

Smart Road Damage Detection and Warning using Machine Learning

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Abstract: *We present a neural network topology, as well as training and prediction algorithms, in this research. To create a safe road environment, we present a deep neural network technique to detect road surface deterioration conditions. For training and testing, we provide an image dataset as input. Various sorts of road anxiety are depicted in the photographs. The suggested approach is compared to a variety of deep learning models from different disciplines. The findings of this study are expected to play a significant role in guaranteeing safe driving in the future by effectively detecting poor road conditions.*

Keywords: Road Damage Detection.

I. INTRODUCTION

All countries' ROAD transportation networks are critical social and economic components. They are, however, collapsing all over the world, sometimes fatally, because to ageing, a lack of routine maintenance, or natural calamities. As a result of the poor road conditions, huge financial losses have occurred, as well as concerns about safety. According to the World Health Organization, vehicle accidents cause millions of injuries each year, with over 300,000 of them being seriously injured, resulting in 1.5 percent to 3% of global economic losses. Poor road conditions are a common cause of car accidents. Despite this, due to the massive road network volume and active real-world surroundings, monitoring road conditions is tough. The majority of the present road damage monitoring technique, which is subjective, labor-intensive, costly, and time-consuming, is done by certified inspectors. Furthermore, past research, such as, has primarily focused on diagnosing road degradation (e.g., cracking), with only a few academics involved.

II. LITERATURE SURVEY

Rui Fan, and Ming Liu, "Road Damage Detection Based on Unsupervised Disparity Map Segmentation." [1] This paper provides an unsupervised disparity map segmentation-based road damage identification technique. To begin, a disparity map is changed by minimising an energy function in relation to the stereo rig roll angle and the road disparity projection model. We find the numerical solution to this energy minimization problem instead of employing non-linear optimization approaches. The damaged road areas can then be retrieved from the altered disparity map using Otus's thresholding method. When detecting road damage, the suggested technique requires no parameters. The results of the experiments show that our suggested approach is both accurate and efficient. The accuracy of pixel-level road damage identification is around 97.56 percent. [https:// github.com/ruirangerfan/unsupervised-disparity-map-segmentation](https://github.com/ruirangerfan/unsupervised-disparity-map-segmentation). git is where you can find the source code.

Dongjun Jeong, "Road Damage Detection Using YOLO with Smartphone Images." [2] Deep learning-based technology holds the key to solving real-world object detection problems. We were able to solve a task that is risky and time-consuming yet must be done every day, such as detecting the state of the road, by employing deep neural networks. In the IEEE BigData Cup Challenge 2020, this article offers a method that uses YOLO to detect various types of road damage. Our YOLOv5x-based system is lightweight and quick, with high accuracy. Our ensemble model using TTA yielded an F1 score of 0.58, suggesting that it could be a good contender for detecting real-time road damage.

Tristan Hascoet; Yihao Zhang, Andreas Persch "FasterRCNN Monitoring of Road Damages: Competition and Deployment" [3] Local and national authorities all around the world are grappling with the difficulty of maintaining aged infrastructure. Continuously monitoring (i.e., quantifying the level of safety and reliability) the state of very big structures is a crucial prerequisite for efficient infrastructure maintenance.

Meanwhile, computer vision has advanced significantly in recent years, owing largely to the effective implementation of deep learning models. These breakthroughs enable the automation of previously impossible-to-automate vision activities, opening up intriguing opportunities to help administrators optimise their infrastructure maintenance operations. In this regard, the IEEE 2020 worldwide Road Damage Detection (RDD) Challenge invites deep learning and computer vision researchers to participate and contribute to the accurate tracking of pavement deterioration on road networks. Two additions to the problem are proposed in this paper: In the first part, we explain how we solved the RDD Challenge. In the second section, we describe our efforts to install our model on a local road network, including the recommended technique and problems encountered.

Yu-Lin Jeng, Sheng-Bo Huang, and Chin-Feng Lai, "Inspect Road Quality by Using Anomaly Detection Approach. "[4] Road quality can reflect a country's development status and have an impact on travel speeds and safety. There is, however, no standard or set of laws in place to safeguard people from the dangers of damaged roadways. The popularity and broad usage of cellphones, as well as the recent rapid growth of information technology and machine learning algorithms, have enabled this study to suggest a method for evaluating road quality. The suggested inspection technique is a smartphone-based road quality inspection app that gathers raw data from smartphone sensors such as GPS and accelerator sensors. Once the data has been acquired, the proposed system's server uses an anomaly detection algorithm to interpret the oscillation amplitude of a specific segment of road. The estimated results are then imported into the Google Maps app, where aberrant road segments are highlighted in different colours.

Naoki Wada, Kenji Kanai, Masaru Takeuchi, Jiro Katto, "Road Crack Detection using U-Net" [5] Recently, it has become necessary to have an effective and automated infrastructure maintenance service. To meet this demand, we present a U-Net-based segmentation-based road damage detection approach in this study. To train the model, we use a smartphone mounted on a bicycle to take 4K photos and create our own road damage dataset. In addition, we use focus loss and image patch for the loss function and input picture, respectively, to improve detection accuracy. The results of the study show that the method is capable of extracting road damages with acceptable accuracy.

Vung Pham, Chau Pham, Tommy Dang," Road Damage Detection and Classification with Detectron2 and Faster R-CNN "[6] Many areas of life are dependent on the road, and road upkeep is critical for human safety. One of the most important jobs in allowing for timely road damage repair is to promptly and accurately detect and classify the damage. The tactics and experiments that were examined for these tasks are detailed in this paper. Detectron2's implementation of Faster R-CNN is evaluated using several base models and parameters. The Global Road Damage Detection Challenge 2020, A Track in the IEEE Big Data 2020 Big Data Cup Challenge dataset, is being used to test these algorithms. The results suggest that the X101-FPN base model for Faster R-CNN with Detectron2's default configurations is effective and general enough to be applied to diverse countries in this challenge. For the test1 and test2 sets of the challenge, this strategy yields F1 scores of 51.0 percent and 51.4 percent, respectively. The F1 scores are poor, despite the fact that the visualisations show good prediction outcomes. As a result, we compare the prediction findings to the current annotations and find some inconsistencies. As a result, we propose ways for improving the dataset's tagging process.

Sadra Naddaf-Sh1, M-Mahdi Naddaf-Sh1, Amir R. Kashani2, Hassan Zargarzadeh1," An Efficient and Scalable Deep Learning Approach for Road Damage Detection "[7] The ability to time preventative or rehabilitative actions and manage the spread of distress is dependent on the quality of the pavement. Failure to conduct timely reviews can result in serious infrastructure structural and financial losses, as well as entire reconstructions. A database of road damage patterns and their locations can be created using automated computer-aided surveying methods. This database can be used to make timely road repairs, resulting in lower maintenance costs and greater asphalt longevity. This research proposes a deep learning-based surveying strategy for real-time analysis of image-based distress data. The researchers employed a database that included a wide population of crack distress kinds such as longitudinal, transverse, and alligator cracks that were taken with a mobile device. Then there's a set of efficient and scalable models that have been fine-tuned for pavement crack spotting is a skill that can be learned.

III. PROPOSED SYSTEM

To detect road surface deterioration, we present a deep neural network technique. We Use the CNN algorithm for training and testing. We provide security through our application.

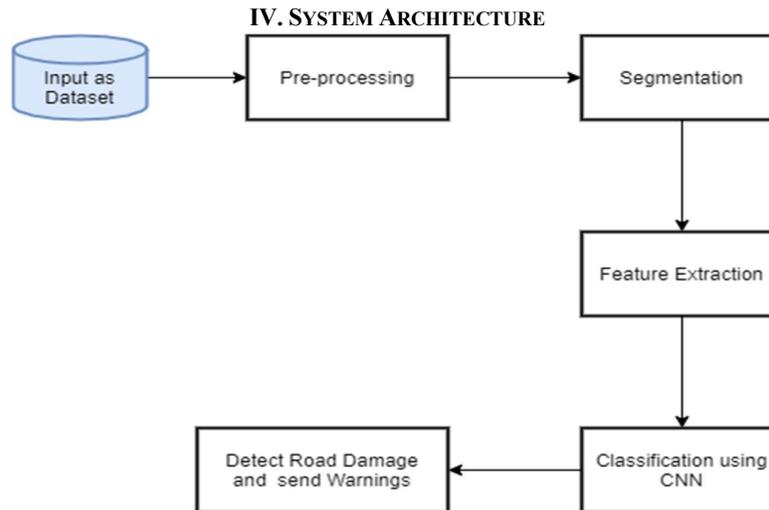


Figure: System Architecture

V. ALGORITHM

CNN stands for Convolutional Neural Networks, which are specialized for image and video recognition applications. Image recognition, object detection, and segmentation are among of the most common image analysis tasks that CNN is employed for. Convolutional Neural Networks have four different sorts of layers:

1. Convolutional Layer: Each input neuron in a conventional neural network is linked to the next hidden layer. Only a small portion of the input layer neurons connect to the hidden layer neurons in CNN.
2. Pooling Layer: The pooling layer is used to minimise the feature map's dimensionality. Inside the CNN's hidden layer, there will be several activation and pooling layers.
3. Flatten: Flattening is the process of transforming data into a one-dimensional array for use in the next layer. To construct a single lengthy feature vector, we flatten the output of the convolutional layers.
4. Fully Connected Layers: Fully Connected Layers are the network's final layers. The output from the final Pooling or Convolutional Layer, which is flattened and then fed into the fully connected layer, is the input to the fully connected layer.

V. CONCLUSION

Road damage detection is essential for road maintenance, which typically involves a lot of manual labour. In order to detect road damage fast, we employ deep learning models to analyse road photos in our system. In order to identify extremely accurate and efficient models, we particularly train and test a number of deep learning algorithms.

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