

# Leveraging the power of C++ for efficient machine learning on embedded devices

Adrian Stanciu

[adrian.stanciu.pub@gmail.com](mailto:adrian.stanciu.pub@gmail.com)

NDC TechTown, 2023

## About me

- ▶ I am a software engineer from Romania
- ▶ I have a bachelor's degree in computer science from Politehnica University of Bucharest
- ▶ I have a master's degree in computer and network security from Politehnica University of Bucharest
- ▶ I have 12 years of professional experience in Linux system programming
- ▶ My main programming languages are C and C++
- ▶ I am interested in algorithms, data structures and operating systems
- ▶ I work at Bitdefender, global leader in cybersecurity, where I develop security software solutions which run on routers

## Disclaimer

- ▶ This presentation is based on a personal project I worked on in my spare time and it is not directly related to the work I do at Bitdefender
- ▶ The outcome of this project is just a proof of concept
- ▶ All mistakes are mine

# Agenda

- ▶ Motivation
- ▶ Image classification
- ▶ Hand gesture recognition
- ▶ Summary
- ▶ Q&A

# Motivation

# Machine Learning (ML)

- ▶ Subfield of Artificial Intelligence (AI)
- ▶ Enables computers to learn from data and then use that knowledge to make predictions
- ▶ Applications:
  - ▶ Computer vision
  - ▶ Medicine
  - ▶ Search engines

# Embedded devices

- ▶ Computing devices designed to perform specific tasks within larger systems
- ▶ Applications:
  - ▶ Consumer electronics (mobile phones, VR headsets)
  - ▶ Home automation (thermostats, lighting control systems)
  - ▶ Medical equipment (pacemakers, insulin pumps)
- ▶ Characteristics:
  - ▶ Limited hardware resources
  - ▶ Low power consumption
  - ▶ May have real-time performance constraints

# Machine learning on embedded devices

- ▶ Alternative to cloud-based machine learning
- ▶ Advantages:
  - ▶ Real-time processing
  - ▶ Low latency
  - ▶ Reduced bandwidth usage
  - ▶ Offline operation
  - ▶ Improved privacy
- ▶ Disadvantages:
  - ▶ Compatibility with various hardware and software platforms
  - ▶ Slower updates

# Using C++ for machine learning on embedded devices

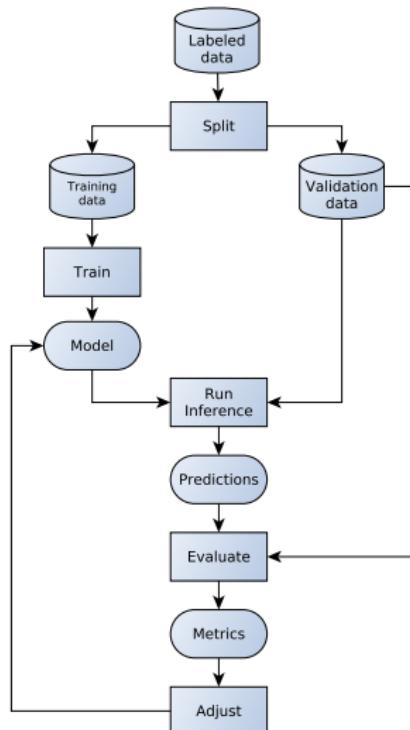
C++ is widely used in embedded systems:

- ▶ Was designed with efficiency in mind
- ▶ Provides both low-level access to hardware resources and high-level abstractions
- ▶ Is supported on most hardware and software platforms

## Image classification

# Supervised learning

Machine learning paradigm in which an algorithm learns from labeled data to make predictions

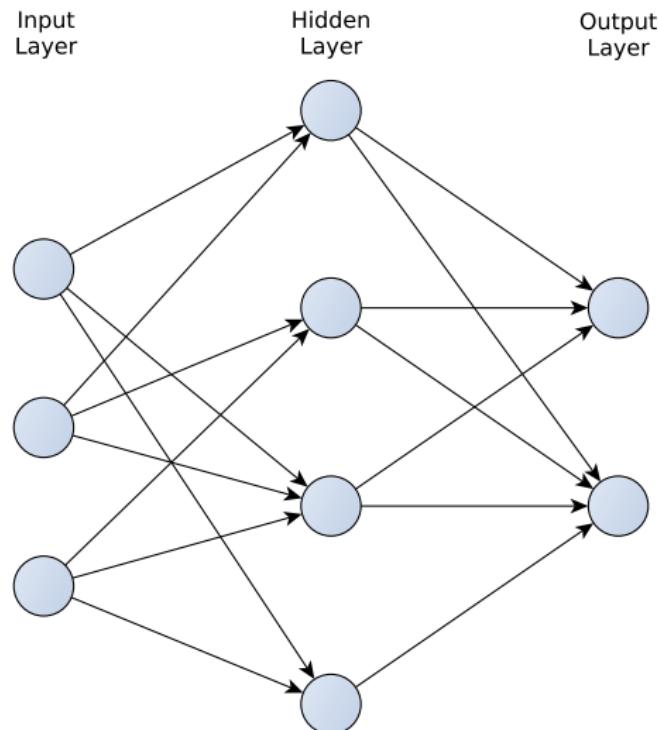


# Supervised learning



Source: xkcd.com

# Neural network (NN)

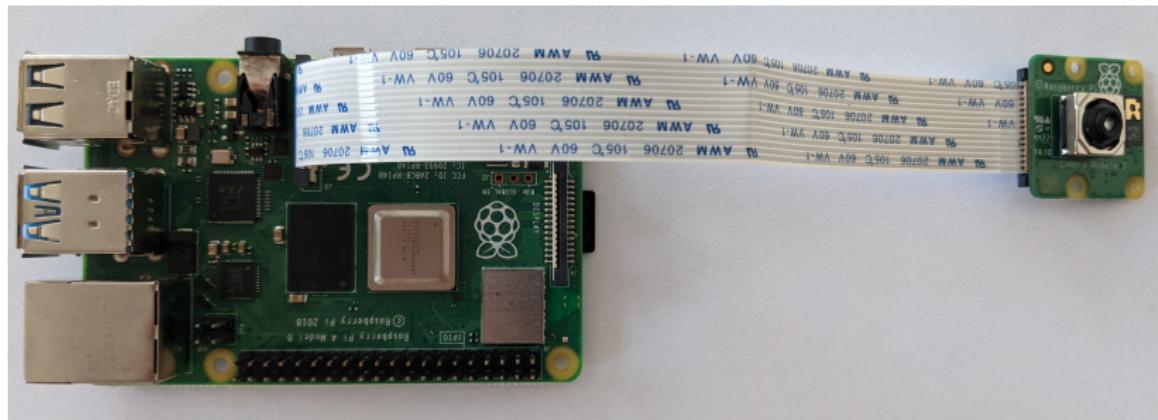


## Convolutional neural network (CNN)

- ▶ Efficient in image classification
- ▶ A convolutional layer can apply filters to detect:
  - ▶ Edges
  - ▶ Shapes
  - ▶ Objects

# Hardware setup

- ▶ Raspberry Pi 4 model B:
  - ▶ Quad core Cortex-A72 (ARM v8) 64-bit SoC @ 1.8GHz
  - ▶ 4GB RAM
- ▶ 8GB microSD card
- ▶ Raspberry Pi Camera module 3



## Software dependencies

- ▶ TensorFlow Lite
- ▶ OpenCV

## MobileNet pre-trained model

- ▶ CNN architecture created by Google
- ▶ Accepts 224x224-pixel images, with 3 color channels per pixel (RGB)
- ▶ Trained on 1000 classes
- ▶ Labels are stored separate from the model:
  - ▶ `labels_mobilenet_quant_v1_224.txt` (11KB)
  - ▶ `mobilenet_v1_1.0_224_quant.tflite` (4.1MB)

# Image classification algorithm

1. Load model and labels
2. Build interpreter
3. Allocate input and output tensors
4. Read image
5. Resize image
6. Copy resized image to input tensor
7. Run inference
8. Extract results from output tensor

Steps 1-3 represent the initialization phase

Steps 4-8 can be repeated multiple times

## 1. Load model and labels

```
1 // defined and properly initialized elsewhere:  
2 // const char *model_path;  
3 // const char *labels_path;  
4  
5 std::unique_ptr<tflite::FlatBufferModel> model{  
6     tflite::FlatBufferModel::BuildFromFile(model_path)  
7 };  
8  
9 std::ifstream labels_ifs{labels_path};  
10 std::string label;  
11 std::vector<std::string> labels;  
12 while (getline(labels_ifs, label)) {  
13     labels.push_back(std::move(label));  
14 }
```

## 2. Build interpreter

```
1 // defined and properly initialized elsewhere:  
2 // std::unique_ptr<tflite::FlatBufferModel> model;  
3 // int num_threads;  
4  
5 tflite::ops::builtin::BuiltinOpResolver resolver;  
6 tflite::InterpreterBuilder builder{*model, resolver};  
7  
8 builder.SetNumThreads(num_threads);  
9  
10 std::unique_ptr<tflite::Interpreter> interpreter;  
11 builder(&interpreter);
```

### 3. Allocate input and output tensors

```
1 // defined and properly initialized elsewhere:  
2 // std::unique_ptr<tflite::Interpreter> interpreter;  
3  
4 interpreter->AllocateTensors();
```

## 4. Read image

```
1 // defined and properly initialized elsewhere:  
2 // const char *image_path;  
3  
4 cv::Mat image{cv::imread(image_path)};
```

## 5. Resize image

```
1 // defined and properly initialized elsewhere:  
2 // cv::Mat image;  
3 // int required_image_width;  
4 // int required_image_height;  
5  
6 cv::Mat resized_image;  
7 cv::resize(  
8     image,  
9     resized_image,  
10    cv::Size{required_image_width, required_image_height}  
11 );
```

## 6. Copy resized image to input tensor

```
1 // defined and properly initialized elsewhere:  
2 // std::unique_ptr<tflite::Interpreter> interpreter;  
3 // cv::Mat resized_image;  
4  
5 std::memcpy(  
6     interpreter->typed_input_tensor<uint8_t>(0),  
7     resized_image.data,  
8     resized_image.total() * resized_image.elemSize()  
9 );
```

## 7. Run inference

```
1 // defined and properly initialized elsewhere:  
2 // std::unique_ptr<tflite::Interpreter> interpreter;  
3  
4 interpreter->Invoke();
```

## 8. Extract results from output tensor

```
1 // defined and properly initialized elsewhere:  
2 // std::unique_ptr<tflite::Interpreter> interpreter;  
3 // std::vector<std::string> labels;  
4  
5 std::span<uint8_t> outputs{  
6     interpreter->typed_output_tensor<uint8_t>(0),  
7     labels.size()  
8 };  
9  
10 std::vector<float> probabilities;  
11 probabilities.reserve(labels.size());  
12 for (auto output : outputs) {  
13     probabilities.push_back(  
14         1.0f * output / std::numeric_limits<uint8_t>::max()  
15     );  
16 }
```

## Demo



```
$ libcamera-jpeg --width=640 --height=480 -o out.jpeg
```

## Demo - Good results



0.96 | tennis ball

## Demo - Bad results



0.30 | vase

0.25 | bell pepper  
ambiguous results

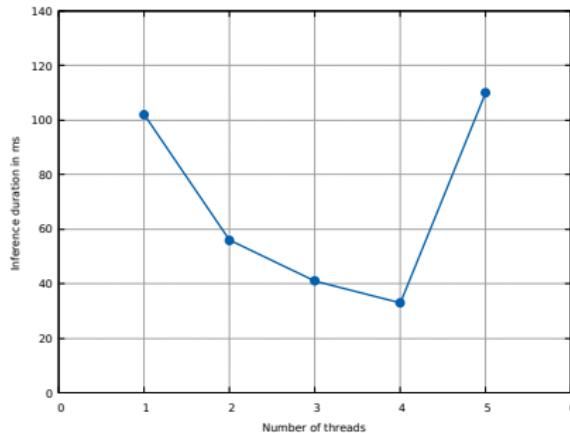
## Demo - Bad results explanation

```
$ grep "tomato" labels_mobilenet_quant_v1_224.txt  
$
```

# Performance

- ▶ Compilation duration (on Raspberry Pi): 35s
- ▶ Binary size: 67KB
- ▶ Running duration: 1s

Number of threads	Inference duration (ms)
1	102
2	56
3	41
4	33
5	110



- ▶ Memory consumption with 4 threads: 93MB

## Comparision with Python

Comparision made with TensorFlow Lite's `label_image.py`

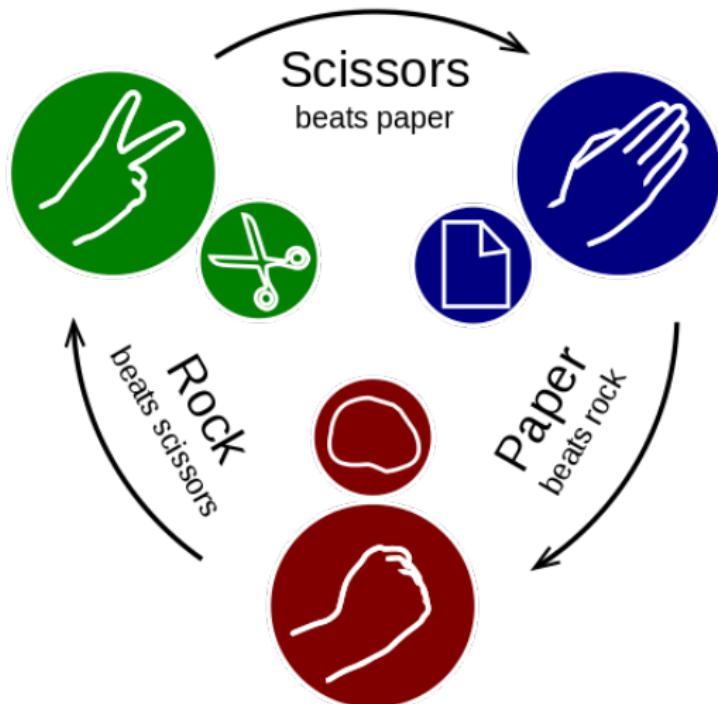
	C++	Python
Running duration (s)	1	7
Number of threads	Inference duration (ms)	
1	102	118
2	56	62
3	41	42
4	33	33
5	110	170

Number of threads	Inference duration (ms)	
	C++	Python
1	102	118
2	56	62
3	41	42
4	33	33
5	110	170

Memory consumption with 4 threads (MB)	C++	Python
93	320	

## Hand gesture recognition

# Rock-Paper-Scissors



Source: wikipedia.org

# Data

- ▶ Google MediaPipe's Rock-Paper-Scissors dataset for hand gesture recognition
  - ▶ Contains 125 images for each class
  - ▶ Images have various sizes
  - ▶ Images have 3 color channels per pixel (RGB)
- ▶ Laurence Moroney's Rock-Paper-Scissors dataset (published by Sani Kamal on Kaggle)
  - ▶ Contains 964 images for each class split into training data (840) and testing data (124)
  - ▶ Images are 300x300 pixels
  - ▶ Images have 3 color channels per pixel (RGB)

## Train a Rock-Paper-Scissors model

- ▶ Transfer learning from a ResNet50 model
- ▶ 80/20 split between training and validation data
- ▶ Run in Python, on a laptop

<b>Dataset</b>	<b>Train duration</b>	<b>Model size (MB)</b>
Small	2m15s	23
Big	7m10s	23

## Test the Rock-Paper-Scissors model

- ▶ Using the testing data of the big dataset (124 images per class)
- ▶ Small dataset results:

<b>Gesture</b>	<b>Correct predictions</b>	<b>Accuracy (%)</b>
Rock	108	87.09
Paper	124	100
Scissors	8	6.45
All	240 out of 372	64.51

- ▶ Big dataset results:

<b>Gesture</b>	<b>Correct predictions</b>	<b>Accuracy (%)</b>
Rock	124	100
Paper	122	98.38
Scissors	97	78.22
All	343 out of 372	92.20

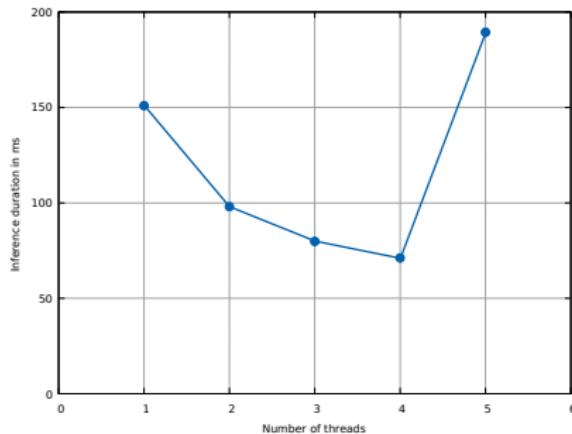
# Demo



# Performance

- ▶ Compilation duration (on Raspberry Pi): 35s
- ▶ Binary size: 67KB
- ▶ Running duration: 1s

Number of threads	Inference duration (ms)
1	151
2	98
3	80
4	71
5	189



- ▶ Memory consumption with 4 threads: 118MB

## Capture live camera stream

- ▶ libcamera backend
- ▶ gstreamer middleware
- ▶ OpenCV frontend

## Capture live camera stream

```
1 static constexpr const char *GstreamerPipeline{R"(  
2     libcamerasrc !  
3     video/x-raw,  
4     width=(int)640,  
5     height=(int)480,  
6     framerate=(fraction)10/1 !  
7     videoconvert !  
8     appsink  
9 )"};  
10  
11 cv::VideoCapture camera{  
12     GstreamerPipeline,  
13     cv::CAP_GSTREAMER  
14 };  
15  
16 cv::Mat image;  
17 camera.read(image);
```

## Live inference

1. Create image classifier
2. Open camera
3. Do in a loop:
  - 3.1 Read image from camera
  - 3.2 Use classifier to run inference on image
  - 3.3 Show predictions

## Live inference - Demo

## Rock-Paper-Scissors game

On each round the AI:

1. Chooses Rock, Paper or Scissors uniformly at random
2. Infers the human's hand gesture
3. Computes the outcome

# Rock-Paper-Scissors game - Demo

# Summary

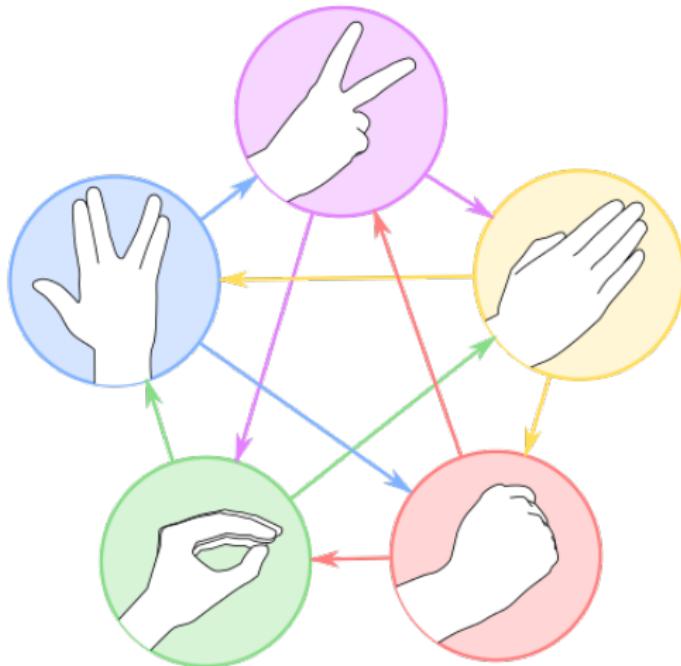
# Recap

Task	Model	Inference
Image classification	pre-trained MobileNet	on-device in C++
Rock-Paper-Scissors hand gesture recognition	transfer learning from ResNet50	

## Future work

- ▶ Reduce the model size and decrease the inference duration by converting images to grayscale
- ▶ Use libcamera's API directly to reduce dependencies

## Future work



Source: wikipedia.org

## Conclusions

- ▶ Code isn't enough... data matters
- ▶ More diverse data leads to better models
- ▶ Building accurate models is an expert job
- ▶ Running on-device inference is here to stay

# Repository

<https://github.com/adrian-stanciu/cpp-embedded-ml>

## Resources

- ▶ <https://github.com/tensorflow/tensorflow/tree/master/tensorflow/lite/examples/python>
- ▶ <https://kaggle.com/datasets/sanikamal/rock-paper-scissors-dataset>
- ▶ <https://raspberrypi.com/products/camera-module-3>
- ▶ [https://storage.googleapis.com/mediapipe-tasks/gesture\\_recognizer/rps\\_data\\_sample.zip](https://storage.googleapis.com/mediapipe-tasks/gesture_recognizer/rps_data_sample.zip)
- ▶ <https://tensorflow.org/lite/examples>

Feedback is welcome

<https://forms.gle/BvSieuMRZbfKFpcq8>



# Q&A

Thank you!