Pothole Detection using TINYML

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Abstract - Potholes present a widespread issue on roadways globally, causing vehicle damage, accidents, and posing safety concerns for drivers and pedestrians. Detecting these potholes involves identifying and pinpointing their locations, a process traditionally performed manually by road inspectors, which is both time-consuming and ineffective. The complexity of pothole detection arises from their varying sizes, shapes, and depths, often obscured by shadows, debris, or other road features, making them challenging to discern. However, automated pothole detection systems are gaining popularity due to their ability to swiftly and accurately identify potholes across extensive areas. As technology advances, particularly with the refinement of machine learning algorithms, these automated systems are becoming increasingly precise and efficient. This progress holds promise for enhancing road safety and reducing the financial burden associated with road maintenance.

***Key Words*:** TinyML, Edge-computing, Fomo mobileNet v2, Pothole detection.

1.INTRODUCTION

In today's dynamic landscape, characterized by thriving urbanization and transportation networks, ensuring the safety of our roadways is of utmost importance. Potholes, enduring imperfections in roads, pose significant risks to drivers, leading to accidents, vehicle damage, and imposing substantial maintenance expenses on road authorities.

The integration of an advanced TinyML (Tiny Machine Learning) model with a camera-based system, operating independently without reliance on cloud services, presents a comprehensive solution to address these safety concerns.

This innovative approach leverages real-time data analysis and predictive capabilities, facilitating a prompt response to road hazards. In addition to the immediate benefits of detecting potholes in real time and alerting drivers to potential dangers, this system extends its functionality to include the detection of speed breakers.

By providing drivers with real-time alerts to navigate speed breakers, it minimizes jolts and enhances overall road safety.

2. METHODOLOGY

Detecting potholes using TinyML (Tiny Machine Learning) models involves creating a compact and efficient machine-learning model that can run on resource-constrained devices like microcontrollers.

Methodology for pothole detection using TinyML.

1. *Preprocessing (Data collection):* Gathered images of roads with and without potholes.

2. *Data labeling*: Annotated images to indicate the presence of potholes.

3. *Data augmentation:* Applied techniques such as flipping, rotation, and scaling to increase dataset diversity.

4. *Normalization:* Ensured uniformity in pixel values across images.

5. *Model Selection:* Edge Impulse FOMO (Faster Objects, More Objects) is a novel machine learning algorithm that brings object detection to highly constrained devices. It lets you count objects, find the location of objects in an image, and track multiple objects in real-time using up to 30x less processing power and memory than MobileNet SSD or YOLOv5.

6. *Defined training parameters*: Batch size, learning rate, and number of epochs. Utilized regularization techniques to prevent overfitting. Evaluated model performance using metrics such as accuracy, precision, and recall. Model training is a critical phase in developing a pothole detection system using TinyML.

7. *Hardware selection:* Opted for Raspberry Pi as the deployment platform. Considered factors such as cost, size, power consumption, and computational capabilities. Evaluated alternatives and justified selection based on project requirements.

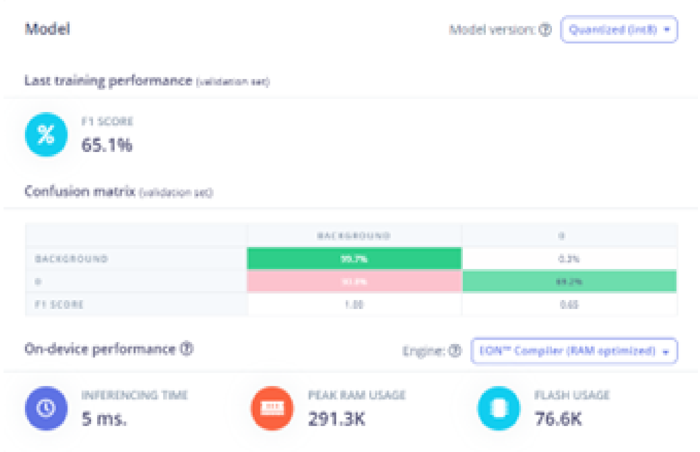

Fig 2.1: FOMO (Faster Objects, More Objects) MobileNetV2 0.1

8. *Deployment* In the deployment phase of our pothole detection system using TinyML, we focused on ensuring that our trained model could be seamlessly integrated into real-world applications, particularly on resource-constrained devices like the Raspberry Pi.

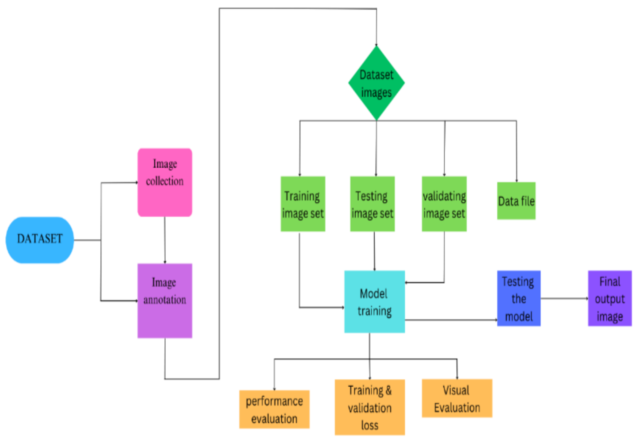

Fig 2.2: Model workflow

3. LITERATURE REVIEW

J. R. Terven et al.,[1] conducted a comprehensive analysis of the evolution of the YOLO framework from versions 1 to 8, encompassing variants such as YOLO-NAS and Transformer. Their study delved into various object detection metrics such as AP, IoU, and NMS, evaluated across datasets like PASCAL VOC and COCO. They highlighted the wide-ranging applications of YOLO across different domains and suggested future research directions, including enhancements in localization, model simplicity, category diversity, attention integration, and the adoption of self-supervised learning techniques.

I. Viktorov et al.,[2] present a novel approach utilizing machine learning to automate code parallelization. Their study evaluates current code parallelization tools and explores the potential of machine learning in optimizing code, particularly for multicore processors. Introducing a microservices-based architecture, the research compares different NLP models and neural network structures for code transformation, proposing a two-phase algorithm. This research serves as a valuable resource for researchers and practitioners seeking to enhance code optimization through the integration of machine learning techniques.

D. Coskun et al.,[3] conducted a comparative analysis of YOLO models for mammogram mass detection, presenting a novel Swin Transformer-enhanced YOLOv5 variant. Their study surveyed existing breast cancer research and evaluated the performance of the models on the INbreast dataset. The findings indicate that the transformer-based YOLO model outperforms others in terms of average precision, recall, mean average precision, F1-score, and robustness across diverse image sizes and augmentation techniques.

C. Saisree et al.,[4] presented a survey focusing on pothole detection utilizing deep learning algorithms for both muddy and highway roads, aiming to tackle the vital task of automating road defect identification. Potholes represent a substantial hazard to road safety and vehicle upkeep, with manual detection methods proving time-consuming and frequently inaccurate.

Dong-Hoe Heo et al.,[5] introduced a novel algorithm for pothole detection in 2D images, leveraging a modified version of YOLOv4. This approach combines spatial pyramid pooling (SPP) and feature pyramid network (FPN) to extract more comprehensive features from images. Additionally, the paper presents an innovative risk assessment algorithm, which categorizes potholes into three severity levels (danger, safety, and caution) by comparing their size with the tire contact patch size.

Eur. Chem. Bull [6] presents a study on gesture recognition utilizing TinyML and the Wio Terminal, a groundbreaking project that integrates machine learning models with the compact and adaptable Wio Terminal microcontroller for real-time hand gesture recognition. Through training a Convolutional Neural Network on a dataset of actual hand gestures and deploying it on the Wio Terminal, the project achieves precise recognition and classification of hand gestures, with corresponding actions displayed on the terminal's LCD screen..

C. H. Brighton et al.,[7] provided an overview of current research on vehicle detection and speed estimation, covering multiple perspectives including frame differencing, motion-based approaches, camera motion, occlusion, diverse vehicle types, congested traffic scenarios, illumination variations, and moving speed analysis.

Antolin et al.,[8] explored adaptive cruise control (ACC) and autonomous emergency braking (AEB) systems, facilitating vehicles to maintain a safe following distance by monitoring the speed of preceding vehicles. The study also delved into diverse sensor technologies for speed detection, such as radar and lidar, comparing their effectiveness across various scenarios.

F. L., Jiang et al.,[9] conducted a review on an ultra-low power TinyML system designed for real-time visual processing at the edge. The system comprises a compact backbone for constructing efficient CNN models and a custom-designed neural co-processor (NCP) connected to an ultra-low-power microcontroller unit (MCU).

M. Xu et al.,[10] introduced an enhanced YOLOv4 model for vehicle detection. Their study compares the accuracy of the original YOLOv4 model with the improved version, demonstrating that the enhanced model outperformed in vehicle identification. Consequently, the improved YOLOv4 model was chosen as the preferred vehicle detection algorithm. Additionally, a literature review highlights YOLOv4 as a deep learning algorithm widely employed for object detection and classification tasks.

R. Lai at al.,[11] detailed an ultra-low power TinyML system designed for real-time visual processing at the edge. Their work emphasized the significance of running models on edge computing devices to minimize power consumption. Furthermore, they proposed TinyML models tailored for standalone computing devices and devised methods for booting the device.

Wenjie Jiang et al.,[12] introduced a system for developing a real-time automatic pothole detection system utilizing Convolutional Neural Network (CNN) technology. The paper addresses the issue of potholes in different countries and discusses the constraints of existing detection approaches.

M. Zennaro et al.,[13] advocate for the integration of Artificial Intelligence (AI) to advance the Sustainable Development Goals (SDGs). However, they highlight challenges in AI implementation, including power consumption, connectivity demands, and high expenses, particularly in developing nations. To address these hurdles, the authors propose the adoption of TinyML, a innovative technology enabling machine learning models to function on low-power microcontrollers.

Zeng, J et al.,[14] offer an overview of general rights and copyright ownership concerning publications in the public portal. Additionally, they delve into the utilization of tinyML for predictive maintenance (PdM), outlining the challenges and advantages of this technology while introducing a tinyML optimization pipeline.

M et al.,[15] presented a project centered on creating a tool to forecast traffic flow through machine learning and deep learning algorithms. Their objective is to enhance driving experiences by leveraging image processing algorithms for traffic sign recognition and pothole detection. The system employs the YOLO algorithm for real-time pothole detection and has demonstrated success in both training and testing phases, achieving a detection accuracy of around 75%.

4. SUMMARY

In today's dynamic world, where urbanization and transportation are rapidly advancing, ensuring road safety is of utmost importance. Potholes, persistent road hazards, pose serious risks to drivers and generate significant maintenance expenses for road authorities.

The integration of cutting-edge TinyML technology with camera-based systems offers a holistic solution to address these safety concern. This innovative approach enables real-time detection of potholes, alerting drivers to potential dangers and facilitating timely responses to road hazards.

Furthermore, the system extends its capabilities to include the detection of speed breakers, providing drivers with instant alerts to navigate them safely and enhance overall road safety.

5. CONCLUSION

The fusion of TinyML technology with camera systems represents a promising advancement in bolstering road safety amidst the ongoing urbanization and expansion of transportation networks. By facilitating the real-time detection of potholes and speed breakers, this innovative solution empowers drivers to navigate roads more securely, thereby reducing the likelihood of accidents and vehicle damage.
Moreover, its ability to operate autonomously, without reliance on cloud services, ensures a swift and comprehensive response to road hazards. Ultimately, this integrated approach holds great potential to contribute to safer and more efficient transportation infrastructures, benefitting communities and stakeholders alike.

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