2020 embedded VISION summit®

Making Edge AI Inference Programming Easier and Flexible

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Texas Instruments

Agenda

2020 embedded vision summit

Challenges with edge inference deployment

Open source inference framework advancement

Easier and flexible programming on TI Jacinto™ 7 processors

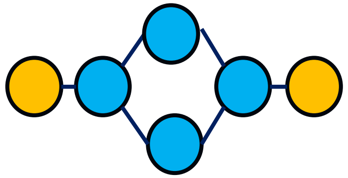
Programming experience with Jacinto 7 processors compared to desktop

Deploying Deep Learning Model for Edge Inference (1/2)

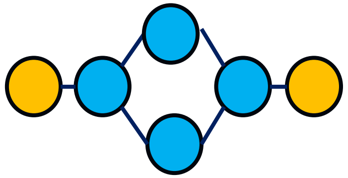
Training framework

Caffe

Trained model



Deploy



Edge Inference

Deploying Deep Learning Model for Edge Inference(2/2)

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Training framework

Caffe

ML

K

Trained model

Learn

Proprietary inference framework

Optimizer

Runtime engine

API | Interpreter | Scheduler

Kernel library

Embedded hardware

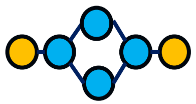
Custom tools

- Vendor A
- Vendor B
- Vendor C
- Vendor D
- Vendor E

Edge Inference Programming Challenges

Training framework

Trained model



Software

Inference framework

Optimizer / Compiler

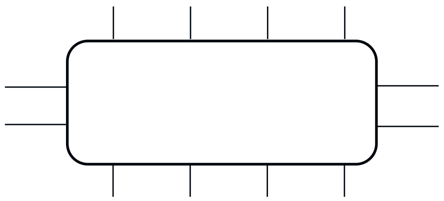
Runtime engine

API | Interpreter | Scheduler

Kernel library

Hardware

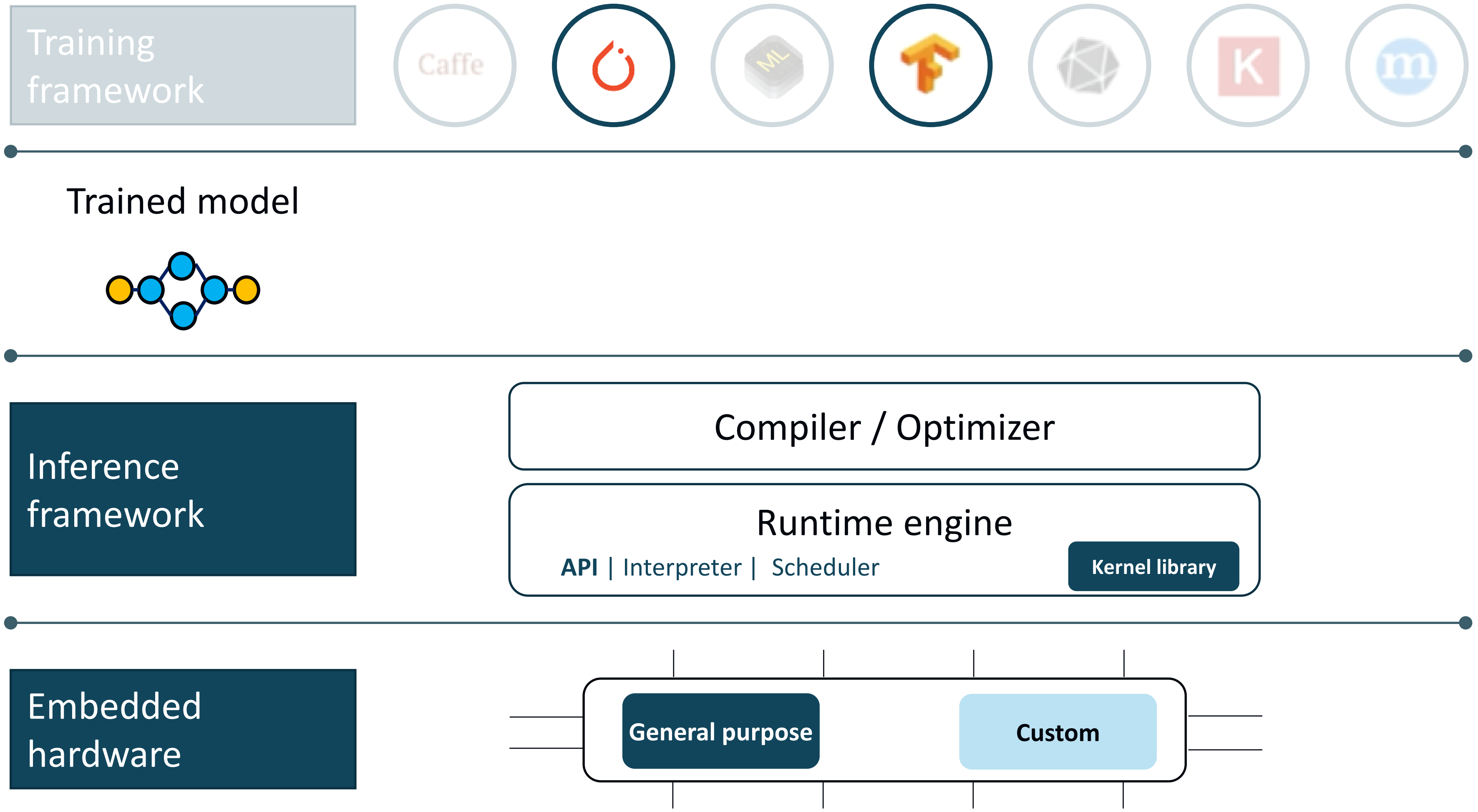
Embedded hardware



Challenges

- Tools not easy to use
- Unsupported operators
- Accuracy goals not met
- Performance not met
- Power goals not met

Open Source Inference Framework Advancement



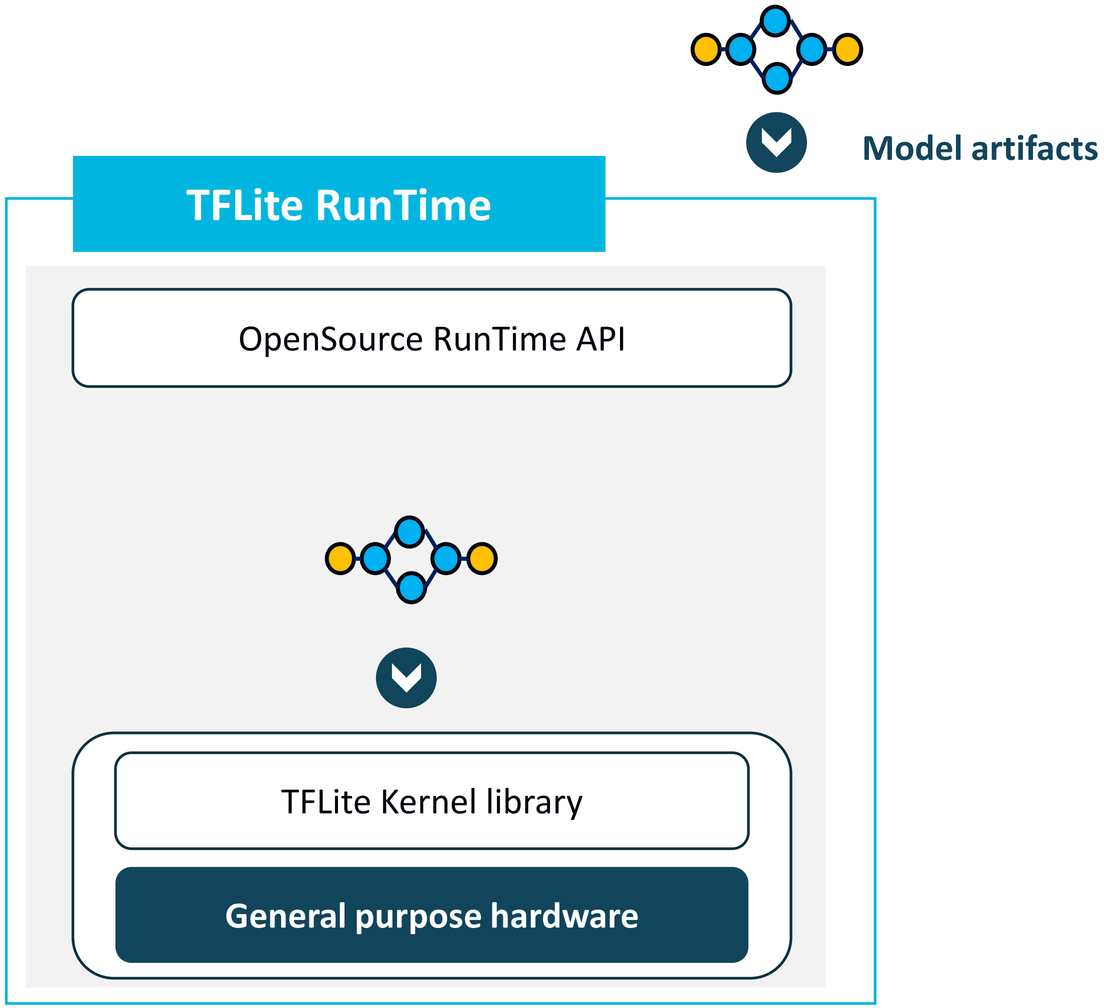
Open source inference framework

- GLOW
- ONNX RUNTIME
- TensorFlow Lite
- ArmNN
- tvm

Promising Open Source Framework Meeting Majority Customers Need

Training framework	Optimizer / Compiler / Graph format	RunTime engine
TensorFlow	TensorFLow Lite format	TFLite RunTime
	ONNX format	ONNX-RunTime
TensorFlowLite	TVM / Amazon SageMaker Neo compiler	Neo-AI-DLR

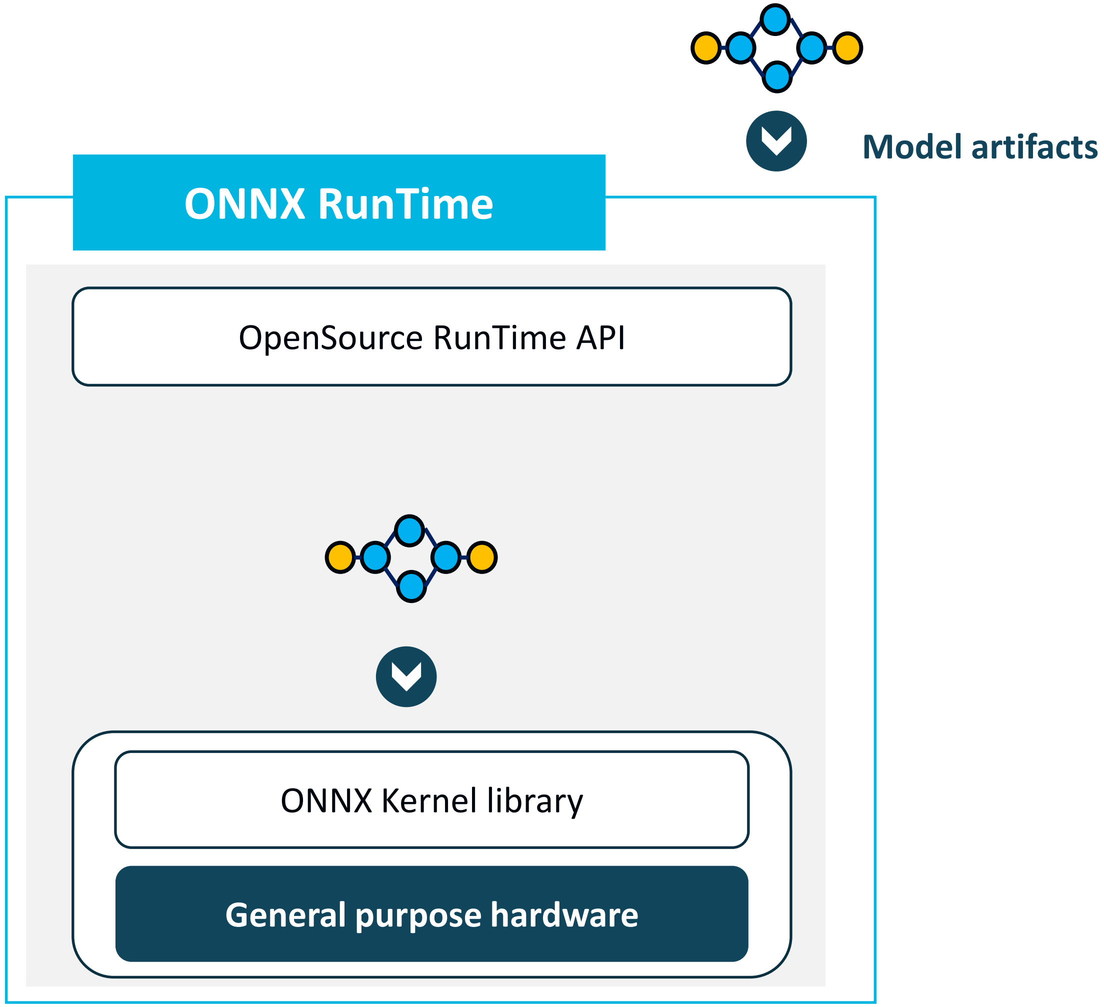
Open Source TFLite RunTime



TFLIte RunTime

- Supporting all inference operators on CPU / GPU

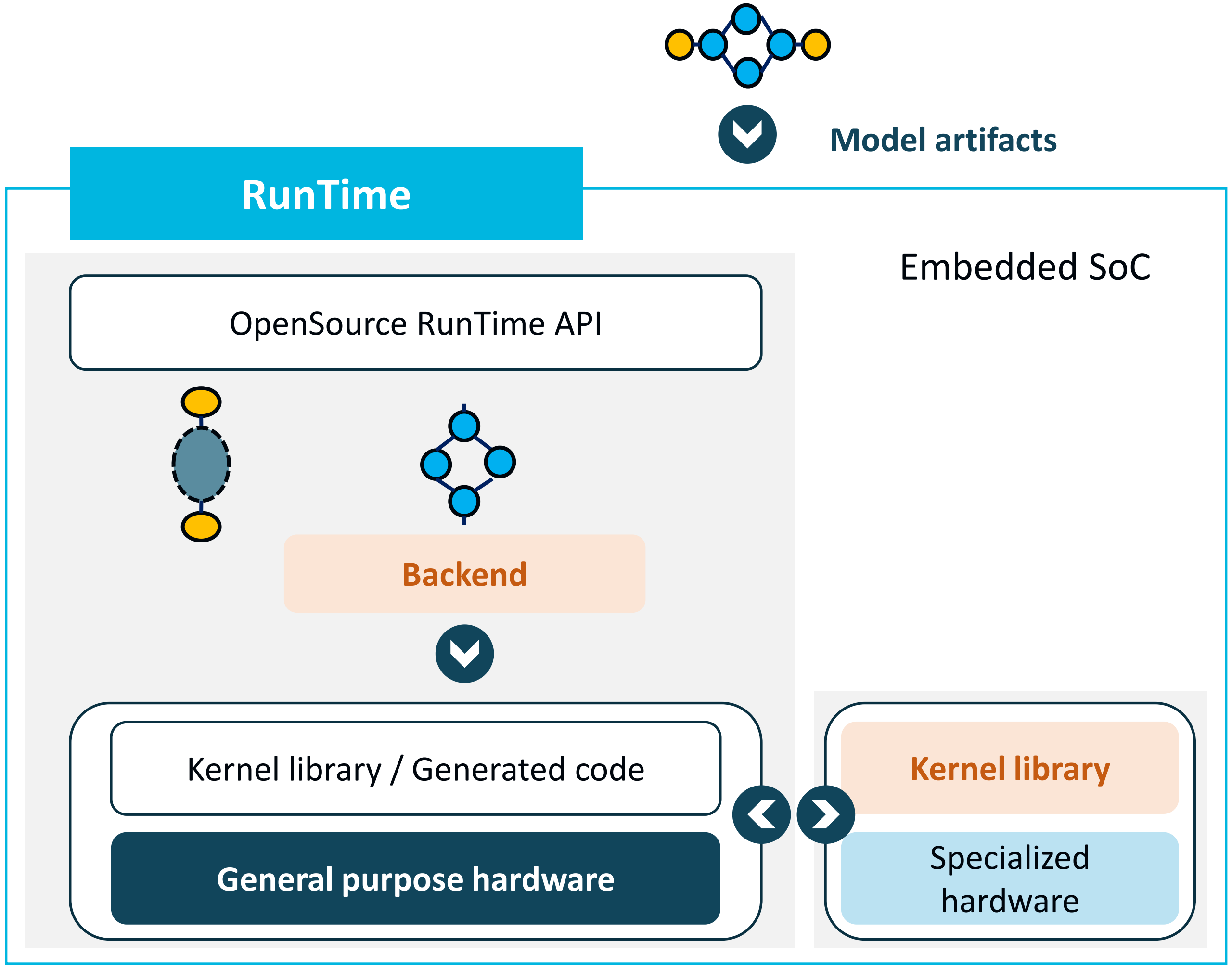
Open Source ONNX RunTime



ONNX RunTime

- Supporting all inference operators on CPU / GPU

Open Source Inference Framework with Hooks for Specialized Hardware



Compiler & RunTime

- Supporting all inference operators on CPU / GPU
- Backend for specialized hardware

TI's First Jacinto™ 7 SoC for Edge Inference

Accelerating key functions lowers power

- DSP for computer vision
- Vision processing
- Video, graphics
- Deep learning

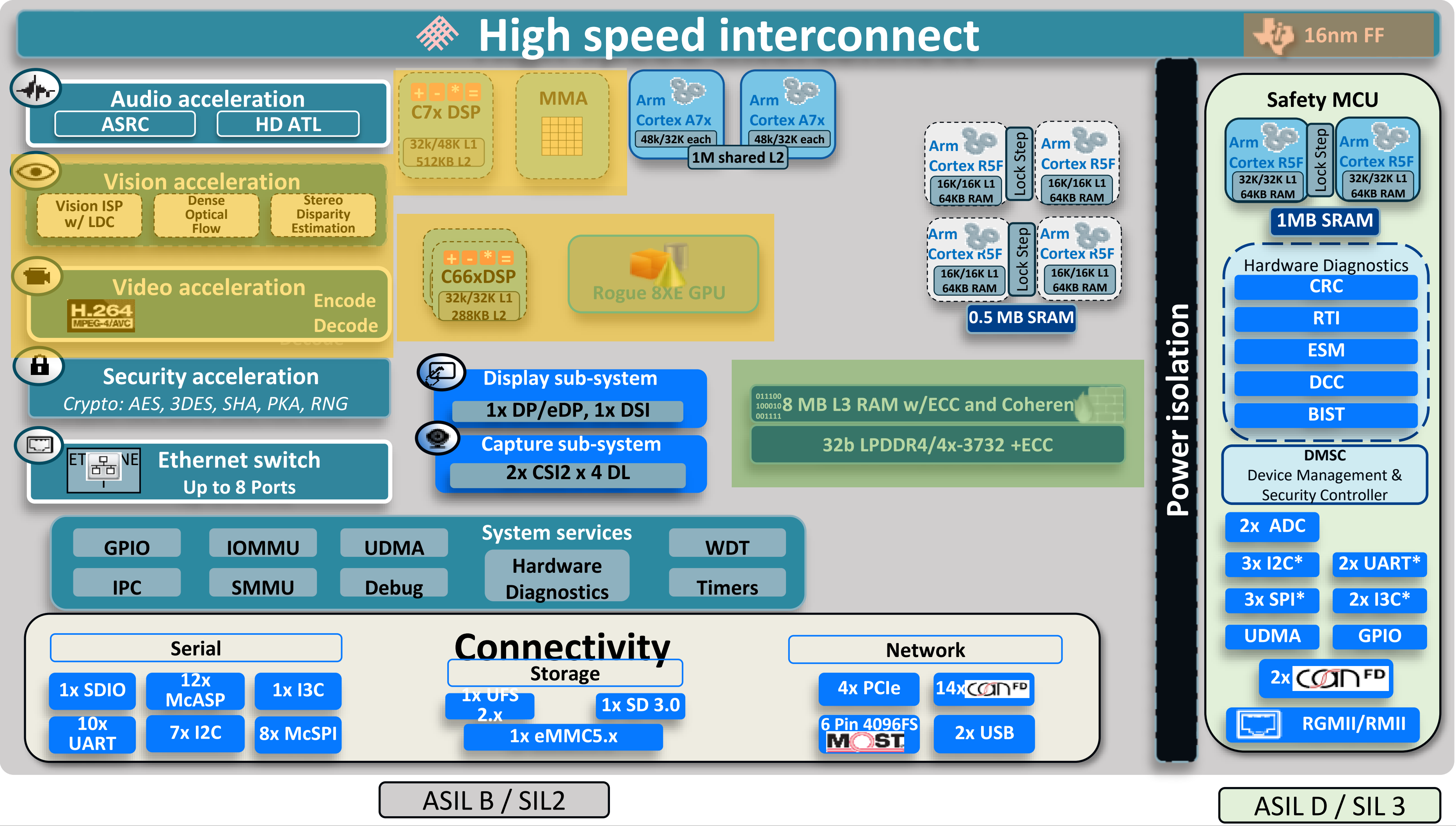
Industry's most efficient DL architecture

- Enables passively-cooling designs
- 90% utilization of deep learning accelerator due to smart memory system

Automotive Quality-ready process technology

- Power reduction is achieved through smart architecture, not process

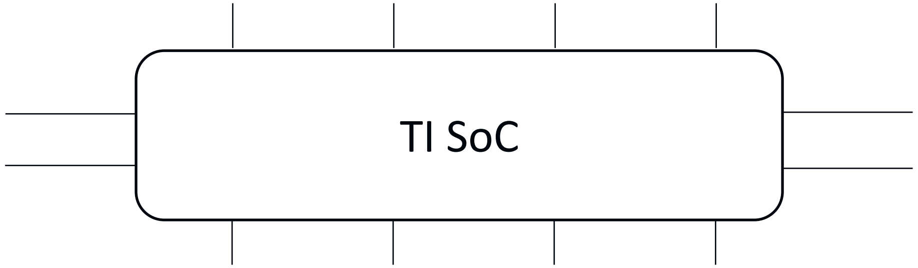
https://www.ti.com/product/TDA4VM

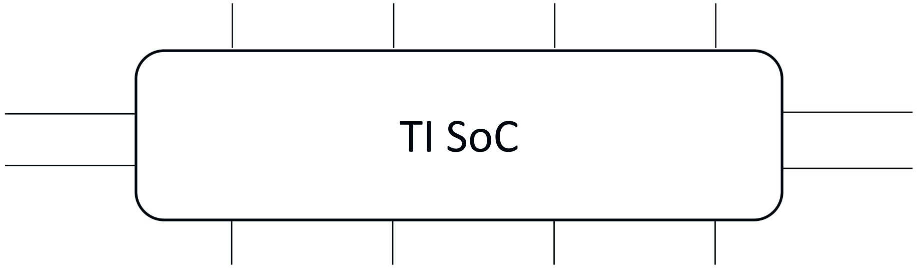


TI Deep Learning (TIDL) Inference Framework

NRE-free, royalty-free tools enable high-performance, fixed-point inference on TI processors

Optimizer	RunTime
TIDL Optimizer	**TIDL RunTime**
• Post training quantization for 8-bit and 16-bit • Range calibration • Hardware independent optimizations • Hardware specific optimizations	• Runtime API • Deep learning library





TIDL Accelerate All Operators You Rely On

TIDL features

- Accelerates all operators commonly used by CNN vision models on our deep learning accelerator cores
- Out-of-box support for 35+ pre-trained CNN models
- List continues to grow

Popular operators supported include

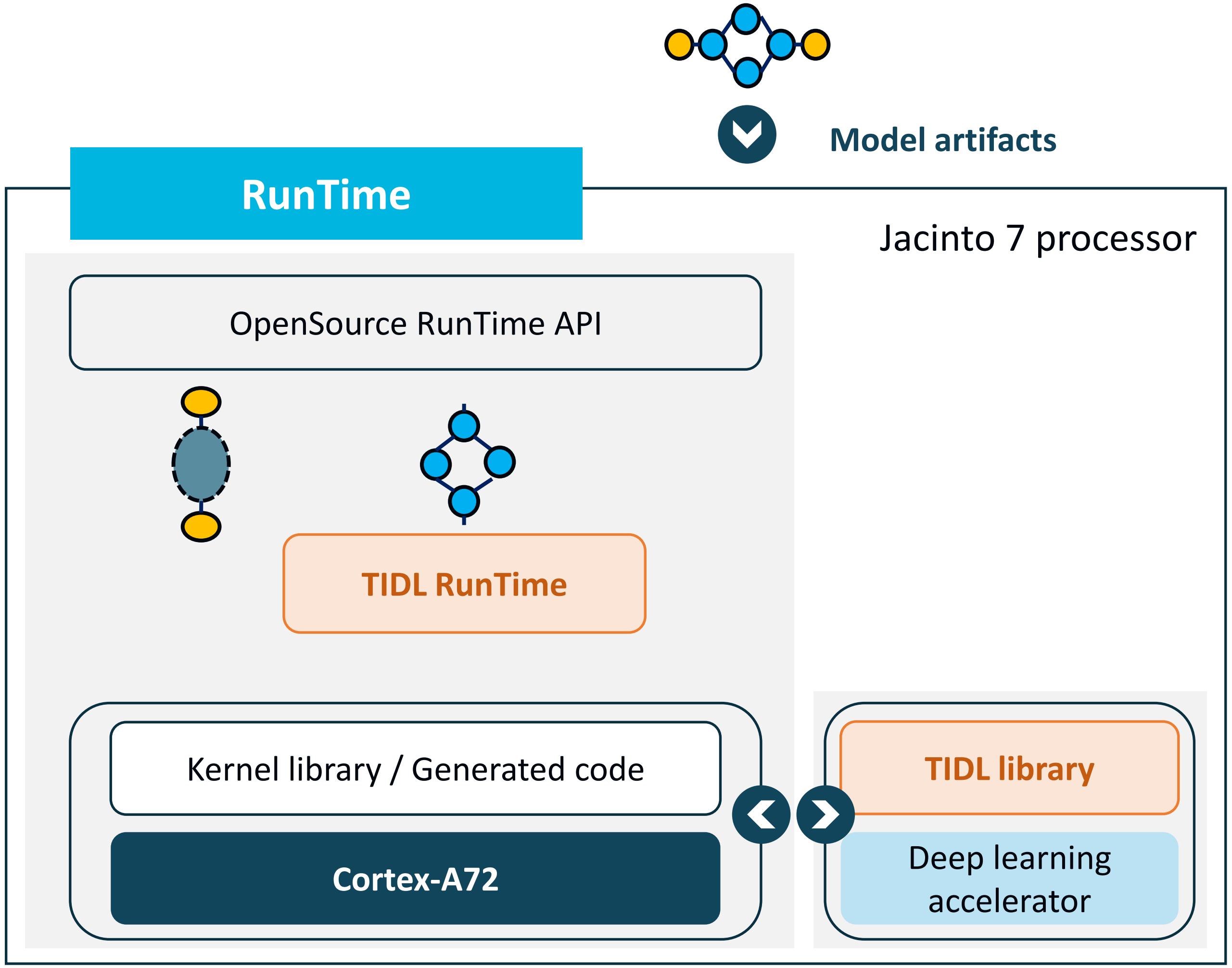
- Convolution
- Pooling
- Element wise
- Inner-product
- Soft-max
- Bias add
- Concatenate

- Scale
- Batch normalization
- Re-size
- Arg-max
- Slice
- Crop
- Flatten

- Shuffle channel
- Detection output
- Deconvolution/ Transpose convolution

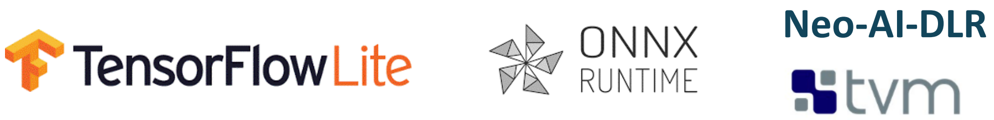
Refer to latest Processor SDK user guide document for complete list of accelerated operators and tested models:
https://software-dl.ti.com/jacinto7/esd/processor-sdk-rtos-jacinto7/latest/exports/docs/tidl_j7_01_02_00_09/ti_dl/docs/user_guide_html/md_tidl_layers_info.html

Texas Instruments adopting open source framework with TI Deep Learning (TIDL) Integration

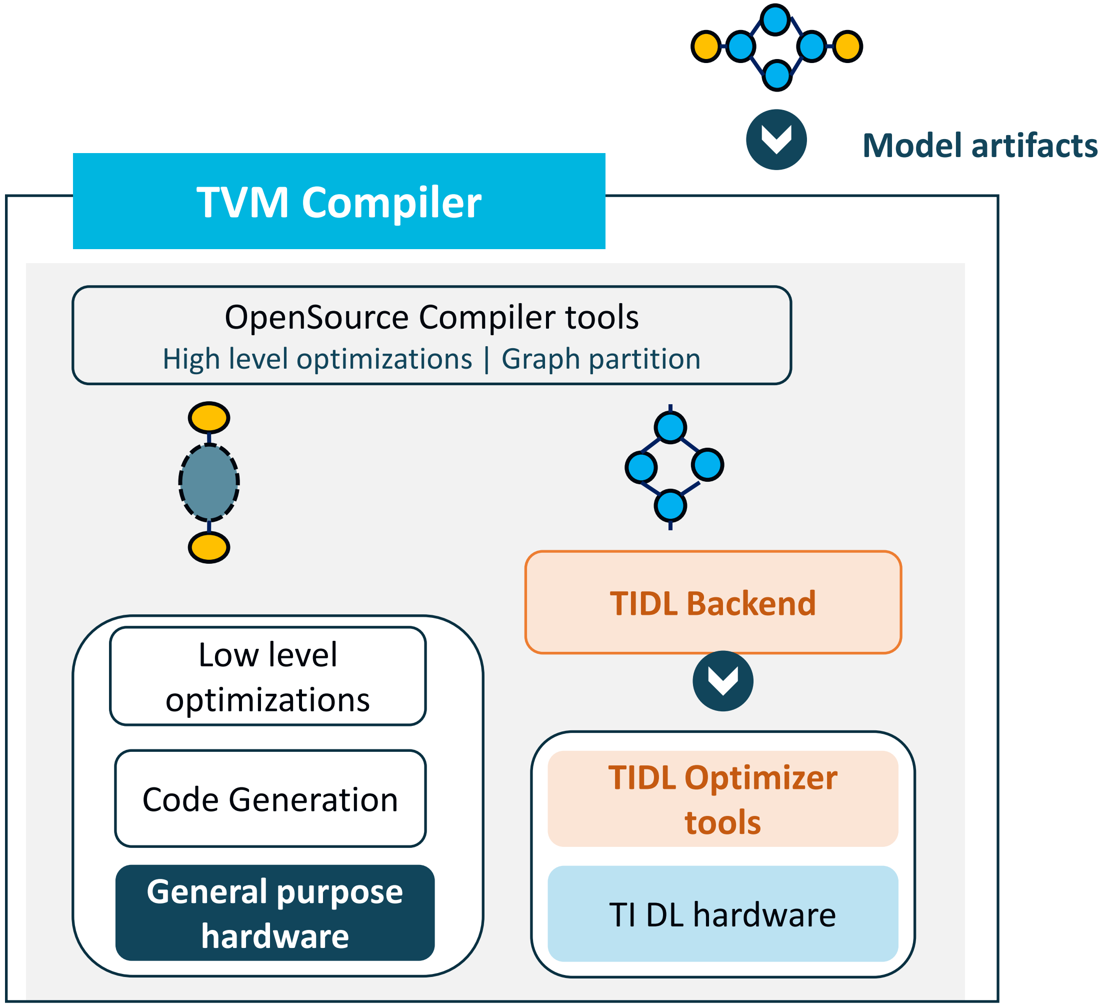


Open source adoption

- Integrating TIDL RunTime in open source RunTime engine



Texas Instruments adopting open source framework with TI Deep Learning (TIDL) Integration



Open source adoption: TVM Compiler

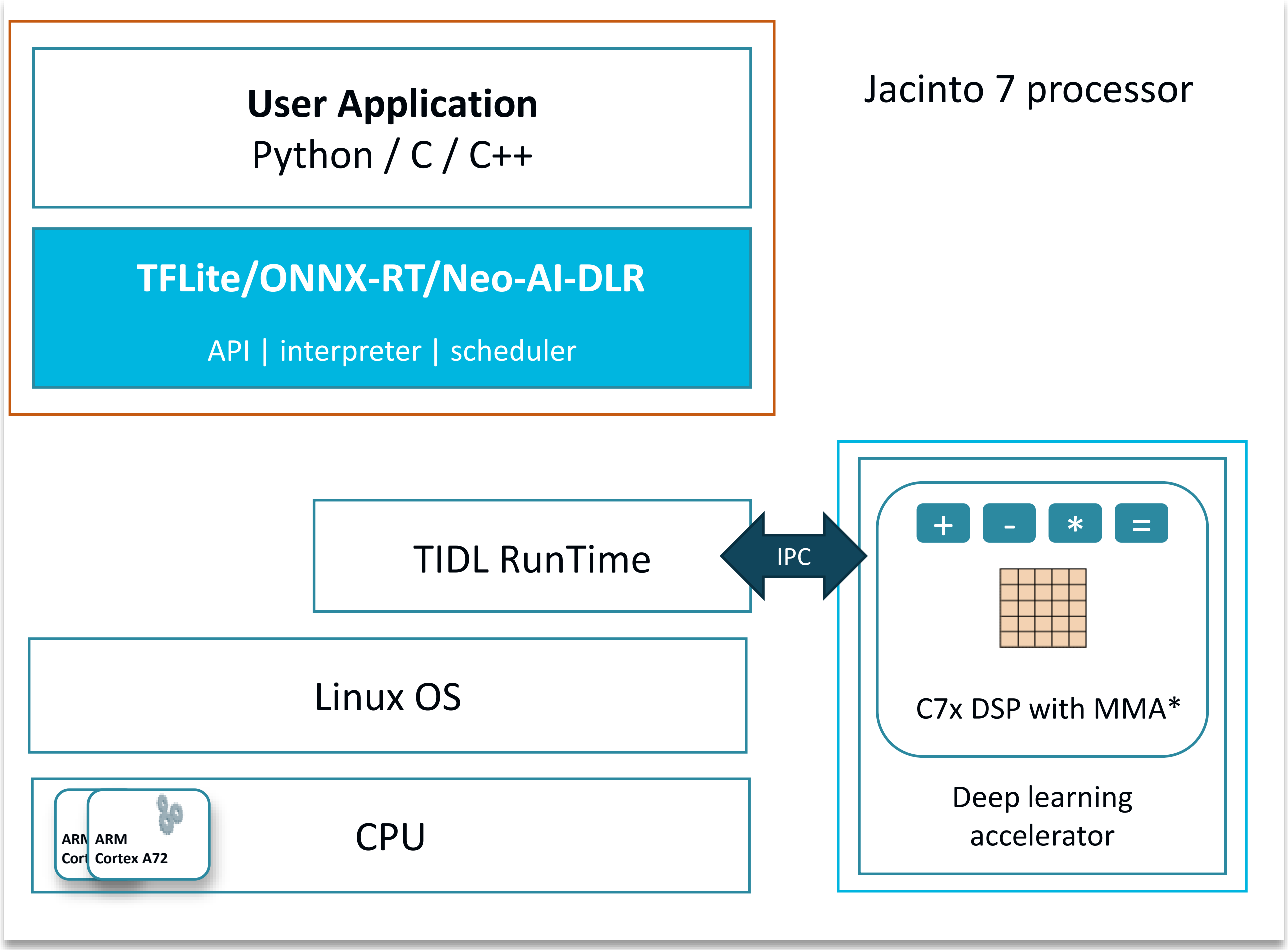
- Integrating TI Optimizer in open source TVM Compiler tool

Now Accelerate All Your Models With Open Source API

- Inference latency in <5 ms for all popular classification models
- Minimal accuracy loss with Post Training Quantization and Quantization Aware Training tools from TI

Run any model from open source inference frameworks on TI processors!

TensorFLow Lite models	TFLite RunTime
ONNX models	ONNX-RunTime
TVM/Amazon SageMaker Neo compiler	Neo-AI-DLR



*MMA: Matrix Multiplication Accelerator (Tensor Processing Unit)

Seamless Migration From PC Validation to Inference Deployment

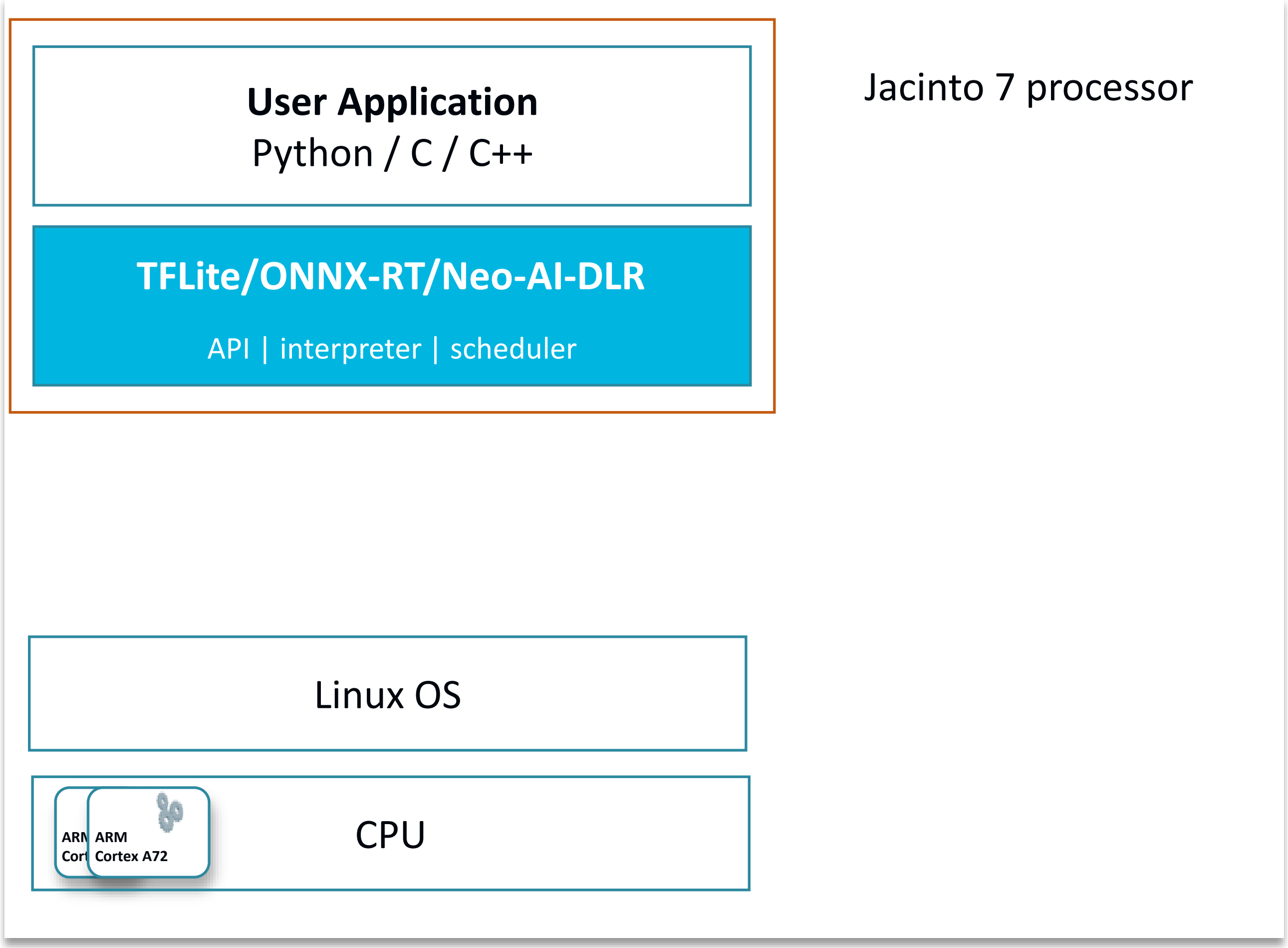
Your DL programming experience on Jacinto 7 processors is the same as desktop computer programming.

This includes -

- Open source LINUX callable APIs in Python / C / C++ between PC and target board
- Jupyter Notebook examples

Download directly from ti.com

http://www.ti.com/tool/PROCESSOR-SDK-DRA8X-TDA4X



Programming Example: Amazon SageMaker Neo & Neo-AI-DLR

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Model compilation

SageMaker Neo console

Location of model artifacts

Amazon SageMaker needs the path to the model artifacts in Amazon S3. To find the path, look in your Amazon S3 directories.

s3://sagemaker-ti-test/mobilenet_v2_1.0_224_frozen.tgz

To find a path, **go to Amazon S3**

Data input configuration

Amazon SageMaker needs to know what the shape of the data matrix is.

{"input": [4,224,224,3]}

Provide model information

Machine learning framework

Choose the machine learning framework that your model was trained in.

TensorFlow

Target device

Amazon SageMaker needs to know where you intend to deploy your model: to an Amazon SageMaker ML instance or to an AWS IoT Greengrass device.

TDA4VM

Select TDA4VM as target device

S3 Output location

Amazon SageMaker needs the path to the S3 bucket or folder where you want to store the compiled module.

s3://sagemaker-ti-test

Provide output location

Cancel | Submit

Compile the model

RunTime

```python
from dlr import DLRModel
import numpy as np
import cv2
from pathlib import Path

MODEL_PATH = Path("../../../build/ssd_mobilenet_v2").resolve()
DATA_PATH = Path("../../../build/street_small.npy").resolve()

def test_ssd_mobilenet_v2_model():
  model = DLRModel(MODEL_PATH.as_posix())
  data = np.load(DATA_PATH)
  assert model.get_input_names() == ['image_tensor']
  assert model.get_output_names() == ['detection_scores:0', 'detection_classes:0', 'num_detections:0']
  assert model.get_input_dtypes() == ['uint8']
  assert model.get_output_dtypes() == ['float32', 'float32', 'float32']
  outputs = model.run({"image_tensor": data})
  assert outputs[0].shape == (1, 100, 4)
  assert outputs[1].shape == (1, 100)
  assert outputs[2].shape == (1, 100)
  detections = np.multiply(np.ceil(outputs[1]), outputs[2])
  expected = np.zeros(detections.shape)
  expected[:,:6] = np.array([[1., 1., 1., 2., 3., 1]])
  comparison = detections == expected
  assert comparison.all()

if __name__ == '__main__':
    test_ssd_mobilenet_v2_model()
    print('All tests passed!')
```

Create RunTime

Run inference

Output

Programming Example: TensorFlow Lite

```
def infer_tflite_model():

  interpreter = tf.lite.Interpreter(model_path=args.model_path)
  interpreter.allocate_tensors()

  input_details = interpreter.get_input_details()
  output_details = interpreter.get_output_details()

  print(output_details)
  # check the type of the input tensor
  floating_model = input_details[0]['dtype'] == np.float32

  # NxHxWxC, H:1, W:2
  height = input_details[0]['shape'][1]
  width = input_details[0]['shape'][2]
  img = Image.open(args.input_file).resize((width, height))

  # add N dim
  input_data = np.expand_dims(img, axis=0)

  if floating_model:
    input_data = (np.float32(input_data) - args.input_mean) / args.input_std

  interpreter.set_tensor(input_details[0]['index'], input_data)

  tidl_delegate =TfLiteTIDLDelegateCreate();
  interpreter.ModifyGraphWithDelegate(tidl_delegate);

  interpreter.invoke()

  output_data = interpreter.get_tensor(output_details[0]['index'])
  results = np.squeeze(output_data)

  top_k = results.argsort()[-5:][::-1]
  print(top_k)

infer_tflite_model()
```

Create RunTime

Init time: Hook TIDL backend

Run inference

Get output

RunTime

Deep Learning System Performance on Jacinto-7 TDA4VM: Example demo

5 simultaneous deep learning algorithms on 3x 1MP camera each @ ~16 fps

- Parking spot detection
- Vehicle detection
- Semantic segmentation
- Motion segmentation
- Depth estimation

Inference resolution: 3x768x384

Resource loading

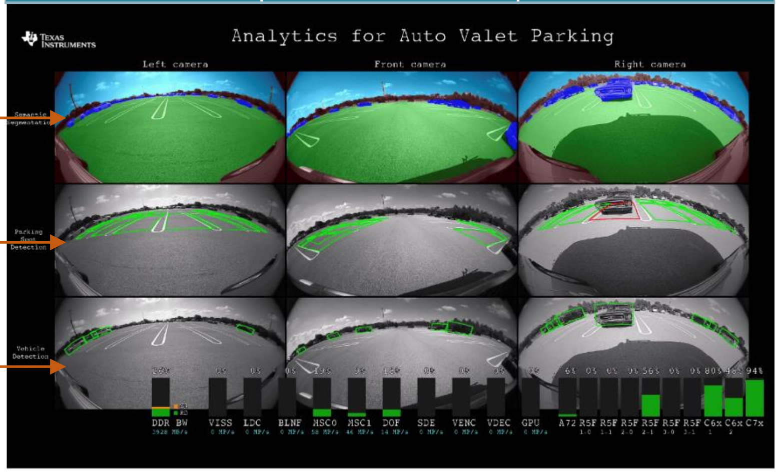
A72:	6%	**C7x+MMA:**	94%
DDR BW:	26%		

Camera 1	Camera 2	Camera 3

Semantic segmentation

Parking spot detection

Vehicle detection

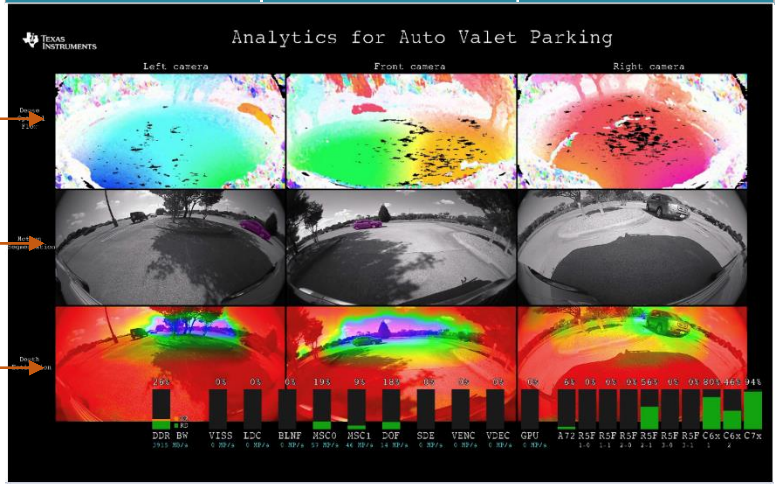


Camera 1	Camera 2	Camera 3

Dense Optical Flow

Motion Segmentation

Depth Estimation



Key Takeaways: Deep Learning Edge Inference at TI

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- **Easier to use**
  - Opensource Linux callable RunTime APIs supported to program SoC
  - Embedded development environment same as a desktop computer environment
- **More flexible**
  - Supports TFLite, ONNX-RT or TVM/Neo-AI-DLR
  - Supports compilation at the edge or in the cloud with Amazon SageMaker Neo
- **Provide wide model coverage**
  - All TFLite, ONNX, TVM and SageMaker Neo models supported on TI SoCs
- **High compute performance, high throughput, low latency and low power consumption**
  - Accelerates the model on TI's deep learning accelerator C7x+MMA to provide the best combination of system power, deep learning performance and latency at the edge

Jacinto 7 processor silicon is available today!

Explore Deep Learning With TI Today

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Full development

TDA4 EVM

http://www.ti.com/tool/TDA4VMXEVM

Turn-key designs

Automotive version of TDA4V Mid

http://www.ti.com/tool/D3-3P-TDAX-DK

Software development kits

TI Processor SDK – Seamlessly reuse and migrate Linux, Linux-RT and TI-RTOS software across TI processors

http://www.ti.com/tool/PROCESSOR-SDK-DRA8X-TDA4X

Support

https://e2e.ti.com

Open source RunTime engines with TIDL acceleration is packaged as part of TI's NRE-free, royalty-free Processor SDK!

Thank You!