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Machine learning analysis of impact sounding test for monitoring bridge deck interlayer condition

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ABSTRACT

The aging infrastructure worldwide requires rapid monitoring and maintenance to ensure the extension of its serviceable life. Bridges are one of the major transportation infrastructures that require intensive monitoring strategies for their proper maintenance. Developments and applications of bridge monitoring systems have become an active research area in recent years addressing the need for rapid assessment and application of mitigation measures in case of disasters such as earthquakes and typhoons. It has been acknowledged that one of the challenges in bridge condition monitoring is its interlayer pavement exposure to direct live loads and harsh environmental conditions. Non-destructive testing strategies are a prevalent monitoring method for bridges, and impact sounding tests are one of them in which integration of machine learning in its analysis improved its speed of providing results. In this study, machine learning methods are implemented to analyze impact-sounding devices for bridge deck pavement condition monitoring.

***Keywords*:** bridge condition, non-destructive testing, impact sounding, machine learning, decision matrix

1. Introduction

Every year, various civil infrastructures experience deterioration which sometimes inadvertently causes accidents, structural damages of varying degree that will eventually require additional investment. In addition, urban development and human mobility contribute to increase in road and bridge usage which add to the stresses the structure must endure during its lifespan. This growing concern resulted in various highway agencies focusing on maintenance and inspection using non-destructive testing techniques (NDTs).

According to the Department of Public Works and Highway (DPWH) [1] in 2017, the Philippines have 8,260 bridges, with a combined length of 367,864 m. Batangas has 154 permanent bridges maintained and operated by four district offices. Based on the calendar year (CY) 2016 bridge condition survey, 40.73 % (3,324 bridges) of the total numbers of bridges are in good condition, 45.91 % (3,747 bridges) in fair condition, 9.04 % (738 bridges) in poor condition, 3.22 % (263 bridges) in bad condition, and 1.09 % (89 bridges) are required for further assessment as they are under maintenance repair and rehabilitation.

The agency uses a bridge management system (BMS) instituted to manage the maintenance/ rehabilitation, retrofitting/ strengthening, upgrading and replacement of bridges required to address the deterioration of bridges, and to maintain the bridge stock to an acceptable standard [2]. It does not directly consider the capacity of a bridge in traffic or structural terms. It is important to recognize that bridge upgrading, and replacement may occur for other reasons including upgrading of a road link to a higher standard, increasing traffic density on a bridge, increased traffic loadings (vehicle weight), and changes in bridge design standards.

Annual condition survey starts every third quarter of the year, conducted by the accredited BIs from the district engineering offices. Said survey is being monitored/ supervised by the regional coordinators, allowing them to complete the task for a period of six months. These tasks include, among others, bridge condition inspection, encoding, preparation and uploading of bridge inventory condition (BIC) stand-alone-program into BMS and file named BMs photographs using the prescribed format: one site visit, three mandatory and eight shots inventory photos [3]. Still, the bridge condition assessment and monitoring method of DPWH relies on a generally subjective approach resulting in a slower speed of presenting the actual condition of Philippine bridges during the inspection and prone to human error as it is mainly based on visual inspection. This serves as a motivation in proposing a more rapid and accurate method of assessment of bridges that is comparable with developed countries.

Developments and applications of bridge monitoring systems have become an active research area in recent years addressing the need for rapid assessment and application of mitigation measures in case of disasters such as earthquake

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and typhoon [4,5]. At present, it is expensive to perform nondestructive tests in the Philippines as there is a scarcity of the available equipment for distribution to different agencies. This study attempted to develop a bridge condition monitoring device using acoustic and imaging sensors and establish a condition rating tool using a deep learning approach. Specifically, it aimed to present the results of bridge deck interlayer condition monitoring device, compare the results with the existing procedures performed by the concerned agency, and present the results of incorporating machine learning algorithms to improve the accuracy of the device.

2. Materials and methods

The overall methodology of the study is presented in the following process (Figure 1).

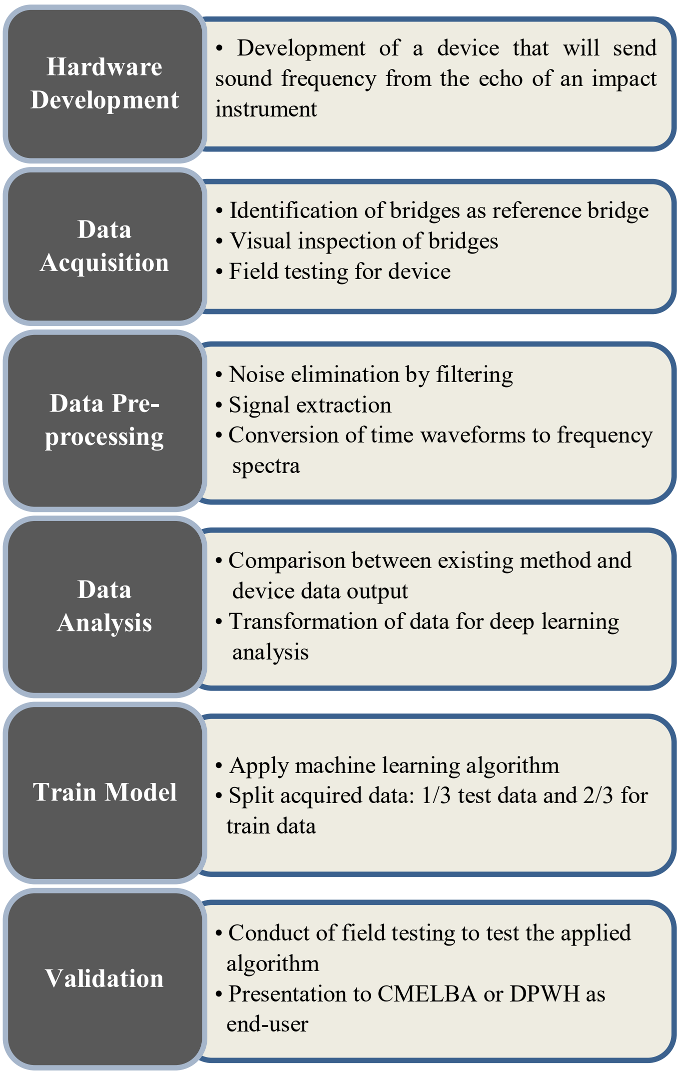


Figure 1. Overall methodology.

The device developed was based on the principle of signal acquisition and analysis and the American Standard for Materials Testing (ASTM) method for measuring delamination of concrete bridge decks by sounding (ASTM 4580-12) [6].

The signal acquisition process consists of impact signal source, receiver collecting signal data, processing software for display, and interpretation of the signal data in time waveform and frequency domain. Figure 2 shows the components of the impact acquisition process used in this study. The impact device such as a hammer hits a specimen then the receiver picks up the impact sounding signals. The data acquisition system (DAQ) transfers the signal to the data preprocessing software in the computer to display graphical output in time waveform and frequency spectra.

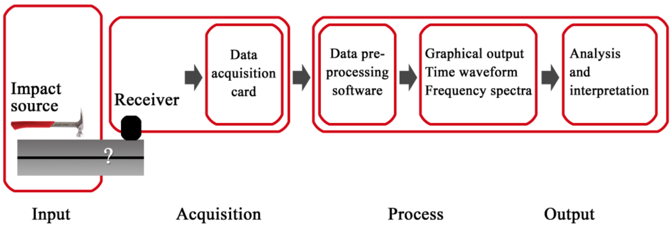
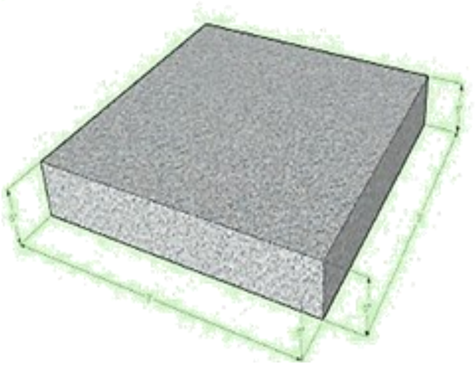


Figure 2. Sounding signal acquisition process.

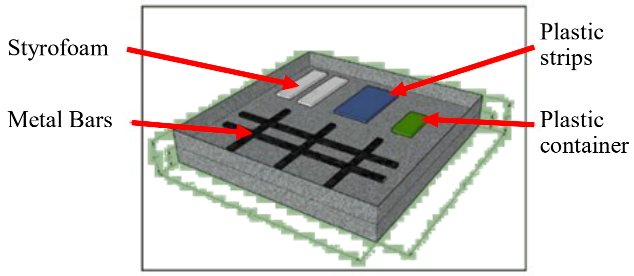
The device developed in this study was capable of recording sound at a user-input interval, recording images of the point where impact sound was collected, and providing immediate interlayer bonding conditions of the deck where the impact sound was performed. The data were collected and further analyzed for visual presentation of the overall bridge condition.

To test the results of the device, the device was tested on a slab prepared for laboratory-controlled conditions replicating the possible internal condition of the bridge deck. There were two types of slabs constructed for the test: a regular slab and a controlled slab. Different sets of tests were done for each slab. Figure 3(a) below shows a regular slab, with the size of 1.0 m in length, 1.0 m in width and 0.15 m in height created with pure concrete. The slab was created perfectly and with no hidden voids. The regular slab was sectioned into nine equal parts composed of 30 cm x 30 cm per section. To validate the accuracy of the device, the device should be able to identify if the slab contains any interlayer condition. Since the slab is created perfectly the results for these slabs are said to be bonded.

On the other hand, the slab with internal condition is presented in Figure 3(b). The slab was implanted with different objects to have deformities or voids within it. Materials used to replicate deformities or voids are metal bars, Styrofoam, plastic containers, and plastic strips. These objects are implanted at a depth of 8 cm from the top of the slab. The hollow or air spaces created by these materials will act as an interlayer condition. To test the accuracy of the device, the controlled slab was divided into nine sections with the dimensions of 30 cm x 30 cm per section. Hidden in section one was the Styrofoam while in section two and three were plastic strips and plastic container, respectively. From section four to nine, metal bars were implanted and covered with concrete. The interlayer status of each section was said to be debonded especially in section two where there was a huge amount of air space. To determine the accuracy of the device, it should be able to detect on which sections in the slab are bonded and/or debonded.



a) Plain slab and its dimension.



b) Slab with implants.

Figure 3. Laboratory-controlled slabs.

The impact sounding data collected in the laboratory and field has been preprocessed by eliminating noise through signal filtering and extraction. Decision matrix rating tool to evaluate the bridge condition has been established in accordance with visual inspection and impact sounding data features. Consequently, a proposed generalized decision matrix approach based on the feature space was presented. In this approach, overall analysis of data by clustering of points resulted in four different zones which can describe the interlayer conditions. The proposed analysis could detect intermediate conditions interlayer, which emphasized the transition of damages in the interlayer section.

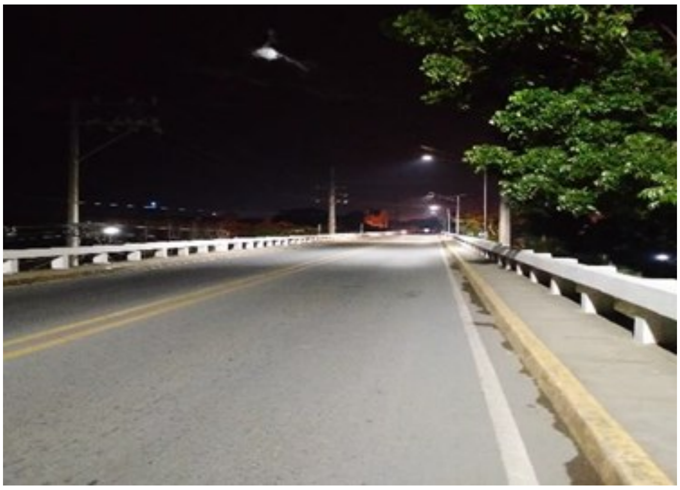
Lastly, different machine learning algorithms were applied to determine the efficiency of the developed decision matrix rating tool for interlayer bonding conditions. Decision tree, logistic regression, neural network, and support vector machine algorithms were applied in combined laboratory and field data. Validation parameters namely accuracy, Cohen kappa statistic, specificity, and sensitivity demonstrated that logistic regression algorithm showed high accuracy results which is recommended to apply in future tests.

3. Results and discussion

The device development aimed to support the two stages of impact sounding: data collection and data analysis. These two stages may be handled separately or combined into one system. In this study, both scenarios were evaluated to determine the potentiality of the proposed technologies. Two prototypes were developed for collecting visual and acoustic data. The first prototype intends to evaluate the data collection system. It primarily focused on the execution of impact acoustics and the capability of full automation of the monitoring device. The first system only captured impact sound signals and the data collected was further analysed in the office. The second developed device was improved to combine the data collection and the analysis into one device.

To test the data gathering capabilities of the device the field test was conducted on the two bridges located at Pallocan West, Batangas City, namely the Bridge of Progress and the Calumpang Bridge (Figure 4). Each bridge was tested by pushing the device along the full length of the bridge, stopping at set intervals to give the device time to store the recorded sounds for each impact.

a) Bridge of Progress, Batangas City.



b) Bridge of Promise, Batangas City.

Figure 4. Field test sites for the hardware.

Field testing was performed to confirm if the data gathered by the device can store the four data file types for each impact made. They are a .csv file. a .wav file, an image, and a .txt file containing the GPS location. It was also observed that the device could collect up to 200 data sets throughout its whole operation time that lasted for 2 h before its battery required charging. The charging time of the battery is 8 h. The challenges encountered on data collection were when there was poor connection on testing location thus GPS coordinates cannot be documented in real time.

Table 1 shows the interlayer condition with its corresponding frequency behaviour. The table was tested and proven in the study of [7] where multiple tests in an actual bridge were performed and the patterns in the amplitude and frequencies of each impact sound was observed, considering the physical condition of the deck surface of each test. The study concluded that there were four different interlayer conditions which correspond to visual inspection.

Table 1. Interlayer conditions and their frequency behavior [8].

Condition	Frequency spectra	Visual inspection
Severe	Peak frequency less than 600 Hz	Deterioration depth is greater than 25 mm. Asphalt concrete is heaved. Traces of moisture are remarkable
Debonded	Peak frequency of 1,000 to 1,300 Hz, peak amplitude higher than 50 Pa^2/Hz	Asphalt concrete is completely detached from the concrete deck
Fair	Peak frequency of 1,000 to 1,300 Hz, peak amplitude lower than 50 Pa^2/Hz	Surface of concrete deck shows minor scaling
Good	Peak frequency higher than 1,500 Hz	Good condition, no inspected damage on the surface of concrete deck

The frequency graph of a debonded condition data is presented in Figure 5. The peak amplitude was measured upon locating the highest point reached to the graph on the y-axis while the frequency was determined on the x-axis where the peak amplitude occurs. The data showed the peak amplitude higher than 50 Pa^2/Hz and a frequency around 1,000 to 1,300 Hz. The behavior of the graph indicated that the interlayer condition of the data was considered as debonded which means that the asphalt was detached from the concrete deck.

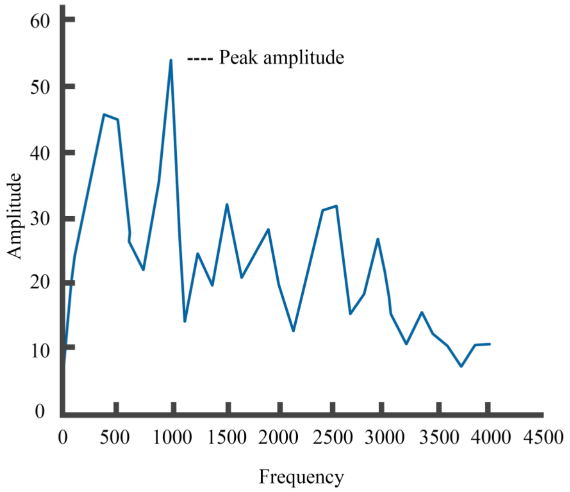


Figure 5. Debonded condition data.

On the other hand, a fair condition data frequency graph is presented in Figure 6 showing the peak amplitude lower than 50 Pa^2/Hz and a frequency around 1,000 to 1,300 Hz. This kind of data showed that the concrete deck surface had minor scaling.

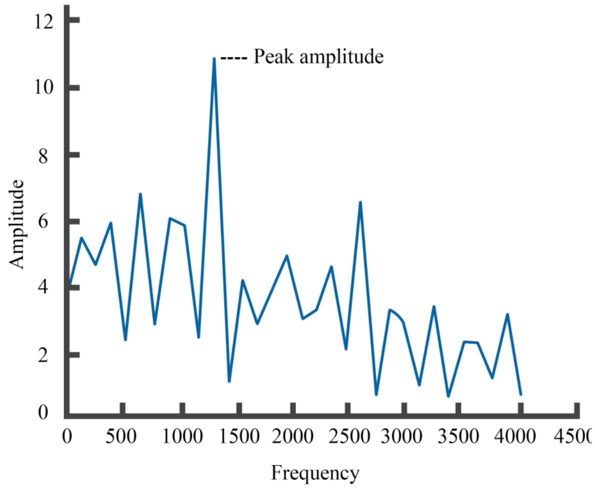


Figure 6. Fair condition data.

Figure 7 shows a frequency graph of the good condition data with a frequency higher 1,500 Hz. This kind of data showed that there was no inspected damage on the surface of the concrete deck.

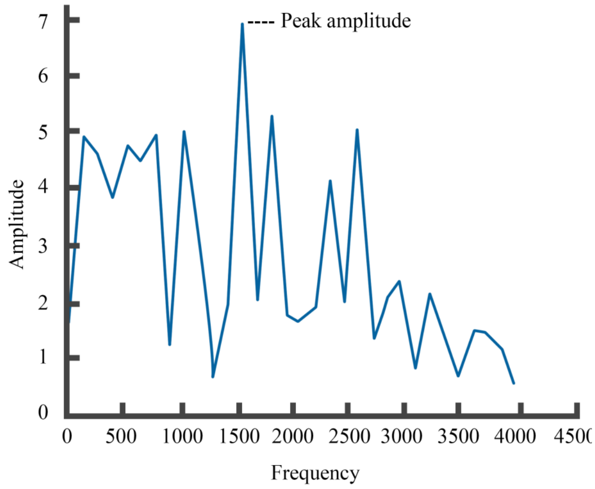


Figure 7. Good condition data.

Lastly, Figure 8 shows a frequency graph of severe condition data with frequency lower than 600 Hz. This kind of data would showed that the deterioration depth was greater than 25 mm.

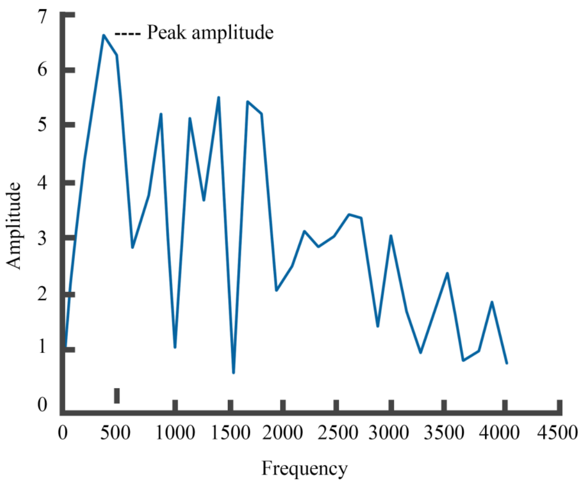


Figure 8. Severe condition data.

Table 2 presents the table of the data captured from the Bridge of Progress, a three-month-old bridge, in Batangas City. The table showed the peak amplitudes were lower than 50 Pa^2/Hz and occurred in frequency ranging from 1,000 Hz to 1,300 Hz, while some were higher than 1,500 Hz. The results showed that the bridge's interlayer condition was good or fair, which was the expected result considering the bridge's age.

Table 2. Collected and analyzed data from Bridge of Progress, Batangas City.

Test	Frequency (Hz)	Peak Amplitude (Pa^2/Hz)	Condition
1	~2,500	~6.7	Good
2	~1,150	~6.8	Fair
3	~1,600	~6.8	Good
4	~1,250	~10.9	Fair

Another data was collected from Pallocan Bridge, a three-year-old bridge, in Batangas City. Table 3 shows the peak amplitudes occur in the frequency lower than 500 Hz. The results showed that the bridge's interlayer condition was severe, which was the expected result considering the bridge's age.

Table 3. Data from Pallocan Bridge, Batangas City.

Test	Frequency (Hz)	Peak amplitude (Pa^2/Hz)	Condition
1	~300	~9.1	Severe
2	~450	~6.6	Severe
3	~500	~7.7	Severe
4	~480	~8.5	Severe

Table 4 shows data captured from a bridge using a recording sound with low sensitivity. The table showed the peak amplitudes occuring in the frequency lower than 600 Hz. The results showed that the bridge's interlayer condition was severe. It provided the idea that using lower sensitivity recording sound on the Raspberry Pi would affect the results of the data collected on the bridges, so it is recommended to change the settings of the sound recording on the Raspberry Pi to the maximum to cater a consistent result of the data.

Table 4. Data from a bridge showing severe conditions.

Test	Frequency (Hz)	Peak amplitude (Pa^2/Hz)	Condition
1	~100	~60	Severe
2	~100	~0.12	Severe
3	~200	~0.23	Severe
4	~500	~0.069F	Severe

The development of condition rating tool required analysis of massive amounts of data and extracting its characteristics in a more defined way. Computational development resulted in the adaptation of machine learning algorithms in this amount of data. To further enhance the accuracy and preciseness of the condition rating tool, data were subjected to various machine learning algorithms.

Adoption of four machine learning algorithms was performed namely decision tree algorithm, logistic regression, neural network, and support vector machine (SVM). The implementation of the machine learning algorithms was performed using Waikato Environment for Knowledge Analysis (WEKA), an open-source software developed by the University of Waikato in New Zealand, in accurately determining the condition of infrastructures [9].

Four performance metrics for each configuration were computed using the following metrics namely: accuracy, kappa statistic, sensitivity, and specificity. Accuracy pertains to the percentage of correctly classified instances whereas kappa statistic measures the inter-agreement between the qualitative classifications. Kappa statistics accounted for the uncertainty guesses of the raters [10]. On the other hand, sensitivity or recall determined the ratio of the positives that were correctly classified, and specificity rated the proportion of negatives that are correctly classified [11].

Table 5 shows the accuracy rating of different machine learning algorithms. Overall, the proposed decision matrix rating tool for impact sounding signal showed high accuracy when logistic regression algorithm was used and low accuracy when support vector machine algorithm was applied. Literature expressed that neural network and support vector machine algorithms need large amounts of training data, which are quite inefficient and labour-intensive to obtain in the field condition [11,12]. Based on the initial application of machine learning algorithms to impact sound, logistic regression machine learning approach provided the highest accuracy result in identifying interlayer debonding conditions.

Table 5. Summary of accuracy rating of different machine learning approaches.

Evaluation method	Decision tree	Logistic regression	Neural network	Support vector machine
Accuracy, %	95.83	98.61	82.99	77.08
Kappa statistic	0.9323	0.9832	0.7268	0.5419
Specificity	0.958	0.990	0.830	0.757

The study showed that the application of machine learning algorithms expedited the condition analysis such that upon establishment of the features of each condition, the result of impact sounds can directly be analyzed in the system. However, with the limiting capacity of determining the intermediate condition (fair condition) due to lack of bridges with such deck condition and difficulty of simulating the condition in the laboratory, the study, from here on, focused on the extreme conditions for bridge deck interlayer condition: bonded and debonded conditions.

Further development of this study used Convolutional Neural Network (CNN) as the main algorithm used for image processing integrated with the inception model. This inception model helped strengthen the logistic approach of analysis. CNNs take advantage of the fact that the input consists of images, and they constrain the architecture in a more sensible way.

From the laboratory validation of the performance and the field test report, it showed the accuracy of trained data sets. From the impact tests conducted on the regular slab, the device had performed 100 % accuracy on regular slab and 93.33 % on the controlled slab indicating an acceptable result of condition evaluation for pavement interlayer of bridges.

4. Conclusions

An impact device can be developed capable of impact sounding, its data collection and analysis. Added feature on collecting its GPS location and camera for image data collection which can provide further pavement condition of bridge deck is also feasible. The device can perform with precise movement and intervals for impact sounding can be 0.50 m and 1.0 m depending on the preference of the operator. Comparing fulling automated and semi-automated movement, the device for impact sounding is best suited in semi-automatic wherein manual push and additional weights on the device can reduce errors in impact hitting and swerving during testing procedures.

Continuous collection of data such as recorded impact sound, GPS location, encoded bridge information and pavement images and condition can be saved or stored for further analysis and interpretation. In addition, impact sounds are being recorded right after each impact; data are viewable on the device. Therefore, the device can provide real time pavement interlayer condition interpretation as well as appropriate data storage.

The use of impact sound testing device for determining bridge deck pavement interlayer condition with machine learning algorithm for analysis are provides comparable accurate method and results of evaluating bridge deck pavement,

Based on the results and conclusions, even though the system was effective and was functioning properly, it was recommended to develop a more improved robust device that can withstand harsh environments during field testing. Specifically, concerns on the battery capacity wherein power demand for impact sound may affect the precision of the impact sounding. Reporting may be improved by using mapping strategies and techniques or providing reporting templates with integration of pavement condition to actual bridge deck plan. Further studies on different machine learning approaches and its combination may be performed using data collection methodology used in this study.

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