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The Spinning Quality Control Management Based on Decision Making by Data Mining Techniques

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Abstract—

This work demonstrated the possibility of using the data mining techniques such as artificial neural networks (ANN) and support vector machine (SVM) based model to predict the quality of the spinning yarn parameters. Three different kernel functions were used as SVM kernel functions which are Polynomial and Radial Basis Function (RBF) and Pearson VII Function-based Universal Kernel (PUK) and ANN model were used as data mining techniques to predict yarn properties. In this paper, it was found that the SVM model based on Person VII kernel function (PUK) have the same performance in prediction of spinning yarn quality in comparison with SVM based RBF kernel. The comparison with the ANN model showed that the two SVM models give a better prediction performance than an ANN model.

***Keywords*— Data mining, Support Vector Machine (SVMs), kernel functions, artificial neural network (ANN), yarn properties.**

I. INTRODUCTION

In recent years there has been a significant increase in application of data mining techniques or machine learning in textile engineering especially in forecasting the quality of yarn spinning and help to decide the right decision to make the process go forward. The corresponding increase in forecasting yarn spinning quality became an important part of this field of application because of the relation between fiber and yarn properties are still more complex and nonlinearly. Therefore, modeling of yarn properties which is an indicator to yarn spinning quality and the relationship between fiber and yarn properties were widely studied in textile engineering. There has been growing use of these data mining techniques such as artificial neural network (ANN) [1-5], fuzzy logic [6-8] and genetic algorithm or Genetic programming (GP) [9-11] to predict various yarn properties and to optimize the process. Most recently, Support vector machines (SVMs) is the one of best machine learning or data mining techniques of knowledge discovery that aims to extracting the information from databases. The suitability of using SVM in the prediction of cotton yarn properties to know the accuracy of prediction was studied by many researchers [12-15]. They found that like ANN model, the SVM model is able to predict with a reasonably good accuracy in most cases. However, one of the main reasons for the popularity of SVM is its ability to model complex nonlinear relationships by selecting a suitable kernel function. Briefly, the kernel function transforms the input space into a high dimensional feature space where non-linear relationships can be represented in a linear form. Some popular kernels are linear, polynomial, Gaussian (radial basis function (RBF)) and Sigmoid kernel. The particular choice of a kernel function to map the non-linear input space into a linear feature space depends highly on the nature of the data, i.e., which kind of underlying relationship needs to be estimated to relate the input data to the desired output property. Because the nature of the data is usually unknown, the best mapping function must be determined experimentally by applying and validating various kernel functions yielding the highest generalization performance. Therefore, searching for a kind of universal kernel, through adjusting the kernel parameters, that can adapt each nature data it is very significant. Pearson VII Universal Kernel was applied as a kernel function of SVM in [16], and referred to as PUK. The Pearson VII function has excellent flexibility and possibility to change easily, from a Gaussian into a Lorentzian peak shape and more by

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adapting its parameters. So it is possible to use the Pearson VII function as a generic kernel which can replace the earlier mentioned set of kernel functions.

In this paper, we focused on nonlinear regression problem of fiber/ yarn properties relationships, and investigated the applicability, suitability, performance of SVM based on Person VII kernel function (PUK) kernel in comparison to the commonly applied SVM based on polynomial and the RBF kernel to predict yarn properties from cotton fiber properties.

II. DATA DESCRIPTION

A. Data Set

This data set consists of 24 samples of cotton fiber properties and corresponding yarn properties which were collected from spinning mill in Zhengzhou, Henan Province, China. The collected data were measured by a high volume instrument (HVI). The fiber properties used as input data were fiber length UHML (mm), length uniformity (%), Sort Fiber Content SFC (%), micronaire (M), fiber strength (cN/dtex), elongation (%), yellowness (+b), and reflectance (Rd), trash content (Cnt), and Neps. The yarn properties of corresponding yarn such as yarn unevenness%, hairiness, tenacity (cN/tex), and Strength CV% were used as the output data and the target.

III. THEORY AND ALGORITHM

A. The Support vector machines (SVM)

Support vector machines (SVMs) introduced by Vapnik [17] are machine learning methods based on statistic theory. Because of their easy usage, relatively high performance, and ability to deal with various problems, including classification and regression [18]. Support vector machine (SVM) was proposed as a novel approach for solving classification problems [17]. The SVM implements the structural risk minimization principle that minimizes the upper bound of the generalization error. This induction principle is based on the fact that the generalization error is bounded by the sum of a training error and a confidence-interval term that depends on the Vapnik–Chervonenkis (VC) dimension. For the classification, the SVM tries to find the optimal hyperplane, which is expressed as a linear combination of a subset of the training data (called support vectors) by solving a linearly constrained quadratic programming (QP) problem with a maximum margin between the two classes.

Additionally, with the introduction of Vapnik's ε-insensitive loss function, the SVM has been extended to solve a nonlinear regression- estimation problem, called the SVM for regression (SVR).

Recently, the SVR has been applied to various fields such as optimal control, time-series prediction, interval regression analysis [19-21]. To obtain better performance, some parameters, called hyperparameters, must be selected carefully in the SVM or SVR [22, 23]. The hyperparameters include the kernel parameters, the epsilon value in Vapnik's ε - insensitive loss function, and the regularization constant (The complexity parameter C).

Given the training sample set $\{(x_1, y_1), \dots (x_i, y_l)\} \subset \chi \times \Re,$ where χ is the space of input sample. $\Re$ is the space of output sample.

The basic idea of support vector regression is to map the input vector x into high dimensional feature space by nonlinear mapping function Φ and then to perform linear regression in the feature space. This transformation is realized by Kernel function $K(x_i, x_j) = \Phi(x_i).\Phi(x_j).$ It can be written as follows:

$$f(x) = w.\Phi(x) + b \tag{1}$$

Where $\Phi : \chi \to H, \quad w \in H, \quad b$ is threshold value.

The coefficients w and b are estimated by minimizing

$$E(w) = C\frac{1}{N}\sum_{i=1}^{N}\left|y_i - f(x_i, w)\right|_{\varepsilon} + \frac{1}{2}\|w\|^2, \tag{2}$$

$C \in R^+$, which determines the trade-off between the empirical risk and the regularization term $\frac{1}{2}\|w\|^2$. $|.|_{\varepsilon}$ is the ε - insensitive loss function given by

$$|x|_\varepsilon := \begin{cases} 0 \quad if \quad |x| < \varepsilon \\ |x| - \varepsilon \quad \text{else} \end{cases} \tag{3}$$

In order to obtain the estimations w and b, Eq. (2) is transformed into Eq. (4) as optimal function, by introducing the positive slack variables ξ_i and ξ_i^* as follows:

Minimize
$$E(w) = C\sum_{i=1}^{n}(\xi_i + \xi_i^*) + \frac{1}{2}\|w\|^2 \tag{4}$$

Subjected to

$$\begin{cases} y_i - f(x_i, w) \le \varepsilon + \xi_i \\ f(x_i, w) - y_i \le \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \ge 0 \end{cases} \tag{5}$$

Slack variables ξ_i and ξ_i^* can be introduced when data can't be estimated by the function f under the precise ε.

Introducing Lagrange multipliers and according to Karush-Kuhn-Tucker conditions, Eq. (4) can be transformed into the form as follows:

Minimize:

$$\begin{aligned} L_P(\alpha^*, \alpha) = \varepsilon\sum_{i=1}^{N}(\alpha_i^* + \alpha_i) + \sum_{i=1}^{\ell} y_i(\alpha_i^* - \alpha_i) + \\ \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}(\alpha_i^* - \alpha_i)(\alpha_j^* - \alpha_i)K(x_i, x_j) \end{aligned} \tag{6}$$

Subjected to:

$$\begin{aligned} &\sum_{i=1}^{N}(\alpha_i^* - \alpha_i) = 0, \\ &0 \le \alpha_i^*, \alpha_i \le C, i = 1, 2, ..., N \end{aligned} \tag{7}$$

In Eq. (7), α_i , α_i^* are Lagrange multipliers. The model output is given by Eq. (8)

$$f(x, \alpha) = \sum_{i=1}^{N}(\alpha_i^* - \alpha_i)K(x_i, x_j) + b. \tag{8}$$

In the function (8) Where K(.,.) is the kernel function. Kernel function can have various forms but the two widely used kernel for real -valued data are polynomial and Gaussian radial basis function (RBF) kernel. The polynomial kernel of degree d is defined as:

$$K(x_i, x_j) = (x_i.x_j + k)^d \tag{9}$$

Where k is the constant. The kernel with d = 1 is the linear kernel function.

The second very widely used kernel is the Gaussian radial basis function (RBF) kernel defined by

$$K(x_i, x_j) = \exp(-\|x_i, x_j\| / 2\gamma)^2 \tag{10}$$

Where γ > 0 is a parameter that controls the width of the Gaussian. It plays a similar role as the degree of the polynomial kernel in controlling the flexibility of the resulting classifier.

Pearson VII universal kernel (PUK) is the other type of kernel function that can be used in support vector machines and based on Ustun et al [16]. The general form of the Pearson VII function for curve fitting purposes is given by

$$f(x) = H / [1 + (2(x - x_0)\sqrt{2^{(1/\omega)} - 1} / \sigma)^2]^\omega \tag{11}$$

Where H is the peak height at the center x_0 of the peak, and x represents the independent variable. The parameters ω and σ control the half-width (also named Pearson width) and the tailing factor of the peak. The main reason to use the Pearson VII function for curve fitting is its flexibility to change, by varying the parameters ω and σ.

Pearson VII function was adopted as an alternative generic kernel function in this paper. It might serve as a kind of universal kernel which can replace (by selecting the appropriate parameter setting) the set of commonly applied kernel functions, i.e., the linear, polynomial, Gaussian and Sigmoid kernels. Adopting Person VII function as kernel function, it might avoid the case that SVM can't match data well if the kind of kernel function of SVM was chosen wrongly. The person VII kernel function of multi-dimensional input space, its form is given by the formula (12).

$$K(x_i, x_j) = 1/[1+(2\sqrt{\|x_i - x_j\|^2}\sqrt{2^{(1/\omega)}-1}/\sigma)^2]^\omega \qquad (12)$$

There are no examples of application of PUK kernel methods available in textile engineering related research despite the many advantages that it offers.

According to the formula (11), Person VII universal kernel function, referred to as PUK in this work is used as SVM kernel function and compared to the commonly kernel the polynomial and Gaussian radial basis (RBF) and ANN.

B. Artificial neural network

Artificial neural network (ANN) is suitable for modeling nonlinear relationship. It is a powerful data modeling tool that is able to capture and represent any kind of input –output relationships. The theory of ANN and application in textile engineering exactly in spinning process and modeling yarn properties studies are extensively discussed in many reviews. The ANN employed in this study was a three layer Back- Propagation (BP) Multilayer Perceptron network, the input layer, one hidden layer, and the output layer. More details on the theory and applications of the ANN can be found in a number of publications [1, 2, 24]

C. Implementation

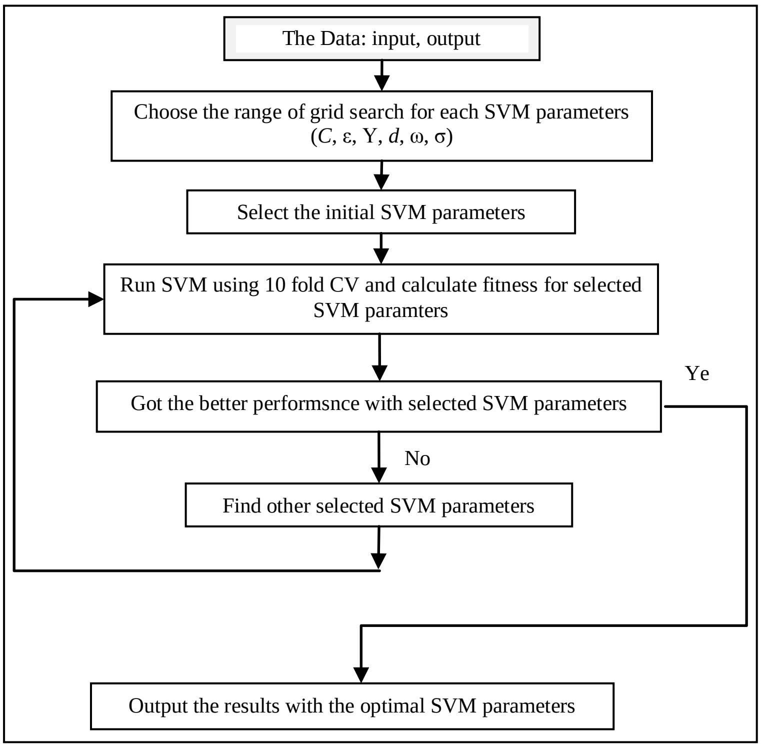

Fig 1: SVM-based model using the grid search to optimize model parameters

The parameters of support vector machine for regression (SVMR) such as the complexity parameter C, and the value of ε - insensitive loss function, and the kernel parameters such as the degree d of polynomial kernel, the

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width of RBF kernel function γ, and PUK kernel parameters (ω and σ) were optimized by using Grid search approach, in the training set data using 10 fold cross validation. This grid search tries values of each parameter across the specified search range using geometric steps. Figure 1 shows a simple diagram of grid search approach. To evaluate the prediction performance of each algorithm we used a 10 fold cross validation technique. This procedure divides the data set into 10 folds or groups and creates the model using 9 of the sets and tests it on the remaining group. This procedure is repeated until each of the 10 groups has served as a test group. Then the error estimates are calculated and then averaged.

The errors that were used as an indicator of the predictive performance of the models were Root mean-squared error (RMSE), Relative error (RE %), and Correlation coefficient (R). For implementation and carry out our experiments, the SVM and ANN models were executed by using Rapid Miner software program.

IV. RESULTS AND DISCUSSION

The goal of this part of research is to compare the prediction results provided by SVM based on polynomial, Gaussian radial basis (RBF) and PUK kernels function as well as the ANN model. The optimization of SVM parameters was performed by using Grid search approach in the data using 10 fold cross validation and depending on smallest RMSR error we selected the optimal parameters of the model. The regularization constant (the complexity parameter C), the ε parameters of the ε - insensitive loss function, and the kernel parameters of the degree d of polynomial kernel, the width of RBF kernel γ and PUK kernel parameters ω and σ were optimized and the results are shown in Table 1.

Table 1 The optimal parameters of SVM based models

Properties	**Optimal parameters of SVM based model**									
	Polynomial			RBF			PUK			
	σ	ε	C	γ	ε	C	ω	σ	ε	C
Unevenness %	3.0	0.04	1.0	0.01	0.001	10.99	1.0	1.0	0.04	1000
Hairiness	3.0	0.1	1.0	0.01	0.001	1.0	105.0	19.1	0.001	1.0
Tenacity	3.0	0.04	250.75	0.01	0.001	250.75	95.0	17.1	0.001	250.75
Strength CV %	3.0	0.001	1.0	0.01	0.001	1.0	95.0	17.1	0.04	1.0

As for the ANN model, the initial architecture of the ANN selected were all the eighth variables the input layer and four neurons in the hidden layer selected by the auto built function and one output neuron. The optimization of the (BP) Multilayer Perceptron model was done with 10 fold cross validation. The ANN optimized parameters such as the optimal learning rate, the momentum coefficient, and the number of epochs were selected lonely according on each target and depending on smaller RMSE the best results were selected. Fig 2 to Fig 5 illustrated the EMSE values of each target, respectively. The optimized parameters of ANN model for each target are given in Table 2.

Table 2 The optimal parameters of ANN based models for carded ring yarn

Properties	**Optimal parameters of ANN based model**		
	Learning rate	Momentum cofficient	Number of epoch
Unevenness %	0.2	0.1	400
Hairiness	0.3	0.1	500
Tenacity	0.3	0.1	300
Strength CV %	0.2	0.1	200

The statistical parameters such as Root mean-squared error (RMSE), Relative error (RE %), and Correlation coefficient (R) were used to compare the predictive power of the SVM-based and ANN based models in prediction of yarn properties and the results are summarized in Table 3.

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Table 3 The comparison of prediction between ANN and SVM models for carded yarn

Yarn properties	Errors	ANN	SVM		
			Polynomial	RBF	PUK
Unevenness %	RMSE	0.119	0.137	0.105	0.097
	RE	0.66	0.70	0.59	0.53
	R	0.794	0.965	0.866	0.892
Hairiness	RMSE	0.209	0.177	0.086	0.086
	RE	4.42	3.47	1.73	1.73
	R	0.633	0.500	0.763	0.766
Tenacity	RMSE	0.542	0.294	0.265	0.265
	RE	2.61	1.33	1.32	1.32
	R	0.578	0.705	0.714	0.717
Strength CV %	RMSE	0.380	0.310	0.285	0.277
	RE	3.61	2.86	2.69	2.63
	R	0.386	0.391	0.358	0.390

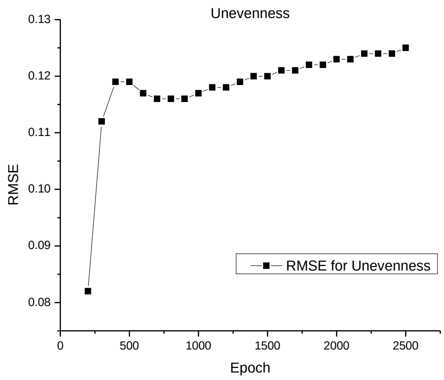

Fig 2 The RMSE value during the change in the epoch number while trying to find the optimal parameters of ANN model of prediction of Yarn Unevenness

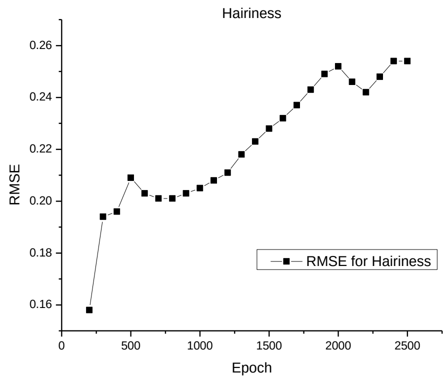

Fig 3 The RMSE value during the change in the epoch number while trying to find the optimal parameters of ANN model of prediction of Yarn Hairiness

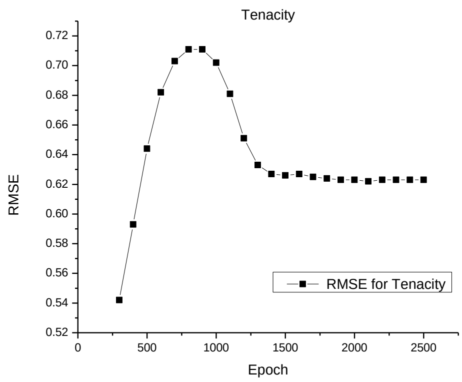

Fig 4 The RMSE value during the change in the epoch number while trying to find the optimal parameters of ANN model of prediction of Yarn Tenacity.

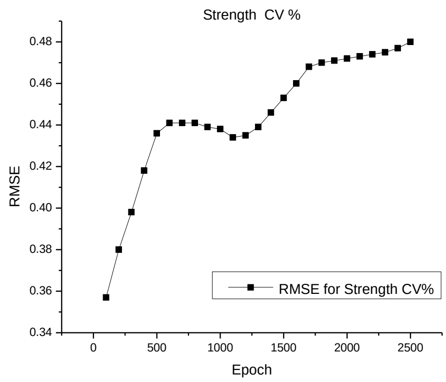

Fig 5 The RMSE value during the change in the epoch number while trying to find the optimal parameters of ANN model of prediction of Yarn Strength CV%.

It can be seen from Table 3 that the values of RMSE, RE and R were provided by SVM based on polynomial kernel have many errors much worse than ANN model. This indicates that the generalization performance of SVM based on polynomial kernel is bad. Therefore, this model does not fit the data well. The RMSE and RE of SVM based on PUK kernel were lower than that of SVM based on RBK kernel in the most cases. The R values provided by SVM based on PUK kernel were higher than that of SVM based on RBK kernel in the most cases too.

On the other hand, the RMSE and RE of both SVM models based on RBK and PUK kernels were lower than ANN model. The R values are higher in both SVM models than ANN model. This comparison shows that both SVM models based on RBK and PUK kernels gives better results than ANN model in terms of the average errors. The comparison of performance of the nonlinear models demonstrates that the SVM based on PUK kernel has the similar ability in predicting yarn properties with SVM based on RBF kernel and all gave more accurately than an ANN model.

V. CONCLUSIONS

A novel kernel function of SVM based on the Pearson VII function was described and applied in this paper, and compared to the commonly applied kernel functions, i.e., the polynomial and Radial Basis Function (RBF), to predict yarn properties. In this study it was observed that, like SVM based on RBF, the SVM model based on PUK kernel have the same applicability, suitability and performance to maps the nonlinear relation between input and output data to predict the yarn properties. A comparison of SVM based on RBF, the SVM model based on PUK with ANN model showed that the two SVM models have a better prediction performance than an ANN model.

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