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Overcoming Process Delays Using JustNN

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***Abstract**: Printers are always seeking higher productivity by increasing their production rates and minimizing process delays. When process delays have known causes, they can be mitigated by acquiring causal rules from human experts and then applying sensors and automated real-time diagnostic devices to the process. However, for some delays the experts have only weak causal knowledge or none at all. In such cases, Artificial Neural Network (ANN) which is a sub field of Artificial Intelligence can collect training data and pre-process it. A proposed ANN model was applied on a collected dataset from UCI machine Learning Repository to predict process delays known as cylinder banding in rotogravure printing. The dataset consist of 40 features with 528 sample cases. The aim of the ANN model is to train it to be able to predict whether the each sample case is a cylinder band or not. The ANN model was trained and validated in JustNN tool. The accuracy rate of predicting cylinder band or not was 81.03%.*

Keywords: Printers, ANN, JustNN, rotogravure

1. Introduction

Rotogravure is a type of intaglio printing process, which involves engraving the image onto an image carrier. In gravure printing, the image is engraved onto a cylinder because, like offset printing and flexography, it uses a rotary printing press. Once a staple of newspaper photo features, the rotogravure process is still used for commercial printing of magazines, postcards, and corrugated and other product packaging [1].

In direct gravure printing, the ink is applied directly to the cylinder and from the cylinder it is transferred to the substrate. One printing unit consists of the following components:

- an engraved cylinder (also known as "gravure cylinder") whose circumference can differ according to the layout of the product being made.
- an ink fountain
- a doctor blade assembly
- an impression roller
- a dryer

For indirect gravure processes, the engraved cylinder transfers ink in the desired areas to a transfer roller, and the transfer roller transfers it to the substrate.

The first step of Gravure is to create the cylinder with the engraved images that need to be printed: the engraving process will create on the cylinder surface the cells that will contain the ink in order to transfer it to the paper. Since the amount of ink contained in the cells corresponds to different color intensities on the paper, the dimensions of the cells must be carefully set: deeper or larger cells will produce more intense colors whereas smaller cells will produce less intense ones. There are three methods of photoengraving that have been used for engraving of gravure cylinders, where the cell open size or the depth of cells can be uniform or variable[1].

Gravure cylinders are usually made of steel and plated with copper, though other materials, e.g. ceramics can also be used. The desired pattern is achieved by engraving with a laser or a diamond tool, or by chemical etching. If the cylinder is chemically etched, a resist (in the form of a negative image) is transferred to the cylinder before etching. The resist protects the non-image areas of the cylinder from the etchant. After etching, the resist is stripped off. The operation is analogous to the manufacture of printed circuit boards. Following engraving, the cylinder is proofed and tested, reworked if necessary, and then chrome plated [2].

While the press is in operation, the engraved cylinder is partially immersed in the ink tray, filling the recessed cells. As the cylinder rotates, it draws excess ink onto its surface and into the cells. Acting as a squeegee, the doctor blade scrapes the cylinder before it makes contact with the paper, removing the excess ink from the non-printing (non-recessed) areas and leaving in the cells the right amount of ink required. The position of the blade relative to the nip is normally variable [3].

Next, the substrate gets sandwiched between the impression roller and the gravure cylinder: this is where the ink gets transferred from the recessed cells to the web. The purpose of the impression roller is to apply force, ensuring that the entire substrate is brought into contact with the gravure cylinder, which in turn ensures even and maximum coverage of the ink. Once in contact with the substrate, the ink's surface tension pulls (part of) the ink out of the cell and transfers it to the substrate [2].

Then the inked substrate goes through a dryer because it must be completely dry before going through the next color unit and accepting another coat of ink. A rotogravure printing press has one printing unit for each color, typically CMYK or cyan, magenta, yellow and key (printing terminology for black), but the number of units varies depending on what colors are required to produce the final image [2].

Because gravure is capable of transferring more ink to the paper than most other printing processes, it is noted for its remarkable density range (light to shadow) and hence is a process of choice for fine art and photography reproduction, though not typically as clean an image as that of offset lithography. A shortcoming of gravure is that all images, including type and "solids," are actually printed as dots, and unless the ink and substrate combination is set up to allow solid areas to flow together, the screen pattern of these dots can be visible to the naked eye [1].

Gravure is an industrial printing process capable of consistent high quality printing. Since the Gravure printing process requires the creation of one cylinder for each color of the final image, it is expensive for short runs and best suited for high volume printing. Typical uses include long-run magazines in excess of 1 million copies, mail order catalogs, consumer packaging, Sunday newspaper ad inserts, wallpaper and laminates for furniture where quality and consistency are desired. Another application area of gravure printing is in the flexible-packaging sector. A wide range of substrates such as polyethylene, polypropylene, polyester, BOPP, etc. can be printed in the gravure press. Gravure printing is one of the common processes used in the converting industry [3].

Rotogravure presses for publication run at 45 feet (14 m) per second and more, with paper reel widths of over 10 feet (3 m), enabling an eight-unit press to print about seven million four-color pages per hour.

The vast majority of gravure presses print on rolls (also known as webs) of paper or other substrates, rather than sheets. (sheet fed gravure is a small, specialty market.) Rotary gravure presses are the fastest and widest presses in operation, printing everything from narrow labels to 12-foot-wide (3.66-meter-wide) rolls of vinyl flooring. For maximum efficiency, gravure presses operate at high speeds producing large diameter, wide rolls. These are then cut or slit down to the finished roll size on a slitting machine or slitter re-winder. Additional operations may be in line with a gravure press, such as saddle stitching facilities for magazine or brochure work [4].

2. An Artificial Neural Network

An Artificial Neural Network is a multilayer perceptron (MLP) is a class of feed forward[5-20]. The term MLP is used ambiguously, sometimes loosely to any feedforward ANN, sometimes strictly to refer to networks composed of multiple layers of perceptron (with threshold activation). Multilayer perceptron are sometimes colloquially referred to as "vanilla" neural networks, especially when they have a single hidden layer[21-29].

An MLP consists of at least three layers of nodes: an input layer, a hidden layer and an output layer. Except for the input nodes, each node is a neuron that uses a nonlinear activation function. MLP utilizes a supervised learning technique called backpropagation for training[30-35]. Its multiple layers and non-linear activation distinguish MLP from a linear perceptron. It can distinguish data that is not linearly separable [36-42].

If a multilayer perceptron has a linear activation function in all neurons, that is, a linear function that maps the weighted inputs to the output of each neuron, then linear algebra shows that any number of layers can be reduced to a two-layer input-output model. In MLPs some neurons use a *nonlinear* activation function that was developed to model the frequency of action potentials, or firing, of biological neurons[43-48].

The two historically common activation functions are both sigmoids, and are described by

$$y(v_i) = \tanh(v_i) \text{ and } y(v_i) = (1 + e^{-v_i})^{-1}$$

In recent developments of deep learning the rectifier linear unit (ReLU) is more frequently used as one of the possible ways to overcome the numerical problems related to the sigmoid [49-50].

The first is a hyperbolic tangent that ranges from -1 to 1, while the other is the logistic function, which is similar in shape but ranges from 0 to 1. Here y_i is the output of the i^{th} node (neuron) and v_i is the weighted sum of the input connections. Alternative activation functions have been proposed, including the rectifier and softplus functions. More specialized activation functions include radial basis functions (used in radial basis networks, another class of supervised neural network models)[51-53].

The MLP consists of three or more layers (an input and an output layer with one or more *hidden layers*) of nonlinearly-activating nodes. Since MLPs are fully connected, each node in one layer connects with a certain weight w_{ij} to every node in the following layer.

Learning occurs in the perceptron by changing connection weights after each piece of data is processed, based on the amount of error in the output compared to the expected result. This is an example of supervised learning, and is carried out through backpropagation, a generalization of the least mean squares algorithm in the linear perceptron [54].

We can represent the degree of error in an output node j in the n^{th} data point (training example) by:

$$e_j(n) = d_j(n) - y_j(n),$$

Where d is the target value and y is the value produced by the perceptron. The node weights can then be adjusted based on corrections that minimize the error in the entire output, given by:

$$\mathcal{E}(n) = \frac{1}{2}\sum_j e_j^2(n).$$

Using gradient descent, the change in each weight is:

$$\Delta w_{ji}(n) = -\eta \frac{\partial \mathcal{E}(n)}{\partial v_j(n)} y_i(n)$$

Where y_i is the output of the previous neuron and η is the *learning rate*, which is selected to ensure that the weights quickly converge to a response, without oscillations [55].

The derivative to be calculated depends on the induced local field v_j, which itself varies. It is easy to prove that for an output node this derivative can be simplified to [56]:

$$-\frac{\partial \mathcal{E}(n)}{\partial v_j(n)} = e_j(n)\phi'(v_j(n))$$

Where ϕ' is the derivative of the activation function described above, which itself does not vary. The analysis is more difficult for the change in weights to a hidden node, but it can be shown that the relevant derivative is [51]

$$-\frac{\partial \mathcal{E}(n)}{\partial v_j(n)} = \phi'(v_j(n)) \sum_k -\frac{\partial \mathcal{E}(n)}{\partial v_k(n)} w_{kj}(n).$$

This depends on the change in weights of the k^{th} nodes, which represent the output layer. So to change the hidden layer weights, the output layer weights change according to the derivative of the activation function, and so this algorithm represents a backpropagation of the activation function.

The term "multilayer perceptron" does not refer to a single perceptron that has multiple layers. Rather, it contains many perceptrons that are organized into layers. An alternative is "multilayer perceptron network". Moreover, MLP "perceptrons" are not perceptrons in the strictest possible sense. True perceptrons are formally a special case of artificial neurons that use a threshold activation function such as the Heaviside step function. MLP perceptrons can employ arbitrary activation functions. A true perceptron performs *binary* classification, an MLP neuron is free to either perform classification or regression, depending upon its activation function[54].

The term "multilayer perceptron" later was applied without respect to nature of the nodes/layers, which can be composed of arbitrarily defined artificial neurons, and not perceptrons specifically. This interpretation avoids the loosening of the definition of "perceptron" to mean an artificial neuron in general.

MLPs are useful in research for their ability to solve problems stochastically, which often allows approximate solutions for extremely complex problems like fitness approximation.

MLPs are universal function approximators as shown by Cybenko's theorem, so they can be used to create mathematical models by regression analysis. As classification is a particular case of regression when the response variable is categorical, MLPs make good classifier algorithms[55].

MLPs were a popular machine learning solution in the 1980s, finding applications in diverse fields such as speech recognition, image recognition, and machine translation software, but thereafter faced strong competition from much simpler (and related) support vector machines. Interest in backpropagation networks returned due to the successes of deep learning[56].

3. Methodology

We have collected the dataset from UCI Machine Learning repository that was developed by University of California, School of Information and Computer Science [57]. This dataset was prepared by Bob Evans, RR Donnelley & Sons Co., Gallatin Division, Gallatin, Tennessee, USA [57].

3.1 Input and output Features

The Cylinder Bands dataset consists of 512 samples and 40 features. The first four features were skipped (timestamp, cylinder number, Customer, and job number). The remaining features either numeric or nominal (categories). All nominal Features were replaced with numeric values starting with 0 to maximal count of different values in the feature. The second step is normalizing all numeric values to be between 0 and 1 (as shown in Table 1). Table 2 shows the output attribute and its distribution.

Table1 : Attribute description

S.N.	Attribute	Type	Possible Values	Category
1	timestamp	Numeric	19500101 - 21001231	Input
2	cylinder number	Nominal		Input
3	Customer	Nominal		Input
4	job number	Nominal		Input
5	grain screened	Nominal	yes, no	Input
6	ink color	Nominal	key, type	Input
7	proof on ctd ink	Nominal	yes, no	Input
8	blade mfg	Nominal	benton, daetwyler, uddeholm	Input
9	cylinder division	Nominal	gallatin, warsaw, mattoon	Input
10	paper type	Nominal	uncoated, coated, super	Input
11	ink type	Nominal	uncoated, coated, cover	Input
12	direct steam	Nominal	yes, no	Input
13	solvent type	Nominal	xylol, lactol, naptha, line, other	Input
14	type on cylinder	Nominal	yes, no	Input
15	press type	Nominal	70 wood hoe, 70 motter, 70 albert, 94 motter	Input
16	press	Nominal	821, 802, 813, 824, 815, 816, 827, 828	Input
17	unit number	Nominal	1, 2, 3, 4, 5, 6, 7, 8, 9, 10	Input

18	cylinder size	Nominal	catalog, spiegel, tabloid	Input
19	paper mill location	Nominal	north us, south us, canadian, scandanavian, mid european	Input
20	plating tank	Nominal	1910, 1911, other	Input
21	proof cut	Numeric	0-100	Input
22	viscosity	Numeric	0-100	Input
23	caliper	Numeric	0-1	Input
24	ink temperature	Numeric	5-30	Input
25	humifity	Numeric	5-120	Input
26	roughness	Numeric	0-2	Input
27	blade pressure	Numeric	10-75	Input
28	varnish pct	Numeric	0-100	Input
29	press speed	Numeric	0-4000	Input
30	ink pct	Numeric	0-100	Input
31	solvent pct	Numeric	0-100	Input
32	ESA Voltage	Numeric	0-16	Input
33	ESA Amperage	Numeric	0-10	Input
34	wax	Numeric	0-4	Input
35	hardener	Numeric	0-3	Input
36	roller durometer	Numeric	15-120	Input
37	current density	Numeric	20-50	Input
38	anode space ratio	Numeric	70-130	Input
39	chrome content	Numeric	80-120	Input
40	band type	Nominal class	band, no band	Output

Table 2: Class feature distribution

Class code	**Class**	**Number of instances**
1	No band	312
2	Band	200

3.2 Dataset preprocessing

There are some missing values in 302 examples of the Cylinder Bands dataset. The missing data was replaced with average value of the attribute. We used the following equation to normalize the features in the Cylinder Bands:

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$$X_i = (X_i - X_{min}) / (X_{man} - X_{min}) \qquad \text{eq.(1)}$$

For the nominal features we have done two things:

- Replaced the different values of that features with numeric values starting with 0
- We normalized the features using the above equation where the possible values between 0 and 1.

For all other features we normalized their values to be in the range of 0 to 1 using the normalized equation stated above.

3.3 Building the ANN Model

We used Just Neural Network (JNN) tool [58] to build a multilayer ANN model. The proposed model consists of five Layers: Input Layer with 33 nodes, First Hidden Layer with 17 nodes, Second Layer with 9 nodes, Third Layer with 5 nodes, and Output Layer with one node as can be seen in Figure 3.

We have sat the parameters of the proposed model as follows: Learning Rate 0.6 and the Momentum to be 0.8, and Average Error rate to be 0.01 (as shown in Figure 2).

3.4 Evaluating the ANN model

The Cylinder Bands dataset consists of 512 samples with 40 attributes as in Table 1 and Table 2. We imported the preprocessed CSV file of the Cylinder Bands dataset into the JNN environment (as seen in Figure 1). During the importing of the dataset two more attributes were skipped by the JNN tool. We divided the imported dataset into two sets (Training and Validation) randomly using the JNN tool. The Training consists of approximately 67% (354 samples) and the validation set consists of 33% of the dataset (174 samples). After making sure that the parameter control was sat properly, we started training the ANN model and kept eye on the learning curve, error loss and validation accuracy. We trained the ANN model for 400 cycles. The best accuracy we got was 81.03% (as seen in Figure 4). We determined the most influential factors in the Cylinder Bands dataset as in Figure 5. Figure 6 shows the summary of the proposed model.

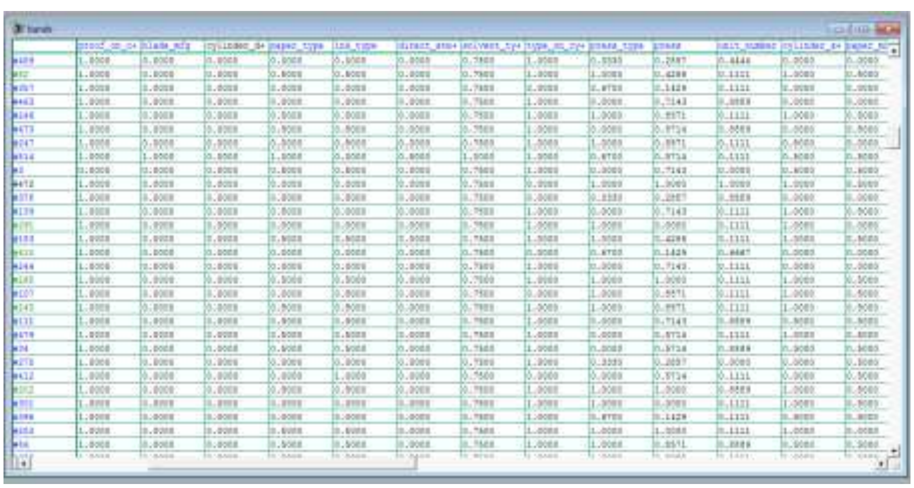

Figure 1: Imported dataset into JNN environment

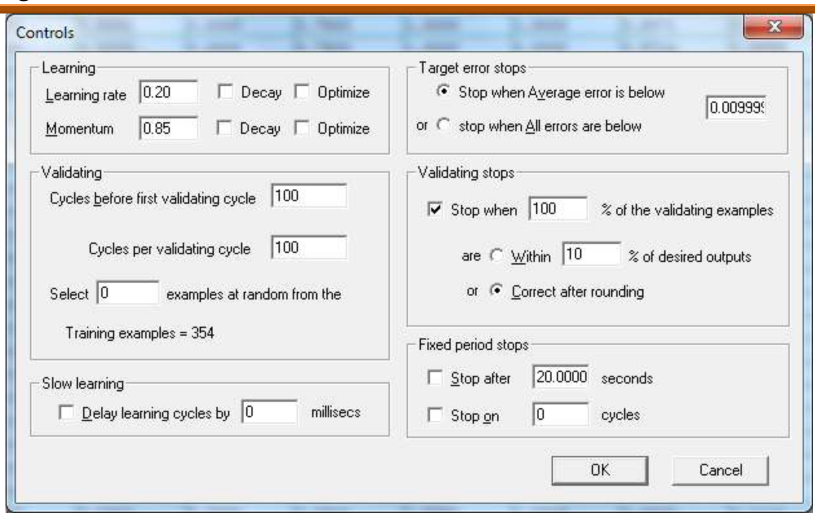

Figure 2: Control of the parameters of the proposed ANN model

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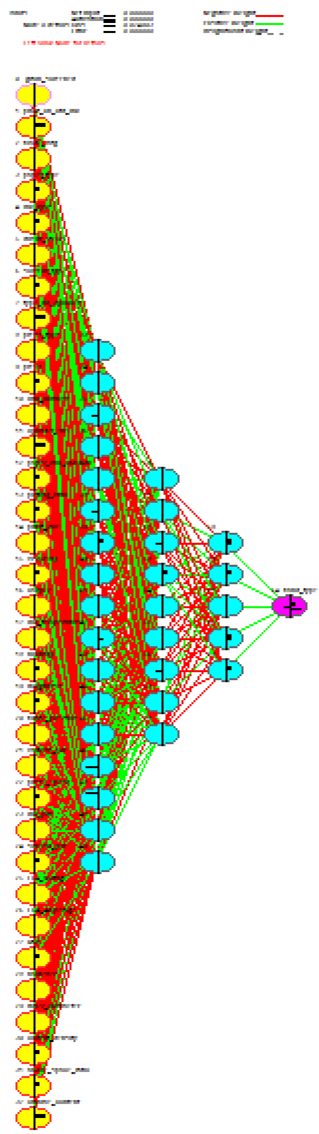

Figure 3: architecture of the final ANN model

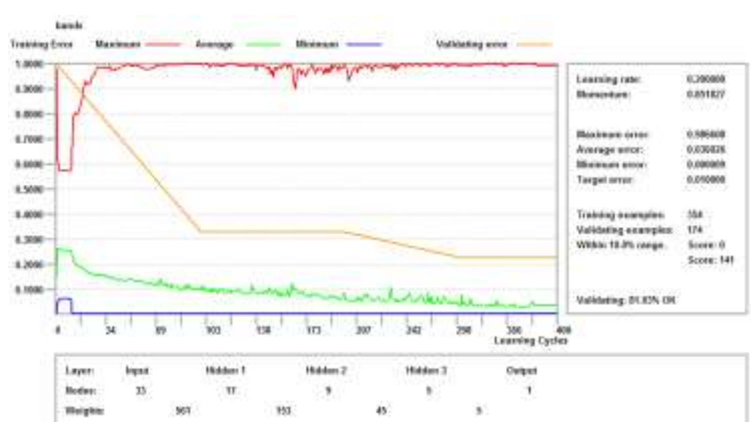

Figure 4: Training and validation curves of the proposed ANN model

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Figure 5: The most influential Feature in the proposed ANN model

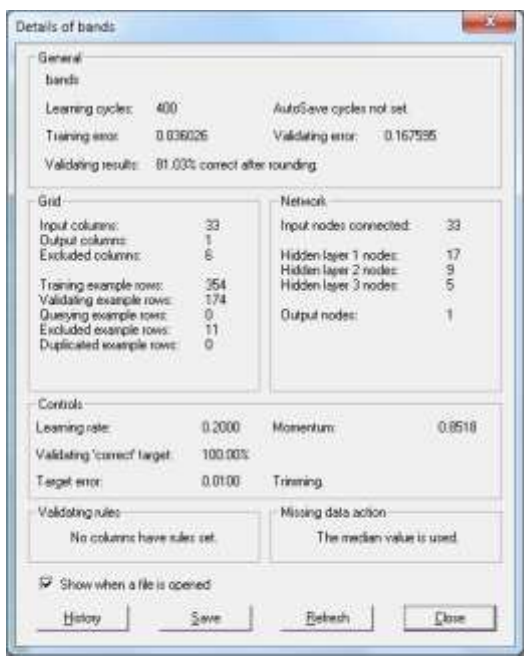

Figure 6: Details of the proposed ANN model

1. Conclusion

An Artificial Neural Network model for predicting two Cylinder Bands dataset: Band, No Band, using features obtained from UCI Machine Learning Repository was presented. The model used feed forward backpropagation algorithm for training the proposed ANN model using JNN tool. The factors for the model were obtained from dataset which represents Cylinder Bands features. The model was tested and the accuracy rate was 81.03%. This study showed that artificial neural network is capable of classifying Cylinder Bands accurately.

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