Road Surface Quality Detection Using Light Weight Neural Network for Visually Impaired Pedestrian

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Road Surface Quality Detection Using Light Weight Neural Network for Visually Impaired Pedestrian

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Abstract: Visually impaired pedestrians often face challenges navigating outdoor environments due to difficulties in identifying road surface quality. To enhance safety, we propose a deep learning-based architecture that can be easily deployed on mobile devices for real-time assistance, potentially reducing road injuries. Our suggested approach builds upon the pre-trained CNN, MobileNetV2, by adding supplementary layers without increasing computational complexity. The model is evaluated on unseen images, with results indicating improved classification performance in terms of F1-score, recall, accuracy, and precision compared to alternative models, including Random Forest, ResNet, EfficientNet, and InceptionNet. Our proposed model achieves 93.20% accuracy relative to MobileNetV2. However, the architecture does not account for obstacles on road surfaces, which could also cause injuries. The modified MobileNetV2 architecture effectively classifies road surfaces to assist visually impaired pedestrians and can be seamlessly integrated into mobile devices. Our work presents a novel, efficient, and low-power system with enhanced accuracy for road quality classification, suitable for deployment on diverse devices such as smartphones.

Keywords VIP (Visually Impaired Pedestrian), road surface quality, convolutional neural network, mobilenetv2

1. Introduction

Visually impaired individuals can face many challenges when it comes to navigation. They may have difficulty detecting obstacles and other hazards in the environment, and may be unable to see important visual cues such as road signs and traffic signals. This can make it difficult for them to move around safely and confidently, particularly in unfamiliar environments. In addition, visually impaired individuals may have difficulty judging distances and spatial relationships, which can make it difficult for them to navigate through tight or cluttered spaces. This can be particularly challenging in urban environments, where there may be a lot of visual clutter and a high density of obstacles and hazards. Overall, visually impaired individuals can face many challenges when it comes to navigation, and may need additional support and assistance to move around safely and confidently in their environment. According to the WHO report 2019[1)], around 2.2 billion pedestrians havenear or distant vision impairment. Thus, the prior information about the road surface type can be a piece of crucial information for the navigation of visually impairedpedestrians because the visually impaired pedestrian can orient themselves and their pace accordingly. The visible surface is the most important criterion on which our work is based. In underdeveloped countries, it is very frequent to find unpaved roads or badly maintained roads. There is a wide range of navigational devices which can assist visually impairedpedestrians ranging from white cane to many other advanced tools. The mostly used assisting tools are the white cane and the guide dogs in rural and urban environments as mentioned in Fig 1. Most of the research in the literature survey is focused on path detection from the image or avoiding obstacles in front of the visually impaired pedestrian. But there is very less research that can give relevant information about the surface type of the road, potholes, water, etc. The latest research and advancement in deep learning or neural networks have opened new pathways for various research-based applications. Nowadays machine learning and neural networks are used in various applications like detection of Asphalt pavement segregation using machine learning[2)], Quality assessment of fruits[3)], System identification for quad-rotor parameters using neural networks[4)], for covid detection using x-ray chest images[26)], Baggage sorting system[27)], safety working environment at highway[28)] and many more. Many researchers are working in the area of helping the visually impaired person in navigation. There is an approach that talks about whether the road is a minor, highway, parking area, or freeway[4)]. In paper[5)] the author did a road classification by using the CNN and compared the result with a support vector machine but with a reasonable choice of features, SVM is performing aspar with the CNN model.

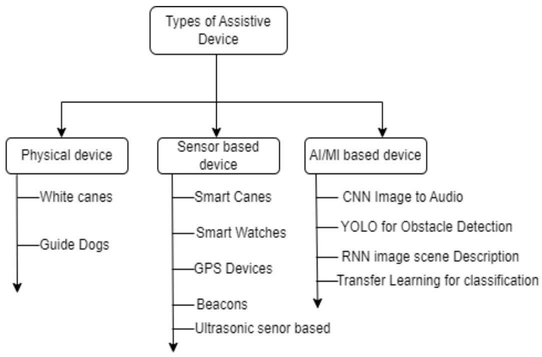

Fig 1: Types of Assistive Device for VIP

In the paper[6] the author Suggested an automatic survey of systems for the paved and unpaved road surface classification analyzing the data which is coming from the accelerometer, gyroscope, and compass. The author used different machine learning algorithms like SVM (Support Vector Machine), HMM (Hidden Markov Model), and ResNet-based CNN for implementing the road surface classification model. The limitation of the paper is that it does not estimate the roughness of the road.

In the paper[7] the author proposes a framework for real-time detection of road anomalies for city municipalities using accelerometers and GPS as mapping tasks to identify the road sand their quality. In this paper, the author relies only onAccelerometer and GPS but no images were being used whiledetecting road anomalies and hence cannot leverage the truepotential of computer vision-based deep learning techniques.

Shahram Sattar et al.[8] did a comprehensive review of surface anomalies using smartphone sensors. The author did a detailed study on current approaches using smartphones to detect road surface anomalies and highlighted future approaches for research using smartphones in road surface anomaly detection. The author has also focused on the road surface monitoring problems, their major issues, and challenges in the current development.

In paper [9] the author proposes the safety of human pedestrians because of the silent nature of the electric vehicle.

In paper[10] and paper[11] the author proposes a work for pothole detection by using a laser sensor such as lidar however some studies suggest that theuse of Lidar has some serious hazards like electrical hazards, air-borne hazards, and health hazards in longer exposure[12]. There are approaches[13] that detect the damage in the roads by using Stereovision for pothole detection but it hassome disadvantage of its own like it may be difficult to accurately detect a pothole due to distorted signal generatedby noise since stereovision detect pothole based on analysis ofimage and video.

In the paper[14] the author suggested a convolutional neural network that performs a bounding box detection and classification of damages on asphalt and concrete roadsurfaces. But the author did not classify the road surface type quality so this paper has limited functionality which makes it not so useful for visually impaired people in different road conditions. In data-driven technology, such a traditional approach will not suit the real-time environment and havesome negative implications also[29]. We will be more focused on passive vision technology (image processing technique) instead of active vision technology such as GPS, Lidar, and Accelerometer[30]. In recent times there is a significant advance in making use of Convolutional Neural networks (CNN), mainly in computer vision problems like path detection, object detection, navigation, etc. Due to such great advancement, it has attracted a lot of researchers. As we already stated that many researchers have used CNN for road classification[31] or obstacle identification in their works and many different applications have used CNN as a classifier in their domainand they can get very promising results.

Keeping all this in mind we propose a novel approach based on MobileNetV2 architecture for the classification of road surface quality by just working with images (passivevision) for visually impaired pedestrians[31]. The remaining paper is organized as follows. Section contains the information about the dataset which is already been published and wehave used it in our research. Section[3] contains the proposed approach, Section[4] contains the result and comparison, and Section[5] contains the conclusion and future work.

2. Dataset

The amount of data is important, but it's not the only factor in determining the success of a machine learning algorithm. Quality of data, diversity of data, and the relevance of data to the problem being solved is also crucial. More data can often improve the performance of a model, but having too much irrelevant or redundant data can hurt performance. We have collected images from the RTK dataset[15]. Images from the RTK dataset are collected by using low-cost cameras like HP Webcam HD-4110 and in real-world conditions. The dataset contains 77547 frames from different conditions like Asphalt roads, Unpaved roads, and Pavedroads. Out of all these images from the RTK dataset, we have made our dataset consisting of a total of 5531 imagesand classified all images into seven different classes. The seven different classes are Good Asphalt, Regular asphalt, Bad Asphalt, Good Paved, Regular Paved, Bad Paved, Regular unpaved, and Bad Unpaved. We split our dataset into Training,Validation, and Testing folders[32]. Around 70% of the data arewithin the Training folder (3868), 20% of the data are in the Validation folder (1104) and 10% are in the Testing folder(548) as depicted in Fig 2. The dataset is not perfectly balanced as it resembles the real-world condition where mostly the dataset is not balanced. RTK dataset contains real-world images with complex environment scenarios like roads with different vehicles, potholes, and road damages[33]. All images are collected during the daytime with a variety of brightness, texture, etc. In each road category, there is a slight difference in the surface patterns such as Bad asphalt roads are lighter in color, and new asphalt roads are darker in color.

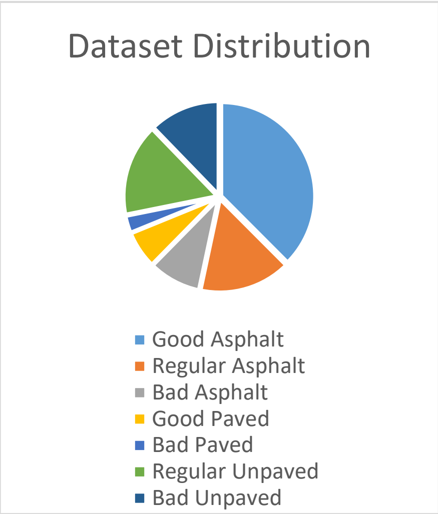

Fig 2: Distribution of Dataset in Different Classes

We have considered that Good Asphalt roads are roads that do not have any sort of bumps, potholes, and other damage like highways and expressways. Regular Asphalt roads are roads that are not in very good condition but they are freefrom potholes and other damage whereas Bad Asphalt roads contain potholes, bumps, and uneven surfaces[34]. Unpaved roads are considered bad to walk upon because they are not made up of hard smooth surfaces and have different types of road anomalies[35]. These roads are full of dirt which is made up of native material of the land surface. Paved roads are roads that are made up of concrete blocks or interlocking. They have different types of patterns on their surfaces. Most of the pedestrian ways are made up of paved or concrete. To ensure that our model can be easily deployed in real-time scenarios without adding any unnecessary computational overhead, we have made a conscious decision not to perform any type of cropping. Instead, we have focused on preprocessing the images before feeding them into the network. One important preprocessing technique we have utilized is image augmentation, which helps to prevent overfitting and improve the robustness of our model. Despite the fact that our dataset is relatively small, we have chosen to employ transfer learning, as it has been shown to deliver good results even with limited amounts of data. Transfer learning leverages pre-trained models on large datasets and fine-tunes them on smaller datasets to achieve high levels of accuracy with less data. Overall, we have taken a pragmatic approach to model development and have employed a range of techniques to ensure that our model is both robust and efficient, while still delivering high levels of accuracy.

Table 1. Summary of the dataset for Road Detection

Name of class	**Train**	**Test**	**Valid**
Good Asphalt	1451	418	204
Regular Asphalt	611	175	87
Bad Asphalt	349	100	50
Good Paved	251	71	35
Bad Paved	116	33	17
Regular Unpaved	616	176	88
Bad Unpaved	474	135	67

Fig 3: Sample Images from Dataset for Road Detection

3: Proposed Approach

In recent times transfer learning approach has brought a lot of advantages like saving training time, better performance of the neural network, and not requiring a lot of data[16]. Most of the state-of-the-art deep learning models have millions of parameters for improving accuracy.

3.1 Selecting the Base learner

There are many pre-trained models available but each one of them is used according to the specific problem domain. Since the author is dealing with navigation for visually impaired people which requires the model to have a smaller size and have lesser parameters which make it suitable for a low-edge embedded device like a smartphone for real-time navigation. The model we have proposed is based on the MobilenetV2 architecture [21]. The MobilenetV2 is a well-known and extensively utilized network architecture designed for computer vision applications. It is considered lightweight and can be deployed effortlessly on embedded devices, making it a popular choice for many applications

Table 2. Size and Parameters for different Pre-trained Models

Model	Parameters	Size
EfficientNet-B2	7.5 million	350 MB
ResNet-50	25.6 million	100 MB
Vgg-16	138 million	553 MB
DenseNet-121	8.8 million	100 MB
MobileNet-V2	5.5 million	14 MB

MobileNetV2 can act as a suitable model for assisting visually impaired people because of its size and the number of parameters used which makes it fit for real-time operation. Despite being a lightweight model MobileNetV2 has demonstrated good performance on a variety of computer vision tasks, including object detection and image classification.

3.2 Fine Tuning the base learner

Models with many parameters are overly time-consuming throughout the training process and cannot be deployed on embedded devices with limited processing capabilities[37]. The model we have proposed is based on the MobilenetV2 architecture[17]. MobilenetV2 is one of the most popular and widely used lightweight network architectures meant for computer vision applications as it can easily deploy on embedded devices. MobilenetV2 architecture is based on an inverted residual and linear bottleneck which results in a significant decrease in the number of parameters and the memory needed while maintaining high accuracy[38]. MobilenetV2 brings an edge over other state-of-the-art deep learning models like fewer operations, fewer parameters, smaller size networks, low power, high efficiency, and low latency. The weights of the networks are initialized with weights from a model pre-trained on ImageNet[18]. To increase the learning capabilities of our model we have to append additional layers. In contrast with other authors' work[39], we have presented a modified MobilenetV2 by appending more layers without compromising computational complexity[40].

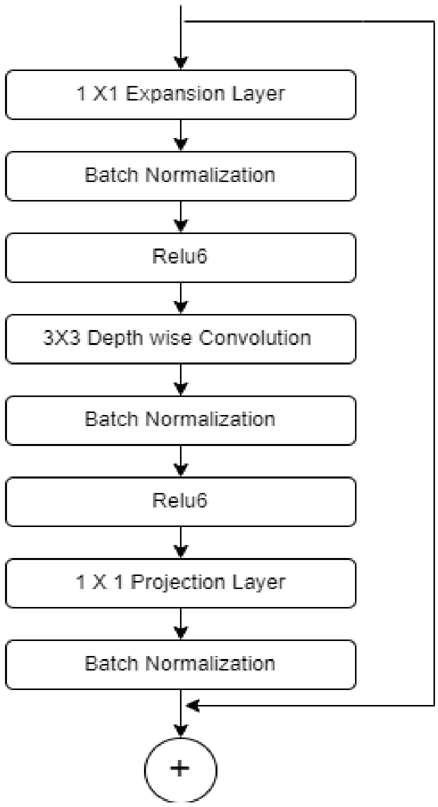

Fig 4: Flowchart of MobileNetV2

The very first layeradded to the classification head of the model is the global average pooling which prevents the model from overfitting by reducing the number of parameters. Global average pooling calculates the average output of each feature map in the previous layer which results in reducing the data significantly and prepares the model for the classification layer[19].

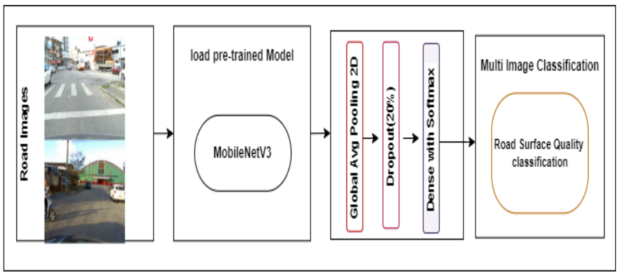

Fig. 5: Our Proposed Approach for Road Surface Detection

The dropout layer is added as the second layer to the proposed model having a dropout rate of 20% to prevent divergence andoverfitting[20]. Dropout is the technique by which randomly selected neurons are ignored during training. The dropout layer acts like a mask that nullifies the contribution of some neuronstoward the next layer and leaves unmodified all others. After that, a dense layer or fully connected layer is added with the number of classes with the SoftMax function as an activation function[21]. The dense layer is used for generating predictions[40]. The mathematical equation of the SoftMax activation function is shown below in equation (1).

$$\sigma(\vec{z}) = \frac{e^{z_i}}{\sum_{J=1}^{K} e^{z_j}} \qquad (1)$$

Table 3. Details of the Proposed Architecture, Parameters, and Output shape

Layer type	Output Shape	Parameters
MobileNet V2	7X7X1280	2257984
Avg. Pooling	0	0
Dropout layer	0	0
Dense Layer	7	8967

Base model MobileNetV2 is pre-trained on the image net dataset which is a very large dataset containing 1.4 M images with 1000 classes. This base model of knowledge will helpus to classify our road images[41]. Training is done in 2 steps; the first step contains the feature extraction and the secondstep contains the fine-tuning. During the initial first step, we freeze the internal layers of the model and train only the newly added layers also called classification head (global average pooling, dense layer, and dropout) for 10 epochs with an Adam optimizer with a learning rate of 0.0001. Under this step, the learning is increased in the features of our dataset. In a second step, the learning rate is reduced to 0.00001 using the RMSprop optimizer for 20 epochs otherwise the model could overfit quickly[42]. In this step, we have unfrozen thebase model and set the lower layers to untrainable because itis preferable to fine-tune small numbers of layers rather than train the whole model. The first few layers are very simple and generic whereas higher layers are more specific to the dataset[43]. The batch size of 10 remains constant throughout the training. Various pre-processing techniques have been used on the input data before feeding it into the neural network like rescaling the input data from [0, 255] to [-1, 1] because the model expects the pixel value from [-1,1]. Along with the rescaling data we have also used data augmentation to increase the dataset as we deal with the smaller dataset[44]. Random flip (horizontal) and Random rotation (0.2) is used. Training and Testing are performed on AMD ryzen 5 5600H with Radeon Graphics with 3.30 GHz with 6 CPU cores and 12 threads. Embedded GPU has shown great acceleration potential which suits our requirement as our research is meant for embedded devices that have low computational power[45]. All the hyperparameters used are presented in Table 3.

Table 4. Details of the Hyperparameters used

Parameters	Value
Optimizer	Adam, RMSprop
Learning rate	0.0001 - 0.00001
Batch Size	10
Dropout	0.20
Loss Function	Categorical cross-entropy
Activation Function at the output layer	SoftMax function
Total training epochs	20

4: Results and Discussion

We have tested the model for detecting the road classification for the visually impaired pedestrian and compared it with traditional machine learning algorithms like Random Forest[22] and with the pre-trained models like EfficientNetB0[23], InceptionResNetV2[24], MobileNetV2, and ResNet50V2[25] which is shown in (Table 4). In comparison with the above-mentioned models, our approach is giving promising results. We ran this test on our manually classified data, consisting of 7 different classes; good asphalt, regular asphalt, bad asphalt, paved good, paved bad, unpaved regular, unpaved bad, and concrete with 70% data as training data, 20% data as validation data and 10% data as test data[46]. We have calculated the F1-score for each class as false negatives and false positives which are more important than true negatives and true positives as in our case the dataset is not balanced[47]. We ran this test on our manually classified dataset which contains 3868 training images and 1104 validation images and 548 testing images[48]. In the dataset, we have included real-world images including images with other vehicles while avoiding images that contained transitions between road surfaces, and frames that consist of the very strong glare of sun rays causing reflection. Even after including the images with complex conditions our approach can detect the surface of vehicles withgood accuracy[49].

The Confusion matrix helps us to understand the model performance in all the classes of the dataset. The matrix compared the actual target with those predicted by our road surface quality classification model.

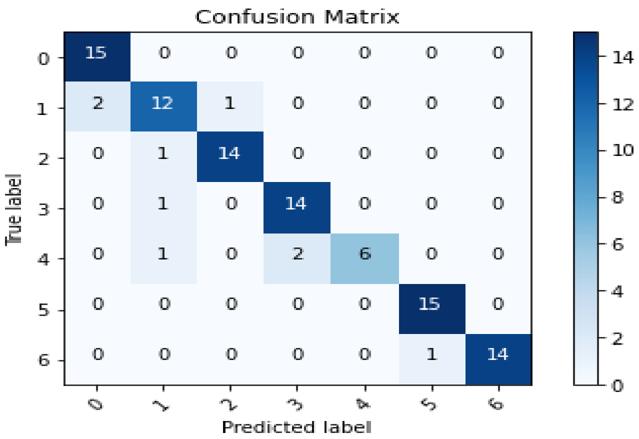

Fig. 6: Confusion Matrix for Road surface classification

These matrices provide detailed information on the model's accuracy, precision, recall, and F1-score, enabling practitioners to pinpoint the model's strengths and weaknesses[50]. By analyzing the confusion matrix, practitioners can identify whether the model is incorrectly classifying certain road surfaces or missing others. model is performing very well on test data but very few images are wrongly predicted.

Table 5 Comparison of Accuracy of Different Model

Classes	Eff Net	ResNet	Inception Net	Random Forest	Mob Net
Good Asphalt	67%	88%	84%	72%	91%
Regular Asphalt	89%	94%	94%	73%	92%
Bad Asphalt	74%	96%	96%	71%	90%
Good Paved	72%	91%	91%	70%	96%
Bad Paved	79%	92%	92%	69%	83%
Regular Unpaved	81%	90%	90%	73%	85%
Bad Unpaved	83%	88%	88%	77%	92%

Our modified MobileNetV2 model has demonstrated exceptional performance by achieving a remarkable testing accuracy of 93.20%, outpacing the standard MobileNetV2 model, which underscores the effectiveness of our adjustments. Our modifications entailed optimizing hyperparameters, boosting the number of epochs, and integrating extra layers to enhance the model's functionality. The outcomes establish the significance of hyperparameter fine-tuning and model modifications in realizing high levels of accuracy in machine learning.

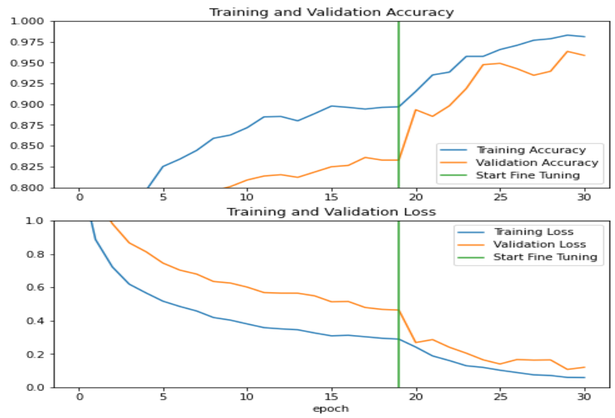

Fig 7: Training and Validation accuracy/loss

Additionally, deploying our model via the Flask application on the Heroku platform has simplified its access and made it more user-friendly. This has facilitated its use in various practical scenarios, such as detecting diseases from medical images, classifying objects in satellite imagery, and identifying anomalies in manufacturing processes. The impressive classification report highlights the model's capacity to correctly classify images into their respective categories, with high precision and recall values. In applications where the cost of misclassification can be severe, such as in medical diagnoses, this is critical.

In summary, our modified MobileNetV2 model has emerged as an exceedingly effective and dependable solution for image classification tasks. Its successful deployment via the Flask application on the Heroku platform has enhanced its accessibility to users and unlocked numerous opportunities for its utilization in different real-world applications. Our findings serve as a remainder of the importance of fine-tuning hyperparameters and incorporating model modifications to attain high levels of accuracy in machine learning. The evaluation report generated for our research in table [6] is a crucial aspect of study as it provides a comprehensive assessment of classification model's performance metrics such as accuracy, precision, recall, and F1-score for each class. This analysis will help us to identify the areas of strength and weaknesses of our model and make improvements accordingly.

Furthermore, this report can be employed to compare different classification models' performance and determine the most effective model for our specific problem. It also serves as a reference for future research in the same field and helps to record your model's performance.

Table 6. Classification Report of Road Surface Detection

Name of the class	Precision	Recall	F1-score
Good Asphalt	97%	96%	98%
Regular Asphalt	96%	92%	94%
Bad Asphalt	82%	87%	95%
Good Paved	94%	99%	97%
Bad Paved	98%	97%	90%
Regular Unpaved	89%	99%	93%
Bad Unpaved	96%	99%	92 %

The Fig. [8] of our paper contains the output of your classification model, which serves to validate the proposed architecture in your study.

Fig 8: Output of the Proposed Road Surface Detection

5: Conclusion and Future work

In conclusion, our research proposes a novel approach to assist visually impaired pedestrians by detecting the quality of the road surface they are walking on. By providing information on the road surface, our model can help visually impaired individuals navigate their surroundings more effectively and safely. Our proposed MobileNetV2-based architecture achieves state-of-the-art results with 93.20% accuracy, making it suitable for real-world applications on low computational power embedded devices.

While our current model focuses on detecting road surface quality, we recognize that there are other obstacles that can pose risks to visually impaired individuals. Our future work includes identifying and detecting different types of obstacles, such as stray animals, potholes, and other hazards that can be challenging for visually impaired individuals to navigate.

We believe that our research has the potential to make a significant impact on the lives of visually impaired individuals, enabling them to move around their surroundings with greater confidence and independence. By improving their awareness of their environment, our proposed model can help reduce the risk of accidents and injuries for visually impaired individuals, ultimately improving their quality of life. We look forward to further exploring this topic and developing new solutions that help to address the challenges faced by visually impaired individuals.

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