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A Pothole Detection Using VGG16

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Abstract A pothole is a flaw that can be discovered on the road surface and it is one of the major contributions to the road accident. The impact of a vehicle on a potholed road is not just making the ride uncomfortable. It can damage the vehicle's suspension system as well as the wheel of the vehicle, resulting in costly repair. Therefore, a regular road maintenance activity and assessment are very important to ensure that it is safe to be used. However, due to the limited number of expensive inspection vehicles, the inspection is performed manually. In this study, we present a mobile pothole detection system, namely HOLETRACKER using VGG16, a deep learning model architecture. The built model is trained using a collection of images taken from Kaggle and Internet in a variety of settings. The experiment used 739 numbers of training images and 144 numbers of testing images. The experimental result achieved the accuracy level rate at 90%. This paper also presents the development of two versions of the HOLETRACKER system, the mobile and web application that can be used by the public users and authorities. With the HOLETRACKER system, people can make a complaint of potholes via their mobile phone at anytime and anywhere. The validation checking of the potholed and location tracking through the GPS are the two main features provided by the system that will be performed before the information reaches the authorities for immediate action. The system is a cost-effective solution as an alternative to the manual pothole inspection management in facilitating the authorities as a measure to reduce accidents caused by potholes.

Keywords Potholes Detection, Deep Learning, VGG16, Mobile Application

1. Introduction

The outcome of global climate change causes extreme weather events, such as heavy rainfall, and cyclone events [1]. Floods may occur due to such incidents which bring severe damage to road infrastructure and pose a major challenge to the road maintenance management. An example of the infrastructure damage is potholes that usually cause the poor condition of the road pavement performance or signs of impending failure. A pothole is a stress in a road surface, often asphalt pavement, where fractured pavement fragments have been removed by traffic. The most common causes of the potholes are the structure of the underlying soil hold a large of water and the affected area has frequent traffic that passing through over it, causing the road to deteriorate due to the weight of heavy vehicles. There are also some other internal factors that cause the potholes, such as pavement deterioration or overall durability of the material because of climate change due to excessive rain. The potholes are dangerous to the road users and may cause fatalities that contributed to the number of road accidents every year. In addition, it may impact the traffic and travel times and the increase of the operation's cost of the vehicle. Due to this reason, periodic maintenance of roads should be made to keep them well functional and safe for the users. There are some works in civil engineering such as Mohamad [2] and Ali [3] proposes the use of recycled materials for the road pavement layer as a substitute for natural aggregates in order to promote sustainability by conserving natural resources. The pavement distress is the defect's main problem of the roads. According to Hawke et al [4], it can be categorized into three: pavement distortion, fracture, and disintegration. The main reason behind such distortions always related to two reasons, environmental conditions and traffic pavement stresses. Therefore, pothole detection is an important part of pavement maintenance because of their high possibility of the negative impact of quality and driving safety. Visual examinations carried out manually by qualified structural engineers or inspectors are time-consuming and expensive. There have been many attempts made by the experts and researchers in the transportation field to develop an automated technique the detection of potholes. In general, the techniques to detect potholes can be categorized into four types [5], vibration approach [6-10], 3D reconstruction approach [11-16], Vision technique approach [17, 18] and Stereo Imaging [19, 20]. Table 1 summarizes the comparison of several pothole detection approaches based on the technology used, response and sense time, processing, cost, pothole characterization, and the accuracy of detection. These technologies have distinction in terms of the benefits and disadvantages it offers; 3D laser-based methods, for example, can offer excellent performance at a high cost. Otherwise, the methods based on vibration are very simple but lack precision and dependability.

Despite the fact that pothole identification through a deep Convolutional Neural Network (CNN) has been investigated for many years, an effective mobile system for pothole detection remains limited. The object of potholes, in many cases, is small in comparison to the image of the road. A large amount of memory is required to train the CNN on a high-quality image, which is not always available. Reducing the spatial scale of the input image is the most common way to overcome this issue [21, 22]. Downsampling an image, on the other hand, raises the alert of missing important discriminative features for pothole detection. Another approach proposed by [23, 24] is learning the image by patching it to the high-resolution CNN to detect class using a sliding window. These methods, on the other hand, require a lengthy process and unsuitable for applications that run in a real time. In this paper, the focus will be on the development of HOLETRACKER, a mobile application to detect potholes using VGG16, CNN's architecture model approach.

Table 1. Techniques for Pothole Detection

References	Device	Technology	Detection response time	Complexity Level	Cost	Accuracy
Vision [17, 18]	Camera	2D Imaging	High	High	High	Highly depend on the algorithm used.
Vibration [6-10]	Accelerometer	Rotation, force, and orientation	Low	Low	Low	High
Laser (requires the use of a laser scanner, stereo vision, and the Kinect sensor) [12, 19]	Laser	Reconstruction of the images in 3D using light reflections	Low	High	Low	High
Stereo Imaging [19, 20]	Camera	Multiple cameras are used to create a 3D reconstruction.	High	High	High	Highly depend on camera alignment and algorithm used

2. Related Study

Instead of relying on the old-fashioned type of methods for detecting potholes, the deep learning algorithms have been employed to learn the discriminative quantitative features from images. A number of works have been done on pothole detection. Koch and Brilakis [16] for example, have built a model for recognizing potholes in asphalt pavement images. The procedure of pothole detection is separated into three steps that depend on the shadows in the image, elliptical forms, and information on grain surface texture, and these steps are;(1) the picture segmentation, (2) the approximation of shape, and (3) the texture extraction [16]. Fox et al [25] used a machine learning method for detecting potholes. They introduced a method based on characteristics derived from crowdsourced sampled data generated from car sensor simulation called CarSim. Based on the simulated model, the authors attained a simulation accuracy at 99.6% and an actual accuracy at 88.9%. Bhatt et al [26] compared two machine learning models in their work (Gradient boosting and SVM). Using an iPhone 6Ss, they gathered 21,300 accelerometer and gyroscope measurements on 96 identified potholes. They achieved 92.9% and 92.02% accuracy level respectively, for both that SVM using an RBF gradient and kernel. However, the accuracy (0.78) and recall (0.42) attained are significantly lower. Bhatia et al [26] proposes a novel pothole detecting approach based on a thermal IR sensor or camera. The technique is based on the differential in temperature between things and their surroundings. A Convolutional Neural Network (CNN) is used to process the road's thermal images. Two different models based on CNN were developed and tested, the built-in CNN and CNN based on ResNet models. The accuracy based on ResNet152 is 97.08%.

Luo et al [27] developed a model using Fast-RCNN, a deep learning algorithm to detect potholes. The model was trained using 900 images of potholes. The authors claimed to have achieved an average accuracy of around 93%. The photos of the potholes, on the other hand, were shot from a close-up perspective of the pavement. In another study, a dashboard camera and a CNN were used to identify potholes. The authors achieved an average accuracy of around 93%. The photos of the potholes, on the other hand, were shot from a close-up perspective of the pavement. The work by Pereira et al [21], used the dashboard camera along with models developed in CNN, the pothole images were captured in various conditions such as wet, dry and shaded from different places. The pictures are scaled to 200x200 pixels and cropped to remove any undesirable areas, leaving just the potholes. In their work, 3250 images were used for the validation while 500 images were used for the testing. Anand et al [22], for example, trained a deep neural network using the texture and spatial information from the camera image. A total of 969 images are used to test the model. The F-score, recall and precision are all 93.0%, 93.8% and 92.4% respectively. This method, however, is computationally intensive, making it unsuitable for a real time detection scenario. Despite the fact that the current potholes detection algorithms have demonstrated the acceptable accuracy rate of precision and recall value, there is still a room for improvement in terms of accuracy rate detection achievement by focusing on the discriminative regions. This study employs the VGG16 architecture to improve accuracy and performance by focusing on discriminative sections of the pothole image rather than the total context.

There are also a number of applications developed to monitor the road pavement, such as Pavemont [25], is a GIS web-based that employs data from a variety of sensors such as microphone, accelerometer, radar, imaging etc. to assess a variety of characteristics related to road distress. However, PAVEMON [28] requires a specialized setup of a vehicle that is not suitable to be a platform for a huge data collection. TrafficSense [29] and Nericell [30] are systems introduced by India's Microsoft Research Lab, detect potholes using basic threshold-based algorithms employing the sensors on a Windows smartphone, for instance, microphone, accelerometer, and GPS. These thresholds, on the other hand, are derived through observation and as a result, they remain highly subjective. Wolverine [31] identifies road bumps by comparing accelerometer measurements along the gravity axis. The thresholds, on the other hand, are based only on standard deviation and mean, with higher-order statistics being ignored [31]. The Pothole Patrol (P2) [8], introduced by MIT employed a rudimentary machine learning technique that uses the Speed-Z ratio and X–Z ratio to analyse trends in accelerometer data. The system collects accelerometer data from three separate points and stores it on an integrated PC.

While there are many studies developed on the pothole detection model, none has presented the development of an end-to-end solution for the pothole detection and complaint management system. Therefore, the main objective is to present the entire development process of HOLETRACKER application that comprises the development of the potholes detection model using VGG16, the development of mobile and web version of HOLETRACKER system. Figure 1 is the VGG16 model architecture. The VGG16 is a deep CNN architecture with 16 layers deep considered to be the best models, in which the arrangement structure of max pool and convolution layers are followed consistently. It is also the most used model architecture for image recognition and classification where each layer in the model has some weight. The function of each layer has been described in [32].

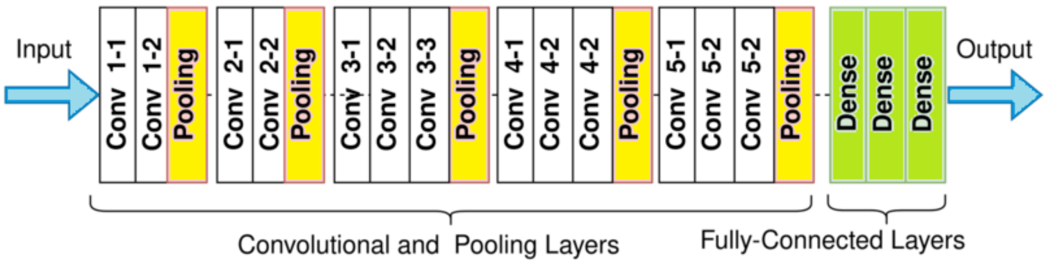

Figure 1. The model architecture of VGG16

3. Method

Figure 2 is the research methodology to carry out this study. The proposed methodology is a suitable approach for this study as it supports the Transfer Learning technique provided in VGG16, which states that the knowledge gained from a pre-trained model can be used to increase the generalization of a new task. In the Image acquisition phase, the data that consists of the collection of pothole images are collected for training and testing purposes both from Kaggle and Internet.

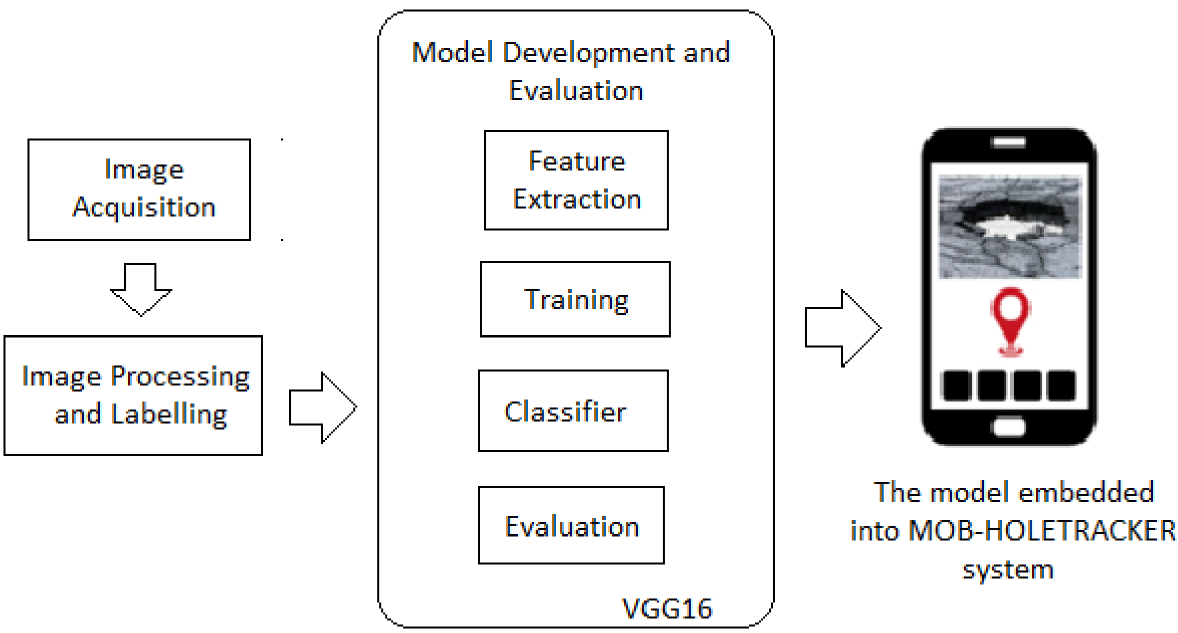

Figure 2. Methodology for potholes detection model development

A total of 739 numbers of images that consist of 439 pothole images and 300 non-pothole images are used for the training purpose. There are a variety of settings considered in the images, including rainy, dry, and shaded conditions of the road. A total of 144 numbers of testing images were all used for testing. Figure 3 is part of data collection of the pothole images. Before feeding all images into the model, cleaning, standardization, and augmentation of all images are all necessary to ensure the model can work as intended. In the Image processing and labelling phase, the quality of images is improved where all are transformed into a form that can be understood by a specific algorithm. Data augmentation is a general pre-processing strategy that is required to improve the quality of datasets by using several techniques such as rotation, reflection, Gaussian blurring, translation, etc. The VGG16 technique is used to develop the pothole detection model since it is one of the best model architectures that offered a distinctive feature; instead of plethora hyper parameters, it concentrates on 3x3 convolutional layer's filter and using stride 1 as and stride 2 with 2x2 filter, the same max pool and padding layer.

There are four processes in the model development and evaluation phase, namely, feature extraction, training, classifier, and evaluation. In the feature extraction process, the pre-process input module is imported to scale pixel values to appropriately fit the VGG16 model. The next process is the classifier algorithm development to categorize the images into two different labels which are pothole and plain road (non-pothole). Image classification analyses the numerical properties of the image features and organizes them into categories. Once the model achieves the intended accuracy rate, the model will then embed into the MOB-HOLETRACKER system. The MOB-HOLETRACKER is the mobile version of the HOLETRACKER system that is developed using several technologies such as Python, Keras, Java, FireBase, PHP, Mysql, and etc.

Figure 3. Example of potholes images

4. Result

In this section, the development of all components of the HOLETRACKER system (i.e., model, database, mobile application, and web application development) is presented. Figure 4 is the workflow process of the proposed system. In the workflow diagram, the citizen users can submit complaints of potholes on the road through the MOB-HOLETRACKER (a mobile application version of HOLETRACKER) by capturing the image of potholes using their phone's camera. Before the complaint is submitted into the system, the MOB-HOLETRACKER will do the validation checking on the captured image and tracking the location of the road to ensure the provided information is valid. The validated report is stored in the database. The authority's user is notified via WEB-HOLETRACKER (the web application version of HOLETRACKER) to take the appropriate action on the pothole based on the given information.

One of the core elements in the HOLETRACKER system is the pothole detection model. To measure the efficiency of the proposed model, accuracy, measurement needs to be done. For the definition, accuracy refers to a technique for calculating a classification model's efficiency. It's usually expressed as a percentage [33]. Accuracy is the value of a forecast that is equal to the true value and is easy to understand [33]. It's always presented as a graph to indicate the precision of a produced model [33]. A loss function, on the other hand, is a forecast value for how far it differs from real value. It is the error total calculated for each sample in the validation set, not a percentage [33]. The most often used loss functions are entropy loss and log loss [33]. In classification and regression issues, the loss function can be applied. Figure 5 and Figure 6 present the performance of training and validation accuracy based on four parameters, namely, the validation accuracy, accuracy, validation loss and a loss for the developed model. In most cases, the loss and accuracy for model validation will vary depending on the difference scenario.

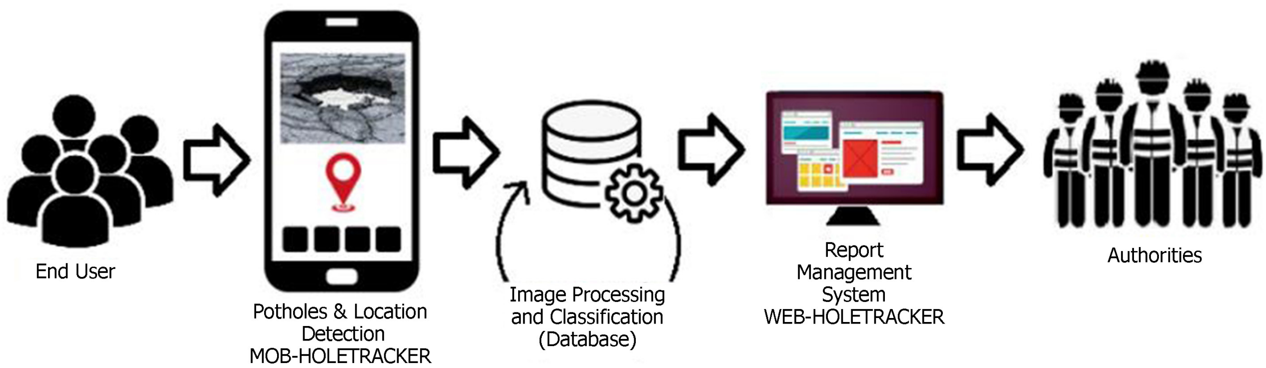

Figure 4. HOLETRACKER system workflow Model Development

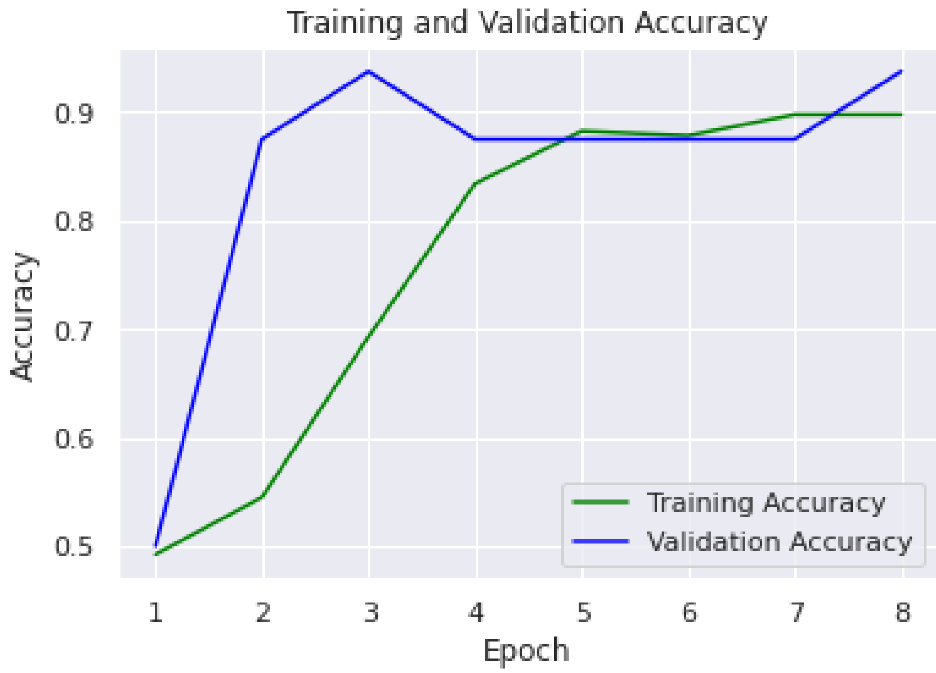

Figure 5. The accuracy performance

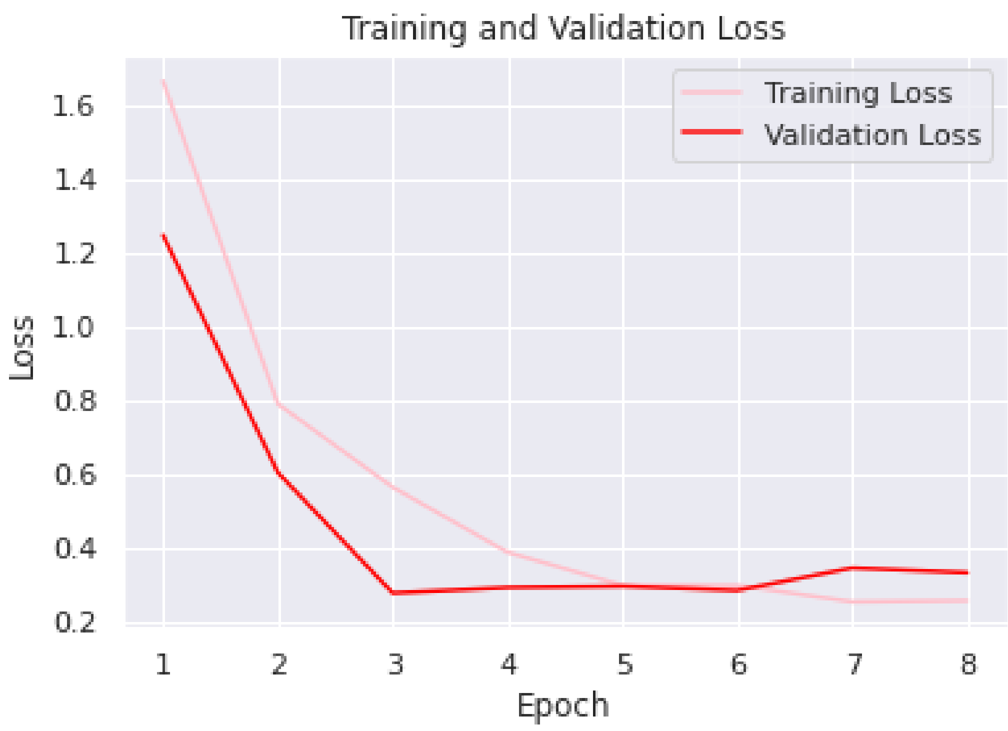

Figure 6. The loss performance

The model's accuracy performance is presented in Figure 5, the running model stops after the eight iterations of epochs. The model achieved the training accuracy rate at 87% and 90% on validation accuracy dataset. The training loss is 0.2585 and validation loss is 0.3341. When compared to previous research, the experimental results acquired in this study produced almost the same pattern and is an acceptable accuracy rate model to be used for the pothole detection system.

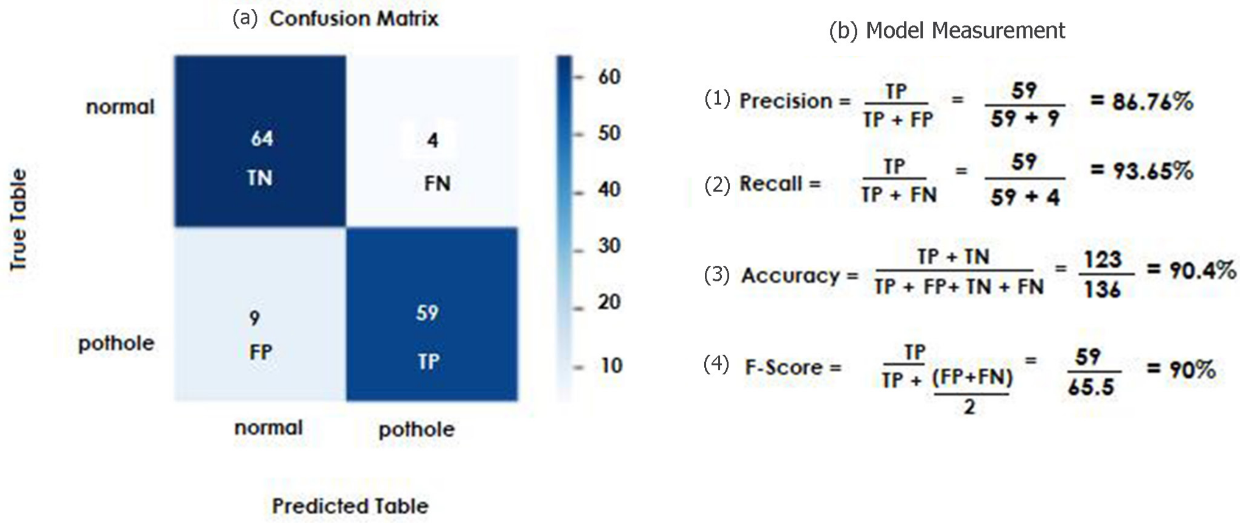

Figure 7. (a) Confusion Matrix and (b) Model measurement

A confusion matrix is a performance measurement that is used to indicate how effective a classifier (model) work on a set of data for the testing when the real values have been established. Examining the Confusion Matrix as shown in Figure 6 (a), it's clearly shows that a pothole does not have a distinct pattern, and the normal (non-pothole) images can be easily labelled as pothole images using simple classification methods and feature extraction. To evaluate the model's performance, three measures were employed, the accuracy, recall and precision. Figure 7(b) presents four equation for determining the model's efficacy, the first equation (Precision) expresses the precision as a relationship with exactness, the second equation (Recall) is the recall measurement to the detection completeness, the third equation (Accuracy) to express the correctness of the model and the last equation (F-Score) or also known as F1 is a binary classification evaluation of the model. A high F1 score suggests a low number of false negatives and false positives in the model. If the F1 score is 1, the model is considered good; if the value is 0, the model is regarded to be a total failure. In the equations, the true positives (depicted as correctly identified potholes), false positives (FP, incorrectly identify potholes), true negatives (TN, correctly identify as non-potholes), and false negatives (FN) are all represented in the equations (FN, incorrectly identify as non-potholes). Based on the confusion matrix, the precision, recall, accuracy, and F-Score calculated based on the formula given in Figure 6 (b) are all 86.76%, 93.56%, 90.4% and 90% respectively.

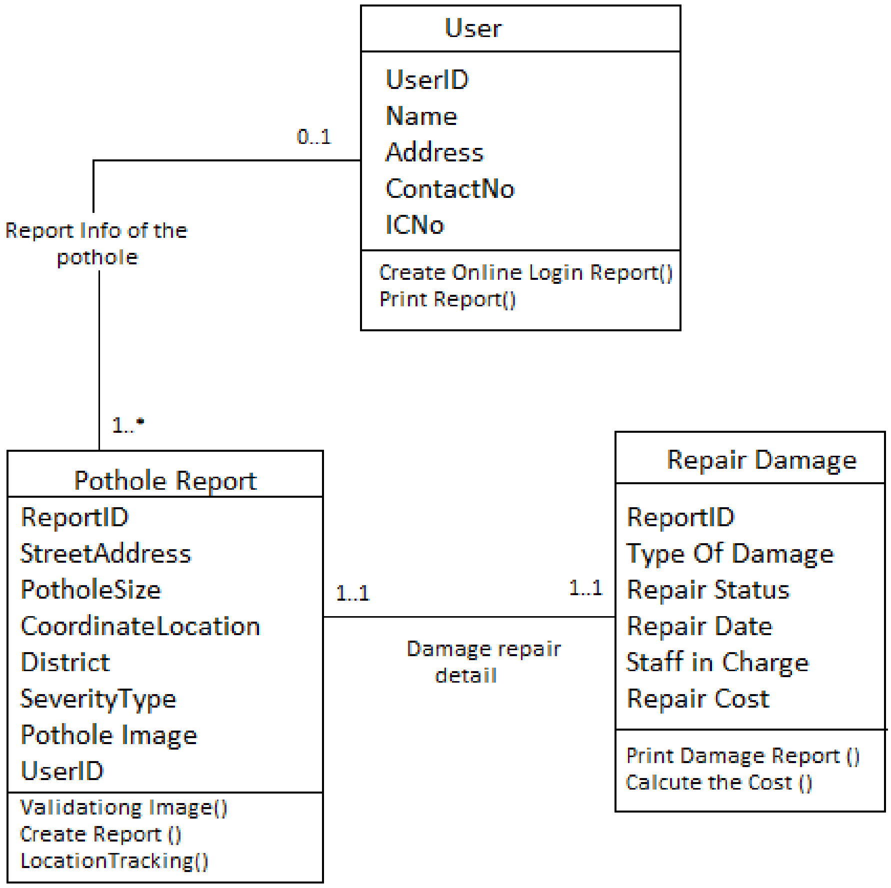

Figure 8. The HOLETRACKER UML Class Diagram

Figure 8 is the HOLETRACKER UML Class designed. There are three main classes in the HOLETRACKER system, namely User, Pothole Report and Repair Damage. The User class diagram represents the end user object, and it consists of several attributes (UserID, Name, address, ContactNo and ICNo) and operations. The UserID is unique for each user and created during the registration process. The Create Online Login Report () operation is an operation that allows users to login and initiate the report by providing personal profile identification for registration. The users are allowed to print the entered information through the PrintReport () operation. The Pothole Report class diagram relates to the detail of pothole information consist of several attributes such as ReportID, StreetAddress, Pothole Size, SeverityType, ReportDate, PotholeImage and UserID. The reportID is a unique report ID created during the complaint submission. To submit a report (complaint), the image of the pothole needs to be captured using the user's mobile camera phone and the system will validate the image through ValidatingImage() operation. The LocationTracking() is an operation to track the location of a pothole. The system will be able to track the coordinate's location through the GPS in the mobile phone. The Repair Damage class diagram is related to the repair status of a particular pothole report; the status is the action (e.g., KIV, In Progress, Done) should be taken by the authority. This class diagram consists of several attributes such as ReportID, Type of Damage, RepairStatus, StaffInCharge and Repair Cost. The authorised user can print the damage report through the Print Damage Report () operation. The repair cost is based on how severe the reported pothole and is calculated through the CalculatetheCost() Operation. The MOB-HOLETRACKER is a mobile version of HOLETRACKER system allowing the public users to send a report or complaint of potholes to the respective authorities by providing the information such as the pothole's location and image for the validation checking. The HOLETRACKER system as a whole is developed using several technologies such as Java, Phyton, Android Studio, Firebase Database, Keras and TensorFlow Mobile, PHP, MySQL and MySQL adapter. The submitted report can be viewed by the authorized user through the WEB-HOLETRACKER. The information related to a particular pothole report displayed on the web page is presented in Figure 8. The system also allows the head of department to escalate the report received to handle specific team or personnel to take immediate action.

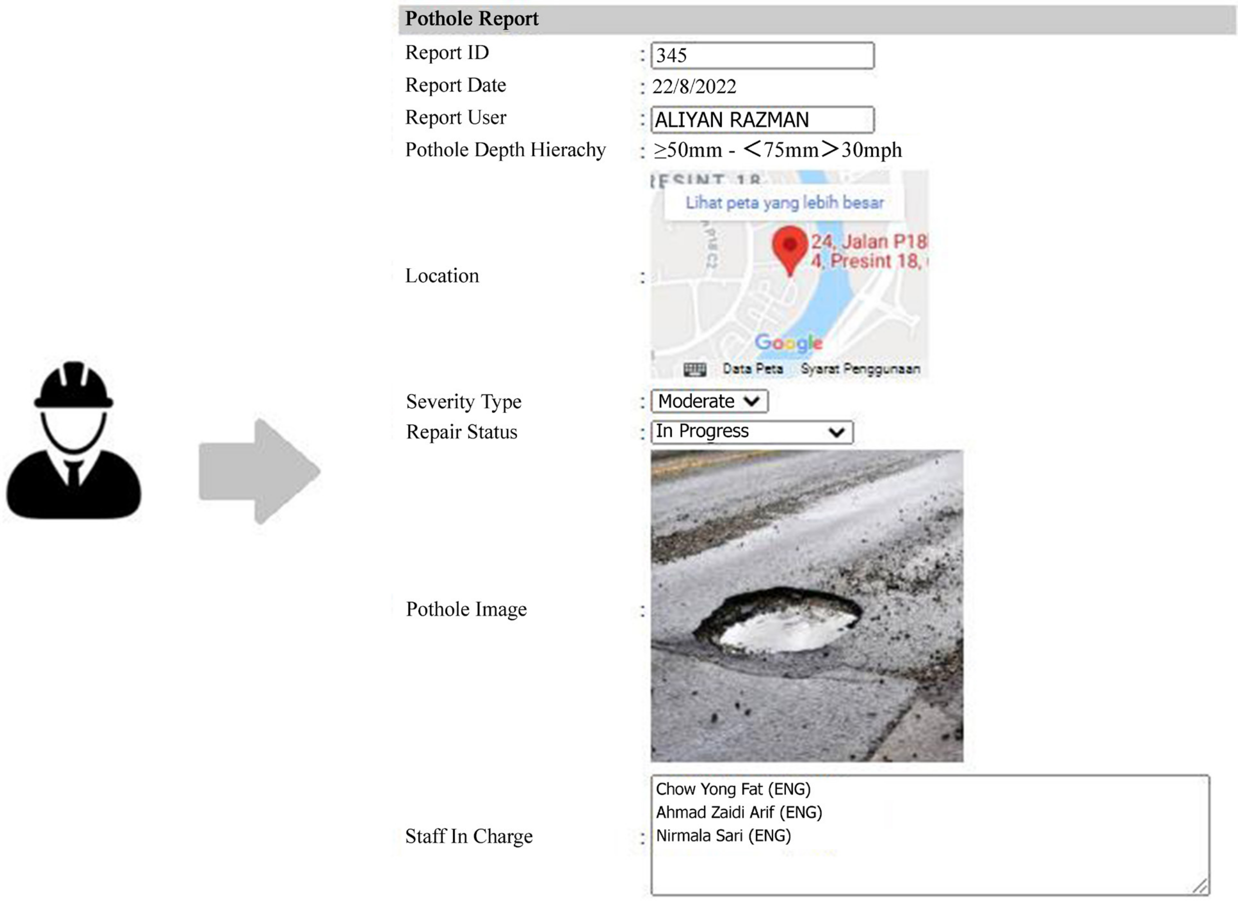

Figure 8. The web version of HOLETRACKER used by the authorities

5. Conclusions

In this paper, we have presented the development of pothole detection models and components using VGG16 and other technologies such as JAVA, TensorFlow, FireBase, PHP and MySQL. The model achieved the accuracy rate level at 90%, yielded almost similar pattern with the existing works. The model's performance is measured using various parameters such as accuracy, precision, and recall score. The developed model is trained and tested using the VGG16 architecture of the data collected from Kaggle and internet. This paper also presents the development of two versions of the HOLETRACKER system, the mobile and web applications that can be used by the public users and authorities. People can make complaints of pothole via their mobile phone anytime and anywhere. All they need to do is to capture the pothole image and turn on the GPS on their phone. The image then needs to be fed into the HOLETRACKER system. The validation checking of the pothole images and location tracking through the GPS are the two main features provided by the system that are firstly performed before the information reaches the authorities for immediate action. The system is a cost-effective solution for an alternative to the manual pothole inspection management to minimize the road accident caused by potholes. For future work, the model needs to be improved in terms of its accuracy rate and more images need to be trained. The HOLETRACKER system can be even more meaningful if it's able to estimate the size and depth of the pothole using stereo images as part of the features of the HOLETRACKER system.

REFERENCES

[1] Pereira J.J., "Direct Impact of Flash Floods in Kuala Lumpur City: Secondary Data-Based Analysis."

[2] Ahmad Yusri Mohamad , Maslina Jamil , Nur Izzi Md. Yusoff , Mohd Raihan Taha , "Performance Characteristics of Road-base Containing Mixed Steel Slag and Cathode Ray Tube Glass," Civil Engineering and Architecture, Vol. 9, No. 1, pp. 42 - 51, 2021. DOI: 10.13189/cea.2021.090104.

[3] Mansour A. M. H., Ali S. A., "Reusing waste plastic bottles as an alternative sustainable building material," Energy for sustainable development, vol. 24, pp. 79-85, 2015.

[4] Hawks N., Teng T., Bellinger W., Rogers R., Baker C., Brosseau K., Humphrey L., "Distress identification manual for the long-term pavement performance project," Strategic Highway Research Program, Washington, 1993.

[5] Kim T., Ryu S.-K., "A guideline for pothole classification," International Journal of Engineering and Technology, vol. 4, no. 10, pp. 618-622, 2014.

[6] Yu B. X., Yu X., "Vibration-based system for pavement condition evaluation," in Applications of Advanced Technology in Transportation, 2006, pp. 183-189.

[7] De Zoysa K., Keppitiyagama C., Seneviratne G. P., Shihan W., "A public transport system based sensor network for road surface condition monitoring," in Proceedings of the 2007 workshop on Networked systems for developing regions, 2007, pp. 1-6.

[8] Eriksson J., Girod L., Hull B., Newton R., Madden S., Balakrishnan H., "The pothole patrol: using a mobile sensor network for road surface monitoring," in Proceedings of the 6th international conference on Mobile systems, applications, and services, 2008, pp. 29-39.

[9] Mohideen A. J. H., Rosli M. F., Hanif N. H. H. M., Zaki H. F. M., Husman M. A., Muthalif A. G. A., Kumar D., "Pavement Condition Analysis Via Vehicle Mounted Accelerometer Data," IIUM Engineering Journal, vol. 21, no. 1, pp. 73-84, 2020.

[10] Anand A., Gawande R., Jadhav P., Shahapurkar R., Devi A.,Kumar N., "Intelligent Vehicle Speed Controlling and Pothole Detection System," in E3S Web of Conferences, 2020, vol. 170: EDP Sciences, p. 02010.

[11] Fawzy H.E.-D., Din E., "Monitoring and assessment OF road cracks and potholes using digital close range photogrammetry 3D reconstruction technique," International Journal of Civil Engineering and Technology, vol. 11, no. 1, pp. 119-128, 2020.

[12] Ahmed A., Ashfaque M., Ulhaq M.U., Mathavan S., Kamal K., Rahman M., "Pothole 3D Reconstruction with a Novel Imaging System and Structure from Motion Techniques," IEEE Transactions on Intelligent Transportation Systems, 2021.

[13] Zhang D., Zou Q., Lin H., Xu X., He L., Gui R.,Li Q., "Automatic pavement defect detection using 3D laser profiling technology," Automation in Construction, vol. 96, pp. 350-365, 2018.

[14] Wang K.C., "Challenges and feasibility for comprehensive automated survey of pavement conditions," in Applications of advanced technologies in transportation engineering (2004), 2004, pp. 531-536.

[15] Hou Z., Wang K.C.,Gong W., "Experimentation of 3D pavement imaging through stereovision," in International Conference on Transportation Engineering 2007, 2007, pp. 376-381.

[16] Koch C., Brilakis I., "Pothole detection in asphalt pavement images," Advanced Engineering Informatics, vol. 25, no. 3, pp. 507-515, 2011.

[17] Kandoi A., Agarwal H., Revadekar A., Chaudhari B.N., "Pothole Detection using Accelerometer and Computer Vision with Automated Complaint Redressal," in 2021 3rd International Conference on Signal Processing and Communication (ICPSC), 2021: IEEE, pp. 257-264.

[18] Lydon D., Taylor S., Lydon M., Early J., "A review of Vision based Methods for Pothole Detection and Road Profile Analysis," 2020.

[19] Haq M. U. U., Ashfaque M., Mathavan S., Kamal K., Ahmed A., "Stereo-based 3D reconstruction of potholes by a hybrid, dense matching scheme," IEEE Sensors Journal, vol. 19, no. 10, pp. 3807-3817, 2019.

[20] Ramaiah N.K.B., Kundu S., "Stereo Vision Based Pothole Detection System for Improved Ride Quality," SAE Technical Paper, 0148-7191, 2021.

[21] Pereira V., Tamura S., Hayamizu S., Fukai H., "A deep learning-based approach for road pothole detection in timor leste," in 2018 IEEE International Conference on Service Operations and Logistics, and Informatics (SOLI), 2018: IEEE, pp. 279-284.

[22] Anand S., Gupta S., Darbari V., Kohli S., "Crack-pot: Autonomous road crack and pothole detection," in 2018 Digital Image Computing: Techniques and Applications (DICTA), 2018: IEEE, pp. 1-6.

[23] Zhang L., Yang F., Zhang Y. D., Zhu Y.J., "Road crack detection using deep convolutional neural network," in 2016 IEEE international conference on image processing (ICIP), 2016: IEEE, pp. 3708-3712.

[24] Eisenbach M., Stricker R., Seichter D., Amende K., Debes K., Sesselmann M., Ebersbach D., Stoeckert U.,Gross H.-M., "How to get pavement distress detection ready for deep learning? A systematic approach," in 2017 international joint conference on neural networks (IJCNN), 2017: IEEE, pp. 2039-2047.

[25] Fox A., Kumar B.V., Chen J., Bai F., "Crowdsourcing undersampled vehicular sensor data for pothole detection," in 2015 12th annual IEEE international conference on sensing, communication, and networking (SECON), 2015: IEEE, pp. 515-523.

[26] Bhatt U., Mani S., Xi E., Kolter J.Z., "Intelligent pothole detection and road condition assessment," arXiv preprint arXiv:1710.02595, 2017.

[27] Luo L., Feng M.Q., Wu J., Leung R.Y., "Autonomous pothole detection using deep region-based convolutional neural network with cloud computing," Smart Structures and Systems, vol. 24, no. 6, pp. 745-757, 2019.

[28] Shamsabadi S. S., Wang M. L., Birken R., "Pavemon: A GIS-based pavement monitoring system using large amounts of near-surface geophysical sensor data," in Symposium on the Application of Geophysics to Engineering and Environmental Problems 2014, 2014: Society of Exploration Geophysicists and Environment and Engineering, pp. 162-165.

[29] Mohan P., Padmanabhan V., Ramjee R., "TrafficSense: Rich Monitoring of Road and Traffic Conditions using Mobile Smartphones, Microsoft Research, 4.2008," ed.

[30] Mohan P., Padmanabhan V. N., Ramjee R., "Nericell: rich monitoring of road and traffic conditions using mobile smartphones," in Proceedings of the 6th ACM conference on Embedded network sensor systems, 2008, pp. 323-336.

[31] Bhoraskar R., Vankadhara N., Raman B., Kulkarni P., "Wolverine: Traffic and road condition estimation using smartphone sensors," in 2012 fourth international conference on communication systems and networks

(COMSNETS 2012), 2012: IEEE, pp. 1-6.

[32] Brock A., Donahue J., Simonyan K., "Large scale GAN training for high fidelity natural image synthesis," arXiv preprint arXiv:1809.11096, 2018.

[33] Rum S.N.M., Nawawi F.A.Z., "FishDeTec: A Fish Identification Application using Image Recognition Approach."