TinyML Contest

1. Introduction

The TinyML Contest at IEEE COINS is a challenging, multi-month, research and development competition, focusing on advanced, real-world problems in the fields of AI, Embedded Systems, and IoT. It is open to multi-person teams worldwide. The focus of this year's contest is on Human activity recognition. Human activity recognition is a common machine learning task that is widely used in multiple domains. This technology uses data from various sensors to help monitor health conditions, recognize abnormal human activities for surveillance, track fitness workouts, and much more.
There are, of course, various challenges associated with implementing complex human activity recognition. To achieve the required accuracy on low-power devices like wearables, embedded engineers have to find ways to run machine learning models on platforms with limited memory and processing capacity. Experts, therefore, need to design neural networks with a size-accuracy ratio that is appropriate for a proposed machine learning task on a memory-constrained device.

2. Objective

We ask participants to design and implement a TinyML solution for human activity recognition using the Neuton.ai AutoML platform on an STMicroelectronics ISPU development kit. Higher scores are awarded to entries that support the highest number of classes and the best confusion matrix that the ISPU memory can easily accommodate with the lowest inference latency. We encourage real-time demos at the conference and will recognize creativity in the class list definition during evaluation.

We invite participants to create a TinyML multiclass model with the Neuton platform to detect different types of daily human activities in real-time using ISPU accelerometer and gyroscope data.

The following activities represent examples, but these should not limit your imagination. The most important thing is to ensure is that the classes fit human activity recognition concepts:

- Brushing hair
- Brushing teeth
- Washing hands
- Washing face
- Wiping the table
- Hand still
- Shaving face
- Chopping
- Ironing

3. MCU and ISPU platform

Participants should use the following development kits:

- NUCLEO-F401 STM32 Nucleo board.
- X-NUCLEO-IKS01A3 STM32 Nucleo expansion board for MEMS sensors.
- DIL24 adapter board with appropriate IMU (with embedded ISPU) based on sample availability on the ST eStore and through distributors:
  - STEVAL-MKI229A DIL24 with LSM6DSO16IS or
  - STEVAL-MKI230KA DIL24 with ISM330IS

NUCLEO-F401

X-NUCLEO-IKS01A3

STEVAL-MKI230KA or STEVAL-MKI229A

4. Data

Participants must independently collect sensor data to train the model. You can use Unicleo-GUI (https://www.st.com/en/development-tools/unicleo-gui.html) and the X-CUBE-ISPU (https://www.st.com/en/embedded-software/x-cube-ispu.html) expansion package for this purpose. The data should represent a 6-axis accelerometer and gyroscope measurements collected in **float** or **int16** format. We recommend collecting at least 10-15 minutes of raw sensor data for each activity. After collecting data, participants must prepare a dataset for training the model on the Neuton AutoML platform (https://neuton.ai/).

Applicants must render datasets available for reproducibility tests and under CC BY-NC-SA license and specify the authorship. The aggregated dataset may eventually be published through a Data In Brief Elsevier publication.

All activities should be merged in one .csv dataset with an appropriate target (label) column added to each row of the dataset. Here is an example of how a dataset header might look:

ax	ay	az	gx	gy	gz	target

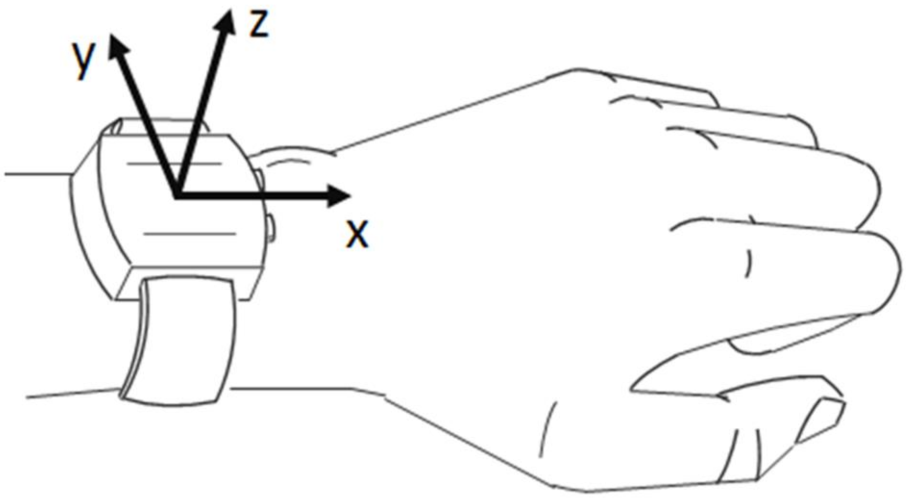
Where:

- **ax** accelerometer X axis;
- **ay** accelerometer Y axis;
- **az** accelerometer Z axis;
- **gx** gyroscope X axis;
- **gy** gyroscope Y axis;
- **gz** gyroscope Z axis;
- **target** activity label in numeric format.

5. Sensor setup

We can offer advice to less experienced participants regarding data collection. The sampling rate of the data acquisition should allow qualitative determination of the difference in activity patterns; we recommend starting with 52 Hz. Sensor sensitivity is very important because a wider dynamic range incurs noisier sensor data, but you also need to avoid sensor data saturation. We recommend starting your experiments with medium sensitivity values for the gyroscope and accelerometer; for example, 8 g for the accelerometer and 1000 dps for the gyroscope.

To collect data, the ISPU sensor **must be** attached to the participant's wrist.

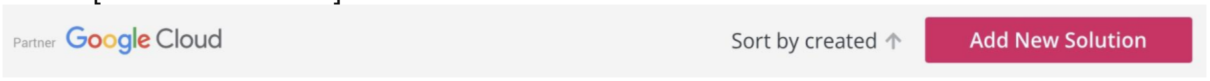


6. Neuton TinyML platform

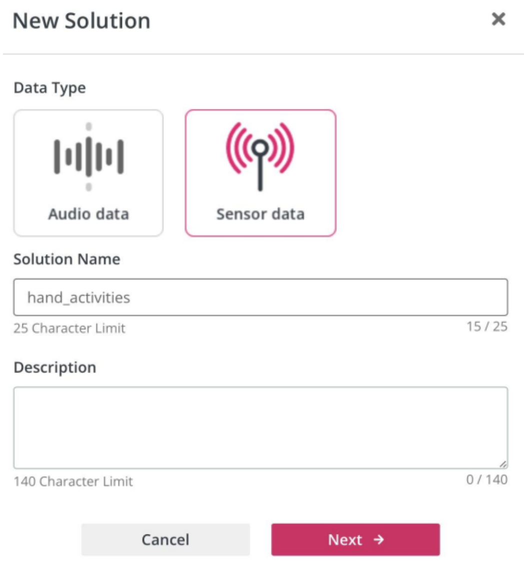
Participants that are not familiar with the Neuton platform can follow these steps to create a TinyML model. To build a TinyML solution, participants should register for a free Neuton account. The registration manual can be downloaded here.

1. Log in to lab.neuton.ai with your registered google account.

2. Select [Add New Solution] in the header



3. Upload your dataset, this may take some time, depending on the size of the dataset and connection speeds.



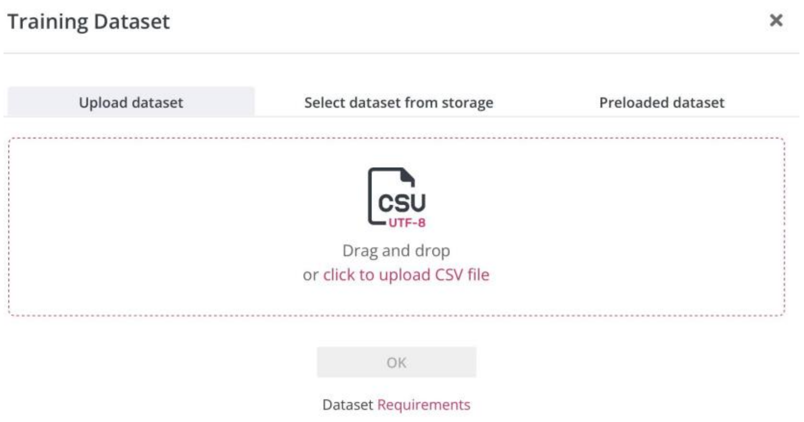
Solution Name

hand_activities

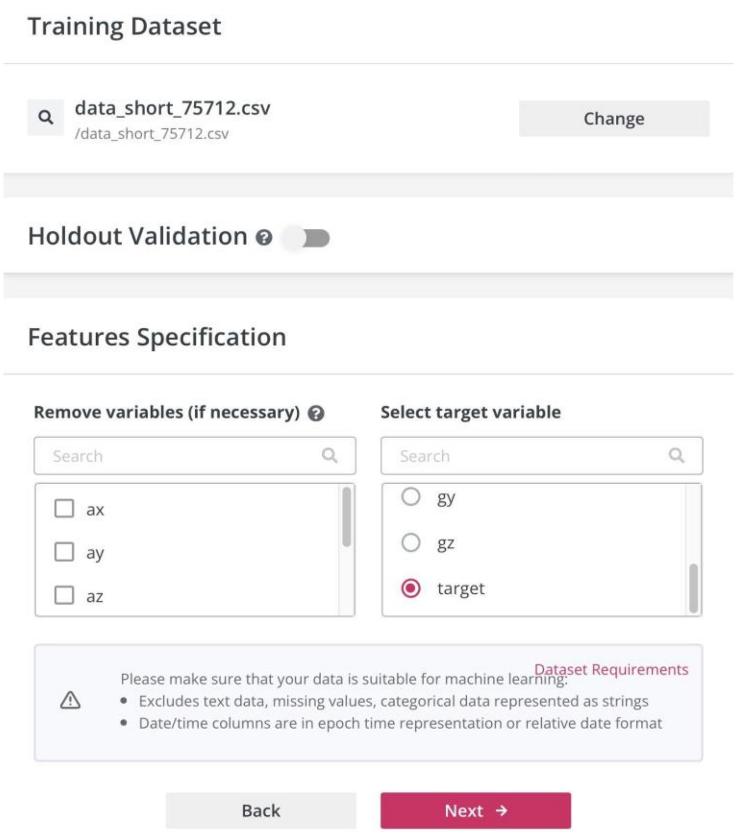
25 Character Limit 15 / 25

Description

140 Character Limit 0 / 140



4. Once the data is uploaded, select the target variable. The generated ‘train.csv’ will contain the ‘target’ column you selected. Click [Next].


Training Dataset

data_short_75712.csv
/data_short_75712.csv

Holdout Validation

Features Specification

Remove variables (if necessary)

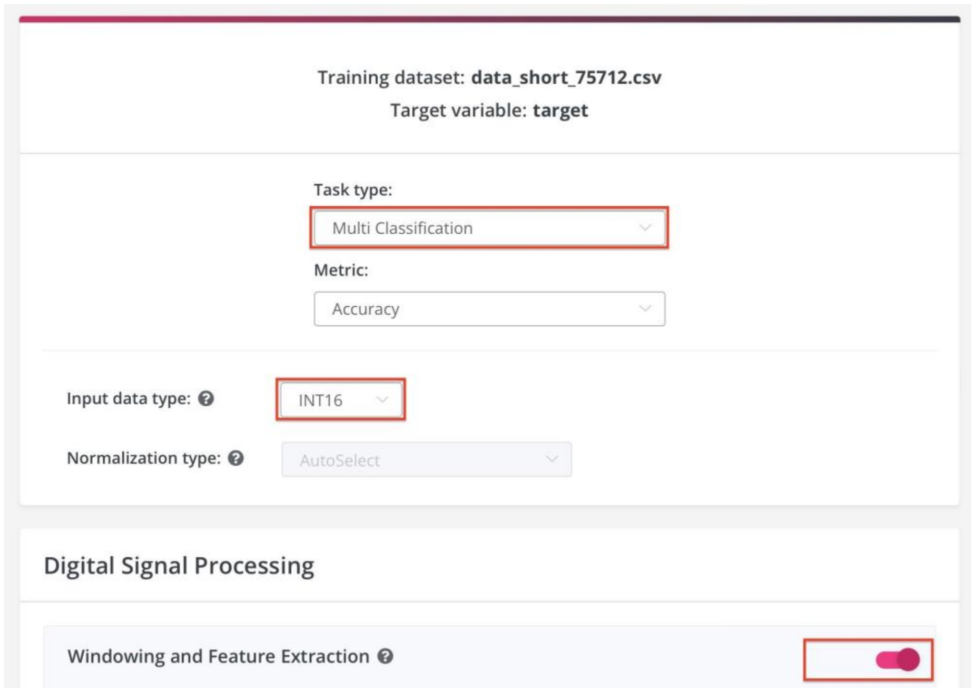
- [ ] ax
- [ ] ay
- [ ] az

Select target variable

gy
gz
[✓ target]

Please make sure that your data is suitable for machine learning:
- Excludes text data, missing values, categorical data represented as strings
- Date/time columns are in epoch time representation or relative date format

5. In the [Training] tab, select [Task type]: Multiclass Classification, as we need to define several different activities. [Input data type]: INT16 or FLOAT, and enable [Windowing and Feature Extraction].


Training dataset: **data_short_75712.csv**
Target variable: **target**

Task type: Multi Classification

Metric: Accuracy

Input data type: INT16

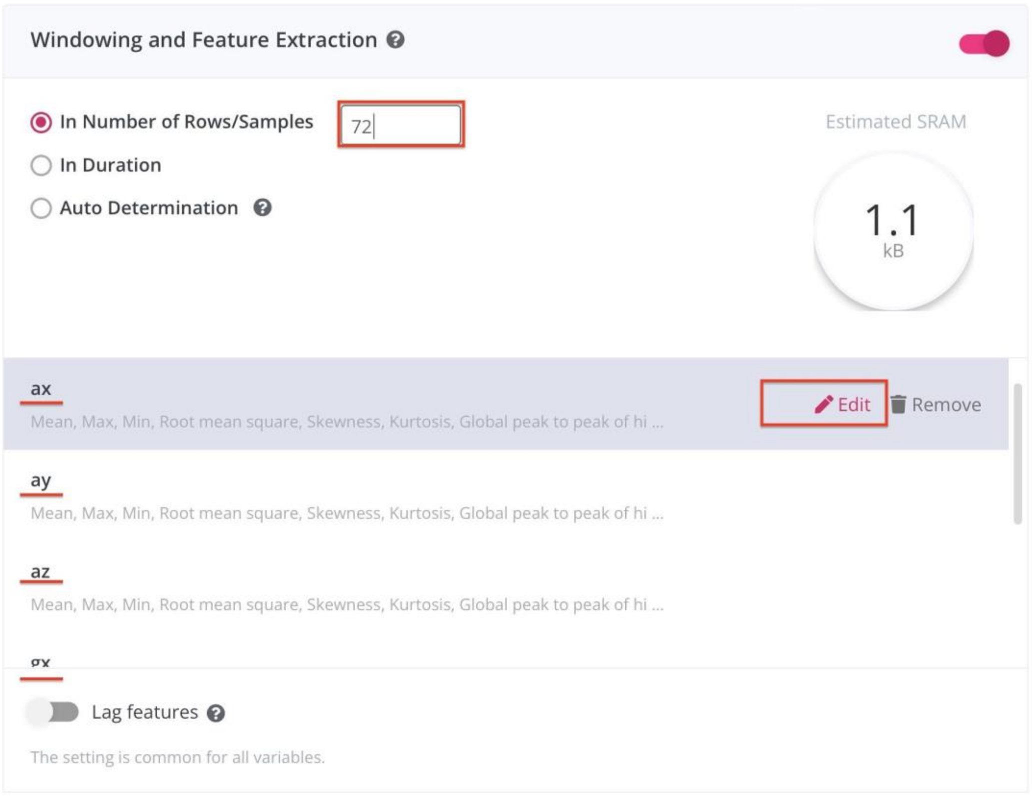
Normalization type: AutoSelect

Digital Signal Processing

Windowing and Feature Extraction

To qualitatively determine activities, we must make predictions on data windows. Depending on your sampling rate, select a window in which activity should be identified; for example 1-3 seconds of collected sensor data.

You can choose which features you want to extract from your data window or can [Select All] and let the platform choose features for you. Click [Edit] for each single axis (ax, ay, az, gx, gy, gz)



Windowing and Feature Extraction

[✓ In Number of Rows/Samples] 72

In Duration

Auto Determination

Estimated SRAM 1.1 kB

ax
Mean, Max, Min, Root mean square, Skewness, Kurtosis, Global peak to peak of hi ...

ay
Mean, Max, Min, Root mean square, Skewness, Kurtosis, Global peak to peak of hi ...

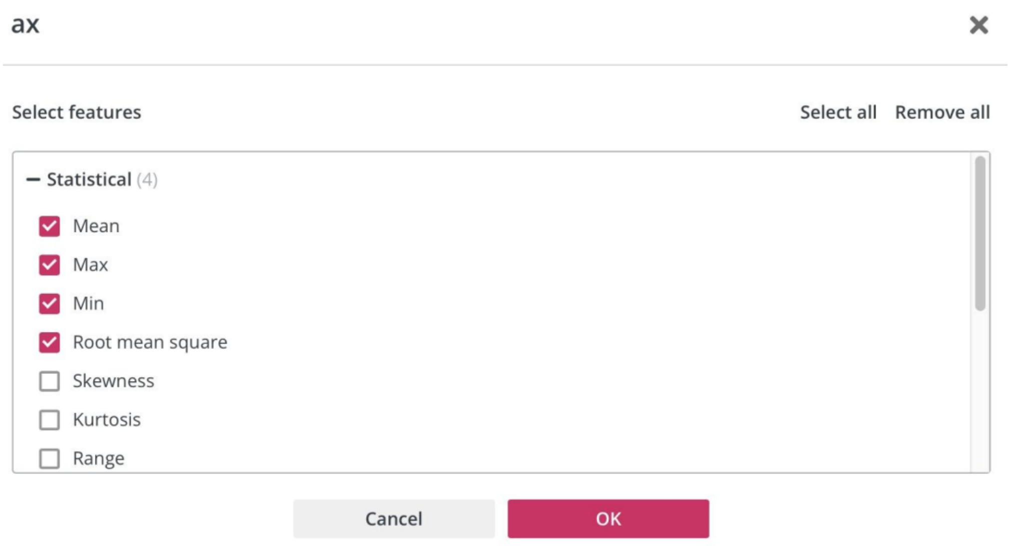
az
Mean, Max, Min, Root mean square, Skewness, Kurtosis, Global peak to peak of hi ...

gx

Lag features

The setting is common for all variables.

In this example, we chose the following features:
Mean; Max; Min; Root mean square; Mean Absolute Deviation; Standard Deviation Mean-crossing rate; Zero-crossing rate.



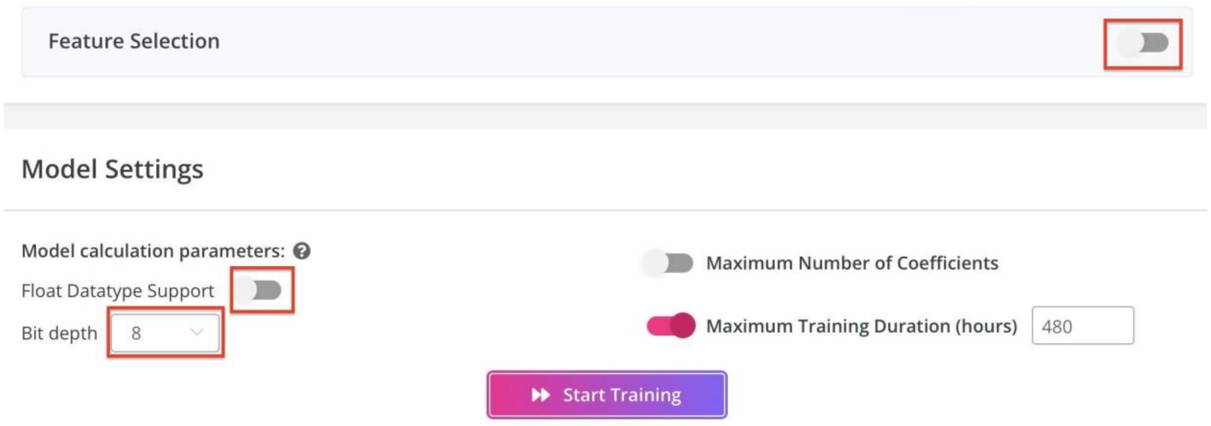
ax

Select features

Statistical (4)

- [x] Mean
- [x] Max
- [x] Min
- [x] Root mean square
- [ ] Skewness
- [ ] Kurtosis
- [ ] Range

6. Finally, you can enable or disable [Feature Selection] and set the [Bit depth] parameter of the model.


Feature Selection

Model Settings

Model calculation parameters:

Float Datatype Support

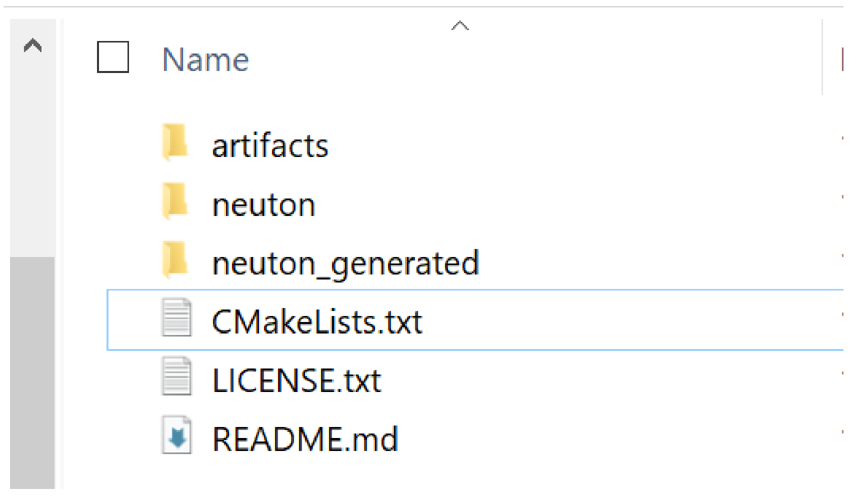
Bit depth 8

Maximum Number of Coefficients

Maximum Training Duration (hours) 480

7. Click [Start Training] and the model will proceed to train for some time. The platform will then redirect you to the [Prediction] tab where you can access the cross-validation scores and download the model archive with everything necessary for embedding the model.

8. When your Neuton TinyML solution is ready, the downloaded archive will have the following structure:


Name

artifacts
neuton
neuton_generated
CMakeLists.txt
LICENSE.txt
README.md

7. Embedding Neuton TinyML

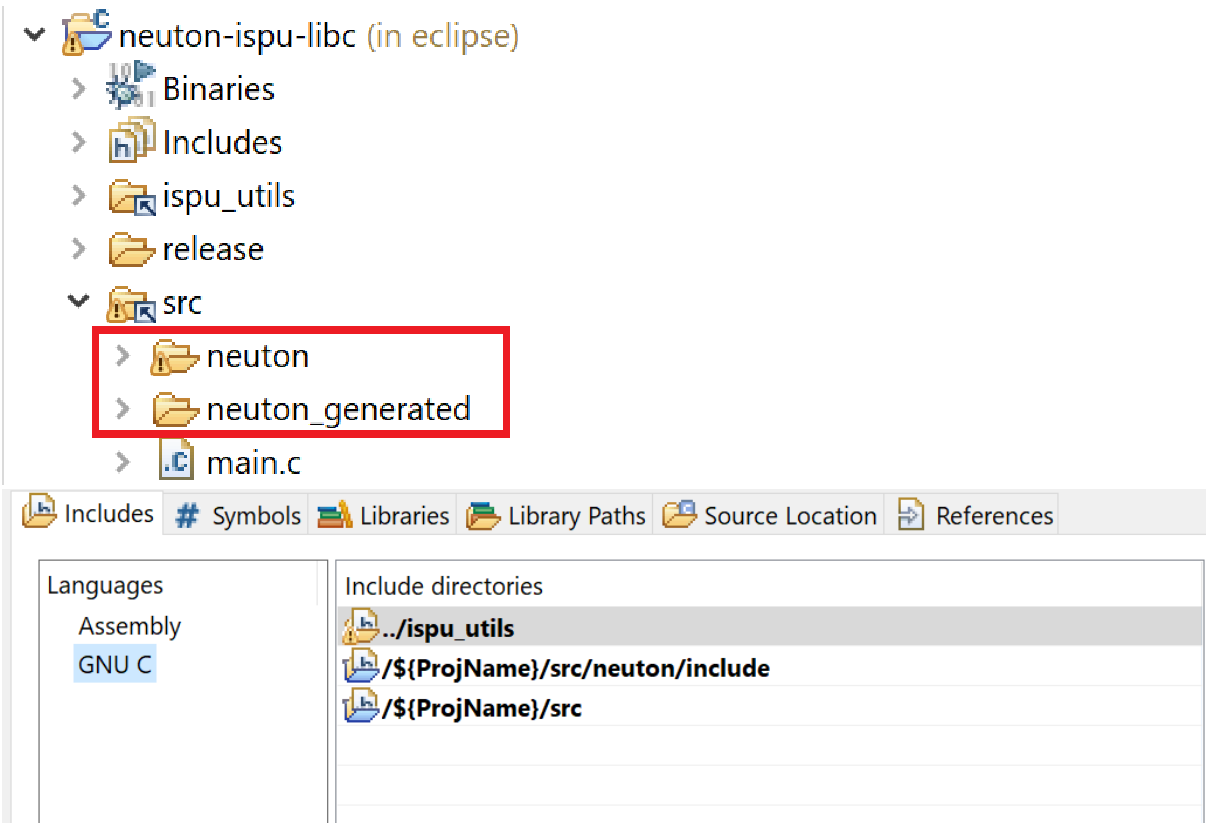
Follow *README.md* file in X-CUBE-ISPU expansion package (en.x-cube-ispu.zip\Ispu\) for the development environment setup.

In the X-CUBE-ISPU (https://www.st.com/en/embedded-software/x-cube-ispu.html) expansion package you can find examples for building ISPU firmware (en.x-cube-ispu\Ispu\ism330is_lsm6dso16is\template\).

There are only two folders that should be added to your ISPU project for integrating Neuton:

- \`*neuton*\` main framework folder in which all Neuton algorithms and utilities are located;
- \`*neuton_generated*\` folder containing all user solution-specific files (neural network model, data preprocessing configuration, etc.).

Also, you should add the folder where \`./neuton_generated\` is located and \`./neuton/include\` folder to your project INCLUDE paths.



Include directories
../ispu_utils
/${ProjName}/src/neuton/include
/${ProjName}/src

Refer to the *README.md* in the Neuton archive folder for integration tips and instructions.

8. Scoring

Our scoring metric for submitted ISPU firmware solutions will assess the overall performance in terms of detection and practical considerations, according to the following criteria:

- **Number of recognized classes:** The number of recognized classes is one of the most important metrics in the final ***Score(S)***. The number of recognized classes will be normalized by ***NCn***=***(1-((NC-NCmin)/(NCmax-NCmin)))***, where ***NCmin***=1 class and ***NCmax***=15 classes.

- **Neuton holdout balanced accuracy:** ***Ah*** is computed using the Neuton Inference Runner tool on the validation dataset. You can find this tool in every download archive at <your_neuton_project>*artifacts**inference_runner*\. Participants should also submit their validation dataset together with the ISPU firmware project.

- **ISPU inference latency:** The average latency ***L*** (in ms) executed on ISM330IS recorded in real time will be measured. The latency score is normalized by ***Ln=(1-((L-Lmin)/(Lmax-Lmin)))***, where ***Lmin***=1 ms, ***Lmax***=1/ODR (sensor output data rate). The latency score (***Ln***) will be used **<u>only</u>** for those participants who limit the ISPU inference latency to lower than 1/ODR.

- **ISPU data RAM occupation:** The memory occupation (in *bytes*) will be measured based on ISPU data RAM occupation on the ISM330IS for the storage of the deep neural network model and the program. Specifically, it is ***Md=data+bss*** section occupation reported by the ISPU toolchain when building the project. ***Md*** is normalized by ***Mdn=(1-((Md-Mdmin)/(Mdmax-Mdmin)))***, where ***Mdmin***=100 bytes, ***Mdmax***=8192 bytes.

- **ISPU program RAM occupation:** The memory occupation (in *bytes*) will be measured based on ISPU program RAM occupation on the ISM330IS for the storage of the deep neural network model and the program. To be more specific, it is ***Mp=text*** section occupation reported by ISPU toolchain when building the project. ***Mp*** will be normalized by ***Mpn=(1-((Mp-Mpmin)/(Mpmax-Mpmin)))***, where ***Mpmin***=1000 bytes, ***Mdmax***=32768 bytes.

- **Realtime demo**: If a real time demo is provided by participants, the ***Score (S)*** will be incremented by adding **RT=100*[0.1-1**], where 0.1-1 is assigned depending on jury evaluation of the real time demo demonstrated during the conference.

The final score is calculated as follows:

$$S=(200*NCn)+(100*Ah)+(80*Ln)+(100*Mdn)+(50*Mpn)+RT$$

Terms and conditions:

Tentative Schedule:

Submission date: 31st May 2023
Conference date: 23-25th July
Notification date: during the conference (will be announced later)

Registration:
Interested parties must email the ST, Neuton, and and COINS contacts listed below.

Contact persons:
ST: marco.bianco@st.com
Neuton.AI: roman.rusak@neuton.ai
IEEE COINS: farshad.firouzi@duke.edu

Awards donated by ST Microelectronics to the top three entries:

1st place wins $1,500
2nd place wins $1,000
3rd place wins $500