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Low Power SoC based Road Surface Crack Segmentation using Unet with Efficientnet-B0 Architecture

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Abstract

The primary objective of this research is to provide a power-efficient solution for real-time road crack segmentation, overcoming the limitations of high computational costs in existing deep learning models. By integrating the Unet model's encoder-decoder structure with EfficientNet-B0, the proposed solution enhances segmentation accuracy while minimizing power consumption. This work aims to fill the gap in the current research by offering a deployable solution on low-power devices without sacrificing performance. The methodology involved training the Unet-EfficientNet-B0 model using a road surface crack dataset and converting the trained model to the ONNX format for deployment on the ZCU104 Ultrascale+ SoC device. The novelty lies in the hybrid architecture, where EfficientNet-B0 is used as the encoder to capture essential features and reduce the computational load, and Unet serves as the decoder to produce fine-grained segmentation maps. This combination allows the model to process high-resolution images with low latency, making it ideal for edge computing.The research demonstrated that the proposed model outperformed other architectures, achieving a mean IoU of 0.9422 and pixel accuracy of 0.9938 on the test set. The results indicate that the model provides accurate segmentation of road cracks with minimal computational overhead, making it suitable for real-time road monitoring applications on SoC platforms. The implementation on the ZCU104 SoC validated its potential for deployment in real-world scenarios.The findings have significant implications for the future of road infrastructure maintenance. The ability to deploy such a model on low-power devices allows for continuous monitoring of road conditions in smart cities, reducing maintenance costs and improving safety. The efficient use of power while maintaining high segmentation accuracy makes this model a breakthrough in automated inspection technologies

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Introduction

The maintenance application of road surface has always been considered critical in case of transportation systems which are safe and efficient. When cracks develop in the road surfaces, it can cause a lot of structural damage and expenses if not discovered earlier. Legacy road inspection practices, meanwhile, can be labour-intensive and slowoften requiring manual checks to identify where problems lie within infrastructure. [1] With the increased use of autonomous systems and smart cities, there is a need for automated algorithms that can accurately detect and segment road surface cracks in real-time.[2]

Recent breakthroughs in deep learning and computer vision have allowed automated crack detection to reach new levels. Nevertheless, these methods usually need heavy-duty computational resources which can hamper their deployment on low-power environments such as embedded systems and edge devices. This reduction in energy consumption is especially critical for deploying such systems practically into the real world, especially when there is a need to process high-resolution images continuously controlling several scenes.[3]

A major issue in this field is achieving a trade-off between the precision of crack detection and low-power hardware limitations. Operational at edge devices and SoC platforms, the overall operation of must be power efficient without losing segmentation performance. Also, road surface conditions are not consistent which makes the segmentation problem complex because cracks may take various shapes and may have different sizes and visibility.[4] Hence, solution is needed which does not only segment cracks accurately but can also be deployed on low-power hardware for real-time operation.

Incorporating deep learning models onto low-power SoC platforms adds another level of complexity due to optimizing the model and co-designing hardware-software. In this idea, it is necessary to have efficient network architectures capable of making crack segmentation with the minimum power they are consuming in order to go beyond these limitations.[5] In the absence of these optimizations, current deep learning techniques may remain impractical for deployment in edge computing environments which will restrict their practical use cases in road surface monitoring.[6]

The Unet model with the EfficientNet-B0 architecture would be a solution to that. Unet is popular encoder-decoder structures for image segmentation in which EfficientNet-B0 acts as the backbone network providing a good trade-off between performance and computational efficiency. Utilizing these architectures the proposed approach is able to segment surface cracks on road images very precisely even for low-power SoC platforms, ensuring that it can be used as an efficient and scalable solution for real-time road infrastructure maintenance.

This investigation is based on a low-power SoC (System-on-Chip) road surface crack segmentation by ahybrid deep learning model. This research aims to tackle the issue of precise road cracks segmentation, introducing energy-efficient hardware integrated with state-of-the-art deep learning methods for enhanced detection performance. The proposed hybrid architecture is designed to optimize feature extraction and crack segmentation, while minimizing power consumption. It aims to build a scalable, easy-to-deploy solution for real-time road maintenance and monitoring systems. The structure of the paper describes as follows: Th literature is discussed in section-II and proposed model is explained in section-III. The results are discussed in section-IV.

Literature

Nhung Hong Thi Nguyen et al[7] suggested a novel approach employing a two-stage convolutional neural network (CNN) for the precise identification and separation of road cracks in photographs at the pixel level. Our innovative contribution entails a framework that consists of two stages. The initial stage is dedicated to eliminating any unwanted disturbances or imperfections and identifying the probable fractures within a limited region. The subsequent step is capable of acquiring knowledge about the surrounding environment of the identified cracks. Therefore, this approach is more efficient than learning over the complete original image with noise.

Wenjun Wang et al[8] presented a crack segmentation model that is lightweight and based on a bilateral segmentation network. This model strikes a favorable balance between the speed of inference and the performance of segmentation. The model consists of two components: the context path and the spatial path. The network utilized in the given context route is based on the Xception architecture, which is employed for efficient downsampling of the feature map. The spatial route utilizes three convolutional layers to effectively encode enough spatial information.

Zhun Fan et al[9] suggested approach takes into account an encoder-decoder architecture called U-Hierarchical Dilated Network (U-HDN), which combines dilated convolution with hierarchical feature learning to conduct crack detection in an end-to-end manner. Crack features with various contexts may automatically pick up new skills and carry out end-to-end crack detection. Next, it is suggested to incorporate a multi-dilation module into an encoder-decoder design. By using dilation convolution with varying dilatation rates, the multi-dilation module may include the crack characteristics of numerous context sizes and acquire a significantly greater amount of crack information. In order to anticipate pixel-wise crack detection, the hierarchical feature learning module is developed to extract multi-scale features from high to low-level convolutional layers.

Seungbo Shim et al[10] presented a rapid and efficient semantic segmentation method capable of identifying regions with road-surface damage in photos, aiming to avoid accidents caused by such conditions. An experiment was done to evaluate the system, involving the creation of over 1,500 training data and 150 validation data. These datasets included newly generated road-surface damage. Based on the data, the authors suggest a novel deep neural network that exclusively consists of an encoder, in contrast to the traditional auto-encoding type which includes both an encoder and a decoder.

In order to assess the effectiveness of the suggested method, they examined four accuracy measures and two speed metrics.

Lu Deng et al[11] suggested a comprehensive framework for the segmentation, measuring, and automated identification of fractures in the road surface. A modified Residual Unity Networking (Res-UNet) algorithm is then proposed for accurate pixel-by-pixel segmentation within the crack regions; lastly, a novel crack surface feature quantification algorithm is developed to determine the pixels of crack in width and length, respectively. Initially, road images are captured, and crack regions are detected based on the You Only Look Once (YOLOv5) algorithm's fifth version. Furthermore, a dataset of complicated environmental noise from road cracks is generated. Various shooting angles, distances, and lighting situations are taken into account.

Alessandro Di Benedetto et al[12] utilized a modified U-Net model-based approach, the crack segmentation process may be optimized for optimal performance. In order to do this, the Crack500 dataset is utilized, and the outcomes are subsequently compared with the outcomes produced from the U-Net method, which is presently considered to be the most accurate and effective algorithm in the existing body of research. The development of a modified U-Net model-based algorithm is the means by which the authors want to achieve the objective of our research, which is to improve the crack segmentation process.

Taehee Lee et al[13] created a CNN-based image pre-processing model and a semantic segmentation model with an autoencoder structure for identifying road surfaces. By modifying the picture brightness prior to its input into the road-crack detection model, this configuration guarantees improved identification of cracks in the road surface. The road-crack segmentation model performed consistently even with different brightness levels when the pre-processing model was used.

Shadrack Fred Mahenge et al[14] suggested a unique modified U-Net Architecture for image segmentation and classification to find cracks on the road surfaces. This involves identifying and categorizing the road photos to decide if there are cracks or not. Finding road degradation is crucial for structural health monitoring (SHM). Conventional manual inspection is often carried out using human visualization, which is costly, time-consuming, risky due to passing cars, susceptible to the inspector's subjective opinion, and makes it impossible to maintain records for future road maintenance and repair.

Proposed Model

The architecture is a combination of Unet and EfficientNet-B0 that is used in order to segment the road surface cracks. Unet-Unet is popularly used for segmentation tasks as it captures both the high-level semantic information and fine details in input images given its encoder-decoder architecture. The encoder captures the vital information, whereas the decoder translates this into a segmentation map in order to detect fine boundaries of crowd cracks on road surfaces. Overall architecture of Unet with EfficientNet-B0 whose design allows us to achieve highly precise crack segmentations even for small or irregular crack shapes.

Unet with EfficientNet-B0

EfficientNet-B0 is a lightweight and scalable convolutional neural network used as an encoder in the Unet architecture. It follows a compound scaling method scales dimensions, depth and resolution equally leading to an efficient model with number of parameters less than other models whilst maintaining low computational cost. By providing an optimal model for the target platform, EfficientNet-B0 reduces both size and power consumption of the overall system with no compromise in its performance. The proposed method makes the best of efficiency and accuracy since it employs EfficientNet-B0 in Unet framework, which is suitable for resource constraint environments.

The EfficientNet-B0 architecture is used in the encoder path of proposed model to down sample input image while extracting essential features, such as crack edges and textures. In this decoder path, convolutions are replaced by transposed convolutions to up sample the feature maps and finally reconstruct segmented image. For retaining spatial information, skip connections are used between corresponding layers in the encoder and decoder which helps retrieve edge locations of cracks.

This work is aimed to create an on-SoC model that segments cracks in the road surface with high accuracy and near real-time speed. By using EfficientNet-B0, it reduces computational overhead so the model can process high resolution images with less latency. Since the model is appropriate for applications requiring some level of energy efficiency, e. g., on mobile platforms running autonomous road maintenance and monitoring systems at this early stage. The architecture of proposed model is depicted in Figure 1.

The Each Layer of the proposed model is described as follows:

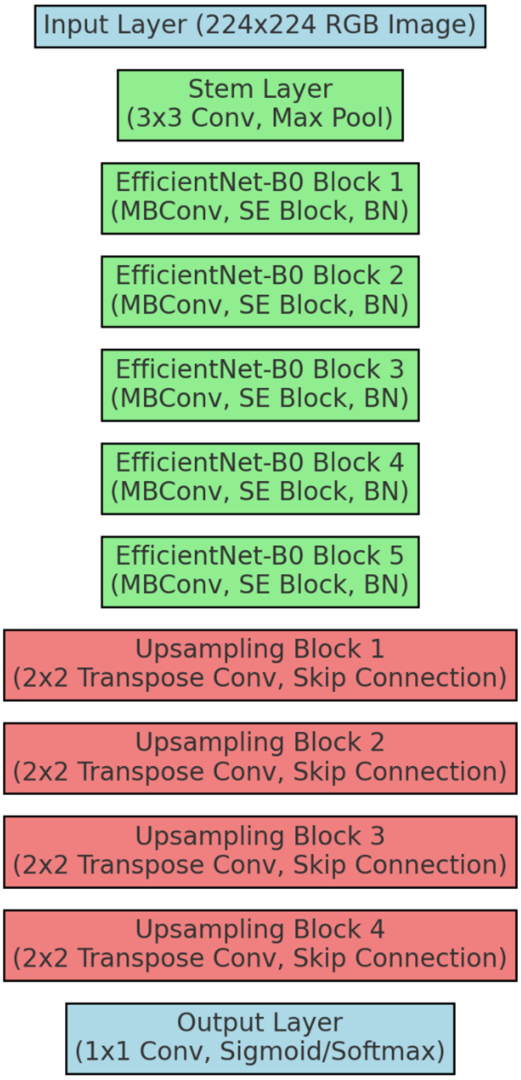

Fig. 1: Proposed Model Architecture

Input Layer:

- Start with a 224x224 RGB image.
- Pass the image to the network.

Stem Layer:

- Apply a 3x3 convolution with a stride of 2.
- Follow this with batch normalization and swish activation.
- Apply 2x2 max pooling to reduce spatial dimensions.

EfficientNet-B0 Blocks (Encoder):

- Apply MBConv block with depthwise separable convolution.
- Implement SE (Squeeze and Excitation) block for feature recalibration.
- Apply batch normalization and swish activation.
- Output a reduced spatial size and increased feature depth.
- **Skip connection**: Store the output for later use in the decoder.

Upsampling Blocks (Decoder):

- Apply 2x2 transposed convolution (upsampling).
- **Concatenate**: Add the stored features from EfficientNet-B0 Block 5 (skip connection).
- Apply 3x3 convolution, followed by batch normalization and ReLU activation.
- Output an upsampled feature map.

Output Layer:

- Apply a 1x1 convolution to reduce the number of channels to the desired number of segmentation classes.
- Apply sigmoid activation (for binary segmentation) or softmax activation (for multi-class segmentation).
- Output the final segmented image of 224x224x1 (or appropriate class dimension).

The layers EfficientNet-B0, UNet can be seen as a layer for feature extraction and up sampling/segmentation respectively thus creating an efficient architecture to detect the road surface crack in power-constrained edge devices.

SoC Implementation

The proposed model is implemented on the ZCU104 Ultrascale+ SoC device to ensure efficient and real-time performance for road surface crack segmentation. The deep learning model is implemented using Unet with an EfficientNet-B0 architecture. Subsequently, the model is converted to ONNX(Open Neural Network Exchange) format consistent with the underlying SoC. The ONNX model is then imported into the ZCU104 device which is a cost-effective, power-efficient processor that is widely used in conducting real-time computation capacity. The ZCU104 model uses low power but it also provides an optimized balance between performance and power, thus can be considered an edge computing machine. It is then fed with new road crack images and the performance is analyzed in terms of accuracy, latency, and power efficiency. Our implementation on the ZCU104 Ultrascale+ SoC device validates the proposed model for future adoption in the real system as it can achieve accurate crack images segmentation with extremely minimal latency and power consumption. The SoC implementation is represented in block diagram and depicted in Figure 2.

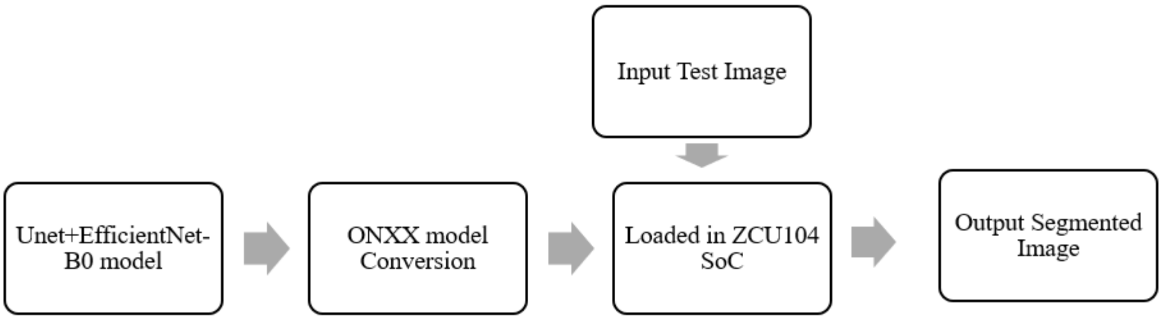

Fig. 2: Block Diagram of SoC Implementation

The step-by-step flow for implementing the proposed model on the ZCU104 Ultrascale+ SoC device is as follows:

Step 1: Model Training

- Implementation ofUnet based on EfficientNet-B0 architecture for the segmentation of road crack career via a Deep Learning framework, TensorFlow / PyTorch.
- Ensuring the model is well-trained and provides good segmentation results on a validation dataset.

Step 2: Model Export

- Convert the trained model to ONNX based format. This makes the model hardware-agnostic and can be exported for deployment on any target environment, down to an SoC device.

Step 3: Prepare the SoC Environment

- Initialize an environment on the ZCU104 Ultrascale+ SoC device for making inferences. This includes setting up the device with the proper operating system (Petalinux) and installing runtime for ONNX models on SoC.

Step 4: Load the ONNX Model

- Transfer the ONNX model to the ZCU104 SoC device.
- Deploy the appropriate ONNX runtime libraries on SoC device. In the case of Xilinx platforms installed Vitis AI library which allows an ONNX model execution on FPGA based SoC.

Step 5: Hardware Acceleration Setup

- Use the Programmable Logic (PL) of a ZCU104 FPGA to speed up an inference. Using the Vitis AI tools to compile the model and generated necessary bitstream for it.
- Program the ZCU104 FPGA with the compiled bitstream so that it is in a state to perform deep learning inference.

Step 6: Inference Execution

- Run the inference on the ZCU104 SoC device using the loaded ONNX model. Ensuring that the model is tested with new road crack images for real-time segmentation performance.
- Observe the inference to see if for FPGAs needs more efficient acceleration or it meets real-time standards.

Step 7: Performance Monitoring

- Evaluate the model's segmentation accuracy on the ZCU104 SoC device by comparing the predictions with ground truth road crack images.
- Check latency, throughput & Power consumption to ensure it meets the goals of a low power and high-efficiency crack detector.

Step 8: Optimization (If Necessary)

- If the performance does not meet desired benchmarks, further model optimization by adjusting network size, prune unused layers & fine-tune hardware parameters on ZCU104 SoC device.
- Recompile the model and reload it onto the FPGA for improved performance.

These steps provide a direct deployment process of the Unet with EfficientNet-B0 model for road surface crack segmentation on ZCU104 Ultrascale+ SoC device and ensure that we successfully implement an efficient and effective SoC.

Experimental Results

The proposed model was tested on the Surface Crack Detection dataset.[15] This dataset consists of thousands of concrete surface images in various conditions. Specifically, half of the images in the dataset are cracked, while the other half are uncracked. The images are organized into two folders: negative, meaning they have no cracks, and positive, for images containing cracks. Each folder contains 20,000 images, totalling 40,000. The resolution of each image is 227 x 227 pixels in RGB format.These images are different from one another in surface finish and light conditions. It does not use any data augmentation such as random rotations, flips, or tilting. The sample images in the dataset are shown in Figure 3.

(a) Image-1

(b) Image-2

(c) Image-3

(d) Image-4

(e) Image-5

(f) Image-6

Figure 3: Sample Input Images in the Dataset

The algorithm began with loading the images from the dataset. The images were 227 by 227 pixels in resolution and in RGB format. The images were then normalized to ensure that pixel values were scaled from 0 to 1. These measures facilitated faster convergence while training. The image 'labels' were assigned based on their storage in folders. If they were stored in a folder entitled 'positive' they were labeled as cracked, and they were labeled as not cracked in the negative folder. The proposed model is trained on timages in the test dataset and corresponding performance metrics such as loss per epoch, mean IoU and accuracy of training and validation graphs are reported in Figure 4, Figure 5 and Figure 6 respectively.

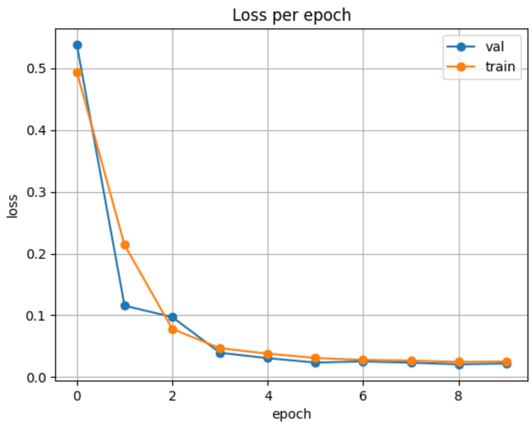

Fig. 4: Loss per Epoch Graph

Loss per epoch train vs validation of a deep learning model depicted in the Figure 4. This plot indicates that loss decreases rapidly for 1 to 3 epoch and later converges toward loss near zero. This means the model is learning well and reducing error with each epoch. The gap between the training and validation curves is minimal, meaning it most probably has very less overfitting at all with respect to new data.

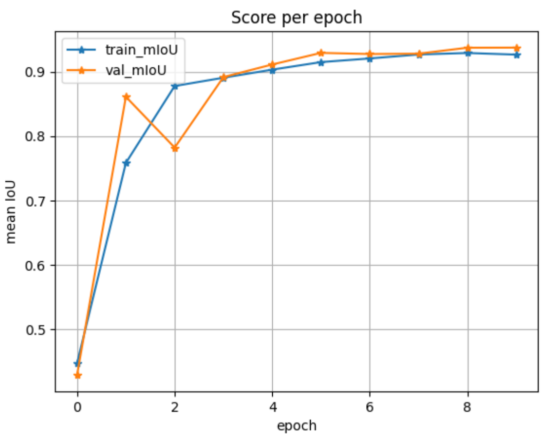

Fig. 5: Mean IoU per epoch Graph

Mean Intersection over Union (mIoU) score per epoch during training and validation is shown in Figure 5. The Figure 5 demonstrates that mIoU increases rapidly in the first few epochs and both training and validation scores settle around 0.9 after three epochs. More specifically, while at the beginning there is some oscillation in validation score but then it becomes stable and increases gradually for both datasets. The results for this evaluation are shown in the image which is a clear indication that the model has high accuracy over segmentation tasks and generalizes well over both training as test data.

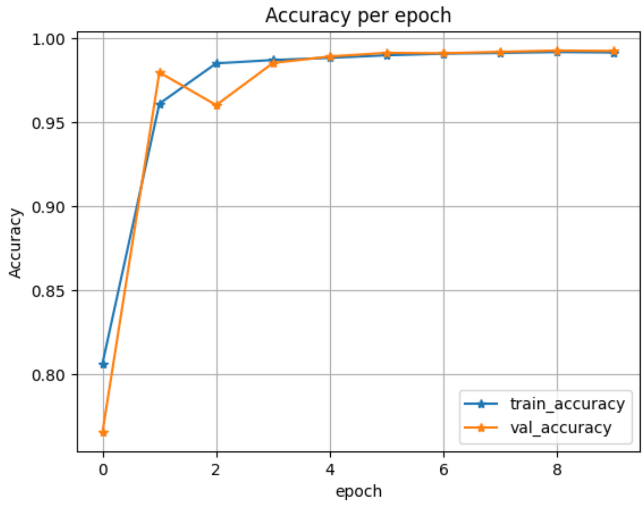

Fig. 6: Accuracy graph of the proposed model

The Figure6 presents accuracy per epoch for training and validation datasets. First, there is a very steep rise in accuracy for both the datasets where it goes above 95% within first three epochs. Training and Validation accuracy both are closely placed to each other, this means model generalize well not overfit on the data. From the sixth epoch, both accuracies hover at around 99%, showing that the model has trained properly to complete this task and perform consistently across datasets. The segmentation output is depicted in Figure 7.

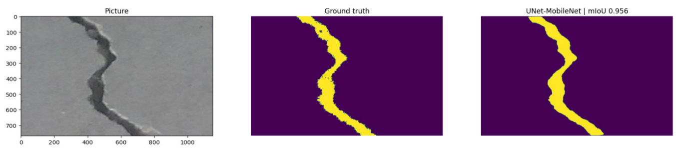

Fig. 7: Segmentation output from the proposed model

The Figure 7 presents the road surface crack segmentation using a UNet with EfficientNet-B0 model. The left side image shows an original image of a road surface that includes a crack in it on image. The image of the center gives us ground truth: The crack is correctly labelled in yellow. The image on the right shows output of results from UNet- EfficientNet-B0 with achieving mIoU score 0.956 in segmentation crack. The prediction from the

Table 1: Comparison Results of Proposed model

Model Name	Test set mIoU	Test set Pixel Accuracy
FPN + EfficientNet-B0	0.9165	0.9916
LinkNet+ EfficientNet-B0	0.6981	0.9674
MANet+ EfficientNet-B0	0.8464	0.9841
Proposed Model	**0.9422**	**0.9938**

model closely resembles ground truth, illustrating that the road crack has been detected and segmented accurately by the proposed method. The proposed model is compared with other deep learning model and performance metrics are reported in Table 1.

The Table 1 presents a comparison of several segmentation models' performance in terms of mean Intersection over Union (mIoU) and Pixel Accuracy on a test set. The FPN + EfficientNet-B0 model obtains a mean Intersection over Union (mIoU) of 0.9165 and a pixel accuracy of 0.9916. In contrast, the LinkNet + EfficientNet-B0 model has a lower mIoU of 0.6981 and pixel accuracy of 0.9674. The MANet + EfficientNet-B0 model demonstrates enhanced performance, achieving a mIoU (mean Intersection over Union) of 0.8464 and a pixel accuracy of 0.9841. The suggested model surpasses all previous models, attaining the greatest mean Intersection over Union (mIoU) score of 0.9422 and a pixel accuracy of 0.9938. This showcases its exceptional ability in accurately segmenting road surface cracks. The proposed model is ported in ZCU104 SoC board and measured the resource utilization and power reports. The resource utilization is depicted in Figure 8.

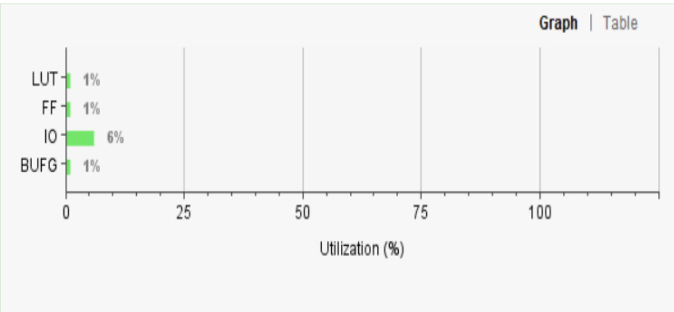

Fig. 8: Resource utilization report of Proposed model

The image above shows a power utilization report for an on-chip system. The total power consumption is split into dynamic and static components. The dynamic power consumption is relatively low at 0.007 W, accounting for only 1% of the total power, with the remaining 99% being static device power, which amounts to 0.592 W. The dynamic power is further broken down into clocks (10%), signals (8%), logic (12%), and I/O (70%). Most

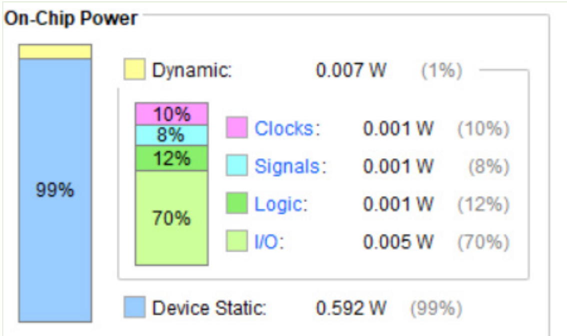

Fig. 9: Power Utilization report of Proposed model

of the dynamic power is consumed by I/O operations, while clocks, signals, and logic contribute relatively smaller portions. This indicates that the device is heavily influenced by static power consumption, with a small percentage being used for active operations.

Conclusion

The research presented a novel approach for road surface crack segmentation, achieving a high mean Intersection over Union (mIoU) of 0.9422 and pixel accuracy of 0.9938. These results affirm the model's effectiveness in accurately segmenting road cracks while maintaining low power consumption, making it highly suitable for real-time deployment on resource-constrained System-on-Chip (SoC) platforms.The key components of the proposed model include the Unet architecture, renowned for its encoder-decoder structure that captures both high-level semantic information and fine details, and EfficientNet-B0, which acts as the encoder, offering a scalable and lightweight solution for feature extraction. Skip connections between the encoder and decoder ensure the preservation of spatial information, critical for precise segmentation.The novelty of the model lies in its successful integration of Unet with EfficientNet-B0, which achieves a balance between segmentation accuracy and computational efficiency. This design allows the model to process high-resolution images while consuming minimal power, making it ideal for edge devices and mobile platforms. The model's ability to perform well across diverse road conditions and lighting environments further underscores its robustness and adaptability.

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