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Smart Road Sense

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ABSTRACT

The quality of the road surface is a key element influencing the security and comfort of transportation networks. For efficient road maintenance, vehicle control and accurate assessment of road surface conditions is essential. To gather data about the road surface, the suggested system combines data from several sensors, including cameras and accelerometers mounted on moving objects. Road conditions are categorized into numerous categories, such as smooth, rough, potholed, wet. The AI-based road surface analysis system offers several benefits, including Improved Safety(By alerting drivers to hazardous road conditions in real time, accidents and vehicle damage can be reduced).Enhanced Maintenance (Road maintenance authorities can prioritize repairs based on real-time data, optimizing resource allocation and reducing road maintenance costs). Efficient Transportation(Vehicles can adjust their speed and handling based on road conditions, improving fuel efficiency and overall transportation efficiency).

Keywords: Road surface classification, convolutional neural network, audio processing, embedded system, image recognition.

INTRODUCTION

Road infrastructure is a vital asset for the economic and social development of a country. However, the quality and condition of road pavements can deteriorate over time due to various factors, such as traffic, weather, aging, and maintenance. Poor road quality can lead to safety hazards, increased fuel consumption, vehicle damage, and environmental pollution. Therefore, it is important to monitor and evaluate the pavement quality of road infrastructure and identify the anomalies and defects that need to be repaired. However, the current methods of roadway monitoring are expensive, time-consuming, and not systematic. They rely on manual inspections, visual surveys, or specialized vehicles that are not widely available or accessible. Moreover, they do not provide real-time feedback or maps of road quality to the drivers, authorities, or maintenance services. Therefore, there is a need for a new system that can evaluate the pavement quality of road infrastructure in a low-cost, efficient, and scalable way.

This paper proposes a novel system that can evaluate the pavement quality of road infrastructure by using the sound of the wheel-road interaction. The system uses a camera and a computer to capture and analyze the acoustic data of the road surface, and a convolutional neural network (CNN) to classify the road surface into four categories: good quality, ruined, silence, and unknown. The system also transmits the data to a map-based management website that shows the location and type of anomalies on the road. The system is integrated in the tyre cavity and communicates with smartphones and car infotainment systems via Bluetooth Low Energy.

The system is based on the idea that different types of road surfaces produce different sounds when the tyres interact with them. By analyzing the frequency, amplitude, and duration of the sound signals, the system can detect the presence and severity of cracks, potholes, or other defects on the road. The system uses a CNN to learn the patterns and features of the sound signals and match them with predefined labels. The CNN is designed to be small and efficient, with a size of 18 kB, and can run on a low-complex embedded system.

The system was tested on different road surfaces in the area of Pisa, Italy, using a vehicle operating at different cruise speeds. The system achieved an accuracy of about 93% on the original model and 90% on the quantized one. The system also showed good performance and reliability in transmitting the data to the map-based management website, which displayed the location, severity, and type of anomalies on the road. The website also provided statistics and reports on the road condition.

The system is the first real-time and fully integrated solution at the state of the art for road pavement quality analysis and classification based on acoustic data. The system can provide real-time feedback and maps of road quality to drivers, authorities, and maintenance services. The system can also help to improve road safety, efficiency, and sustainability. You can read more about this topic from these sources:

RELATED WORK

Road surface classification is the process of categorizing road surfaces based on their physical and mechanical properties. The classification of road surfaces is important for various applications, including vehicle safety, road maintenance, and pavement design[1]. There are several methods for classifying road surfaces, including the use of deep learning methods-based convolutional neural network (CNN) architecture. The tire-pavement interaction noise (TPIN) is adopted as a data source for road surface classification. The TPIN signal reflects the surface profile properties of the road and its texture properties. The TPIN signal is also robust compared to those in which the image signal is affected. The measured TPIN signal is converted into a 2-dimensional image through time–frequency analysis. Converted images were used together with a CNN architecture to examine the feasibility of the road surface classification system. Flexible pavement consists of four layers, namely, surface course, base course, subbase course, and subgrade course. However, rigid pavement consists of three layers; surface course, base course, and subgrade course.

A Convolutional Neural Network (CNN) is a type of deep learning neural network architecture that is commonly used in computer vision. It is used to extract features from images or videos and make predictions based on the output of multiple layers 123. CNNs are particularly useful for finding patterns in images to recognize objects, classes, and categories. They can also be quite effective for classifying audio, time-series, and signal data 3.

In a CNN, the input image is passed through a series of convolutional layers, pooling layers, and fully connected layers. The convolutional layer applies filters to the input image to extract features, the pooling layer down samples the image to reduce computation, and the fully connected layer makes the final prediction. The network learns the optimal filters through backpropagation and gradient descent.

Audio signal processing is a subfield of signal processing that deals with the electronic manipulation of audio signals. Audio signals are electronic representations of sound waves, which are longitudinal waves that travel through air, consisting of compressions and rarefactions. The energy contained in audio signals or sound power level is typically measured in decibels. As audio signals may be represented in either digital or analog format, processing may occur in either domain. Analog processors operate directly on the electrical signal, while digital processors operate mathematically on its digital representation.

METHODOLOGY:

The embedded system records and processes the acoustic data of the wheel-road interaction and classifies roadways' health in real-time using integrated AI solutions. The measurements to produce the dataset for training a convolutional neural network (CNN) were collected using a vehicle operating at different cruise speeds in the area of Pisa .The raw audio signals were split, labelled, and converted into images by calculating the Mel spectrogram .A tiny CNN with a size of 18 kB was designed to classify between four different classes: good quality road, ruined road, silence, and unknown .The CNN architecture achieved an accuracy of about 93% on the original model and 90% on the quantized one.A custom electronic board was developed, with the core being the ESP32-WROOM-32D module, which supports TensorFlow Lite and most of the libraries used for data processing. The system was evaluated in three phases: training and comparing the CNNs, selecting the best performing model and quantizing it, and integrating the classifier into the embedded firmware and testing its functioning on real hardware.

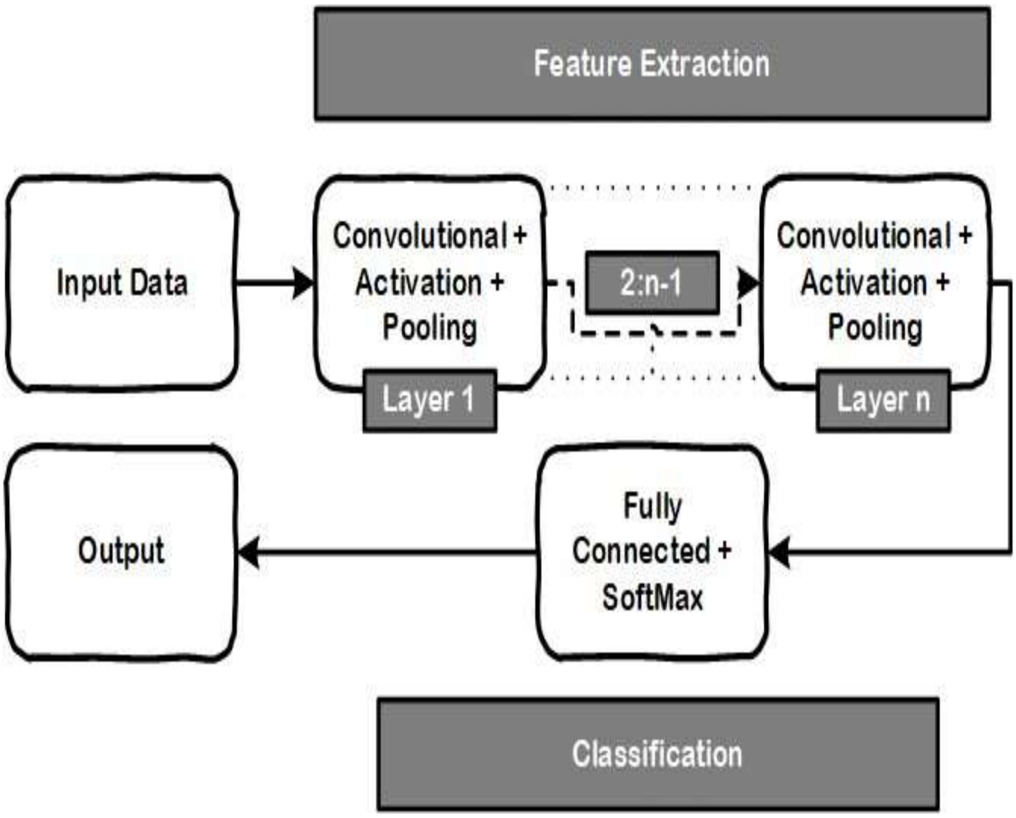

Figure 1: CNN architecture

Convolutional Neural Network (CNN), which is a type of artificial neural network that can process images and other types of data.

Input Data: This is where the image or other data enters the network. The data is usually represented as a matrix of numbers, where each number corresponds to a pixel value. Feature Extraction: This is the stage where the network learns to detect patterns and features in the data, such as edges, shapes, colors, etc. This is done by applying convolutional, activation, and pooling layers, which are explained below.

Convolutional Layer: This layer applies a set of filters or kernels to the input data, producing a set of feature maps. Each filter is a small matrix of numbers that slides over the input data and performs a dot product operation, resulting in a single number. The filters can learn to detect different features depending on the data and the task.

Activation Layer: This layer applies a non-linear function to the feature maps, such as ReLU, sigmoid. This introduces non-linearity to the network, allowing it to learn complex functions and patterns. The activation function also helps to normalize the feature maps and reduce the effects of noise and outliers.

Pooling Layer: This layer reduces the size and dimensionality of the feature maps, making the network more efficient and robust. This is done by applying a pooling operation, such as max, average, or min, to a small region of the feature map, resulting in a single number.

Fully Connected Layer: This layer connects all the neurons from the previous layer to the output layer, where the final classification or prediction is made. The output layer usually has a softmax function, which converts scores into probabilities that sum up to one.

Output: This is where the network produces the final result, such as a class label or a numerical value. The output can be compared to the ground truth or the desired outcome, and the network can be trained to minimize the error or loss using a learning algorithm, such as gradient descent or backpropagation.

Large-scale road surface image dataset with one million samples created. Detailed labeling of road friction level, unevenness level, and material properties. CNN classification model trained with a combined loss function and adapted optimization strategies. Decision-level fusion method based on improved Dempster-Shafer evidence theory used. Top-1 accuracy for classifying road surface images reaches 92.05% by CNN model.

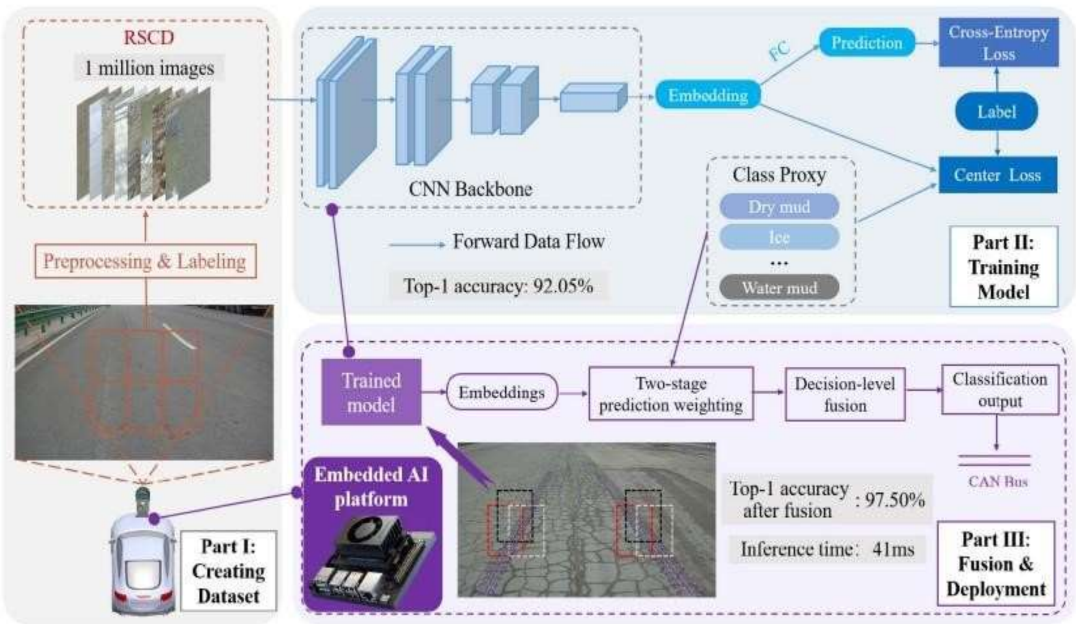

Figure 2: RSCD-CNN

The process of creating a dataset, training a model, and deploying it for an AI embedded platform. It involves preprocessing and labelling 1 million images, using CNN for training with a top-1 accuracy of 92.05%, and deploying the trained model with an embedded AI platform that achieves a top-1 accuracy of 97.50% after fusion.

RSCD: This stands for Road Surface Condition Dataset, which is a large-scale dataset of images captured by a camera mounted on a vehicle. The images contain various road surface conditions, such as dry, muddy, icy, etc. The dataset is used for training and testing the model.

CNN Backbone: This is the core part of the model that consists of several convolutional, activation, and pooling layers. The CNN backbone extracts features from the input images and produces embeddings, which are low-dimensional representations of the images.

Center Loss: This is a loss function that aims to minimize the intra-class distance and maximize the inter-class distance of the embeddings. This means that the embeddings of the same class should be close to each other, while the embeddings of different classes should be far apart. Center loss helps to improve the discriminative power of the embeddings.

Fusion & Deployment: This is the stage where the trained model is deployed on an embedded AI platform, which is a hardware device that can run AI applications. The model uses a two-stage prediction weighting and a decision-level fusion to combine the embeddings and the class proxies.

RESULT

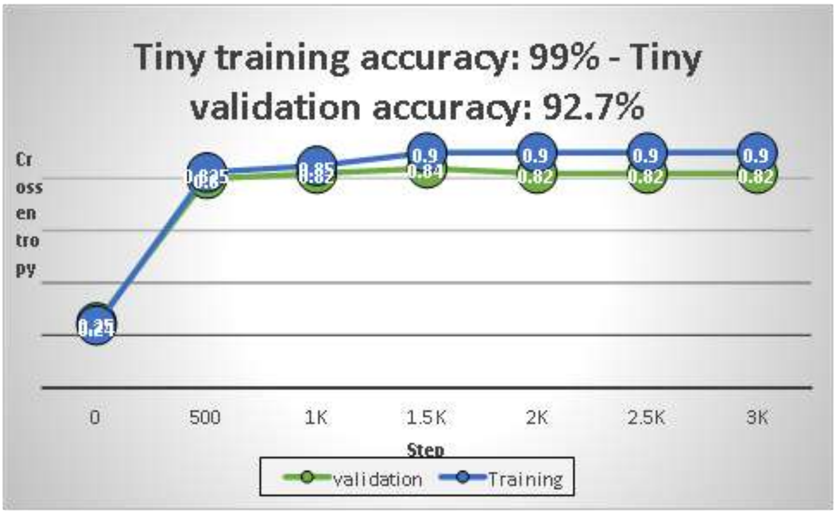

Fig 3: **Training ,Validation cross entropy**

The graph depicts training and validation accuracy over 3K steps for a compact model (18 kB) effectively classifying road surface conditions. Training accuracy starts at 0.3 and reaches 99%, while validation accuracy begins at 0.5 and peaks at 92.7%. The title summarizes achievements: "Tiny training accuracy: 99% - Tiny validation accuracy: 92.7%." Notably, the model avoids overfitting and underfitting, showcasing a balanced learning process. The graph assures the model's proficiency in generalizing to new data, affirming its efficiency in accurately classifying road conditions without excessive model complexity.

This section presents and analyses the training results of the CNN model for road surface image classification and the performance of the fusion algorithm. The model is implemented with the PyTorch framework and is trained on the server with Intel i912900K CPU and NVIDIA 3090 GPUs. We randomly sample 50 thousand images for the test-set and 20 thousand images for the validation-set. To reduce the computational burden, the model parameters are initialized with that pre-trained on the ImageNet dataset. The models are trained for 6 epochs to prevent overfitting. An exponential decay of 0.8 for LR in every epoch is set to keep the training stable in the later stage, and the other hyperparameters are tuned through grid search.

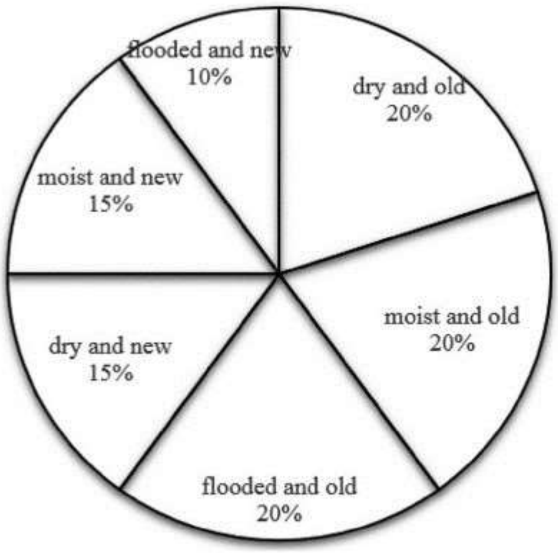

Fig 4: **Index of road surface roughness used as a training data**.

The distribution of different road surface conditions.Pie chart: This is a circular chart that is divided into segments, each representing a proportion of the whole. The pie chart shows the percentage of each road surface condition out of the total number of samples.

Road surface condition: This is the label for each segment of the pie chart, which indicates the type and quality of the road surface. The labels include combinations of dry, wet, flooded, new, and old conditions, such as “dry and old” or “flooded and new”.

Percentage: This is the number at the end of each segment, which shows the proportion of each road surface condition out of the total. The percentages range from 10% to 20%.

Dry and old: This is the segment with the highest percentage, at 20%. It represents the road surface that is dry and old, meaning it has low moisture and high wear and tear.

Wet-gravel: This is the segment with the lowest percentage, at 10%. It represents the road surface that is wet and gravel, meaning it has high moisture and low pavement.

CONCLUSION

This work introduces a real-time road surface monitoring application using AI on a microcontroller board with a tire cavity microphone. The algorithm, based on the Tiny architecture and Mel-inspired spectrogram, achieves 91% accuracy in asphalt quality detection. The innovation lies in embedding AI into lightweight, low-power, and costeffective devices, a forefront in current research. Resilient to light conditions and environmental noise, the algorithm, tested on Espressif and custom boards, exhibits realtime processing, classification, and BLE communication with promising results. Future steps involve new acquisition campaigns to enhance model robustness and expand categories. The ultimate goal is developing a smartphone app and web platform, offering road location and health information as a service. The study anticipates high expectations for future advancements and wider application possibilities.

REFERENCES

[1] Gagliardi, V. Staderini and S. Saponara, "An Embedded System for Acoustic Data Processing and AI-Based Real-Time Classification for Road Surface Analysis," in *IEEE Access*, vol. 10, pp. 63073-63084, 2022, doi:

10.1109/ACCESS.2022.3183116.

[2] J. R. M. Acurio, ‘‘Incorporating risk and uncertainty into pavement network maintenance and rehabilitation budget allocation decisions,’’ M.S. thesis, Dept. Civil Eng., Texas A&M Univ., College Station, TX, USA, 2014.

[3] G. de León, L. G. D. Pizzo, L. Teti, A. Moro, F. Bianco, L. Fredianelli, and G. Licitra, ‘‘Evaluation of tyre/road noise and texture interaction on rubberised and conventional pavements using CPX and profiling measurements,’’ Road Mater. Pavement Des., vol. 21, no. 1, pp. S91–S102, Sep. 2020.

[4] T. Zhao, J. He, J. Lv, D. Min and Y. Wei, "A Comprehensive Implementation of Road Surface Classification for Vehicle Driving Assistance: Dataset, Models, and Deployment," in *IEEE Transactions on Intelligent Transportation Systems*, vol. 24, no. 8, pp. 8361-8370, Aug. 2023, doi: 10.1109/TITS.2023.3264588.

[5] V. Vassilev, “Road surface recognition at mm-wavelengths using a polarimetric radar,” IEEE Trans. Intell. Transp. Syst., vol. 23, no. 7, pp. 6985–6990, Jul. 2022.

[6] M.-H. Kim, J. Park, and S. Choi, “Road type identification ahead of the tire using D-CNN and reflected ultrasonic signals,” Int. J. Automot. Technol., vol. 22, no. 1, pp. 47–54, Feb. 2021.

[7] Z. Qin, L. Chen, M. Hu, and X. Chen, “A lateral and longitudinal dynamics control framework of autonomous vehicles based on multiparameter joint estimation,” IEEE Trans. Veh. Technol., vol. 71, no. 6, pp. 5837–5852, Jun. 2022.

[8] J. Cho, H. R. Hussen, S. Yang and J. Kim, "Radar-Based Road Surface Classification System for Personal Mobility Devices," in *IEEE Sensors Journal*, vol. 23, no. 14, pp. 16343-16350, 15 July15, 2023, doi: 10.1109/JSEN.2023.3279785.

[9] H. Feng, G. Mu, S. Zhong, P. Zhang, and T. Yuan, “Benchmark analysis of YOLO performance on edge intelligence devices,” Cryptography, vol. 6, no. 2, p. 16, 2022.

[10] B. Jamali, D. Ramalingam, and A. Babakhani, “Intelligent material classification and identification using a broadband millimeter-wave frequency comb receiver,” IEEE Sensors Lett., vol. 4, no. 7, pp. 1–4, Jul. 2020.

[11] M. Aki et al., "Road Surface Recognition Using Laser Radar for Automatic Platooning," in IEEE Transactions on Intelligent Transportation Systems, vol. 17, no. 10, pp. 2800-2810, Oct. 2016, doi: 10.1109/TITS.2016.2528892.

[12] L. Hui, J. Chen, and L. Jian, “Road surface disease detection algorithm based on improved YOLOv4,” Laser Optoelectronics Prog., vol. 58, no. 14, Jul. 2021.

[13] J. Otegui, A. Bahillo, I. Lopetegi, and L. E. Diez, “Performance evaluation of different grade IMUs for diagnosis applications in land vehicular multi-sensor architectures,” IEEE Sensors J., vol. 21, no. 3, pp. 2658–2668, Feb. 2021.

[14] H. Gao, T. Wei, and S. Li, “High-precision extrinsic calibration method of a time-of-flight IMU RGB-camera with loop closure constraints,” IEEE Sensors J., vol. 21, no. 21, pp. 24388–24397, Nov. 2021.

[15] Zhang, Y., Ma, Z., Song, X., Wu, J., Liu, S., Chen, X., & Guo, X. (2021). Road Surface Defects Detection Based on IMU Sensor. IEEE Sensors Journal, 22(3), 27112721.