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A Deep Learning Approach for Real Time Road Damage Detection via Image Processing

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ABSTRACT :

Due to the use of subpar building materials in the construction of road drainage systems, traffic accident identification and prevention are becoming increasingly tough and challenging issues in India. The aforementioned issues lead to early road deterioration and potholes, which result in accidents. An estimated 4,64,910 incidents occur in India annually, according to a report published by the Ministry of Road Transport and Highways' transport research wing in New Delhi. This study suggested a deep learning-based approach that uses photos to identify potholes early, lowering the risk of an accident. Inception-V2, Faster Region-based Convolutional Neural Network (F-RCNN), and Transfer Learning serve as the fundamental foundations for this model.There are fewer pothole recognition models that just use machine learning methods to detect potholes, but several models combine machine learning methods with accelerometer data (without the need for images). The study's results show that our proposed model outperforms other pothole detecting techniques currently in use.

I. INTRODUCTION :

India has the world's second-largest road network, which is essential to both its social and economic development. Over the last ten years, the road transport industry has outperformed the overall GDP growth rate of 6%, achieving an annual GDP growth rate of around 10%. Road development has been moving quickly, but because of inadequate drainage systems and overloaded cars, road maintenance is still quite difficult. One of the main causes of traffic accidents is potholes, which are created by several variables. Between 2013 and 2016, potholes resulted in 36,421 injuries and 11,836 fatalities. Environmental variables like floods and severe rainfall make regular maintenance even more difficult, thus it's critical to implement creative strategies to lower the number of incidents.Numerous cutting-edge technologies have been developed to address pothole detection. Using algorithms like Z-THRESH and G-ZERO, accelerometer-based models—such those created by Artis M. et al.—achieve a 90% true positive rate and may be implemented on Android devices with little hardware. In order to handle 64x64 grayscale images that have been normalized using eigenvalues with a sufficient level of accuracy, non-linear SVM models with Gaussian radial basis functions have been used. However, with an accuracy of up to 99.80%, Convolutional Neural Networks (CNN) have surpassed SVM models. For better feature extraction and prediction, CNN-based approaches make use of strategies including convolution, pooling, ReLU activation, Adam optimizer, and Sigmoid function.For real-time road condition monitoring, sensor-based networks such as "BusNet," which employ cameras and GPS installed on public buses, provide an affordable option. Nevertheless, weather-related sensor damage can affect these systems. The availability of cameras and their potential to replace manual inspections have also contributed to the growth of image processing techniques. Discrete wavelet transform-based pavement distress detection techniques have an accuracy of 88.4%. Other methods identify potholes using features including discolouration, dark areas, and rough textures, however they may mistakenly identify manholes, road markings, and shadows as potholes.Even though these methods greatly improve the efficiency and accuracy of pothole detection, problems including uneven pothole formations, shadows, and environmental impacts still exist. However, combining deep learning, computer vision, and sensor-based technologies provides a strong basis for successfully tackling the pothole issue and lowering traffic accidents.

II. LITERATURE SURVEY :

This study suggests utilizing a convolutional neural network (CNN) to detect road potholes in images at a minimal cost. All of the images used to train our model were taken from various locations and varied in terms of weather, including rainy, dry, and shaded areas. Using 500 test photos, the experiment demonstrated that our model can concurrently achieve 100% accuracy, 100% precision, 99.60% recall, and 99.60% F-measure.

Much more research has been done on identifying fractures in distressed pavement, while comparatively less has been done on potholes. This study builds a non-linear support vector machine to determine whether a target region is a pothole by extracting texture measures based on the histogram as characteristics of the image region. An algorithm for identifying the pavement's potholes is suggested based on this. A high recognition rate can be attained by the algorithm, according to the experimental data.

III. PROPOSED SYSTEM :

Faster R-CNN is a powerful and efficient object detection algorithm that simplifies the process by combining multiple stages into a single end-to-end trainable model. One of its key innovations is the Region Proposal Network (RPN), which generates region proposals more quickly and efficiently than traditional methods like Selective Search. This significantly reduces processing time while maintaining accuracy.

Another notable feature of Faster R-CNN is its use of the ROI Pooling layer. This layer extracts a fixed-length feature vector from each proposed region, ensuring consistency in data representation for further processing. Although training the model can take a considerable amount of time depending on the hardware available, the results are worth the effort.

Once the model is trained, additional coding can be implemented to enable the system to capture images and identify potholes within them. Testing has shown that the system performs well, demonstrating its potential to detect potholes accurately and contribute to safer road conditions.

METHODOLOGIES:

1.TENSOR FLOW-OBJECT DETECTION API:

Anyone may swiftly create and implement a potent image recognition system with the help of TensorFlow's object detection API. After fine-tuning, it offers a large number of pre-trained models (trained on various datasets) that may be used to create unique classifiers, detectors, and recognizers. The "F-RCNN inception v2" model is the one we have chosen.

2.TRANSFER LEAVING:

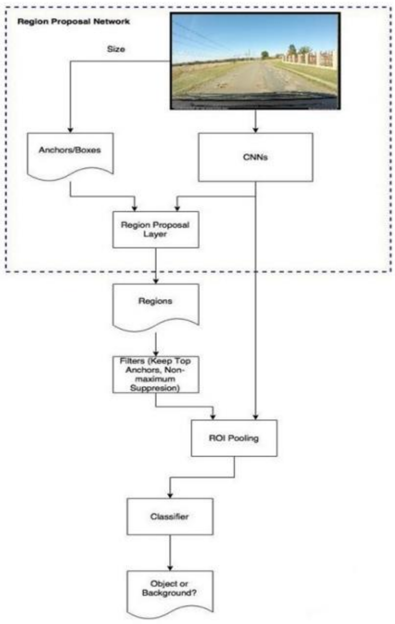
In order to save time and money, transfer learning is applying knowledge from a previously trained model to a similar but distinct problem. The weights from the pre-trained model can be used again for feature extraction if the new dataset is comparable to the original training data. The latter layers, which are unique to the original dataset, are re-trained on the new data, while the early layers, which capture general features like edges and color patterns, are kept (frozen) when the datasets are significantly different. When working with minimal data for the new task, this method is quite helpful.

3.F-RCNN(Faster Region - based Convolutional Neural Network):

For object detection, Faster R-CNN is superior to Fast R-CNN. Whereas Faster R-CNN incorporates a Region Proposal Network (RPN) into its architecture, Fast R-CNN depends on an external selective search for region suggestions. Fast R-CNN extracts feature maps using CNN and max-pooling, then resizes these features for the fully linked layers using ROI pooling. By directly creating region proposals, scanning the image, and producing bounding boxes with scores indicating the presence of objects, the RPN in Faster R-CNN lowers computational complexity. Because of this integration, Faster R-CNN is more effective and able to handle objects with different sizes and aspect ratios.

4.INCEPTION -V2 :

Using the perspective transformation [24], a 3D world view can be transformed into a 2D image. Although thresholding and undistorting aid in covering the important information, we can further separate that information by draking the portion of the road surface image. We shift our point of view to the best down viewpoint of the street in order to focus on the road portion of the picture. Even while this phase doesn't give us any additional information, it makes it much simpler to measure things like curvature and separate lane lines. The combined thresholding's Perspective Transform.



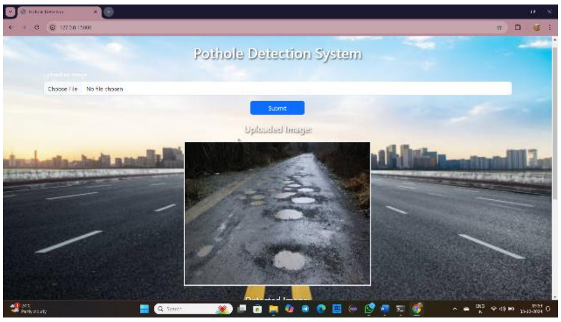
SYSTEM ARCHITECTURE

IV. FUTURE ENHANCEMENT:

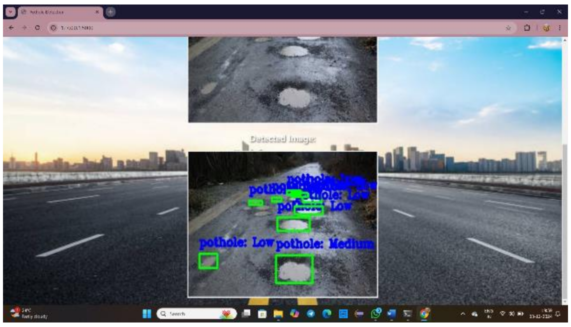
Future work includes improving accuracy with advanced CNNs, integrating GPS for real-time pothole mapping via an Android app, and deploying the system on Raspberry Pi or Android devices for public use.

V. RESULT AND IMPLEMENTATION :

INPUT IMAGE :



OUTPUT:



VI. CONCLUSION :

In this work, we suggested a system that can identify potholes in real-time from photos or videos taken by a car's mounted camera and notify the driver of a pothole in front of the car. Additionally, our system will identify the pothole's position and upload it to a map, which will be reflected in an Android app we developed. This way, other users who do not have a camera installed on their vehicle can receive alerts about the pothole by using the app alone (albeit this is still a work in progress). We employed well-known and intricate CNN architectures in this system, including Inception v1 (GoogLeNet), Inception v2, and ultimately Inception v2 in our system. The system performs remarkably well in the experiment data.

VI. REFERENCES :

[1]https://www.ibef.org/industry/roads- presentation

[2]https://sodhganga.inflibnet.ac.in/bitstream/10603/747 47/10/10/ chapter-3.pdf

[3]https://www.thehindu.com/opinion/op-ed/fixthepotholeproblem/article24436287.ece

[4] Artis Mednis, Girts strazdins, reinholds zviedris, georgijs kanonirs, leo selavo Digital Signal processing laboratory, Institute of Electronics and computer science, “Real time pothole detection using android smartphones with accelerometers”, 14 December str., Riga, LV 1006, Latvia

[5] Lin, J., & Liu, Y. (2010, August). Potholes detection based on SVM in the pavement distress image. In 2010 Ninth International Symposium on Distributed Computing and Applications to Business, Engineering and Science (pp. 544-547). IEEE.

[6] Pereira, V., Tamura, S., Hayamizu, S., & Fukai, H. (2018, July). 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) (pp. 279-284). IEEE.

[7] S. Nienaber, M.J. Booysen, R.S. Kroon, “Detecting potholes using simple image processing techniques and real-world footage”, SATC, July 2015, Pretoria, South Africa

[8] S. Nienaber, M.J. Booysen, R.S. Kroon, “A comparison of Low-cost Monocular Vision Techniques for Pothole Distance Estimation”, IEEE CIVTS, December 2015, Cape Town, South Africa.

[9] Chun-Jung Hsu, Chi-Farn Chen, Chau Lee, Shu-Meng Huang, “Airport pavement distress image classification using moment invariant neural network,” The 22nd Asian Conference On Remote Sensing , pp. 5-9, November 2001.

[10] H.D.Cheng, Jim-Rong Chen, Chris Glazier, Y.G.Hu, “Novel approachto pavement cracking detection basedon fuzzy set theory,” Journal of Computing in Civil Engineering, Vol.13, No.4, October 1999.

[11] ZHANG Da-qi1, QU Shi-ru1, LI Wei-bin2, HE Li1, “Image Enhancement Algorithm on Ridgelet Domain in Detection of Road Cracks,” China Journal of Highway and Transport, Vol.22, No.2, pp.26~31, 2009.

[12] LI Gang,H E Yu-yao, ZHAO Yan,“Automatic Recognition Algorithm of Pavement Defect Image Based on OTSU and Maximizing Mutual Information,” Microelectronics & Computer, Vol.26, No .7, pp. 241~247, 2009.