Prediction of Asphalt Mixture Resistance Using Neural Network via Laboratorial X-ray Images

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***Abstract*—This paper presents a relation between Marshall Resistance of asphalt samples and their visual and physical features. Laboratorial samples with known mixture scheme are prepared in laboratory and are digitized through a CT-scan system. The physical features of asphalt, captured by scanning the asphalt samples, include air void percentage, bitumen percentage, aggregate percentage, arrangement and the direction of aggregate .Then some analytically model using visual characteristics and artificial intelligence methods are proposed. Finally the results from attained multi-pages image processing are related to laboratory parameters. The proposed model provides closed-form solution for predicting the Marshall resistance of asphalt mixtures.**

***Index Terms*—artificial neural network; C.T scan images; asphalt concrete; marshall stability**

I. Introduction

The Marshall Stability (MS) of Asphalt Concrete (AC) is one of the important features for performance of asphalt pavement. Asphalt Concrete (AC) is made by heterogeneous material includes air void, mastic and aggregates; these three phases of material and their interactions have main effect on the Marshall Stability (MS).This study have been tried to find an algorithm that illustrate a relation between the Marshall Stability (MS) of Hot Mixed Asphalt (HMA) and physical characteristics which come from the microstructure of asphalt. These features are captured from X-ray Computed Tomography (CT) images. An Artificial Neural Network (ANN) method is used to achieve this purpose .The main reason of this study is to knowing accuracy of measuring Marshall Resistance from (CT), in Non-Destructive Testing (NDT) realm which could lead to cost and time reduction.

Some recent studies suggest achieving Marshall Stability using artificial neural network [1]-[3]. Some researchers tried to predict asphalt mixture properties by using ANN [4]-[7]. Studies have performed to achieve application of Digital Image Processing Techniques for Asphalt Concrete Mixture and Characterization of damage [8]-[12].

It is noted that in this study the features of asphalt mixture are achieved from image processing technique and different algorithms are compared to identify the most accurate.

II. Material, Data and Method

In this research, a total of 60 asphalt samples were studied. The samples were cylindrical shape with 10 cm diameter and 7cm height. These samples with specified features (Volume of Air void, Bitumen percentage, Temperature, Marshall Stability, etc.) were gathered from Tehran - Saveh highway (Km: 55+350 to 110+975) section in the city of Tehran, Iran .The average of specific gravity of used aggregate in asphalt core samples was 2.489 Ton/m3. Physical properties of bitumen used in asphalt cement are demonstrated in "Table I".

Sieve analysis result for aggregate used in asphalt core samples is given in "Table II".

TABLE I. Physical Properties of the Bitumen Used in Asphalt Core Samples

Properties of the bitumen	Range	Specification used
Specific gravity @25/25 C	1.01-1.06	ASTD D 70
Penetration @25 C	60/70	ASTD D 5
Softening point C	49/56	ASTD D 36
Ductility @25 C	100 Min	ASTD D 113
Loss on heating (wt)%	0.2 Max	ASTD D 6
Drop in penetration after heating %	20 Max	ASTD D 6 &D 5
Flash point C	250 Min	ASTD D 92
Solubility in CS2 (wt)%	99.5 Min	ASTD D 4

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TABLE II. SIEVE ANALYSIS RESULT FOR AGGREGATE USED IN ASPHALT CORE SAMPLES

Sieve no	Passing ratio (%)
3"	100
2½"	100
2½"	100
2½"	100
1½"	100
1"	96.72
¾"	72.59
3/8"	56.81
4	36.96
50	11.63
200	6.20

On the contrary same features of asphalt mixture are captured using X-ray Computed Tomography (CT) system. The AC core was scanned at each 1mm interval section to yield 70 images per core “Fig. 1,”.

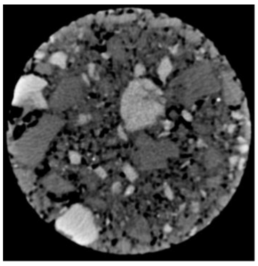

Figure 1. X-ray CT image of asphalt Core.

Therefore each sample had 70 images from its interval section which demonstrate airvoid, mastic and aggregates in each layer of sample. Then phases of each section are obtained using image processing technique “Fig. 2,”.

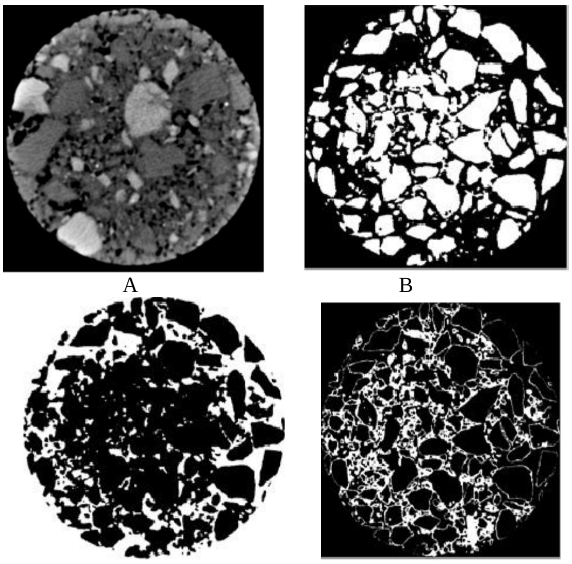

Figure 2. Result of x-ray ct image and image processing technique,(a) X-ray image,(b) Aggregate phase in white, (c) Mastic phase in white, (d) Airvoid phase in white[11].

"Table III" shows percentage of each phase that obtained from image processing technique.

All the result for image processing technique (bitumen volumetric percentage, airvoid volumetric percentage) compares with the experimental result “Fig. 4,” and “Fig. 5,”.

III. ARTIFICIAL NEURAL NETWORKS(ANN)

A typical structure for an Artificial Neural Network (ANN) and Multi-layer neural network was shown in “Fig. 3,” and “Fig. 6,”. All neural networks contain three layers: input layer, hidden layer(s) and output layer [1]. In each layer there are many neurons that have interconnections with neurons of next layers. Desire accuracy and system dynamics is related to number of neurons in each layer. A single neuron in artificial neural network structure was shown in “Fig. 7,”. The layers have interconnection. Weighting vector of each neuron determines strength of the connection. Each neuron had an input function and output function, the input function is the sum of all the inputs from prior layer based on their weighting factors “(1),”. The output functions process result of input functions by a non-linear sigmoid function “(2),”.

$$net_l = \sum_k w_{kl} o_k \tag{1}$$

$$o_l = f(net_l + \theta_l) \tag{2}$$

where; “w_{kl} “weight between the *k*th neuron and the *l*th neuron in two adjacent layers.” θ_l ” threshold of the *l*th neuron,” O_k ” output of the *k*th neuron,” O_l “Output of the *l*th neuron and “f (.)” sigmoid function [1].

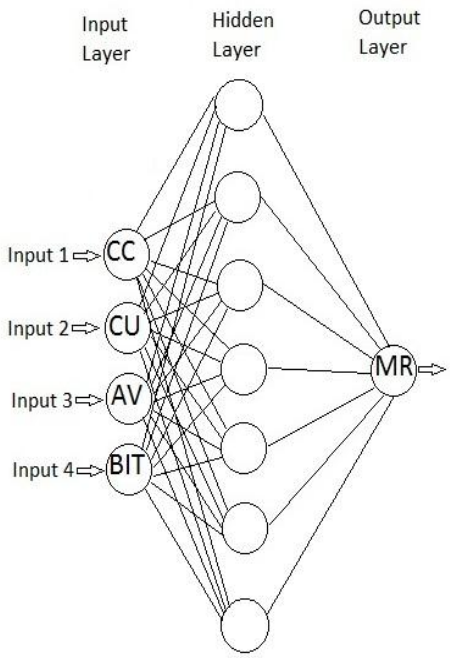

Figure 3. A typical structure for an artificial neural network.

TABLE III. PHYSICAL PROPERTIES OF ASPHALT CORE SAMPLES USING IMAGE PROCESSING TECHNIQUE

Number	Bitumen	Void	Aggregate	CU	CC	Number	Bitumen	Void	Aggregate	CU	CC
1	11.88%	4.88%	83.24%	4.87	1.08	31	12.25%	4.19%	83.56%	5.15	0.98
2	10.37%	5.16%	84.47%	5.12	0.98	32	12.60%	3.98%	83.42%	4.21	1.14
3	12.29%	4.30%	83.41%	5.09	1.02	33	10.87%	5.16%	83.98%	4.34	1.13
4	11.62%	4.82%	83.56%	4.57	1.00	34	11.21%	4.53%	84.26%	4.90	1.05
5	13.30%	4.54%	82.16%	4.12	1.13	35	12.95%	3.98%	83.07%	4.44	1.04
6	11.82%	4.44%	83.74%	5.09	1.03	36	12.69%	4.22%	83.08%	4.75	1.01
7	11.48%	4.79%	83.73%	5.17	0.98	37	11.91%	4.65%	83.45%	4.14	1.04
8	12.38%	4.46%	83.17%	4.71	0.96	38	11.30%	4.82%	83.88%	4.88	1.09
9	12.34%	4.65%	83.01%	4.81	1.14	39	13.18%	4.34%	82.49%	4.67	1.01
10	11.41%	4.77%	83.82%	4.18	1.04	40	10.66%	4.73%	84.61%	4.78	1.08
11	11.72%	4.37%	83.91%	4.77	0.97	41	11.02%	4.68%	84.30%	4.78	1.05
12	11.24%	4.86%	83.90%	4.47	1.12	42	12.43%	4.77%	82.81%	4.80	1.12
13	12.21%	4.81%	82.98%	4.76	0.99	43	11.10%	4.96%	83.95%	4.39	0.96
14	10.37%	5.03%	84.61%	4.44	1.10	44	13.75%	4.06%	82.19%	4.43	1.09
15	10.92%	4.89%	84.19%	4.66	1.10	45	12.63%	4.03%	83.35%	4.64	1.04
16	10.90%	4.69%	84.41%	4.32	0.98	46	11.36%	4.97%	83.67%	4.56	1.02
17	10.73%	4.77%	84.51%	4.73	1.13	47	11.64%	4.34%	84.02%	4.27	1.10
18	11.33%	4.40%	84.28%	5.18	1.05	48	10.59%	4.57%	84.84%	4.18	1.01
19	12.01%	4.64%	83.36%	4.73	1.00	49	10.36%	5.20%	84.44%	4.73	1.13
20	12.40%	4.73%	82.87%	4.80	1.01	50	12.24%	4.98%	82.78%	4.12	1.09
21	11.47%	5.03%	83.50%	4.79	0.97	51	11.83%	4.97%	83.20%	4.25	1.03
22	10.13%	4.89%	84.98%	4.67	1.12	52	10.31%	5.01%	84.68%	4.27	0.98
23	11.32%	4.45%	84.24%	4.24	1.02	53	11.19%	4.47%	84.34%	4.48	1.10
24	12.26%	4.54%	83.21%	4.55	1.04	54	11.92%	4.57%	83.51%	5.07	1.13
25	12.35%	4.46%	83.19%	4.77	1.12	55	11.31%	4.80%	83.89%	5.12	1.06
26	10.63%	4.96%	84.41%	4.86	0.97	56	12.80%	4.49%	82.71%	4.24	1.05
27	11.10%	4.85%	84.05%	4.77	1.00	57	12.33%	4.45%	83.22%	4.58	1.05
28	11.04%	5.05%	83.91%	4.90	1.14	58	10.49%	4.73%	84.78%	4.23	1.09
29	10.72%	5.01%	84.27%	4.97	1.10	59	10.75%	4.58%	84.67%	4.88	1.01
30	10.07%	4.77%	85.16%	4.15	1.12	60	10.39%	4.77%	84.84%	4.30	1.05

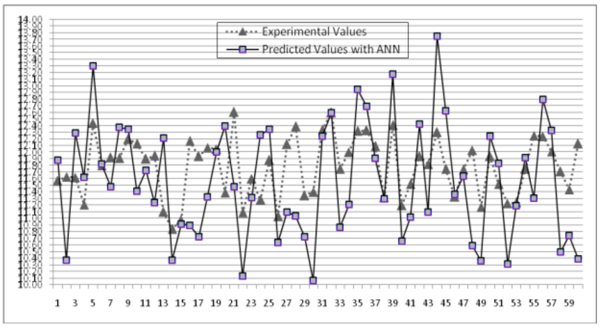

Figure 4. Compare the result of bitumen volumetric percentage by image processing technique and experimental data.

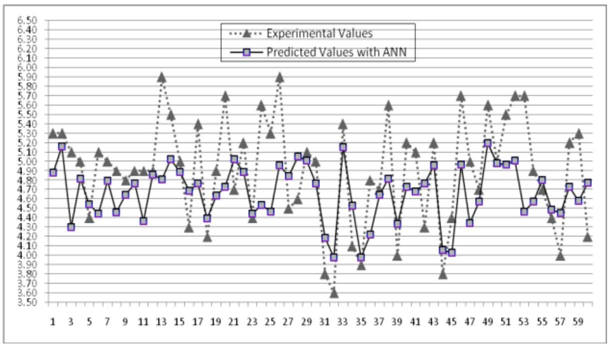

Figure 5. Compare the result of airvoid volumetric percentage by image processing technique and experimental data.

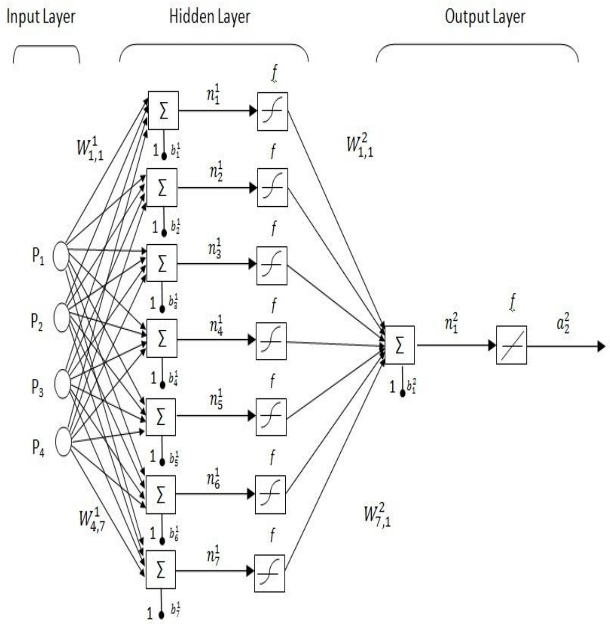

Figure 6. Multi-layer neural network structure.

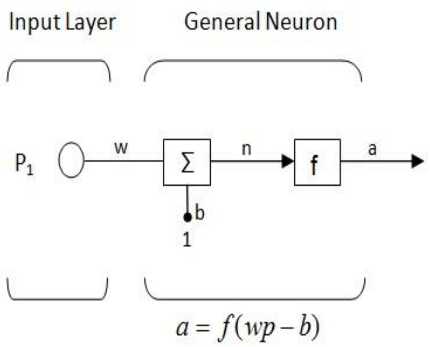

Figure 7. A single neuron structure.

IV. Training of Neural Network

The Back error Propagation Neural Network algorithm (BPN) is the most prevalent and useful, learning model for artificial neural networks. The algorithm is based on the gradient search technique in which minimization process is done by adjusting the weighting vector of the NN [1]. In each period of the algorithm (BPN) a relation between input and output is created, after that obtained error backwards to the input layer through the hidden layer, this process continues to achieve the minimum error and obtain the best desired output. The procedure of the BPN repeatedly adjusts the weights of connections in the network, so as to minimize the measure of the difference between the actual output vector of the net and the desired output vector [13].

$$E = \frac{1}{2}\sum_f (T_f - O_f)^2 \tag{3}$$

where E is the error function at the output neuron, T_f is value of the target and O_f is output value.

According to the gradient error the gradient decent algorithm adjusts the weights which given by

$$\Delta W_{kl} = -\gamma \frac{\partial E}{\partial W_{kl}} \tag{4}$$

$$\frac{\partial E}{\partial W_{kl}} = -\nu_l^m D_l^{m-1} \tag{5}$$

$$\Delta W_{kl} = \gamma \nu_l^m D_l^{m-1} \tag{6}$$

When neuron l is in output layer:

$$\nu_l = (T_l - X_l) X_l (1 - X_l) \tag{7}$$

When neuron l is in output layer:

$$\nu_l = (\sum_l \nu_l (W_{fl})_{hl}) H_h (1 - H_h) \tag{8}$$

where:

γ = Learning rate.

D_l^{m-1} = Output value for sub-layer associated to connective weight (W_{kl}).

ν_l^m = The error signal (Calculated according to whether or not neuron l in the output layer.

H_h = value of hidden layer.

$$W_{kl}^m = W_{kl}^{m-1} + \Delta W_{kl}^m = W_{kl}^{m-1} + \gamma \nu_l^m D_l^{m-1} \tag{9}$$

$$W_{kl}^m = W_{kl}^{m-1} + \gamma \nu_l^m D_l^{m-1} + \omega W_{kl}^{m-1} \tag{10}$$

where ω is a coefficient between 0 and 1 that accelerates convergence of the error in learning procedure [13].

V. Increasing Virtual Data

As it is obvious obtaining more accuracy requires analyzing further data. By having more data the accuracy of algorithm got enhanced. In this study due to limitation of data, virtual data were produced by K-fold method. Thus 60 samples divided to 6 categories evenly in a way that each category consist similar range of properties. As a result, in each step of training, one category was used for test and the others were for train.

VI. Network Testing

40 samples (70 % of all samples) were selected for training the algorithm, and 15 % for test, and the residual for validation of the algorithm. The feed forward back propagation algorithm was used with one hidden layer. For hidden layer and output layer respectively tan-sigmoid transfer function and linear transfer function were used. Trainlm algorithm for training function was used as an activation function.

Different algorithms were used to find the best training performance. In this study by changing algorithm structure, different results obtained. The results have been investigated using different neuron numbers. Finally 7 neurons in hidden layer were chosen as the bests "Fig. 8,".

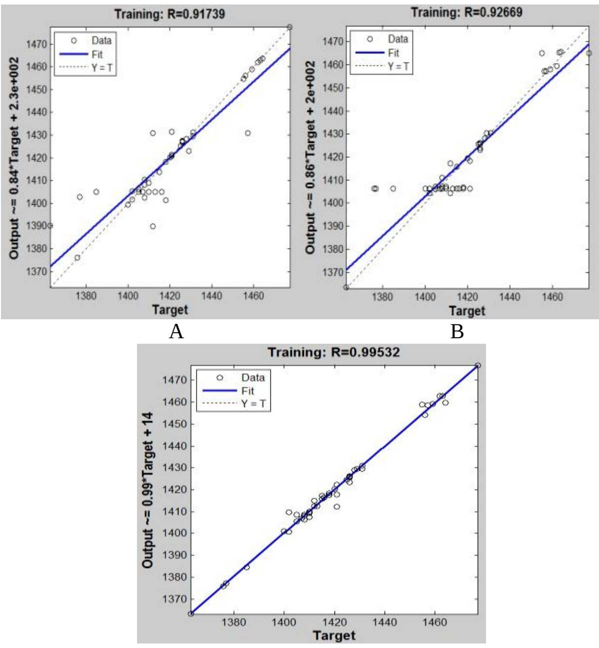

Figure 8. Result of testing different neurons in chosen algorithm, (a) 3 neurons in hidden layer, (b) 3 neurons in hidden layer,(C) 7 neurons in hidden layer.

For training the network fix different parameter and select the best network after training and model selection for training set.

By used trained network run the data for each sample and compare the result with experimental result. In training, validation and testing step duo to choose the best parameter in the developed network ANN represent the best correlation between prediction and experimental Marshall Stability.

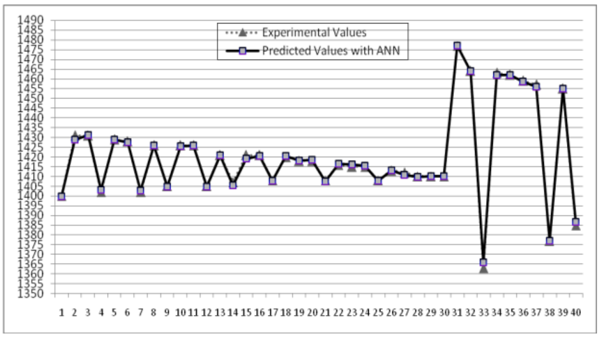

Figure 9. Compare the result by prediction and experimental for training step.

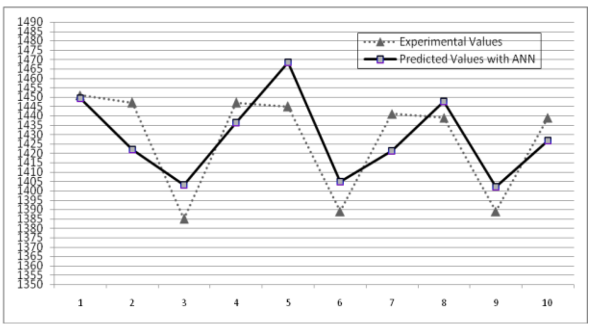

Figure 10. Compare the result by prediction and experimental for validation step.

After trained and developed the network used the validation data and run the algorithm. By obtain the error improve the network and in next step run the algorithm by test data. All the results for developed network in each step compare with the experimental result “Fig. 9- Fig. 14,”.

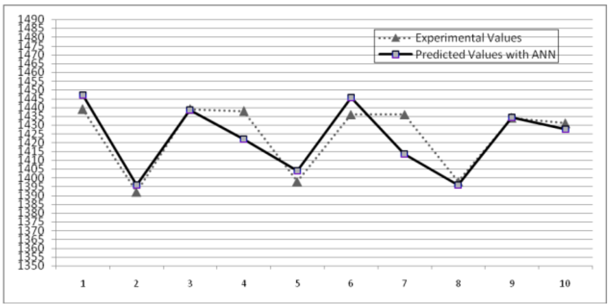

Figure 11. Compare the result by prediction and experimental for test step.

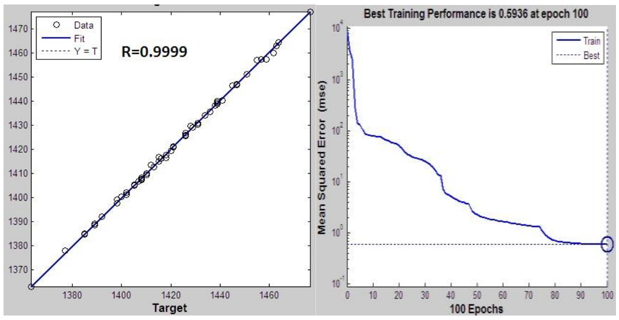

Figure 12. Regression value and mean squared error in training step.

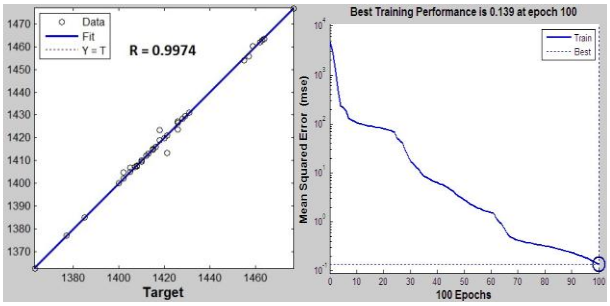

Figure 13. Regression value and mean squared error in validation step.

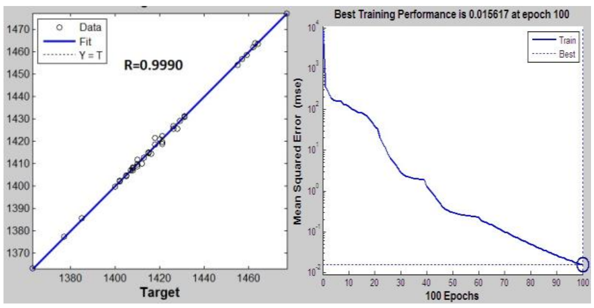

Figure 14. Regression value and mean squared error in testing step.

VII. Simulation Result and Discussion

Marshal stability is very important feature in asphalt mixture. In nondestructive test method, made a model to predict the marshal stability. Linear models and other models that used in previous study were not eventuated to actual result. In this study, by used an developed ANN method, the correlation between asphalt features (airvoid, mastic and aggregate) that comes from image processing technique and stability of asphalt concrete for varying samples is created to model the marshal stability of asphalt concrete. Several algorithms were examined by various structures (number of layer, learning function, transfer function, number of neuron, etc.) to achieve the most effective algorithm format.

VIII. Conclusions

In this study, a model was developed based on image processing and ANN for pavement MS in asphalt concrete. The results show that the proposed model can make reliable outcomes.In brief, the ANN has been demonstrated to be an effective tool for prediction MS. However, the proposed method is robust. This means that with this method, MS can be extracted with an approach different from the traditional destructive analyses. Laboratories testing as one of the traditional and destructive methods compared with the proposed system for checking reliability. In destructive test considerable time and accuracy to be spent in order to preparing sample and test. Whereas analysis of samples and anticipate the MS is very fast (roughly a minute) which makes the immediate response during real-time applications. Marshall Stability of asphalt could obtain by used ANN and process on result data from image processing on sample asphalt. As a result the correlation that achieved, could predict the Marshall Stability resistant with the maximum error of 5%.The test performances of this study show the advantages of the proposed method: it is fast, real, and flexible. However this study is in its first steps and in order to achieve more reliable results, more work is needed.

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