculated with (1) and (2) to compute the accuracy of the model predictions. After the successful completion of the training cycle, the trained network was evaluated using additional experimental tests.

$$\mathrm{RMSE} = \sqrt{\sum_{p=1}^{P}\sum_{j=1}^{n^0}\left(O_{pj}^{0} - d_{pj}^{0}\right)} \quad (1)$$

$$\mathrm{MAPE} = \frac{1}{N}\sum i\,\frac{|t_i - o_i|}{t_i} \times 100 \quad (2)$$

The MAPE values presented in Table VII are essential indicators of the accuracy and reliability of the developed ANN model in predicting the mechanical properties of 3D-printed parts. The MAPE values range between 1% to 3.55% for all the mechanical properties in the training dataset. A low MAPE indicates that the model's predictions are very close to the actual values in the training dataset. In this case, the MAPE values being below 3.55% suggest that, on average, the model's predictions deviate by only around 1% to 3.55% from the true values for the respective mechanical properties. A low MAPE for training data signifies that the ANN model has successfully learned the underlying patterns and relationships within the data it was trained on, implying that the model has captured the complexities of the relationships between the input parameters and the mechanical properties, enabling it to make accurate predictions when faced with similar data points during training.

MAPE values less than 2.6% for all the mechanical properties in the validation data indicate the model's ability to generalize well to unseen data. The validation data represent new, independent data points that were not used during the training process. A low MAPE on validation data demonstrates that the model's predictions remain accurate and consistent when applied to data it has not encountered before. Having MAPE values below 2.6% in the validation data showcases the model's robustness and generalization capabilities, implying that the ANN model is not overfitting to the training data and can effectively handle variations in the input parameters and their impact on the mechanical properties. Such low MAPE values on validation data are crucial for ensuring that the model's predictions are reliable and applicable to real-world scenarios beyond the training dataset.

TABLE VII. MAPE VALUES FOR TRAINING AND VALIDATION DATA

Response	MAPE for training data (%)	MAPE for validation data (%)
All	2.98	2.61
Yield stress	3.55	2.01
Ultimate tensile strength	3.48	0.49
Young modulus	1.08	1.66
Elongation	3.21	8.03
Flexural strength	3.56	0.86

Table VIII presents the RMSE values for the designed responses, indicating strong model predictions for the remaining 5 experiments which were used for validation. The significance of RMSE lies in its ability to measure the average magnitude of the errors between the predicted values and the actual experimental data. Lower RMSE values indicate that the model's predictions are closer to the true values, reflecting a higher level of accuracy. In this case, the RMSE values for yield stress, ultimate tensile strength, Young modulus, elongation, and flexural strength fall within the range of 0.21 to 0.62. These values suggest that the model's predictions have relatively small errors when compared to the actual experimental data for these mechanical properties.

The performance validation further reinforces the reliability and effectiveness of the developed ANN model in predicting the mechanical properties of 3D-printed parts. The close agreement between the model outputs and the experimental data, as indicated by the low RMSE values, demonstrates the accuracy of the ANN predictions. By validating the model with additional experimental tests, the robustness of the ANN model was confirmed. The ability of the model to accurately capture the complex relationships between the input parameters and the mechanical properties provides confidence in its predictive capabilities. Overall, the validation results affirm the successful development and optimization of the ANN model for predicting the performance of 3D-printed parts. The strong predictive performance of the model highlights its potential for guiding process optimization and improving the quality of 3D-printed components.

TABLE VIII. RSME AMONG RESPONSES

RMSE				
Yield stress	**Ultimate tensile strength**	**Young modulus**	**Elongation**	**Flexural strength**
0.53	0.11	0.34	0.30	0.25
0.21	0.62	0.38	0.39	0.41
0.60	0.20	0.25	0.32	0.39
0.33	0.27	0.31	0.41	0.33
0.58	0.51	0.28	0.29	0.38

IV. CONCLUSION

In this study, an Artificial Neural Network (ANN) model was developed to quantitatively predict the mechanical properties of 3D-printed parts, including yield stress, Young's modulus, ultimate tensile strength, flexural strength, and elongation at fracture. The results demonstrate the potential of ANN models to enhance existing optimization techniques, revolutionizing the field of structural and material design. The optimized ANN model achieved excellent performance in predicting the mechanical properties of 3D-printed parts. The ANN predictions exhibited a remarkable accuracy, with an average error significantly below the expected error threshold of 10%, validating the reliability of the simulation forecasts. The successful development of the ANN model provides valuable insights into the performance optimization of 3D printing processes. The model's ability to accurately predict the mechanical properties based on input parameters opens up new possibilities for optimizing the design and production of 3D-printed components. The ANN model serves as a powerful tool for engineers and researchers to achieve better control over material properties and improve the overall quality of 3D-printed parts.

In conclusion, the ANN model presented in this study demonstrated its effectiveness in predicting the mechanical properties of 3D-printed parts. By leveraging the capabilities of ANNs, significant advancements can be made in many fields [22-24], and in this case, the field of additive manufacturing, leading to enhanced product performance and increased efficiency. Future research can explore further applications of ANNs in optimizing other aspects of the 3D printing process, such as material selection, geometry optimization, and process parameter tuning, to unlock the full potential of this innovative technology.

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