ASPHALT PAVEMENT OXIDATION LEVEL MAPPING:AN ANALYSIS OF PIXEL DATA OF SATELLITE IMAGES USING ARTIFICIAL NEURAL NETWORK

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A study dedicated on developing a software to determine the condition asphalt pavement with respect to its oxidation level using in-situ images through Artificial Neural Network. The software provides an efficient approach that may be used by the organizations associated with the maintenance and development of asphalt pavements. The study focuses on determining the asphalt oxidation level namely: fair, good, and poor through the use of Artificial Neural Networks(ANN). The researchers were able to develop a program using MATLAB for the application of the study. After using in-situ images for testing, the program were able to produce different output showing the pavements' condition either fair, good or poor.

Keywords: asphalt, asphalt oxidation, Artificial Neural Network, oxidation level

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1. INTRODUCTION

Oxidation is one of the causes of asphalt pavement deterioration. Oxidation occurs right after the asphalt pavement is laid down. Oxygen causes new bonding sites to be created which allows the molecules to search for new bonding to reach its thermodynamic state or equilibrium. As this process continues over time, the asphalt pavement will become stiff and brittle (Pavement Lifecycle, 2009). With significant loss of elasticity, asphalt starts to show cracks that are called as alligator cracking or spider webbing as it resembles the back of an alligator or shape of a spider web. These cracks allow moisture to penetrate the base of the asphalt pavement which causes potholes and other structural damage to occur (Water's Effect on Asphalt Deterioration, 2017). (Millare, 5 Causes of Asphalt Damage, 2014)

A significant amount of loss in load-bearing strength of the pavement is an effect of saturation of the base of the pavement. This loss of bearing capacity causes the asphalt to bear more stress which eventually leads to fatigue. Once the pavement reached its limit, it will begin to fail. Failure of asphalt is described as the increase of cracks in the surface that will result to portions of asphalt to be removed exposing the base and creating a pothole (Pavement Lifecycle, 2009).

Asphalt oxidation is due to the reaction of the oxygen to the bitumen and causes a lot of changes on the asphalt. As time and oxidation advances, asphalt color will turn to a lighter black and eventually turns grey. As a physical characteristic of good asphalt, it is charcoal black in color and flexes through the load of its surface. For fair asphalt, it is gray in color and exposure of gravel occurs. Lastly, for poor asphalt, the pavement is worn out and it has much lighter color in gray. Cracking and several asphalt damages will occur at this point. (X.Luo, F. Gu, & R.Lytton, 2015)

Image processing using ANN has been successfully used in various fields of activity (Pandela, Budescu, & Covatarui, 2015).These fields include civil engineering, mechanics, industrial surveillance, defense department, automatics, etc. Specifically, it resolved a lot of issues with regards to civil engineering. Composite structures used ANN for crack identification wherein a scanned image that resembles an ultrasound is used for the analysis.

There are three methods that can be used in ANN: the back propagation algorithm that calculates the gradient of the loss function; the maximum likelihood method that estimates the parameters of a statistical model; and the multilayer feed-forward neural network that is usually used for classification. In comparing the three methods, back propagation proves to be the most effective since it is the most adaptive among these procedures. (K. Saravanan & S. Sasithra, 2014)

This studydiscusses theANNused for automatic recognition, classification, description and grouping of the pattern which is supported by data representation, data acquisition, and preprocessing and decision-making.This also aims to make the decision automatically to be the perfect process of domain knowledge and use of available sensor. (Tai-hoon, 2010)

2. PROPOSED METHODOLOGY

2.1 DATA GATHERING AND INITIAL DATA PREPARATION

The data gathering for the on-site images is done by checking satellite images for probable pavement conditions first, then surveying the site for on-site inspection and gathers the data for on-site images. The researchers used Google Earth and Google Maps for locating asphalt pavements. Gathering the desired data for the research might be difficult for the researchers. Weather and traffic condition can affect the results as it is both related to time which is a vital part of the study.

The images will be segregated into their respective condition(good, fair, poor) according to the properties described by (X.Luo, F. Gu, & R.Lytton, 2015): good asphalt, it is charcoal black in color and flexes through the load of its surface. For fair asphalt, it is gray in color and exposure of gravel occurs. Lastly, for poor asphalt, the pavement is worn out and it has much lighter color in gray and cracking on several places can be observed during this stage.

Training images are taken from the same road segment as the validation images but are about 100m to 200m apart. These images are also taken on times of day with ample lighting

The raw images intended for training are collated and are divided into 3 types. All asphalt pavement images(for training) that were physically evaluated as 'Good' are collated into a single image, This were also done for Fair and Poor condition.

The collated images(3 in total) will then be imported into Matlab where their pixel data will be extracted in form of a matrix. After which the matrixes are converted into column matrices and will be used to train the proposed ANN architectures.

In addition, Due to the sheer number of elements within the matrix which is originally about 7.5million pixels, the memory requirement exceeds that of the available hardware owned by the researchers therefore the image size was intentionally reduced to 20% of the original number of pixels.

2.2 IMAGE PROCESSING OF STANDARD ASPHALT PAVEMENT

MATLAB software is used in various steps in this study and one of that is image processing. An image contains different colors and pixels like cells in a matrix which contains three different data of different colors namely red, green and blue. Extraction of image means collection of pixel values to obtain numerical values at a particular row and column of the spectrum matrix.

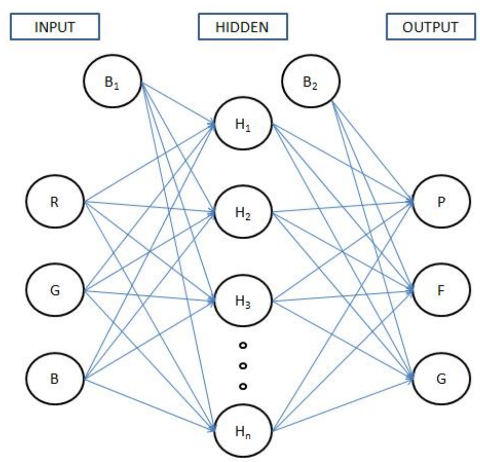
2.3 ARTIFICIAL NEURAL NETWORK ARCHITECTURE AND CONSTRUCTION

I. Training and Activation Function

There are various types of learning algorithms for an ANN model in a training function. Levenberg-Marquadt algorithm (LM) ,which is used to solve non-linear problems, is applied in this study.

The Tangent-Sigmoid activation function, which is already available in MATLAB, is used in this study for the activation function of the hidden layer and the output layer. This function provides faster analysis but the results can have very small discrepancies in values.

II. Neural Network Architecture



The Artificial neural network will have 3 Input nodes namely, Red, Green, and Blue column matrix respectively. It will also have the same number of hidden nodes of 3 namely, Poor, Fair and Good respectively.

The hidden nodes will vary from 4 to 14 to find the optimum number of hidden nodes for the current problem. The optimum number of hidden nodes will be determined by the architecture that has the highest value of overall correlation coefficient (R) .

III. TARGET VALUE

Each set of input data point will have its corresponding TARGET VALUE that are pre determined by the researchers. If the input data belongs to a training image representing a Good condition asphalt pavement, the target value for the Good output node will be 1 while the Fair output node and Poor output node are set to 0. Similarly, if the data points belong to Poor and Fair group, the respective target of these data point will be set to 1 and the other target be zero.

3. RESULTS AND DISCUSSION

This study used nine (9) in-situ images gathered by the researchers for the training phase of this study. These images are used to determine the condition of the asphalt pavement *(Good, Fair, Poor)* as shown below. The first row shows good condition of asphalt pavement, the second row shows fair asphalt condition and the third row shows poor asphalt condition.

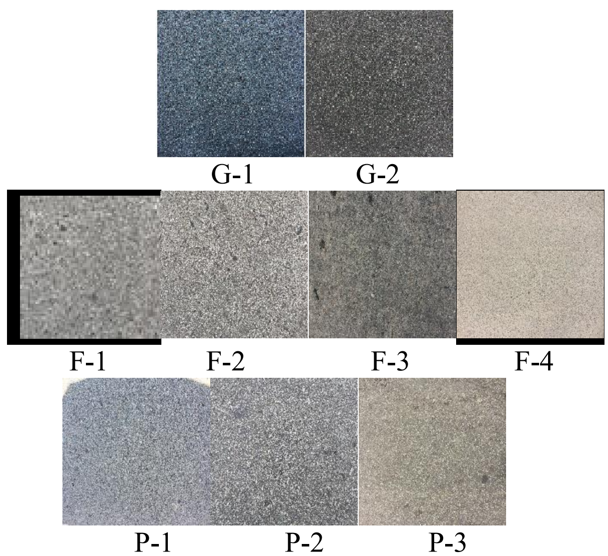


Figure 3.1*Standard Asphalt Pavement Condition (SAPC)*

A. ARTIFICIAL NEURAL NETWORK TRAINING RESULTS

The table bellow shows the results of the ANN training through the *nntool* command of Matlab. The parameters of the training in the ANN training interface were left to their default values.

NEURAL NETWORK	TRAINING	VALIDATION	TEST	ALL
3-4-3	0.62483	0.62543	0.62462	0.62489
3-5-3	0.69209	0.69063	0.69045	0.69163
3-6-3	0.69971	0.6992	0.69872	0.69949
3-7-3	0.70723	0.70667	0.70639	0.70702

3-8-3	0.70835	0.70619	0.70815	0.708
3-9-3	0.7019	0.70381	0.70298	0.70235
3-10-3	0.71354	0.71488	0.71293	0.71365
3-11-3	0.71364	0.7123	0.71292	0.71333
3-12-3	0.70029	0.70074	0.70199	0.70061
3-13-3	0.71373	0.71168	0.71328	0.71335
3-14-3	0.71336	0.71225	0.71184	0.71297

B. NEURAL NETWORK ARCHITECTURE

The neural network was trained using a total of 1532252 data points scattered among the 3 types of asphalt pavement considered in this study. Among all the neural network that was created, network 3-10-3 showed the highest value of correlation coefficient of R=0.71(Overall) which showed a significant correlation between the input and output. Furthermore, this means that 50.41%(R^2=0.5041) of the variation of the output can be correlated to the variation of the input variables. Although 3-10-3 was chosen the difference between 3-10-3 and the 2nd highest R value is only 0.0003 and there are not much difference either with the 3rd and 4th. The small difference may be attributed to the natural randomness of the ANN training and production therefore it may be said that the researchers may have used 3-10-3, 3-11-3, 3-13-3 and 3-14-3. If there are neural networks that have almost similar performance, it is better to use the network with lesser nodes since it will result in a much simpler model.

C. FINAL OUTPUT AND VALIDATION

In this section, the results of are shown along the original raw image. This section aims to prove the validity of the neural network produce by the training. It should be noted that the pixels are color coded to immediately identify the condition of a particular pixel; Green, Yellow and Red represents Good, Fair and Poor Condition respectively.

Furthermore, The result of Image Evaluation relies on the Type of pixel that is most abundant in a particular sample. (e.g. figure 4.2b is evaluated as good since the percentage of GOOD pixels is higher among the other types)

A. RESULTS WITH IMAGE EVALUATION OF 'GOOD CONDITION'

I. Marikina-Infanta Highway
(On-site evaluation: **GOOD,** Image evaluation: **GOOD**)

The image in Figure 4.1a shows an image which is directly used in the training of the neural network. This trial was intended to validate the integrity of network 3-10-3. In the figure 4.1b it can be noticed that almost all of the pixels are shown in green(Good condition) which is what is expected.

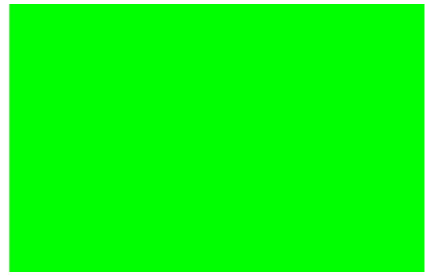


Figure4.1a *Figure4.1b*

PIXEL TYPE	PERCENT(%)
POOR	0.0032%
FAIR	0.0000%
GOOD	99.9968%

II. PresidentJose P. Laurel Highway, Batangas City

(On-site evaluation: GOOD, Image evaluation: GOOD)

The on-site evaluation of Figure 4.2a, a road segment in President Jose P. Laurel highway in Batangas, is GOOD which coincide with its Image evaluation. By closely inspecting the asphalt road, it is evident that the aggregates used in the asphalt are only slightly visible and the asphalt binder used is still intact. However, by inspecting the processed image, it is clear that there are occasionally some aggregate(white spots) that are cleanly exposed, these spots can have an evaluation of POOR condition individually. Therefore, the result shows RED spots scattered evenly across figure 4.2b.

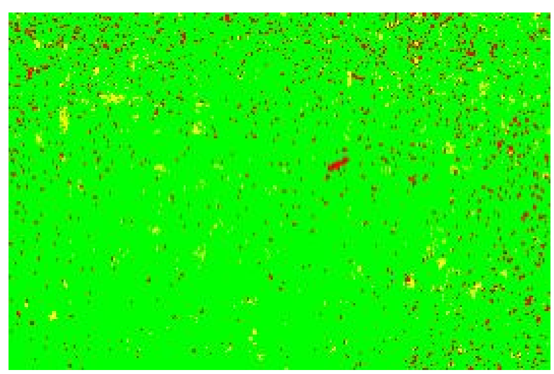


Figure4.2a *Figure4.2b*

PIXEL TYPE	PERCENT(%)
POOR	4.0987%
FAIR	2.1216%
GOOD	96.7796%

B. RESULTS WITH IMAGE EVALUATION OF 'FAIR CONDITION'

In can be observe that the asphalt pavements presented in this section has the top layer of asphalt binder partially oxidized but not so much as to let the aggregates experience direct wear and tear due to traffic loads. This condition resulted on a much lighter reflectance as compare to the GOOD condition asphalt pavement in the previous section.

The Resulting images produced by Matlab matches the on-site evaluation of these pavements. By looking at the results, it can be seen that majority of pixel in the Processed images are Yellow in collor(FAIR condition) thereby labeling these paement images as FAIR condition.

I. Strawberry Street, Barangay San Francisco, Mabalacat Pampanga

On-site evaluation: FAIR, Image evaluation: FAIR)

Figure 4.3a

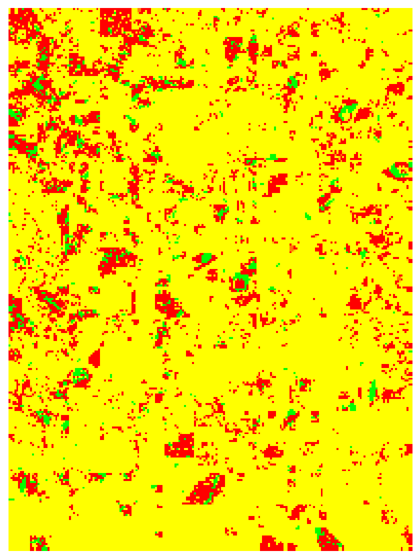


Figure 4.3b

PIXEL TYPE	*PERCENT(%)*
POOR	*14.1118%*
FAIR	*83.3325%*
GOOD	*2.5557%*

II. President Jose P. Laurel Highway, Batangas City

(On-site evaluation: FAIR, Image evaluation: FAIR)

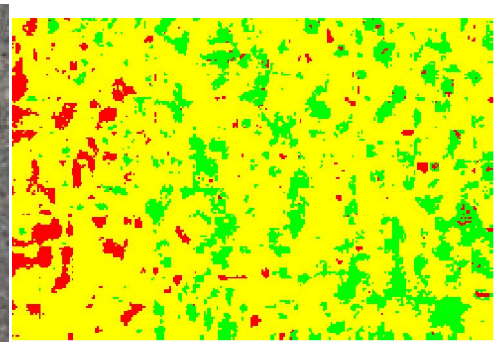



Figure 4.5a *Figure 4.5b*

PIXEL TYPE	*PERCENT(%)*
POOR	*5.7583%*
FAIR	*78.0216%*
GOOD	*16.2201%*

II. San Nicholas Highway, San Roque, Bamban, Tarlac

(On-site evaluation: FAIR, Image evaluation: FAIR)

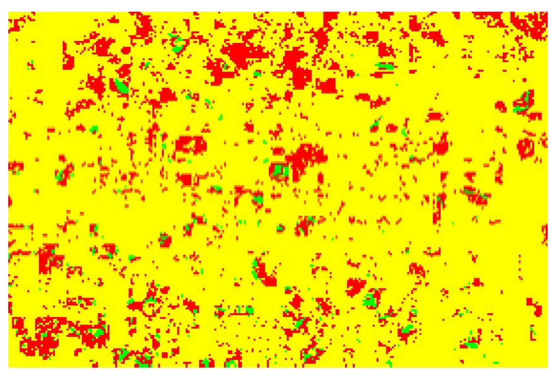



Figure 4.6a *Figure 4.6b*

PIXEL TYPE	*PERCENT(%)*
POOR	*14.1877%*
FAIR	*84.2914%*
GOOD	*1.5209%*

C. RESULTS WITH IMAGE EVALUATION OF 'POORCONDITION'

In this section, it can be seen that the on-site condition of asphalt pavement is POOR due the evident direct wear and tear of the aggregate. The asphalt binder at the top layer of the asphalt pavement have greatly been removed making the aggregates directly carry traffic loads resulting in abrasion. Abrasions are represented by Light colored spo

ts in shape of the aggregates used.

I. Tagaytay-Nasugbu Highway, Lipa, Batangas

(On-site evaluation: POOR, Image evaluation: POOR)

Figure 4.7a

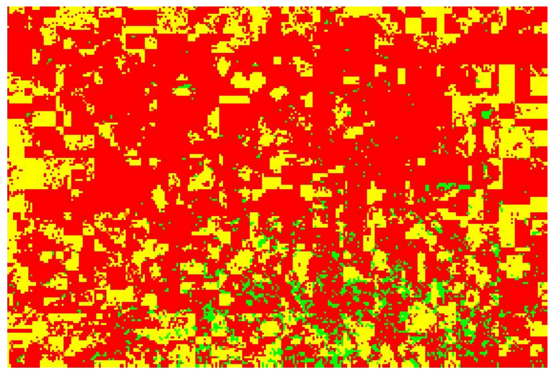


Figure 4.7b

PIXEL TYPE	*PERCENT(%)*
POOR	***68.7701%***
FAIR	***26.7055%***
GOOD	***4.5244%***

4. CONCLUSION

According to the results, Artificial Neural Network can be utilized to create a platform to be used in asphalt pavement condition monitoring by creating a suitable Network Architecture. It is evident that the values produced by the network are in match with the on-site evaluation of the researchers.

It can also be included that for a neural network with input nodes representing Red, Green and Blue column matrices and output nodes representing the 3 types of asphalt condition, network 3-10-3 has the highest correlation coefficient of R=0.71(Overall). Although the results of the training show that there are only small differences between the overall R among all the networks produced. Network 3-10-3 ,with confidence, can produce results that are similar to the on-site physical evaluation of asphalt pavements. Although it may be noteworthy that because of the fact that ANN is not inclined to extrapolating its data pool, a large amount of data must be used in the training process to be able to commercialize this system.

ANN may be used to produce models that can help concerned organizations with the maintenance of asphalt pavements to easily determine the oxidation level of asphalt pavements. It may also be used to create an oxidation level mapping for better road maintenance planning.

These results can also be used by future studies and offices as basis in adapting the use of remote sensing and machine learning in creating systems that can remotely assess the state of infrastructure and environment in remote areas by using satellite images.

5. RECOMMENDATION

Because of the property of ANN that it cannot extrapolate from the data set the researchers recommend that future researchers must gather data of a particular road through different time of the day to account for the angle and intensity of reflection or possibly create a standard image capturing tool that is not dependent to the ambient condition (e.g. light, weather, etc.).

This method can also be used in segmenting land type to monitor the development of rural and urban areas by quantifying the amount of change in land types between the satellite images from different time period.

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