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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.

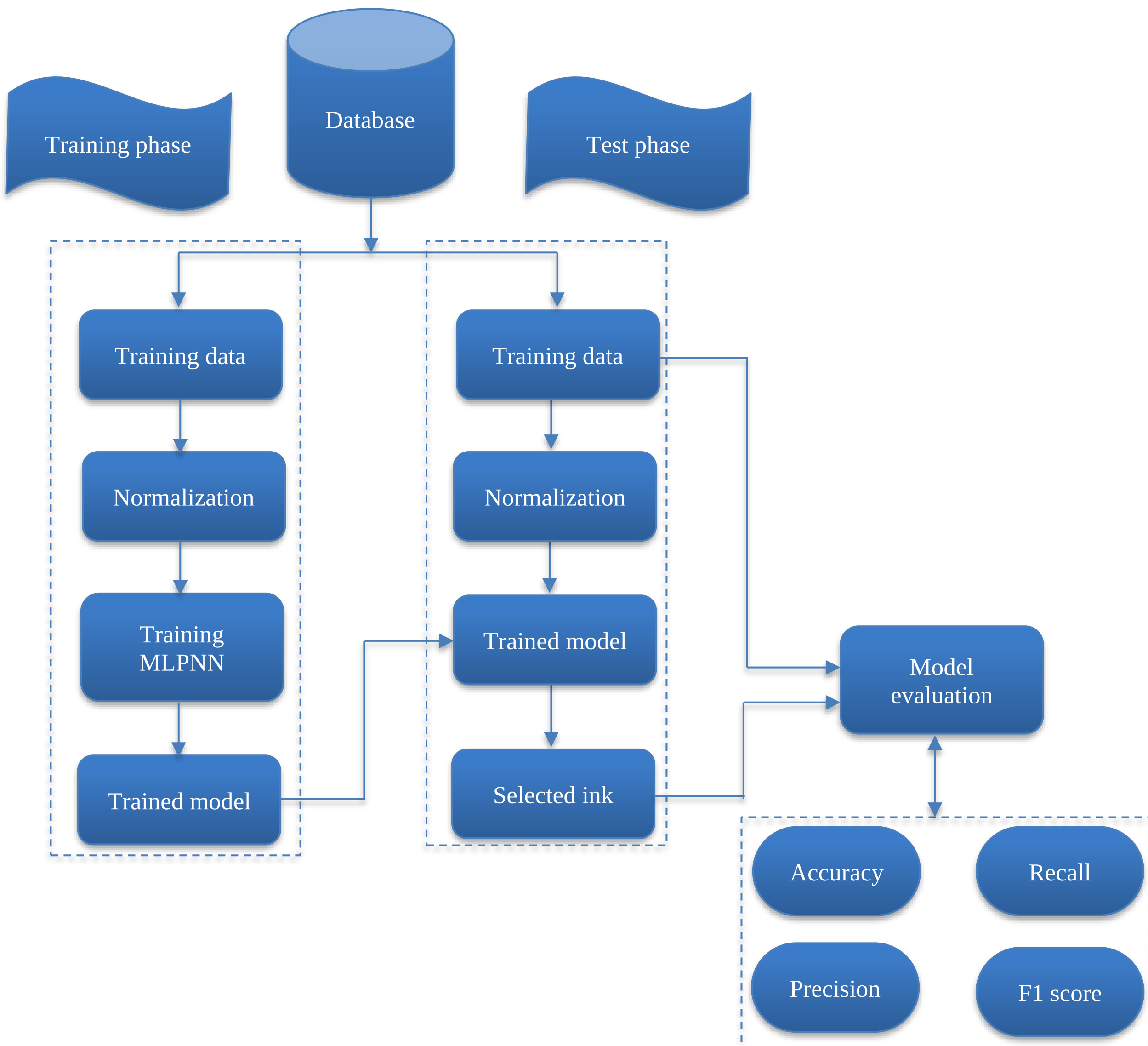

Fig. 1 The overall operational stages of the proposed system

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,

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

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,

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

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

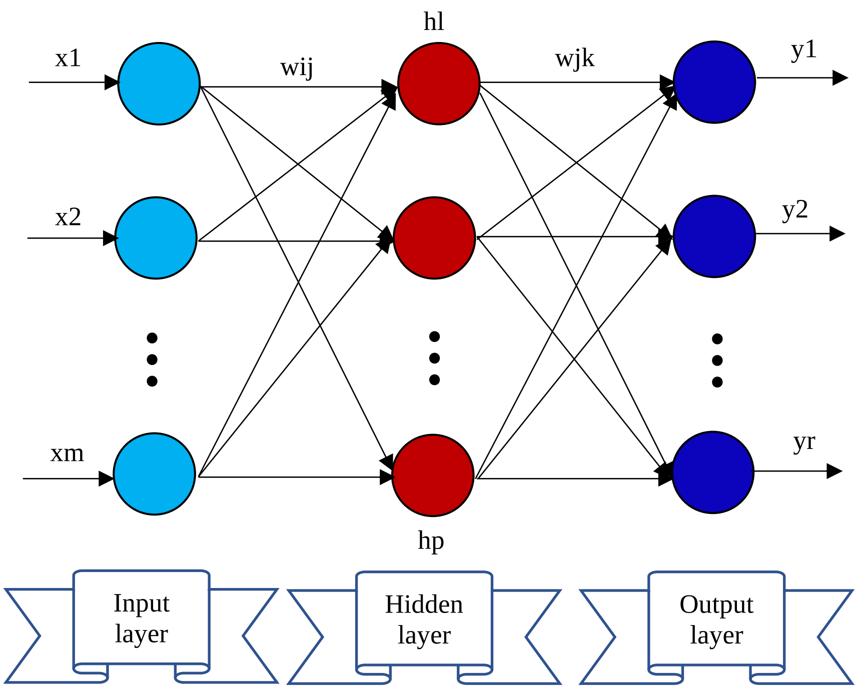

Fig. 2 The overall operational stages of the proposed system

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

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

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

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

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

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

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

$$f(x) = x \qquad (6)$$

Equation (5) can be rewritten as,

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

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

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

$$w_{new} = w_{old} + \Delta w \qquad (9)$$

$$\Delta w = \eta y \delta_k \qquad (10)$$

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,

$$H = J^T J \qquad (11)$$

$$\text{Gradient},\ \ g = J^T e \qquad (12)$$

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

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	$2\times\frac{Pr\,e\,cision \times Re\,c\,all}{Pr\,e\,cision + Re\,c\,all}$

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 $1x10^{-6}$ 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.

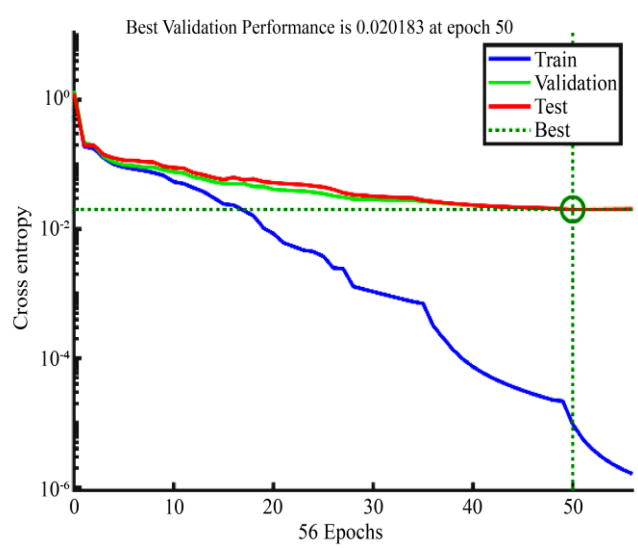

Fig. 3 Performance of the training phase

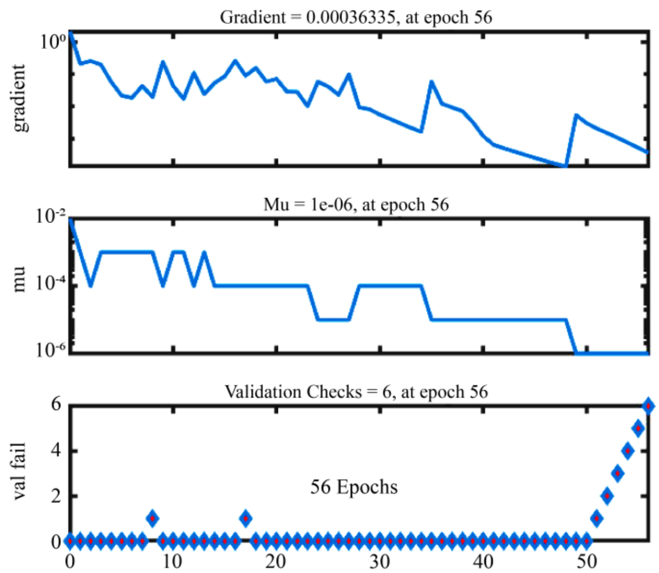

Fig. 4 Training state of the MLPNN

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.

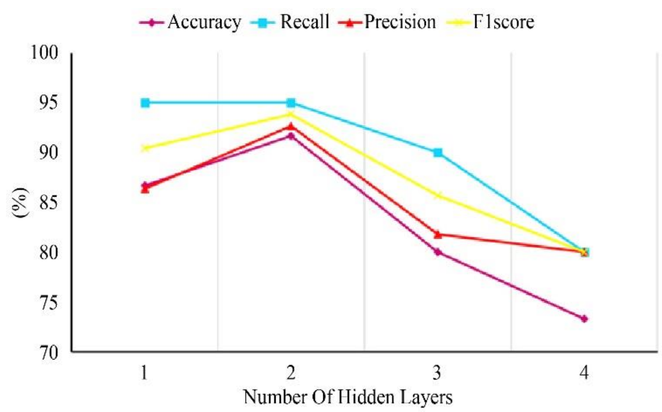

Fig. 5 Performance of the introduced method for varying hidden layers

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

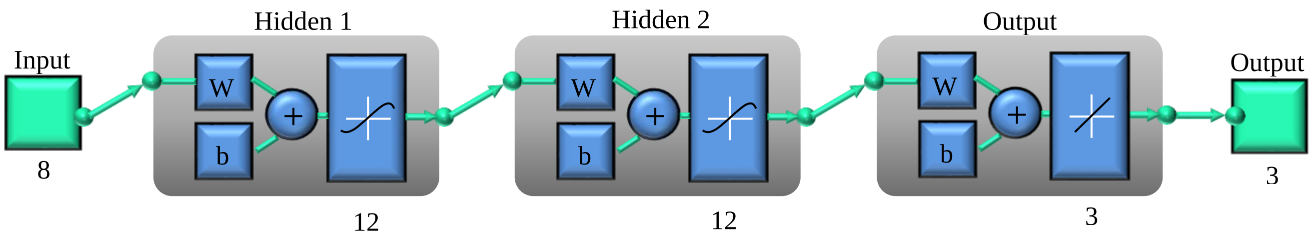

Fig. 6 The best MLPNN structure for printing applications

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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