Deep Learning Model Compression for Resource Efficient Activity Recognition on Edge Devices: A Case Study

Dieter Balemans[1,3], Benjamin Vandersmissen[2], Jan Steckel[3], Siegfried Mercelis[1], Phil Reiter[2] and José Oramas[2]

[1]*Faculty of Applied Engineering, University of Antwerp - imec - IDLab, Sint-Pietersvliet 7, 2000 Antwerp, Belgium*

[2]*Faculty of Science, University of Antwerp - imec - IDLab, Sint-Pietersvliet 7, 2000 Antwerp, Belgium*

[3]*Faculty of Applied Engineering, University of Antwerp - CoSysLab, Groenenborgerlaan 171, 2020 Antwerp, Belgium*

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Abstract: This paper presents an approach to adapt an existing activity recognition model for efficient deployment on edge devices. The used model, called YOWO (You Only Watch Once), is a prominent deep learning model. Given its computational complexity, direct deployment on resource-constrained edge devices is challenging. To address this, we propose a two-stage compression methodology consisting of structured channel pruning and quantization. The goal is to significantly reduce the model's size and computational needs while maintaining acceptable task performance. Our experimental results, obtained by deploying the compressed model on Raspberry Pi 4 Model B, confirm that our approach effectively reduces the model's size and operations while maintaining satisfactory performance. This study paves the way for efficient activity recognition on edge devices.

1 INTRODUCTION

Activity recognition is a crucial task in various industries, including unmanned aerial vehicle monitoring, autonomous driving, and urban security systems. However, one of the challenges in this field is the computational complexity associated with large deep learning models. This, makes it infeasible to deploy these models on edge devices, where resources are generally limited. Nevertheless, the recent push toward making decisions at the edge extends to the field of activity recognition. For example, activity recognition is being used on remote construction sites for onsite progress monitoring (IMEC, 2023)(Braun et al., 2020). Deploying complex algorithms on edge devices offers several benefits. Firstly, it reduces system latency since data does not need to be sent to the cloud for processing. This also enhances the security and privacy of the system as data does not leave the device. Lastly, it decreases the cost of the system, as it removes the need for a powerful server to process the data. Therefore, we aim to investigate the feasibility of deploying deep learning-based activity recognition on edge devices. More specifically, we will explore how to adapt existing deep learning models to make them suitable for edge deployment.

This paper focuses on the YOWO (You Only Watch Once) model proposed by Köpüklü et al. (Köpüklü et al., 2019). YOWO is a widely used convolutional neural network architecture for activity recognition. However, due to its size and complexity, it is not initially suitable for edge deployment. The goal is to adapt this model an make it more suitable for edge computing, by reducing its size and operations. The target device is the Raspberry Pi 4 Model B. We aim for the model to maintain high enough performance while fitting within an applications requirements. These requirements can be a time (latency) constraint, a memory constraint or an energy constraint. To achieve this, we propose a two-stage compression approach: structured channel pruning and quantization.

In the first stage, structured channel pruning, our goal is to decrease the size of the model and the number of operations needed to execute the model, without affecting its accuracy. This technique selectively removes channels from convolutional layers, resulting in a smaller and faster model. This is because tensors can be reduced in size without the need for specialized hardware. Moreover, we merge pruning with quantization to further shrink the model's size by representing the weights and activations with fewer bits.

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We present our compression approach in combination with a sensitivity analysis to determine the impact of pruning the model and to find the optimal parameters for scheduling the pruning. We assess the effectiveness of our approach by deploying the compressed YOWO model on the Raspberry Pi 4 Model B. We then measure its latency, energy consumption, and memory usage. The results show that we can considerably decrease the latency and memory consumption of the YOWO model while keeping task performance at an acceptable level.

In the next section we provide an overview of related work in the field of activity recognition and deep learning model compression. Section 3.1 describes the YOWO model and its training process. Sections 3.2 and 3.3 explain the compression techniques used in this work. Section 4 describes the experimental setup and presents the results. Finally, Section 5 concludes the paper and discusses future work.

2 RELATED WORK

Activity Recognition. Activity recognition is the task of recognizing activities from a sequence of frames. In other words, it is the spatiotemporal localization of activities in observations. Numerous approaches have been proposed to solve this task. A common approach is to use a sliding window to extract features from the observations and use these features to classify the activity. The features can be extracted using a variety of methods, such as hand-crafted features, or deep learning. Earlier deep learning methods, rely on a two-stream convolutional neural network (CNN) to extract spatial and temporal features separately and fuse them to classify the activity (Simonyan and Zisserman, 2014)(Feichtenhofer et al., 2016). However, these methods are computationally expensive and can be very time-consuming. More recently, the use of 3D CNNs has become more popular. Its is able to learn both spatial and temporal features simultaneously. These models are proven to perform better on the activity recognition task (Qiu et al., 2017)(Tran et al., 2017)(Feichtenhofer et al., 2018)(Tran et al., 2014). However, these models are even more expensive in terms of size and operations. 3D convolutions have much more parameters and require more operations than 2D convolutions. This makes them difficult to deploy on edge devices. Therefore, in this work, we investigate the possibility of compressing a 3D CNN for activity recognition. We choose the YOWO model proposed by Köpüklü et al. (Köpüklü et al., 2019) as base model. This model is a unified, single-stage architecture which consist of 2 two branches. The YOWO model is the fastest model for activity recognition, however, it is still too large for edge deployment. We provide more details about the model in Section 3.1.

Compression. Neural network compression is a field of research that aims to reduce the size and operations of a neural network. There are several techniques that can be used to achieve this. Techniques like pruning and quantization are among the most popular ones, and often used in combination. Pruning is the process of removing weights, neurons or channels from a neural network. In the field there are numerous techniques, all which differ in the way to determine the importance of connections (i.e. where to remove connections), the granularity (i.e. which connections to remove) and the scheduling (i.e. when to remove connections). Generally, pruning is done by removing the connections and neurons that have the smallest impact on the network's output. This paved the way to pruning methods based on weights (Han et al., 2016), activations (Georgiadis, 2018) and gradients (Liu and Wu, 2019). For instance, Lee et al. (Lee et al., 2018) use a saliency-based criterion consisting of the lowest absolute value of the normalized gradient multiplied by the weight magnitude for a given set of mini-batch inputs.

For the granularity, there are two main types of pruning: unstructured (Frankle and Carbin, 2018)(Tanaka et al., 2020) and structured pruning (Li et al., 2016)(He et al., 2017). Unstructured pruning removes individual connections from the network. This means the weight tensor of the network will be very sparse and highly irregular. These methods allow for the highest compression rates with the lowest impact on accuracy. However, this sparsity is (currently) not suitable for hardware acceleration. On the other hand, structured pruning removes entire block-like structures from the network (Crowley et al., 2018). For example, in channel pruning, entire channels of a convolutional layer are removed. This allows for the weight tensors to be actually smaller by removing the entire row or column of the channel, removing a lot of OPs (operations). On current hardware, and especially on CPU only devices, this is the most suitable type of pruning. One drawback of structured pruning is that it is less flexible than unstructured pruning, and has a much bigger impact on the network's performance. In this work we focus on structured pruning, more specifically channel pruning.

In this work we combine pruning with quantization. We follow the philosophy of the work of Han et al. (Han et al., 2016) where pruning is combined with quantization. They show that quantizing after

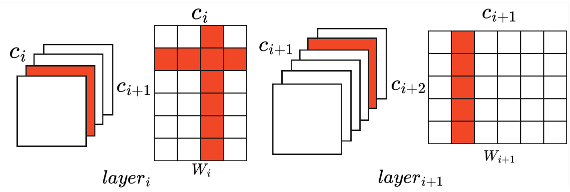


Figure 1: Overview of the structured channel pruning process. Here we show the removal of one channel from layer i and one channel from layer $i+1$. The effect of the removal is visible in red.

pruning is possible without losing accuracy. Therefore, we propose a similar approach in this work for compression of large activity recognition models.

3 METHODOLOGY

3.1 Activity Recognition

As mentioned previously, we use the You Only Watch Once (YOWO) model (Köpüklü et al., 2019) as our baseline model. YOWO is a single-stage architecture which consist of 2 two branches to extract temporal and spatial information from video frames. Specifically, the 2D backbone is a YoloV2 model (Darknet-19) (Redmon and Farhadi, 2016). The 3D backbone is a ResNext-101 model (Xie et al., 2016). Ultimately, the model predicts the activity class and the bounding box of the activity in the video frame. Note that there are variation of the YOWO model with different 2D and 3D backbone configurations. For this paper we only use the standard (Darknet-19 and ResNext-101) configuration. The goal is the evaluate the compression of this standard configuration.

This configuration makes the model altogether a fairly large model, with over 121 million parameters and 43 billion operations, making it difficult for deployment on edge devices with limited resources. Therefore, we investigate the possibility of compressing the YOWO model to enable inference and analysis on the edge device. In the next section we will discuss the compression techniques that we use to compress the model.

In this work we perform post-training compression. This means we train the YOWO model beforehand, and use it as a starting point for the compression process. We provide more details about the training and evaluation in section 4.

3.2 Neural Network Pruning

In this work we employ neural network pruning to reduce the size and amount of operations of the YOWO

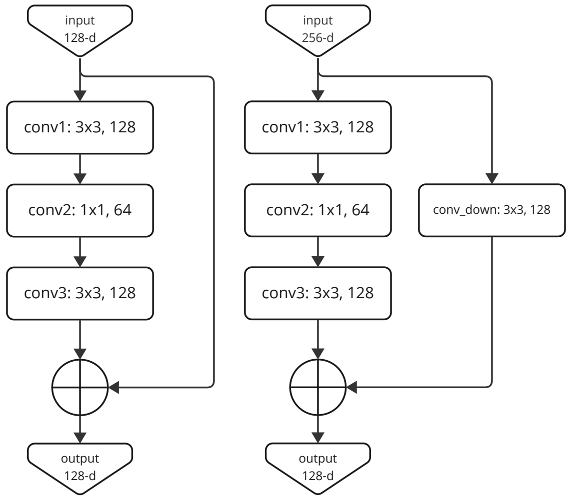


Figure 2: Sample of bottleneck blocks as used in the YOWO model. **(Left)** An example of a bottleneck block without downsampling layer. The block takes in 128 channels. In this block, the addition operation creates a dependency between the channels of the third convolution operation (conv3: 3x3, 128), the first convcolution operation (conv1: 1x1, 128) and the input. **(Right)** An example of a bottleneck block with downsampling layer. The block takes in 256 channels. In this block, the addition operation creates a dependency between the channels of the third convolution operation (conv3: 3x3, 128), the downsampling convolution operation (conv_down: 3x3, 128), the fist convcolution operation (conv1: 1x1, 128) and the input.

model. We use a structured iterative channel pruning technique (Wen et al., 2016) to remove unimportant channels from the convolutional layers of the YOWO model. The YOWO model has both 2D and 3D convolutional layers. In both cases we use the same pruning technique. In order to estimate the importance of each channel, we use two different criteria: weight magnitude (Han et al., 2016) and activation (Georgiadis, 2018). The weight magnitude criterion is based on the magnitude of the connection weights. We utilize the l_1-norm of the weights to determine the importance of each channel. The activation criterion is based on the activation of the neurons. We follow the same approach to estimate the importance of each channel, using the l_1-norm, but this time using the output activations instead of the weights. We compare the results of both criteria in Section 4.

The pruning process itself is scheduled in an iterative fashion. In each iteration, we prune a certain percentage of the channels from the layers. This is followed by a fine-tuning step, where we fine-tune the model to recover the performance lost during pruning. As we will see in our sensitivity analysis results in Section 4, the pruning process can be quite

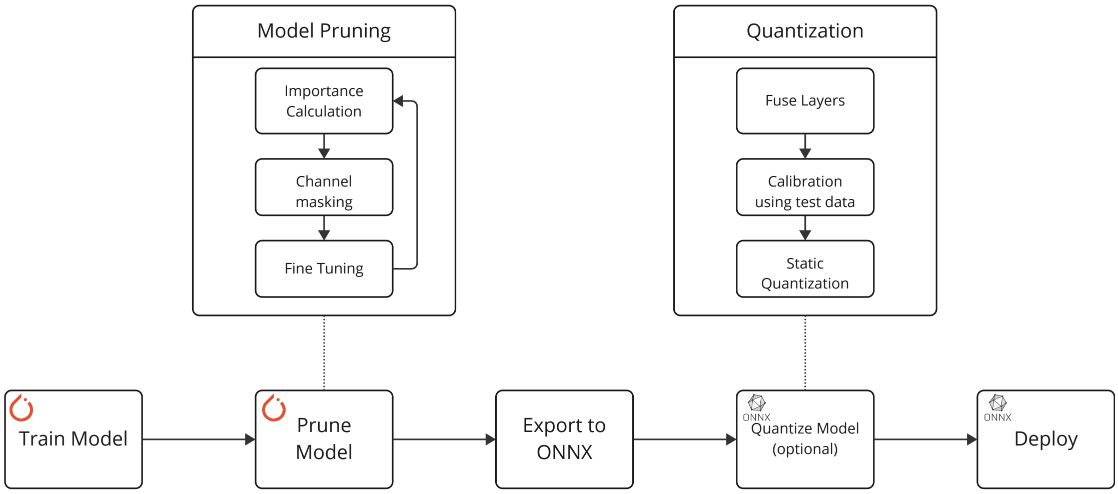


Figure 3: Overview of the full compression pipeline. The pipeline starts with training the model in PyTorch. Then we prune the model using structured channel pruning. After pruning, we export the model to the ONNX format. Next, we quantize the model using static post-training quantization. Finally, the model can be deployed on the target device.

aggressive. Especially when pruning both the 2D and 3D backbone simultaneously. Therefore, we split the pruning process into two phases. In the first phase, we prune the 2D backbone and fine-tune the model. In the second phase, we prune the 3D backbone and fine-tune the model. This way, we can have finer control of the pruning and prevent the performance drop from becoming unrecoverable.

As explained before, we opted for a structured pruning technique, as opposed to unstructured pruning. This because structured pruning is more suitable for deployment on edge devices. Unstructured pruning techniques, such as magnitude-based pruning as used in the Lottery Ticket Hypothesis (Frankle and Carbin, 2018), are very effective in creating sparse models that maintain performance very well. However, since the tensors are sparse in a very irregular fashion, it is difficult to take advantage of this sparsity in the inference phase. Therefore, we use structured pruning techniques, such as channel pruning, which create sparse models in a structured fashion. This structure allows us to take advantage of the sparsity in the inference phase. Using channel pruning we can remove entire channels from the convolutional layers, resulting in physically smaller tensors. This is shown in Figure 1. This results in smaller models, that require less operation and gain a speedup natively from the sparsity. It is important to note that due to the models architecture, not all channels can be pruned. We have to make sure the model matrix operations remain valid. For example, this is the case when we use bottleneck blocks (shown in Figure 2) where the number of input channels needs to be equal to the number of output channels, since we add the input to the output. These dependencies between channels are taken into account when pruning the model.

3.3 Quantization

We use quantization to further reduce the size of the YOWO model. Quantization involves representing the weights and/or activation with fewer bits. The original model uses 32-bit floating point numbers to represent the weights and activations. In this work we use static post-training quantization (PTQ) (Krishnamoorthi, 2018). We quantize the model after training and pruning. This method is static because the quantization parameters are calculated once and are fixed. The goal is that after quantization both the weights and activations are represented with 8-bit integers. This allows for a significant reduction in size for storing the model, and depending on hardware and software support, a reduction in latency as well.

This process is performed in two steps. The first step is a calibration step where we collect statistics of the weights and activations. In our case we collect the minimum and maximum values of the weights and activations. These values are subsequently used for a range-based linear quantization (Jacob et al., 2017). This is done by running the model on a representative test dataset. The second step is the actual quantization step. Here the actual weights and model operations are replaced with the quantized counterparts.

It is important to note that after quantization various hardware and software limitations arise. We perform the quantization in the ONNX framework (ONNX, 2023). This makes deployment of the compressed model easier, since the ONNX framework is supported by many platforms, including the Raspberry Pi 4 Model B. However, currently, the ONNX framework (and its execution providers) does not support all operation types in quantized form on our target device. This means that, though the models weights are quantized, the operations are still performed in floating point depending on hardware support. This means the main benefit of quantization in this work is storage, not latency.

3.4 Full Compression Pipeline

In this section, we provide an overview of the full compression pipeline. In Figure 3, we show the complete pipeline. We begin with the original YOWO model trained in PyTorch. Then, we prune the model using the structured channel pruning technique described in Section 3.2. After pruning, the model is exported to the ONNX format. Next, we quantize the model using the post-training quantization technique described in Section 3.3. As mentioned the main benefit of quantization is storage reduction, not latency improvement. Therefore, this quantization step is optional if the model is already small enough. Finally, the model can be deployed on the target device, which in our case is the Raspberry Pi 4 Model B. We utilize the ONNX runtime for inference of the model on the device. Once all of these steps are completed, we can measure the latency, energy consumption, and memory usage of the model on the device. The results of these measurements are presented in Section 4.3.

4 EXPERIMENTS AND RESULTS

In this section we describe the experiments we performed to evaluate the performance of the proposed compression pipeline. The experiments involve using the originally trained activity recognition model as described in Section 3.1. The compression is, just as the performance evaluation, task dependent. Therefore, before we propose an actual pruning schedule for the full compression stack, we perform a sensitivity analysis on the model. A sensitivity analysis is a common technique used to determine the impact of pruning the model, and allows us to find the optimal parameters for scheduling the pruning. In this paper we perform experiments using the YOWO model trained on two different datasets. The JHMDB-21 dataset (Jhuang et al., 2013) is a subset of the HMDB-51 dataset (Kuehne et al., 2011) and contains 928 short videos of 21 different activities. Each video has a single action across all frames. The actions in this dataset include human actions and poses. The UCF-24 dataset is a subset of the UCF-101 dataset (Soomro et al., 2012) and contains 3207 videos of 24 different activities. In this dataset multiple instances of the same activity can occur in a single video. The actions in this dataset are more related to sports activities. The YOWO model is trained on both datasets separately and each model is used as a starting point for the compression process. The models are trained using standard gradient descent with the AdamW optimizer (Loshchilov and Hutter, 2017). More information about the training of these baseline models, such as the used hyperparameters, can be found in Sec. 5.

The compression itself was computed on a Nvidia Tesla V100-SXM2-32GB GPU. The resource consumption was measured on a Raspberry Pi 4 Model B. We assess model compression in two ways: by evaluating resource consumption and task performance. For the resource consumption, we focus on the computational complexity and measurements on a target device. This is done by measuring a range of metrics, including: (i) the number of parameters, (ii) the number of operations (FLOPs or OPs), (iii) the model file size (quantized and unquantized), (iv) the models compression ratio ((Eq. I) $\frac{size_{original}}{size_{compressed}}$), (v) the models theoretical speedup ((Eq. II) $\frac{\#OPs_{original}}{\#OPs_{compressed}}$), (vi) the models latency measured on a target device, (vii) the models runtime memory usage measured on a target device, (viii) and the models energy consumption measured on a target device. The task performance is evaluated by measuring the performance of the model on the on a validation dataset. For this we use the mean Average Precision (mAP) metric. More specifically we use the frame-mAP metric. This metric measures the area under the precision-recall curve of detection for each frame. The mAP is calculated using a IoU threshold of 0.5.

In the next section, we show the results for the performed sensitivity analysis on the YOWO model. Afterwards, we use the results of this analysis to set up a pruning schedule for the full compression pipeline. We show results of the full compression pipeline using multiple different schedules. Finally, in section 4.3 results of the resource consumption measurements on the Raspberry Pi 4 Model B are shown.

4.1 Sensitivity Analysis

As mentioned, we utilize a sensitivity analysis to make an informed decision regarding the pruning criterion to be employed in the full compression stack. This analysis entails pruning the network using a specific criterion and measuring its performance as the level of sparsity increases. The objective is to deter-

Table 1: Results of the full compression pipeline (pruning and quantization). The models are labeled using an ID. This ID is used in the following tables to refer to the models. Results are shown for the JHMDB-21 and UCF-24 datasets. The mAP and Q. mAP are the mean average precision of the original and quantized models, respectively. The Params and OPs are the number of parameters and operations of the models. The Size and Q. Size are the size of the compressed and quantized models. The Speedup is the calculated theoretical speedup (Eq. II) of the compressed model compared to the original model.

ID	Dataset	Attribution	mAP / Q. mAP (%)	Params	OPs	Size / Q. Size (MB)	Speedup
0	JHMDB-21	—	67.54 / 66.76	1.21e+08	4.34e+10	462.00 / 121.61	1.00
1	JHMDB-21	weight	62.77 / 62.08	7.02e+07	2.06e+10	282.45 / 70.90	2.10
2	JHMDB-21	weight	56.66 / 55.30	6.74e+07	1.59e+10	271.04 / 68.05	2.73
3	JHMDB-21	activation	71.51 / 71.10	7.02e+07	3.54e+10	282.25 / 70.86	1.23
4	JHMDB-21	activation	60.69 / 59.07	6.88e+07	1.87e+10	276.66 / 69.46	2.32
5	JHMDB-21	activation	32.23 / 32.17	5.95e+07	1.37e+10	239.30 / 60.12	3.16
6	UCF-24	—	75.87 / 75.80	1.21e+08	4.34e+10	462.00 / 121.63	1.00
7	UCF-24	weight	75.61 / 75.53	1.01e+08	1.05e+10	404.07 / 101.30	4.15
8	UCF-24	weight	73.63 / 72.03	8.31e+07	9.09e+09	333.56 / 83.68	4.78
9	UCF-24	activation	75.85 / 73.43	8.48e+07	7.73e+09	340.39 / 85.38	5.62
10	UCF-24	activation	71.94 / 71.43	6.83e+07	6.58e+09	274.31 / 68.86	6.60

mine which criterion enables the model to maintain the highest performance while achieving the highest level of sparsity. In this research, we compare two different criteria. Specifically, we utilize the commonly used weight magnitude method, as well as an activation magnitude method. As mentioned earlier, both methods are used for structured channel pruning, which involves pruning entire neurons in dense layers and entire channels in convolution layers. This applies to both the 2D and 3D backbone of the YOWO model. In the Figure 4c, we present the results of the global sensitivity analysis after pruning both the 2D and 3D backbone of the model. It is evident that the model is significantly affected by structured pruning, resulting in a noticeable decrease in performance to a suboptimal level. Therefore, retraining will be necessary to achieve higher sparsity levels. Additionally, using the same level of sparsity for both may be a naive approach. Therefore, we also conducted a sensitivity analysis for each backbone separately. It is important to note that in this setting, we leave the other backbone untouched and still measured the performance of the entire model. The results are shown in Figure 4a and Figure 4b.

These graphs, confirm our hypothesis that using the same pruning ratio for both backbones is not optimal. Both backbones react differently to the pruning. Overall we see that the 2D backbone is more sensitive to pruning than the 3D backbone. This is logical as the 2D backbone will generally be used for the localization of the activity instance.

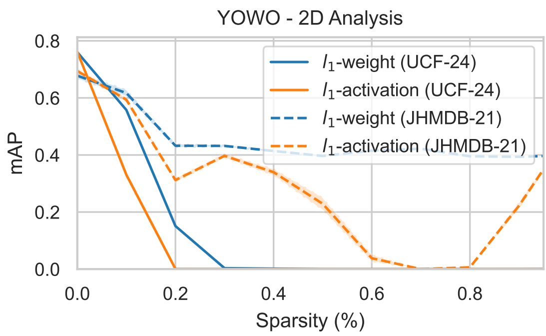
Additionally, we observe that the 3D backbone is less affected by low sparsity levels. This is partly due to the architecture used in this backbone (ResNext-101), which employs channel grouping in its convolutional layers. Channel grouping divides the input channels into groups and performs separate computations on each group using separate kernels. For example, if a layer has 128 input channels and grouping is set to 32, the layer will use only four sets of kernels. This means the number of channels to remove is very limited and will have a significant impact on the model. The model is only impacted when the pruning ratios are high enough, for example at least 25% in this example. Therefore, for pruning the 3D backbone, we use higher pruning ratios than for the 2D backbone.

Finally, we observe a significant difference in sensitivity between datasets. In our experiments, the model trained on UCF-24 is barely impacted when we prune the 3D backbone. However, with the model trained on JHMDB-21, we see a noticeable decrease in performance. We believe this disparity is due to the nature of the datasets. As such, a separate pruning schedule will be needed for each dataset.

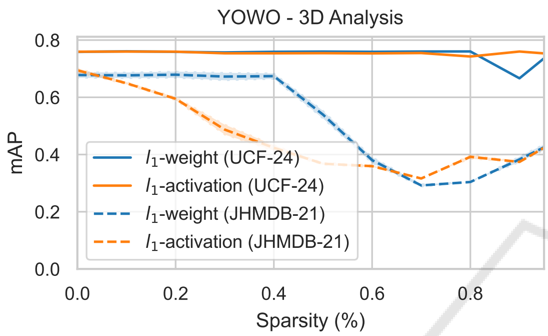
In the next section, we will use these results to make an informed decision on setting up a pruning schedule for compressing the model.

4.2 Combined Compression Results

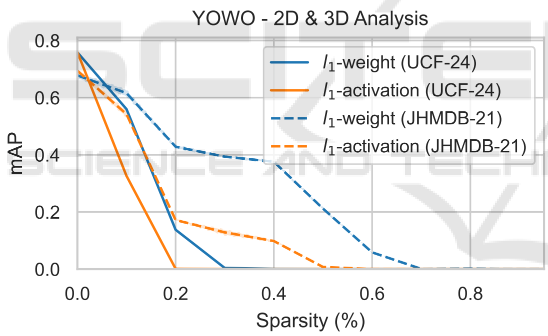
In this section we show the results of the combined (pruning and quantization) compression of the YOWO model. As mentioned previously, we use an iterative pruning schedule with fine-tuning to prune the model. We prune the YOWO model in two separate stages: the first stage involves pruning the 2D backbone, while the second stage involves pruning the 3D backbone. After each iteration within each stage, a fine-tuning step is performed. This fine-tuning is done using the same hyperparameters as the original training, except for the number of epochs. From the sensitivity analysis (4.1), we conclude that pruning the network separately has less impact on the



(a)



(b)



(c)

Figure 4: The graphs demonstrate the impact of pruning by assessing the model's (frame) mAP with increasing sparsity. *(a)* displays the sensitivity analysis when pruning the 2D backbone. *(b)* displays the sensitivity analysis when pruning the 3D backbone. *(c)* displays the sensitivity analysis when pruning both the 2D and 3D backbone.

model's performance. Using the results of the sensitivity analysis, we set up a pruning schedule for the full compression pipeline. This schedule is then further tuned experimentally. We show the results of the compression using different pruning schedules. The schedule is defined by the pruning ratio per step and for each backbone, the number of steps for each backbone and the number of epochs used for fine-tuning. The different scheduling settings used for the results presented in this section can be found in section 5 in the appendix.

The compression results can be found in Table 1. This table contains the results for the pruning and quantization of the YOWO model on the JHMDB-21 dataset and the UCF-24 dataset. We show the results for different pruning schedules with their quantized counterparts.

These results show a considerable reduction of the model size and number of operations are achieved. Overall we are able to generate the smallest models using the activation based pruning. However, this is very dataset/task dependent. For the UCF-24 dataset, we are able to maintain the mAP very well using both pruning criteria. However, for this dataset the activation based pruning is able to generate slightly smaller and faster models. For the JHMDB-21 dataset, we see a bigger drop in mAP, as this model is more sensitive to pruning. For this dataset we are not able to compress as aggressively. For the results on the JHMDB-21 we targeted a theoretical speedup of at least two, while maintaining an acceptable mAP. For the UCF-24 dataset we targeted a theoretical speedup of at least four.

Please note that this does not apply to the JHMDB-21 model with ID 3. For this model we see an increase of the mAP when pruning the 2D backbone using the activation based criterion. In this case, the model was not pruned too aggressively, which, in combination with the fine-tuning, resulted in a better performing model. This also follows the results of (Bartoldson et al., 2020) who show that pruning can be used during training to improve generalization.

Overall, we managed to speed up the model by at least a factor of two while maintaining an acceptable mAP score. For the UCF-24 dataset, we (theoretically) speed up the model by a factor of 6.6, reducing the mAP by only about 4%. Observing the combined pruned and quantized results, we found that the generated models are approximately six times smaller than the original model. This significant size reduction is highly beneficial for edge deployment. The smallest models were achieved for the JHMDB-21 dataset. We can conclude that the most substantial size impact occurs when pruning the 2D backbone more aggressively, as demonstrated by the JHMDB-21 models. The largest impact on speedup is achieved when pruning the 3D backbone, as shown by the UCF-24 pruned models.

4.3 Resource Consumption on the Raspberry Pi 4 Model B

In this section, we present the results of resource consumption measurements from running the compressed model on the Raspberry Pi 4 Model B. The re-

Table 2: Results of the resource consumption measurements on the Raspberry Pi 4 Model B. We show the results of the original model trained on the UCF-24 dataset, the activation pruned model (ID: 9) and the quantized version of the activation pruned model. The latency is the average time it takes to process a single iteration. The runtime memory is the average memory usage of the model during inference. The energy consumption is the total energy consumption of the model during inference during the measurement period. The results are gathered by running each model for 100 iterations and measuring the resource consumption during this period. The average power consumption is measured by running each model at a fixed framerate of 3.2.

Pruned	Quantized	Latency (ms)	Runtime Memory (MB)	Energy Consumption (J)	Avg. Power Consumption (W)
✗	✗	4381.91	678.13	2032.20	4.19
✓	✗	1345.98	450.46	638.27	2.70
✓	✓	8583.75	408.16	2774.22	3.04

source consumption is assessed by measuring latency, memory usage, energy consumption, and power consumption when running inference of the models. We then compare these results with those of the uncompressed model. Latency and memory usage are measured using built-in Python tools, while energy consumption is measured with a JouleScope JS110. The JouleScope measures current and voltage to compute power and energy. The findings are summarized in Table 2.

We measure a model's latency, memory usage and energy consumption by running the model for a fixed number of iterations. It's important to note that the duration of this experiment can vary, as compressed models operate faster than their uncompressed counterparts. The CPU operates at full capacity continuously, which means there is no difference in power consumption between models when working in this mode. It is due to the lower number of operations that the compressed models are faster and consume less energy. In a real-world scenario, the models would run in a fixed number of iterations per second (or framerate) mode. In this case, compressed models would idle the CPU for extended periods, resulting in power and energy savings. We evaluated the total energy consumption, average latency, and average memory usage of the model over 100 iterations without a limitation on the framerate. The average power consumption was measured in a separate experiment by running each model at a fixed framerate of 3.2 for the same number of iterations.

We observe that pruning has the most significant impact on the models. It significantly reduces the energy consumption by 69% and power consumption by 36%, while making the model 3.3 times faster. However, there's a notable difference between the theoretical speedup (5.62) and the actual measured speedup. We attribute this discrepancy to factors like the scheduler, memory access delays, and general background tasks of the operating system.

Additionally, while quantization does improve memory, it unfortunately worsens latency and energy consumption. This is primarily due to the software limitations of the Raspberry Pi. Currently, the used ONNX runtime and its execution providers do not support 3D convolutions in quantized mode. This could be improved in future work.

5 CONCLUSION AND FUTURE WORK

In this work, we investigate the feasibility of deep learning-based activity recognition on edge devices. More specifically, we investigate the compression the YOWO model proposed by (Köpüklü et al., 2019). This model has a single-stage architecture consisting of two branches: a 2D backbone and a 3D backbone. This architecture is very large, consisting of millions of parameters and requiring billions of operations, making it too large and complex for edge deployment.

We propose a two-stage compression approach: structured channel pruning and quantization. By applying iterative structured channel pruning, we aim to reduce the size and the number of operations of the YOWO model while maintaining its accuracy. This pruning technique removes the least important channels from the network. We compare two importance criteria, namely, the weight magnitude and the activation magnitude. Additionally, we combine pruning with quantization, further reducing the size of the model by representing the weights and activations with fewer bits.

To evaluate the effectiveness of our approach, we deploy the compressed YOWO model on the Raspberry Pi 4 Model B and measure its latency, memory usage, energy and power consumption. The compressed models were generated after a sensitivity analysis to determine the impact of pruning the YOWO models and to find the optimal parameters for scheduling the pruning. The results of the combined pruning and quantization approach show that we can significantly reduce the size and operations of the YOWO model while maintaining task performance. For the UCF-24 dataset, we are able to speed up (theoretically) the model by a factor of 6.6 while only reducing the mAP by about 4%.

This result can also be observed in the energy consumption, where there's a reduction by a factor of 3.2. This significant decrease is especially vital considering energy consumption is a crucial factor for edge deployment, enabling the model to be utilized on battery-powered devices. By examining the memory usage and latency of the deployed models, it's clear that the compressed models are more suitable for edge deployment.

For future work, other pruning criteria and scheduling methods can be investigated. Currently, we used sensitivity analysis to determine a pruning schedule. However, this is not the optimal way to determine the schedule. This could potentially be automated, as done in the field of AutoML. For example, in the work of (He et al., 2018), a reinforcement learning approach is used. Furthermore, we used a static post-training quantization method. In future work, we could investigate the use of quantization-aware training. Finally, the quantization results can also be improved by better software support, as discussed in Section 3.3.

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A Appendix

A.1 Scheduling Hyperparameters

In Table 3 the different scheduling hyperparameters used for the pruning experiments are shown. These settings where chosen based on the results of the sensitivity analysis and experimentally tuned.

A.2 Training Hyperparameters

In this section the different training hyperparameters used for the experiments are shown. We utilized two different datasets to train the base models for compression. Table 4 lists the hyperparameters used for training these base models.

Table 4: Training Hyperparameters for UCF-24 and JHMDB-21 datasets.

Dataset / **Parameter**	UCF-24	JHMDB-21
Downsample	1	1
Temporal Downsample	2	1
Clip Length	16	16
Confidence Threshold	0.3	0.3
NMS Threshold	0.5	0.5
Confidence Threshold (Validation)	0.005	0.005
NMS Threshold (Validation)	0.5	0.5
Freeze 2D Backbone	False	False
Freeze 3D Backbone	False	False
Batch Size	8	4
Test Batch Size	8	8
Accumulate	16	16
Optimizer	adamw	adamw
Momentum	0.9	0.9
Weight Decay	0.0005	0.0005
Max Epoch	5	5
Base Learning Rate	0.0001	0.0001
Learning Rate Decay Ratio	0.5	0.5
Warmup Strategy	linear	linear
Warmup Factor	0.000667	0.000667
Warmup Iterations	500	500

Table 3: Different scheduling hyperparamters used for the pruning for the in the full compression pipeline.

ID	Dataset	Attribution	2D Iterations	3D Iterations	2D Pruning Ratio	3D Pruning Ratio	Fine-tuning Epochs
0	JHMDB-21	—	—	—	—	—	—
1	JHMDB-21	weight	1	4	0.90	0.60	6
2	JHMDB-21	weight	5	8	0.50	0.80	5
3	JHMDB-21	activation	5	0	0.50	—	5
4	JHMDB-21	activation	1	4	0.90	0.60	6
5	JHMDB-21	activation	5	2	0.50	0.80	5
6	UCF-24	—	—	—	—	—	—
7	UCF-24	weight	0	12	0.00	0.90	6
8	UCF-24	weight	1	12	0.20	0.90	6
9	UCF-24	activation	0	12	0.00	0.90	6
10	UCF-24	activation	1	12	0.20	0.90	6