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Fabric Defect Classification using Artificial intelligence Technique

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ABSTRACT

In textile industry, the poor quality of raw materials and improper conditioning of yarn result in fabric quality defects and effects such as color or width inconsistencies, hairiness, slubs, broken ends, etc. Inspection of fabric defects plays on important role in the quality control. However, the current inspection task is primarily performed by human inspectors. Over the years significant research has been performed for automated, i.e. machine vision based fabric inspection systems in order to replace manual inspection, which is time consuming and not accurate enough. Automated fabric inspection systems mainly involve two challenging problems, one of which is defect classification. The amount of research done to date to solve the defect classification problem is insufficient. Scene analysis and feature selection play a very important role in the classification process, more affordable and precise technique to classify fabric defect is of incredible reasonable essentialness. The Efficient classifiers in light of using WHT transform with Multilayer Perceptron (MLP) Neural Network. An alternate Cross-Validation dataset is used for authentic appraisal of the proposed gathering computation with respect to basic execution measures, for instance, MSE and request accuracy. The Average Classification Accuracy of MLP Neural Network containing one hidden layers with 20 PE's dealt with in an ordinary topology is seen to be unrivaled (96.87%) for Training and cross-validation. Finally, perfect count has been delivered dependent on the best classifier execution.

Keyword : - Neural solution, Mat Lab, Microsoft excel, Fabric Defect images

1. INTRODUCTION

Scientifically, a process quality control means conducting observations, tests and inspections and thereby making decisions which improve its performance. Because no production or manufacturing process is 100% defect-free, the success of a weaving mill is significantly highlighted by its success in reducing fabric defects. For a weaving plant, in these harsh economic times, first quality fabric plays the main role to insure survival in a competitive marketplace. This puts sophisticated stress on the weaving industry to work towards a low cost first quality product as well as just-in-time delivery. First quality fabric is totally free of major defects and virtually free of minor structural or surface defects. Second quality fabric is fabric that may contain a few major defects and/or several minor structural or surface defects [1]. The non-detected fabric defects are responsible for at least 50% of the second quality in the garment industry. Although quality levels have been greatly improved with the continuous improvement of materials and technologies, most weavers still find it necessary to perform 100% inspection because customer expectations have also increased and the risk of delivering inferior quality fabrics without inspection is not acceptable. The key issue, therefore, is how and under what conditions fabric inspection will lead to quality improvement. To address this issue, we proposed this classification system. The modern weaving Industry faces a lot of difficult challenges to create a high productivity as well as high-quality-manufacturing environment. Because production speeds are faster than ever and because of the increase in roll sizes, manufacturers must be able to identify defects, locate their sources, and make the necessary corrections in less time so as to reduce the amount of second quality fabric. This in turn places a greater strain on the inspection departments of the manufacturers. Due to factors such as tiredness, boredom and, inattentiveness, the staff performance is often unreliable. The inspector can hardly determine the level of faults that is acceptable, but comparing such a level between several inspectors is almost impossible. Therefore, the best possibility of objective and consistent evaluation is through the application of an automatic inspection system. From the early beginning, the human dream is to improve the manufacturing techniques to achieve optimum potential benefits as quality, cost, comfort, accuracy, precision and speed. To imitate the wide variety of human functions, technology was the magic stick that advanced humanity from manual to mechanical and then from mechanical to automatic. The rare existence of automated fabric inspection may be attributed to the methodologies, which are often unable to cope with a wide variety of fabrics and defects, yet a continued reduction in processor and memory costs would suggest that automated fabric inspection has potential as a cost effective alternative. The wider application of automated fabric inspection would seem to offer a number of potential advantages, including improved safety, reduced labor costs, the elimination of human error and/or subjective judgments, and the creation of timely statistical product data. Therefore, automated visual inspection is gaining increasing importance in weaving industry.

An automated inspection system usually consists of a computer-based vision system. Because they are computer-based, these systems do not suffer the drawbacks of human visual inspection. Automated systems are able to inspect fabric in a continuous manner without pause. Most of these automated systems are offline or off-loom systems. Should any defects be found that are mechanical in nature (i.e., missing ends or oil spots), the lag time that exists between actual production and inspection translates into more defective fabric produced on the machine that is causing these defects. Therefore, to be more efficient, inspection systems must be implemented online or on-loom. The proposed method in this synopsis represents an effective and accurate approach to automatic defect detection. It is capable of identifying all five type defects. Because the defect-free fabric has a periodic regular structure, the occurrence of a defect in the fabric breaks the regular structure. Therefore, the fabric defects can be detected by monitoring fabric structure. Fourier Transform gives the possibility to monitor and describe the relationship between the regular structure of the fabric in the spatial domain and its Fourier spectrum in the frequency domain. Presence of a defect over the periodical structure of woven fabric causes changes in its Fourier spectrum. By comparing the power spectrum of an image containing a defect with that of a defect-free image, changes in the normalized intensity between one spectrum and the other means the presence of a defect. The fabric defect could be simply defined as a change in or on the fabric construction. Only the weaving process may create a huge number of defects named as weaving defects. Most of these defects appear in the longitudinal direction of the fabric (the warp direction) or in the width-wise direction (the weft direction). The yarn represents the most important reason of these defects, where presence or absence of the yarn causes some defects such as miss-ends or picks, end outs, and broken end or picks. Other defects are due to yarn defects such as slubs, contaminations or waste, becoming trapped in the fabric structure during weaving process. Additional defects are mostly machine related, and appear as structural failures (tears or holes) or machine residue (oil spots or dirt). Because of the wide variety of defects as mentioned previously, it will be gainful to apply the study on the most major fabric defects. The chosen major defects are hole, oil stain, float, coarse-end, coarse-pick, double-end, double-pick, irregular weft density, broken end, and broken pick.

1.1 Defect analysis

In this proposed work, we have dealt with four types of defect, which often occur in knitted fabrics in Bangladesh, namely color yarn, and hole, missing yarn, and spot. All of the defects are shown in Fig. 1. All of them are discussed here below.

(a)color yam (b) hole (c) Missing yam (d) Spot

Fig-1: Different types of defect occurred in knitted fabric

• Color Yarn: Fig. 1(a) shows the defect of color yarn. Color yarn appears in a shape, close to a small rectangle of one color, on a fabric of another color. A camera of high resolution and proper lighting are required in order to clearly capture the image of the defect of color yarn.

• Hole: Fig. 1(b) shows the defect of hole. Hole appears in a shape, close to a circle of the color of the background, on a fabric of another color. Its size varies from small to medium. Background color is another issue. In some cases, background color can become close to fabric color.

• Missing Yarn: Fig. 1© shows the defect of missing yarn. Missing yarn appears as a thin striped shade of the color of fabric. It is usually long. It is of two types, namely vertical and horizontal.

• Spot: Fig. 1(d) shows the defect of spot. Spot does not appear in any specific shape. It usually appears in a scattered form of one color on a fabric of another color. Moreover, its size varies widely. A camera of high resolution and proper lighting are required in order to clearly capture the image of the defect of spot.

2. RESEARCH METHODOLOGY

It is order of fabric defect images Using Neural Network Approaches… Information obtaining for the proposed classifier intended for the characterization of fabric images. The most vital un associated includes and in addition coefficient from the images will be separated .In request to remove highlights WHT changed area will be utilized.

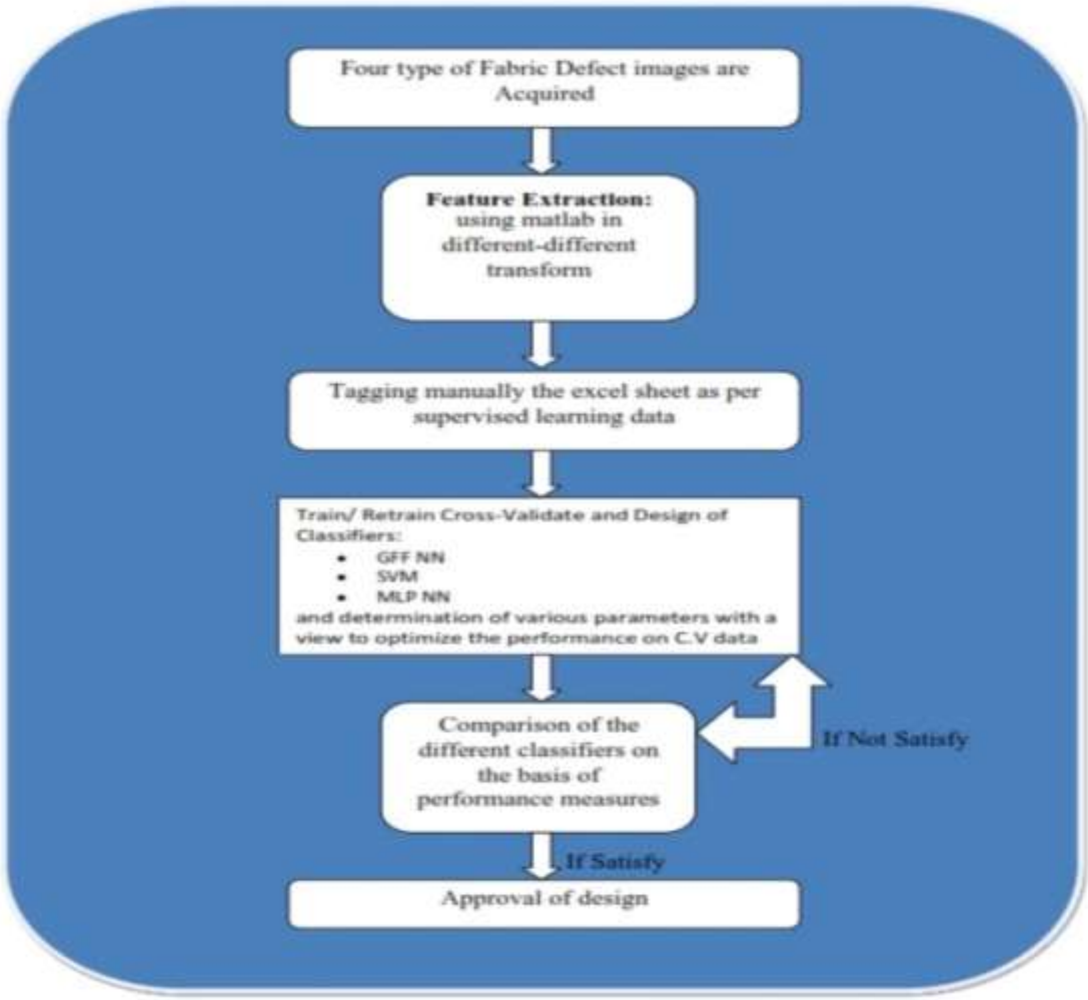

Fig -2: Methodology of the work

2.1 Neural network

Multilayer perceptron (MLP): The most widely recognized neural system demonstrate is the multi layer perceptron (MLP). This sort of neural system is known as a directed system since it requires a coveted yield with the end goal to learn. The objective of this sort of system is to make a model that accurately maps the contribution to the yield utilizing verifiable information with the goal that the model would then be able to be utilized to create the yield when the coveted yield is obscure. A graphical portrayal of a MLP is demonstrated as follows:

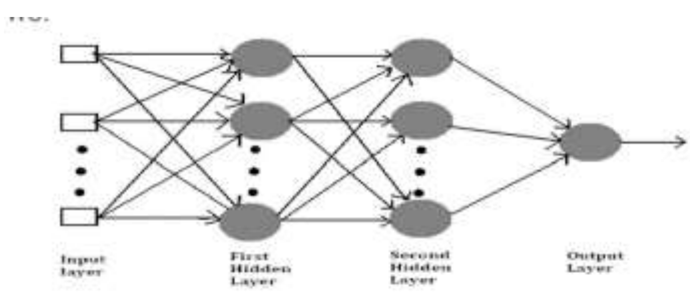

Fig-3: The structure of neural network model mlp.

The MLP and numerous other neural systems pick up utilizing a calculation got back to engendering. With back-proliferation, the info information is over and over displayed to the neural system. With every introduction the yield of the neural system is contrasted with the coveted yield and a mistake is processed. This mistake is then nourished (back-engendered) to the neural system and used to alter the weights to such an extent that the blunder diminishes with every emphasis and the neural model draws nearer and closer to delivering the coveted yield. This procedure is known as "preparing".

2.2 Learning rules used

a. Momentum: Momentum simply adds a fraction m of the previous weight update to the current one. The momentum parameter is used to prevent the system from converging to a local minimum or saddle point. A high momentum parameter can also help to increase the speed of convergence of the system. However, setting the momentum parameter too high can create a risk of overshooting the minimum, which can cause the system to become unstable. A momentum coefficient that is too low cannot reliably avoid local minima, and can also slow down the training of the system.

b. Conjugate Gradient: CG is the most prevalent iterative technique for unraveling vast frameworks of direct conditions. CG is successful for frameworks of the shape A=xb-A (1) where x _is an obscure vector, b is a known vector, and A _is a known, square, symmetric, positive-unmistakable (or positive-uncertain) lattice. (Try not to stress in the event that you've overlooked what "positive-distinct" implies; we will survey it.) These frameworks emerge in numerous imperative settings, for example, limited contrast and limited component techniques for fathoming incomplete differential conditions, auxiliary examination, circuit investigation, and math homework. Created by Widrow and Hoff, the delta govern, additionally called the Least Mean Square (LMS) strategy, is a standout amongst the most usually utilized learning rules. For a given information vector, the yield vector is contrasted with the right answer. In the event that the thing that matters is zero, no learning happens; generally, the weights are changed in accordance with lessen this distinction. The adjustment in weight from ui to uj is given by: dwij = r* ai * ej, where r is the learning rate, ai speaks to the initiation of ui and ej is the distinction between the normal yield and the genuine yield of uj. On the off chance that the arrangement of information designs shape a directly autonomous set then subjective affiliations can be gotten the hang of utilizing the delta run the show. It has been demonstrated that for systems with direct initiation capacities and with no shrouded units (concealed units are found in systems with in excess of two layers), the blunder squared versus the weight chart is a parabolic in n-space. Since the proportionality steady is negative, the chart of such a capacity is inward upward and has a base esteem. The vertex of this parabolic speaks to the point where the mistake is limited. The weight vector relating to this point is then the perfect weight vector.

c. Quick Propagation: Quick propagation (Quick prop) [1] is one of the most effective and widely used adaptive learning rules. There is only one global parameter making a significant contribution to the result, the e-parameter. Quick-propagation uses a set of heuristics to optimize Back-propagation; the condition where e is used is when the sign for the current slope and previous slope for the weight is the same.

d. Delta by delta: Created by Widrow and Hoff, the delta manages, likewise called the Least Mean Square (LMS) technique, and is a standout amongst the most regularly utilized learning rules. For a given information vector, the yield vector is contrasted with the right answer. In the event that the thing that matters is zero, no learning happens; generally, the weights are changed in accordance with diminish this distinction. The adjustment in weight from ui to uj is given by: dwij = r* ai * ej, where r is the learning rate, ai speaks to the initiation of ui and ej is the distinction between the normal yield and the genuine yield of uj. In the event that the arrangement of info designs shape a directly free set then discretionary affiliations can be gotten the hang of utilizing the delta run the show. It has been demonstrated that for systems with direct actuation capacities and with no shrouded units (concealed units are found in systems with in excess of two layers), the blunder squared versus the weight chart is a parabolic in n-space. Since the proportionality steady is negative, the diagram of such a capacity is inward upward and has a base esteem. The vertex of this parabolic speaks to the point where the mistake is limited. The weight vector relating to this point is then the perfect weight vector. [10].

3. RESULT

The MLP neural system has been reproduced for 164 distinct four type of fabric defect Images out of which 148 were utilized for preparing reason and 16 were utilized for cross approval. The simulation of the Best Neural network with maximum accuracy is shown below:

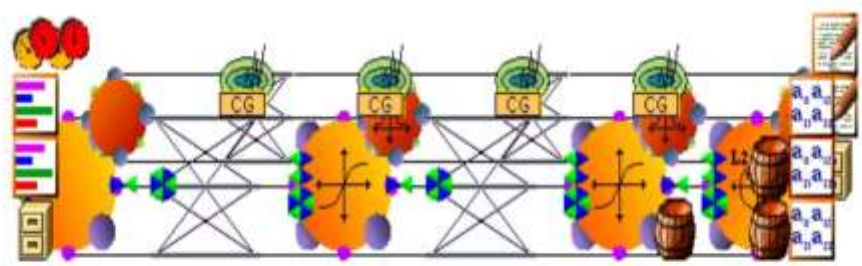

Fig-4: The Best Neural network with maximum accuracy (MLP-CG)

Training report of best classifier:

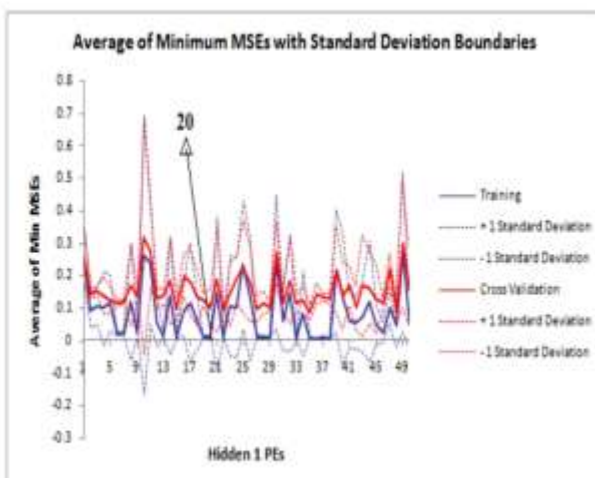

Table-1: Training and cross validation Report of the Best Classifier MLP-CG

Best network	Training	Cross validation
Hidden 1PEs	27	20
Run#	3	1
Epoch#	958	194

Minimum MSE	0.000595233	0.0459354
Final MSE	0.000595233	0.052268862

Test on cross validation:

Table-2: Confusion matrix table of Cross validation (CV)

Output / Desired	NAME(HOLE)	NAME(SPOT)	NAME(MISSING YARN)	NAME(BUNCHIN G UP)
NAME(HOLE)	4	0	0	1
NAME(SPOT)	0	5	0	0
NAME(MISSING YARN)	0	0	4	0
NAME(BUNCHIN G UP)	0	0	0	3

Table-3: Performance Measures for cross validation

Performance	NAME(HOLE)	NAME(SPOT)	NAME(MISSING YARN)	NAME(BUNCHIN G UP)
MSE	0.080976267	0.002119995	0.014453187	0.001920306
NMSE	0.450041178	0.010211309	0.080326366	0.01067247
MAE	0.160263248	0.042098317	0.082896353	0.036184083
Min Abs Error	0.016159095	0.000927305	0.00155176	0.000744441
Max Abs Error	0.894972966	0.055544529	0.327848173	0.105083723
r	0.7563384	0.999624934	0.965484911	0.996200316
Percent Correct	100	100	100	75

Test on testing

Table-4: Confusion matrix table of Training

Output / Desired	NAME(HOLE)	NAME(SPOT)	NAME(MISSING YARN)	NAME(BUNCHIN G UP)
NAME(HOLE)	32	0	0	0
NAME(SPOT)	0	43	0	0
NAME(MISSING YARN)	0	0	40	0
NAME(BUNCHIN G UP)	0	0	0	32

Table-5: Performance Measures for training

Performance	NAME(HOLE)	NAME(SPOT)	NAME(MISSING YARN)	NAME(BUNCHIN G UP)
MSE	0.01283816	0.001848925	0.003986185	0.005953079
NMSE	0.075385814	0.008934127	0.020125576	0.034956544
MAE	0.056847307	0.038131666	0.037127233	0.048446094
Min Abs Error	0.004155357	2.69813E-05	6.40551E-05	0.00075
Max Abs Error	0.788960875	0.066586739	0.519487626	0.6071262
r	0.962177047	0.99833827	0.990431115	0.9830687
Percent Correct	100	100	100	100

4. CONCLUSIONS

A From the results obtained in WHT domain it concludes that the MLP Neural Network with CG and hidden layer 1 with processing element 20 gives best results of 93.75% in Cross Validation while in training it gives 100% so overall accuracy is 96.87%.

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6. REFERENCES

[1] J. Tou, R. Gonzalez, Pattern Recognition Principles. Massachusetts, USA: Addison-Wesley Publishing Company, 1981.
[2] R. Stojanovic, P. Mitropulos, C. Koulamas, Y.Karayiannis, S. Koubias, and G. Papadopoulos,"Real-time vision based system for textile fabric inspection," Real-Time Imaging, vol. 7, no. 6, pp. 507-518, 2001.
[3] R. Saeidi, M. Latifi, S. Najar, and A. Saeidi, "Computer vision-aided fabric inspection system for on-circular knitting machine," Textile Research Journal, vol. 75, no. 6, pp. 492-497, June 2005.
[4] A. Islam, S. Akhter, and T. Mursalin, "Automated textile defect recognition system using computer vision and artificial neural networks," Proceedings World Academy of Science, Engineering and Technology, vol. 13, pp. 1-7, Jan. 2006.
[5] V. Murino, M. Bicego, and I. Rossi, "Statistical classification of raw textile defects," in Proceedings of the 17th International Conference on Pattern Recognition (ICPR'04), pp. 311-314, 2004.
[6] Y. Karayiannis, R. Stojanovic, P. Mitropoulos, C. Koulamas, T. Stouraitis, S. Koubias, and G. Papadopoulos, "Defect detection and classification on web textile fabric using multiresolution decomposition and neural networks," in Proceedings of the 6th IEEE International Conference on Electronics, Circuits and Systems, pp. 765-768, Sept. 1999, Cyprus.
[7] A. Kumar, "Neural network based detection of local textile defects," Pattern Recognition, vol. 36, pp. 1645-1659, 2003.
[8] D. Karras, S. Karkanis, and B. Mertzios,"Supervised and unsupervised neural network methods applied to textile quality control based on improved wavelet feature extraction techniques," International Journal on Computer Mathematics,vol. 67, pp. 169-181, 1998.
[9] C. Kuo, C. Lee, "A back-propagation neural network for recognizing fabric defects," Textile Research Journal, vol. 73, pp. 147-151, 2003.
[10] P. Mitropoulos, C. Koulamas, R. Stojanovic, S.Koubias, G. Papadopoulos, & G. Karayanis, "Real-time vision system for defect detection and neural classification of web textile fabric," in Proceedings of SPIE Conference, vol. 3652, pp. 59-69, Jan. 1999, USA.
[11] E. Shady, Y. Gowayed, M. Abouiiana, S. Youssef, and C. Pastore, "Detection and classification of defects in knitted fabric structures," TextileResearch Journal, vol. 76, pp. 295-300, 2006.
[12] J. Campbell, C. Fraley, D. Stanford, F. Murtagh,and A. Raftery, "Model-based methods for textile fault detection," International Journal of Imaging Systems and Technology, vol. 10, pp. 339-346, Jul. 1999.
[13] F. Cohen, Z. Fan, and Z. Attali, "Automated inspection of textile fabrics using textural models," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 8, pp. 803-808, Aug. 1991.
[14] J. Campbell, A. Hashim, T. McGinnity, and T.Lunney, "Flaw detection in woven textiles by neural network," in Proceedings of the 5th Irish Neural Networks Conference, pp. 92-99, Sept. 1995, Ireland.
[15] K. Mak, P. Peng, and H. Lau, "A real-time computer vision system for detecting defects in textile fabrics," in Proceedings of the IEEE International Conference on Industrial Technology (ICIT'05), pp. 469-474, 14-17 Dec. 2005, Hong Kong, China.
[16] M. Salahudin, M. Rokonuzzaman, "Adaptive segmentation of knit fabric images for automated defect detection in semi-structured environments," in Proceedings of the 8th International Conference on Computer and Information Technology, pp.255-260, 2005, Bangladesh.