1 Theoretical description of system building blocks

1.1 Machine learning

According to Arthur Samuel (qtd. in Geron [1]) machine learning is a field of study that gives computers the ability to learn without being explicitly programmed. This ability to learn is the property of various machine learning algorithms. We will be using terms "machine learning" and "learning" interchangeably. In order to learn, these learning algorithms need to be trained on a collection of examples of some phenomenon [2]. These collections are called **datasets** and can be generated artificially or collected in nature.

In order to better understand how ML approach can solve problems, we can examine an example application. Let us say that we would like to build a system that can predict a type of animal movement from an accelerometer data. To train its learning algorithm, also known as a **model**, we need to expose it to a dataset which would contain accelerometer measurements of different types of movement, such a walking, running, jumping and standing still. Input to the system could be either raw measurements from all three axis or components extracted from raw measurements such as frequency or amplitude. These inputs are also known as **features**, they are values that describe the phenomenon being observed [2]. The output of the system would be a predicted type of movement. Although we would mark each example of measurement data what type of movement it represents, we would not directly define the relationship between the two. Instead, we would let the model figure out connection by itself, through the process of training. The trained model should be general enough so it can correctly predict the type of movement on unseen accelerometer data.

There exists a large variety of different learning algorithms. We can broadly categorize them in several ways, one of them depends on how much supervision learning algorithm needs in the training process. Algorithms like K-nearest neighbours, linear and logistic regression, support vector machines fall into the category of supervised learning algorithms. Training data that is fed into them includes solutions, also known as **labels** [1]. Described above example is an example of a supervised learning problem.

Algorithms like k-Means, Expectation Maximization, Principal Component Analysis fall into the category of unsupervised learning algorithms. Here training data is unlabeled, algorithms are trying to find similarities in data by itself [1]. There exist other categories such as semi-supervised learning which is a combination of previous two and reinforcement learning, where model acts inside environment according to learned policies [1].

Neural networks, algorithms inspired by neurons in human brains [1] [3], can fall into either of categories. They are appropriate for solving complex problems like image classification, speech recognition, and autonomous driving, but they require a large amount of data and computing power for training. They fall into field of deep learning, which is a sub-field of machine learning.

Training of deep learning algorithms is computationally demanding and is usually done on powerful servers or computers with dedicated graphic processing units to speed up training time. After a model has been trained, data can be fed in and prediction is returned. This process is also known as **inference**. The inference is computationally less intensive compared to the training process, so with properly optimized models, we can run inference on personal computers, smartphones, tablets, and even directly in internet browsers.

1.1.1 Common machine learning workflow

There are several steps in ML workflow that have to occur in order to get from an idea to a working ML based system as seen on Figure 1.1. First problem has to be studied, it has to be understood what are objectives and which approach will be used. Here we decide on rough architecture of the ML model that we will use. In second step we collect and clean up data. We should always strive to collect large amount of quality and diverse data that represents real word phenomenon. Collecting that kind of data can be hard and expensive, but we can use various tools of for producing synthetic data from our original data, thus increasing data size and variety. Third, we train ML model. We might create something from scratch or use an existing model. We can train several different types of models and chose the one that performs the best. To achieve desired accuracy, steps two and three can be repeated many times. In step four we deploy our model and monitor its accuracy. We can also use it to collect more data and retrain the model.

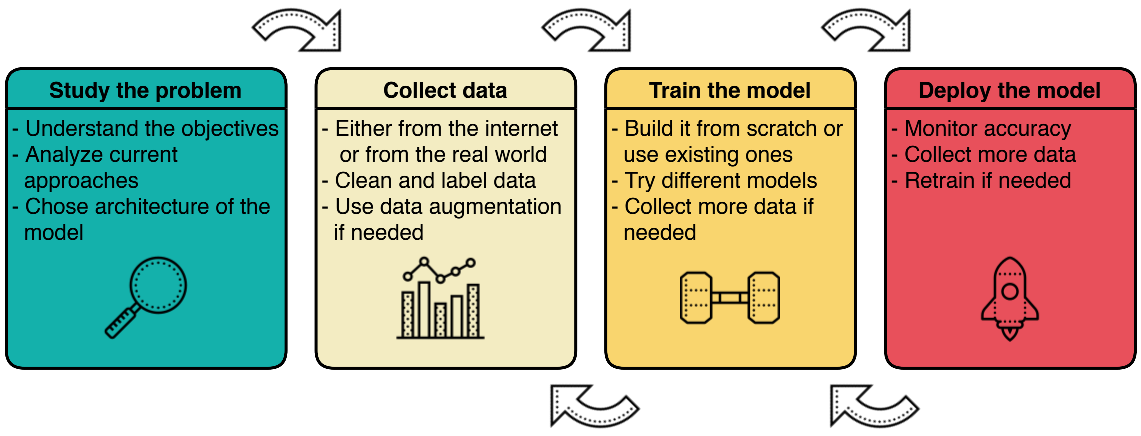

Study the problem
- Understand the objectives
- Analyze current approaches
- Chose architecture of the model
Collect data
- Either from the internet or from the real world
- Clean and label data
- Use data augmentation if needed
Train the model
- Build it from scratch or use existing ones
- Try different models
- Collect more data if needed
Deploy the model
- Monitor accuracy
- Collect more data
- Retrain if needed

Figure 1.1: Workflow of solving a generic machine learning problem. Icons source: www.icons8.com

1.1.2 Machine learning on embedded devices

Machine learning on embedded devices is an emerging field, which nicely coincides with the Internet of things. Resources about it are limited, especially when compared to the wast number of resources connected with machine learning on computers or servers. Most of the information about it can be found in form of scientific papers, blog posts and machine learning framework documentation [4] [5] [6].

Running learning algorithms directly on smart devices comes with many benefits. One of them is reduced power consumption. In most IoT applications devices send raw sensor data over a wireless network to the server, which processes it either for visualization or for making informed decisions about the system as a whole. Wireless communication is one of the more power hungry operations that embedded devices can do, while computation is one of more energy efficient [6]. For example, a Bluetooth communication might use up to 100 milliwatts, while MobileNetV2 image classification network running 1 inference per second would use up to 110 microwatts [6] As deployed devices are usually battery powered, it is important to keep any wireless communication to a minimum, minimizing the amount of data that we send is paramount. Instead of sending everything we capture, is much more efficient to process raw data on the devices and only send results.

Another benefit of using ML on embedded devices is decreased time between event and action. If the devices can extract high-level information from raw data, they can act on it immediately, instead of sending it to the cloud and waiting for a response. Getting a result now takes milliseconds, instead of seconds.

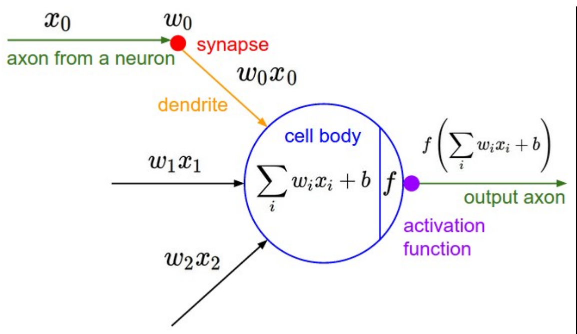
Such benefits do come with some drawbacks. Embedded devices are a more resource constrained environment when compared to personal computers or servers. Because of limited processing power, it is not feasible to train ML models directly on microcontrollers. Also it is not feasible to do online learning with microcontrollers, meaning that they would learn while being deployed. Models also need to be small enough to fit on a device. Most general purpose microcontrollers only offer several hundred kilobytes of flash, up to 2 megabytes. For comparison, MobileNet v1 image classification model, optimized for mobile phones, is 16.9 MB in size [7]. To make it fit on a microcontroller and still have space for our application, we would have to greatly simplify it.

Usual workflow, while developing machine learning models for microcontrollers, is to train a model on training data on some powerful computer or server. When we are satisfied with the accuracy of the model we then quantize it (more about quantization in chapter TODO: ADD CHAPTER NUMBER, SHOULD THIS BE A FOOTNOTE?) and convert it into a format understandable to our microcontroller.

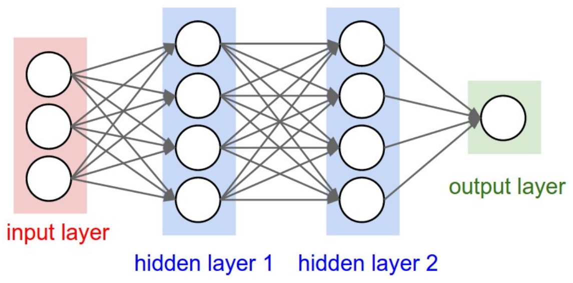
1.1.3 Neural networks

Although first models of neural networks (NN) were presented in 1943 (by McCulloch and Pitts) [1] and hailed as the starting markers of the artificial intelligence era, it had to pass several decades of research and technological progress before they could be applied to practical, everyday problems. Early models of NNs, such as the one proposed by McCulloch and Pitts were inspired by how real biological neural systems work. They proved that a very simple model of an artificial neuron, with one or more binary inputs and one binary output is capable of computing any logical proposition when used as a part of a larger network [1].

To learn how NNs work we can refer to Figure 1.2a, which shows a generic version of an artificial neuron.



(a) Artificial neuron



(b) 3-layer neural network

Figure 1.2: (a) Mathematical model of an artificial neuron, similarities with biological neurons can be seen. (b) Fully connected 3-layer neural network. Image source: [3]

Neuron takes several inputs, multiplies each input with its **weight** and sums them up. It adds to the sum the **bias** term and then applies an activation function.

NNs consist of many neurons, which are organized into **layers**. Neurons inside the same layer do not share any connections, but they connect to layers before and after them. First layer is known as **input** layer and last one is known as **output** layer. Any layers between are said to be **hidden**. On Figure 1.2b we can see neural network with an input layer with three inputs, two hidden layers with four neurons each and a output layer with just one neuron. If all inputs of neurons in one layer are connected to all outputs from previous layer, we say that a layer is **fully connected** or **dense**, Figure 1.2b is an example of one. NNs with many hidden layers fall into category of deep neural networks (DNN).

Activation functions

Activation functions introduce non-linearity to chain of otherwise linear transformations, which enables ANNs to approximate any continuous function [1]. There are many different kinds of activation functions as seen on Figure 1.3, such as sigmoid function and rectified linear activation function (ReLu). Sigmoid function was commonly used in the past, as it was seen as a good model for a firing rate of a biological neuron: 0 when not firing at all and 1 when fully saturated and firing at maximal frequency [3]. It basically takes a real number and squeezes it into range between 0 and 1. It was later shown that training NNs with sigmoid activation function often hinders training process as saturated outputs cut of parts of networks, thus preventing training algorithm reaching all neurons and correctly configuring the weights [3]. It has since fallen out of practice and is nowadays replaced by ReLu or some other activation function.

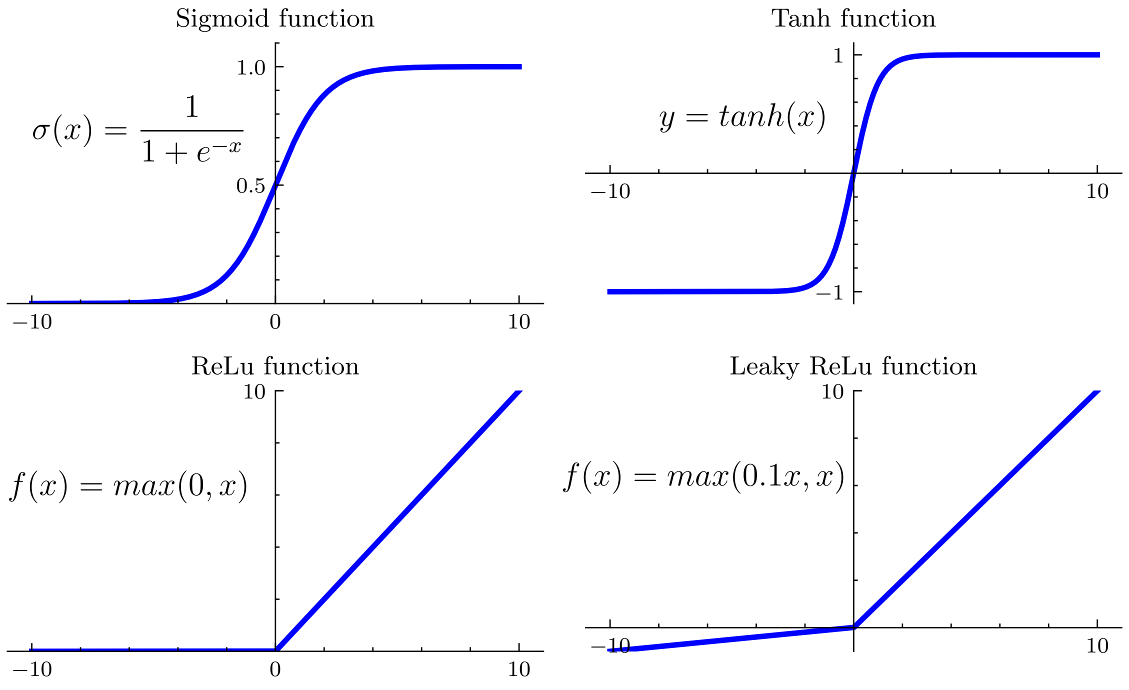


Figure 1.3: Different activation functions and their equations.

Backpropagation

Training of neural networks is done with a training algorithm, known as **backpropagation**. As mentioned before, we train the neural network by showing it a large amount of training data with labels. At the start of the training phase, all weights and biases are set to randomly small values. During each training step neural network is shown a small batch of training data. Each instance is feed into NN and final output label is calculated. This is known as **forward pass**, which is exactly the same as making predictions, except that intermediate results from each neuron in every layer are stored. Calculated output is compared to an expected one using a **loss** (also known as **cost**) function. Loss function returns a single value, which tells us how badly is our NN performing, higher it is, worse is our NN performing. The goal is to minimize the loss function, thus increasing the accuracy of our NN. In the context of multivariable calculus this means that we have to calculate negative gradient of weights and biases which will tell us in which direction we have to change each weight and bias so that value of loss function decreases.

Doing this for all weights and biases at the same time would be complicated, so backpropagation algorithm does this in steps. After computing loss function algorithm analytically calculates how much each output connection contributed to loss function (essentially local gradient) with the help of previously stored intermidiate values. This step is recursively done for each layer until first input layer is reached. At that moment algorithm knows in which direction should each weight and bias change so that value of loss function lowers. Procedure known as **Gradient Descent** is then performed. All local gradients are multiplied with a small number known as **learning rate** and then subtracted from all weights and biases. This way in each step we slowly change weights and biases in the right direction, while minimizing loss function. Gradient Descent is not only used when training neural networks, but also when training other ML algorithms.

We do not have to execute backpropagation algorithm for each training instance, instead we can calculate predictions for a small set of training data, calculate average loss function and then apply backpropagation.

1.1.4 Convolutional neural networks

As an aside, in practice it is often the case that 3-layer neural networks will outperform 2-layer nets, but going even deeper (4,5,6-layer) rarely helps much more. This is in stark contrast to Convolutional Networks, where depth has been found to be an extremely important component for a good recognition system (e.g. on order of 10 learnable layers). One argument for this observation is that images contain hierarchical structure (e.g. faces are made up of eyes, which are made up of edges, etc.), so several layers of processing make intuitive sense for this data domain.

1.2 Thermal cameras

Thermal cameras are transducers that convert infrared (IR) radiation into electrical signals, which can be used to form a thermal image. A comparison between a normal and a thermal image can be seen on figure **??**. IR is an electromagnetic (EM) radiation and covers part of EM spectrum that is invisible to the human eye. IR spectrum covers wavelengths from 780 µm to 1 mm, but only small part of that spectrum is used for IR imaging (from 0.9 µm to 14 µm) [8]. We can broadly classify IR cameras into two categories: photon detectors or thermal detectors [8]. Photon detectors convert absorbed EM radiation directly into electric signals by the change of concentration of free charge carriers [8]. Thermal detectors covert absorbed EM radiation into thermal energy, raising the detector temperature [8]. Change of detector's temperature is then converted into an electrical signal. Since photon detectors are expensive, large and therefore unsuitable for our use case, we will not describe them in greater detail.

Common examples of thermal detectors are thermopiles and microbolometers. Thermopiles are composed of several thermocouples. Thermocouples consists of two different metals joined at one end, which is known as hot junction. Other two ends of the metals are known as cold junctions. When there is a temperature difference between the hot and cold junctions, voltage proportional to that difference is generated on open ends of the metals. To increase voltage responsivity, several thermocouples

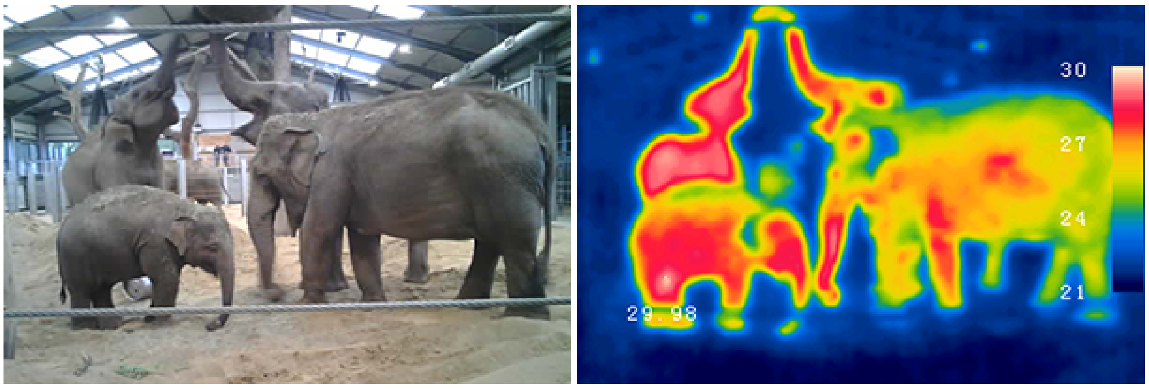
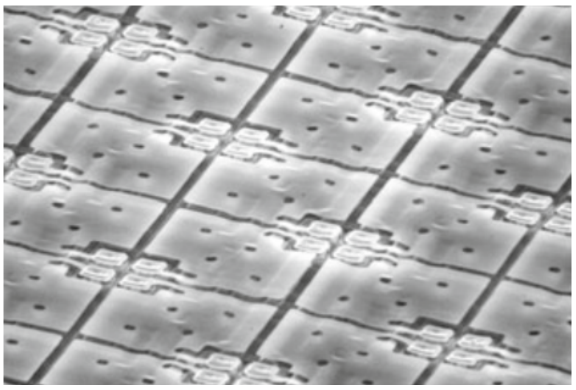


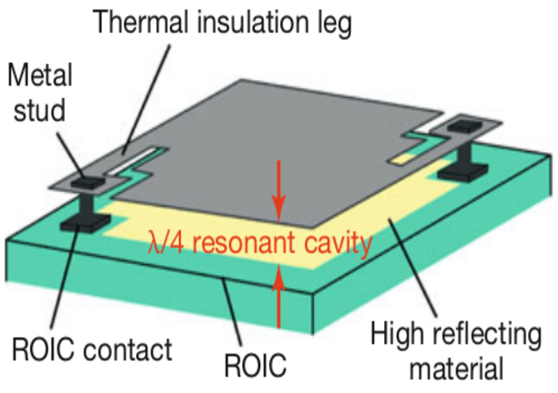
Figure 1.4: Comparison between a picture taken with a normal camera (left) and image taken with a low resolution thermal camera FLIR Lepton 2.5 (right). Image source: Arribada Initiative [9]

are connected in series to form a thermopile [8]. Thermopiles have lower responsivity when compared to microbolometers, but they do not require temperature stabilization [8].

Microbolometers can be found in most IR cameras today [8]. They are sensitive to IR wavelengths of 8 to 14 µm, which is a part of longwave infrared region (LWIR) [8]. Measuring part of an microbolometer is known as focal point array (FPA) (Figure 1.5a). FPA consists of IR thermal detectors, bolometers (Figure 1.5b), that convert IR radiation into electric signal. Each bolometer consists of an absorber material connected to an readout integrated circuit (ROIC) over thermally insulated, but electrically conductive legs [10].



(a) Focal point array



(b) Bolometer

Figure 1.5: (a) Focal point array under electronic microscope. (b) Bolometer with $\lambda/4$ resonant cavity. Image source: Vollmer, Möllmann [8]

Absorber material is made either out of metals such as gold, platinum, titanium or more commonly out of semiconductors such as vanadium-oxide (VOx) [10]. Important property of absorber materials is that electrical resistance changes proportionally with material's temperature [8]. When IR radiation hits absorber material, it is converted into thermal energy, which raises absorber's temperature, thus changing its resistance. To detect change in resistance, ROIC applies steady-state bias current to absorber material, while measuring voltage over conductive legs [8].

When deciding between different types of thermal cameras we are often comparing them in the terms of cost, size and image resolution. One important property that also has to be taken into account is temperature sensitivity, also known as noise equivalent temperature difference (NETD). NETD is measured in mK and tells us minimum temperature difference that can still be detected by a thermal camera. In microbolometers NETD is proportional to the thermal conductance of absorber material, among other factors [8]. Thermal conductance of bolometers is minimized by enclosing FPA into vacuum chamber, thus excluding thermal convection and conduction due to surrounding gasses. Only means of heat transfer that remain are radiant heat exchange (highly reflective material below absorber is minimizing its radiative losses) and conductive heat exchange through supportive legs. NETD also depends on the temperature inside the camera, higher ambient temperatures can raise the internal temperature, thus increasing NETD and noise present in thermal image. Today's thermopiles can achieve NETD of 100 mK, microbolometers 45 mK, while photon detectors can have NETD of 10 mK. Although tens of mK does not seem a lot, we can see on Figure 1.6 what a difference of 20 mK means for image resolution and noise.

1.2.1 Choosing the thermal camera

Choice of thermal camera was made by Arribada Initiative [9]. They tested several different thermopiles and microbolometers, while searching for desired properties. Camera had to be relatively inexpensive and small enough so that it could be inte-

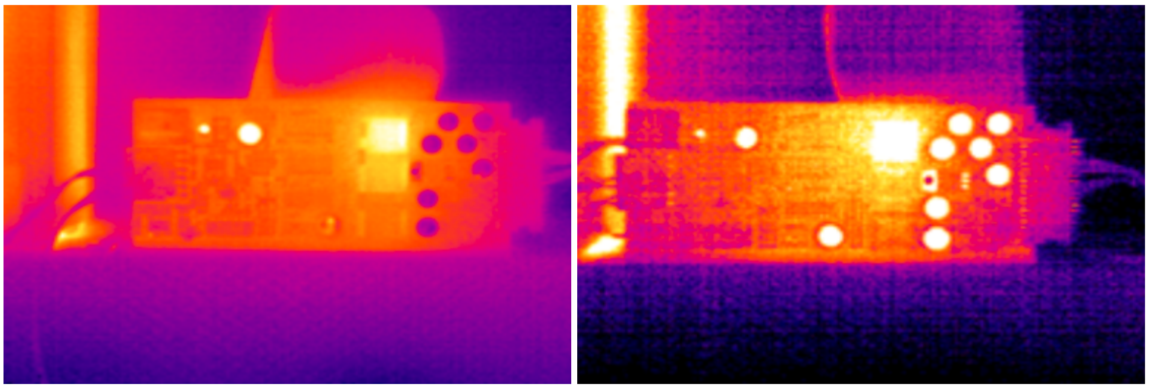

(a) NETD is 60 mK (b) NETD is 80 mK

Figure 1.6: Comparison of images of the same object taken with cameras with different NETD values. Low NETD values are more appropriate for object recognition. Image source: MoviTherm [11]

grated into relatively small housing. Main property that they searched for was that elephants could be easily recognized from thermal images. That meant that camera needed to have decent resolution and low NETD. Cameras were tested in Whipsnade Zoo and the Yorkshire Wildlife Park where images of elephants and polar bears could be made.

They tested two thermopile cameras (Heimann 80x64, MELEXIS MLX90640) and two microbolometer cameras (ULIS Micro80 Gen2, FLIR Lepton 2.5). Although thermopile cameras were cheaper from microbolometer cameras, quality of images they produced was inferior, as can be seen on Figure 1.7.

MELEXIS MLX90640 camera had resolution of 32 x 24 pixels and NETD of 100 mK, while Heimann camera had resolution of 80 x 64 pixels and NETD of 400 mK. It was concluded that images taken by either one of thermopile cameras could not be used for object recognition, merely only if object was present or not [9].

Microbolometers produced better results. Both Ulis Micro80 and FLIR Lepton had similar resolution, 80 x 80 and 80 x 60 respectively, but Ulis Micro80 had two times bigger NETD compared to FLIR Lepton camera, 100 mK and 50 mK, respectively. Images produced by FLIR Lepton were much cleaner, so it was chosen as appropriate camera for the task.

It is important to note that FLIR Lepton, as all microbolometers, requires frequent

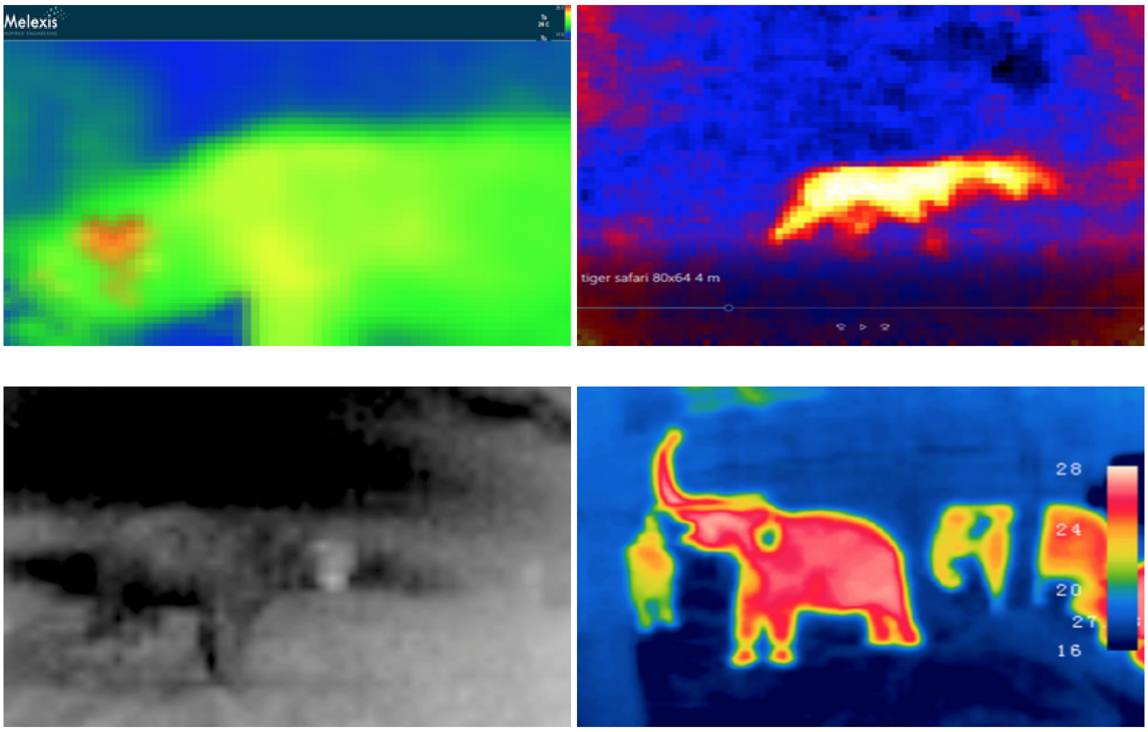


Figure 1.7: Comparison of image quality made by different thermal cameras, MELEXIS MLX90640 (top left), Heimann 80x64 (top right), ULIS Micro80 Gen2 (bottom left) and FLIR Lepton 2.5 (bottom right). Image source: Arribada Initiative [9]

calibration to function properly. In temperature non-stabilized cameras small temperature drifts can have a major impact on image quality [8]. Calibration is done either by internal algorithms of the camera or by exposing the camera to uniform thermal scene. FLIR Lepton camera comes with a shutter, which acts as a uniform thermal signal and enables regular calibration. Calibration in FLIR Lepton is by default automatic, triggering at startup and every 3 minutes afterwards or if camera temperature drifts for more than 1.5 °C.

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