University of Padova

Department of Information Engineering

Master Thesis in Ict For Internet and Multimedia

Master Thesis Title

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Academic Year
2022-2023

"Milano non è Milan, Italia è Milan"
— Zlatan Ibrahimović

Abstract

This paper aims to illustrate the laboratory experience carried out during March-July 2023 at Hochschule Darmstadt having as its goal the writing of a master's thesis.
The initial goal of the project was to use machine learning techniques to analyze the physical characteristics (i.e:ISO/OSI layer 1) of a wireless cellular channel in order to detect the presence of an attacker.
Thus, the expected outcome of the project is to construct a binary classifier, which takes in input information from the wireless channel and outputs the state of the channel through a binary classification: that is, whether the channel is in a state recognized as normal or whether it has been corrupted by the presence of an attacker.
Lab experiences were carried out using software to implement SDR, both user-side and attacker-side. Therefore, the methodologies used to conduct these experiments will be explained, specifying the theoretical background and commenting from a technical point of view on the results obtained.

Contents

Listing of figures

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Listing of acronyms

SDR . . . . Software Defined Radio

IoT . . . . Internet of Things

AI . . . . Artificial Intelligence

ML . . . . Machine Learning

NN . . . . Neural Network

CNN . . . . Convolutional Neural Network

AE . . . . Auto Encoder

SVM . . . . Support Vector Machine

1
Introduction

Cellular networks have become an essential part of modern society, transforming the way we communicate and so access information.
Given the mass use of smartphones and other mobile devices, these networks have revolutionized the way people interact and connect with the world around them.
Suffice it to say that until 30 years ago the idea of communicating remotely with other people via a connection that was not wired, such as landline telephones or early Internet connections via Ethernet, was unthinkable for an ordinary citizen.
The arrival of these devices in the early 1990s thus marked a turning point in the way people interfaced with the world, allowing them to access more and more information.
Over the years and with the advancement of information technology, these devices have become more and more intelligent and capable of storing more and more information within them. Suffice it to say that in this decade a person through their smartwatch, a device about 5 centimeters in diameter, is able to receive calls, text messages, and pay at the supermarket.
Given the enormous potential of these technologies to transmit or receive information, they are not only used for civilian use, but also for industrial use.
The advent of so-called IoT has made it possible to radically change the way factories are designed and conceived, making the production of them more efficient.
The market therefore for these technologies has been growing steadily in recent years, in fact:

- Experts expect the global IoT in manufacturing market size to grow from USD 33.2 billion in 2020 to USD 53.8 billion in 2025 at a Compound Annual Growth Rate of

10.1%. [1].

- Experts highlight that discrete Manufacturing, Transportation & Logistics, and Utilities industries will spend $40B each on IoT platforms, systems, and services.[2]

The advent, therefore, of these technologies in areas considered critical to a business or a governament has triggered the emergence of new attacks aimed at compromising the integrity of the proper functioning of these technologies.
Some examples of such attacks are:

- **Jamming**: is a tool used to prevent wireless devices from receiving or transmitting radio information.
  Jammers block the use of devices by sending jamming radio waves on the same band used to transmit information. This, for example, causes interference that inhibits communication between cell phones and repeater towers, paralyzing all telephone activity within its range. On most cellular phones what appears during such jamming is simply a no-network signal.
  In fact, the smartphone interprets the incapability to transmit information as the absence of a cellular network.

- **Covert channel**: is defined as any communication method used to communicate and/or transfer information in a covert and stealthy manner. The primary purpose in using a covert channel is to overcome the security policies of systems and organizations. There are multiple types of cyber threats that can affect the multilevel security (MLS) of ICT infrastructure and systems, and they are increasing daily at an impressive rate. Any shared resource as a bandwidth of a spectrum can potentially be used as a covert channel and this makes everything more difficult, in other words, covert channels are not everywhere but can be anywhere.

After briefly describing the possible attacks that can be carried out, it is easy to deduce that all companies that want to remain competitive in the market need to develop prevention systems for these types of attacks, so that a malicious attacker cannot jeopardize, for example, the continuity of a factory's production.
This aspect turns out to be very important when entering the economic-business world, since in the event of a stop in production, the damage done to the company itself can be considerable. Without going into technical-economic details, it should be considered useful to show a case of this kind, in order to get familiar to the reason why security solutions will take hold on the market more and more in the next years:

- In March 2022 a Toyota facility in Japan was cyber-attacked and the production was affected for more than a day and influenced about 10000 vehicles, which is equivalent to 5% of the production of a month of the group in Japan.[3]

This then primarily explains the reason why the previously described project took place in the first place, which is to try to study more robust solutions than those currently in the literature that can go about detecting possible attacks and intruders present in a wireless cellular network.

2
Ground theory and state of the art

3

Machine Learning

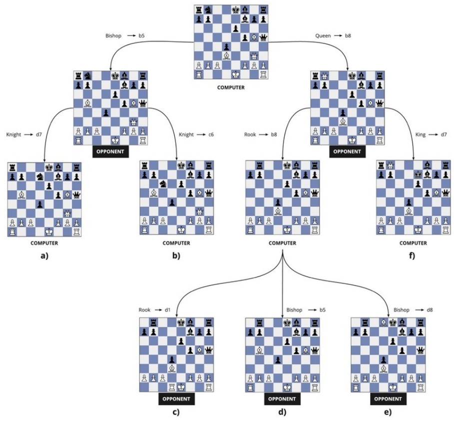
3.1 Introduction

The term Artificial Intelligence (henceforth AI) was invented by John McCarthy in 1956, at a two-month seminar (which he organized at Dartmouth College in Hanover, New Hampshire, USA) that had the merit of acquainting 10 U.S. scholars (on automata theory, neural networks and intelligence) with each other, and of giving the imprimatur to the term ”Artificial Intelligence” as the official name of the new field of research.[4]
Since then, AI has established itself and evolved; today it is recognized as a branch autonomous, although connected to computer science, mathematics, cognitive science, neurobiology and philosophy.
Artificial Intelligence therefore represents a field of research and development that aims to create systems that are able to emulate and automate some human cognitive functions.
AI then is the ability of a machine to mimic some of the human cognitive functions, including machine learning, reasoning, planning, sensory perception, natural language understanding, and social interaction. AI can be divided into two main categories: **weak AI**, which focuses on specific and limited tasks, and **strong AI**, which aims to develop a machine with general intelligence comparable to human intelligence.
These goals nowadays are reached in two ways:

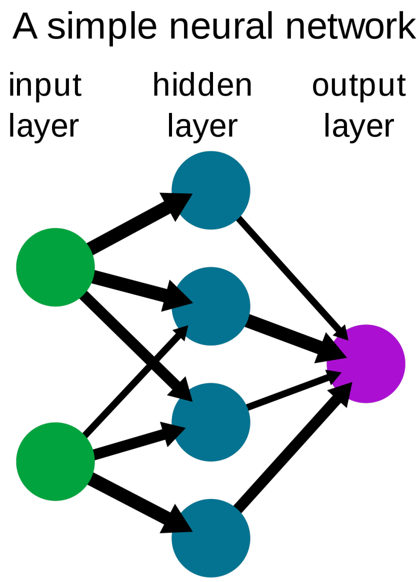
- As a first approach, AI can be created by telling to a model the rules to follow to solve

problems or to take decisions.
This is the case with the implementation of a machine attempting to play chess: here the chessboard is modeled and each possible move in the subsequent rounds is ranked according to its quality (via trees for example; see figure below) by predetermined heuristic algorithms, and the machine is required to choose the move that is rated most convenient, so as to maximize the probability of victory.
It is clear then that only simple-modelled problems can be solved by setting some set of rules in order to make the machine behave as a human; when it comes to deal with more complex structures (such as images, videos or texts) this approach shows its limits.

- The most common way nowadays to deal with more complex data structures is the so called **Machine Learning** which is a branch of AI that allows machines to learn from data without being explicitly programmed to solve that specific problem, thus making a model trainable to solve multiple problems.
  It is easy to see that ML radically changed the approach to solve problems: whereas before we tended to study a problem to find the rules for solving it, now we tend to create a model to which we feed solved examples of that problem (so-called supervised learning) so that it learns to solve that problem on its own.
  The machine learning literature nowadays is widely developed and includes various approaches, ranging from a simple linear separator such as the perceptron to the more modern and now commonplace artificial neural networks, which allow extremely complex data structures to be handled and have extremely high performance.
  Without going into details (which will be explained later), it is possible to describe NNs as models that try to replicate the behavior of the human brain: a set of neurons (main elements of the network) are connected in order to take a datum as input and make a prediction or a decision attempting to minimize an error that is specified a priori during the training phase.
  A simple example will be shown below.



(a) Example of a decision tree for chess playing



(b) Example of a simple feed forward NN

Figure 3.1: Two examples of AI.

3.2 State of the art

As it was said before, the goal of the project was to apply a machine learning model in order to detect a jamming attacker; to understand the reasons why some models have been preferred to other ones, the most common ML models will be briefly explained.

3.2.1 Perceptron

The perceptron algorithm is a simple supervised learning problem that tries to solve a binary classification problem of linearly separable data.
The input of the model is a set X=(x_1,...., x_n) of data and Y=(y_1,...., y_n) of the corresponding labels. The goal of the algorithm is to find a vector W=(w_1,...., w_n) of weights representing a separating hyperplane such that the classification error is avoided. Whenever a classification error is found, the vector W is updated. [5]
Recall that data is linearly separable if, given the training set composed by X and Y and the halfspace defined by (w, b) we have:

$$\forall i : (< w, x_i > +b)y_i \geq 0$$

i.e.: it perfectly separates all the data in the training set.
Here below a pseudocode of the iterative algorithm:

Algorithm 3.1 Perceptron algorithm

Require: $X = (x_1, ..., x_n), Y = (y_1, ..., y_n)$
  $w_1 \leftarrow (0, ..., 0)$
  for $t \leftarrow 1$ to ...
    if $\exists i$ s.t. $< w_i, x_i > y_i \leq 0$
      $w_{t+1} \leftarrow w_t y_i$
    end if
  else
    return w_t
  end for

From the pseudocode above it is easy to see that this algorithm could be easy implemented in any high level programming language nowadays and it is also demonstrated that if data is linearly separable the algorithm will stop in a finite number of steps.[6]
This model, however, shows its limitations:

- First of all, the convergence is not guaranteed when it is not dealing with a linearly separable training set, which is possible in more complex data structures.
- This algorithm can output different solutions depending on the starting values of the vector W.
- The output of this classifier can only be a binary classifier, and so cannot be used in multiple class classification problem.

3.2.2 Support Vector Machine

After recalling the definition of linearly separable data (see section above) before talking about SVM, it is useful to definine the concept of margin, which will be useful later.
Given a separating hyperplane defined by L:

$$L = \{v :< v, w > +b = 0\}$$

and a sample x, the distance between x and L is:

$$min\{||x - v|| : v \in L\}$$

The margin then, is defined as the minimum distance between a sample and L. [7]
The closest samples are called **support vectors**.
Here below an example of how SVM works:

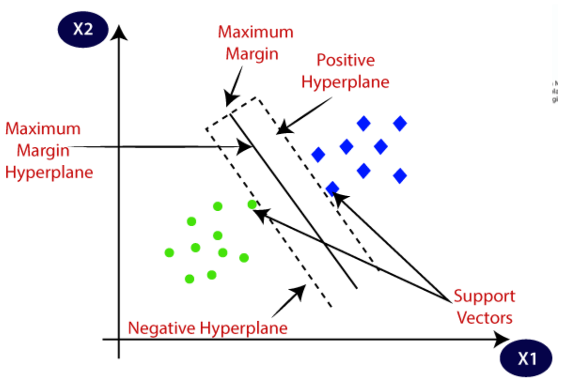


Figure 3.2: Representation of how SVM works in 2D dimensional space.

SVMs are also divided in two types:

- **Hard SVM**: a linear model that work with linearly separable data.
- **Soft SVM**: a linear model that work with non-linearly separable data.

Hard SVM

Hard SVMs seek for the separating hyperplane with the highest margin, under the assumption that the data is linearly separable. The mathematic formulation of Hard SVMs is expressed as follows:

$$\underset{(w,b):||w||=1}{argmax} \; \underset{i}{min}| < w, x_i > +b \;|$$

Soft SVM

As mentioned earlier, hard SVM has the main problem that it assumes linearly separable data, which is impossible in most problems found in case studies.
Soft SVM therefore relaxes the previously set constraints taking into account their violation at the same time.
This implies in relaxing the constraints as follows:

- First of all, a set of slack variables are introduced: $\xi = (\xi_1, ..., \xi_n) : \xi_i \geq 0 \ \forall i$.
- For each $i = 1$ to n the constraint becomes : $(< w, x_i > +b)y_i \geq 1 - \xi_i \ \forall i$.
- The model then tries at the same time to minimize the norm of w (to maximise the margin) and the average of ξ_i (to minimize the violations of the constraints).
- The objective function of the optimization problem then becomes:

  $$\min_{(w,b,\xi)} (\lambda||w||^2 + \frac{1}{n}\sum \xi_i)$$

  Subject to the constraint defined before.
  It is clear then that a large λ makes the algorithm focus on the margin, while a small value of the variable makes the model to minimize the constraint violations.

This reformulation of the SVM model thus represents a way to solve a binary classification problem while having more complex data structures, however, which are not always linearly separable.[8]

3.2.3 Neural Networks

As mentioned earlier, neural networks are models whose structure is inspired by the functioning of an animal brain.
As a first general overview, a neural network can be regarded as a non linear mathematical function which transforms a set of input variables into a set of output variables. [9]
The network can me modeled as an acyclic graph $G = (V, E)$, divided into layers :

- The vertexes of the graph are the **neurons**, which take in input the sum of the outputs of the connected neurons from previous layer weighted by the edge weights and applies to this result a simple scalar function called activation function.

- The edges of the graph connect a neuron to other neurons of the next layer; to each edge is associated a weight. This implies also that the edges are directed and the flow is performed only in one direction.

The computation of the output is done by processing the input at each layer and forwarding it to the next layer, until the output layer is reached.
The activation functions of the neurons are defined a priori and cannot be changed during the training phase, making so the weights the trainable parameters.
Given a training set composed by $X = (x_1, ..., x_n)$ and $Y = (y_1, ..., y_n)$, where X is the training dataset and Y is the set of labels associated to the data of X and given a loss function l, the goal of the NN is to find the optimal values of the weights in order to minimize the loss L in the training set, that is:

$$L = \frac{1}{n}\sum l(x_i, y_i)$$

To do that, the most common way nowadays is the so-called **backward propagation** algorithm: at each epoch, the loss of the output is computed, and after that, it is propagated backwards to the input. Using the gradients calculated during error back-propagation, the network weights are updated. The update rule for the weights is defined as follows:

$$w_{ij}^{(t)[s+1]} = w_{ij}^{(t)[s]} - \eta \frac{\partial L}{\partial w_{ij}^{(t)[s]}}$$

Where $w_{ij}^{(t)[s+1]}$ stands for the weight at layer t computed at iteration s+1.
The gradient so is computed for each weight of the network, but after having computed the output at the last layer.
This procedure is repeated for many iterations, after a stopping criteria is reached, that could be:

- The maximum number of iterations.
- The reaching of a value in the training loss.
- The increasing of the validation loss for n epochs. (Recall that the validation set is a set with the same distribution of the training set but on which the NN is not trained; it is often used to set hyperparameters the ML models).

The simplest example of NN that can be shown is the so called *feedforward*: in this case each neuron is connected to every neuron of the next layer and the output is propagated from

the input layer throught the hidden layers and then to the output layer; an example was shown above in figure 3.1.b.
Here below will be shown a graphical representation of how a neuron works:

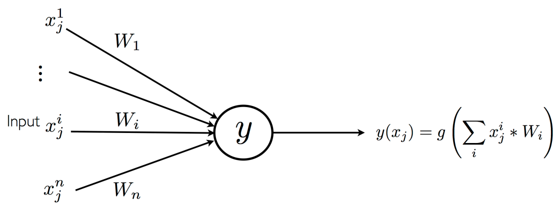


Figure 3.3: Representation of how a neuron works.

Convolutional Neural Networks

A convolutional neural network is one of the most significant networks in the deep learning field. Since CNN made impressive achievements in many areas, including but not limited to computer vision and natural language processing, it attracted much attention from both industry and academia in the past few years.[10]
The CNN is a kind of feedforward neural network that is able to extract features from data with convolution structures. Different from the traditional feature extraction methods, CNN does not need to extract features manually.
The main problem that occurs in feedforward NNs is the fact that the model does not take into account that a neuron can be more related to others and less to other ones; in fact, in this case every neuron is connected to each neuron of the next layer, without taking into account any kind of correlation.
CNNs then use some structures to achieve feature extraction:

- **Local connections**: each neuron is no longer connected to all neurons of the previous layer, but only to a small number of neurons, which is effective in reducing parameters and speed up convergence.
- **Weight sharing**: a group of connections can share the same weights, which reduces parameters further.
- **Downsampling dimension reduction**: a pooling layer harnesses the principle of image local correlation to downsample an image, which can reduce the amount of data while retaining useful information. It can also reduce the number of parameters by removing trivial features. These three appealing characteristics make CNN one of the most representative algorithms in the deep learning (see definition below) field.

The dimensional reduction is also reached using **pooling layers**: at first used to reduce computational complexity, but turned out to be crucial to improve performance in many applications since they increase the receptive field of the inner layers. One of the most common pooling layer is the max-pooling, that it takes in input a window of samples and outputs the highest value of it.

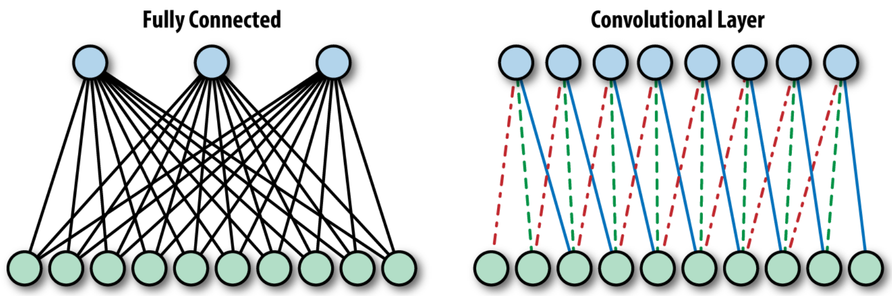


Figure 3.4: Graphical representation of the difference in terms of connections between feedforward NNs and CNNs.

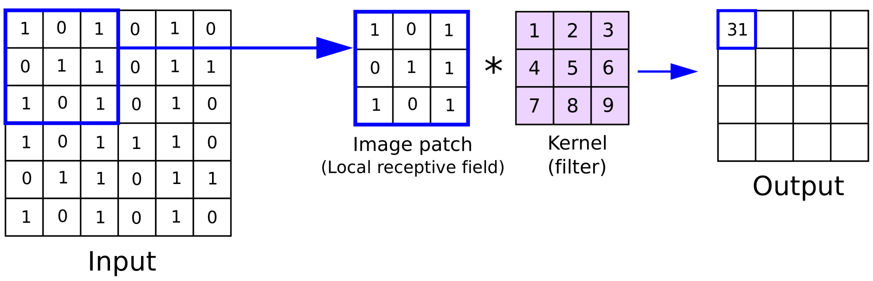


Figure 3.5: Graphical representation of how a convolutional filter can be viewed to process a 2D matrix.

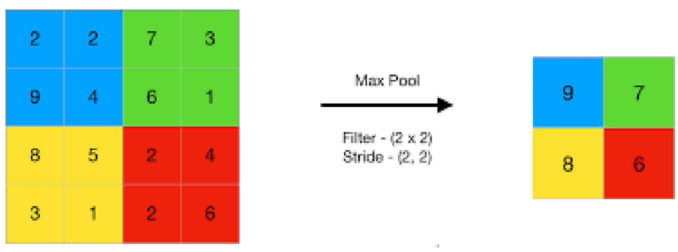


Figure 3.6: Graphical representation of a max pooling layer applied to a 2D matrix.

From figure 3.5 it is easy to see how convolutional filters can be represented as windows that slide along the input data.

To design a better CNN, it will be very important to set properly the **size** of the windows and the **stride**.
The term **deep learning** was previously mentioned: it is a branch of machine learning that defines all models of NNs that have many layers.

4
Lab Setup and Experiments

5
Models and Results

6
Conclusion and future works

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Acknowledgments

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