Rapid development of a neural network for image classification using fine-tuning techniques and implementation on SoC systems

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***Abstract*—The intent of this project is the rapid development of a neural network for image classification. After a brief theoretical presentation of the functioning of a neural network, the reader is introduced to the world of deep neural networks and classification. Thanks to the use of framework like Keras is possible to develop refinement techniques starting from already known models. There is discussion of the architecture of a USB commercial device, Intel Movidius neural compute stick, with low power consumption for neural network execution on SoC systems such as Raspberry. Finally, there are the problems and limitations that occurred during the development and distribution of the software implemented.**

***Index Terms*—Python, Keras, Movidius, Intel, Neural Network, Inception, TensorFlow, ImageNet, ncsdk, API, backend.**

I. Introduction

In this era, a large amount of structured and unstructured data became available. **Machine Learning** (**ML**) has evolved as a branch of artificial intelligence: it envisages the development of self-learning algorithms, which are capable of acquiring knowledge from data with the aim of making predictions. Instead of requiring a human presence who manually enact the rules and build models for the analysis of large amounts of data, machine learning offers a more efficient alternative to capture the knowledge in the data. Machine learning aims to gradually improve the performance of forecasting models and to make data driven decisions. In this section we will examine the three different types of machine learning: *supervised learning*, *unsupervised learning* and *reinforcement learning*. Where we will show the fundamental differences between these types of learning. [1]

A. Supervised learning

The main purpose of supervised learning is to derive a model from training data, which allows us to make predictions for data that are not available or future. Here, the term "supervision" refers to the fact that the output signal labels of the sample sets are already known. A supervised learning task, which is based on discrete class labels, is also called a classification task, in figure 1 it is possible to observe a process diagram. Another supervised learning subcategory is regression, whose resulting signal is a continuous value. Classification is a sub-category of supervised learning, which has the goal to provide class category labels for new instances, based on observations made in the past. These labels are discrete, unordered values that can be considered as belonging to a group of instances. However, the set of class labels does not necessarily have to be a binary nature. The predictive model identified by a supervised learning algorithm can consider each class label that is present in the learning dataset of a new instance, which is not labelled.
A typical example of *multi-class classification* is the recognition of hand-written text. [1]

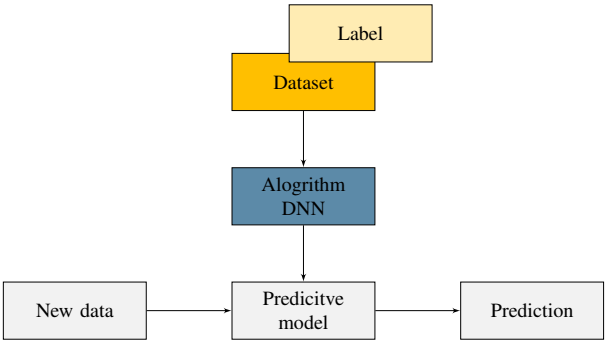


Fig. 1: supervised learning scheme

B. Reinforcement learnig

Another type of machine learning is reinforcement learning. Here, the goal is to develop a system (*agent*) for people to improve their performance. In order to

do so, that system is based on interactions with the environment. Since information relating to the current state of the environment include also a *reward* signal, we can consider strengthening learning as an example of supervised learning. However, this feedback is not the correct label or the true value of truth, but it represents the quality of the measurement of the performance measured by the reward function. Through interaction with the environment, an agent can then use reinforcement learning to learn a series of actions, which maximize this reward through a trial-and-error exploratory approach or deliberative planning. [1]

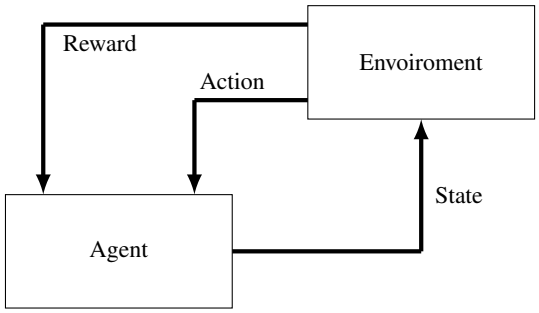


Fig. 2: reinforcement learning scheme

C. Unsupervised learning

In supervised learning, we know in advance the correct answer when we describe our model, while in reinforcement learning we define a measure, or reward, for the specific actions performed by the agent. In unsupervised learning, on the other hand, we are dealing with unlabelled data or data from the unknown structure. Using unsupervised learning techniques, we are able to observe the structure of our data, to extract meaningful information from them without being able to rely on the guide nor a variable known relative result, nor a reward function. Clustering is an exploratory technique of data analysis that allows us to organize a series of information within meaningful groups (*cluster*) without having any previous knowledge of memberships in such groups. Each cluster that can be derived during the analysis defines a group of objects that share a certain degree of similarity, but which are more dissimilar than the objects present in the other clusters, which is why clustering is sometimes called *"unsupervised classification"*. Clustering is an excellent technique for structuring information to identify meaningful relationships in the data. [1]

II. Deep learning

Deep learning lies at the heart of the most advanced machine learning solutions, such as those that have

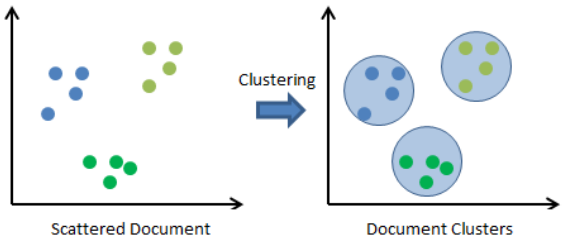


Fig. 3: example of clustering

learned to recognize items and images, determine the sentiment of text, and drive vehicles. These neural networks are complex and can be challenging to build, but Keras removes much of the effort. Keras acts as an API[1], letting us quickly create a network that might take hours or days to hand code in Python or other languages.

A. Introducing Keras

Let's use the definition from the documentation at keras.io. Keras is a high-level neural network API, written in Python and capable of running on top of *TensorFlow*, *CNTK* or *Theano* [3], [4]. That is, it lets us build neural networks easier by providing us with a high-level set of constructs. These constructs handle much of the plumbing involving in wring up neural networks and thus reduce programming errors. Also, as an API, it provides an interface that we can develop against and a detailed description of what happens when we invoke various objects and methods. Keras is Python centric in its code and is implemented as a Python library. It is imported and used just like any other Python library you might be familiar with, so the learning curve is minimal. Finally, Keras runs on top of *TensorFlow*, *CNTK*, or *Theano*. These are three of the most widely used libraries for performing work with neural networks. Keras calls these libraries to perform the actual execution of operations that create, populate, train, and evaluate the neural networks we specify in Keras. Keras utilizes either TensorFlow, CNTK, or Theano as the *backend*[2]. Keras itself does not create or execute the neural network.

[1] An Application Programming Interface (API) provides an abstraction for a problem and specifies how clients should interact with the software components that implement a solution to that problem. [2]

[2] In software engineering, the terms front end and back end refer to the separation of concerns between the presentation layer (front end), and the data access layer (back end) of a piece of software, or the physical infrastructure or hardware. In the client–server model, the client is usually considered the front end and the server is usually considered the back end, even when some presentation work is actually done on the server. [5]

Rather, Keras defines an API we code against. In our code we invoke Keras methods and pass the appropriate parameters. Keras evaluates these for correctness and constructs whatever objects are required. Keras then calls the appropriate backend methods to do the actual neural network operations, such as defining structures, training the neural network model, and evaluating the trained model. Any result from these operations are returned by the backend to Keras, which processes them and returns to our code the appropriate results.

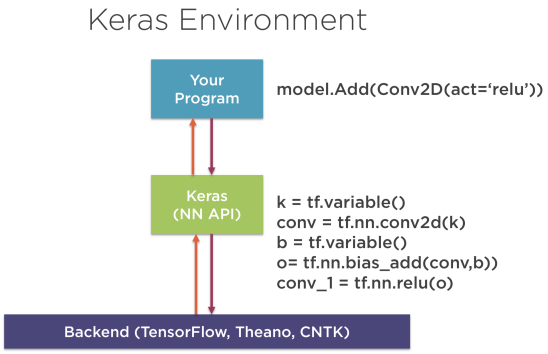


Fig. 4: Block diagram environment

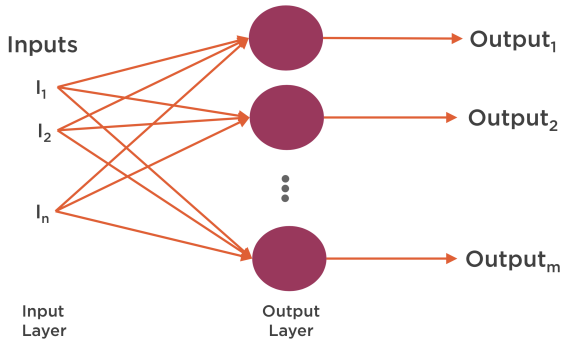


Fig. 5: Neural networks layers

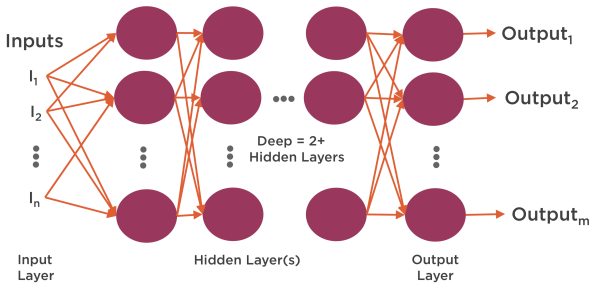


Fig. 6: Deep neural networks layers

III. Neural Networks

The neural network, in figure 5, that can be divided into trhee parts, tkes data from input nodes and feeds the network. This data could be values from a data table, images from a camera, sounds from a recording, or output from a sensor. The input layer does not change the data, it simply passes it for processing by the remaining layers. The data from the input layer is passed to another layer of neurons. These layers can be of different types with the different layer types performing different transformations on the data as required by our solution. In a simple network, the input layer can be directly connected to an output layer of neurons, which provide the final outputs.

But in most networks, the input layer is connected to hidden layers. Hidden layers are defined as not being input or output layers, and therefore, are hidden to the code that's using the neural network. The network can have many hidden layers and if there are two or more hidden layers we call the network a deep neural network, as shows in figure 6. In this learning process we adjust the structures of our neurons. To understand this, let's look at a single neuron. Here we see the inputs and outputs we showed in the network diagram, with the inputs going in and the outputs going out. However, what is not showing in this diagram is how the neurons work internally. To do that, we need to open the neuron so we can see how it is constructed. As we see, the neuron is performing a simple mathematics summing of weights, times the input value and adds a bias. The product of these operations is passed through a non-linear activation function. And the output of the activation function is the output of the neuron. A key feature of the neural network is the ability to use the input data to train the weights and biases so the signal passed out of the neuron changes based on the input data. To do this training, we expose the network to data. With each set of data, an algorithm is used to adjust the weights and bias to minimize the error the network has in predicting the data's values. This is done through processes called forward propagation and back propagation. And when these processes are complete, the network is said to be trained, and the weights and biases of all the neurons have been adjusted to give the best results on the training data. So to summarize, the neural network consists of three layer types: input, hidden, and output. By passing training data through the network, the network of neurons is trained to give results with the least error. This training is done by adjusting weights and biases in the neurons, utilizing the

processes of forward propagation and back propagation, and if there are two or more hidden layers in the network, we say it's a deep neural network.

IV. Building Convolutional Neural Network with Keras

As we discussed in the last section (II-A), Keras has a series of layers that were specifically created to support convolutional neural networks. By definition, a fully connected layer connects every neuron in the layer and at the first layer it's connected to all the inputs. And all these connections create a problem known as the curse of dimensionality. That is, the more neurons and connections we have, the more weights we must train. This issue appears often, it is one of reasons why deep neural networks can take a long time to learn. To understand this issue a bit more, let's consider the case of working with images. Assume that we have an 8 megapixel image and that we want to learn something from this image. To do that, we construct a network with a dense layer. Since every pixel in the image can contain unique data, they each contribute uniquely to determining the logic resulting from analysing the image. Therefore we need to connect each pixel to each neuron in our first layer. Let's say that we have 1000 neurons in the first dense layer. We have to connect the data from each pixel to each neuron so we end up with 1000 neurons connected to 8 million pixel values, with each connection having its own weight that needs to be trained. That works out to 8 billion weights we have to train. And with most images it's even more. In a color image, each pixel has three colors. One for red, green, and blue channels of the image. So there are actually 24 billion weights to train. Solving this explosion in the number of weights we have to train is one of the key reasons convolutional neural networks were developed.

A. How works CNNs

Convolutional neural network address our two concerns of working with image type data namely, many weights to train and being able to detect objects based on their general appearance rather than precisely matching an image. A lot of research has been performed when working with images and has resulted in subtle layers that you find in almost all convolutional neural networks. And these are the convolution layers you find in Keras. To understand the function of these layers, let's go over the structure of a convolutional neural network, which classifies objects and images. Let's walk through this diagram so we can get an overview of how convolutional neural networks work and how we implement them using Keras. We see the image data is passed through the convolutional layer, then through a non-linear ReLU activation and then to a pool layer. And then to a second convolution with ReLU layer and a second pool layer. Finally, to a fully connected layer and then to a second fully connected layer for classification. So we can divide our convolutional neural network into four operations. Convolution, non-linearity, you see via ReLU, pooling, and classification. You will find these four operations in almost all convolutional neural networks. Let's look at each operation in detail so we understand how to set parameters and pass data when we construct our convolutional neural network in Keras. Convolutional neural networks are the current state-of-art architecture for image classification. They are used in practice today in facial recognition, self driving cars, and detecting whether an object is a hot-dog.

B. Convolution

A convolution consists of a kernel, shows in figure 7, (green square above), also called filter, that is applied in a sliding window fashion to extract features from the input. This filter is shifted after each operation across the input by an amount called strides. At each operation, a matrix multiply of the kernel and current region of input is calculated. Filters can be stacked to create high-dimensional representations of the input. There are two ways of handling differing filter size and

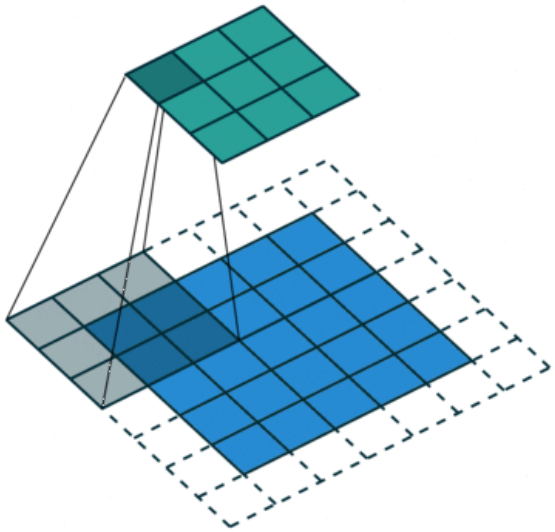


Fig. 7: Deep neural networks layers

input size, namely same padding and valid padding.

Same padding will pad the input border with zeros (as seen above) to ensure the input width and height are preserved. Valid padding does not pad. Typically, you will want to use same padding or you will rapidly reduce the dimensionality of your input. Finally, an activation function (typically a ReLU[3]), represented in figure 8, is applied to give the convolution non-linearity. ReLUs are a bit different from other activation functions, such as sigmoid or tanh, as ReLUs are one-sided. This one-sided property allows the network to create sparse representation (zero value for hidden units), increasing computational efficiency.

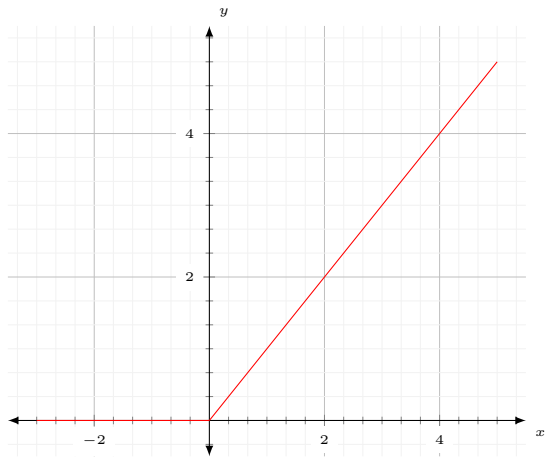


Fig. 8: Rectified linear unit (**ReLU**)
$F(x) = x^+ = \max(0, x)$

C. Pooling

Pooling is an operation to reduce dimensionality. It applies a function summarizing neighbouring information. Two common functions are max pooling and average pooling. By calculating the max of an input region, the output summarizes intensity of surrounding values. Pooling layers also have a kernel and padding, and are moved in strides, as represented in figure 9. To calculate the output size of a pooling operation, you can use the formula:

$$\text{Input Width} - \text{kernel width} + 2 * \text{padding} / \text{strides} + 1 \quad (1)$$

D. Fully Connected Layer

Fully connected layers you are likely familiar with from neural networks. Each neuron in the input is

[3]In the context of artificial neural networks, the rectifier is an activation function defined as the positive part of its argument:
$f(x) = x^+ = \max(0, x)$

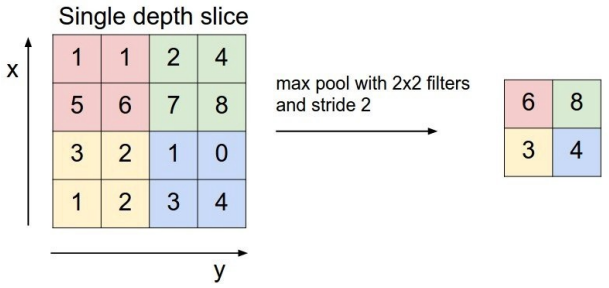


Fig. 9: Max pooling is the application of a moving window across a 2D input space, where the maximum value within that window is the output

connected to each neuron in the output; fully-connected. Due to this connectivity, each neuron in the output will be used at most one time.

$$\sum_{i=1}^{n} x \cdot W + b \quad (2)$$

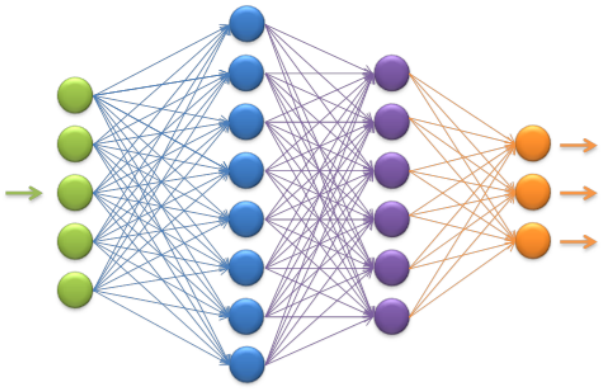


Fig. 10: Deep neural networks layers

In a CNN, the input is fed from the pooling layer into the fully connected layer. Depending on the task, a regression or classification algorithm can be applied to create the desired output, a representative example is shown in figure 10.

V. The Project

The goal of this project is the rapid development of a neural network for low power systems, hence the need to resort to a technique known as 'fine-tuning' for the realization of our neural network. In general, if our dataset is not drastically different in context from the dataset which the pre-trained model is trained on, we

should go for fine–tuning. Pre-trained network on a large and diverse dataset like the *ImageNet* captures universal features like curves and edges in its early layers, that are relevant and useful to most of the classification problems. Of course, if your data set represents some very specific domain, we should then consider training the network from scratch. One other concern is that if our dataset is small, fine-tuning the pre-trained network on a small dataset might lead to over-fitting, especially if the last few layers of the network are fully connected layers, as in the case for *VGG* network. If we have a few thousand raw samples, with the common data augmentation strategies implemented (translation, rotation, flipping, etc.), fine-tuning will usually get us a better result.

A. Fine-tuning Techniques

Some general guidelines for fine-tuning implementation:

- The common practice is to truncate the last layer (softmax layer) of the pre–trained network and replace it with our new *softmax* layer that are relevant to our own problem. For example, pre-trained network on *ImageNet* comes with a *softmax* layer with 1000 categories.

If our task is a classification on 10 categories, the new *softmax* layer of the network will be of 10 categories instead of 1000 categories. We then run back propagation on the network to fine-tune the pre–trained weights. Make sure cross validation is performed so that the network will be able to generalize well.

- Use a smaller learning rate to train the network. Since we expect the pre–trained weights to be quite good already as compared to randomly initialized weights, we do not want to distort them too quickly and too much. A common practice is to make the initial learning rate 10 times smaller than the one used for scratch training.
- It is also a common practice to freeze the weights of the first few layers of the pre-trained network. This is because the first few layers capture universal features like curves and edges that are also relevant to our new problem. We want to keep those weights intact. Instead, we will get the network to focus on learning dataset-specific features in the subsequent layers.

VI. Fine-tuning in Keras

I have implemented starter scripts for fine-tuning convnets in Keras. The scripts are hosted in my remote repository[4] page. Implementations of VGG16, VGG19, Inception-V3, and ResNet50 are included. With that, you can customize the scripts for your own fine-tuning task. Below is a detailed walk through of how to fine-tune VGG16 model using the scripts.

[4]https://github.com/frank1789/NeuralNetworks

A. Datatset

Particular attention is needed in the construction of a good training dataset, in fact, as seen before in (I-A), we deal with a supervised learning where we know the response of our labels. A script is provided that can build a dataset divided into folders: training, validation and testing; as you can see in figure 11.
A large number of figures per sample that clearly highlights the characteristics that you want to study allows a greater rate of success of the training preventing the *overfitting*. Acquiring a large number of images is not always achievable, using some augmentation techniques, virtually allows to increase the observability of a images, for example, by rotating, distorting and translating them. The two train and validated folders are essential for the addition of the neural network. Instead, the test folder contains a set of images that the network has never seen and so necessary to measure the degree of confidence acquired in the network.

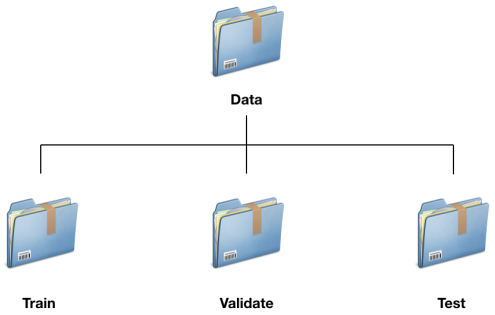


Fig. 11: Dataset structure

The choice of using a structure history derives from some methods provided by the Keras API, in fact these methods used in the script guarantee greater efficiency in the management of the network training process. In fact, thanks to these, it is possible to automatize the processes:

- crossing the folder structure constituting the dataset;
- creation of labels within the network;
- efficient memory management during the training phase;
- randomness of the set of samples processed;

- efficient memory management during the validation phase;
- randomness of the validated sample set;

B. Fine-tune VGG16

VGG16 is a 16-layer Covnet used by the Visual Geometry Group (VGG) at Oxford University in the 2014 "ILSVRC" (*ImageNet*) competition, structure is visible in figure 12. The model achieves a 7.5% top five error rate on the validation set, which is a result that earned them a second place finish in the competition.

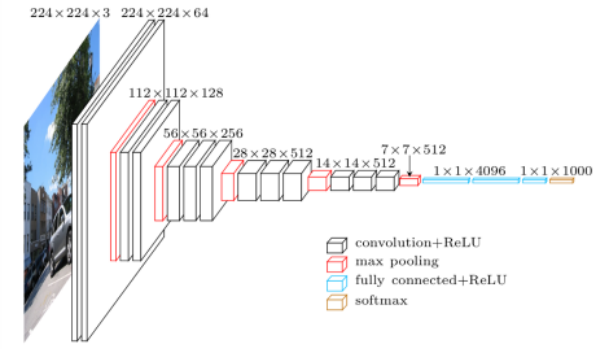
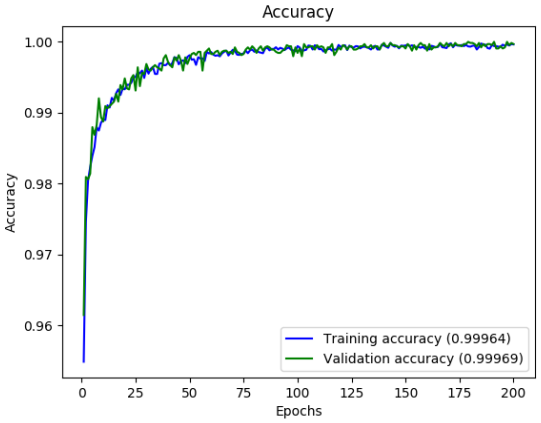
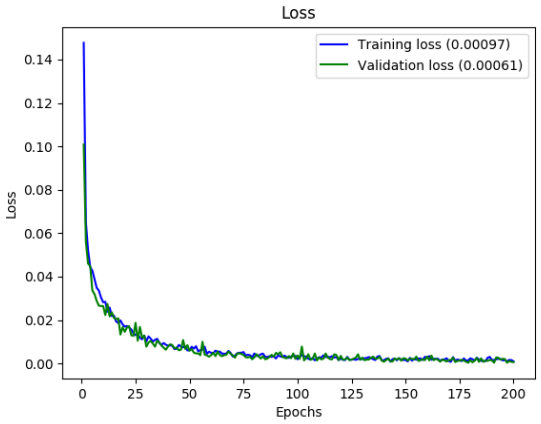


Fig. 12: Schematic Diagram of VGG16 model

For the first experiment, the network was trained with a dataset from the Kaggle[5] specialist site. Withdrawing a binary dataset[6], which consists of only two classes: "dog" and "cat". After using the script, presented in section (VI-A), the network is trained, then fine-tuning the model by minimizing the "*categorical cross entropy*" loss function using *stochastic gradient descent* (SGD) algorithm. Notice that we use an initial learning rate of 0.0001, which is smaller than the learning rate for training scratch model usually 0.01. It was decided to use this optimization because it has better performance during the binary classification. In fact, after two hundred epochs an accuracy of about 99.96% is reached. After it is done, we use the model the make prediction on the validation set and return the score for the cross entropy loss, as shown in the figure 13.



(a) *Cross entropy accuracy.*



(b) *Cross entropy loss.*

Fig. 13: VGG16 binary label training result

VII. Intel Movidius Neural Compute Stick

Today, low-power consumption is indispensable for unmanned vehicles and IoT[7] devices. In order to develop deep learning inference application at the edge, we can use Intels both energy efficient and low cost Movidius USB[8] stick (figure 14). Movidius Neural Compute Stick (NCS) is produced by Intel and can be run without any need of Intenet. This software development kit enables rapid prototyping, validation, and deployment of deep neural networks. Profiling, tuning, and compiling a DNN on a development computer is possible with the tools provided by the Intel Movidius Neural Compute SDK. The Movidius NCS compute capability comes from Myriad 2 VPU[9]. Intel Movidius VPUs drive the demanding workloads of modern computer vision and AI applications at ultra-low power. By coupling highly parallel programmable compute with workload-specific

[5]https://www.kaggle.com
[6]https://www.kaggle.com/c/dogs-vs-cats-redux-kernels-edition/data
[7]Internet of Things
[8]Universal Serial Bus
[9]Vision Processing Unit

hardware acceleration, and co-locating these components on a common intelligent memory fabric, Movidius achieves a unique balance of power efficiency and high performance. Movidius technology allows device makers to deploy deep neural network and computer vision applications in categories such as smart-phones, drones, intelligent cameras and augmented reality devices. Running Deep Learning models efficiently on low capacity graph processors is very painful. Movidius allows us to optimize the operation of large models such as GoogLeNet. with multi-use support. It is an easy-to-use kit that allows you to design and implement applications such as classification and object recognition as physical products. We can simply think of Movidius NCS as a GPU[10] running on USB. However, training of the model is not performed on this unit, the trained model works optimally on the unit and is intended to be used in physical environments for testing purposes.

Fig. 14: Intel Movidius in package

A. *Inside Intel Movidius*

Movidius provides the ultimate in low-power vision processing solutions, which include the Myriad 2 family of vision processing units (VPUs) plus a comprehensive Myriad Development Kit, a reference hardware EVM and optional Machine Vision Application Packages. The Myriad 2 MA2x5x family of system-on-a-chip (SoC)[11] devices offers significant computation performance and image processing capability with a low-power footprint. The Myriad 2 line up includes the following product configurations:

[10]Graphics Processing Unit
[11]System on Chip

- MA2150: 1 Gbit DDR
- MA2155: 1 Gbit DDR and secure boot
- MA2450: 4 Gbit DDR
- MA2455: 4 Gbit DDR and secure boot

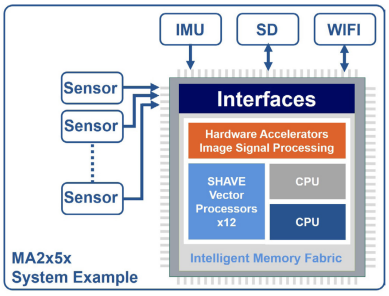


Fig. 15: System example

Myriad 2 VPUs offer TeraFLOPS (trillions of floating-point operations per second) of performance within a nominal 1 Watt power envelope. The Myriad 2 architecture, show in figure 16, includes enough performance to support multiple cameras with flexible image signal processing pipelines for each camera, and software programmable vision processing with fixed- and floating-point data-types supported.
A robust overall data-flow design ensures mitigation of processing bottlenecks. Myriad 2 MA2x5x incorporates an innovative approach to combine image signal processing with vision processing.
A set of imaging/vision hardware accelerators supports a world-class ISP pipeline without any round trips to memory; at the same time they are re-purposed to accelerate developers' vision processing algorithms in conjunction with a set of special purpose VLIW[12] vision processor cores. All processing elements are tied together with a multi-ported memory that enables implementation of demanding applications with high efficiency. [6]

MYRIAD 2 SoC SPECIFICATIONS

- Heterogeneous, high throughput, multi-core architecture based on:
  - 12 VLIW 128-bit vector SHAVE Processors optimized for machine vision
  - Configurable hardware accelerators for image and vision processing, with line-buffers enabling zero local memory access ISP mode
  - 2 x 32-bit RISC processors

[12]Very Long Instruction Word

  - Supports data and task parallelism
  - Programmable Interconnect
- Support for 16/32-bit floating point and 8/16/32-bit integer operations
- Homogeneous, centralized memory architecture
- 2MB of on-chip memory
- 400 GB/sec of sustained internal memory bandwidth
- 256 KB of L2 Cache
- Power management: 20 power islands; low power states
- Nominal 600 MHz operation at 0.9 V
- Rich set of interfaces:
  - 12 Lanes MIPI, 1.5 Gbps per lane configurable as CSI-2 or DSI
  - I2C, SPI for control and configuration
  - I2S for audio input
  - Banks of configurable GPIO, PWM
  - USB3 with integrated PHY
  - 2-Slot SDIO
  - Debug interface
  - 1 Gbit Ethernet
- Available package configurations:
  - MA2150/MA2155: 6.5mm x 6.5mm 0.4mm pitch, 225 Ball BGA 1Gb LPDDR II
  - MA2450/MA2455: 8mm x 9.5mm 0.5mm pitch, 270 Ball BGA, 4Gb LPDDR III
- Advanced low-power 28nm HPC process node

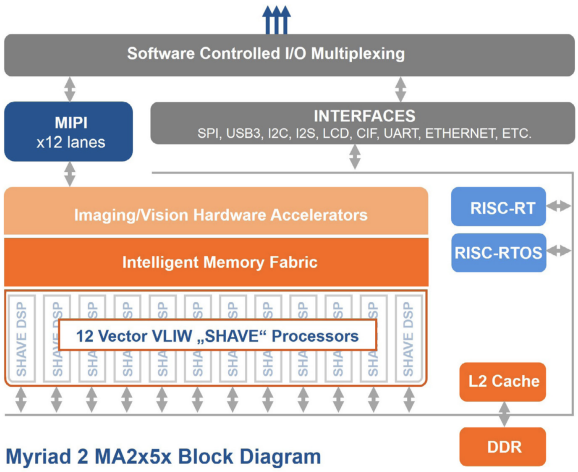


Fig. 16: MYRIAD 2 SoC architecture

VIII. Validate a network

The Intel Movidius Neural Compute SDK enables rapid prototyping and deployment of deep neural networks (DNNs) on compatible neural compute devices like the Intel Movidius Neural Compute Stick.
The NCSDK includes a set of software tools to compile, profile, and check (validate) DNNs, as well as the Intel Movidius Neural Compute API (Intel Movidius NCAPI) for the development of applications in C/C++ or Python. The NCSDK has two general usages:

1) Profiling, tuning, and compiling a DNN model on a development computer (*host system*) with the tools provided in the NCSDK.
2) Prototyping a user application on a development computer (*host system*), which accesses the neural compute device hardware in order to accelerate DNN inferences using the NCAPI.

Once the neural network training is complete, the file containing the definitions and weights of the various levels must be checked for compatibility by using the Intel NCSDK command line tool.

A. Check network

As part of the NCSDK, mvnCheck is a command line tool that checks the validity of TensorFlow neural network on a neural compute device. The check is done by running an inference on both the device and in software on the host computer using the supplied network and appropriate framework libraries. The results for both inferences are compared to determine a if the network passes or fails. The top 5 inference results are provided as output. This tool works best with image classification networks. As part of the NCSDK, mvNCCheck serves three main purposes:

- ensure accuracy when the data is converted from `fp32` to `fp16`;
- quickly find out if a network is compatible with the Intel NCS;
- quickly debug the network layer by layer;

To ensure accurate results, mvNCCheck compares inference results between the Intel Movidius NCS and the networks native framework. Since the Intel Movidius NCS and NCSDK use 16-bit floating point data, it must convert the incoming 32-bit floating point data to 16-bit floats. The conversion from `fp32` to `fp16` can cause minor rounding issues to occur in the inference results, and this is where the mvNCCheck tool can come in handy. First the mvNCCheck tool reads in the network and converts the model to Intel Movidius NCS format. It then runs an inference through the network on the Intel Movidius NCS, and it also runs an inference with the networks native framework. Finally the mvNCCheck tool displays a brief report

that compares inference results from the Intel Movidius NCS and from the native framework. These results can be used to confirm that a neural network is producing accurate results after the `fp32` to `fp16` conversion on the Intel Movidius NCS. mvNCCheck can also be used as a tool to simply check if a network is compatible with the Intel Movidius NCS. There are a number of limitations that could cause a network to not be compatible with the Intel Movidius NCS including, but not limited to, memory constraints, layers not being supported, or unsupported neural network architectures.

```
Result: (1, 1, 2)

1) 0 0.9062

2) 1 0.0936

Expected: (1, 1, 2)

1) 0 0.9060939

2) 1 0.093906164

------------------------------------------------------------

Obtained values

------------------------------------------------------------

Obtained Min Pixel Accuracy: 0.030707026598975062% (max allowed=2%), Pass

Obtained Average Pixel Accuracy: 0.0239676621276885 27% (max allowed=1%),

Pass

Obtained Percentage of wrong values: 0.0% (max allowed=0%), Pass

Obtained Pixel-wise L2 error: 0.0248971448497004 14% (max allowed=1%), Pass

Obtained Global Sum Difference: 0.0004343390464782715

------------------------------------------------------------
```

Now the output of mvNCCheck above (box above) will be examined:

- The first three lines represent the top five Intel NCS inference results.
- The following second three lines are the top five framework outcomes from either Caffe or TensorFlow.
- The comparison output (indicates as "*Obtained values*") shows various comparisons between the two inference results.

B. Profile a network

As seen before in section (VIII), mvNCProfile is part of the SDK. It runs the network on a connected neural compute device, and then outputs texts (box below) and HTML profile reports. The profiling data contains layer-by-layer statistics about the performance of the network. This is helpful in determining how much time is spent on each layer to narrow down potential changes to the network to improve the total inference time.

```
Detailed Per Layer Profile
                                                    Bandwidth             time
Layer    Name                          MFLOPs        (MB/s)               (ms)
==============================================================================
0        block1_conv1/Relu            173.4          304.6              8.496
1        block1_conv2/Relu           3699.4          672.8             82.044
2        block1_pool/MaxPool            3.2          833.9              7.345
3        block2_conv1/Relu           1849.7          413.7             33.660
4        block2_conv2/Relu           3699.4          304.5             91.443
5        block2_pool/MaxPool            1.6          925.0              3.311
6        block3_conv1/Relu           1849.7          173.1             43.093
7        block3_conv2/Relu           3699.4          171.3             87.044
8        block3_conv3/Relu           3699.4          172.4             86.472
9        block3_pool/MaxPool            0.8          935.1              1.638
10       block4_conv1/Relu           1849.7          159.0             35.866
11       block4_conv2/Relu           3699.4          164.2             69.409
12       block4_conv3/Relu           3699.4          163.9             69.538
13       block4_pool/MaxPool            0.4          927.7              0.826
14       block5_conv1/Relu            924.8          302.7             20.588
15       block5_conv2/Relu            924.8          301.1             20.697
16       block5_conv3/Relu            924.8          300.7             20.722
17       block5_pool/MaxPool            0.1          900.5              0.214
18       dense_1/Relu                 205.5         2186.2             89.679
19       dense_2/Relu                  33.6         2174.6             14.722
20       predictions/BiasAdd            0.0          351.7              0.067
21       predictions/Softmax            0.0            0.2              0.043
------------------------------------------------------------------------------
         Total inference time                                          786.92
------------------------------------------------------------------------------
```

C. Compile network

Once the compatibility has been verified using the tools of the trained network, it is necessary to perform the compilation by the tool mvNCCompile. In fact, the tool (made available by Intel) allows to compile the file obtained by simply typing the following expression from the command line:

```
$ mvNCCompile model.pb -s 12 -in input_1
-on predictions/Softmax -is 224 224
-o conv_model.graph
```

In the command of the above expression, some arguments are present. Now, they will be examined:

- **model.pb** the trained network file.
- **[-s max_number_of_shaves]** Specify the maximum number of SHAVEs to use for network layers (default: 1). The number of available SHAVEs depends on your neural compute device; refer to figure 16
- **[-in input_node_name]** This option is required for TensorFlow networks. You can use the name parameter (available for most layers) when creating your network and pass that name into this option.
- **[-on output_node_name]** Specify an alternative end point for the network. By default the networks end point is the output layer. This option enables partial network processing. When used together with the -in option, the user can isolate one or more layers in a network for analysis.
- **[-is input_width input_height]** Specify input dimensions for networks that do not have dimension constraints on the input layer. This option assumes that the batch size is 1 and the number of channels is 3.

- **[-o output_graph_filename]** Specify an output graph file-name. If this is not provided, *"graph"* will be used for the file-name.

Once the model is converted into a format readable by the Movidius device, the inference can be performed on a laptop or any other devices, such as Raspberry board.

IX. Conclusion

In conclusion, it can be observed that a trained neural network can reach an accuracy of 99% by setting a sufficient number of epochs. In addition, a good training and validation dataset is necessary, but not sufficient to guarantee the result, given that it is a supervised learning as seen in the section I-A. Hence, it is necessary to prepare meaningful images.

On the other hand, it is not possible to train a neural network using a home computer neither a laptop; a HPC is needed and all its computing nodes have to be equipped with GPUs. Nowadays, GPUs are guaranteed by Nvidia hardware and CUDA libraries. At present there is no single encoding to save the neural network model, this necessarily implies that the network must be converted from time to time in the most appropriate format, depending on the chosen framework. This fact entail that some operations or information are not correctly represented or, in the worst case, unsupported. Thanks to the API made available by Intel, it is possible to prototyping and deepening neural networks for the Movidius neural stick on the development computer and on SoC devices, such as Raspberry. However, it is still a not-whole-developed software; hence, to run, it requires:

- a specific version of Linux Ubuntu - only the version 16.04 is supported, while the higher versions are not supported;
- the convertion of a model, because the Keras framework is not officially supported;
- the modification or the elimination of some operations available in the framework because they are not supported.

Operation on Raspberry is difficult because the *Raspbian* operating system is a derivative of Debian Linux and it does not officially support TensorFlow. Although the demos, released by Intel and based on the Caffe framework, run normally, the custom models may present malfunctions due to dependencies and porting libraries, because they are developed through other frameworks (as in our case TensorFlow).

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