**Machine Learning for IoT——HW2**



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**Exercise 1 - Training & Deployment of a “Go/Stop” Classifier**

In order to find compliant hyper-parameters, we applied the following strategies:

According to these hyper-parameters, we get the following number of frequency bins and number of frames:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Downsampling\_rate** | **frame\_length\_in\_s** | **dbFSthres** | **duration\_time** | **Latency** | **Accuracy** |
| **16000** | **0.0005** | **-135** | **0.1** | **8.67** | **98.1111%** |
| Affects a lot  Accuracy and  Latency because it applies an additional overhead | Affects a lot  Accuracy and  Latency because  by changing this hyper-parameter we modify the numbers of frames and number of frequency bins | Affects a lot  Accuracy  because we are trying to find the energy threshold  Affects little bit Latency | Affects a lot Accuracy  Affects little bit Latency |  |  |

**Exercise 2 - Memory-constrained Timeseries Processing**

The timeseries that calculates and stores the number of plugged\_seconds in a day was set up with a rule to SUM all values of the {mac\_address}: power timeseries == 1. The rule is

applied to an entire day, so we calculated the bucket size in milliseconds.

The chunk size is set to 128KB and the header size was neglected. We took into account the average compression ratio which is 90%,so we end up with the calculations below:

the number\_of\_compressed\_values = number\_of\_uncompressed\_values ✕ 10

***{mac\_address}*:battery & {*mac\_address}*:power**

***{mac\_address}*:plugged\_seconds**