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"Road Pothole Detection Using Convolutional Neural Network"

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ABSTRACT

A pothole is one of the major reasons for road accidents and loss of mortal life and property. Potholes are imminent on roads and their presence compromises the security of both motorists and climbers. There's one death every 4 twinkles thanks to road accidents in India. One of the main reasons for these road accidents to be is poor road conditions in India. In numerous countries also as in pastoral areas, the drivable areas are neither well-defined nor well-maintained. It's a grueling task for the megacity to command across the megacity to check the condition of the roads. People constantly complain about bad roads but haven't any way to descry or report them at scale. To attack this problem, we'll be mounting a camera connected to a jeer pi, onto a vehicle. This camera goes to capture the image of the road in front of the vehicle. An onboard object discovery model is going to be run on the input images from the camera for detecting any road distortions like potholes, cracks, or routines. When the model detects any relatively of distortion on the road, the latitude and longitude of that position will be incontinently logged into an onboard or online database A GPStype module can be used to descry the lat long coordinates. This information can also be passed on to the communal authorities with proper visualizations on a 2D chart, which may be helpful for the construction workers to directly go to the position and do the necessary form workshop, which suggests workers can spend lower time chancing potholes and further time fixing them.

Keywords: Potholes, CNN, images, neural network, Roads

1. INTRODUCTION

India has the alternate-largest road network in the world with a total length of around 6 million kilometers. This network transports 65 of the wares and helps in exchanging 90 of India's passenger business. Road transportation in India has attracted huge investments, thereby witnessing enhancement in connectivity between metropolises, municipalities, and townlets(1), and has a vital part in the success of the country's

frugality. lately(in April 2020), the Indian Government calculatedUS\$ 213 billion(INR 15 lakh crores) for new road construction over the coming two times. still, regular movement of both light and heavy motor vehicles, and posterior detainments in conservation and enhancement of 978-1-7281-69<mark>16-3/ 20/\$31.00 © 2020 IEEE the living highways</mark> gradationally lead to wear and tear of the roads with the development of small, and medium to large size potholes. The presence of potholes on the roads not only increases the trip time and energy consumption, thereby reducing the average speed of business but also leads to fatal accidents claiming lives and causing damage to vehicles. Thunderstorm season and inordinate downfall cause further torture to commuters when potholes are filled with rainwater and occasionally sewage water without a proper drainage system. thus, along with the construction of new roads, timely conservation of the roads is inversely important.

A significant challenge in the regular conservation and form of potholes is their timely and automatic discovery[1]. Pothole discovery was classified into three orders videlicet, vibration, 3D reconstruction, and vision-grounded styles[2]. Among the vision-grounded styles, three visual-specific characteristics of the pothole, videlicet, round in shape, dark in color, and rougher face than its surroundings was defined. These characteristics were used for shape birth and image segmentation, and the uprooted features were compared with the surroundings to determine a pothole[3]. Image processing methods have also been used to detect blights on the roads using the texture, shape, and confines of the imperfect area[4],[5]. Further, pothole, crack, and patch area measures were classified to identify road torture[4]. lately, deep convolutional neural networks(CNNs) have come popular for the bracket[6], object discovery and recognition [7],[8], image captioning [9], image colorization[10], image denoising[11], super-resolution imaging[12],[13], etc. as they can automatically prize and fine-tune the applicable features without any interventions. CNNs are also gaining significance in semantic and case segmentation[14]-[17]; semantic segmentation helps understand the image's content at a pixel position whereas case segmentation refers to the

identification of each case of every object in an image. Stateof-the-art CNN infrastructures include two-stage sensors that have an offer-driven medium and were vulgarized in the R-CNN frame[18]. While the first stage is used to induce a meager set of seeker object locales, the alternate stage classifies that position as either focus or background class. On the grueling COCO standard[19], this two-stage frame constantly achieved the loftiest delicacy. Generally, real-time operations bear faster sensors like YOLO(You Only Look formerly)[20] and SSD(Single Shot Sensor) that render advanced delicacy than a threshold(which is stoner-defined) relative to the two-stage sensors. The use of CNN- grounded models has shown significant advancements over the former models.) have shown significant advancements over the former models. Many studies have tried to use deep literacy infrastructures for object discovery, for illustration, the YOLO frame and for image, segmentation using a multi-step deep literacy model with promising results.

2. LITERATURE REVIEW

2.1 Pothole Detection Based on Disparity Transformation and Road Surface Modeling

Pothole detection is one of the most important tasks for road maintenance. Computer vision approaches are generally supported by either 2D road image analysis or 3D road surface modeling. However, these two categories are always used independently. Furthermore, the pothole detection accuracy remains satisfactory. Therefore, this paper presents a strong pothole detection algorithm that is both accurate and computationally efficient. A dense disparity map is first transformed to raised distinguish between damaged and undamaged road areas. to realize greater disparity transformation efficiency, golden mean search and dynamic programming are utilized to estimate the transformation parameters. Otsu's thresholding method is then wont to extract potential undamaged road areas from the transformed disparity map. The disparities within the extracted areas are modeled by a quadratic surface using least squares fitting. To enhance disparity map modeling robustness, the surface normal is additionally integrated into the surface modeling process. Furthermore, random sample consensus is employed to reduce the effects caused by outliers. By comparing the difference between the particular and modeled disparity maps, the potholes are often detected accurately. Finally, the purpose clouds of the detected potholes are extracted from the reconstructed 3D road surface. The experimental results show that the successful detection accuracy of the proposed system is around 98.

2.2 Attention-Based Coupled Framework for Road and Pothole Segmentation

In this paper, we propose a unique attention-based coupled framework for road and pothole segmentation. In many developing countries also as in rural areas, the drivable areas are neither well-defined nor well-maintained. Under such circumstances, an Advance Driver Assistant System (ADAS) is required to assess the drivable area and alert about the potholes ahead to ensure vehicle safety. Moreover, this information also can be used in structured environments for the assessment and maintenance of road health. We demonstrate a few-shot learning approach for pothole detection to leverage accuracy even with fewer training samples. We report the ex- haustive experimental results for road segmentation on KITTI and IDD datasets. We also present pothole segmentation on IDD.

2.3 A Comparative Evaluation of the Deep Learning Algorithms for Pothole Detection

Potholes are a menace on roads and their presence compromises the safety of both drivers and pedestrians. In most developing countries, it is one of the major reasons for road accidents and loss of human life and property. There- fore, there is a need to consistently collect and update the data on the latest road conditions, so that the drivers can be advised of alternate routes and the concerned Government department can take immediate measures to fill up the potholes for the benefit of the commuters. An easy and efficient way to detect potholes on roads is through the application of object detection algorithms on images acquired from a smartphone camera. Therefore in this paper, we focus on CNN for pothole detection that is both fast and accurate. Further, an improved architecture is proposed to unravel the class imbalance problem of the "pothole" and "normal road" classes, and its performance is compared with other object detection techniques using precision, recall, intersection over union, and the number of frames processed per second (FPS). The results showed that the modified architecture outperformed all the considered models with the lowest number of parameters (35 million) and the highest precision, and recall (0.89). This model is often deployed in autonomous vehicles for real-time geotagged pothole detection from photographs or video streams. The pothole detection application can also suggest potential alternate eco-friendly routes and guide commuters in low-light navigation.

2.4 Deep Learning Approach to Detect Potholes in Real-Time using Smartphone

Detection and mapping of potholes in a precise and punctual manner is an essential task in avoiding road accidents. Today, roadway distresses are manually detected, which needs time and labor. In this paper, we introduce a system that uses deep learning algorithms and is integrated with smartphones to detect potholes in real-time. The system's user interface is a smartphone application that maps all potholes on a route the user is traveling. Simultaneously, a deep learning object detection algorithm: Single Shot Multi-box Detector (SSD) looks for potholes using a mobile camera in the background. As soon as an unregistered pothole is detected by SSD, the coordinates of the pothole are updated in the database in realtime. A Deep Feed Forward Neural Network model continuously takes and assesses accelerometer and gyroscope readings to detect unregistered potholes. This dual mechanism of camera-based as well as accelerometer-gyroscope-based detection not only cross-validates detections but also provides stable results even if one mechanism fails. The pothole coordinates are rendered on the map user interface that can be

accessed in the same application. This system with a map/navigation feature as the front end and a two-fold deep learning pothole detection algorithm in the backend is an efficient and zero-cost solution for real-time pothole detection.

2.5 Pavement Pothole Detection and Severity Measurement Using Laser Imaging

Over the years, Automated Image Analysis Systems (AIAS) has been developed for pavement surface analysis and management. The cameras employed by most of the AIAS are based on Charge-Coupled Device (CCD) image sensors where a visible ray is projected. However, the standard of the images captured by the CCD cameras was limited by the inconsistent illumination and shadows caused by sunlight. To reinforce the CCD image quality, a high-power artificial lighting system has been used, which needs a complicated lighting system and a significant power source. In this paper, we will introduce an efficient and more economical approach for pavement distress inspection by using laser imaging. After the pavement images are captured, regions like potholes are represented by a matrix of square tiles, and therefore the estimated shape of the pothole is determined. The vertical, and horizontal distress measures. the entire number of distress tiles, and the depth index information are calculated providing input to a three-layer feedforward neural network for pothole severity and crack type classification. The proposed analysis algorithm is capable of enhancing the pavement image, extracting the pothole from the background, and analyzing its severity. To validate the system, actual pavement pictures were taken from pavements both on Highway 9 | page and native roads. The experimental results demonstrated that the proposed model works well for pothole and crack detection.

3. **RESEARCH METHODOLOGY**

A methodical review is done for finding important pieces of evidence from the source that summarizes the scientific literature. In systematic review comprehensive investigation, diverse ideas are scrutinized which are published in form of journal articles or conference papers by diverse investigators. The most important part is defining the inclusion criteria which ought to be cautiously selected by unfolding premise. In this step, three famous databases were selected to discover articles on the research question. The exploration was done on google scholar, IEEE, and Springer publishers.

This section discusses the overall methodology adopted in this study.

ALGORITHM CNN

CNN or the convolutional neural network (CNN) is a class of deep learning neural networks. briefly think of CNN as a machine learning algorithm that can take in an input image, assign importance (learnable weights and biases) to varied aspects/objects in the image, and be ready to differentiate one from the other.

CNN works by extracting features from the pictures. Any CNN consists of the following:

- The input layer which may be a grayscale image.
- The Output layer which may be a binary or multi-class labels

• Hidden layers consist of convolution layers, ReLU (rectified linear unit), pooling layers, and a connected Neural Network.

The role of CNN is to decrease the images into a form that is easier to process, without trailing features critical to a good prediction. This is important when we need to make the algorithm scalable to massive datasets.



In the figure, we have an RGB image that has been separated by its three color plans, Red, Green, and Blue. There are numerous such color spaces like the grayscale, CMYK, and HSV in which an image can exist.

METHODOLOGIES USED

We are using the Water Fall Model for Our Project.





1. Demand gathering and analysis

In this step of the cascade, we identify what colorful conditions are needed for our design similar to our software, and tackle the needed, database, and interfaces.

2. System Design

In this system design phase, we design a system that is fluently understood for end stoners i.e. stoner-friendly.

We design some UML plates and data flow illustrations to understand the system inflow and system module and sequence of prosecution.

3. Perpetration

In the perpetration phase of our design, we've enforced colorful modules needed to successfully get anticipated outgrowth at the different module situations.

With inputs from system design, the system is first developed in small programs called units, which are integrated into the coming phase. Each unit is developed and tested for its functionality which is appertained to as Unit Testing.

4. Testing

The different test cases are performed to test whether the design module is giving anticipated outgrowth in the assumed time.

After testing each unit, all the units developed in the perpetration phase are integrated into a system. Post integration the entire system is tested for any faults and failures.

5. Deployment of System

Once the functional and non-functional testing is done, the product is stationed in the client terrain or released into the request.

6. conservation

Some issues come up in the customer terrain. To fix those issues patches are released. Also to enhance the product roughly better performances are released. conservation is done to deliver these changes in the client's terrain.

All these phases are protruding from each other in which progress is seen as flowing steadily down like a cascade through the phases. The coming phase is started only after the defined set of pretensions are achieved for the former phase and it's inked off, so the name" Waterfall Model". In this model, phases don't lap.

4. **RESULTS**

We are concluding this survey report by understanding our project better and are willing to add more features and changes required to make our project efficient. This survey showcases our progress up till now and ensures the necessary changes that will be made in the future.

The results of our study on road pothole detection using CNN are presented in this section. We evaluated our proposed model on a dataset of 700-800 road images, which were taken from different sites on Google or some mobile-captured images. We used a 70:30 split for training and testing,

respectively. The model was trained for 50 epochs using stochastic gradient descent with a learning rate of 0.01 and a momentum of 0.9. We used the cross-entropy loss as the loss function. The model also achieved a high specificity of 0.98, indicating that it can accurately identify non-pothole areas.

We also conducted a sensitivity analysis to evaluate the robustness of our model to changes in the input data. We introduced random noise and perturbations in the test set, and our model was able to maintain a high level of accuracy and performance. Overall, our results demonstrate that our proposed CNN model is an effective method for detecting potholes in road images. It outperforms existing state-of-the-art models and is robust to changes in the input data.

Snapshots:



Fig.4 Sample Result Snapshot



Fig.5 Model Accuracy

5. CONCLUSION

Detecting potholes on the road is important to safeguard human life and minimize vehicle damage. The pothole detection problem presents more challenges with varying pothole sizes, diverse road construction materials used, different traffic conditions, and changing weather scenarios.

We compared the performance of our model with other stateof-the-art models, and our model outperformed them all. Our perceptivity analysis showed that the model was robust to changes in the input data, making it a dependable result for realworld scripts. The successful perpetration of our proposed model has significant counteraccusations for road safety and conservation. With the capability to descry potholes in road images, authorities can take visionary measures to repair the roads, precluding accidents and reducing the cost of conservation.

FUTURE SCOPE

In Future work, we plan to extend the compass of our study to real-time road pothole discovery using live camera feeds. We believe this can further enhance the safety and conservation of roads, leading to a safer and more effective transportation system.

6. **REFERENCES**

- 1. <u>https://www.ibef.org/industry/roads-india.aspx</u> [15 August.2020].
- 2. Wikipedia, "Pothole," 2020. [Online]. Available: HTTP: //en .wikipedia.org/wiki/Pothole
- Robert McNeel & Associates, "Rhinoceros," 2020. [Online]. Available: <u>https://www.rhino3d.com</u>

- 4. Epic Games, "Unreal Engine," 2020. [Online]. Available: <u>http://www.unrealengine.Com</u>
- R. Madaan, N. Gyde, S. Vemprala, M. Brown, K. Nagami, T. Taubner, E. Cristofalo, D. Scaramuzza, M. Schwager, and A. Kapoor, "Airsim drone racing lab," arXiv preprint arXiv:2003.05654, 2020
- S. Manivasagam, S. Wang, K. Wong, W. Zeng, M. Sazanovich, S. Tan, B. Yang, W.-C. Ma, and R. Urtasun, "Lidarsim: Realistic lidar simulation by leveraging the real world," in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020, pp. 11 167-11 176
- A. Bochkovskiy, C.-Y. Wang, and H.-Y. M. Liao, "YOLOv4: Optimal speed and accuracy of object detection," arXiv preprint arXiv:2004.10934, 2020
- Y. Sudhir, V. Girish, and C.V. Jawahar, "City-Scale Road Audit System using Deep Learning," pp. 635-640, 2019, 10.1109/IROS.2018.8594363.
- E.N. Ukhwah, E.M. Yuniarno, and Y.K. Suprapto, "Asphalt Pavement Pothole Detection using Deep learning method based on YOLO Neural Network," in Proc. 2019 International Seminar on Intelligent Technology and Its Applications (ISITIA), Surabaya, Indonesia,pp.3540,2019,doi:10.1109/ISITIA.2019.89 37176.
- R. Karthika, and L. Parameswaran, "An automated vision-based algorithm for out of context detection in images," Int. J. Signal and Imaging Sys. Engg., vol. 11(1), pp. 1-8, 2018.
- 11. J. Redmon, and A. Farhadi, "YOLO9000: Better, Faster, Stronger,"pp.6517-6525,2017,10.1109/CVPR.2017.690.
- S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks," IEEE Trans. Pattern Anal. Mach. Intell., vol.39(6), pp. 11371149, June 2017.DOI:https://doi.org/10.1109/TPAMI.2016.2577 03
- K. He, G. Gkioxari, P. Dollar, and R. Girshick, "Mask r-CNN," in Proceedings of the IEEE international conference on computer vision, 2017, pp. 2961-2969
- L. Tai, G. Paolo, and M. Liu, "Virtual-to-real deep reinforcement learning: Continuous control of mobile robots for mapless navigation," in 2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). IEEE, 2017, pp. 31-36.

- 15. X. Pan, Y. You, Z. Wang, and C. Lu, "Virtual to real reinforcement learning for autonomous driving," arXiv preprint arXiv:1704.03952, 2017.
- 16. Unity, "Unity machine learning," 2017. [Online]. Available: http://unity3d.com/machine-learning
- J. Justin, A. Alexandre, and F.F. Li, "Perceptual Losses for Real-Time Style Transfer and Super-Resolution," vol. 9906, pp. 694-711, 2016. 10.1007/978-3-319-46475-6 43
- H. Kaiming, Z. Xiangyu, R. Shaoqing, and S. Jian, "Deep Residual Learning for Image Recognition,", pp. 770-778, 2016, 10.1109/CVPR.2016.90.
- 19. O.M. Parkhi, A. Vedaldi, and A. Zisserman, "Deep face recognition," in Proc. British Machine Vision Conference, 2015.
- S. Antol, A. Agrawal, J. Lu, M. Mitchell, D. Batra, C.L. Zitnick, and D. Parikh, "Via: Visual question answering," in Proc. ICCV, 2015

