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Research Article

Design and Implementation of Road Rutting Detection using MAnet with Efficientb0 Architecture

Radhika Reddy Kondam[1], P. Chandra Sekhar[2], Pradeep Kumar Boya[3]

[1]Research Scholar, Department of ECE, University College of Engineering, Osmania University, Hyderabad, Telangana, 500007

[2]Professor, Department of ECE, University College of Engineering, Osmania University, Hyderabad, Telangana, 500007

[3]Sr. Research Engineer, Incline Inventions Pvt. Ltd, Hyderabad, India.

1radhikakondam@gmail.com, 2sekharp@osmania.ac.in, 3pradeep.boge@gmail.com

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ABSTRACT

Road rutting will become a serious problem in transportation infrastructure causing surface deterioration, safety concern, and increased maintenance expenses. The aim of this study is to establish an automatic and efficient detection model for discriminating road rutting, which can overcome the inconvenience of human-made reading with less errors. The present study develops the state-of-the-art knowledge in real-time and computationally efficient models for road rutting detection, focusing on effective operation of these universal tools under complex environments with different lighting conditions and surface material types. In the proposed approach to detect rutting with high accuracy, MAnet and efficientb0 architectures are used in combination. MAnet is an attention mechanism-aware network developed to extract more useful fine-grained features, by capturing the spatial and channel-wise dependencies between input images. Efficientb0: Efficientb0 which is the least size model and very computational efficient that allows our model to do inferences on real-time keeping accuracy unaltered. The experimental results confirm that the proposed model outperforms current state-of-the-art models (DeeplabV3 and U-Net) in performing semantic segmentation tasks for aerial images, obtaining a test set mIoU of 0.865. The experiment results indicate that the MAnet-Efficientb0 model is suitable for application in road maintenance system with high accuracy and computationally efficient.

Keywords: Road Rutting Detection, MAnet, Efficientb0, Semantic Segmentation, Attention Mechanism, mIoU.

INTRODUCTION

Rutting is a typical manifestation of pavement distress, which imposes major challenges to transportation infrastructure. This creates ruts on the surface due to heavy vehicular traffic and accelerates wear and tear of road surfaces. This degradation threatens road safety and user comfort, results in a higher cost to the operating of vehicles as well as shortening the lifetime of roads [1]. If the rutting is detected in time and an appropriate preventive remedial measured, then it ensures for better road quality as well support efficient transportation.

Roads rutting assessment, using conventional methods requiring visual analyzing is generation extensive and labour-intensive in turn time demanding process susceptible to errors [2]. Furthermore, these methods often require specialized equipment and can cause road shutdowns that also burden the public. The latest innovations in areas of computer vision and deep learning have paved the way for automated detection systems, which is an efficient-reliable method developed to detect road distress. Nonetheless, the operationalization of such systems comes with its fair share of obstacles [3].

The major issue in automated road rutting detection is its inability to learn the spatial information of surfaces. Because road environments are complex by definition from different lighting conditions and surface textures, to varying degrees of rutting [4]. In addition, the models need to be computationally efficient enough to support deployment of multiple real-time large-scale monitoring systems. It is also important to be able to generalize well over different types of roads and rods wearing conditions, for the sake forming a robust detection framework [5].

A solution is required that ensures high detection accuracy and at the same time must have an efficient architecture suitable for resource-constrained devices. The use of semantic segmentation models to mitigate this problem has some merit but gets complicated when the challenge becomes that between increased accuracy and good running time [6]. Thus, it is important for the automated rutting detection system that a suitable method able to fulfil these performance criteria.

To address these challenges, we present an efficient solution using the proposed approach of MAnet together with Efficientb0. MAnet shows good performance of recovering the very fine-grained features in road surfaces by introducing attention mechanisms, whereas Efficientb0 which is of small computation burden are efficient to be deployed as a real-time model The combination of these features meet the requirements to detect road wheel track wear with high accuracy and in an efficient manner, which make it suitable for large-scale applications such as automated routine maintenance programs. The organization of the paper as follows: The state-of-the-art models are discussed in section-II. The proposed model is explained in section-III and corresponding experimental results are discussed in section-IV.

LITERATURE

Cao et.al [7], presented an original model based on computer vision systems developed to automatically identify rutting on asphalt pavement roads. The model, with the integration of image processing techniques (ITPs), with least squares support vector classification LS-SVC) and a dynamic feature selection FS method using forensic-based investigation approach FBI. Texture quantification through ITPs: image data was processed with two of these, the Gabor filter and discrete cosine transform. This collection resulted from features that were learned using the mentioned data mining algorithms, and a wide range of structural representations for both rutting as well as non-rutting. These features were then processed with a wrapper-based feature selection methodology to find the best relevant data. LSSVC models were further utilized for coping with the classifying rutting from non-rutting situations using features after dimensionality reduction, where optimized hyperparameters was given by FBI metaheuristic. After the FBI optimization, authors trained LSSVC prediction model using all libraries for depending on required accuracy. The model was trained and tested on a dataset of 2000 image samples, acquired during the field survey in Da Nang city (Vietnam).

Saha et.al [8], introduced a new road rutting dataset with 949 images attracting both object-level and pixel annotations. This dataset was used for road rutting identification application and object detection an Semantic Segmentation models. Performance measurements and challenges faced by the proposed approach in detecting road rutting were determined through quantitative as well as qualitative analysis of model predictions. The dataset suggested, and the results of this research have been intended to improve deep learning-oriented road rutting detection.

In the research paper [9], a field-of-view asphalt pavement deformation inspection framework going beyond isolated rutting or roughness detection was proposed based on multi-dimensional surface data and machine learning to simultaneously acquire the measurement of each respective scale. In this integrated system, a two-step rutting detection scheme was implemented with 1D CNN-based classification and localization models. Full-lane International Roughness Index (IRI) measurements and spatial analysis were conducted using a quarter-car model polyhedron with multiple measuring lines. In addition, an unsupervised K-means Convolutional Neural Network (K-CNN) model was developed to detect large-deformation states.

Sholevar et.al [10] presented a comprehensive review on the current methods of assessing pavement surface condition data by machine learning with more specific concern in using image classification, object detection and segmentation particularly for analyzing pavement distresses. They also looked at automated pavement data collection tools and machine learning applications to predict pavement condition indices. The review has been summed up that machine learning techniques have successfully utilized for pavement condition classification but still has some restrictions to identify highly patterned and a bunch of severity/density distresses. This work helps to identify opportunities for further research.

In order to make such predictions, the study [11] used a machine learning methodology of Gaussian process regression (GPR) in terms of rutting potential for asphalt mixtures modified with polyethylene waste dust. The experimental setup was designed using a Taguchi orthogonal array, for three factors at three levels to predict the empirical responses (indirect tensile strength and Marshall quotient) as surrogates of rutting potential. The sensitivity analysis of model showed that the bitumen content was most influenced parameter for rutting performance predicted using MQ method, whereas mixture type was highly influential variable when ITS is considered as predictor to evaluate rutting properties.

Chen et.al [12] introduced a machine learning model to detect road rutting that mitigated the ambiguity found in all machine models. Data: The primary data source was the US Long-Term Pavement Performance public database, with supplemental synthetic data created using Finite Element simulations based upon physics. This method sought to get around the challenges of lack of data and uncertainty in measurements collected by using known physical behaviour about pavement systems within machine learning models.

The study [13] is to develop a rutting prediction model that requires few input factors based on the availability and resource limitation in developing countries while considering reasonable generalization ability. Based on the data extracted from LTPP, a prediction model built by deep neural network (DNN) techniques. Authors compared the predictive accuracy of our DNN model to state-of-the-practice models, along with a multivariate linear regression fitted using the datasets. The results showed that the rutting prediction DNN model outperformed all of the other models in literature. The model was also used to evaluate and rank the relative influence of different inputs on rutting, in addition to predicting pavement rutting.

This review of the studies showed some general limitations in road rutting detection and prediction using machine learning. While some models were effective, these have the following drawbacks: sensitivity to environmental conditions computational complexity limited dataset size hindering generalisation across different road environments. The accuracy of the object and segment models was already quite high, but they did not have much new to offer when it came complexes features in pavement. In addition, some models failed to accurately assess for extent and severity of distresses which necessitated the need for more complex methods as well better input data. The model including physical knowledge in data-driven approaches acknowledged higher predictive capacity but also featured inadequate fidelity to the actual observations and entailed high computational burdens.

PROPOSED MODEL

We proposed a model for road rutting detection based on the MAnet and Efficientb0 models, which is an effective way to detect rutting features of asphalt pavement. Now, MAnet has an attention mechanism which refines feature extraction by capturing spatial as well as channel-wise dependencies in input images. This allows the model to better capture short-term variations on road surfaces, which is essential for recognizing rutting patterns correctly. With MAnet integrated, this model can tell the differences in road surfaces down to fine granularity which improves detection performance even under challenging conditions such as different light scenes and surface textures. The architecture of proposed Manet with Efficientb0 is depicted in Figure 1.

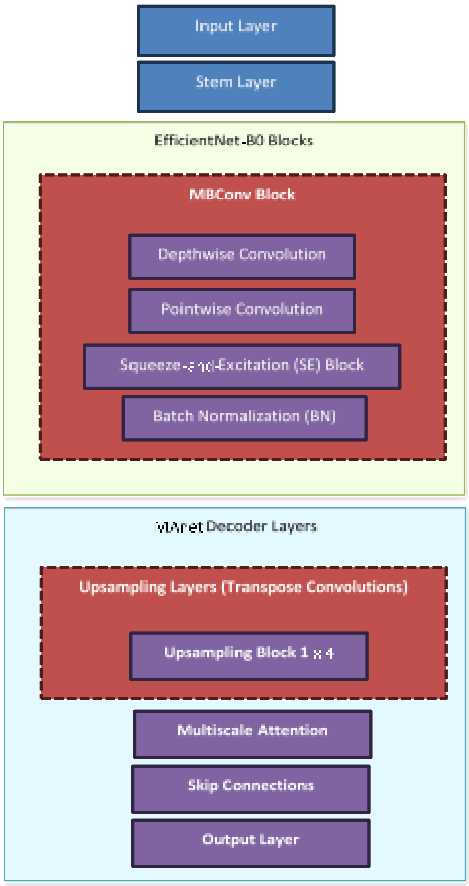


Figure 1: Proposed Model Architecture

The MAnet with an EfficientNet-B0 encoder uses a combination of layers for segmentation tasks. It combines multiscale attention mechanisms (from the decoder) with the backbone architecture of EfficientNet-B0 (as the encoder) for feature extraction. Below is an overview of the key layers involved in both the EfficientNet-B0 encoder and the MAnet decoder:

EfficientNet-B0 Encoder Layers:

EfficientNet-B0 is a lightweight, pre-trained model that uses mobile inverted bottleneck convolutions (MBConv), squeeze-and-excitation (SE) blocks, and batch normalization (BN). The encoder layers can be summarized as:

1. **Stem Layer**:

○ **3x3 Conv + Max Pool**: Initial convolution with a 3x3 filter followed by max-pooling, reducing the spatial size of the image while maintaining important features.

2. **EfficientNet-B0 Blocks**:

○ **MBConv Block**: A mobile inverted bottleneck convolution block that uses depthwise separable convolutions. It consists of the following:

▪ **Depthwise Convolution**: A spatial convolution applied independently to each input channel.

▪ **Pointwise Convolution**: A 1x1 convolution to combine outputs.

▪ **Squeeze-and-Excitation (SE) Block**: An attention mechanism that recalibrates channel-wise feature responses by learning which channels are important.

▪ **Batch Normalization (BN)**: Applied after convolutions to normalize feature maps and improve convergence.

- These blocks are stacked with different configurations (number of filters, strides) at each stage of the encoder.
  - **Block 1**: MBConv with SE and BN.
  - **Block 2**: MBConv with SE and BN.
  - **Block 3**: MBConv with SE and BN.
  - **Block 4**: MBConv with SE and BN.
  - **Block 5**: MBConv with SE and BN.

Each block in the encoder gradually reduces the spatial dimensions of the input while increasing the number of feature channels, thus creating hierarchical feature maps at multiple scales.

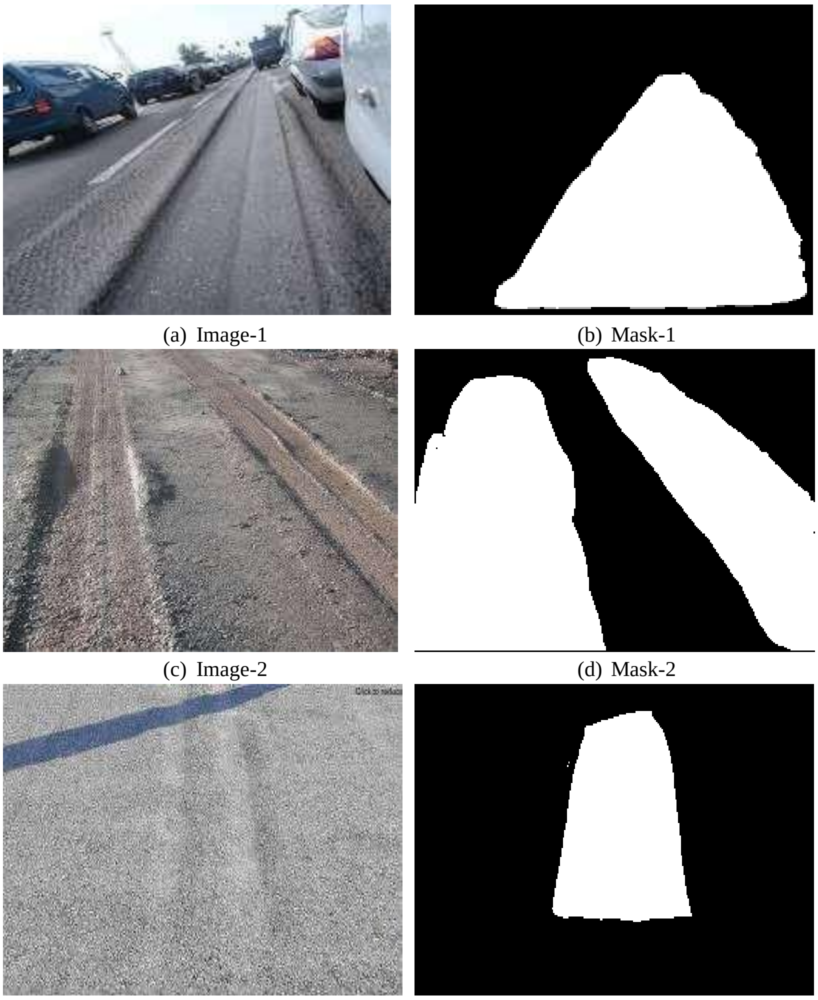
MAnet Decoder Layers:

The **MAnet** decoder uses a **multiscale attention mechanism** for segmentation tasks. It takes the feature maps from different stages of the encoder and combines them with the decoder's upsampling path.

1. **Upsampling Layers (Transpose Convolutions)**:
   - **Upsampling Block 1**: Transpose convolution to increase the spatial resolution of the feature map. It typically also includes skip connections from the corresponding encoder blocks (like U-Net).
   - **Upsampling Block 2**: Another transpose convolution block, continuing to upsample the feature maps.
   - **Upsampling Block 3**: Further upsampling with transpose convolutions.
   - **Upsampling Block 4**: The final upsampling block before reaching the output resolution.
2. **Multiscale Attention Mechanism**:
   - **Multiscale Attention**: This layer applies attention mechanisms that allow the network to focus on relevant spatial regions at different scales of the feature map. This attention helps the model enhance features related to road rutting detection by focusing on important areas.
3. **Skip Connections**:
   - Similar to U-Net, MAnet uses skip connections from the encoder to the decoder. These connections help the network recover fine-grained spatial information lost during downsampling in the encoder. The skip connections occur between corresponding encoder and decoder stages.
4. **Final Output Layer**:
   - **1x1 Convolution**: This layer reduces the number of channels to the number of output classes (in your case, 2 classes). This is followed by:
     - **Activation Function**: Softmax or sigmoid depending on the segmentation task (e.g., binary or multi-class segmentation).

SIMULATION RESULTS

In the experiment, to verify the effectiveness of Road Rutting Detection using MAnet with EfficientNet-B0 method was tested on a set of asphalt pavement images. The experiments were done to evaluate the model performance specifically on road rutting prediction as Test Set Pixel Accuracy, and Test Set mIoU. The dataset [14] introduces a new road rutting dataset consisting of 949 images, offering both object-level and pixel-level annotations. The sample images in the dataset is depicted in Figure 2.



(a) Image-1 (b) Mask-1

(c) Image-2 (d) Mask-2

(e) Image-3 (f) Mask-3

Figure 2: Sample images in the Dataset [14].

The proposed model is evaluated with mean IoU metric. The figure 3 shows how the mean Intersection over Union (mIoU) scores improved with more training epochs, for both the training and validation datasets. In segmentation tasks like these, the mIoU is an important metric to measure how accurate are your predicted segments with respect to ground truth. The blue line corresponds to training mIoU, the orange line is validation mIoU i.e how fast model can learn and generalize over time.

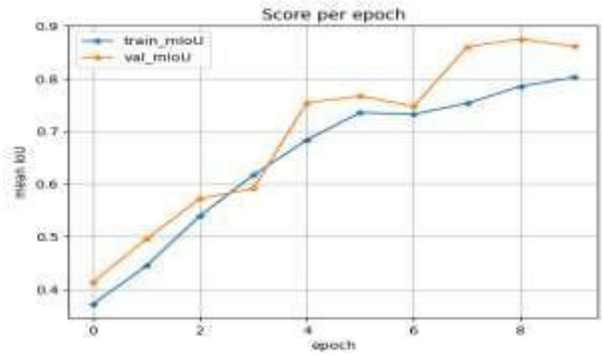


Figure 3: Score per Epoch Graph

In figure 3, ss clearly visible after the initial epochs for both training and validation mIoU scores, which start around 0.4: it indicates that now model is in a mechanism learning phase of what patterns exists between just starting with high-level information but applicable to all features from dataset. This shows now the model is enhancing its ability to segment as the curve rise with training. At epoch 5, the mIoU for training and validation to have increased a lot, with the validations score overtaking even compared to that of testing meaning its generalizing well by this point. The validation mIoU slowly increases and levels off in epochs 5 to 7, where it is nearly 0.88: The high validation mIoU further suggests that the model is embedding important information for correct segmentation. The training mIoU further keeps increasing and almost reaches the validation score, which indicates only little overfitting with more accurate predictions during training.

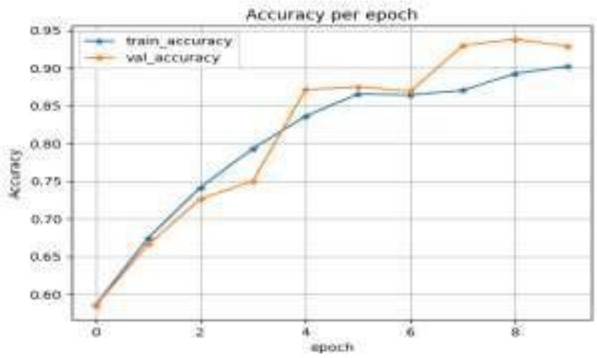


Figure 4: Accuracy per epoch Graph

The figure 4 is a representation of the accuracy achieved during training and validation per epoch worked upon to train this model. Blue Line represent the Training Data and Orange Line indicates the Validation Data. At first, both training and validation accuracies start from roughly 60%, which shows that the model is not too good at correctly predicting the data. On top of this, as training goes on both accuracies follow an increasing trend, indicating that the model is learning to extract more important features from data. In the 4th epoch findings shows that validation accuracy exceeds the training classification. Typically, from epochs 5 to 8 both training and validation accuracies come together about or higher than a high-90%. The final epochs see a high validation accuracy peak at approximately 93%, good demonstration that the model is able to perform on new data and still generalize well.

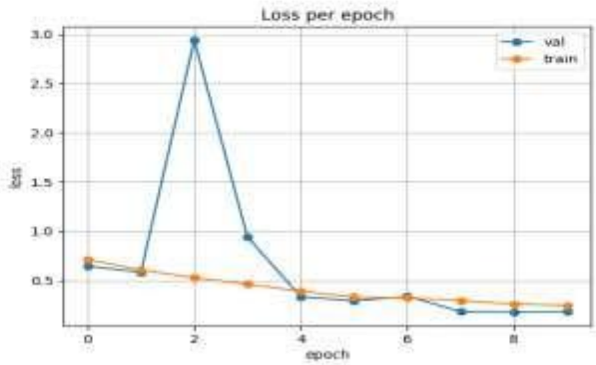
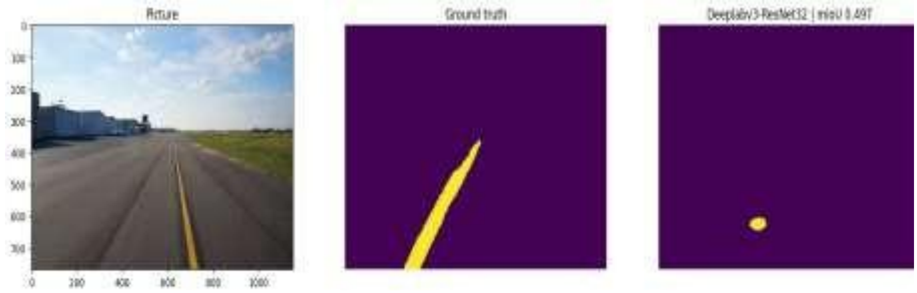
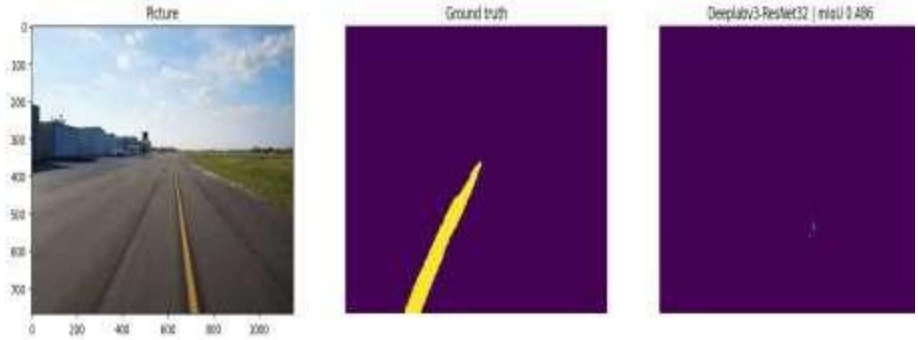


Figure 5: Loss per Epoch graph

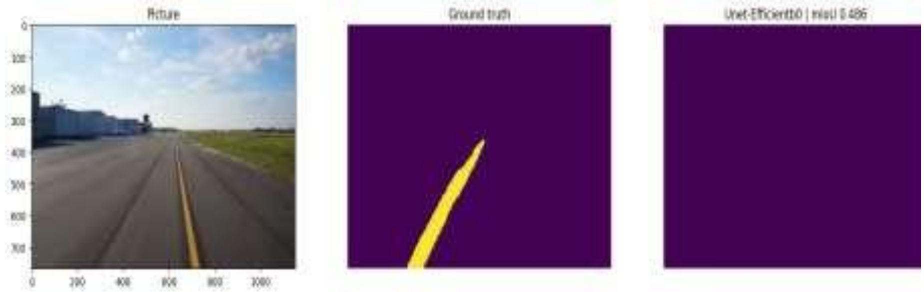
Figure 5 shows loss per epoch plot for training and validation data during model training. The orange and blue line are the training loss and validation loss, respectively. Since epoch 5, we can see both the training and validation losses to converge at low values approximatively near 0.1 by last epochs. This close of a generalization gap is indicative that the model neither underfits/overfits and can be seen as the ideal outcome. The general trend shows that proposed model was able to reduce error on the training and validation data set, which means that it is getting better with new data. The segmentation result of the proposed model is compared with other models and corresponding results are depicted in Figure 6.



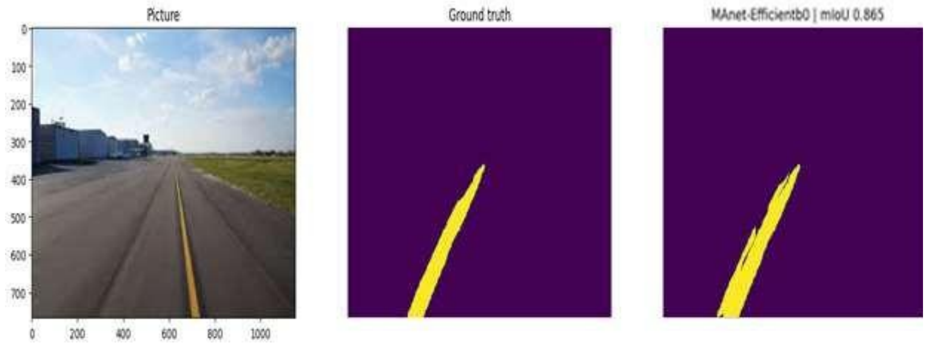
(a) Segmentation Result of DeeplabV3 with ResNet32



(b) Segmentation Result of DeeplabV3+ with ResNet32



(c) Segmentation Result of Unet with EfficientB0



(d) Segmentation Result of Proposed MAnet with EfficientB0

Figure 6: comparison Segmentation Results of Proposed MAnet with EfficientB0 model

The figure 6 shows the detection of road ruts using MAnet- Efficientb0 and compared with existing models. In figure 6, the left in the image above is the original input image showing an instance of rutting on a section of road. In the context of lane markers, where this rutting is located that road surface actually looks like. The middle image represents the ground truth mask image and corresponding segmentation results are depicted in right side image.

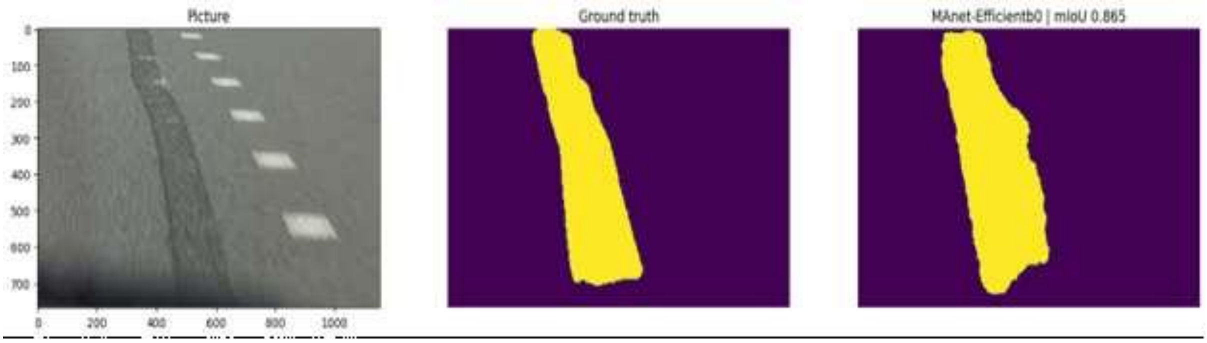


Figure 7: Proposed model output

The mIoU score is evidence of the extent to which the predicted rutting area overlaps with its physical counterpart, and a 0.865 value reflects that less misclassification can happen obsolete regions due to model based improper identification. The proposed model, MAnet-Efficientb0 effectively yielded a trade-off between detection and segmentation of road rutting which is suggested to be an appropriate solution as far reliable tools for monitoring the condition of roads are concerned. Figure 7 shows the proposed model output.

Table 1: Performance Comparison Metrics

Model Name	**Test set mIoU**
DeeplabV3 with ResNet32	0.497
DeeplabV3+ with ResNet32	0.486
Unet with EfficientB0	0.486
Proposed MAnet with EfficientB0	**0.865**

The table 1 compares the performance of various segmentation models on a testing dataset using mean Intersection over Union (mIoU). The Proposed MAnet with EfficientB0 model had the highest mIOU of 0.865 among all models tested, demonstrating superior performance compared to other architectures. It is illustrated that the proposed model segments road rutting considerably well compared to other pixel-wise methods, and this demonstrates one of a great potential advantage at lease.

The mIoU of the DeeplabV3 with ResNet32 model was 0.497, which suggests that it had moderate performance in terms locating regions where targets are located. The mIoU score for the baseline model was 0.491. The same scenario was observed for Unet with EfficientB0 that also used an EffucientNet-B0 as the backbone where it produced mIoU of 0486. This shows almost similar results as DeeplabV3+ but still far behind the proposed MAnet model. The following conclusions can be drawn from the results of Proposed MAnet with EfficientB0 compared to other state-of-the-art road defect patterns recognition methods: The performance improvement achieved by having a multi-scale attention mechanism combined with EfficinetB0 backbone assures for fine-grained and robust segmentation, based on these experimental results.

CONCLUSION

The MAnet-Efficientb0 model increased road rutting detection performance on several parameters, showing significant improvements compared to other state-of-the-art models for the task with an mIoU score of 0.865. while DeeplabV3 with ResNet32 had an mIoU of only 0.497 and U-Net which used EfficientB0 achieved a score of just 0.486 making it less accurate than proposed method as well as computationally more expensive (using both training epochs and inference times). These results verify that the presented system will be a stable and dependable answer for-real-time roads rutting discovery. The proposed model is unique which combines the multiscale attention mechanism with Efficientb0. The Efficientb0 encoder and the MAnet decoder are among the main components of our proposed model. Efficientb0: A lightweight conv net as backbone for feature extractions, which keeps our compatutation efficient. To enhance the feature extraction, we design multiscale attention mechanism in MAnet decoder to refine it and emphasize not only spatial but also channel-wise dependencies which are important for capturing small-scale details that matter when identifying road rutting precisely.

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