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Appendix L2

(Item No 5 of Check List)

Details of Research Publications

S.No	Article	Journal	Other Details Vol/No/Page No/ Year	Published in UGC-CARE / Scopus Indexed/ Web of Science
1	A Reliable and Intelligent Ink Selection System for Printed Electronics using Artificial Neural Network	International Journal of Engineering Trends and Technology ISSN 2231-5381	Volume 72 Issue 1, 193-201, Jan 2024	Scopus Indexed
2	A Novel Optimized Neural Networks Model for Ink Selection in Printed Electronics	International Journal of Electrical and Electronics Research (IJEER)	Volume 11, Issue 4, Page No: 1103-1109, Dec 2023	Scopus Indexed

*Proof of list of Journals from Internet to be attached along with copies of reprints.

Scholar : AlegaDda

Supervisor : Sivashree 10/4/24

Checked By:

HoD/Dean of Respective School

Sivashree 10/4/24 Sargu 10/4/24

The scholar Miss. Alagusundari, N (18PHEOP001) has published her article in the following journals:

1. SSRG International Journal of Engineering Trends and Technology - is indexed and active in Scopus from 2019 to present,
2. International Journal of Electrical and Electronics Research - is indexed and active in Scopus from 2019 to present.

This may be considered.

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Original Article

A Reliable and Intelligent Ink Selection System for Printed Electronics Using Artificial Neural Network

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Abstract - *Printed electronics is rapidly expanding in the industrial sector and attracting a lot of interest from a wide range of sectors due to its potential to fabricate components with intricate features. For the functionality of the products in printed electronics, the printing of conductive ink is crucial. Conductive inks are used to print flexible electronic circuits and make objects more communicative. Particularly based on consumer requirements, it is crucial to select ink for printing purposes. Ink selection has always relied on the experience of designers. Manual ink selection is a laborious and time-consuming process. Therefore, this paper intends to design an automatic ink selection system for printing applications using a novel Artificial Neural Network (ANN) framework. The literature and experimental data are used to construct the material feature dataset. The min-max approach is used for preprocessing data to align all characteristics within a common range of 0 to 1. Lastly, to choose the ink according to the input characteristics, a Multilayer Perceptron Neural Network (MLPNN) is created. The performance of the proposed system is analyzed by varying the number of hidden layers, hidden neurons, and training samples. The experimental results showed that the MLPNN appropriately selects ink for printing applications when it has optimal topology.*

Keywords - *Artificial Neural Network, Ink selection, Multilayer perceptron, Printed electronics, Screen printing.*

1. Introduction

Printed Electronics (PE) employs numerous advanced printing methods, such as screen printing, offset, spin-coating, and inkjet printing, to fabricate electronic circuits. Recently, there has been a lot of interest in employing ordinary printing techniques to create inexpensive, large-area, flexible electrical devices [1]. PE has numerous advantages over silicon-based technology, including lower resource usage, higher throughput, and far less complex fabrication processes [2]. It is projected that PE will capture a major part of the market over the next two decades due to its benefits of printing. PE has been significantly adopted to make Radio Frequency Identification (RFID) displays, sensors, and transistors using inkjet and screen printing methods [4, 5].

Screen Printing (SP) is a method of pressing a stencilled design onto a flat surface using a mesh, ink, and a squeegee. The primary methodology involves creating a stencil of high quality on a mesh screen, followed by the subsequent application of ink to transfer and imprint a designated pattern onto the surface. The SE generally consists of a screen, a frame, and a stencil with printed information [6]. The most popular screen-printed surfaces are paper and fabric, but only with specialized inks. Printing on wood, plastic, and metal is also possible.

The frame is among the most significant factors in plate-making. Aluminum, wood, and steel are used to make screen frames. The actual print image is determined by the cloth stencil. The ink is forced through the stencil created on the screen using a tool called a squeegee. Posters, plastic bottles, wood, textiles, Printed Circuit Boards (PCBs), and product displays are just a few examples of the materials that SP is used in. Ink plays a significant role in SP.

A variety of inks are used for printing cards. The quality of inks varies depending on the application. This information has an impact on the final product. For successful printing, choosing the appropriate ink is a crucial step. By altering the material's qualities, one may control the product's quality. Here, this study will concentrate on the selection of conductive ink for printing, which is the crucial step in printing cards. The printed cards will have flaws if the ink is improperly selected. As a result, the quality and appearance of the printed cards may suffer. Therefore, it is essential to develop an automatic technique to choose appropriate ink printing uses.

The PE technique has many process variables that can affect the quality of the final product and requires interdisciplinary knowledge of materials like material characteristics, substrates, solid-liquid interactions, etc.

These parameters are typically done using physics-based methods, which are difficult, tedious, and error-prone as they necessitate the automated system. To deal with the problems of physics-based methods and to boost the quality of the final product, Machine Learning (ML) models have been utilized in the printing field. Regression and classification issues may be resolved with the use of ML, a potent approach. The advantage of machine learning algorithms is that, via training, they can capture the intricate relationships between variables used as inputs and outputs. Over the past years, pattern recognition, computer vision, medical image analysis, and printing applications are just a few of the sectors that have used machine learning methods.

Researchers have used ML techniques for design feature recommendation [7], ejection of drops [8], and process optimization [9]. Based on their expertise, a professional designer can be able to choose the right ink [23, 24]. However, with so many cards available, it can be difficult to select the right ink to produce the intended card. Until now, the process of choosing conductive ink for printing purposes has relied on manual intervention. This manual selection has been associated with many challenges, including its tediousness, time-consuming nature, and dependence on the experience of designers. Identifying these issues and the potential for improvement, this research is devoted to solving these problems by introducing an automated system. The principal target of this study is to build an automated system to select the most suitable conductive ink for printing cards based on consumer requirements. By automating the ink selection process, the study intends to address the problems associated with manual selection. The following are this work's primary, distinctive contributions:

- A review of recent studies on PE using different methods has been provided.
- An automated system is designed to select ink for printing applications using Artificial Neural Network (ANN). This is the very first attempt made to use ANN for ink selection.
- To choose the best network architecture for printing applications, the efficacy of the generated system is examined by changing the number of training samples, hidden layers, and hidden neurons.
- The generated system's performance is evaluated using the real-world dataset, and comprehensive testing is done. Empirical findings imply that the ANN can select the correct ink for printing applications.

Here is a summary of the remainder of the paper. Section 2 provides a comprehensive summary of related studies. Section 3 explains the characteristics of the suggested system. Section 4 presents the findings from the performance analysis. In Section 5, the study is concluded, and some suggestions for further research are made.

2. Review of Existing Methods

Numerous research studies have tried to enhance the quality and reproducibility of PEs. The application of ML approaches to the different PE issues is briefly summarized in this section. Yao et al. [7] presented Hierarchical Clustering (HC) with Support Vector Machines (SVM) to create a hybrid approach for design feature selection. The SVM is used to enhance the HC result in the search for the suggested design elements, while the HC is utilized to classify design features. This technique helped new designers to find suitable design features for car components.

Brishty et al. [8] focused on exploring the influence of ML algorithms in the categorization of ink and printer parameters via jetting management.

The authors employed three ML algorithms for this purpose, namely K Nearest Neighbor (KNN), Decision Tree (DT), and Neural Network (NN). Their research findings demonstrated that the NN showed superior performance to the KNN and DT in light of accuracy. Brunton et al. [10] used the error-diffusion halftone method to allow smooth tonal representation in printing. This method enables the representation of colors, which is limited to inks and materials.

Nagasawa et al. [11] proposed a novel technique using NN and the line spread function to simulate color and translucency. This method required creating color patches with many layers that resembled human skin. The line spread function was initially calculated by the authors, and then they utilized NN to predict the skin color arrangement. The outcomes of their research achieved promising results, indicating that the color and translucency achieved through this approach closely approximated the target.

An intriguing technique for selecting inks for spectrum reproduction was shown by Ansari et al. [12]. This approach took a painting and found out the optimal inks for spectral reproduction using mixed integer programming. NN was designed and trained to select appropriate ink for spectral reproduction. Wu and Xu [14] employed NN to predict the amount of ink and the drop speed.

Three input characteristics, including voltage, rising time, and pulse length, were used to train the NN model to make a prediction. Huang et al. [15] adopted an unsupervised ML model for jetting prediction and attained better results. Kamyshny et al. [16] presented a thorough analysis of the uses of PE-specific metal-based inkjet inks. The authors covered several sintering techniques used to prepare inks and create conductive patterns. Also, applications of metal-based inkjet inks were given. Rama et al. [17] discussed the development of conductive inks and how to use them with flexible electronics and PE. It was determined that the optimum way to create Ag-ink is by chemical processes.

Jansson et al. [18] analyzed the flexography and SE used to examine the performance and printability of several paper-based substrates with metal conductor layers. Additionally, they assessed the employed paper-based substrates' capability for re-pulpability.

Kwon et al. [19] presented a possible way for creating biosensors and wearable electronics that are made of recyclable and disposable PE. Lall et al. [20] proposed an inkjet platform's deep learning model for correlating print parameters with electrical performance and geometry estimates. Wang et al. [21] constructed a new model to analyze droplet behaviors and enhance the stability of the printing process. They extracted various features and characteristics from the image and employed a neural network to determine the necessary adjustments in drive voltage for achieving stable printing.

Leng et al. [22] built a two-layer feed-forward network for the selection of screen-printed graphite nanoplate conductive ink in radio frequency identification sensors. The network was trained with a scaled conjugate gradient algorithm. Experimental results showed that the network had satisfactory performance. He et al. [25] utilized Support Vector Regression (SVR) to quantify the primary color ink content of PE. Median and wavelet filtering techniques were used to remove the noise from the image. A successive projection algorithm was used to extract wavelengths from the filtered image. Finally, SVR was used to predict the primary color ink content of PE. Saba et al. [26] conducted experiments to print silver nanoparticles on the top of a glass substrate by electrohydrodynamic jet printing. The study focused on three parameters, namely voltage, duty ratio, and frequency, in order to successfully achieve the desired print outcome.

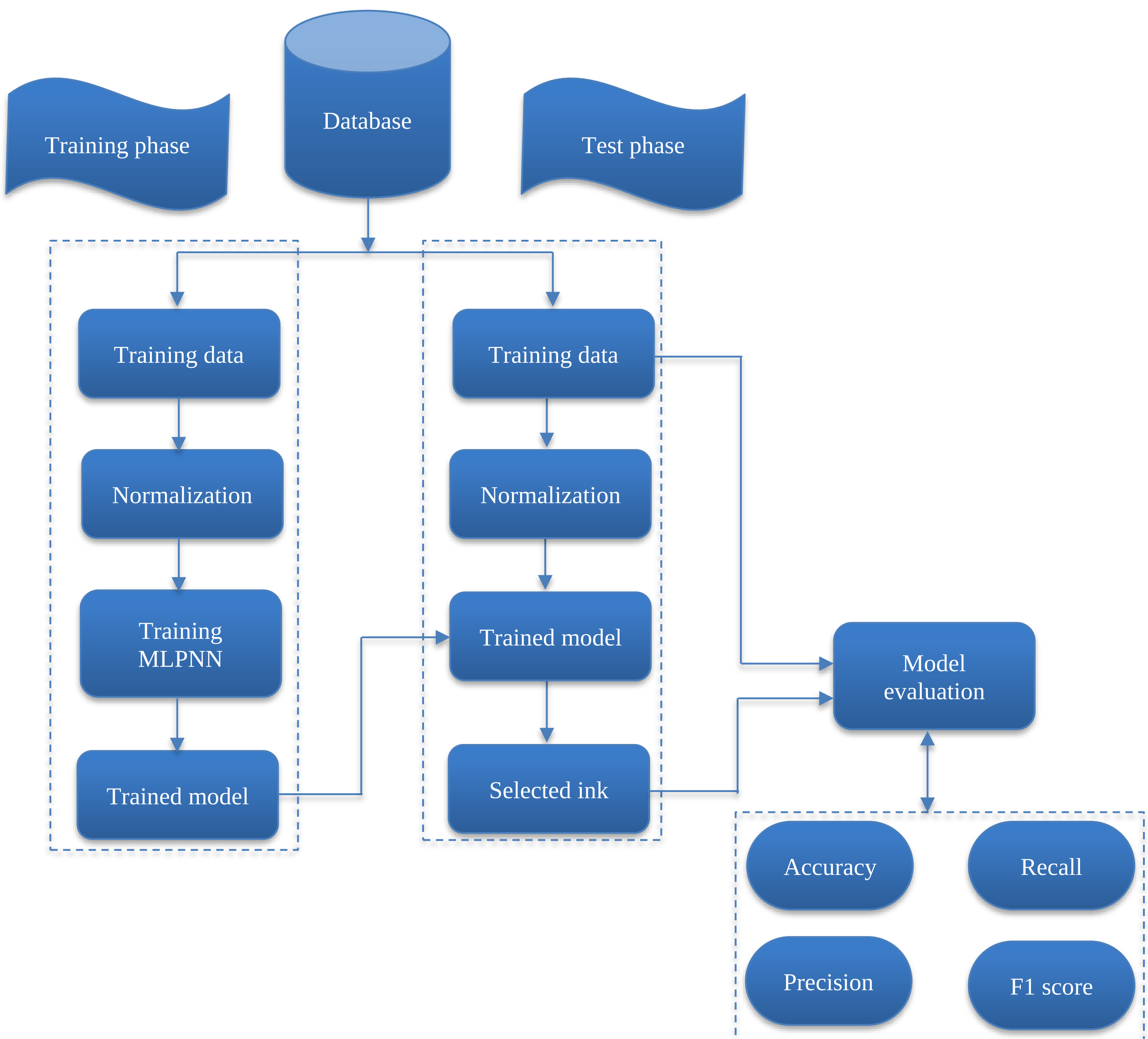

Fig. 1 The overall operational stages of the proposed system

Shi et al. [3] designed a fully-connected neural network to select ink in drop-on-demand printing applications. The network design consists of an output layer, three hidden layers, and an input layer. The output layer used rectified linear unit activation, while the hidden layers used a sigmoidal activation function. The findings demonstrated enhanced performance in comparison to the conventional approaches.

3. Proposed Methodology

The primary target of this present study is to design an automated system for ink selection using a Multilayer Perceptron Neural Network (MLPNN). The organized system's pipeline is shown in Figure 1. The following phases are involved in the designed system: (i) Data collection, (ii) Data normalization, (iii) Modelling ANN for ink selection, and (iv) Validation.

3.1. Data Collection

Data collection is the process of collecting essential input features and targets for the ANN model. It is the fundamental step for modeling an ANN model for printing applications. Data collection was done in two ways: material properties and conductive inks. As a function of material characteristics, the MLPNN selects the suitable ink for printing. Three types of conductive inks are considered such as carbon, copper, and silver inks. The critical material characteristics that are considered for successful printing are product life, quality, usage, and handling, Grams per square meter (GSM), caliper, brightness, tear resistance, and moisture content, as listed in Table 1.

3.2. Data Normalization

Since ANNs are sensitive to input data, to lie between 0 and 1, the target and input characteristics are normalized. Utilizing the min-max approach, data is normalized [13]. This could be mathematically expressed as,

$$z_{norm} = \frac{z - min(z)}{max(z) - min(z)} \tag{1}$$

Where Z and Z_{norm} are the normalized values and the input values, in that order. Moreover, min and max denote the corresponding minimum and maximum values.

3.3. Modelling MLPNN

MLPNN is a type of ANN, supervised learning network. It has three layers: an input layer, which is responsible for receiving input features from an external source; multiple hidden layers, which are processing layers; and output layers, which indicate the network output. The structure of the MLPNN developed is depicted in Figure 2.

As shown in Figure 2, the MLPNN has m input neurons representing input features and each input, xi, is connected to the hidden layer by weight. The activation function is applied to the input features after they have been multiplied by starting weights in a weighted sum, and they are then propagated to the next layer. The net input at j^{th} hidden neuron can be expressed as,

$$net_{inj} = \sum_{i=1}^{m} x_i w_{ij} + b_j \tag{2}$$

Table 1. The work's input characteristics and target

Input features								Targets
Product Life (1 to 5)	**Product Quality (1 to 5)**	**Product Usage and Handling (1 to 5)**	**Grammage (gsm)**	**Caliper/Thickness (mm)**	**Brightness (%)**	**Tear Resistance (mN)**	**Moisture Content (g/m^2)**	**Conductive Inks**
2	2	3	78	103	93	63	41	Carbon Ink
5	5	5	101	112	95	68	40	Silver Ink
4	2	1	83	109	92	65	42	Silver Ink
3	3	5	200	250	93	101	18	Silver Ink
4	2	1	110	108	94	72	20	Carbon Ink
3	3	4	280	261	92	151	19	Silver Ink
3	3	2	98	115	93	121	38	Carbon Ink
4	2	4	250	255	92	131	39	Silver Ink
4	2	3	68	115	89	125	37	Carbon Ink
3	2	4	68	115	89	125	36	Carbon Ink
2	3	2	100	132	94	115	12	Copper Ink

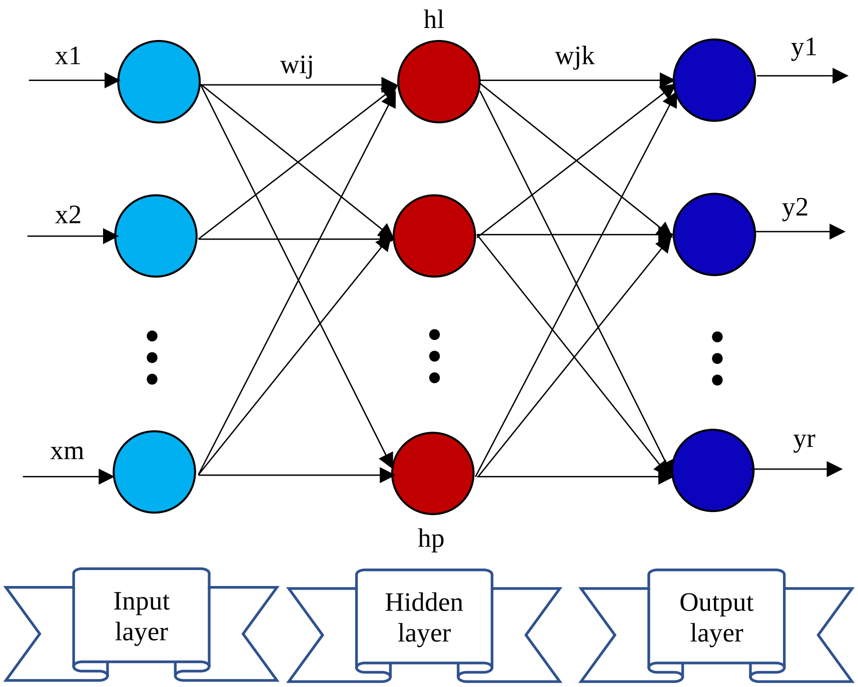

Fig. 2 The overall operational stages of the proposed system

To generate output at the j^{th} hidden neuron, the net must be activated using the activation function, g.

$$h_j = g(net_{inj}) = \sum_{i=1}^{m} x_i w_{ij} + b_j \tag{3}$$

The sigmoidal activation function is used by the hidden layer. The activation of the hidden layer, g represented as,

$$g(x) = \frac{1}{1+e^{-x}} \tag{4}$$

It is possible to calculate the k^{th} neuron's output at the output layer as,

$$y_{ink} = \sum_{j=1}^{p} h_j v_{jk} + b_k = \sum_{j=1}^{p} v_{jk}\, g\left(\sum_{i=1}^{m} x_i w_{ij} + b_j\right) + b_k \tag{5}$$

The output value is produced at the output layer using just pure linear activation. The pure linear activation function, f can be expressed as,

$$f(x) = x \tag{6}$$

Equation (5) can be rewritten as,

$$y(k) = f(y_{ink}) = f\left(\sum_{j=1}^{p} h_j v_{jk} + b_k = \sum_{j=1}^{p} v_{jk}\, g\left(\sum_{i=1}^{m} x_i w_{ij} + b_j\right) + b_k\right) \tag{7}$$

The weights between the hidden and output layers are updated by computing an error using the following equations,

$$\text{Error},\ \delta_k = \frac{1}{r}\sum_{r=1}^{r}(a_k - y_k)^2 \tag{8}$$

$$w_{new} = w_{old} + \Delta w \tag{9}$$

$$\Delta w = \eta y \delta_k \tag{10}$$

The developed MLPNN is trained with the Levenberg-Marquart Back Propagation Algorithm (LMBPA). The LMBPA algorithm uses gradient descent and Gauss neutron to minimize the error. The Hessian approximation can be computed as,

$$H = J^T J \tag{11}$$

$$\text{Gradient},\ \ g = J^T e \tag{12}$$

$$\Delta w = w_{old} - [J^T J + \mu I]^{-1} J^T \delta \tag{13}$$

3.4. Validation

In the training phase, the MLPNN receives inputs and is trained using LMBPA to understand the connection between input features and output classes.

Test data that was not used in the training phase is used to evaluate the trained MLPNN's performance during the validation phase.

4. Results and Discussions

4.1. Evaluation Criteria

The MATLAB 2022a platform is used to build the suggested automated system. The created model's performance is assessed using computing metrics, namely accuracy, recall, precision, and F1-score.

Table 2. Evaluation metrics

Metrics	Equation
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
Precision	$\frac{TP}{TP+FP}$
Recall	$\frac{TP}{TP+FN}$
F1-score	$2\times\frac{Precision\times Recall}{Precision+Recall}$

Table 3. Parameters for simulation

Parameters	Value
Input neurons number	8
The number of layers is hidden	1 to 4
Number of hidden neurons	10 to 15
Number of output neurons	3
Hidden layer transfer function	Sigmoidal
Output layer transfer function	Linear
Epoch	1000
Momentum	0.01
Training algorithm	LMBPA

The confusion matrix, which contains four values: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN), is used to examine the performance of the produced system. This study focuses on multiclass classification, where the TP class represents the specific label being analyzed, while the negative class refers to all other labels. Table 2 lists the performance metrics used for evaluation.

4.2. Experimental Details

The key parameters to develop the reliable and accurate MLPNN were fixed by experimentation. Several experiments were conducted to finalize the MLPNN's parameters. Table 3 provides the desired simulation parameters.Three scenarios were used to evaluate the effectiveness of the created MLPNN:

Scenario 1: Modify the quantity of hidden neurons to evaluate the system's efficacy.

Scenario 2: Modify the amount of hidden layers in the built system to assess its performance;

Scenario 3: Adjust the amount of training samples to examine the performance of the introduced network.

Initially, an input layer, a hidden layer, and an output layer made up the architecture used to construct the MLPNN. The output layer used a linear transfer function, whereas the hidden layer utilized a sigmoidal function. The training phase involves the application of the LMBPA to iteratively adjust the MLPNN's weights to improve its ability to generalize patterns from the input vectors.

Subsequently, in the testing process, the efficacy of the trained MLPNN was assessed with a set of samples that were different from those utilized during the training process. This step ensured that the designed network showed robust performance and could generalize its learned patterns to unseen samples.

4.2.1. Scenario 1

In the first experiment, the normalized data were split into training and testing samples: 80% of the samples were utilized as training data, with the remaining 20% being used as testing data. The hidden neurons are varied from 10 to 15. During the training phase, MLPNN finds the relation between input and output variables by analyzing training data repeatedly. The process of updating weight based on the data is being performed.

The performance plot is utilized to identify the cross entropy within the network to select ink for printing applications. An example training graph of the MLPNN is displayed in Figure 3. The MLPNN achieved its best validation score of 0.020 at epoch 50.

The training process is represented by the blue line, while the green line indicates the validation error. The fault in testing is shown by the red line. One achieves a decreased error on the training data as the number of training epochs expands. Once the validation error stops decreasing, the training process also stops.

Figure 4 shows the training state of the MLPNN at each iteration. At epoch 56, the gradient value of the MLPNN is 0.00036, and the Marquart adjustment parameter value is $1\text{x}10^{-6}$ at epoch 56. The performance validation at epoch 6 is presented. The trained network was used to select the ink based on the test data.

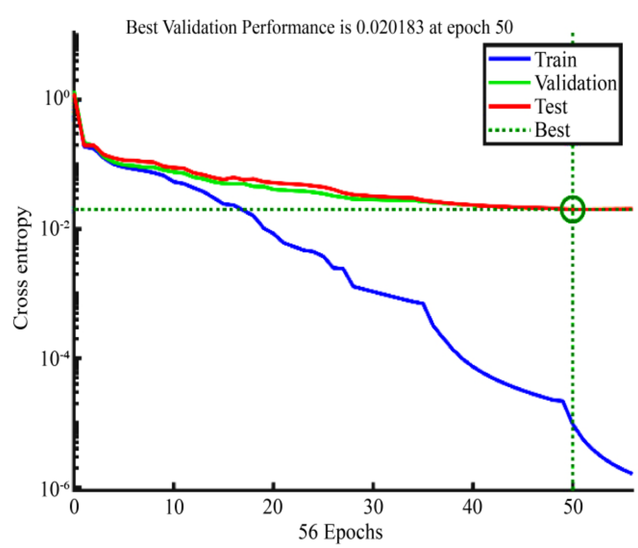

Fig. 3 Performance of the training phase

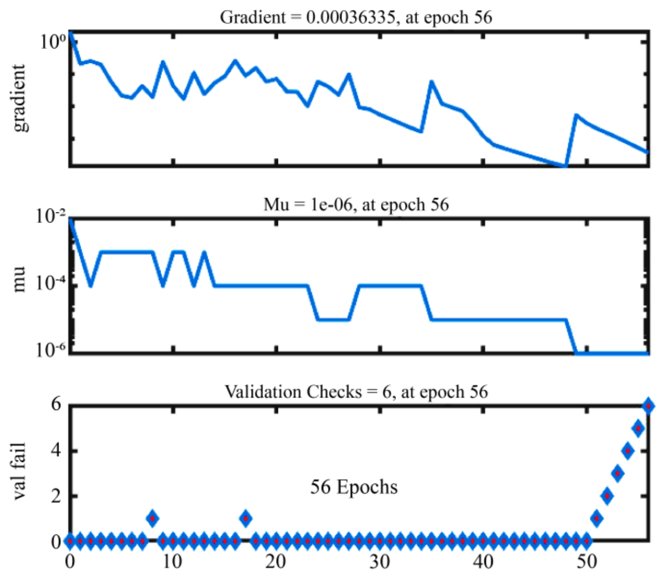

Fig. 4 Training state of the MLPNN

Table 4. Performance of the developed MLPNN for varying hidden neurons

No. of hidden neurons	Accuracy (%)	Recall (%)	Precision (%)	F1-score (%)
10	70.01	82.50	75.01	78.57
11	73.33	82.50	78.57	80.49
12	**86.67**	**95.00**	**86.36**	**90.48**
13	81.67	90.00	83.72	86.75
14	85.00	87.50	89.74	88.61
15	80.00	85.00	85.00	85.00

Table 4 provides a summary of the results of the first experiment. Table 4 shows that the constructed MLPNN with a single hidden layer and 10 hidden neurons had the lowest accuracy (70.01%), recall (82.50%), precision (75.01%), and F1-score (78.57%).

For 12 hidden neurons, the developed system provided excellent performance by reaching accuracy, recall, precision, and F1-score values of 86.67%, 95%, 86.36%, and 90.48%, respectively. The system produced an F1-score of 85%, recall of 85%, accuracy of 80%, and precision of 85% for 15 hidden neurons. This finding shows that the developed system with 12 hidden neurons provided better performance.

Therefore, the hidden neuron is set to 12. The developed system achieved the lowest accuracy for 10 and 11 hidden neurons. The system's performance would not be steady if the number of hidden neurons increased above 12. Hence, hidden neurons were fixed to 12 to get better results.

4.2.2. Scenario 2

In the second case of the experiment, hidden layers were increased from 1 to 4. The number of hidden neurons was fixed as 12. The performance of the developed system for varying numbers of hidden layers is illustrated in Figure 5. As seen in Figure 5, the system gave an accuracy of 86.67%, 91.67%, 80%, and 73.33% for 1, 2, 3, and 4 hidden layers, respectively.

Concerning recall, the system achieved the same level of 95% with both 1 and 2 hidden layers. However, the precision, F1-score, and accuracy of a single hidden layer are lower than that of MLPNN with two hidden layers. If the hidden layers were increased to 3 or 4, the system's performance declined. Therefore, the optimal number of hidden layers for printing applications is 2.

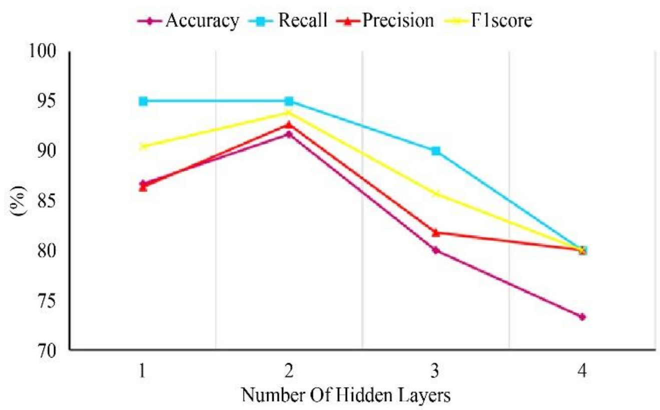

Fig. 5 Performance of the introduced method for varying hidden layers

4.2.3. Scenario 3

Based on the first and second experiments' outcomes, the parameters of the created MLPNN were set to 12 hidden neurons and 2 hidden layers, respectively. In the third scenario, changing the quantity of training samples is used to assess how successful the system that was constructed is. The training sample range in this instance was 50% to 90%. Table 5 displays the system performance that has been created for different training data.

Table 5. Effectiveness of the MLPNN by varying the training data

Training data (%)	Accuracy (%)	Recall (%)	Precision (%)	F1-score (%)
50	85.23	88.89	88.89	88.89
60	86.67	91.67	88.71	90.16
70	88.24	91.14	91.14	91.14
80	**91.67**	**95.00**	**92.68**	**93.83**
90	90.00	95.00	90.48	92.68

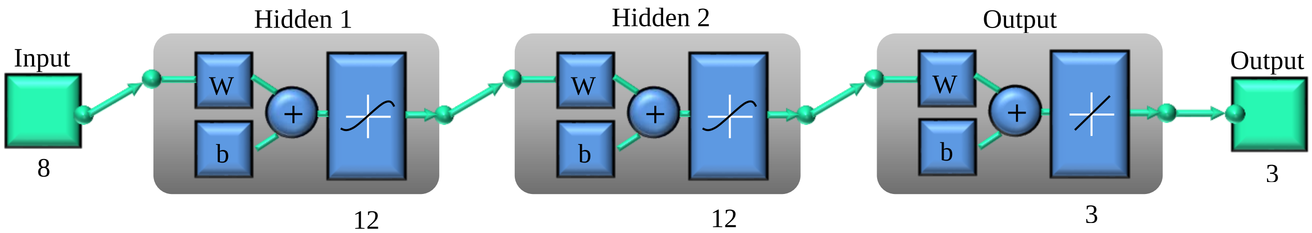

Fig. 6 The best MLPNN structure for printing applications

It can be apparently seen from Table 5 that the designed system's performance gets improved if from 50% to 80% more training examples are available. The system achieved 85.23% accuracy, 88.89% recall, 88.89% precision, and 88.89% F1-score for 50% of the training data. The system achieved 90% accuracy, 95%, 90.48%, and 92.68% for 90% of the training data, respectively, in terms of recall, precision, and accuracy. For 80% of the training data, the system provided outstanding results by achieving a higher accuracy of 91.67%, recall of 95.01%, precision of 92.68%, and F1-score of 93.83%. The developed system with the topology of 8-12-12-3 worked better than the system with other topologies, such as 8-12-3, 8-12-12-12-3, and 8-12-12-12-12-3, according to the empirical data. The best MLPNN structure for ink selection is shown in Figure 6.

4.3. Discussions

In this study, an MLPNN was designed to choose conductive ink for printing applications. As stated in the innovative aspects of the study, the exploration of several configurations exposed insightful recommendations. Through experimentation, it was found that MLPNN with 12 hidden neurons stands out as an optimal model for the selection of conductive ink for printing applications.

The investigation extended to the examination of the impact of hidden layers on the performance of the MLPNN. The findings suggested that utilizing two hidden layers improves the efficacy of the MLPNN as a classification model for selecting conducting ink. In addition to this, the research examined the impact of different amounts of training data on the performance of the MLPNN.

The outcomes indicated that using 80% of the training samples optimally positions the MLPNN as a reliable classification model for the selection of conductive ink for printing applications. The findings of this study also demonstrated the effectiveness of the MLPNN in precisely choosing conductive ink for printing applications based on consumer requirements. The design and exploration of parameters show the MLNN's capabilities to improve the decision-making process in the field of conductive ink selection for printing applications.

5. Conclusion and Future Works

This paper proposes a unique framework for selecting ink for printing applications. The system was developed using ANN. Primarily, input data were collected and then normalized into a common range of [0,1]. The normalized data were divided into training and test samples. Finally, a multilayer perceptron was designed and trained with training data. The potential of the trained MLPNN was validated using test data. We varied the number of training data, hidden neurons, and hidden layers to examine the system's performance. Experimental results demonstrated that the designed system with a structure of 8-12-12-3 provided better results. In future research, more samples will be considered to analyze the effectiveness of the developed system. Furthermore, other networks will be explored to choose ink for printing applications.

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A Novel Optimized Neural Network Model for Ink Selection in Printed Electronics

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ABSTRACT- The field of Printed Electronics (PE) is experiencing significant growth in the industrial sector and generating considerable interest across various industries due to its ability to produce intricate components. The functionality of printed electronic products heavily relies on the utilization of conductive ink during the printing process, which plays a vital role in developing flexible electronic circuits and improving the communicative functionalities of objects. Selecting the right ink for printing is crucial to meet consumer requirements. However, the conventional approach to this process has been manual, labor-intensive, and time-consuming, relying on the expertise of designers. This paper presents an automated ink selection model for printed circuits. This novel method has been incorporated with Multilayer Perceptron Neural Network (MLPNN) and Particle Swarm Optimization (PSO), named PSO-MLPNN. A dataset containing material features is generated by gathering information from both literature and experimental observations. To ensure uniformity, the data undergoes preprocessing using the min-max method, which scales all features to a standardized range between 0 and 1. A four-layer MLPNN is constructed to choose the most suitable ink. The network is trained with the PSO algorithm. The bias and weight values of MLPNN are tuned using the PSO algorithm to attain high accuracy. The computed findings confirm that the ink selection is highly effective and more accurate when compared to both the standard MLPNN.

Keywords: Conductive ink, Ink selection, Multilayer perceptron, Printed Electronics, Particle swarm optimization.

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1. INTRODUCTION

For over six decades, electronic devices have been manufactured through a complex series of photo-lithographic and chemical processes, resulting in the creation of electronic circuits on materials like silicon or semiconductors. Printed Electronics (PE) offers an alternative approach to manufacturing electronic circuits. It utilizes standard graphic arts printing techniques to create diverse electronic devices by forming conductive traces on a typically organic and flexible substrate. The market for printed sensors on flexible substrate is expanding rapidly, with estimates suggesting it will reach $7.6 billion by 2027 [1], [2]. PE possesses unique attributes, including novel physical forms (flexible, stretchable, ultra-thin), compatibility with various substrates (paper, plastic, textile), and cost-effective mass production. These characteristics present opportunities for numerous applications in consumer electronics, pharmaceuticals, packaging, touchscreen displays, Radio Frequency Identification (RFID) tags, electronics, textiles, and other sectors [3].

Conductive ink is a substance that can be printed, and processed to enable the flow of electricity. It serves as a foundational component in PE, forming the essential structure of circuit boards and devices. Conductive inks are responsible for creating low-resistance circuit interconnects, antennas, contact electrodes within transistors, and other integrated functionalities [4]. The significance of conductive inks in the production of PE devices has gained significant recognition in recent years. Different types of inks are utilized for printing applications. The quality of these inks varies based on their intended applications, and this variation significantly impacts the final product. Choosing the correct ink is a critical prerequisite for achieving suitable results [5]. Manipulating the material properties can influence the quality of the product. In this context, this study focuses on the crucial step of selecting the appropriate conductive ink for card printing. If the ink selection is not done correctly, the printed cards may exhibit flaws, adversely affecting the overall quality and appearance. Hence, the development of an automated technique for ink selection in printing is imperative.

The PE technique involves numerous process variables that will directly influence the product quality. Accomplishing optimal results requires interdisciplinary knowledge encompassing factors such as material characteristics, substrates, and more. Characteristically, these parameters are determined using physics-based approaches, which can be challenging, time-consuming, and prone to errors. To address the constraints of physics-based approaches and enhance the

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final product's quality, Machine Learning (ML) models have been adopted in PE. In previous studies, ML methods have been applied by researchers to suggest design features [6], enhancing the overall printing process [7], and optimizing the ejection of drops [8]. Conductive ink significantly influences the quality of final products. However, an automated system for conductive ink selection has not yet been established. Therefore, the creation of an automated system for conductive ink selection is essential to improve the final product's quality. This study is chiefly motivated by the objective of developing an automated system that utilizes ML and PSO algorithms to choose the most appropriate ink for printing applications based on the input values. The principal contributions of this study are outlined as follows:

(i) A four-layer Multilayer Perceptron Neural Network (MLPNN) is built to select ink for PE.

(ii) Weight and bias values are optimized using the PSO procedure.

(iii) To determine the optimal network configuration for printing applications, the developed system's effectiveness is evaluated by varying the counts of hidden layers, hidden neurons, as well as the training and testing samples.

(iv) Extensive experiments are carried out using real-world data to assess the effectiveness of the developed system. The empirical outcomes indicate that the PSO-MLPNN is capable of accurately selecting ink for printing applications.

The organization of the paper is as follows. *Section 2* offers a concise overview of earlier approaches. *Section 3* outlines the ink selection system that is developed. *Section 4* overviews the outcomes of the performance evaluation. Lastly, *section 5* gives the conclusion for this study.

2. LITERATURE SURVEY

This section provides a brief overview of the use of machine learning techniques in various aspects of PE. Matsuhisa et al. [3] provided a detail about elastic conductors for textile applications. Huang et al. [4] introduced graphene laminate for printed radio frequency applications.

Li et al. [5] presented a multi-color display system using phot-patterning and transfer printing. Yao et al. [6] introduced a hybrid technique that combines Hierarchical Clustering (HC) and Support Vector Machine (SVM) for design feature recommendation. HC was employed to categorize design features, while SVM enhanced the HC outcomes to identify recommended design features. This technique proved useful in helping new designers identify suitable design features for printing applications.

Brishty et al. [8] explored the potential of machine learning algorithms in categorizing ink and printed parameters based on the jetting regime. Three algorithms, namely K-nearest Neighbour (KNN), Neural Network (NN), and Decision Tree (DT), were utilized for ink classification. The NN classifier outperformed KNN and DT.

Vahabli & Rahmati [9] used the Radial Basis Function Neural Network (RBFNN) to enhance the quality of printed circuits. Ansari et al. [11] presented an interesting method for selecting inks for spectral reproduction. This approach involved taking a painting and utilizing mixed-integer programming to detect optimal inks for spectral reproduction.

Nagasawa et al. [12] introduced a method for determining skin color and translucency using the line spread function and NN. This method generated multi-layered color patches of human skin, computed the line spread function, and employed NN to estimate the layout.

Wu & Xu [13] employed an NN model to predict drop speed and ink volume. The model was trained using input features such as rise time, voltage, and pulse duration to carry out accurate prediction. Rama et al. [14] discussed the preparation of conductive inks and their application in PE and flexible electronics. The superiority of chemical methods for synthesizing Ag-ink was demonstrated.

Jansson et al. [15] analyzed the printing effectiveness of metal conducting layers on dissimilar paper-based substrates utilizing flexography as well as scanning electron microscopy. The re-pulpability capability of the substrates was also assessed accordingly.

3. PROPOSED METHODOLOGY

The general structure of the model suggested is depicted in *figure 1*. The key elements in the suggested model are data collection, data division, training, and testing. The data collection unit collects the required input and output variables.

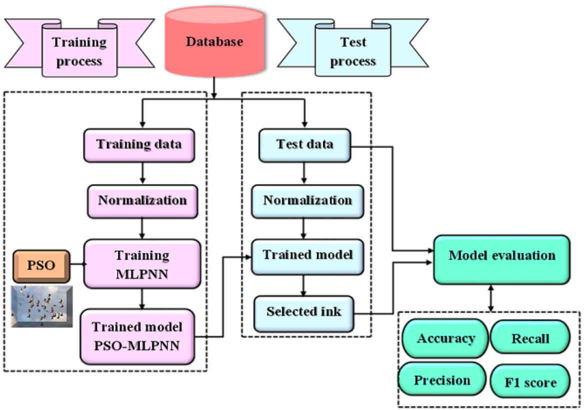

Figure 1: Workflow of the proposed system for printing applications

The data division unit then separates the data into in-sample and out-sample datasets, which are used for training and testing purposes, correspondingly. The training unit is responsible for training the MLPNN to establish the association among input and output parameters. Finally, the testing unit assesses the trained ink.

3.1. Data gathering

Data gathering is a crucial step in modeling an Artificial Neural Network (ANN) for printing applications. The data collection phase in this study encompassed two main aspects: material properties and conductive inks. The MLPNN utilizes the material characteristics to determine the appropriate ink for

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printing. The study focused on three types of conductive inks: carbon, copper, and silver inks. To ensure successful printing, several key material characteristics are considered, including product life, quality, handling and usage, grammage, caliper, brightness, tear resistance, and moisture content. Three conductive inks are chosen as targets such as Carbon, Copper, and Silver inks. These properties are listed in Table 1.

3.2. Data division

Data division involves separating the data into two distinct sets: in-sample and out-sample data. The training set comprises 80% of the data and is utilized for training the model, whereas the testing set comprises 20% of the data and is utilized for evaluating the model's performance.

Table 1: Input variables and targets used in this work

Input Features								Targets
Product life (1-5)	Product Quality (1-5)	Product usage and handling (1-5)	Grammage (gsm)	Caliper/ Thickness (mm)	Brightness (%)	Tear resistance (mN)	Moisture content (g/m^2)	Conductive ink
2	2	3	78	103	93	63	41	Carbon Ink
5	5	5	101	112	95	68	40	Silver ink
4	2	1	83	109	92	65	42	Silver ink
3	3	5	200	250	93	101	18	Silver ink
4	2	1	110	108	94	72	20	Carbon ink
3	3	4	280	261	92	151	19	Silver ink
3	3	2	98	115	93	121	38	Carbon ink
4	2	4	250	255	92	131	39	Silver ink
4	2	3	68	115	89	125	37	Carbon ink
3	2	4	68	115	89	125	36	Carbon ink
3	2	2	62	110	91	84	35	Carbon ink
3	5	3	170	100	90	78	40	Silver Ink
3	2	3	180	190	50	56	43	Carbon ink
3	2	4	100	105	80	86	46	Copper Ink
3	2	2	80	102	50	83	41	Copper ink
2	3	2	100	110	60	92	36	Carbon ink
2	2	2	160	171	65	87	38	Carbon ink
3	4	3	200	250	98	142	12	Silver ink
2	4	2	190	208	96	125	15	Silver ink
2	3	2	100	132	94	115	12	Copper ink

3.3. Data normalization

Due to the sensitivity of ANN input data, the input features and target values are scaled to a range of 0 to 1 via data normalization. This normalization is achieved using the min-max method, as described in [9]. The normalization can be mathematically represented as follows:

$$x_{norm} = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{1}$$

Where x and x_{norm} are the input and normalized values, respectively. Also, *min* and *max* are minimum and maximum values, correspondingly.

3.4. Particles swarm optimization

In this study, an MLPNN is designed with an input layer with m input neurons, two hidden layers with 12 hidden neurons in each layer, and an output layer with three neurons. The weights and bias values are optimized using the PSO algorithm.

PSO is a population-based algorithm, presented by Eberhart & Kennedy [10]. It is widely used for fine-tuning the parameters of neural networks [16] [17] [18].

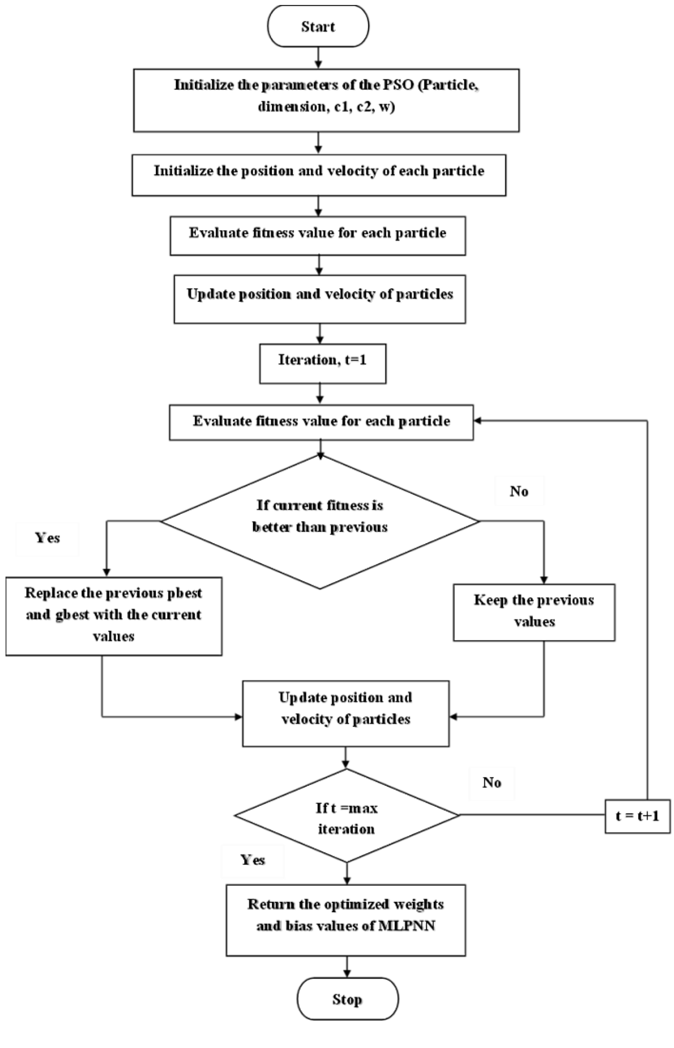

Figure 2: Flowchart of the PSO-MLPNN for ink selection

In this study, the PSO is adopted to tune the parameters of the MLPNN because of its capacity to adapt, flexibility, faster convergence, fewer control parameters, and superior ability to balance both exploration and exploitation.

PSO is based on the imitation of the communal behavior of birds within a group. Let the population size, M, and dimensional size of the problem, D. Each particle is a possible solution, characterized by a velocity of $Vn= [Vn,1, Vn,2, \ldots Vn, D]$ and a position vector of $Xn=[Xn,1, Xn, 2, \ldots Xn, D]$, where, $n=1, 2, \ldots M$. During the t^{th} iteration of the searching procedure,

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the new velocity $V_{n,d}^{t+1}$ of all n-th particles in any dimension, *D* is varied based on the equivalent dimensional elements of the personal best position $X_{n,d}^{pbest,t}$ (self-cognitive component) and global best position $G_{n,d}^{best,t}$ (social component) as below:

$$V_{n,d}^{t+1} = \omega V_{n,d}^{t} + c_1 r_1 \left(X_{n,d}^{pbest,t} - X_{n,d}^{t}\right) + c_2 r_2 \left(G_{d}^{best,t} - X_{n,d}^{t}\right) \quad (2)$$

where *ω*-inertia weight, *c1*and *c2*-acceleration coefficients, *r1*, *r2* -random numbers [0,1]. The upcoming position of all the n-th particles in all dimensions is updated as:

$$X_{n,d}^{t+1} = V_{n,d}^{t+1} + X_{n,d}^{t} \quad (3)$$

The fitness values of all the n^{th} particles are calculated and equated with those of the personal best position and global best positions. Both will be restructured if the last solution is greater. The search procedure is continued until the predefined criteria are met.

In this study, the PSO procedure is utilized for optimizing the MLPNN parameters. The flowchart of the PSO-MLPNN designed for ink selection is shown in *figure 2*. The necessary algorithmic steps of the proposed system are as follows:

Step 1: Read input data and target.
Step 2: Preprocess the collected data using *equation (1).*
Step 3: Divide the preprocessed data into train and test samples.
Step 4: Design an MPLNN and initialize the parameters.
Step 5: Initialize the parameters of the PSO algorithm.
Step 6: Optimize the MLPNN parameters using PSO.
Step 7: Test the MLPNN with test data.
Step 8: Compare the classified output with the test target.

4. EMPIRICAL STUDY

In this section, a comprehensive overview of the numerical outcomes obtained from the ink selection system for printing applications. The presented system has been successfully implemented using the MATLAB 2022a platform.

4.1. Performance metrics

The effectiveness of the designed system is assessed through the calculation of different parameters like accuracy, recall, precision, and F1 score. The system's viability is analyzed using a confusion matrix, which consists of four values: True positive (TP) is when a system appropriately categorizes the positive classes, True Negative (TN) corresponds to the class when the system appropriately categorizes the negative classes when the system incorrectly classifies the positive classes, the outcome is a False Positive (FP), and when the system incorrectly classifies negative class, it generates a False Negative (FN).

In this work, multiclass classification is considered. The TP classes are the labels for which the calculations are being carried out and the negative classes are the remaining labels. The metrics are given below:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

$$Precision = \frac{TP}{TP+FP} \quad (5)$$

$$Recall = \frac{TP}{TP+FN} \quad (6)$$

$$F1-score = 2\,X\,\frac{Precision\ X\ Recall}{Precision+Recall} \quad (7)$$

4.2. Performance analysis

Through a series of experiments, the essential parameters for designing PSO- MLPNN were determined. Various tests were carried out to establish the optimal PSO-MLPNN structure. *Table 2* lists the simulation variables used in these experiments.

Table 2: MLPNN parameters

S.No.	Parameters	Value
1.	No. of input neurons	8
2.	No. of hidden layers	1 to 4
3.	No. of hidden neurons in the hidden layer	10 to 15
4.	No. of output neurons	3
5.	Hidden layer activation function	Sigmoidal
6.	Output layer activation function	Linear
7.	Epoch	1000
8.	Momentum	0.01
9.	Training algorithm	PSO and LM

The effectiveness of the PSO-MLPNN was evaluated through three different scenarios:

Experiment 1: The performance of the system was analyzed by varying the count of hidden neurons.

Experiment 2: The efficacy of the system was evaluated by changing the count of hidden layers.

Experiment 3: The effectiveness of the system was assessed by varying the count of training and testing data.

The MLPNN was built with input, hidden, and output layers. The hidden layer utilized a sigmoidal activation function, while the output layer employed a linear activation function. During the training phase, the MLPNN was trained separately using PSO and LM procedures to augment its parameters. In the testing phase, the performance of the trained network was assessed using test data. All experiments were repeated several times and mean values were reported.

4.2.1. Experiment 1

In the first experiment, the input data was divided into two sets: 80% of the samples were assigned for training, whereas the leftover 20% were utilized for testing. The range of hidden layers explored was from 10 to 15. The developed MLPNN was separately trained using LM and PSO algorithms. The outcomes of the first experiment are summarized in Table 3. It

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is observed from *table 3* that the PSO-MLPNN provided better performance than MLPNN for all cases. Upon examining *table 3*, it is evident that the MLPNN attained the lowest accuracy of 70.01%, recall of 82.50%, precision of 75.01%, and F1-Score of 78.57% when using a single hidden layer with 10 hidden neurons. However, the developed PSO-MLPNN yielded higher performance with an accuracy of 88.19%, recall of 88.57%, precision of 76.68%, and F1-Score of 83.33% compared to the MLPNN approach.

An increase in the number of neurons from 10 to 12 ensued in an improvement in the classification rate. With 12 hidden neurons, both the MLPNN and PSO-MLPNN exhibited exceptional performance, reaching accuracy of 86.67% and 94.48%, recall of 95% and 96%, precision of 86.36% and 88.42%, and F1-score of 90.48% and 92.05%, respectively. However, if the number of neurons increases further to 13, 14, or 15, the classification rate is decreased. For a single hidden layer with 15 hidden neurons, the MLPNN achieved an accuracy of 80%, while PSO-MLPNN yielded an accuracy of 90.86%. This comparison indicates that the system with 12 hidden neurons performed the best. As a result, 12 hidden neurons were chosen as the optimal configuration. *Figure 3* provides a graphical representation of the data presented in *Table 3*. Notably, the system attained the lowest accuracy for 10 hidden neurons. Increasing the number of neurons beyond 12 led to unstable performance. So, 12 hidden neurons were selected to ensure improved performance.

Table 3: Efficacy comparison between MLPNN and PSO-MLPNN for dissimilar numbers of hidden neurons

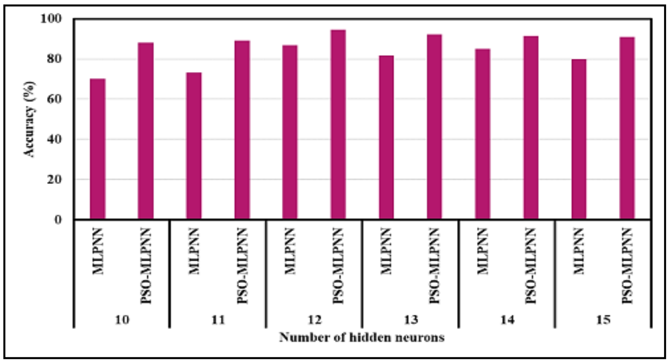
No. of hidden neurons	Models	Accuracy (%)	Recall (%)	Precision (%)	F1 score (%)
10	**MLPNN**	70.01	82.5	75.01	78.57
	PSO-MLPNN	88.19	88.57	78.68	83.33
11	**MLPNN**	73.33	82.5	78.57	80.49
	PSO-MLPNN	89.14	89.71	80.1	84.64
12	**MLPNN**	86.67	95	86.36	90.48
	PSO-MLPNN	94.48	96	88.42	92.05
13	**MLPNN**	81.67	90	83.72	86.75
	PSO-MLPNN	92.19	94.29	84.18	88.95
14	**MLPNN**	85	87.5	89.74	88.61
	PSO-MLPNN	91.43	93.14	83.16	87.87
15	**MLPNN**	80	85	85	85
	PSO-MLPNN	90.86	92.57	82.23	87.1

4.2.2. Experiment 2

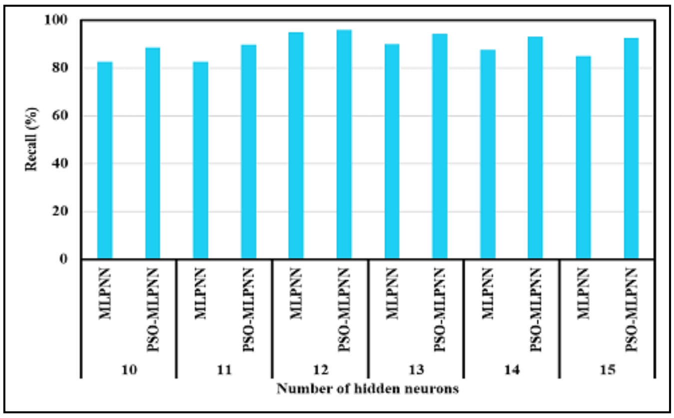
In the second phase of the experiment, the hidden layers were varied from 1 to 4, while the hidden neurons were fixed at 12. The performance of the developed system was evaluated for each configuration, and outcomes are reported in *table 4*. According to *table 4*, both the MLPNN and PSO-MLPNN achieved their highest accuracy, recall, and F1-score values were 91.67% and 96.38%, 95% and 97.71%, 92.68%, and F1-score of 93.83% and 94.74%, respectively, when using two hidden layers with 12 hidden neurons. However, increasing the number of hidden layers to 3 or 4 resulted in a degradation of the system's effectiveness. Consequently, it shall be fixed that the optimal number of hidden layers for the MLPNN is 2. The pictorial delineation of *table 4* is given in *figure 4*.

Table 4. Performance comparison between MLPNN and PSO-MLPNN for different numbers of hidden layers

No. of hidden neurons	Models	Accuracy (%)	Recall (%)	Precision (%)	F1 score (%)
1	**MLPNN**	86.67	95	86.36	90.48
	PSO-MLPNN	94.48	96	88.42	92.05
2	**MLPNN**	91.67	95	92.68	93.83
	PSO-MLPNN	96.38	97.71	91.94	94.74
3	**MLPNN**	80	90	81.82	85.71
	PSO-MLPNN	92.38	93.71	84.97	89.13
4	**MLPNN**	73.33	80	80	80
	PSO-MLPNN	90.48	92	81.73	86.56



(a)



(b)

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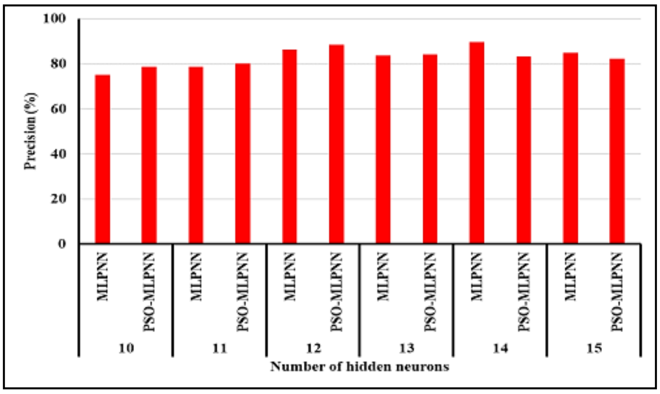
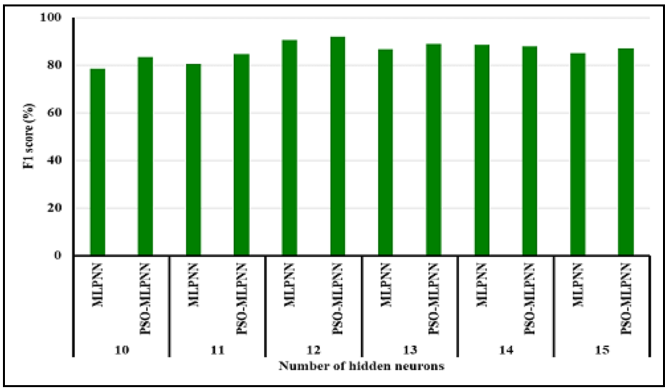
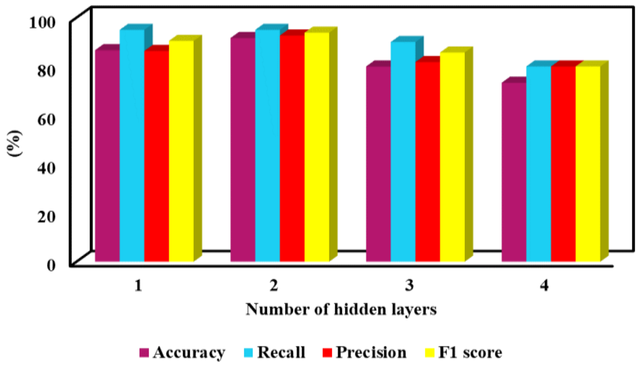


(c)

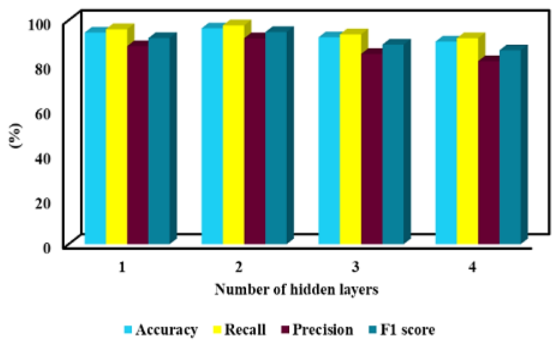


(d)

Figure 3: Performance assessment in terms of (a) accuracy, (b) recall, (c) precision, and (d) F1-score



(a) MLPNN



(b) PSO-MLPNN

Figure 4: Effectiveness comparison for varying number of hidden layers

4.2.3. Experiment 3

Based on the results obtained from the first and second experiments, the hidden layers and hidden neurons were set to 2 and 12, respectively. In the third scenario, the effectiveness of the MLPNN and PSO-MLPNN was analyzed by varying the number of training and test samples. The training samples ranged from 50% to 90%. The performance of the developed system for different training and testing data proportions is tabulated in *table 5*. It clearly demonstrates that the effectiveness of the developed system improved as the number of training samples increased from 50% to 80%. For the 50% testing data, the MLPNN and PSO-MLPNN achieved an accuracy of 85.23% and 90.29%. On the other hand, for the 10% test data, the MLPNN and PSO-MLPNN attained an accuracy of 90% and 93.14%, and F1-score values of, respectively. Notably, both the MLPNN and PSO-MLPNN produced outstanding results with 80% training and 20% testing data, reaching a higher accuracy of 91.67% and 96.38%, recall of 95% and 97.71%, and F1-score of, 93.83% and 94.74%, respectively. The empirical findings confirm that the developed system with a topology of 8-12-12-3 outperformed systems with other topologies, such as 8-12-3, 8-12-12-12-3, and 8-12-12-12-12-3. *Figure 5* graphically compares the effectiveness of the MLPNN and PSO-MLPNN for dissimilar numbers of test data.

The proposed PSO-MLPNN system provided improved results compared to the standard MLPNN. This improvement was evident as the system achieved higher values across all metrics assessed. The enhanced outcomes of the 8-12-12-3 topology can be attributed to the precise fine-tuning of the parameters of MLPNN using PSO. The superior results observed with the 8-12-12-3 topology can be directly linked to the optimization of MLPNN parameters utilizing the application of the PSO algorithm. The precision in fine-tuning the MLPNN parameters using PSO notably contributed to the system's enhanced performance and overall effectiveness.

Table 5: Performance comparison between MLPNN and PSO-MLPNN for different numbers of training and testing samples

Data ratio (%)	Models	Accuracy (%)	Recall (%)	Precision (%)	F1 score (%)
50:50	MLPNN	85.23	88.89	88.89	88.89
	PSO-MLPNN	90.29	92	81.31	86.33
60:40	MLPNN	86.67	91.67	88.71	90.16
	PSO-MLPNN	92.19	93.71	84.54	88.89
70:30	MLPNN	88.24	91.14	91.14	91.14
	PSO-MLPNN	94.67	96.57	88.48	92.35
80:20	MLPNN	91.67	95	92.68	93.83
	PSO-MLPNN	96.38	97.71	91.94	94.74
90:10	MLPNN	90	95	90.48	92.68
	PSO-MLPNN	93.14	95.43	85.64	90.27

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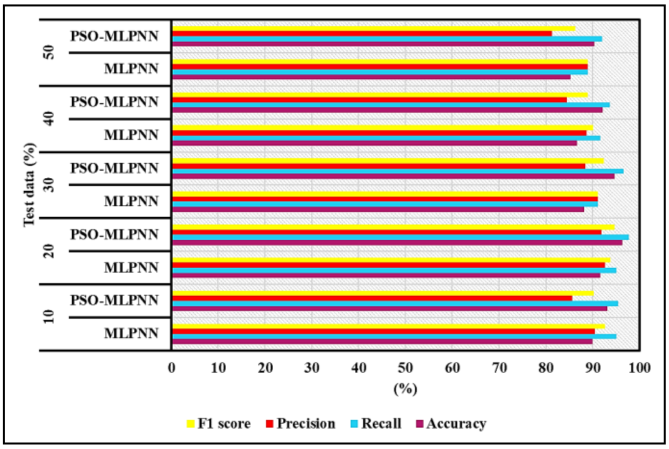

Figure 5: Effectiveness comparison for varying numbers of training and testing data

To further display its effectiveness, the performance of the proposed system, PSO-MLPNN is compared against two methods, namely NN [8] and mixed integer programming [11]. A comparative evaluation between the PSO-MLPNN and earlier approaches is given in *table 6*. From *table 6*, it is quite clear that the proposed method outperformed other methods notably because of the integration of PSO for optimization purposes.

Table 6: Performance comparison with earlier methods

Contributors	Method	Accuracy (%)
Brishty et al. [8]	NN	87.38
Ansari et al. [11]	Mixed integer programming	85.41
Proposed method	PSO-MLPNN	96.38

5. CONCLUSION

In this study, a novel framework for ink selection in printing applications has been presented. The system was designed using PSO and MLPNN. Initially, input data were gathered and then normalized using the min-max method. An MLPNN was designed and trained using the PSO and LM algorithms. The effectiveness of the proposed system was evaluated by altering the number of hidden neurons, hidden layers, as well as the training and testing data. The experimental results highlighted that the PSO-MLPNN with an architecture of 8-12-12-3 yielded superior results. However, the main constraint of this system pertains to the limited sample size used for analysis. For future investigations, deep learning models will be explored to enhance the ink selection process in printing applications. Other metaheuristic algorithms will also be taken into consideration to improve optimization and drive further advancements in results.

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