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Real-time Pothole Detection using YOLOv5 Algorithm: A Feasible Approach for Intelligent Transportation Systems

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***Abstract*— Potholes are a significant concern for maintaining safe and efficient daily commutes. This research work focuses on applying YOLO V5, a state-of-the-art deep learning model for object identification, to edge devices for detecting potholes on highways. The proposed model evaluates the performance of YOLO V5 on a dataset of images, including potholes in varying road conditions and illumination fluctuations, as well as on real-time video acquired from a moving car. In order to identify potholes in moving cars in real time, the YOLO V5 model needs to have high accuracy and a fast frame rate. Our study shows that YOLO V5 is an effective deep-learning model for pothole detection and can be deployed on edge devices for real time detection. The high accuracy and fast processing speed of YOLO V5 make it a suitable model for moving vehicles, helping improve road safety and reduce the risk of accidents caused by potholes. Furthermore, the YOLO V5 model has been demonstrated to be lightweight and run on edge devices with low computational power. The results demonstrate the feasibility of using YOLOv5 for real-time pothole detection and pave the way for developing intelligent transportation systems that automatically detect and alert drivers to road hazards.**

Keywords— Artificial intelligence (AI), Pothole detection, traffic flow, Deep Learning, YOLO V5, Machine Learning.

I. INTRODUCTION

Pothole detection is an important technology that can help to identify and locate potholes on roads, streets, and highways. Potholes can be a hazard to drivers, cyclists, and pedestrians and can cause accidents, damage vehicles, and lead to injuries or even fatalities. Pothole detection can help to identify and repair these hazards before they cause harm. Repairing potholes can be expensive, and the cost increases if they are not detected and repaired promptly. Pothole detection can help identify and repair potholes before they become more extensive and costly to fix. Additionally, infrastructure maintenance plays a significant role in the regular monitoring and maintenance of road infrastructure, can help to prolong its life and reduce the need for expensive repairs. Pothole detection can be part of a larger infrastructure maintenance program to help keep roads and streets in good condition. Further, pothole detection can help identify potholes' exact location and size, which can be useful information for road maintenance crews. This information can help to prioritize repairs and allocate resources efficiently. Potholes can contribute to environmental pollution by increasing fuel consumption, emissions, and noise levels. Pothole detection and repair can help reduce the negative environmental impact. Henceforth, pothole detection is significant because it can improve safety, reduce costs, prolong infrastructure life, increase efficiency, and reduce environmental impact.

Artificial intelligence (AI) can play an essential role in pothole detection by enabling automated and accurate identification of potholes. AI can be trained to recognize potholes from images captured by cameras mounted on vehicles or drones. By analyzing potholes' size, shape, and depth, AI algorithms can accurately detect potholes and alert maintenance crews to their location. AI can also be used to analyze data from road sensors, such as accelerometers and GPS receivers, to identify areas with high levels of road roughness. This data can help to identify potential pothole locations and prioritize repairs. Further, AI can analyze weather patterns, traffic volume, and road usage data to predict when potholes will likely form. Maintenance crews can proactively repair roads before potholes appear by identifying areas with a high risk of pothole formation. AI can automatically generate reports on potholes' location, size, and severity, which can help maintenance crews prioritize repairs and allocate resources more efficiently. AI can also be used to manage large amounts of data related to pothole detection and repair, such as images, sensor data, and repair records. By organizing this data and making it easily accessible, AI can help maintenance crews make more informed decisions about road repairs. Therefore, AI can be used for image recognition, sensor data analysis, predictive maintenance, automated reporting, and data management to improve pothole detection and repair. By leveraging AI technology, road maintenance crews can more efficiently identify and repair potholes, leading to safer roads, reduced costs, and improved infrastructure maintenance.

Artificial intelligence (AI) is broken down into many subfields, one of which is machine learning. In machine learning, algorithms are used to search for patterns in data. Machine learning can be applied to pothole detection by using large datasets to train algorithms to recognize patterns associated with potholes. Machine learning algorithms can be trained to recognize potholes in images captured by cameras mounted on vehicles or drones. By using labeled images of potholes and non-pothole areas, the algorithms can learn to identify the visual patterns associated with potholes. In addition to recognizing visual or sensor patterns, machine learning can also be used to identify key features associated with potholes. For example, machine learning algorithms can identify potholes' depth, size, and location based on image or sensor data. Machine learning can be used to identify anomalous patterns in road data, such as sudden changes in road roughness. This can help identify potential potholes before they become dangerous to drivers.

The proposed scheme employs YOLO, a well-known object recognition approach that uses deep learning to identify and locate items inside an image. YOLO v5 can be used to recognize potholes in images captured by cameras mounted on vehicles or drones. By training the algorithm on labeled images of potholes and non-pothole areas, YOLO v5 can accurately detect the presence and location of potholes in real-time. It is optimized for speed, allowing it to detect potholes in real time. This can be especially useful for detecting potholes while driving or for monitoring large areas quickly and efficiently. Further, YOLO v5 is optimized for accuracy, which means it can reliably detect potholes even in challenging lighting or weather conditions. This can help to ensure that all potholes are accurately identified and repaired. Additionally, YOLO v5 can be used to detect potholes across large areas, such as highways or city streets. By analysing a large number of images, YOLO v5 can identify potholes that human inspectors might have missed.

II. LITERATURE REVIEW

In recent years, sensor-based technologies have gained significant attention in the field of pothole detection. One such sensor-based network is "BusNet", which utilizes a camera mounted on public transport buses and various other sensors and GPS to effectively monitor road conditions [1]. This system has been proven to be fast, sensitive, and cost-efficient. However, it is not suitable for all conditions, as weather can damage the sensors and decrease performance. Another popular sensor-based approach is the use of vibration sensors, which detect changes in the road surface and can indicate the presence of potholes [2]. Thermal imaging has also been used as a means of pothole detection, as it can detect differences in temperature that may be caused by potholes. Despite the effectiveness of these sensor-based methods, computer vision and image processing techniques have become increasingly popular in recent years. The widespread availability of inexpensive cameras has made it more feasible to implement these techniques, and they have been shown to be a viable replacement for manual inspection methods [3]. However, image processing-based pothole detection is still a challenging task, as it requires the ability to detect irregular pothole textures, structures, and other road features such as bumps, manholes, and shadows. In recent research, various computer vision-based approaches have been studied to address this challenge. In one study, a cost-effective solution was proposed that utilizes image processing techniques to detect and classify potholes. The system model was able to achieve an accuracy of 88.4% and was found to be less time-consuming than manual methods [4]. Another approach utilized the discrete wavelet transform to detect pavement distress, while yet another method proposed the use of discolorations to detect potholes. While these methods have shown promise, they are not without their limitations. For example, discolorations may not always indicate the presence of a pothole, as they may also be caused by other factors such as road markings, shadows, and wet roads [5]. Various sensor-based and computer vision-based methods have been proposed for pothole detection, each with their own advantages and disadvantages. The BusNet which uses a camera mounted on public transport buses is one of the most efficient methods among all. However, further research is needed to improve the effectiveness and reliability of these methods, and to develop new approaches that can overcome the limitations of existing methods [6,7].

In recent years computer vision and image processing-based techniques have gained popularity for pothole detection due to the accessibility of inexpensive cameras [8]. One such software that has been widely studied is YOLO (You Only Look Once), a real-time object detection system. YOLO is a convolutional neural network (CNN) based system that is able to detect and classify objects in an image or video in a single pass. The algorithm is able to process images in real-time and has been widely used in various applications such as traffic monitoring, surveillance, and self-driving cars. In the context of pothole detection, YOLO has been used to detect and classify potholes in road images. The system is trained on a dataset of images of roads with and without potholes, and is able to detect potholes in new images with high accuracy [9]. One of the key advantages of YOLO is its ability to process images in real-time, making it suitable for use in a variety of applications such as monitoring road conditions in real-time. Additionally, YOLO is also able to accurately detect irregularly shaped potholes, which is a common challenge in pothole detection using image processing techniques [10-12]. Overall, YOLO is a powerful software for pothole detection, and has been widely studied and used in the literature. Its real-time processing ability and high accuracy make it a suitable choice for a variety of pothole detection applications

The use of embedded systems in pothole detection has gained significant attention in recent years [13]. This is due to the increasing demand for real-time monitoring and automated systems that can detect and classify potholes efficiently. Embedded systems are used to integrate sensing, computation, and control functionality into a single device, making them suitable for pothole detection [14]. These systems typically consist of a microcontroller, memory, and peripherals such as sensors, cameras, and GPS. One example of an embedded system used for pothole detection is the sensor-based network "BusNet" [9]. This system utilizes sensors and GPS mounted on public transport buses to monitor road conditions. However, the performance of this system may be affected by weather conditions that may damage the sensors. Another example is the proposed cost-effective solution for pothole detection and severity estimation based on image processing techniques [15]. This system utilizes a lightweight camera to overcome shadow effects and achieve an accuracy of 88.4%. Additionally, the use of embedded systems allows for real-time monitoring and the ability to transmit data wirelessly, making it possible to remotely monitor and maintain road conditions. Overall, the use of embedded systems in pothole detection provides a promising solution for efficient and accurate road monitoring.

III. PROPOSED SYSTEM

In order to effectively detect potholes in real-time, the proposed methodology utilizes the YOLO V5 deep learning model. The process begins with the explicit annotation of collected dataset images, which are then split into training and testing data. These data are then fed into the YOLO V5 model for custom training, with the obtained weights used to evaluate the model's performance on the testing data. These custom weights are then converted into the OpenVino IR format, allowing for real-time detection to be performed on the OAK-D. The quality and effectiveness of the pothole detection model heavily rely on the dataset used for training. To ensure the model's performance and reliability, it is essential to use a dataset that contains realistic pothole images. In this research, the latest publicly available pothole image dataset is utilized, consisting of 850 images that simulate real-world scenarios and factors such as shadows, moving vehicles, and illumination variations. The images of the dataset are sourced from the internet, including both high and low-quality images.

The YOLO v5 working process can be broken down into Image pre-processing, non-maximum suppression, Class predictions and confidence scores and Final object detection. The input image is resized to a fixed size and normalized to adjust for differences in lighting and contrast. Forward pass through the network: The image is fed into the YOLO v5 network, which consists of multiple convolutional and activation layers. The network outputs a set of predictions for each grid cell in the image. The predictions for each grid cell are combined and overlapping bounding boxes are removed to produce a set of final bounding boxes for the objects in the image. The network outputs class probabilities for each object and the confidence scores for each bounding box. The bounding boxes with the highest confidence scores are selected as the final detections and displayed on the input image.

In the proposed model, YOLO v5 is used for pothole detection by training the model on a dataset of images containing potholes and non-potholes. During training, the model learns to associate specific features with potholes, such as shape, texture, and color. Once trained, YOLO v5 can be used to detect potholes in new images by processing them through the network and outputting bounding boxes around detected potholes. The confidence scores for each bounding box can be used to determine the accuracy of the pothole detections. Henceforth, YOLO v5 can be integrated into systems such as autonomous vehicles or road maintenance tools to detect and locate potholes in real-time, helping to improve road safety and efficiency.

YOLO v5 can be used to perform real-time object detection on video captured from cameras or other sources. The video is fed into the YOLO v5 model as a sequence of individual frames. Each frame is processed by the YOLO v5 network to detect objects within the frame. The network outputs the location and class of each object detected in the frame. The overlapping bounding boxes are removed using non-maximum suppression to produce a set of final detections for each frame. The network outputs class probabilities for each object and the confidence scores for each bounding box. The final detections are displayed on each frame of the video, producing an annotated real-time video output.

A. *Proposed Architecture of a pothole detection model using yolo V5 model*

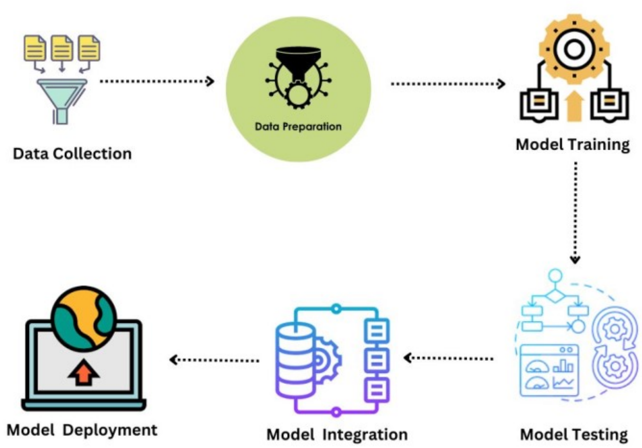

Fig 1: Proposed Yolo v5 model-based Pothole Detection

The YOLOv5 algorithm uses a convolutional neural network to detect objects in images. The algorithm works by dividing the image into a grid and predicting the presence, location, and class of objects in each grid cell. The YOLOv5 model is trained on a large dataset of images and can detect objects with high accuracy and speed. Further, to apply the YOLOv5 algorithm to pothole detection, modification of the train model to detect potholes instead of general objects. This would involve training the model on a dataset of pothole images and adjusting the network architecture and parameters to optimize pothole detection performance. Once the model is trained, it can be integrated into a pothole detection system that can process images in real-time and alert drivers or authorities about potholes' presence, as mentioned in figure 1.

1. Data collection: Collect a large dataset of images containing potholes and non-potholes.
2. Data preparation: Label the images with annotations to indicate the location of potholes in the images.
3. Model training: Train a YOLOv5 model on the annotated dataset.
4. Model testing: Test the trained model on a separate dataset to evaluate its performance.
5. Integration: Integrate the trained model into a pothole detection system that can process images in real-time.
6. Deployment: Deploy the pothole detection system in the target environment, such as on a vehicle or on a surveillance camera.

B. Algorithm for pothole detection using YOLOv5:

Input *A set of images containing roads and potholes.*

Step 1: *Label the images with annotations and split the dataset into training, validation, and testing sets.*

Step 2: *Train a neural network on the annotated dataset.*

Step 3: *Monitoring and validation to ensure that the model is not overfitting the training data*

Step 4: *Load the trained model and an input image containing a road.*

Step 5: *Pass the image through the model to obtain a set of predicted bounding boxes around potential potholes.*

Step 6: *Apply non-max suppression to remove redundant bounding boxes and retain only the most likely ones.*

Output: *Bounding boxes around detected potholes.*

The proposed hybrid yolov5 algorithm has specific details of each step which may vary depending on the specific application and dataset.

C. Proposed YOLOv5 algorithm mechanism

The YOLOv5 algorithm takes an input image and resizes it to a fixed size. The algorithm can handle various input image sizes. The input image is passed through a convolutional neural network (CNN), which extracts a set of features from the image as mentioned figure 2. The CNN typically consists of several convolutional layers, followed by activation functions and pooling layers. The purpose of the CNN is to learn features that are useful for object detection. The feature map obtained from the CNN is then used to predict the presence of objects in the image. The YOLOv5 algorithm divides the feature map into a grid of cells and indicates a set of bounding boxes for each cell. Each bounding box contains information about the location, size, and confidence level of the detected object. The algorithm applies a non-max suppression algorithm to remove redundant bounding boxes and retain only the most likely ones. The YOLOv5 algorithm uses a classification head to predict the class of the detected object. The classification head is typically a fully connected layer that takes as input the features extracted by the CNN and the coordinates of the bounding boxes. The proposed algorithm applies some post-processing steps to refine the output, such as thresholding the confidence scores and eliminating small or irrelevant objects.

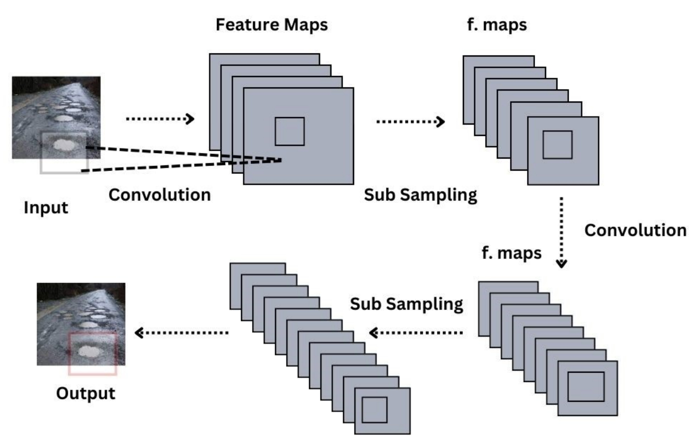

Fig 2: Proposed YOLOv5 algorithm mechanism

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The proposed algorithm is trained on a large dataset of images with annotations of object locations and class labels. During training, the algorithm optimizes the network parameters to minimize a loss function that measures the discrepancy between the predicted and ground truth bounding boxes and class labels. The proposed algorithm uses backpropagation to update the weights of the network, and it can be fine-tuned on a specific task, such as pothole detection, by using a customized dataset and loss function.

IV. PERFORMANCE ANALYSIS

To completely assess a model's efficacy, precision and recall must be examined. Unfortunately, precision and memory are frequently in conflict. In other words, increasing accuracy usually decreases recall and inversely as mentioned in figure 3 and figure 4. Increasing accuracy reduces the number of false positives, while increasing recall reduces the number of false negatives. With accuracy, we are categorizing the positive class, a sample of the positive class, which decreases recall. With recall, attempt is made not to overlook any positive class samples, allowing numerous false positives to slip in and diminishing accuracy.

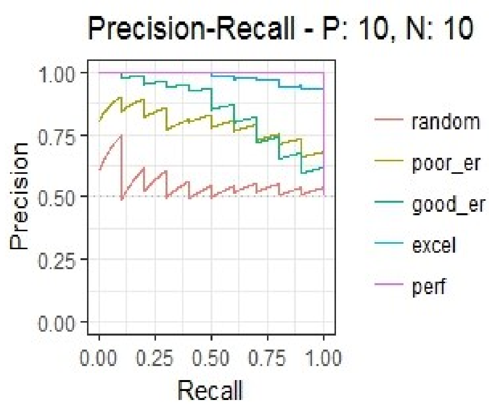

Fig 3: Performance Analysis –Precision Vs Recall - Before error detection

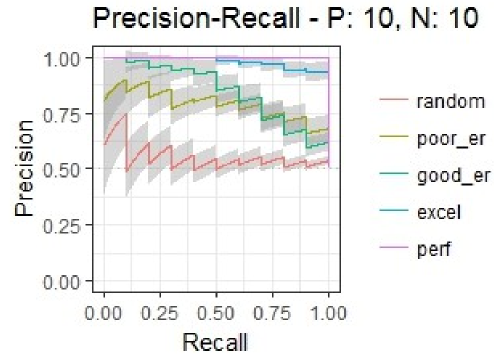

Fig 4: Performance Analysis – Precision Vs Recall - After error deduction

The accuracy of the suggested approach may be determined by dividing the number of accurate positive (+VE) forecasts by the total number of positive (+VE) predictions.

V. CONCLUSION

This article presents a method for pothole detection using the YOLOv5 object detection algorithm. The proposed approach utilizes a dataset of road images containing various pothole types and sizes to train the YOLOv5 algorithm. The proposed algorithm shows promising results for pothole detection in real-time. The proposed approach achieved high accuracy and processing speed, which is essential for developing a robust system for detecting potholes in real-world scenarios. With the increasing number of vehicles on the road, detecting potholes automatically can significantly prevent accidents and reduce road maintenance costs. The YOLOv5 algorithm's ability to detect potholes of various sizes and types makes it a reliable solution for pothole detection on roads. Further research can be conducted to improve the detection system's accuracy, such as incorporating additional features to differentiate potholes from other road defects. Overall, the proposed method can be a significant step forward in the development of intelligent transportation systems that can enhance road safety and reduce maintenance costs.

REFERENCE

[1] M. V. Thekkethala and S. Reshma, "Pothole detection and volume estimation using stereoscopic cameras", Proc. Int. Conf. Mixed Design Integr. Circuits Syst., pp. 47-51, 2016.

[2] Kumar, Chakrapani, D. J. Kalita and V. P. Singh, "A Modern Pothole Detection technique using Deep Learning," 2nd International Conference on Data, Engineering and Applications (IDEA), Bhopal, India, 2020, pp. 1-5, doi: 10.1109/IDEA49133.2020.9170705.

[3] M. Ghadge, D. Pandey and D. Kalbande, "Machine learning approach for predicting bumps on road", *Proc. Int. Conf. Appl. Theor. Comput. Commun. Technol.*, pp. 481-485, Oct. 2015.

[4] C. Ng, T. Law, F. Jakarni, and S. Kulanthayan, "Road infra-structure development and economic growth," in IOP con-

ference series: materials science and engineering, vol. 512, no. 1, Article ID 012045, IOP Publishing, 2019.

[5] V. Pereira, S. Tamura, S. Hayamizu and H. Fukai, "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, 2018, July.

[6] Alfred Daniel, J., Chandru Vignesh, C., Muthu, B.A. et al. Fully convolutional neural networks for LIDAR–camera fusion for pedestrian detection in autonomous vehicle. Multimed Tools Appl (2023). https://doi.org/10.1007/s11042-023-14417-x

[7] Rajmohan G, Chinnappan CV, John William AD, Chandrakrishan Balakrishnan S, Anand Muthu B, Manogaran G. Revamping land coverage analysis using aerial satellite image mapping. Transactions on Emerging Telecommunications Technologies. 2021 Jul;32(7):e3927.

[8] Daniel A, Subburathinam K, Anand Muthu B, Rajkumar N, Kadry S, Kumar Mahendran R, Pandian S. Procuring cooperative intelligence in autonomous vehicles for object detection through data fusion approach. IET Intelligent Transport Systems. 2020 Nov;14(11):1410-7.

[9] Muhammad Haroon Asad, Saran Khaliq, Muhammad Haroon Yousaf, Muhammad Obaid Ullah, Afaq Ahmad, "Pothole Detection Using Deep Learning: A Real-Time and AI-on-the-Edge Perspective", Advances in Civil Engineering, vol. 2022, Article ID 9221211, 13 pages, 2022. https://doi.org/10.1155/2022/9221211

[10] Alfred Daniel, J., Chandru Vignesh, C., Muthu, B.A. et al. Fully convolutional neural networks for LIDAR–camera fusion for pedestrian detection in autonomous vehicle. Multimed Tools Appl (2023). https://doi.org/10.1007/s11042-023-14417-x

[11} A. K. M. Jobayer Al Masud, S. T. Sharin, K. F. T. Shawon and Z. Zaman, "Pothole Detection Using Machine Learning Algorithms," 2021 15th International Conference on Signal Processing and Communication Systems (ICSPCS), Sydney, Australia, 2021, pp. 1-5, doi: 10.1109/ICSPCS53099.2021.9660216.

[12] S. Hegde, H. V. Mekali and G. Varaprasad, "Pothole detection and inter-vehicular communication", IEEE International Conference on Vehicular Electronics and Safety, pp. 84-87, 2014.

[13] E. J. Reddy, P. N. Reddy, G. Maithreyi, M. B. C. Balaji, S. K. Dash and K. A. Kumari, "Development and Analysis of Pothole detection and Alert based on NodeMCU", 2020 International Conference on Emerging Trends in Information Technology and Engineering (ic-ETITE), pp. 1-5, 2020.

[14] P. Ping, X. Yang and Z. Gao, "A Deep Learning Approach for Street Pothole Detection", 2020 IEEE Sixth International Conference on Big Data Computing Service and Applications (BigDataService), pp. 198-204, 2020.

[15] H. Maeda, Y. Sekimoto, T. Seto, T. Kashiyama and H. Omata, "Road Damage Detection and Classification Using Deep Neural Networks with Smartphone Images: Road damage detection and classification", Computer-Aided Civil and Infrastructure Engineering, vol. 33, June 2018.