# Optimal Distribution of CNN Computations on Edge and Cloud

Paul Albert Leroy and Toon Goedemé
*PSI-EAVISE, KU Leuven, Campus De Nayer, Belgium*

Keywords: Fog Computing, Edge, Cloud, CNN Model Partitioning.

Abstract: In this paper we study the optimal distribution of CNN computations between an edge device and the cloud for a complex IoT application. We propose a pipeline in which we perform experiments with a Jetson Nano and a Raspberry Pi 3B+ as the edge device, and a T2.micro instance from Amazon EC2 as a cloud instance. To answer this generic question, we performed exhaustive experiments on a typical use case, a mobile camera-based street litter detection and mapping application based on a MobilenetV2 model. For our research, we split the computations of the CNN model and divided them over the edge and cloud instances using model partitioning, also including the edge-only and cloud-only configurations. We studied the influence of the specifications of the instances, the input size of the model, the partitioning location of the model and the available network bandwidth on the optimal split position. Depending on the choice of gaining either an economic or performance advantage, we can conclude that a balance between the choice of instances and the calculation mechanism used should be made.

## 1 INTRODUCTION

As artificial intelligence algorithms become more and more complex and computationally demanding, for every network-connected embedded application, one of the most important design choices is where to run the AI calculations: either on the edge device, or in the cloud. Moreover, the choice is even more difficult, as one can imagine *fog computing* too, where the calculations are distributed over both instances: a part runs on the edge device, another part in the cloud. In this paper we study which of these computing mechanisms (edge only, cloud only, split at an intermediate position) is the most optimal, and which parameters influence this optimum.

In order for conducting our research, we based ourselves on (Loghin et al., 2019) and introduce a pipeline consisting of an instance on the edge of the network and an instance in the cloud. This gives the opportunity of running computations on two locations, the edge device and the cloud instance.

Each of the two extremes have their specific advantages. When computations run on the cloud instance solely, benefits can be made since hardware resources offered by a cloud provider are used instead of using own acquired hardware. This means clients don't have to worry about complicated hardware and its additional costs like electricity and purchase pricing. The greatest advantage is the cloud's scalability and elasticity which give the opportunity of adding additional instances or upgrading the specifications of the used instances. Since all data needs to be transmitted from the edge of the network to the cloud, increased bandwidth, delay and security risk drawbacks are introduced.

These drawbacks can be avoided by running all the computations on the edge device of the pipeline. Since the desired output of the computations is available in an earlier stage, the data can then be reduced to specific harmless analysis results to send over causing that less information has to be sent over and thus a decrease in previously stated drawbacks can be seen. Despite this, hardware disadvantages emerge due to the limited amount of resources available on an edge device. These can be linked to trade-offs between quality, cost and speed when designing the edge device.

In this paper, we study hybrid edge/cloud computing where computations are spread over both instances. We want to examine whether a distribution of computing between edge and cloud can obtain any economical or performance benefits. The research question of this paper is as follows: which parameters determine the optimal distribution between edge- and cloud computing to maximise benefits? The used computations originate from a convolutional neural network which will be split between a certain layer position. Using this method, the two resulting



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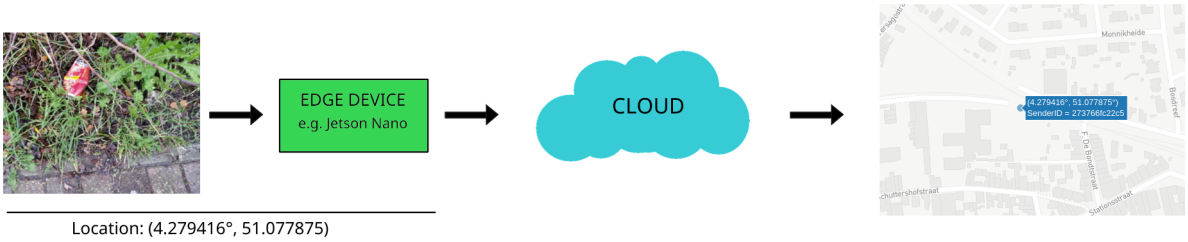



Figure 1: Application pipeline: The device located at the edge of the network captures images and geographical information. This is then sent over to the cloud which visualises it.

submodels can be deployed on the two available instances. By splitting in between various layers, several submodels with each a different amount of computations are tested. We also study the effects of scaling this approach to multiple users.

The experiments for this study are based on a use case in which an image processing algorithm determines whether or not litter is present in a camera image, captures the geographical coordinates of it, and eventually visualises it on a map as seen in figure 1.

The remainder of this paper is structured as follows. Section 2 gives an overview of related work on hybrid edge/cloud computing. In section 3 we discuss the litter detection use case and our chosen CNN model. The approach of realising our pipeline and the used computation splitting method can be found in section 4. Results of conducted experiments are evaluated in section 5. Conclusions follow in section 6.

## 2 RELATED WORK

In (Loghin et al., 2019), experiments were done on a variety of well-known computing applications (excluding CNN), one computationally more demanding than the other. The authors conclude that computing on cloud is usually faster than edge-only, but counterbalanced by the latency of sending over data to the cloud. They also state that hybrid edge/cloud-only has benefits when not a lot of bandwidth is available, and the application uses a large input with small intermediate results. The paper overall stated that a benefit in speed performance depends on the specifications of the used application and the available bandwidth.

More related to our research is Deepdecision (Ran et al., 2018) as their computations also are derived from a CNN. This work proposes a method called offloading with the purpose of gaining accuracy and framerate. The system uses a larger CNN running on the cloud and a smaller CNN running on the edge. With offloading, a decision is made on the edge partition whether to use the smaller local convolutional neural network or send over the data to the cloud. This decision is based on variables like available bandwidth, required accuracy, etc. In contrary to our work, the CNN runs solely on a single instance.

(Teerapittayanon et al., 2017b) proposed distributed deep neural networks (DDNNs) which show similarities with Deepdecision. In their work, a reduction of communication cost is achieved by a factor of over 20x as oppose to cloud-only computing. Based on their earlier work Branchynet(Teerapittayanon et al., 2017a), the number of computations done by a neural network can be decreased with the introduction of early exit points. These points create the possibility of classifying samples in an earlier stage of the network by adding a classifier in between intermediate layers. An entropy-based confidence criterion decides whether or not any further computations have to be applied by the following layers of the network. DDNN benefits from this concept by applying it in a pipeline and partition the model over edge and cloud. Primary layers of the NN, in conjunction with an exit point, are deployed on the edge device. On the edge instance, the decision is made whether additional computations is needed due to the lack of the prediction's confidence. If not, the intermediate result is sent over and further computations are executed by the remaining part of the neural network on the cloud.

In this paper, we base our pipeline architecture on (Loghin et al., 2019), but extend it towards convolutional neural networks and see of their conclusions hold. To spread our computations, we use a simplified method of the one introduced in (Teerapittayanon et al., 2017b): instead of adding an intermediate classifier, we plainly split the CNN model into two submodels and deploy these individually on two instances.

## 3 LITTER DETECTION USE CASE

To give this research an additional useful purpose, we chose a use case on which we based our experiments


Figure 2: Examples of our trained model making predictions about the presence of litter in the image.

on. The idea for this arose from a problem humanity is confronted with globally: litter. Virtually everywhere you walk or bike around on this planet, you can see trash, such as paper, cans, and bottles, that is left lying on the ground. We work towards a mobile embedded device that detects litter in its camera images, capture the geographical coordinates of it and eventually visualise it on a map. With many users in parallel, a quick litter density mapping of a large region can be obtained, yielding important input for efficient cleanup operations.

### 3.1 Neural Network Architecture

Previous work (Mittal et al., 2016; Vo et al., 2019) show that the majority of proposed techniques for litter detection, often rely on convolutional deep neural networks. For realising the use case, we chose to train a convolutional neural network for classification instead of object detection. As we only know the GPS position of the mobile device taking the litter photos, and not the orientation of it, information about the location of the litter in the image has no added value in our use case.

During the experiments of this paper, we want to compare different hybrid edge/cloud splits to the cloud-only and edge-only extremes. Therefore we need to take into account that a CNN architecture needs to be chosen which is capable of running entirely on an edge device with limited resources. Two of the most promising architectures are the well-known MobilenetV2(Sandler et al., 2018) and YOLOv2(Redmon and Farhadi, 2016). The main difference is that MobilenetV2 is a network used for classification, whereas YOLOv2 is used for object detection. Since object detection does not have any benefit in our use case as described above, our preference goes to MobilenetV2. This lightweight architecture offers fairly good accuracy and fast inference speeds for a minimal amount of operations, thus making it possible to run on devices with limited resources (e.g. Raspberry Pi).

### 3.2 Training

We selected the Garbage In Images dataset (GINI) (Mittal et al., 2016) to train our network on. It provides us with the required classes: garbage-queried-images and non-garbage-queried-images. GINI contains 907 images of scenes with litter and 1605 images where litter is not present.

To train our network we utilised Tensorflow 2.0.0 and Keras and performed transfer learning from a MobilenetV2 model pre-trained on ImageNet. We first trained our classification layers using 20 epochs, and then fine-tuned our model for 10 epochs to increase the accuracy. Additionally, as is described in section 5, we want to test if the image input size influences the latency. In order to do this, we trained two models with different input size: $160 \times 160$ and $224 \times 224$ pixels. Figure 2 shows example predictions of our trained model on self captured data.

## 4 APPROACH

The goal of this paper is to identify which parameters influence the most advantageous choice of how to distribute CNN computations over an edge device and the cloud. These advantages can be economically or in terms of performance. In this section, we explain our test setup to conduct experiments on. We will first (section 4.1) present the pipeline we designed which uses computations of our self-trained MobilenetV2 model. In order to divide our computations and spread these over the available instances, we used a model partitioning procedure explained in section 4.2.

### 4.1 Pipeline

For this paper we developed a pipeline, based on the one used in (Loghin et al., 2019), but altered to our use case (see figure 3 for an overview). Notice the two instances where computations can be done, the edge and the cloud. This gives us the possibility of applying the three different computing mechanisms

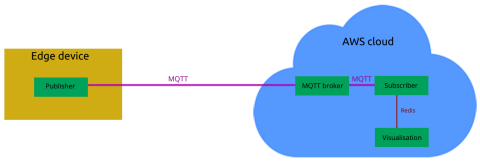



Figure 3: Overall pipeline designed for our research. Docker containers run on the edge instance (Raspberry Pi or Jetson Nano) and cloud instance (T2.micro).

discussed in section 1. We further discuss the implemented instances first.

A large variety of instances can be chosen to be placed on the edge of the device depending on the application. When choosing our edge device we want to use, we needed to keep in mind that the possibility of running deep learning architectures on the device was possible. We decided to compare two edge devices in this study: Jetson Nano and Raspberry Pi. In table 1 an overview of specifications from both can be seen. We can see that the Jetson Nano is equipped with a very powerful GPU as opposed to the Raspberry Pi. This is due to the fact that the Nano is designed with the main purpose of running machine learning algorithms, which can be noticed on the AI Performance specification. We observe that this compute performance is a trade-off with device cost. For this reason, we want to compare it with a less powerful, but cheaper alternative. We have decided to go with the popular Raspberry Pi, model 3B+ in particular.

For our cloud instance we configured a t2.micro instance provided by Amazon Web Services. Due to our limited budget costs, we decided to use AWS since it offers an AWS educate programme. Specifications of the used instance can be found in table 2. As we notice, the cloud instance is capable of reaching higher clock speeds opposite to the chosen edge devices.

During the development of this test setup, we have taken advantage of Docker containers. This simplifies the task of deploying and running applications independent from the used operating system. In our pipeline, we created four containers: publisher, MQTT broker, subscriber and a visualisation container. The communication between these is established using the MQTT (Message Queuing Telemetry Transport) protocol. Our flow begins with the publisher on the Edge device which is responsible for collecting image data, resizing it to the appropriate input size, if needed processing the data using a model, and eventually parsing our data to JSON format. The choice of data we need to send over depends on the computing mechanism we are applying. For example the cloud-only mechanism needs data of the entire image to transfer, while for the splitted networks, an intermediate activation tensor must be transferred.

Our JSON data is sent over to another container which is running an instance called a broker. The objective of the broker is to handle incoming and outgoing data messages sent over MQTT, we need to run this application in the cloud since it needs to handle the messages of multiple edge devices. Running alongside the broker is a container holding a subscriber application. MQTT messages of multiple publishers, hence multiple edge devices, are received by this application. When receiving the data, the subscriber decodes the JSON, if needed run a model to make a prediction for the received information, and saves this data. The end objective of our use case is to use the information we have gathered to visualise the litter locations on a map. For this task, we uilised the Plotly Dash framework. To communicate with this container, Redis is used since using the application as MQTT subscriber simultaneously gave problems. The map is automatically updated when new data is added by the MQTT subscriber.

### 4.2 Model Partitioning

We selected a number of places, spread over the MobilenetV2 architecture, where we could to split the model. As we can see on figure 4 plots the size of the intermediate activation tensor of the CNN when using a $160 \times 160$ pixels input architecture, and the 14 points where we will try to split it. The decision of a certain point is based on how much information is outputted by the previous layer, to be sent over to the second partition of the model which is located in the cloud. It is evident that we want to minimise the amount of data sent over. Usually, these places occur between two overall bottleneck blocks or inside a linear bottleneck block. This is no coincidence since it is logical to not split inside an inverted residual block. As we can read in (Sandler et al., 2018), we can conclude that the data of the first link layer's output also is needed by the next layers on the second part of the model. This introduces the drawback of sending over more data. We have chosen a variety of split points spread over the whole architecture of MobilenetV2 since we want to research the model partitioning method with the interest of obtaining any benefits economically or performance-wise.

To analyse these split points theoretically, we counted the amount of Multiply-Add operations each resulting submodel of the CNN architecture needs. This is a coarse approximation of the flops needed by each submodel, as one Multiply-Add can be approximated as two flops. The calculated[1] amount of MAdds for each layer are visualised in figure 5.

## 5 EVALUATION

In this section, we describe the experiments we conducted to research the performance advantages. These were performed on the pipeline we introduce

[1] https://machinethink.net/blog/how-fast-is-my-model/

Table 1: Specifications of the Jetson Nano and the Raspberry Pi 3B+.

| Specification | Jetson Nano Dev Board | Raspberry Pi 3B+ |
|---|---|---|
| AI Performance | 472 GFLOPs | 21.4 GFLOPs |
| GPU | 128-core NVIDIA Maxwell | Broadcom VideoCore IV |
| CPU | 1.4 GHz 64-bit Quad-Core ARM Cortex-A57 MPCore | 1.4 GHz 64-bit quad-core ARM Cortex-A53 |
| Power usage $P$ | 5 to 10 Watts | 1.7 to 5.1 Watts |
| RAM | 4GB LPDDR4 | 1GB LPDDR2 SDRAM |
| Price per device | ±€122 | ±€40 |

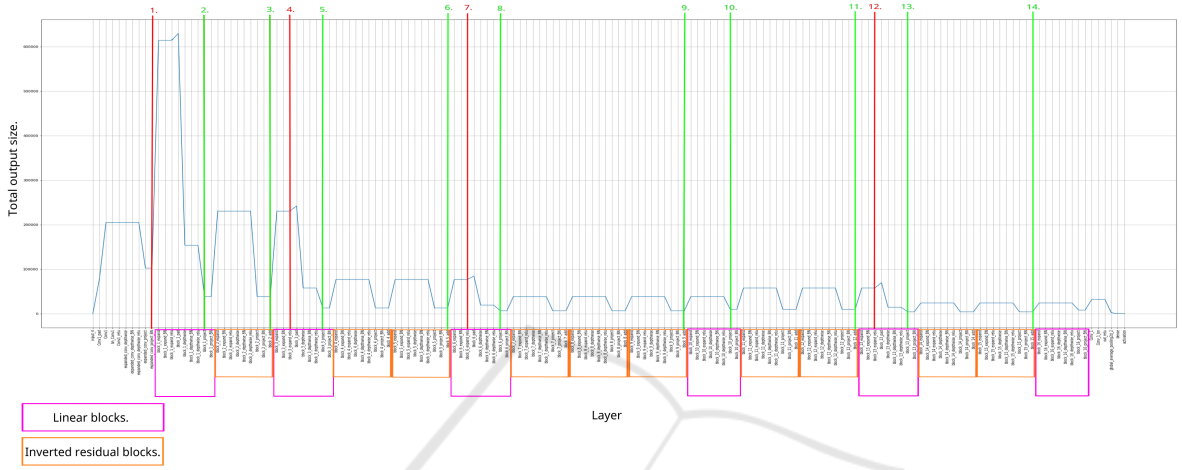



Figure 4: MobilenetV2 architecture with input size $160 \times 160$: output size of every layer plotted, as well as the linear and inverted residual blocks. Vertical lines are proposed CNN split points.

Table 2: T2.micro instance specifications and pricing. The instance is equipped with a powerful CPU.

| Specification | t2.micro: |
|---|---|
| vCPU | 3.3 GHz Intel Scalable Processor |
| RAM (GiB) | 1.0 |
| CPU Credits/hr | 6 |
| On-Demand Price/hr | $.0116 = €.01 |
| 1-yr Reserved Price/hr | $.007 = €.0062 |
| 3-yr Reserved Price/hr | $.005 = €.0044 |

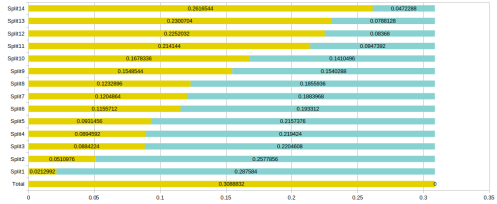


Figure 5: Total Giga flops for each splitted model. Yellow: edge, blue: cloud.

in section 4.1. For each test we used the same 40 test pictures, with associated geographical data, read in by the edge instance, being respectively a Jetson Nano or a Raspberry Pi. These send data over to the AWS t2.micro cloud instance. The content of this data depends on the mechanism as we explained in section 4.1. We timed every interesting stage of the pipeline,

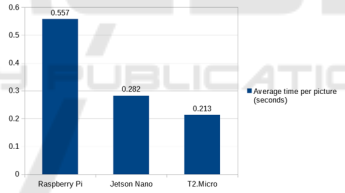



Figure 6: Average time for predicting single picture when running the $160 \times 160$ model solely on each available instance.

and measured these using the partitioned models described in section 4.2 as well as running the entire model on the edge or cloud individually. One of the advantages of edge-only computing is that we do not need to send over all our data. We apply this in our case study by only sending over the data of images containing litter, thus sending over fewer data to the cloud. For each of the split positions, the amount of data sent over depends on the size of the activation tensor of the CNN at the chosen point (see fig. 4).

## 5.1 Processing Time Experiments

Various parameters were observed during our experiments including: different computing mechanisms, varying the image resolution and networks with dif-

ferent bandwidths.

During the analysis of the results we gathered, we noticed that the time, data sits in the waiting queue of MQTT to be sent over, is not consistent. Because it is an obvious future work optimisation to make sure queue waiting times are minimal, we neglect this waiting time in our measurements. Therefore we will report below all latencies as "Hypothetical Total Per Image", where we neglect the waiting time in the queue.

#### 5.1.1 Individual Processing Power of Edge and Cloud Instances

Since each of the instances we used has various specifications, hence different performances, it may be interesting to inspect these individually. Figure 6 shows the average inference time we measured of each instance. We observe that the cloud has the fastest inference time, followed by the GPU-powered Jetson Nano.

#### 5.1.2 Influence of the Computing Mechanism

In the first experiment we conducted, we wanted to discover whether a split architecture has any performance benefits. We visualise our measured results in figure 7 for the $160\times160$ model. When we analyse our measurements, we observe that overall a partitioned model has a better performance in comparison to cloud-only. In both cases, a split model is the fastest among the researched models. The reason for this is probably the fact that the size of the intermediate data is smaller than the input size when comparing it with the cloud-only mechanism. Edge-only also shows great results, but this is overshadowed due to the computing power of the cloud.

#### 5.1.3 Influence of the Image Resolution

Another parameter which could affect the performance is the input size of the used model. When adjusting the input size, the output size of all intermediate layers changes simultaneously. When studying our results in fig.8, we can conclude the Jetson is faster due to its GPU performance. More interesting is when we compare these results with previous results for a $160 \times 160$ model found in figures: 7a and 7b, we notice a decrease in time performance. This can be linked to two occurrences in our measured data. To start off, we observe that the prediction time of our model will increase when the input size is increased. We can see this phenomenon both on the edge and cloud side. Additionally, a second reason for the increase in our total measured latency the increase in sending over time, due to the increased amount of data to be sent over.

When reviewing the total latency per image, we notice that the Jetson Nano benefits most with split13. This behaviour can be linked to the small intermediate activation tensor of split13 as seen in figure 4. The Raspberry has more advantage when sending over the resized input to the cloud. When comparing this with split13, we notice the relatively fast prediction times of the cloud counterbalances the slower prediction times of the Raspberry Pi.

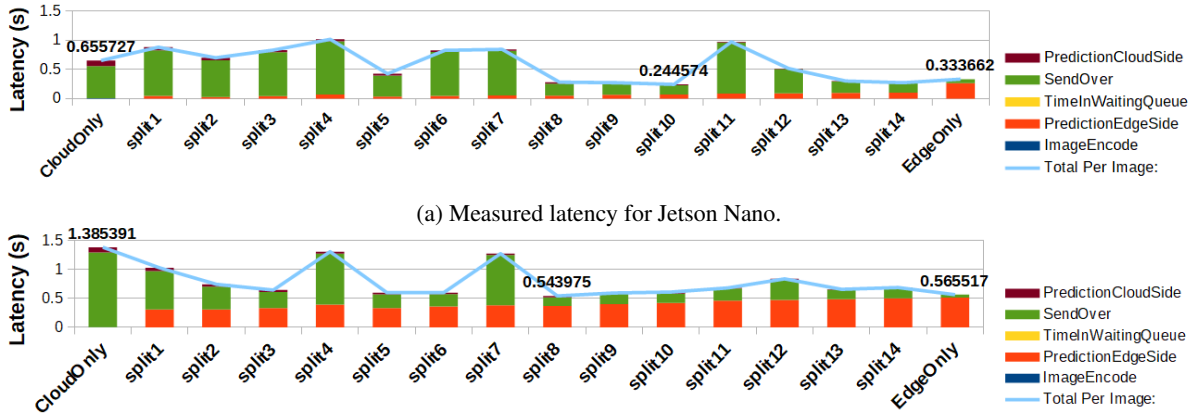
#### 5.1.4 Influence of the Network Speed

We have to keep in mind that in the future, our use case application will run on portable edge devices. This means in order to have a connection with the cloud, a mobile network must be used, e.g. 4G. The disadvantages with these are the limited upload and download speeds. For this reason, it is interesting to research whether these setbacks have any consequences that influence our speed performance. Measurements are visualised in figure 9. As expected we can see our send over times increase due to slower upload speed leading to edge only being the better performing mechanism.

### 5.2 Economical Model

The purpose of this paper is to research whether we can gain any benefits by utilising this pipeline with different instances and splitting mechanisms. The optimal choice, however, depends on the optimisation criterium: calculation speed performance or total economical cost. As in many cases, these two form a trade-off.

When speed performance is very important, for example for a monitoring system for a dangerous industrial process, our experiments described above suggest that the best choice is using a pipeline with a powerful edge device. If a normal or high amount of bandwidth is available, a split model might be the best option. When in a case with limited bandwidth, we are better off with running the entire model on the edge and only send over the necessary data to the cloud. In this situation, we have a big economical drawback since powerful edge devices cost a lot of money and have large power consumption as can be seen in table 1. When the costs need to be minimised, a cheaper edge device can be used, but latency will increase as seen in the test results. To know where this trade-off lies, in this section we will calculate an estimated cost for the different computing mechanisms of our test case at hand, the MobilenetV2 litter detection application.

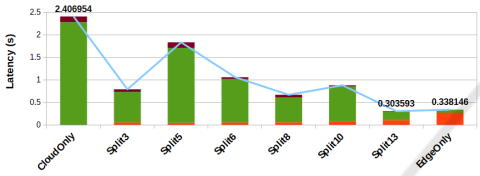



(a) Measured latency for Jetson Nano.

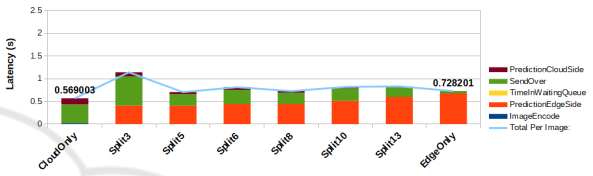



(b) Measured latency for Raspberry Pi.

Figure 7: Measured timings with 160×160 model.

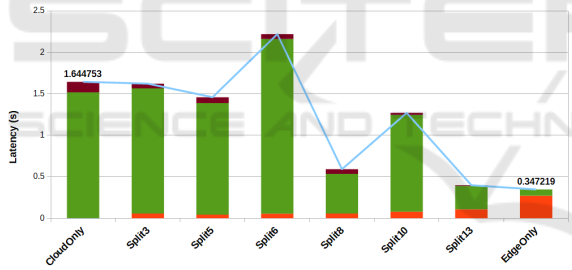



(a) Measured latency for Jetson Nano.

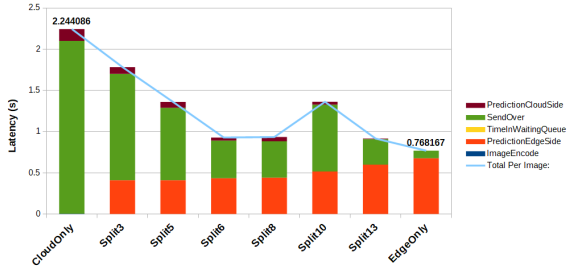



(b) Measured latency for Raspberry Pi.

Figure 8: Measured latencies with 224 × 224 model.




(a) Measured latency for Jetson Nano.




(b) Measured latency for Raspberry Pi.

Figure 9: Measured latencies with 224 × 224 model using 4G.

We first clarify the costs between using a cheap and expensive edge device. We take worst-case values for power consumption: the energy prices for Belgian companies in April 2020 (€0.20/$kWh$). In table 3, we calculated the total price for purchasing a device and running it one month. As we can tell from the results, using a more powerful edge device can almost triple the costs in worse case scenarios.

Table 3: Comparing costs between the Jetson Nano and the Raspberry Pi.

| | Jetson Nano | Raspberry Pi |
|---|---|---|
| Purchase price | ±€122 | ±€40 |
| Energy usage E | 0.01$kW$ | 0.0051$kW$ |
| Energy costs/hour | €0.002 | €0.001 |
| Energy costs/month per device | €1.46 | €0.73 |

Not only the choice of the edge device makes a difference. When multiple users are deployed simultaneously, the computing cost of the instance in the cloud and the choice of the used mechanism need to be taken into account. This is due to the different amounts of cloud processing power usage across various mechanisms.

Applied to our test case, let assume we have 5000 edge devices running simultaneously for a month's time, which are connected to the same t2.micro instance as used in the example with a limited CPU load of 95%. Specifications of this instance can be found in table 2. For this example, we measured the computing power usage of the cloud for various choices of computing mechanisms and calculated the required amount of instances needed for 5000 edge devices.

Table 4: Example calculation of cloud processing costs for 5000 users for the computing mechanisms. (Hardware and energy cost of the edge devices is not taken into account).

| | Cloud only | Edge only | Split5 | Split10 | Split13 |
|---|---|---|---|---|---|
| $\#users/instance$ | 10 | 228 | 29 | 32 | 143 |
| $\#instances_{total}$ | 500 | 22 | 173 | 157 | 35 |
| total costs/month | €3763.5 | €165.594 | €1302.171 | €1181.739 | €263.445 |
| monthly costs/user | €0.7526 | €0.0331 | €0.2604 | €0.2363 | €0.0526 |

Also, we calculated the costs of running the t2.micro instance for these 5000 users for a month were calculated. Results are listed in table 4.

As we can see in table 4, pricing can change drastically depending on the used computing mechanism. We notice that the costs depend on the number of needed instances, thus on the maximum amount of users per instance. When we combine the results of table 3 and table 4, we can calculate the total costs per month for the global pipeline. Results of these costs can be found in table 5 for the Jetson Nano and table 6 for the Raspberry Pi. We assume that the devices keep functioning one year, such that the purchase cost of the edge hardware needs to be ventilated over 12 months. As previously mentioned, we can see a huge difference between the various computing mechanisms. Another noticeable fact, which we already noticed in table 3, is the huge difference in expenses depending on the used edge device. These originate from the energy costs difference and the total costs of purchasing 5000 devices.

We can conclude that a balance needs to be found between the costs of the edge device and the used mechanism depending on the requirements of the application. For example, when using an edge-only method we can see cloud costs are minimal, but as stated earlier a splitted model may have more speed performance benefits. This benefit has the disadvantage of a higher monthly cost due to the higher CPU usage of the cloud. This trade-off between time performance and cost is visualised in fig. 10. It is remarkable that indeed for different situations, different distribution mechanisms are optimal. We observe that, for smaller edge devices, edge-only computation is the cheapest and the fastest solution for this network, while for larger devices a middle split between edge and cloud is preferable.

# 6 CONCLUSION

In this paper, we studied which parameters determine the optimal distribution of CNN computations between edge and cloud computing to maximise speed and performance benefits. In order to answer this question we studied a practical use case, the detection of litter on a fleet of cloud-connected embedded devices. We trained a MobilenetV2 CNN model, and performed experiments on a self designed pipeline in which we splitted this CNN model over the edge and cloud instances.

We first conducted research on the three different instances separately. Our used instances were two possible edge devices: a Jetson Nano and a Raspberry Pi, and the cloud. These each have distinctive specifications, hence different performance values.

In our experiments, we splitted the MobilenetV2 architecture between the convolution layers. We compared these partitioned models with ordinary computing mechanisms (egde-only and cloud-only) by timing each interesting process of the pipeline. When analysing the tests done on the $160 \times 160$ model, we can see a partitioned model has more gain in benefits. This behaviour can be linked to the amount of data sent over. We observed that edge computing can reduce latency by sending over less data, but this is counterbalanced by the computing power of the cloud.

For a larger input image size, $224 \times 224$, the model gave different results. The obvious difference we first notice is the prediction times on both the edge and the cloud increased. Due to the change in input size of the neural network, intermediate activation tensor sizes change simultaneously. Because of this split13 becomes the fastest choice for the Jetson Nano as opposed to the $160 \times 160$ model. Because of the weaker computational performance of the Raspberry Pi and the good computing power of the cloud, the fastest mechanism is offloading this larger model to the cloud and sending over the resized input image.

As we see that sending intermediate results over the network consumes a substantial amount of the total latency, we investigated the influence of the speed of this network. We conclude that networks with limited specifications (like 4G) indeed have an impact on the performance of the pipeline. The most beneficial mechanism for this situation is running the entire model on the edge device, indeed sending over the least amount of data.

Next to an optimisation towards maximal speed performance, we also studied the economical cost of each mechanism, an optimisation criterium that is orthogonal to performance. When speed is important, we can conclude a high bandwidth together with a splitted mechanism and a powerful but expensive edge device is recommended. Economically, our choice of the used mechanism makes a huge difference in expenses. From our detailed cost estimate, we can state that when the CPU usage of the cloud increases, costs will increase simultaneously since more instances are needed to divide the workload. This

Table 5: Total costs between the various computing mechanisms with a Jetson Nano edge instance.

| Jetson Nano | | | | | |
|---|---|---|---|---|---|
| Edge device costs: | | | | | |
| Total purchase price for 5000 devices | €610000 | | | | |
| Purchase per month spread over 1 year | €50833.333 | | | | |
| $Energycosts_{device}$/month | €7300 | | | | |
| Total for edge device: | €58133.333 | | | | |
| Cloud costs: | | | | | |
| | Cloud-only | Edge-only | Split5 | Split10 | Split15 |
| Cloud costs/month | €3763.5 | €165.594 | €1302.171 | €1181.739 | €263.445 |
| Total cost per month | €61896.83 | €58298.93 | €59435.5 | €59315.07 | €58396.78 |
| Total monthly cost per user | €12.37 | €11.66 | €11.88 | €11.86 | €11.67 |

Table 6: Total costs between the various computing mechanisms with a Raspberry Pi edge instance.

| Raspberry Pi | | | | | |
|---|---|---|---|---|---|
| Edge device costs: | | | | | |
| Total purchase pricing for 5000 devices | €200000 | | | | |
| Purchase per month spread over 1 year | €16666.667 | | | | |
| $Energycosts_{device}$/month | €3650 | | | | |
| Total for edge device: | €20316.667 | | | | |
| Cloud costs: | | | | | |
| | Cloud-only | Edge-only | Split5 | Split10 | Split15 |
| Cloud costs/month | €3763.5 | €165.594 | €1302.171 | €1181.739 | €263.445 |
| Total cost per month | €24080.17 | €20482.26 | €21618.84 | €21498.41 | €20580.11 |
| Total monthly cost per user | €4.816 | €4.096 | €4.324 | €4.300 | €4.116 |

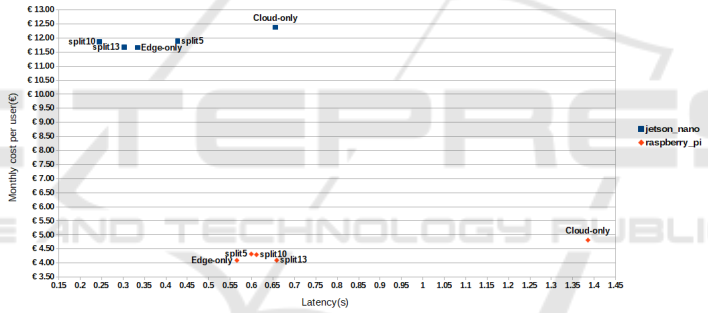



Figure 10: Monthly costs per user w.r.t. the latency for the 160×160 model and standard network bandwidth.

means a more powerful cloud instance can also make a difference. In this paper we used two edge devices from different price classes, resulting in a huge total cost difference.Remarkable, for the more expensive device we notice a partitioned mechanism is the best trade-off when both performance and total cost are taken into account.

The overall conclusion is that indeed a balance needs to be found between the choice of the edge device and the decision of the used splitting mechanism. This balance is based on the criterion in which we want to gain benefits. In our case study, the edge-only mechanism appears to be the cheapest, a split model has the best benefit in speed performance.

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