applied sciences

MDPI

Article

Classifying Four Carbon Fiber Fabrics via Machine Learning: A Comparative Study Using ANNs and SVM

Min Zhao [1,*], Zijun Li [1] and Wanfei He [2]

1 College of Light Industry, Textile and Food Engineering, Sichuan University, Chengdu 610065, Sichuan, China; lizijun_scu@163.com

2 Department of Art, Jincheng College of Sichuan University, Chengdu 610000, Sichuan, China; karena-he@hotmail.com

* Correspondence: zhao_min@scu.edu.cn; Tel.: +86-136-9905-6601

Academic Editor: Christian Dawson

Received: 31 March 2016; Accepted: 15 July 2016; Published: 27 July 2016

Abstract: Carbon fiber fabrics are important engineering materials. However, it is confusing to classify different carbon fiber fabrics, leading to risks in engineering processes. Here, a classification method for four types of carbon fiber fabrics is proposed using artificial neural networks (ANNs) and support vector machine (SVM) based on 229 experimental data groups. Sample width, breaking strength and breaking tenacity were set as independent variables. Quantified numbers for the four carbon fiber fabrics were set as dependent variables. Results show that a multilayer feed-forward neural network with 21 hidden nodes (MLFN-21) has the best performance for classification, with the lowest root mean square error (RMSE) in the testing set.

Keywords: carbon fiber fabrics; classification; machine learning; artificial neural networks; support vector machine

1. Introduction

Carbon fiber is a new engineering material, which has become popular in aerospace, missile and rocket development [1–5]. In recent years, these materials have been developed rapidly in the field of civil construction, including in architecture and sports [6,7]. The resin composite sheet of carbon fiber fabrics is an enhanced product with unidirectional (UD) carbon fiber, which is frequently used because of its excellent mechanical properties and easy repairability [8]. Due to these superior properties, it is currently becoming a promising material in construction industries.

However, because the appearances of different carbon fiber fabrics have no significant difference, different types of carbon fabric fibers are very easy to confuse during productions [9,10], causing a large number of issues related to applications and construction. Also, there is a huge potential risk of compromised security in engineering processes using the resin composite sheet of carbon fiber fabrics without an exact classification [9]. So far, a direct classification approach for different fabrics is to measure the density [10]. However, this measurement is complicated and has high requirements with relevant instruments. Thus, there is still no study that reports an effective solution.

To classify different types of resin composite sheets of carbon fiber fabrics in a simpler way, we should firstly note that differences in density may lead to differences in tensile strength and relevant properties, which can be easily measured by fabric strength machines. Therefore, we can rationally assume that measuring the fabric of carbon fiber using a fabric strength machine can help us obtain a method for classification. Then the question becomes simpler: how do we find out the relationship between the properties acquired from the fabric strength machine and the classification result? Theoretical studies have offered several equations that describe relevant testing processes. Nevertheless, there is still a lack of an available method that can quantify different carbon fiber fabrics. Here, we successfully classify four different carbon fiber fabrics using a simple, defined quantification method with the strong classification capacity of machine learning techniques. Knowledge-based machine learning models were developed after the training process based on a large number of experimental data groups. To acquire enough experimental results, tensile stress and strain performances of four different types of carbon fiber fabrics were tested. All experimental data were measured from 231 samples in four different sample sizes. Based on the experimental data, novel machine learning techniques including artificial neural networks (ANNs) and support vector machine (SVM) were developed, respectively, for the classification of the four types of carbon fiber fabrics. This study, as an application research, aims at using user-friendly modeling techniques to help people classify different fabrics quickly based on the experimental data of tensile tests in research and practical applications. Therefore, the requirements of tensile strength can influence the selection of carbon fabrics by using our modeling techniques in practical applications.

2. Materials and Methods

2.1. Experimental

2.1.1. Preparation of a Resin Composite Sheet of Carbon Fiber Fabrics

To acquire an experimental database for model training, four typical carbon fiber fabrics were used during the experiments (Table 1). It can be apparently seen that the significant difference among the four fabrics is the density, ranging from 24 to 27.

Table 1. Specifications of the four carbon fiber fabrics.

No.	Specification of Carbon Fiber Multifilament [a] (K)	Mean Fabric Density [b]	Grammes per Square Meter (g/m^2)
1	12	25	200
2	12	24	200
3	10	27	200
4	18	25.7	300

[a] Carbon fiber multifilament consists of a certain number of monofilament yarns; [b] Fabric density: number of carbon fiber multifilament in every 10 cm length of carbon fiber fabric.

To prepare resin composite materials, carbon fiber fabrics were impregnated with epoxy resin for 72 h. Specifications of epoxy resin were in accordance with the practical applications of the four kinds of carbon fiber fabrics respectively [9]. Afterwards, 30 cm of the carbon fiber fabric was extracted from the samples. The glass pane, polyester resin sheet and related tools were cleaned by absolute ethyl alcohol and dried. A polyester resin sheet was placed on a 10-cm-thick glass plane. Four-fifths of uniform epoxy resin was poured out and shaved to the polyester resin sheet. Carbon fiber laminates were placed on the uniform epoxy resin and rolled by a metal drum. The fiber should be kept being straight and epoxy resin should be kept transferring from the bottom to the surface of the fiber. Then the remaining one-fifth of epoxy resin was poured out to the surface of fiber uniformly. Afterwards, the samples were covered with polyester resin sheets. Bubbles and redundant resin were shaved away by a blade. A 5-mm-thick glass sheet was covered and all the samples were dried for seven days.

2.1.2. Sampling

In order to avoid data distortion caused by uneven fabric of carbon fiber itself and to ensure the randomness of samples, the central fabrics of carbon fiber were selected randomly from the whole width of 2~2.5 m. Then 30 cm of the fabric being perpendicular to the edge was cut from the distance of the first 5 cm of the end of the fabric. The fabric defect and the joints of the carbon fiber were avoided.

After being stuck during impregnations, the end of the reinforced sheet of fabrics could be drawn by testing machines. The shapes of all tested samples were long rectangular (Figure 1).

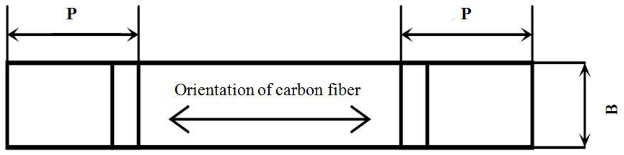

Figure 1. Schematic diagram of a tested sample. *B*: Sample wide; *P*: Length of carbon fiber reinforced sheet.

The lengths of the tested samples referred to the standards of both China and Japan [11–13], which were 230 mm. The widths of samples were designed as four specifications at the interval of 5 mm, including 15, 20, 25 and 30 mm.

2.1.3. Measurement

All samples were tested by the electronic universal testing machine (Shimadzu Co. Ltd., Kyoto, Japan, AG-10TA) for acquiring the breaking strengths and breaking tenacities. The environmental temperature was 14 °C and the humidity was 76%. The stretching speed was 5 m/min, which is in accordance with the standard GB/T1447–1983 [13].

2.2. Machine Learning Models

2.2.1. ANNs

ANNs are statistical learning tools for predictions and classifications in practical applications [14–19], which were invented from the inspiration of human brains. In an ANN, neurons in one layer are connected with all neurons in the next layer. Inter-connected neurons can tune the weight values combining the inputs in order to approximate the actual outputs. Therefore, ANNs are able to classify different objects with the same types of independent variables. Figure 2 is a schematic structure of a typical ANN for the classification of four carbon fiber fabrics, which contains the input, hidden and output layers.

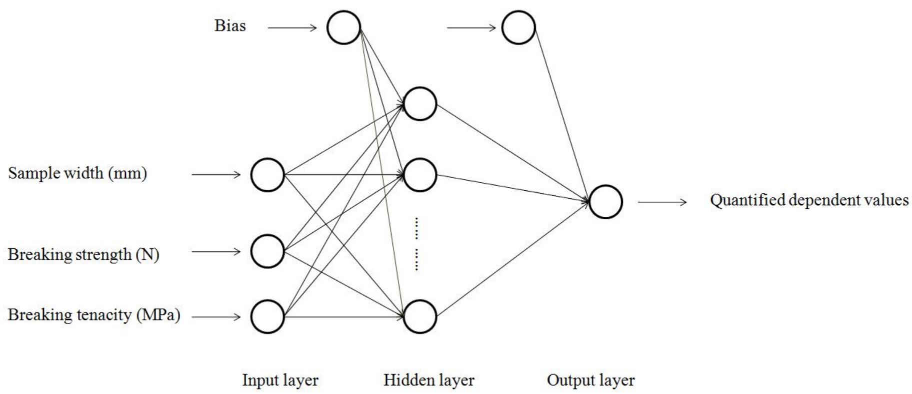

Figure 2. Schematic structure of an ANN (artificial neural network) for classifying the four carbon fiber fabrics.

2.2.2. SVM

SVM is a powerful machine learning method based on the statistical learning theory [20–22]. With limited information of samples between the complexity and learning ability of models, this theory is capacity of global optimization. In the basic principle of SVM, the target of a SVM is to find the optimal hyper-plane, a plane that separates all samples with the maximum margin [16,17,19,20]. This plane not only helps improve the predictive ability of the model, but also helps reduce the error which occurs occasionally when classifying. Figure 3 is the main structure of a typical SVM [16,22]. The letter "*K*" represents kernels. Small subsets extracted from the training data by relevant algorithm help develop the SVM. For applications, choosing suitable kernels and parameters is of great crucial to get a good classification result. With the development of programming, the use of software packages is able to help us solve this problem in a relatively reliable way [21].

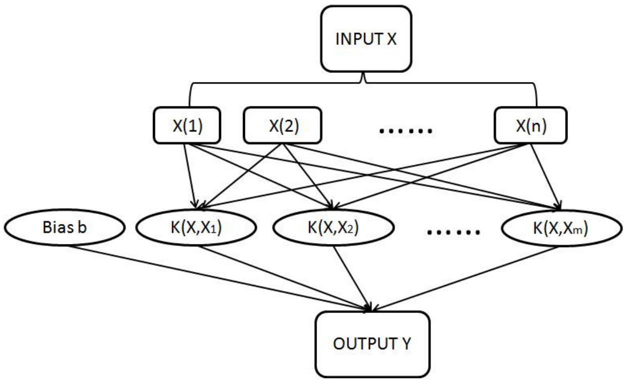

Figure 3. Schematic structure of an SVM (support vector machine) [22].

3. Results and Discussion

3.1. Model Development

Since machine learning models are developed based on the existing database acquired from experiments, here all the experimental results were used for the model training and testing. Statistical descriptions of the experimental results are shown in Table 2.

Table 2. Statistical descriptions of the experimental results.

Statistical Item	Sample Width (mm)	Breaking Strength (N)	Breaking Tenacity (MPa)
Minimum	15	3867.3	1621
Maximum	30	22,618	5988
Range	15	1875.7	4367
Average	239	110,662	3087.61
Standard deviation	5.39	4011.17	1020.92

Due to the powerful learning capacity of ANNs and SVM, we can define the corresponding quantified values by ourselves to classify the four different carbon fiber fabrics, respectively. Here, we define the samples numbers 1–4 as 200, 400, 600 and 800, respectively. Sample width, breaking strength and breaking tenacity were set as the independent variables, while the defined quantified classification for the four kinds of typical samples were set as the dependent values. Then, 85% of the data groups were set as the training set, while the remaining 15% were set as the testing set. ANNs were developed by NeuralTools® software (trial version, Palisade Corporation, Ithaca, NY, USA) [22,23]. A general regression neural network (GRNN) [24,25] and multilayer feed-forward neural networks (MLFNs) [26,27] were used from the software. The SVM model was developed by Matlab software (Libsvm package [21]). The computer for model development was a Lenovo G480 (laptop). To find out the best results of the MLFNs, the nodes in the hidden layer were set from 2 to 50. To measure the performance of different machine learning models, root mean square error (RMSE) and required training time were used as indicators that could help us define the most suitable model. Model development results are shown in Table 3. Results show that the MLFN with 21 nodes

(MLFN-21) has the lowest RMSE for the testing process (36.03), while the SVM and other ANNs have comparatively higher RMSEs and lower classification accuracies. The change regulation of MLFNs with different numbers of nodes (Figure 4) also shows that with the increase of the node numbers, the required training times of the MLFNs gradually increase with a fluctuation. Though the training time of MLFN-21 is slightly longer than those of SVM, GRNN and other MLFNs with lower numbers of nodes, it is still acceptable because the training time will decrease with a high-performance computer. Therefore, the MLFN-21 can be rationally considered as the best model for classifying the four different carbon fiber fabrics in our experiments.

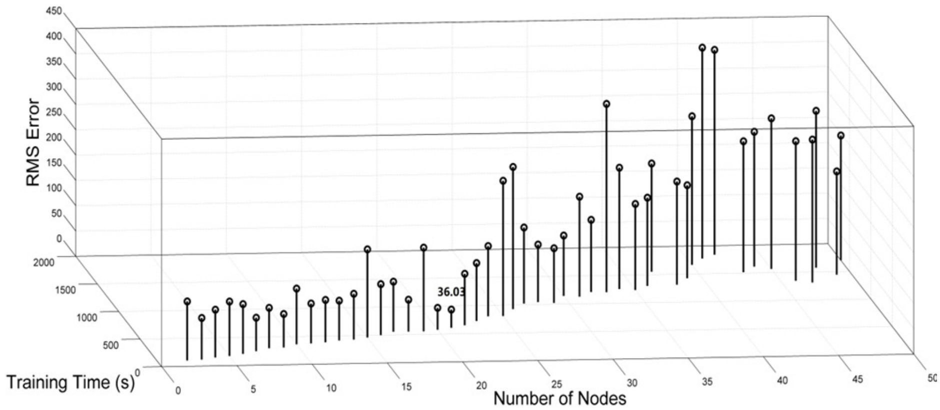

Figure 4. Change regulation of RMSEs (root mean square errors) in MLFNs (multilayer feed-forward neural networks) with different number of nodes.

Table 3. Best net search in different models. SVM: support vector machine; GRNN: general regression neural network; MLFN: multilayer feed-forward neural network.

Model	RMSE (for Testing)	Required Training Time
SVM	157.18	0:00:01
GRNN	154.79	0:00:01
MLFN 2 Nodes	116.51	0:01:45
MLFN 3 Nodes	81.92	0:01:58
MLFN 4 Nodes	94.38	0:02:30
MLFN 5 Nodes	107.45	0:02:52
MLFN 6 Nodes	98.24	0:03:27
MLFN 7 Nodes	65.92	0:04:11
MLFN 8 Nodes	79.64	0:05:01
MLFN 9 Nodes	66.09	0:05:09
MLFN 10 Nodes	109.95	0:06:02
MLFN 11 Nodes	78.88	0:06:13
MLFN 12 Nodes	83.69	0:06:28
MLFN 13 Nodes	78.48	0:06:59
MLFN 14 Nodes	90.54	0:07:09
MLFN 15 Nodes	174.10	0:07:42
MLFN 16 Nodes	100.59	0:08:21
MLFN 17 Nodes	98.58	0:09:19
MLFN 18 Nodes	62.81	0:09:17
MLFN 19 Nodes	165.28	0:09:15
MLFN 20 Nodes	43.10	0:09:40
MLFN 21 Nodes	36.03	0:10:11
MLFN 22 Nodes	101.73	0:10:51
MLFN 23 Nodes	114.28	0:12:06
MLFN 24 Nodes	138.72	0:13:26
MLFN 25 Nodes	266.98	0:13:27
MLFN 50 Nodes	246.41	0:28:23

3.2. Model Analysis

To analyze the performance of MLFN-21, its non-linear fitting process should be firstly discussed. In the model training process (Figure 5), the predicted values are generally close to the actual values (Figure 5a). Residual values are generally close to zero except for several discrete points (Figure 5b,c). The results of the training process show that the non-linear fitting process of MLFN-21 for classifying the four carbon fiber fabrics is decent. In terms of the model testing process (Figure 6), the predicted values in the testing set are very close to the actual values (Figure 6a), with comparatively low residual values (Figure 6b,c). The results of the testing process show that the MLFN-21 has a strong capacity for classifying the four carbon fiber fabrics, with the use of the four quantified dependent values: 200, 400, 600 and 800.

To evaluate the reproducibility of the ANNs, it should be firstly noted that the initial values of the weights are chosen randomly at the beginning of training. Then the initial weights are tuned according to the errors between the actual and desired outputs. Therefore, the training results of each single model development with the same component of the training and testing sets are always different, which is reflected in the fluctuation of RMSEs in the testing set. To prove that an ANN has good reproducibility, repeated experiments should be done in order to evaluate whether the RMSEs in the dependent training process have a stable fluctuation. To test the reproducibility of the MLFN-21 of this study, we repeated the training 100 times using the same component of the training and testing sets (Figure 7). It shows that MLFN-21 has a very stable fluctuation in the RMSE in testing during all repeated experiments. All RMSEs in testing are in the range between 21.1 and 41. The repeated experiments show that MLFN-21 has very good reproducibility for classifying the four carbon fiber fabrics.

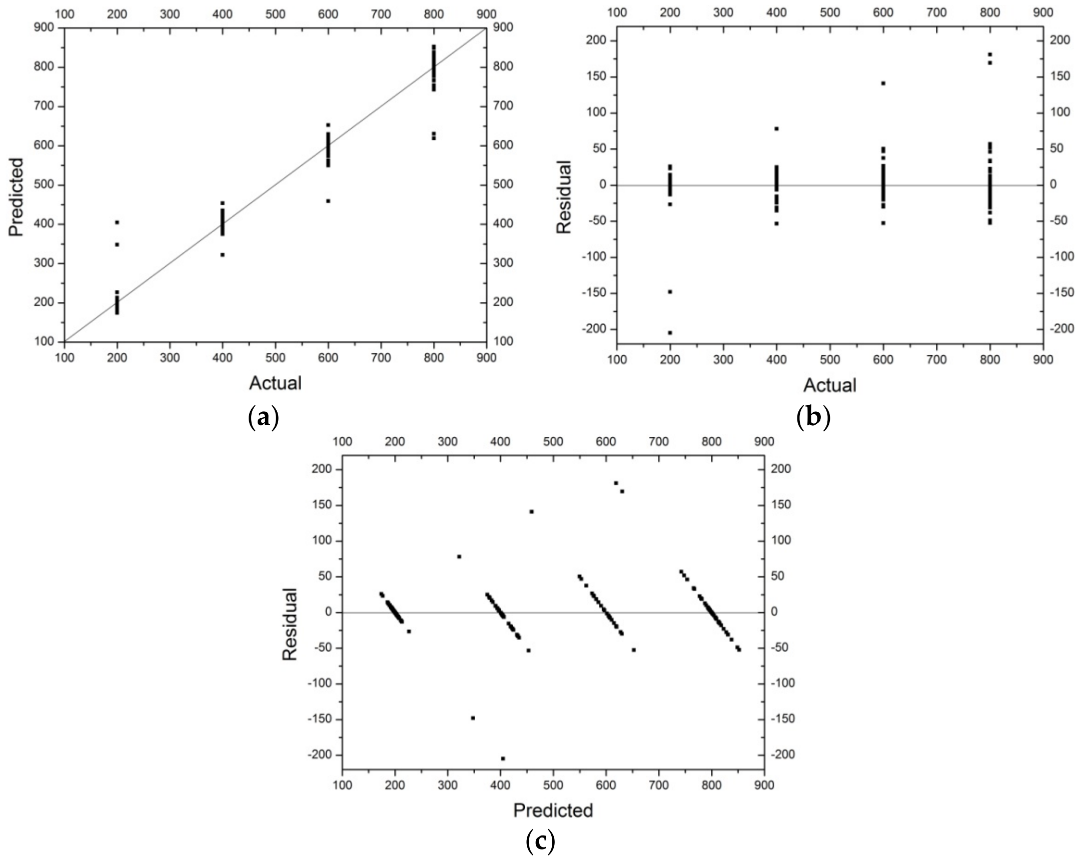

Figure 5. Training results of MLFN-21. (**a**) Predicted values versus actual values; (**b**) residual values versus actual values; (**c**) residual values versus predicted values.

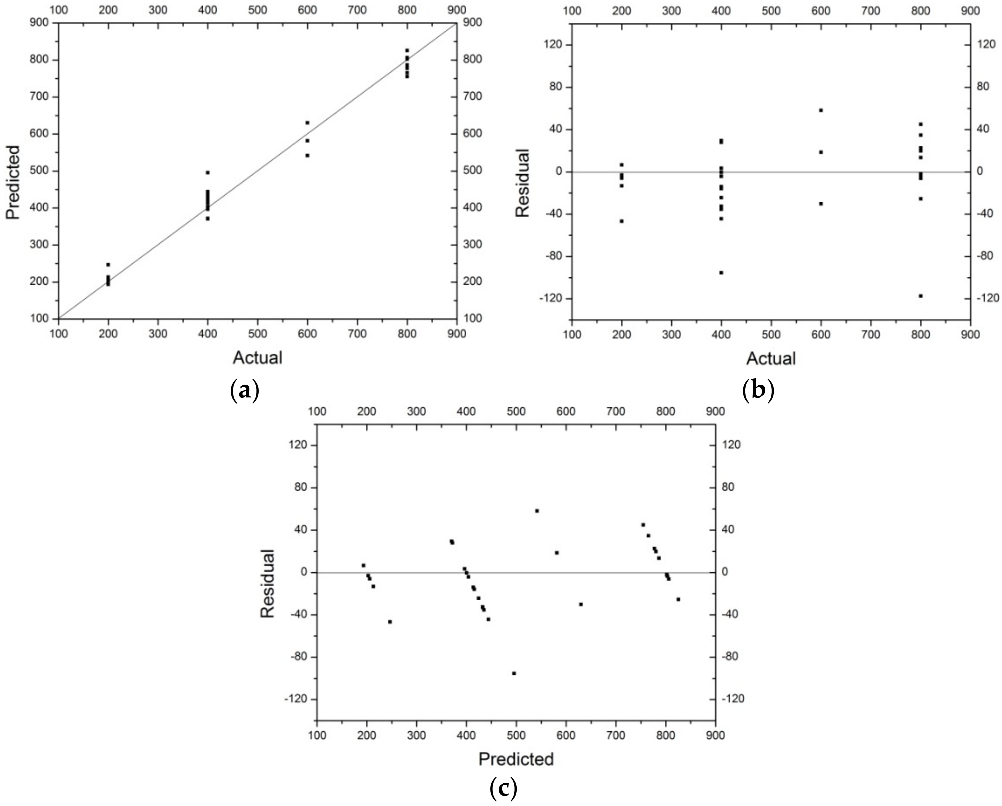

Figure 6. Testing results of MLFN-21. (a) Predicted values versus actual values; (b) residual values versus actual values; (c) residual values versus predicted values.

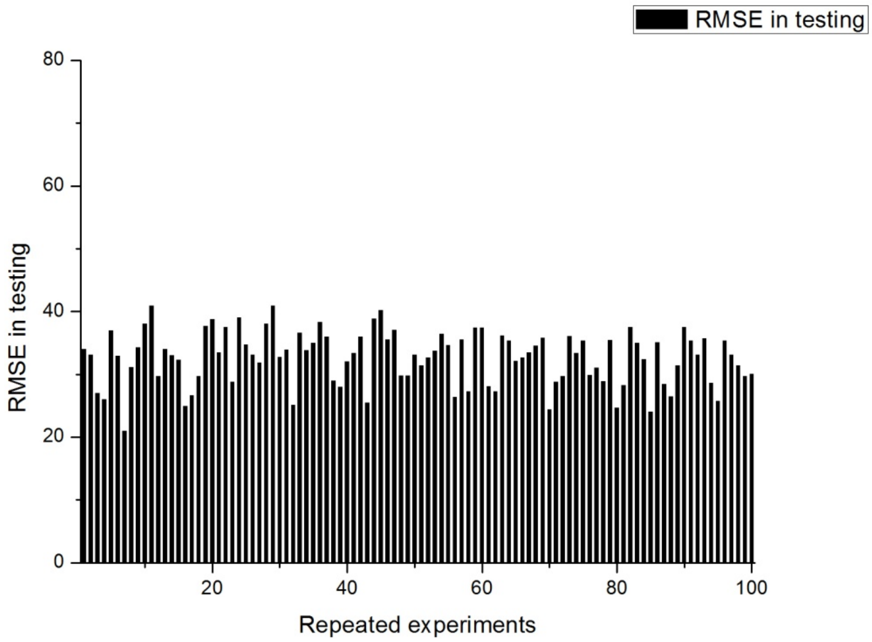

Figure 7. RMSEs of repeated experiments for developing the MLFN-21.

4. Conclusions

Here, ANNs and SVM are developed for classifying four types of carbon fiber fabrics. Results show that using four different numbers to represent the outputs of the four different fabrics with the use of the MLFN-21 model can help us classify different carbon fiber fabrics in real applications. With the inputs of sample width, breaking strength and breaking tenacity, this study successfully shows that machine learning methods, such as the MLFN-21, can effectively help us classify different carbon fiber fabrics based on the training of experimental data. It can be seen that ANNs are powerful tools to make good classification results due to their strong non-linear data-learning capacity. Also, it should be noted that in this study, the most important thing we were concerned with was the classification of carbon fiber fabrics, not the production. For classification, according to the principle, the ANN model is a "black box" non-linear training model. Thus, the determination of weights between different neuron layers was trained according to the iterations, not the exact correlations between independent and dependent variables. Therefore, it is uncertain to say which production factor will greatly affect the results in this study. Further research can be undertaken to develop a wider model for the determination of the correlation between the production factor and the types of carbon fabric fibers.

Author Contributions: Zijun Li did the experimental and modeling studies; Wanfei He and Min Zhao analyzed the results; all authors took part in the paper writing.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ANNs	artificial neural networks
SVM	support vector machine
GRNN	general regression neural network
MLFN	multilayer feed-forward neural network
RMSE	root mean square error

References

1. Motoyuki, S. Activated carbon fiber: Fundamentals and applications. *Carbon* **1994**, *32*, 577–586.
2. Chen, W.C. Some experimental investigations in the drilling of carbon fiber-reinforced plastic (CFRP) composite laminates. *Int. J. Mach. Tool. Manuf.* **1997**, *37*, 1097–1108. [CrossRef]
3. Kumar, S.; Doshi, H.; Srinivasarao, M.; Park, J.; Schiraldi, D. Fibers from polypropylene/nano carbon fiber composites. *Polymer* **2002**, *43*, 1701–1703. [CrossRef]
4. Bekyarova, E.; Thostenson, E.T.; Yu, A.; Kim, H.; Gao, J.; Tang, J.; Hahn, H.T.; Chou, T.W.; Itkis, M.E.; Haddon, R.C. Multiscale carbon nanotube-carbon fiber reinforcement for advanced epoxy composites. *Langmuir* **2007**, *23*, 3970–3974. [CrossRef] [PubMed]
5. Sidoli, G.E.; King, P.A.; Setchell, D.J. An in vitro evaluation of a carbon fiber-based post and core system. *J. Prosthet. Dent.* **1997**, *78*, 5–9. [CrossRef]
6. Norris, T.; Hamid, S.; Mohammad, R.E. Shear and flexural strengthening of R/C beams with carbon fiber sheets. *J. Struct. Eng. ASCE* **1997**, *123*, 903–911. [CrossRef]
7. Seible, F.; Nigel Priestley, M.J.; Hegemier, G.A.; Innamorato, D. Seismic retrofit of RC columns with continuous carbon fiber jackets. *J. Compos. Constr.* **1997**, *1*, 52–62. [CrossRef]
8. Gay, D. *Composite Materials: Design and Applications*; CRC Press: Boca Raton, FL, USA, 2014.
9. Luo, L.L.; Zhao, M.; Xu, C.X.; Zhou, F.X. A research on test methods for carbon fiber sheet. *Build. Sci. Res. Sichuan*; **2004**, *3*, 98–101.
10. Zhao, Q.; Zhao, M.; Xu, C.X. Tensile stress test for carbon fiber/epoxy composite sheet. *Sichuan Text. Technol.* **2004**, *4*, 40–41.
11. Research Subcommittee on Test Method and Specifications for Concrete Concrete Committee. *JSCE-E 542-2000 Tensile Strength Test Methods for Carbon Fiber Sheet*; Japan Society of Civil Engineers: Tokyo, Japan, 2000.
12. National Technical Committee on Fiber Reinforced Plastic of Standardization Administration of China. *GB-3354-82 Tensile Performance Test Methods for Unidirectional (UD) Reinforced Composite Fiber*; Standards Press of China: Beijing, China, 1998.

13. National Technical Committee on Fiber Reinforced Plastic of Standardization Administration of China. *GB-1447-83 Tensile Performance Test Methods for Glass Fiber Reinforced Plastic (GFRP)*; Standards Press of China: Beijing, China, 1983.
14. Hopfield, J.J. Artificial neural networks. *IEEE Circuit. Devices* **1988**, *4*, 3–10. [CrossRef]
15. Drew, P.J.; Monson, R.T. Artificial neural networks. *Surgery* **2000**, *127*, 3–11. [CrossRef] [PubMed]
16. Chen, F.D.; Li, H.; Xu, Z.H.; Hou, S.X.; Yang, D.Z. User-friendly optimization approach of fed-batch fermentation conditions for the production of iturin A using artificial neural networks and support vector machine. *Electron. J. Biotechnol.* **2015**, *18*, 273–280. [CrossRef]
17. Li, H.; Chen, F.D.; Cheng, K.W.; Zhao, Z.Z.; Yang, D.Z. Prediction of Zeta Potential of Decomposed Peat via Machine Learning: Comparative Study of Support Vector Machine and Artificial Neural Networks. *Int. J. Electrochem. Sci.* **2015**, *10*, 6044–6056.
18. Li, H.; Yang, D.Z.; Chen, F.D.; Zhou, Y.B. Application of Artificial Neural Networks in predicting abrasion resistance of solution polymerized styrene-butadiene rubber based composites. In Proceedings of the 2014 IEEE Workshop on Electronics, Computer and Applications, Ottawa, ON, Canada, 8–9 May 2014; pp. 581–584.
19. Yang, D.Z.; Li, H.; Cao, C.C.; Chen, F.D.; Zhou, Y.B.; Xiu, Z.L. Analysis of the Oil Content of Rapeseed Using Artificial Neural Networks Based on Near Infrared Spectral Data. *J. Spectrosc.* **2014**, *2014*. [CrossRef]
20. Suykens, J.A.K.; Vandewalle, J. Least squares support vector machine classifiers. *Neural Process. Lett.* **1999**, *9*, 293–300. [CrossRef]
21. Chang, C.C.; Lin, C.J. LIBSVM: A library for support vector machines. *ACM TIST* **2011**, *2*. [CrossRef]
22. Li, H.; Tang, X.; Wang, R.; Lin, F.; Liu, Z.; Cheng, K. Comparative Study on Theoretical and Machine Learning Methods for Acquiring Compressed Liquid Densities of 1,1,1,2,3,3,3-Heptafluoropropane (R227ea) via Song and Mason Equation, Support Vector Machine, and Artificial Neural Networks. *Appl. Sci.* **2016**, *6*. [CrossRef]
23. Mohamed, M.; Nedret, B. Recognition of western style musical genres using machine learning techniques. *Expert Syst. Appl.* **2009**, *36*, 11378–11389.
24. Specht, D.F. A general regression neural network. *IEEE Neural Netw.* **1991**, *26*, 568–576. [CrossRef] [PubMed]
25. Leung, M.T.; Chen, A.S.; Daouk, H. Forecasting exchange rates using general regression neural networks. *Comput. Oper. Res.* **2000**, *27*, 1093–1110. [CrossRef]
26. Svozil, D.; Kvasnicka, V.; Pospichal, J. Introduction to multi-layer feed-forward neural networks. *Chemomet. Intel. Lab.* **1997**, *39*, 43–62. [CrossRef]
27. Liu, Z.; Li, H.; Zhang, X.; Jin, G.; Cheng, K. Novel Method for Measuring the Heat Collection Rate and Heat Loss Coefficient of Water-in-Glass Evacuated Tube Solar Water Heaters Based on Artificial Neural Networks and Support Vector Machine. *Energies* **2015**, *8*, 8814–8834. [CrossRef]