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شكر وتقدير

نشكر الله عز وجل ان وفقنا لإنجاز هذه الدراسة وان سخر لعبده الضعيف الممكن والمستحيل .
ولا يتم شكر الله تعالى إلا بشكر عباده الذين كثيرا ما ساعدوننا لكي يظهر هذا العمل على هذا
الشكل ولهذا اتقدم :

بالشكر الجزيل والتقدير إلى حضرة الاستاذ الدكتور: **قياة طلال**

بدل ما في وسعه من جهد في سبيل الإشراف العلمي طيلة مراحل الدراسة .

كذلك اتقدم بالشكر والتقدير الخالص إلى مجموعة الأساتذة الكرام الذين أسدوا إلينا

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مدير الجامعة، وسعادة عميد الكلية الدكتور/ **شمسة علي**. ووفقهما لكل خير لما يبذلانه من اهتمام

بطلاب كلية التكنولوجيا بصفة خاصة وطلاب جامعة الشهيد حمه لخضر بصفة عامة.

إهداء

إلى أبي الذي جد وبذل كل جهده ودعمني مادياً ومعنوياً وبكل ما بوسعة وإلى أمي التي دائماً كانت ترافقني بدعواتها المباركة وكلماتها اللطيفة أهديكما من عميق قلبي وقلبي ينبض لكما باشكر والامتنان يا أغلى ما في وجودي. يستحق منا أهلنا وأحبابنا أن نقدم لهم كل عبارات الشكر والتقدير من وقت لآخر، فهذا التصرف يشعر من حولنا بمدى أهميتهم بالنسبة لنا ومدى حبهم في قلوبنا. وأخيراً، أتقدم بجزيل شكري إلي كل من مدوا لي يد العون والمساعدة في إخراج هذه الدراسة على أكمل وجه .

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GENERAL INTRODUCTION

The production, transportation, and distribution of electricity contribute significantly to the economic growth of countries, as most modern economic activities such as manufacturing and agriculture are heavily reliant on it. Transportation serves as the vital link between production and consumption. The transfer of energy from the power source to the consumer necessitates either overhead or underground power lines[1]. Overhead lines are exposed to various natural and industrial factors, including insulator pollution[2].

Insulators are essential components of overhead transmission networks. They provide mechanical support and connect high voltage elements (e.g., conductors) with grounded parts (e.g., pylons), ensuring electrical isolation between these two constitutive parts of the line. Therefore, careful consideration must be given to the choice of insulator type, reception controls, and operational surveillance to ensure proper functioning and continuity of the line[3].

The behavior of polluted insulators is of increasing interest in many countries due to the desire to select the most appropriate insulator material, given the numerous disruptions caused by pollution. Electrical bypassing of insulators leads to severe repercussions on overhead electricity distribution networks, as it causes electrical outages of varying duration [3].

Over the past fifty years, several studies have been conducted to understand the mechanisms leading to the bypassing of polluted insulators and to develop tools for predicting this phenomenon. Our current work will focus on monitoring the surface condition of high-voltage insulators using artificial intelligence techniques.

To conduct our study effectively, we have divided our work into three chapters:

The first chapter will discuss the different types of insulators used in overhead high-voltage lines. This chapter will also define the phenomenon of insulator pollution and its types.

The second chapter will address methods for diagnosing the condition of insulators and the approaches used in object detection.

The third chapter, which is the core of this thesis, will apply artificial intelligence techniques for the detection of the surface condition of high-voltage insulators.

This structured approach will allow us to comprehensively explore various aspects related to the monitoring and analysis of high-voltage insulators, with a focus on the application of

advanced technologies such as artificial intelligence to enhance the reliability and durability of electrical networks.

I Chapter High Voltage Insulators and Pollution Phenomenon

I.1 INTRODUCTION

In power transmission lines, the main insulator is air; however, insulators attached to pylons are used to keep the cables suspended in the air. In this case, the insulator plays essentially a mechanical role. Nevertheless, the material used must possess excellent electrical insulation properties. Insulating materials play a significant role in electrical applications. They are found wherever there are electrical conductors. They must be surrounded by insulation.[4]



Overhead lines and substations in electrical power transmission networks are subjected to various constraints. Among these, pollution of insulators is one of the most important factors affecting the quality and reliability of energy transmission. Indeed, during rainy or foggy weather, pollutant deposits on insulating surfaces significantly reduce surface resistivity, leading to potential flashover. Moisture in the polluted layers facilitates leakage current flow on insulating surfaces, causing local overheating and subsequent drying of the pollution layer.[5]

In this chapter, we will present a study on insulators, specifying their role and different types, as well as pollution, which is one of the constraints faced by insulators in electrical networks.

I.2 High Voltage Insulators

Support insulators, also known as supporting insulators, are insulating components designed to support, while isolating, conductive elements of traverses. They are used, for example, as supports for busbars in transformer substations [4]. They are made up of insulating material and a metallic piece that serves to connect two insulators and provide some flexibility to the insulator chain. The insulator chain is mounted on the pylon either vertically (alignment chain) or horizontally (anchoring chain)[10].

There are two main types of chain elements:

-  Insulators with hood and rod
-  Insulators with long rod

I.2.1 Definition of Insulators

The insulator is mainly made of a solid insulating material that exhibits very high resistance to the passage of current and whose conductivity is practically nil[6] . The insulator is used , as its name suggests, for isolating between two bodies or two parts under different voltages to prevent short circuits, current losses, and electrocution hazards. The insulator can be a solid, liquid, or gas material that has very high resistance to the passage of current and practically nil conductivity[7].

The insulators of overhead lines have two main functions. On one hand, they electrically isolate the power transmission lines at the pylons, which are grounded. On the other hand, they have a mechanical role in supporting these same lines and therefore resisting the various mechanical stresses, mainly due to the weight of the line, its movement in the presence of wind, etc [7].

I.2.2 Operation and structure of an insulator

Insulators are indispensable components for the transmission and distribution of electrical energy. Their importance is directly related to:

- ✚ Establish a mechanical connection between conductors at different potentials hung on pylons of overhead lines.
- ✚ Maintain the conductors in the specified position (alignment and anchoring insulators).
- ✚ Ensure the transition between internal insulation (oil, SF6) and external insulation (atmospheric air).
- ✚ Connect electrical equipment to the network (transformer bushings, cable ends).
- ✚ Serve as an enclosure for certain devices (circuit breakers, surge arresters, measurement reducers)[8].
- ✚ Insulators are designed and dimensioned to withstand predictable stresses introduced by the environment[8]. From an electrical point of view, the insulator is considered as two electrodes with an interval comprising three zones, thus forming three insulators in parallel with different behaviors. These three zones are as follows:
 - ✚ The air gap.

- ✚ The dielectric material.
- ✚ The air-dielectric material interface (the length of the interface constitutes the leakage path: the line along which leakage current would flow)[9].

1.2.3 Types of Insulators

The use of solid dielectrics is widespread in overhead lines and substations[10]. Two main types of insulators can be distinguished:

rigid insulators and chain elements[11].

They are encountered in various forms.

1.2.3.1 *Fdv Bushing Insulators:*



Figure I-1 Crossarm insulators

1.2.3.2 *Rigid Insulators*

A rigid insulator (Figure I.2) is connected to the support by a fixed fitting. All standardized rigid insulators are supplied with a sealed socket so that they can be directly screwed onto the corresponding fittings[12][10]. This insulator is mainly subjected to bending and compression forces when placed in a vertical position[10]. In some cases, it can be placed horizontally or

even obliquely. This type of insulator is used for overhead lines that do not exceed the voltage level of 60 kV. [11]



Figure I-2 Rigid Insulators

I.2.3.3 Support Insulators

Support insulators, also known as supporting insulators, are insulating components designed to support, while isolating, conductive elements of traverses. They are used, for example, as supports for busbars in transformer substations [4]. They are made up of insulating material and a metallic piece that serves to connect two insulators and provide some flexibility to the insulator chain. The insulator chain is mounted on the pylon either vertically (alignment chain) or horizontally (anchoring chain)[10].

There are two main types of chain elements:

- ✚ Insulators with hood and rod.
- ✚ Insulators with long rod.

I.2.3.3.1 Insulators with Hood and Rod

The hood and rod insulator consists of three parts:

- ✚ Insulating block with an inner steel rod with grooves.
- ✚ Upper part in the form of a sealed hood made of malleable cast iron in glass (or porcelain).
- ✚ The lower end of the rod is rounded, forming the lower part which has dimensions adapted to penetrate the hood of the next element, and to remain held there by a pin [13].

Each element consists of a hood, an insulating skirt-shaped part, and a rod. The cross-section of such an insulator is schematically shown in (Figure I.3)[7]. The shape of the head is designed so that the tensile forces applied to the insulator are transformed, as much as possible, into compression of the dielectrics, although inevitably some shear stresses occur [9] . A chain of insulators is made up of several elements of the hood and rod type or others. These elements are mainly subjected to tensile forces. They are generally used in suspension and form insulator chains either vertically (alignment) or horizontally (anchorage) [11].



Figure I-3 hood and pin insulators

I.2.3.3.2 Insulators with Long Rod

a) Ceramic Type:

The long rod insulator (Figure I.4) consists of a cylindrical rod made of ceramic, porcelain, or synthetic materials with fins, at each end of which a metallic connecting piece is fixed [14]. They are used for high-voltage lines. Their advantage is being lighter than hood and rod insulators, with a disadvantage of susceptibility to mechanical shocks [11].

I.2.3.3.3 ceramic long rod insulator Synthetic Materials Type



Figure I-4 ceramic long rod insulator

b) Synthetic Materials Type

Consisting of a synthetic material whose main characteristic is good resistance to pollution, compactness, resistance to vandalism, and lightness, especially when compared to insulator chains for high-voltage lines[15].

This type of insulator is called composite, and it consists of three parts according to their roles:

- ✚ A core made of fiberglass, impregnated with resin, capable of providing insulation and supporting the mechanical forces generated by the conductors.
- ✚ A covering made of EPDM (Ethylene Propylene Diene Monomer) elastomer, vulcanized hot, which defines the profile and specifies the leakage path while protecting the core against any attack from external agents, ensuring sealing at the connection with the metallic end pieces. Its profile with alternating fins helps to increase pollution withstand capability.
- ✚ Metallic parts, made of malleable cast iron or hot-dip galvanized forged steel, are necessary for the assembly of the insulator and for transmitting the mechanical forces [16].



Figure I-5 long rod insulator made of synthetic materials

I.2.4 Some Definitions Concerning Insulators

I.2.4.1 Flashover

It is a disruptive discharge accompanied by sparks moving across the interface of an insulator from one electrode to another [7]. Flashover usually triggers network protections (circuit breakers, etc.) and causes degradation of the insulators[4]. Flashover is due to the movement of free charges accelerated by the applied electric field[17]. It manifests as an electric arc in the surrounding air between two conductive parts. Damage is superficial due to the thermal energy released by the arc [11].

I.2.4.2 Flashover Distance

The flashover distance (L) is the shortest distance in a gas between the electrodes [18].

I.2.4.3 Leakage Distance

The leakage distance (Lf) is the shortest distance along the surface of an insulator between the two electrodes [17].

I.2.4.4 Punch-through Distance

The punch-through distance is the shortest distance in the insulating material of an insulator between two conductive parts

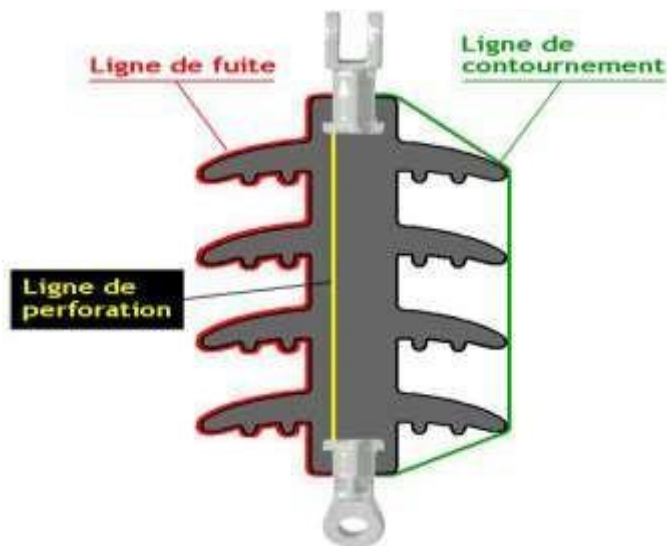


Figure I-6 The characteristics of an insulator

I.2.5 The characteristics of an insulator

Insulators account for a very modest percentage, around 7%, of the cost of an average medium-voltage overhead line. However, they are an essential element on which the operational safety, quality, and continuity of service depend [19].

One characteristic of line insulators is their shape, which resembles standing mushrooms stacked on top of each other. The design of insulators is largely dictated by the need to limit leakage currents due to the film of moisture and precipitated salt found on the surface of insulators. This film is much more conductive than the material itself. In the long run, this can result in a destructive electric arc. Therefore, an insulator that significantly lengthens the path of the current flowing on its surface will be chosen [4].

The insulating material chosen for this function (insulation) will be determined by its mechanical resistance in bending or tension (depending on the type of insulation) and by its surface porosity. A very smooth material, such as porcelain, will be less prone to capturing air pollutants like salt on its surface than a highly porous material. Additionally, the material should have the highest possible resistivity to prevent the insulator itself from becoming a conductor of electricity [4].

I.3 Insulator Pollution

By definition, the term "pollution" refers to the degradation of a medium caused by the direct or indirect introduction of substances harmful to the environment or by the modification of its biological, chemical, or physical characteristics. This implies that when we talk about insulators, the phenomenon of pollution is defined as the degradation of the insulating surface by soluble electrolytes or non-soluble inert particles, which are substances capable of altering the electrical performance of the insulators [20].

The term "polluted," often associated with "dirty" in the usual sense, takes on another meaning when used to describe the condition of an insulator. In other words, a polluted insulator does not necessarily appear dirty. Indeed, an insulator that is heavily polluted by salt spray may appear clean while its electrical performance undergoes significant degradation. On the other hand, another insulator covered in soot, which appears dirty, may have remarkable electrical performance. Hence, an insulator is considered to increase the surface conductivity of that insulator. The term "contamination" is then more appropriate in this case to describe the phenomenon of insulator pollution, and it refers more to the electrical conductivity of the insulator surfaces than to their external appearance [20].

Even when well chosen, insulation is never immune to an incident. The severity of pollution at a site can change. The appearance of a new factory near a substation, the construction of a nearby road structure, or simply an exceptional weather event can increase, either permanently or temporarily, the pollution at a site where a substation or a line is already in operation. The initially correct sizing of the insulators may then become insufficient, and it is necessary to protect existing installations against new sources of pollution [11].

I.3.1 Sources of Pollution

The polluting substances that contaminate insulators can come from different sources depending on the type of environment in which the site is located. For example, in a marine environment, soluble electrolytes come from salt spray from the sea present in the atmosphere, constituting what is called marine pollution. In an industrial environment, insulators are exposed to industrial pollution, with soluble substances coming from the smoke produced by thermal power plants (coal or oil-fired), steel mills, or refineries, while non-soluble inert substances come from dust generated by cement plants or cement mines. Particularly in winter,

most insulators installed near highways are subject to winter pollution, with the main sources of soluble electrolytes being road salting.

It sometimes happens that smoke from domestic heating in densely populated urban areas also constitutes a source of pollution in winter. Indeed, there are other types of environments that are also likely to produce polluting substances according to the IEC 60815 (2008) standard [20].

1.3.1.1 *Types of Pollution*

1.3.1.1.1 Natural Pollution

Natural pollution originates from [21]:

- Marine salts in coastal regions.
- Soil dust (especially during major construction projects).
- Sand carried by the wind in desert regions.

Marine Pollution

In installations along the coast, spray carried by the wind gradually deposits a layer of salt on the insulators, which, over time, covers the entire surface of the insulator, including the best-protected parts. This salt layer, moistened by the spray itself, fog, or simply condensation, becomes conductive. Leakage current then flows through the surface layer, and electric arcs can occur under certain conditions, eventually leading to total flashover of the insulator [22].

Desert Pollution

In desert regions, frequent sandstorms gradually deposit a layer of pollution containing salts on the surfaces of insulators. Once moistened, this layer becomes much more conductive and generates leakage current [11], which can abruptly lead to the appearance of partial arcs followed by total flashover of the insulator [21].

1.3.1.1.2 Industrial Pollution

This type of pollution is common in industrial areas, especially near factories and production facilities emitting smoke (refineries, cement plants, etc.). Additionally, exhaust gases from thermal power plants and fertilizers used in agriculture also contribute to deposits observed on the surface of insulators [23][24].

In the presence of high humidity, the salt contained in these pollutants significantly reduces the surface resistivity of insulators, and flashover may occur [25].

Factories are not the only contributors to this kind of pollution; vehicle exhaust gases and fertilizers used in agriculture also contribute to the deposits observed on the surface of insulators [21].

I.3.1.1.3 Mixed Pollution

This type of pollution is actually the most common and severe for the operation of electrical facilities. Mixed pollution results from the combination of different types of pollution, such as marine and industrial pollution when industrial installations are located near the coast[21].

I.3.1.2 *Classification of Pollution Types*

The composition of this pollution varies depending on the sources of contamination and the conditions to which the insulators are subjected. The CES 815 standard provides a classification of pollution according to its origin. Essentially, the types of pollution that exist are natural pollution, industrial pollution, and mixed pollution[26].

Table I-1 Classification of Pollution According to Environmental Type:

Pollution Level	Examples of Typical Environments
I. Low	- Areas without industries and with low-density housing equipped with heating installations.
	- Areas with low density of industries or residences but often exposed to winds and/or rains.
	- Agricultural regions.
	- Mountainous regions.
II. Mediu	- Areas with industries that do not produce particularly polluting fumes and/or with moderate density of housing equipped
	with heating installations.
	- Areas with high density of housing and/or industries but often exposed to winds and/or precipitation.
	- Areas exposed to sea winds, but not very close to the coast.
III. High	- Areas with high density of industries and suburbs of large cities with high density of polluting heating installations.
	- Areas located near the sea, or at least exposed to relatively strong winds coming from the sea.
IV. Very High	- Areas generally small in size, subject to conductive dust and industrial fumes producing particularly thick deposits.
	- Areas generally small in size, very close to the coast and exposed to strong winds and pollutants coming from the sea.
	- Desert areas characterized by long periods without rain, exposed to strong winds carrying sand and salt and subject to
	regular condensation.

I.3.2 Formation and Distribution of Pollutant Layers

Following the flow of air carrying various dust particles, a layer of pollution forms on the surface of insulators. The non-uniform and non-homogeneous distribution of this layer depends on the profile of the insulator, the position of the chain relative to the ground (vertical, horizontal, inclined), the voltage level, and the degree of pollution at the site where the insulator is located [7].

The non-uniformity of pollution can be classified into three categories:

a) Longitudinal Non-Uniformity by Group: It is characterized by a set of groups of insulators, subject to different conductivities of the pollution layer, whose value is constant in each group. We find this type of pollution in the following cases: • Temporarily during tension washing. • In chains of insulators in a "T" shape. • Due to the electric field effect where the concentration of pollution is accentuated on the insulators closest to the high voltage terminal [27].

b) Transverse Non-Uniformity: This type is characterized by sectors or bands of different surface conductivities of the pollutant layer. These bands are distributed transversely around the surface of each insulator in the chain. The conductivity in each sector is the same along the leakage line. This type of pollution is mainly due to the existence of a preferred direction of winds and rains [27].

c) Periodic Longitudinal Non-Uniformity: This type is the most common. It is characterized by a periodic variation in the conductivity of the pollution layer along the leakage line, but it maintains a circular symmetry. Its main specifications are:

- The underside of the insulator has a higher conductivity than the upper side.
- Pollution concentration increases from the peripheral zone to the central zone.
- Pollution is more pronounced between the ribs [27].

I.3.3 Consequences of Pollution

The pollutant layers that accumulate on the surface of insulators cause surface electrical conductivity [28]. This alters the distribution of potential along the leakage line. Depending on atmospheric conditions (fine rain, fog, etc.), the dielectric breakdown voltage of the air can be reached between two points on the insulating surface, leading to the initiation of an electrical

arc that short-circuits a part of the leakage line [11]. Three cases may occur depending on the constraints to which the insulator is subjected :

a) Non-localized Arc: An arc is called non-fixed (non-localized) when it ignites and extinguishes rapidly to reignite in another location on the surface of an insulator [4]. Leakage current appears, leading to a small loss of energy, generally tolerable by the installation [29].



Figure I-7 Initialization of Electric Arcs.

b) Fixed Arcs:

Figure I.7. Initiation of Electrical Arcs

Unlike the previous type, fixed arcs attach to the surface of the insulator, either by remaining there (for direct current) or by re-igniting at the same location (for alternating current). This type of arc can cause insulation degradation due to its thermal effect [4].

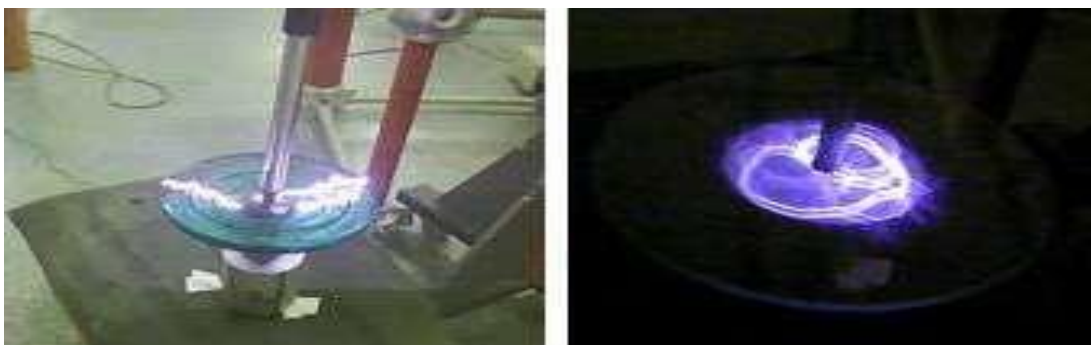


Figure I-8 Evolution of Electric Arcs

c) Isolator Flashover:

When an arc tracks along a polluted and moistened surface, it can bridge to the opposite electrode [4]. This results in the generation of leakage current accompanied by the formation of a dry band and partial arcs, leading to the propagation of the arc that can cover the entire insulator [30]. This phenomenon ultimately leads to insulation breakdown.

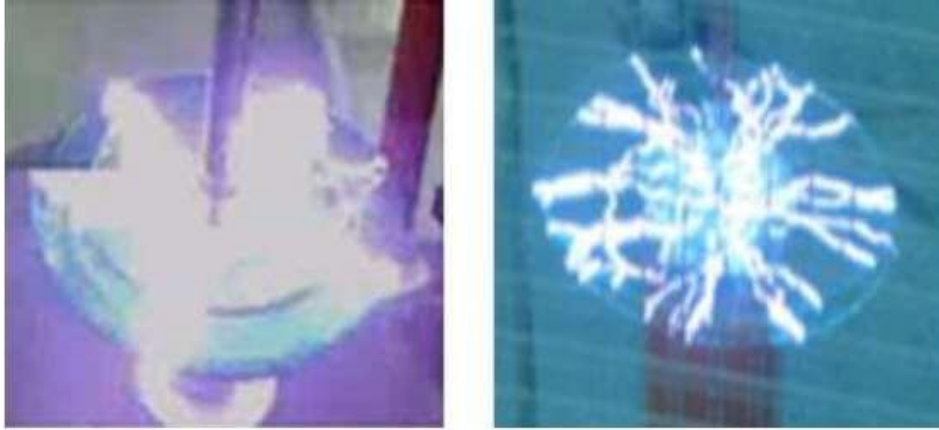


Figure I-9 Total Circumvention

I.4 Conclusion

Through this chapter, it can be concluded that in order to fulfill their role, insulating materials and insulators must meet mechanical, electrical, and environmental criteria. Each type of insulator is designed for specific insulation purposes. Therefore, the choice or sizing of the insulator is made considering the aforementioned criteria (constraints) to ensure quality and continuous service, as well as to achieve an optimal balance between quality and cost [4.]

Pollution of insulators is a crucial factor to consider in the design of high-voltage power lines. To better size the insulator, it is essential to know the severity of pollution at the sites in question. Understanding this severity involves studying various parameters that define the state of insulation degradation [11].

The flashover voltage of a polluted insulator depends mainly on the conductivity of the pollutant deposit (pollution level) and the distribution of the pollution layer on the insulating surface. Therefore, knowledge of this pollution level is a prerequisite and essential condition for assessing the isolation level of installed facilities on-site, in order to properly size the insulation [1].

II Chapter Diagnostic and Object Detection Methods

II.1 Introduction

Outdoor-type insulators are subjected to various operational and environmental constraints. Surface contamination of insulators is one of the major factors increasing the likelihood of bypass. Over the past two decades, a variety of techniques based on leakage current signal processing have been proposed to monitor the behavior of polluted insulators in real-time. Among these techniques, we can mention the Fourier transform, wavelet transform, recurrent plot technique, and others. Supervised learning methods have also been exploited by several researchers to predict the severity of pollution deposited on the surface of insulators [31].

Object detection in an image is an operation that involves distinguishing the object region from the background based on a defined criterion. Tracking an object in a sequence of images is an operation that involves locating the object region. Several techniques can be used to perform these operations [32].

In this chapter, we provide a synthesis of the most recent works on pollution as well as the diagnosis of polluted insulators. Additionally, we present the most important techniques used for object detection.

II.2 Diagnostic Methods

II.2.1 Definition

In essence, these methods assume that no model is available to describe cause-and-effect relationships. The only knowledge relies on human expertise supported by a solid feedback. In this category, we find all methods based on artificial intelligence, pattern recognition, expert systems, and artificial neural networks [33].

II.2.2 Determination of the Probability of Occurrence of Composite Insulators Bypass Using Harmonic Components of Leakage Current Signal

In previous studies, they [34] proposed a new method to predict the bypass of Silicon Rubber (SIR) type insulators and its probability of occurrence by analyzing the harmonic components of the leakage current signal. Tests were conducted on samples of polluted insulators with different profiles (Figure II.1) (Table II.1) [31].



Figure II-1 Tested Insulators

Insulator No	1	2	3	4	5
Nominal Voltage (kV)	33	24	24	24	24
Length of Insulator Chain (mm)	720	520	520	449	449
Leakage Line (mm)	1070	770	590	674	630

Table II.1. Insulator Characteristics

In order to validate their new method, these researchers measured the leakage current on different insulators, for various humidity levels and distinct contamination levels. The results obtained for Insulator No. 1 are depicted in Figure II.2. [31].

These researchers [34] demonstrated that when the amplitude of the 5th harmonic component is greater than that of the 3rd harmonic component, it indicates that the insulator is clean or very lightly polluted. They also observed that if bypass does not occur at the beginning of humidification, it will not occur with humidity saturation. In the same study, the researchers proved that the variation of the ratio between the amplitudes of the 5th and 3rd harmonics is an excellent criterion for assessing the surface condition of a given insulator.

Amplitude of the 5th harmonic

$K5/3$ = Amplitude of the 3rd harmonic

According to tests conducted in the same laboratory, the researchers noticed that under normal service conditions, the $K5/3$ index exceeds 100%. Therefore, they concluded that if this condition is met, then bypass is very remote. Furthermore, they also observed that for all cases where bypass occurs, the $K5/3$ index is less than 30%. Thus, they deduce that recognizing an insulator with $K5/3$ less than 30% is a necessary but not sufficient condition. They demonstrate that the probability of bypass occurrence in this latter case is 90% [34].

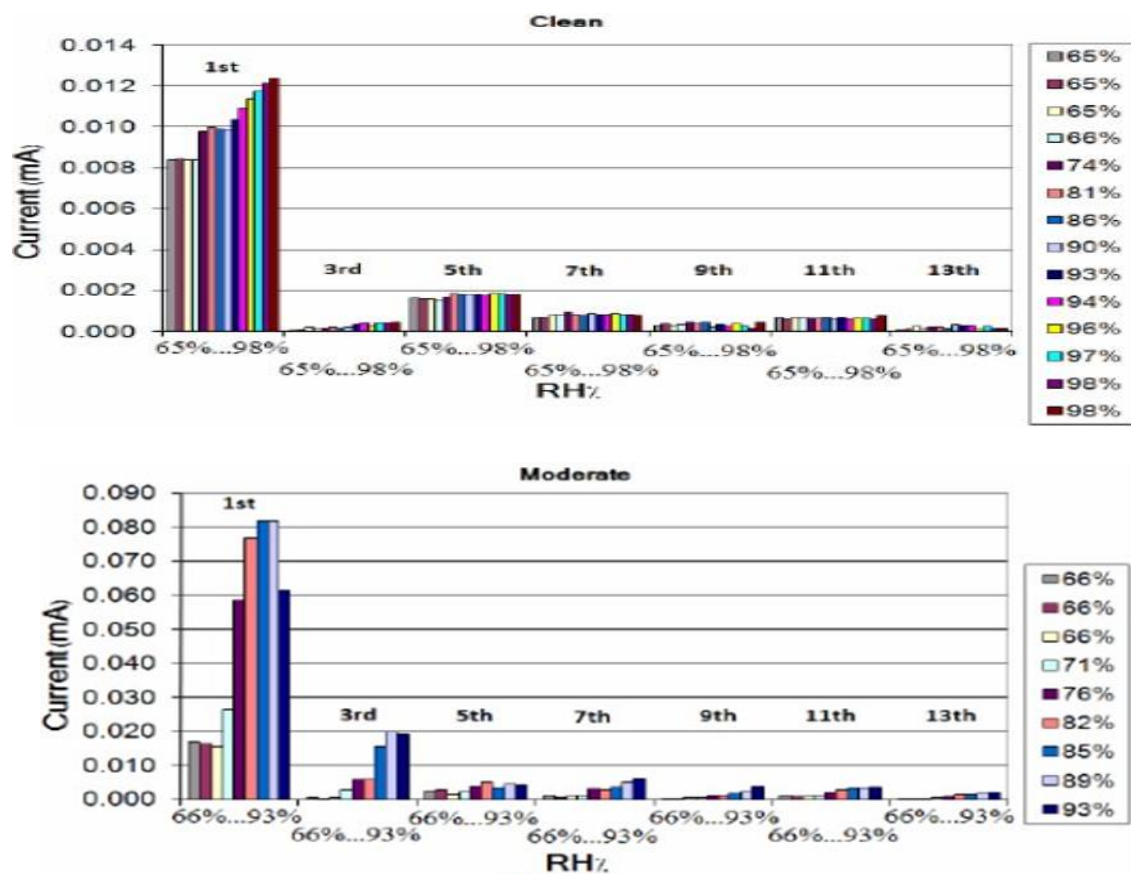
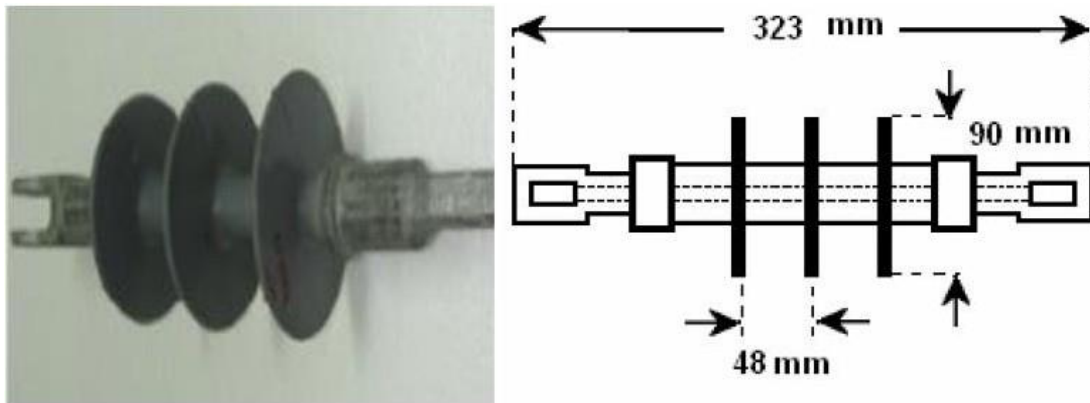


Figure II-2 Variation of the harmonic amplitudes of the leakage current for different humidity levels and contamination levels

II.2.3 Partial Discharge Analysis for the Diagnosis of Surface Condition of Polymer Insulators

In order to estimate the severity of pollution on line insulators, S. Chandrasekar et al [35] analyzed partial discharges on SIR (Silicon Rubber) insulators. Subsequently, tests were

conducted on several samples (Figure I.3) under alternating voltage with different pollution



levels and different relative humidities of the air (RH) [31].

Figure II-3 Photograph and diagram of a 11 kV SIR sample

. The insulators are suspended in a chamber (1.5 m × 1.5 m × 1.5 m) where fog (NaCl) is injected to vary the ESDD in mg/cm^2 from 0.06 to 0.25. For this experiment, the setup used is that of Figure II.4 [31].

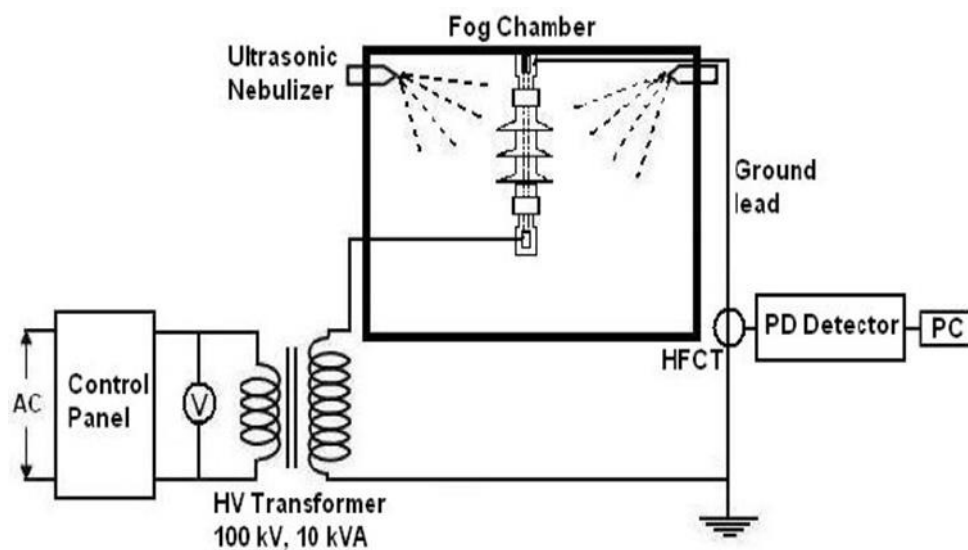


Figure II-4 Experimental Setup

Several tests were conducted:

- Tests on a clean SIR insulator, under different relative humidity levels (30 to 40%);
- Tests on an SIR insulator (ESDD = $0.08mg/cm^2$, RH=60 to 100%);

- Tests on an insulator (SIR) at RH=100%, (ESDD varies from 0.06 to 0.25 mg/cm^2). For clean insulators, the authors noted the absence of partial discharges.

For a pollution level of 0.08 ESDD, and a relative humidity ranging from 60 to 100% (Figure II.5), the authors observed that:

- The amplitude of the PDs increases with increasing RH;
- For low RH values (60% to 80%), the dominant frequency components of the PD signal are within the 6-25 MHz band;
- For high RH values (above 90%), the frequency components are within the 2-6 MHz band [34].

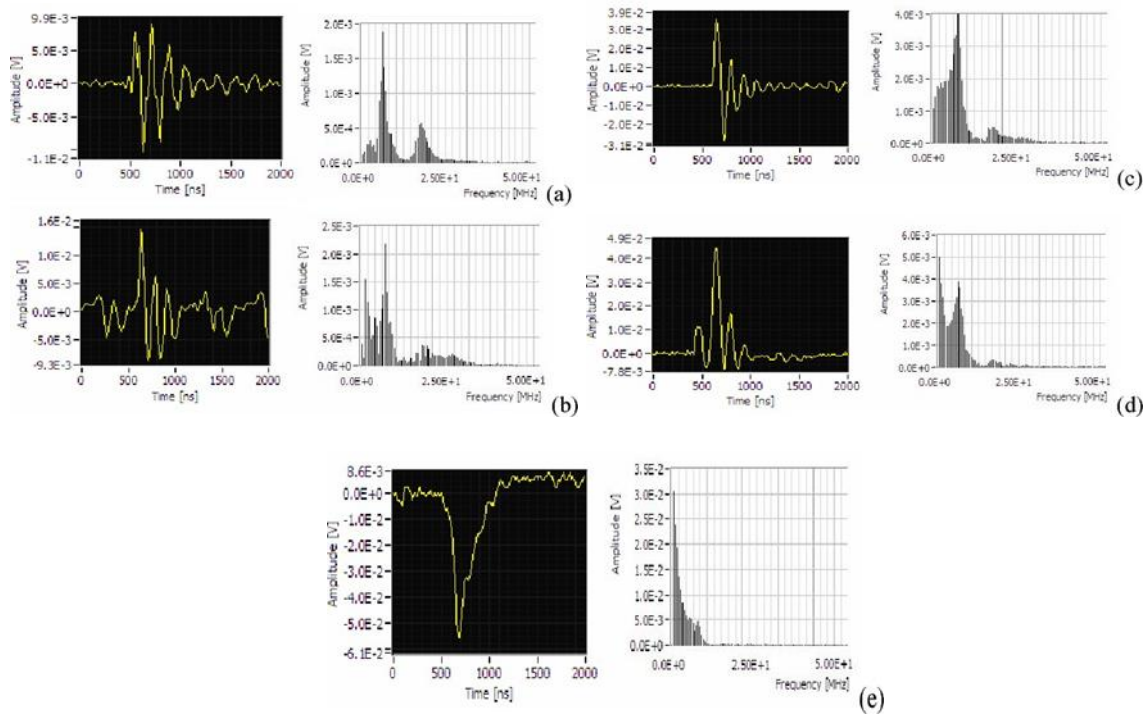


Figure II-5 . Signals obtained (temporal and frequency representations) of PDs at 0.08 ESDD: (a) 60%RH, (b) 70%RH, (c) 80%RH, (d) 90%RH, (e) 100%RH

For a pollution level ranging from 0.06 ESDD to 0.25 ESDD with RH=100% (Figure II.6), the authors concluded that as the pollution level increases:

- PD amplitudes increase;
- Repetition rate (occurrence of all PDs within a specific time interval) decreases;
- Frequency component amplitudes increase in the 1-6 MHz band.

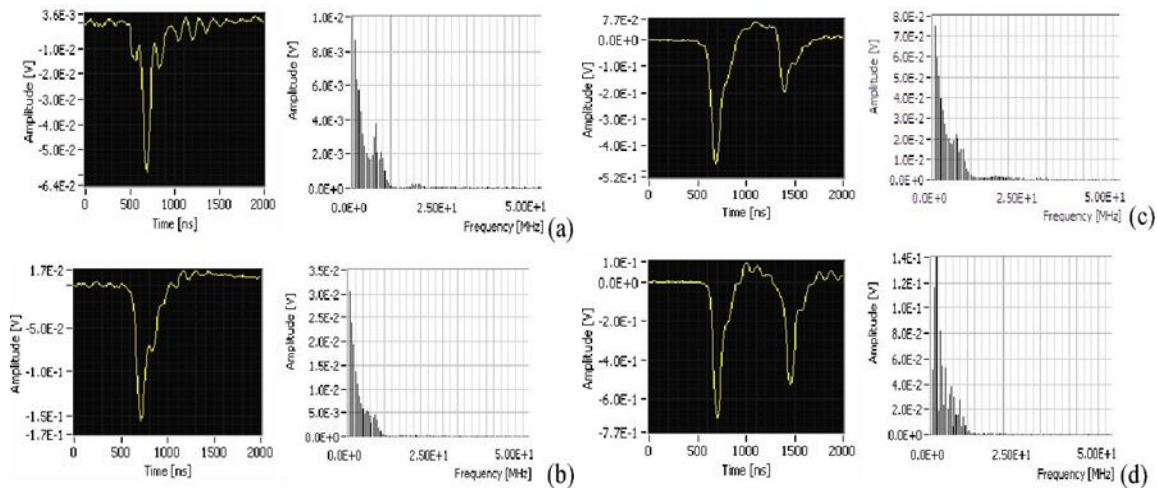


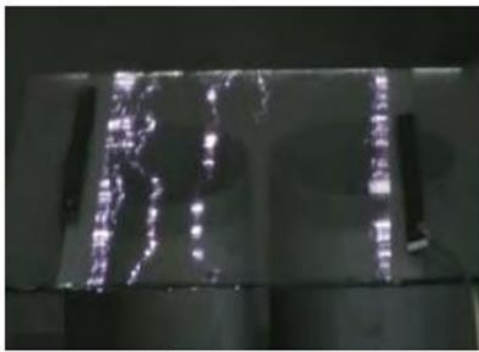
Figure II-6 Signals obtained (temporal and frequency representations) of PDs for $RH=100\%$: (a) 0.06 ESDD, (b) 0.08 ESDD, (c) 0.12 ESDD, (d) 0.25 ESDD

Based on the results and figures obtained, the authors concluded that at high levels of pollution, the asymmetry value of the DP (Partial Discharge) signal decreases significantly with increasing pollution. However, they believe that using this parameter alone is not sufficient for diagnosing the condition of the insulator. This study was completed with a statistical analysis, including parameters such as the shape factor (β) and the mean phase of the DP signal, for different ESDD (Equivalent Salt Deposit Density) and RH (Relative Humidity) conditions. The variation of the β parameter and the mean phase proved to be effective tools for diagnosing the severity of pollution.³⁵

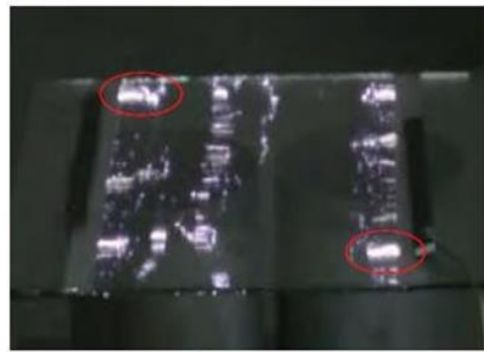
II.2.4 Image Processing Methodology

The described work [36] presents a new methodology for analyzing electrical discharge activity and monitoring bypassing. Tests were conducted on a polluted flat surface to ensure better visibility of the appearance and propagation of discharges. After a detailed analysis of the discharge activity, 8 discharge states were discovered on the surface of the insulator (Figure II.7). Among these 8 states, 4 include the formation of electrical arcs. Consequently, an algorithm was developed to detect the appearance of these arcs. For this purpose, it proposes to calculate four indicators (NI, Np, L, and W) describing and quantifying the activity of electrical discharges on the insulating surface. Then, these indicators are used as inputs for different classification methods (K-nearest neighbors, Naïve Bayes, and Support Vector Machines) to discern the presence of arc-type discharge cases.

In this work, the Otsu segmentation method yields very good results and adequately represents the texture of the images extracted from test videos showing the propagation of electrical discharges on the planar model of the insulator. However, images segmented by the Otsu method also contain noise. This noise is due to both the lighting of the test laboratory and daylight reflected on the upper edge of the insulator (Figure II.8). To address this, the use of morphological filtering is proposed. This filtering combines erosion and dilation operations to remove pixels that are not representative of electrical discharges. Thus, it is observed that morphological filtering is essential to allow a correct view of the discharges.



(a) Step 1 (4 kVrms)



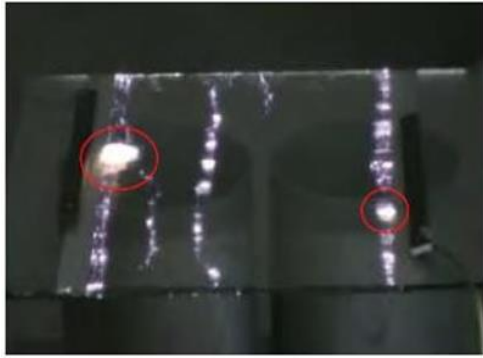
(b) Step 2 (6 kVrms)



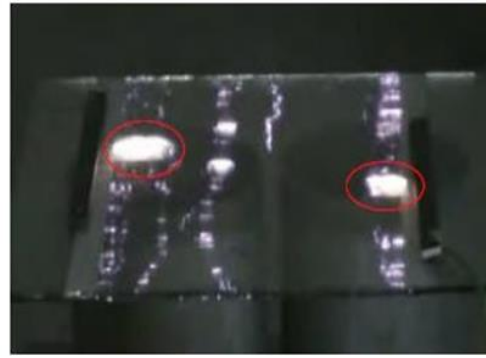
(c) Step 3 (15 kVrms)



(d) Step 4 (20 kVrms)



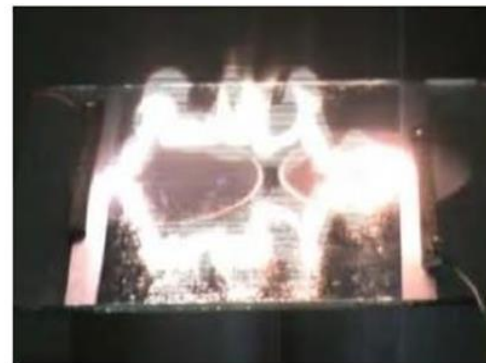
(e) Step 5 (24 kVrms)



(f) Step 6 (28 kVrms)



(g) Step 7 (30 kVrms)



(h) Flashover discharge (32 kVrms)

Figure II-7 Steps of the flashover process

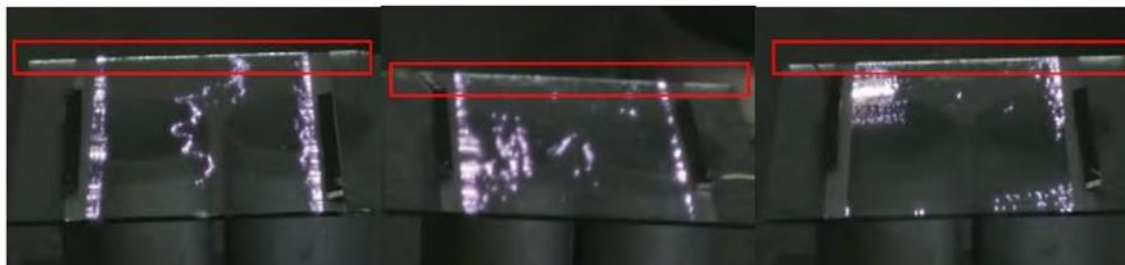


Figure II-8 Noise present in the images, caused by light reflection on the upper edge of the flat insulator

The four extracted indicators allow for the estimation and characterization of very interesting discharge phenomena:

- Fluctuations in N_I and N_p before the barrier highlight the phenomenon of electrical discharge intermittence.

- With the increase in applied voltage, the number of electrical discharges on the insulating surface, quantified by N_l , increases. However, this number decreases just before the barrier (1 kVeff before the barrier voltage), indicating the appearance of the final barrier arc.

- N_p , being the number of pixels for the largest discharge, indicates the presence of arcs. Indeed, a fluctuation in N_p signifies electrical arc activity.

- L and W quantify the space occupied by electrical arcs. Indeed, at low levels of applied voltage, discharges are dispersed over wider or narrower areas.

- The decrease in W indicates the formation of electrical arcs.

- The four indicators help prevent the phenomenon of insulator barrier. As N_p , L , and W describe the most prominent discharge, they increase as the barrier approaches. However, N_l counts the number of discharges on the insulator surface, so it decreases before the barrier.

Choosing the classification method is far from straightforward. It greatly depends on the type of input data. In our work, Support Vector Machines (SVMs) provide the best classification rate for preventing the occurrence of the barrier.

Table II.2. Results of discharge classification

	Success Rate (%)
SVM	95.57
KNN	92.47
Bayes	88.05

The work carried out throughout this chapter demonstrates the effectiveness

of image processing for monitoring and surveilling the surface condition of a planar insulator under pollution. Through an algorithm combining segmentation, feature extraction, and classification, the occurrence of electrical arcs has been successfully detected, thereby preventing the phenomenon of electrical flashover [36].

II.2.5 Measurement of Electric Field in Case of a Polluted Insulator String

In previous studies, they [37] proposed a method for measuring the electric field around an insulator string subjected to various constraints; the study was conducted under several circumstances; in this work, we summarize the test of measuring the electric field in the case of a polluted insulator string, this contamination was achieved by spraying the surface of the insulator string with a solution containing distilled water and desert dust. For proper diffusion of pollution on the surface of the insulators:

- This process was applied 5 times on each side and at a distance of 30 cm from the central axis of the insulator string (Figure II.9).
- The distribution of the electric field on an axis parallel ($d=1\text{m}$) to the central axis of the insulator string in pollution conditions was represented to illustrate the areas of maximum field.
- Different values of pollution conductivity were used to simulate a potential degree of pollution affecting the performance of the string in a desert region (from low to extreme degrees), such as 0.5, 1.4, 1.72, and 1.97 mS/cm.
- In this study, all waveforms of the electric field were recorded using a personal computer and via USB connection with the Arduino Uno board.
- To measure the values of the electric field for most points along and around the insulator string, different detection positions were chosen on the vertical and horizontal axes, as illustrated in Figure II.10.

Figure II.12 shows an example of the electric field waveform captured by the 7th probe (see Figure II.11), when the applied voltage is equal to 80 kV under clean conditions and at different horizontal distances.



Figure II-9 Spray Method



*Figure II-10 The Chain of Insulators Used
and the Measurement Axes of the Field*

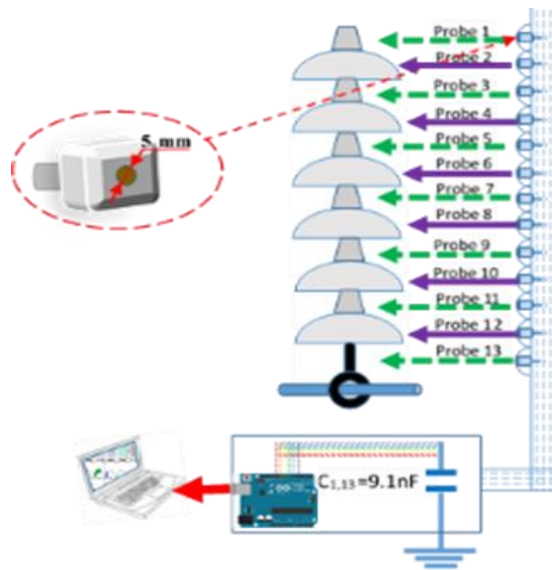


Figure II-11 Diagram Showing the Measurement Method

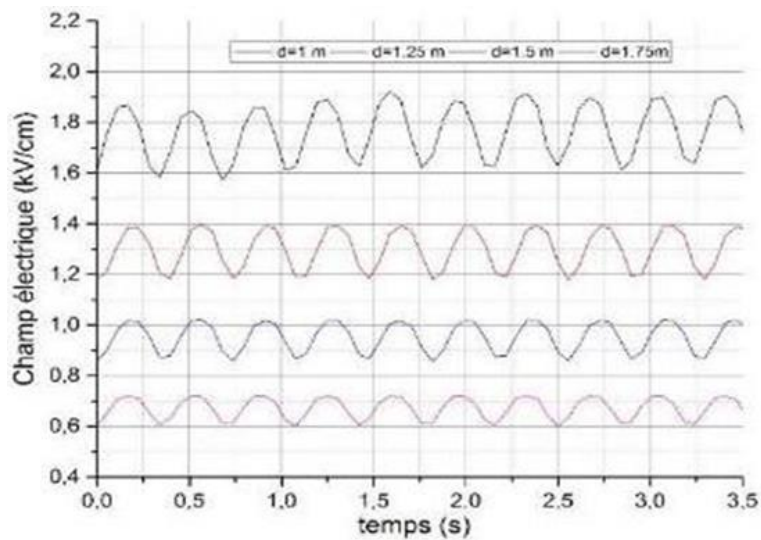
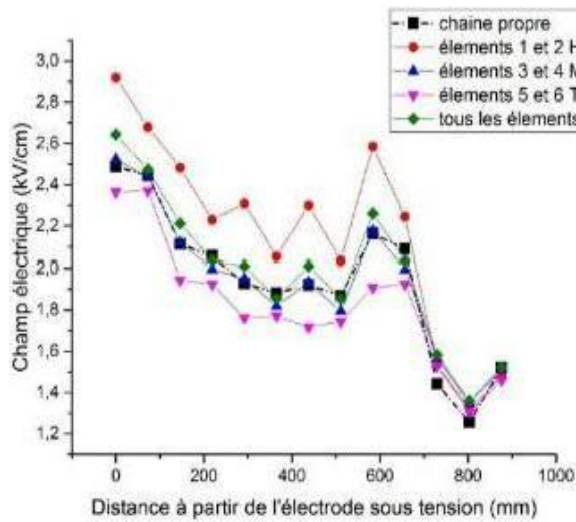


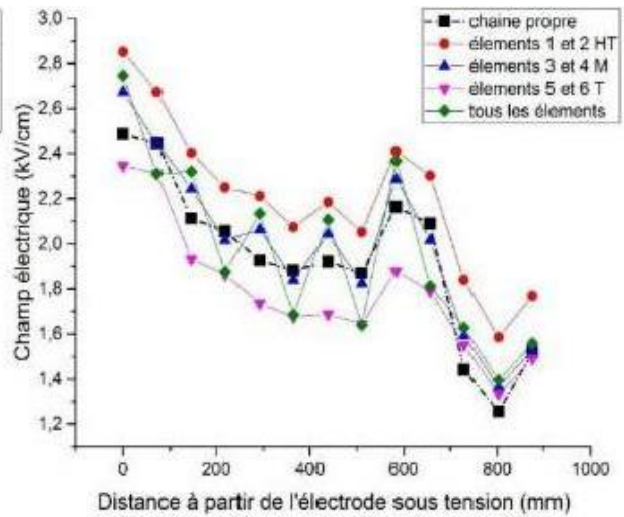
Figure II-12 Waveform provided by the Arduino Uno

II.2.5.1 Resultats

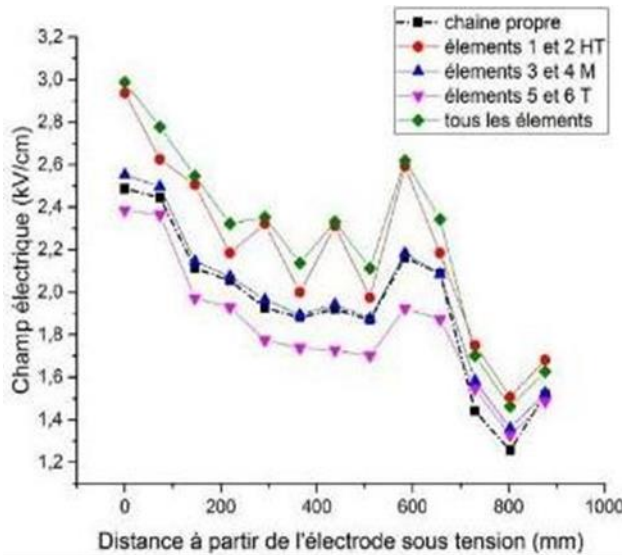
Figure III.13 représente la distribution du champ le long de l'axe longitudinal ($d=1$ m) pour différentes valeurs de conductivité superficielle (0,5, 1,4, 1,72 et 1,97 mS/cm) de la pollution déposée sur différents éléments de la chaîne (éléments 1 et 2 côté de l'électrode HT, 3 et 4 au milieu, 5 et 6 côté de l'électrode Terre et sur tous les éléments de la chaîne). La tension appliquée pour chaque configuration de pollution est de 80 kV [37].



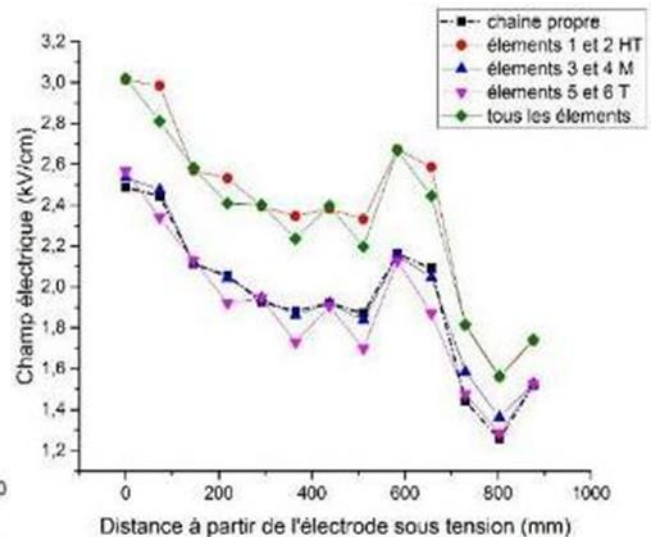
(a) Conductivity = 0.51 mS/cm



(b) Conductivity = 1.4 mS/cm



(c) Conductivity = 1.72 mS/cm



(d) Conductivity = 1.97 mS/cm

Figure II-13 Effect of the polluted layer on the distribution of the electric field along the longitudinal axis ($d=1m$) and for different pollution positions on the insulator chain

• **Note:**

From Figure II.13, the following observations can be made:

- The field is maximal for all cases where elements 1 and 2 next to the HT electrode are polluted.

- It reaches a value of 3.01 kV/cm around the HT electrode and 2.67 kV/cm around the metallic connection zone between elements 4 and 5 of the chain for a conductivity of 1.97 mS/cm (Figure II.13(d)).

- **Explanation:**

This can be interpreted by the fact that the tangential component of the electric field becomes very important compared to the measured normal component, which may result in a greater contribution of the resulting electric field oriented towards the polluted elements 5 and 6 (floating Earth electrode). This could also be due to the decrease in the creepage distance of the suspension insulator chain.

II.3 Methods of Object Detection

II.3.1 Definition

Object detection is a highly active research area that aims to classify and localize regions/zones of an image or video stream. This field intersects with two others: image classification and object localization. The principle of object detection is as follows: for a given image, regions that may contain an object are searched for, and for each of these discovered regions, it is extracted and classified using an image classification model, for example. Regions of the original image with good classification results are retained, and others are discarded. Thus, to have a good object detection method, it is necessary to have a robust region detection algorithm and a good image classification algorithm. Locating an object in an image is complex, and measuring the performance of localization requires a suitable metric. Furthermore, unlike classification, there can be multiple objects in the same image, and the detector must be able to identify them (Figure II.15)[41].



Figure II-14 Example of object detection

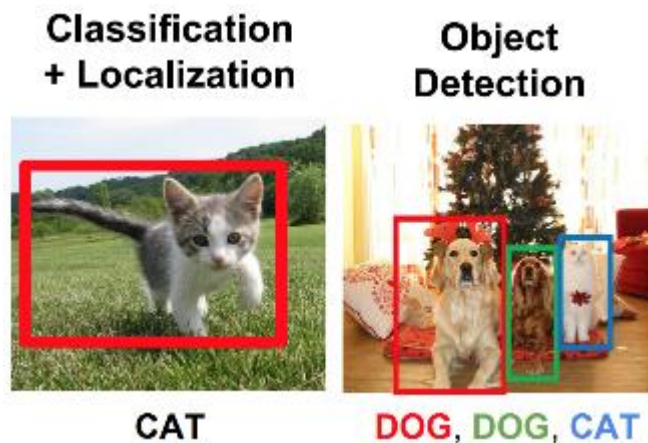


Figure II-15 Illustration of the difference between classification and object detection

II.3.2 Open CV

II.3.2.1 Open CV Definition

Open CV (Open Source Computer Vision) is an open-source computer vision library. This library is written in C and C++ and can be used on Linux, Windows, and Mac OS X. Interfaces have been developed for Python, Ruby, Matlab, and other languages. Open CV is oriented towards real-time applications. One of the goals of Open CV is to help people quickly build

sophisticated computer vision applications using a simple computer vision infrastructure. The Open CV library contains more than 500 functions[42].

II.3.2.2 Features

The Open CV library provides numerous diverse functionalities for creating programs ranging from raw data to basic graphical interfaces. It offers most of the standard operations in low-level image and video processing[43].

II.3.2.2.1 Image Processing

Open CV provides most of the standard operations in low-level image processing:

- Reading, writing, and displaying an image.
- Calculation of grayscale or color histograms.
- Smoothing, filtering.
- Image thresholding (Otsu's method, adaptive thresholding).
- Segmentation (connected components, Grab Cut).
- Mathematical morphology.

II.3.2.2.2 Video Processing

This library has become a standard in the research field because it offers a significant number of state-of-the-art tools in computer vision, such as:

- Reading, writing, and displaying a video (from a file or a camera).
- Line, segment, and circle detection using Hough Transform.
- Face detection using the Viola-Jones method.
- Boosted cascade classifiers.
- Motion detection, motion history.
- Object tracking using mean-shift or Camshift.
- Detection of interest points.
- Optical flow estimation (Lucas-Kanade method).
- Delaunay triangulation.

- Voronoi diagram.
- Convex hull.
- Fitting an ellipse to a set of points using the least squares method[43].

II.3.2.3 *Open CV Modules*

Open CV has a modular structure. The main modules of Open CV are listed below:

Open CV has a modular structure. The main modules of Open CV are listed below:

a. Cx Core (Open CV Core):

Contains basic data structures and mathematical operations. It allows for matrix algebra functions, data transformation, memory management, error handling, dynamic code loading, and also enables graphing[43].

b. High Gui (Graphical User Interface Library):

Open CV integrates its own high-level library for opening, saving, and displaying images and video streams. It also includes a number of functions for creating very simple graphical interfaces, sufficient for testing programs[43].

c. ImgProc (Image Processing):

This module includes basic image processing algorithms, including image filtering, image transformations, color space conversions, and more[43].

d. Video (Video Processing):

This is a video analysis module that includes object tracking algorithms, background subtraction algorithms, and more[43].

e. ObjDetect (Object Detection):

This includes object detection and recognition algorithms for standard objects[43].

f. ML (Machine Learning Library):

Contains functions for classification, data analysis, and clustering tools[43].

g. Calib3D:

Camera calibration and 3D reconstruction[44].

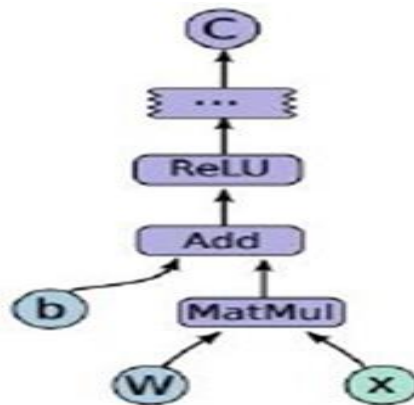
II.3.3 TensorFlow

II.3.3.1 Definition

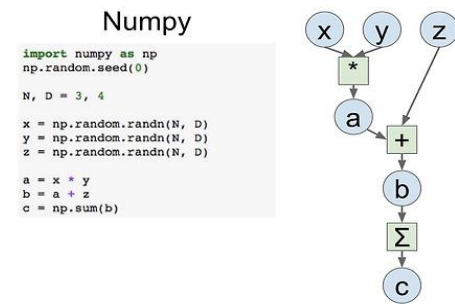
TensorFlow is a tool used to implement and test deep artificial learning algorithms quickly. One of its features is its adaptability to hardware architectures dedicated to computation (GPU) and its ability to distribute this computation across clusters of machines very easily[45]. It allows for the use of many ready-to-use algorithms. It has been utilized for research and deployment of machine learning in a wide range of domains, including speech recognition, computer vision, robotics, information retrieval, natural language processing, and more[46].

II.3.3.2 Operation

The internal operation of TensorFlow is the key to its success. A TensorFlow computation is described by a graph, which consists of a set of nodes. The graph represents a flow of data and its transformations, with extensions allowing certain types of nodes to maintain and update persistent states. Different clients (Python, C++, others) can generate this type of computation graph. An example of code constructing a computation graph and then executing it is shown in Figure II.16.



Computational Graphs



Fei-Fei Li & Justin Johnson & Serena Yeung

Lecture 8 -2626 April 27, 2017

Figure II-16 Example of generating a computation graph from code (Tensor Flow)

II.3.3.3 Components of Tensor Flow

1. **Computation Graph**: Contains information about all the operations that can be performed. Each node represents an operation with inputs and outputs. Edges define the flow of tensors in the graph. Tensors are arrays of undefined dimensionality with known or inferred types. Operations represent abstract computations and may have attributes for execution. Kernels are specific implementations of operations executed on devices like CPUs or GPUs[41].

2. **Program Interaction**: Programs interact with TensorFlow by creating a session, during which a run is called to compute specified variables and optional tensors. TensorFlow computes all necessary nodes to calculate requested outputs and organizes their execution[41].

The detailed knowledge of the computation graph has multiple impacts. It facilitates parallelization or distribution of operations across devices and allows symbolic computation and automatic differentiation, crucial for deep learning and creating new structures[41].

II.4 Conclusion

The most effective current techniques for evaluating the severity of insulator pollution rely heavily on applying signal processing methods to leakage current waveforms or images of the field. The literature review of various previous studies conducted in this chapter allows us to draw inspiration from the application of these methods in the field of high voltage, especially in insulator pollution.

The application of these methods proves to be a very effective tool for predicting the behavior of insulators in service under pollution constraints. It should be noted that these methods can also be combined with supervised learning methods to predict the severity of pollution.

Object detection methods can be used to diagnose the surface condition of insulators. This is a highly effective tool for predicting insulator surface conditions.

III Chapter Detection of Insulator Surface Condition Using Artificial Intelligence Techniques

III.1 Introduction

In light of technological advancements, the introduction of meta-heuristic methods has become a necessity in all areas of life, and the transmission of electrical energy is no exception. Our objective in this chapter is to develop a model capable of detecting the surface condition of high-voltage insulators using artificial intelligence techniques. In this study, we use the TensorFlow method in the Python programming interface.

III.2 Required Modules and Toolboxes

To implement our approach, we have used the following modules and toolboxes:

Table III.1. Accessories for the Object Detection Model

Requirements:
Windows10
Anaconda3
Python 3.6
TensorFlow v1.12
CUDA Toolkit v8.0
CuDNN v6.0
LabelImg

We also need to install several packages, they must be installed in the Anaconda3 environment (See also the appendix).

Table III.2. Packages for the Object Detection Model

Package
Anaconda protobuf
Pillow
Lxml
Cython
contextlib2
Jupyter
Matplotlib
Pandas
OpenCV-python

III.3 Process of Creating an Object Detection Model

We create a folder for our model in a directory named "project".

III.3.1 1st Step: Gathering Photos for Different States of Insulators

In this step, we gathered several images by taking photos ourselves and downloading others from the internet (Figure III.1). Then, we divided our photo database into two different folders (test and train); where the test folder contains 20% and the train folder contains 80% of the entire database.

We create the folders in C:\project\models\research\object_detection\images.

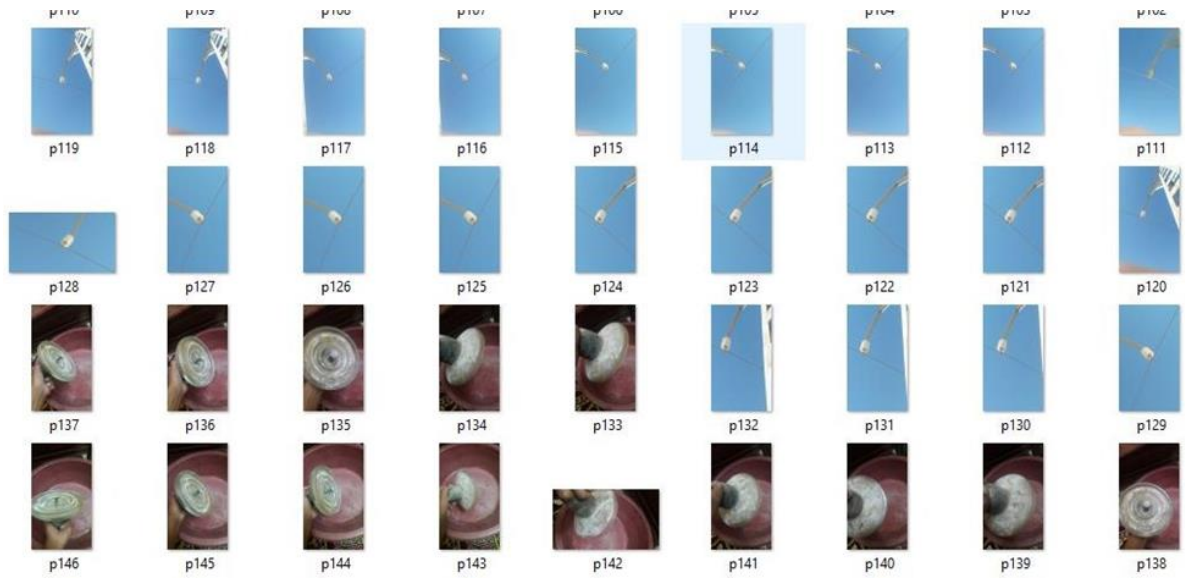


Figure III-1 Crossarm insulators Samples of Gathered Photos

We managed to gather more than 400 images.

III.3.2 2nd Step: Labeling Images in the Database

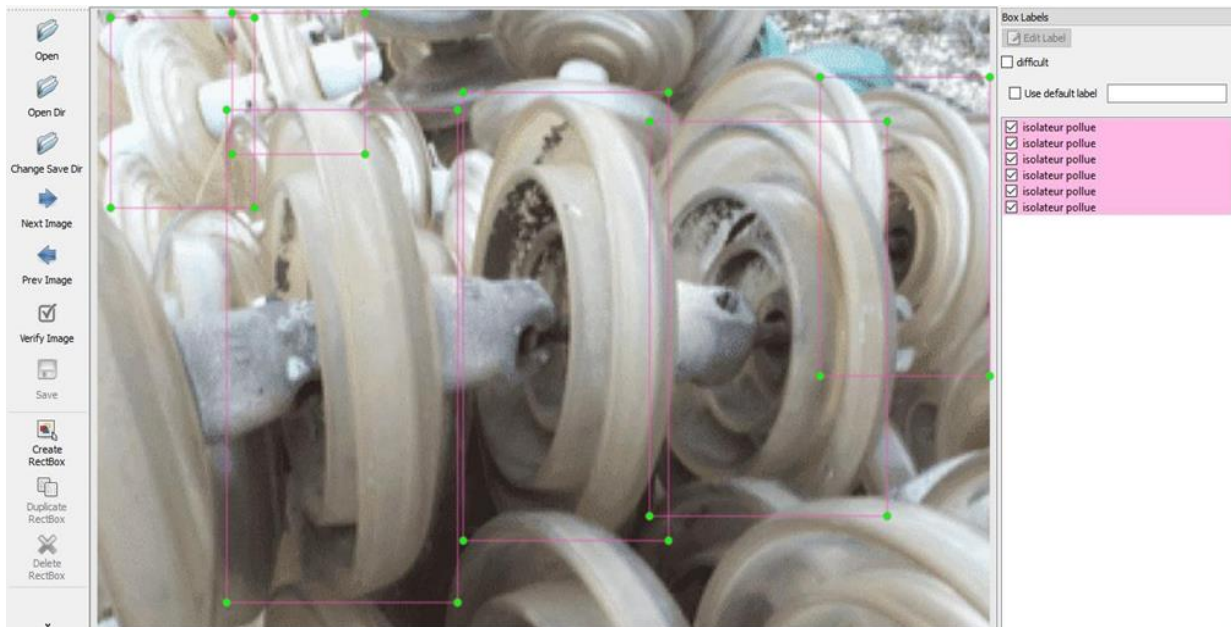
In this step, we use a program called Labellmg (Figure III.2) to label the images. We select the insulator and also its surface condition (clean, polluted) (Figure III.3).



Figure III-2 Labellmg Program



a- Clean Insulator



b- Polluted Insulator

Figure III-3 Selecting Insulators and Labeling Them

After labeling, the files are saved in .xml format in the folders created at C:\project\models\research\object_detection\images

III.3.3 3rd Step: Generating Training Data

III.3.3.1 *Converting the Database from .xml to .csv*

To convert the images saved in the folders (test and train) from xml format to csv format, we develop a code program in Python (Figure III.4):

```
import os
import glob
import pandas as pd
import xml.etree.ElementTree as ET

def xml_to_csv(path):
    xml_list = []
    for xml_file in glob.glob(path + '/*.xml'):
        tree = ET.parse(xml_file)
        root = tree.getroot()
        for member in root.findall('object'):
            value = (root.find('filename').text,
                    int(root.find('size')[0].text),
                    int(root.find('size')[1].text),
                    member[0].text,
                    int(member[4][0].text),
                    int(member[4][1].text),
                    int(member[4][2].text),
                    int(member[4][3].text)
                    )
            xml_list.append(value)
    column_name = ['filename', 'width', 'height', 'class', 'xmin', 'ymin', 'xmax', 'ymax']
    xml_df = pd.DataFrame(xml_list, columns=column_name)
    return xml_df

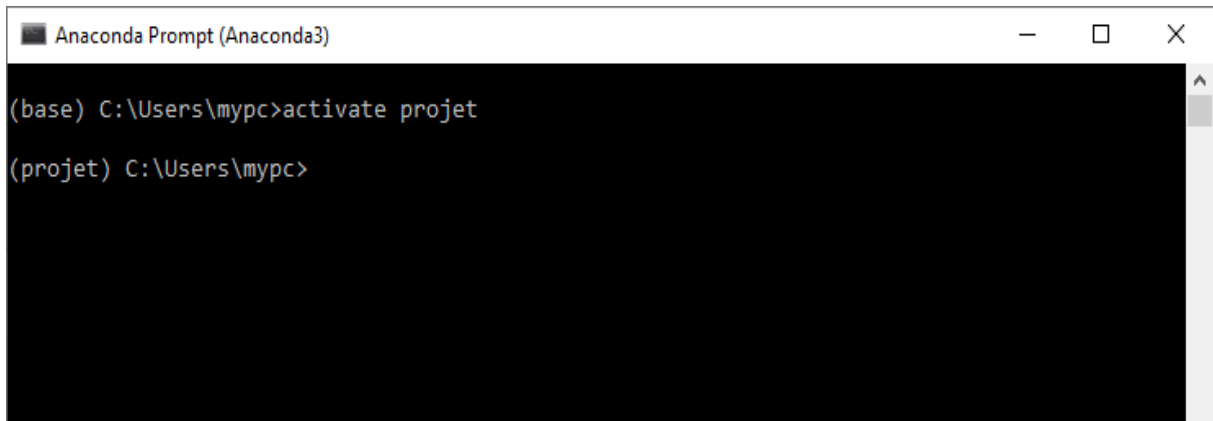
def main():
    for folder in ['train', 'test']:
        image_path = os.path.join(os.getcwd(), ('images/' + folder))
        xml_df = xml_to_csv(image_path)
        xml_df.to_csv(('images/' + folder + '_labels.csv'), index=None)
        print('Successfully converted xml to csv.')

main()
```

Figure III-4 Code for Converting from XML to CSV

1) Activation de l'environnement du projet de détection des isolateurs et de leurs états de surface:

The activation of our project's environment is done in the Anaconda environment using the command prompt.

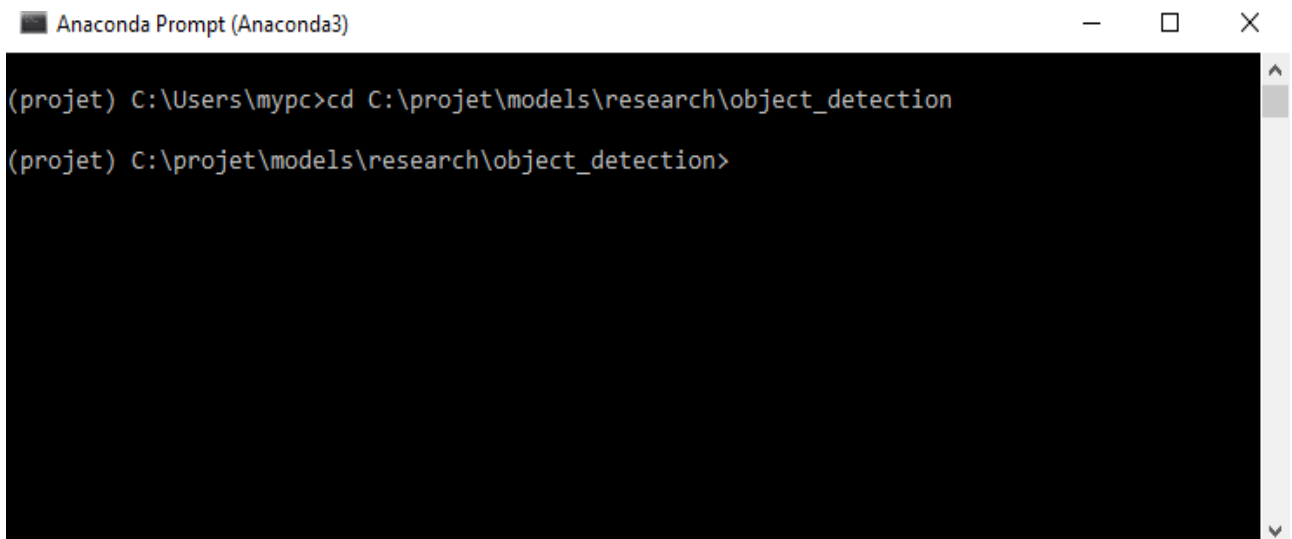


```
Anaconda Prompt (Anaconda3)
(base) C:\Users\mypc>activate projet
(projet) C:\Users\mypc>
```

Figure III-5 Activation of the Insulator Detection and Surface Condition Detection Environment.

2) Préparation du dossier de travail:

The object_detection folder is the working directory of our model. Access to the object_detection folder is done using the command presented in the figure below.

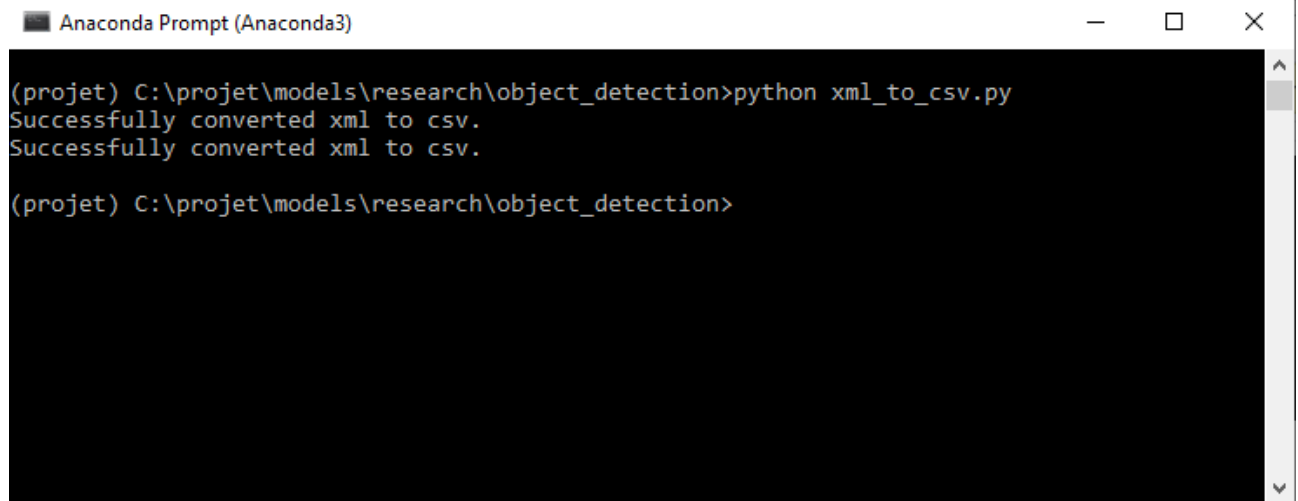


```
Anaconda Prompt (Anaconda3)
(projet) C:\Users\mypc>cd C:\projet\models\research\object_detection
(projet) C:\projet\models\research\object_detection>
```

Figure III-6 Transition to the object_detection folder

3) Conversion des fichiers .xml en .csv:

Finally, we convert .xml files to .csv using the following command

The image shows a terminal window titled "Anaconda Prompt (Anaconda3)". The prompt is at the directory "C:\projet\models\research\object_detection". The user has run the command "python xml_to_csv.py", and the output shows two lines of "Successfully converted xml to csv." followed by a new prompt.

```
Anaconda Prompt (Anaconda3)
(projet) C:\projet\models\research\object_detection>python xml_to_csv.py
Successfully converted xml to csv.
Successfully converted xml to csv.

(projet) C:\projet\models\research\object_detection>
```

Figure III-7 Conversion from .xml to .csv

Finally, two files are created named `test_labels` and `train_labels` in `C:\project\models\research\object_detection\images`.

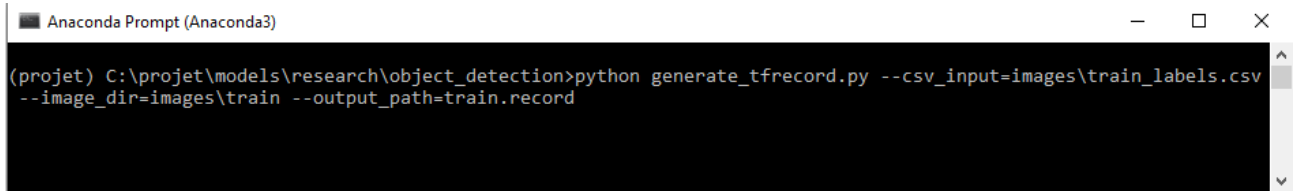
III.3.3.2 *Generating Object Indexes*

We adopted a sub-program called `generate_tfrecord.py` [47] (Figure III.8), to assign numbers to the objects. The objects in our work are clean insulators and polluted insulators. These numbers will be used in training the model. We assigned the number 1 for clean insulators and the number 2 for polluted insulators.

```
# TO-DO replace this with label map
def class_text_to_int(row_label):
    if row_label == 'isolateur propre':
        return 1
    elif row_label == 'isolateur pollue':
        return 2
    else:
        None
```

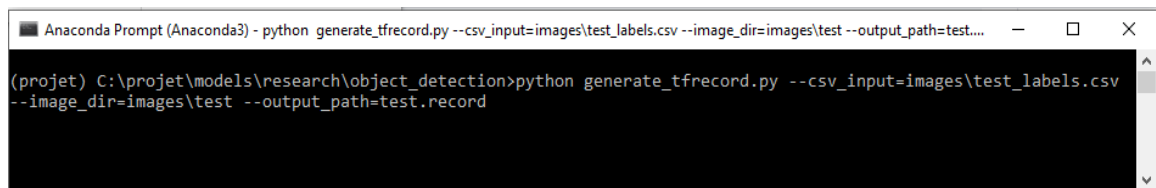
Figure III-8 Object Indexing

We will create TF Record files by executing the program code `generate_tfrecord.py` in Anaconda. This code is executed by the following command.



```
Anaconda Prompt (Anaconda3)
(projet) C:\projet\models\research\object_detection>python generate_tfreord.py --csv_input=images\train_labels.csv
--image_dir=images\train --output_path=train.record
```

a- Create train.record file



```
Anaconda Prompt (Anaconda3) - python generate_tfreord.py --csv_input=images\test_labels.csv --image_dir=images\test --output_path=test...
(projet) C:\projet\models\research\object_detection>python generate_tfreord.py --csv_input=images\test_labels.csv
--image_dir=images\test --output_path=test.record
```

b- Create test.record file.

Figure III-9 Creating TF Record Files

After this step, we create two files: train.record and test.record.

III.3.4 4th Step: Creating a Label Map

In this step, we create a labelmap.pbtxt file for labeling objects

```
        } item |
        id: 1
    'name: 'isolateur propre
    {

        } item
        id: 2
    'name: 'isolateur pollue
    {
```

Figure III-10 labelmap.pbtxt File

III.3.5 5th Step: Training Configuration

This step is the final one before training. In this step, we gather all the previously mentioned files using the program `faster_rcnn_inception_v2_pets.config` [48] as follows:

- Object classification (Figure III.11.): Dividing objects into two different classes. In our work, there are two classes of objects: clean insulator and polluted insulator num_classes .

```
model {
  faster_rcnn {
    num_classes: 2
    image_resizer {
```

Figure III-11 Classification of Files

- Configuration of the fine_tune_checkpoint file in the training folder.
- Configuration of the input_path and label_map_path files.
- Configuration of the evaluation dataset using the train_input_reader file

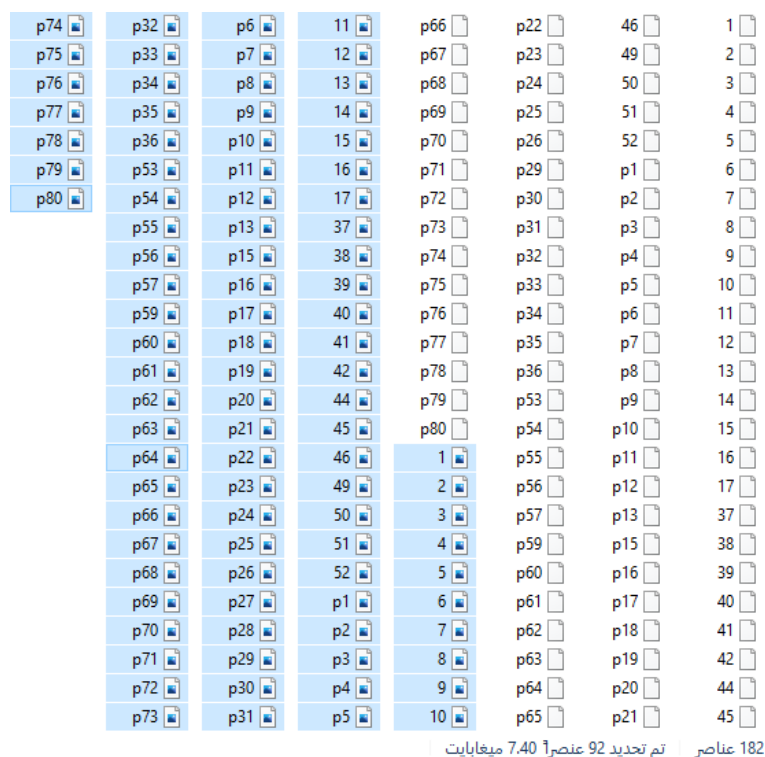
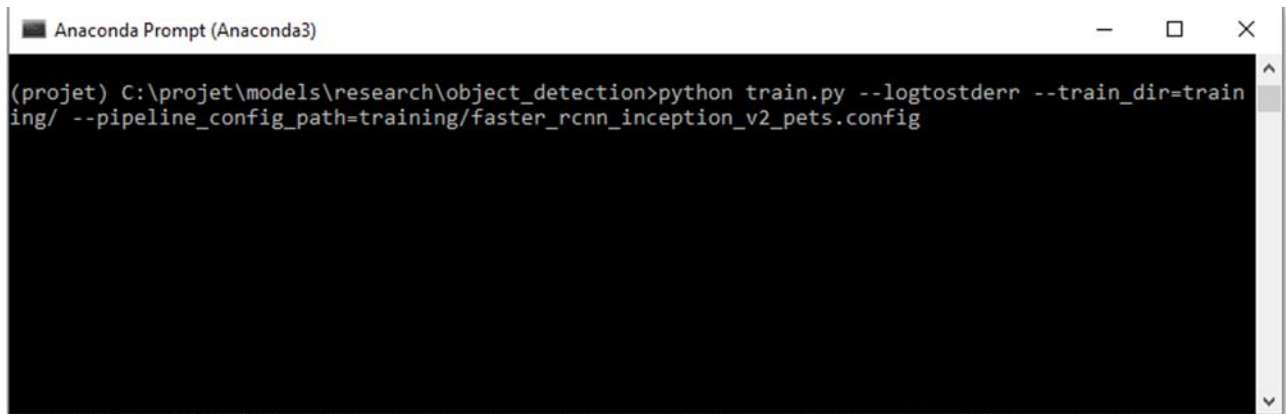


Figure III-12 Test Folder Configuration

III.3.6 Training Execution

Now, the real work begins. The computer will learn from the dataset and create a neural network. Since we are modeling the training on a CPU (processor) version, it will take several days to achieve good results.

Training execution is done using the following command in Anaconda:

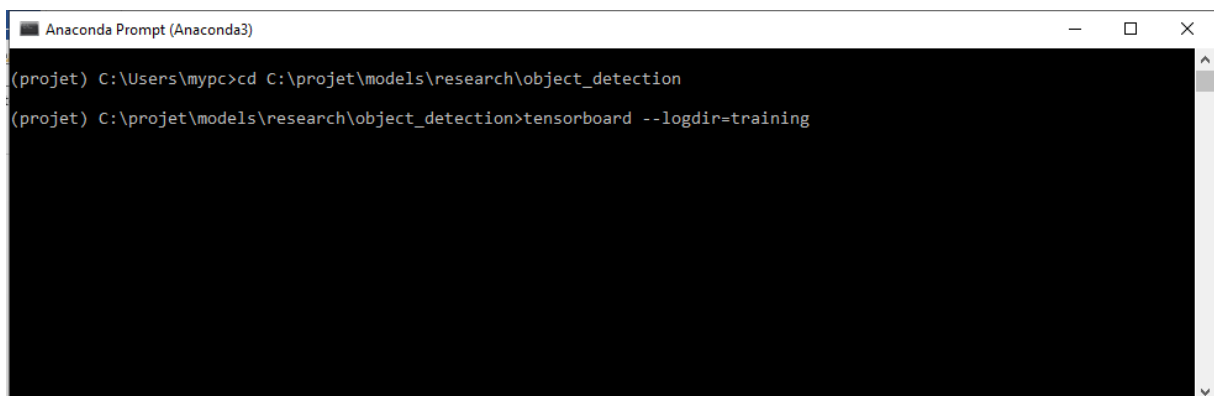


```
Anaconda Prompt (Anaconda3)
(proj) C:\projet\models\research\object_detection>python train.py --logtostderr --train_dir=train
ing/ --pipeline_config_path=training/faster_rcnn_inception_v2_pets.config
```

Figure III-13 Training Execution

Loss is another very important parameter in our work that gives us the instantaneous evolution of the divergence between the estimated value and the actual value. Loss is a set of loss functions for classification, designed to determine the decision boundary as far as possible from each learning example, in order to maximize the margin between examples and the boundary. Lclasses is generally a "log-loss". Log-loss is often more interesting than simple accuracy because it allows us to understand how close our prediction is to the actual value. We monitor the maximum margins (losses) of training using TensorBoard. We control the training evaluation by following the steps described below:

- Open a new Anaconda environment.
- Activate the project environment.
- Select the object_detection folder.



```
Anaconda Prompt (Anaconda3)
(proj) C:\Users\mypc>cd C:\projet\models\research\object_detection
(proj) C:\projet\models\research\object_detection>tensorboard --logdir=training
```

Figure III-14 Monitoring Training Evaluation

After copying the link and pasting it into the web browser;

While tracking the loss curve, we observed 7 steps as examples, where the loss decreased as the subsequent steps progressed:

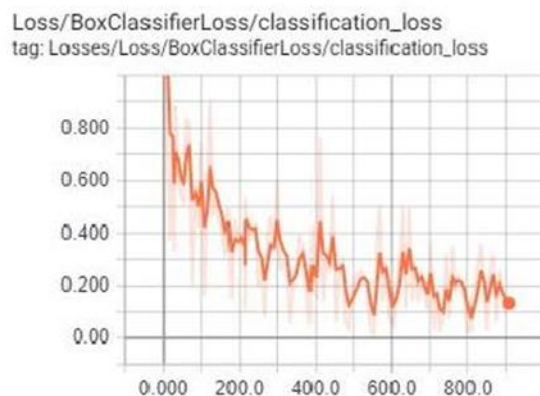
- The lowest value reached by the loss at step 120 is: 0.45
- The lowest value reached by the loss at step 550 is: 0.2
- The lowest value reached by the loss at step 910 is: 0.1
- Loss stability at a value of 0.1 in step 1430
- The lowest value reached by the loss at step 4021 is: 0.08
- The lowest value reached by the loss at step 5000 is: 0.03
- The lowest value reached by the loss at step 10270 is: 0.0089



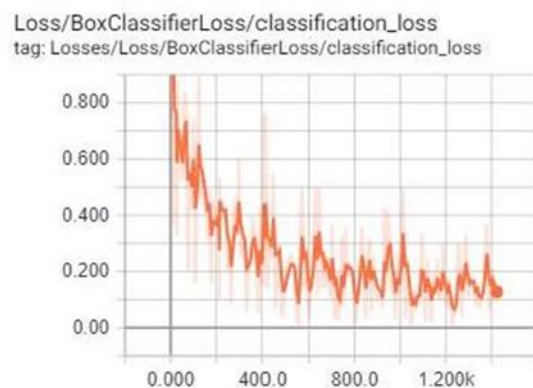
a. step 120



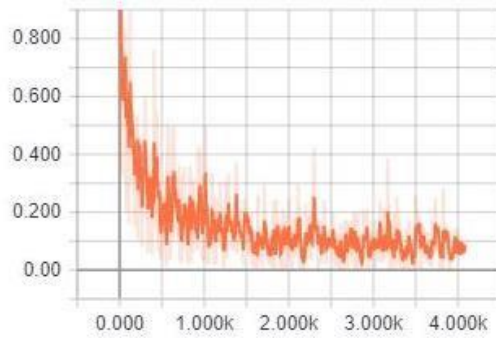
b. Step 550



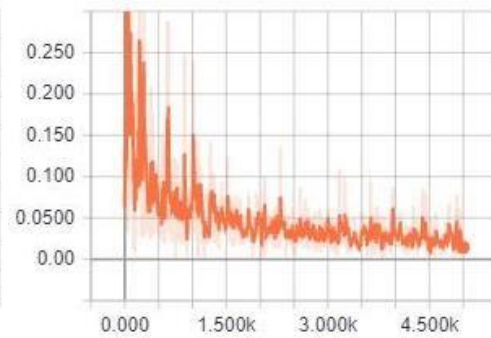
c. Step 910



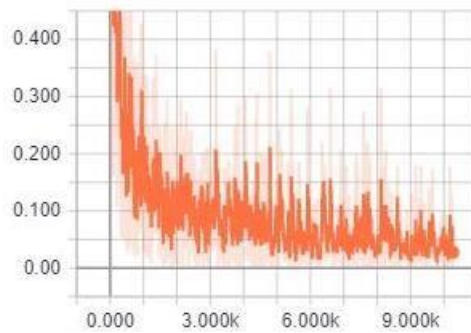
d. step 1430



e. Step 4021



f. step 5000



g. step 10270

Figure III-15 Loss Curves

After 10,270 steps, where the loss equals 0.0089, it becomes sufficient for the model to produce accurate results. Now, we can stop the training .

```
Anaconda Prompt (Anaconda3)
INFO:tensorflow:global step 10262: loss = 0.0558 (21.013 sec/step)
INFO:tensorflow:global step 10263: loss = 0.0089 (14.844 sec/step)
INFO:tensorflow:global step 10263: loss = 0.0089 (14.844 sec/step)
INFO:tensorflow:global step 10264: loss = 0.0254 (13.790 sec/step)
INFO:tensorflow:global step 10264: loss = 0.0254 (13.790 sec/step)
INFO:tensorflow:global step 10265: loss = 0.0196 (19.294 sec/step)
INFO:tensorflow:global step 10265: loss = 0.0196 (19.294 sec/step)
INFO:tensorflow:Recording summary at step 10265.
INFO:tensorflow:Recording summary at step 10265.
INFO:tensorflow:global step 10266: loss = 0.0582 (24.351 sec/step)
INFO:tensorflow:global step 10266: loss = 0.0582 (24.351 sec/step)
INFO:tensorflow:global step 10267: loss = 0.0708 (25.274 sec/step)
INFO:tensorflow:global step 10267: loss = 0.0708 (25.274 sec/step)
INFO:tensorflow:global step 10268: loss = 0.0591 (21.742 sec/step)
INFO:tensorflow:global step 10268: loss = 0.0591 (21.742 sec/step)
INFO:tensorflow:global step 10269: loss = 0.0139 (15.208 sec/step)
INFO:tensorflow:global step 10269: loss = 0.0139 (15.208 sec/step)
INFO:tensorflow:global step 10270: loss = 0.0354 (16.928 sec/step)
INFO:tensorflow:global step 10270: loss = 0.0354 (16.928 sec/step)
INFO:tensorflow:Saving checkpoint to path training/model.ckpt
INFO:tensorflow:Saving checkpoint to path training/model.ckpt
INFO:tensorflow:Recording summary at step 10270.
INFO:tensorflow:Recording summary at step 10270.
INFO:tensorflow:global step 10271: loss = 0.0845 (22.877 sec/step)
INFO:tensorflow:global step 10271: loss = 0.0845 (22.877 sec/step)
INFO:tensorflow:global step 10272: loss = 0.0163 (18.347 sec/step)
INFO:tensorflow:global step 10272: loss = 0.0163 (18.347 sec/step)
Traceback (most recent call last):
  File "train.py", line 184, in <module>
    tf.app.run()
```

Figure III-16 Training Progress by Step

III.3.7 Exporting the Graph for Inference

Now that the training is complete, the final step is to create the inference graph (a .pb file). From the object detection folder of our project, we execute the command shown in Figure III.20, where the file model.ckpt-10270 has the highest number in the training folder.

```
Anaconda Prompt (Anaconda3)
(base) C:\Users\myopc>activate projet
(proj) C:\Users\myopc>cd C:\projet\models\research\object_detection
(proj) C:\projet\models\research\object_detection>python export_inference_graph.py --input_type image_tensor
--pipeline_config_path training/faster_rcnn_inception_v2_pets.config --trained_checkpoint_prefix training/model.ckpt-10270 --output_directory inference_graph
```

Figure III-17 Creating the Inference Graph

III.3.8 Diagnosing the Surface Condition of High-Voltage Insulators Using the Created Model

After all the previously adopted steps, the diagnostic model for the surface condition of high-voltage insulators is ready to determine their condition. To test the model, we follow these steps:

- Activate the environment of our project in the Anaconda space.
- Execute the "idle" command to open Python.



```
Anaconda Prompt (Anaconda3) - idle
(base) C:\Users\mypc>activate projet
(proj) C:\Users\mypc>idle
```

Figure III-18 Opening the Python Interface

Next, the Python interface opens, and we execute our model `object_detection_image.py` [49] and determine the following parameters:

1) `NUM_CLASSES`: This is the number of objects in our model, which are two objects describing the surface condition of insulators (clean insulator and polluted insulator), so `NUM_CLASSES=2`.

2) `MODEL_NAME`: This is the name of the inference graph, so `MODEL_NAME=inference_graph`.

3) `IMAGE_NAME`: These are the test images, so `IMAGE_NAME=test.jpg`.

After configuring the model parameters, we execute the Python file for detecting the surface condition of insulators.

```
*Object_detection_image.py - C:\projec\models\research\object_detection\Object_detection...
File Edit Format Run Options Window Help
# Import utilites
from utils import label_map_util
from utils import visualization_utils as vis_util

# Name of the directory containing the object detection module we're using
MODEL_NAME = 'inference_graph'
IMAGE_NAME = 'test.jpg'

# Grab path to current working directory
CWD_PATH = os.getcwd()

# Path to frozen detection graph .pb file, which contains the model that is used
# for object detection.
PATH_TO_CKPT = os.path.join(CWD_PATH,MODEL_NAME,'frozen_inference_graph.pb')

# Path to label map file
PATH_TO_LABELS = os.path.join(CWD_PATH,'training','labelmap.pbtxt')

# Path to image
PATH_TO_IMAGE = os.path.join(CWD_PATH,IMAGE_NAME)

# Number of classes the object detector can identify
NUM_CLASSES = 2
```

Figure III-19 Configuration of the Insulator Surface Condition Detection Mode

Also, you can use object_detection_video.py [50] or object_detection_webcam.py [51].

4) Presentation of the Insulator Surface Condition Results .



Figure III-20 Clean Insulators



Figure III-21 Polluted Insulators

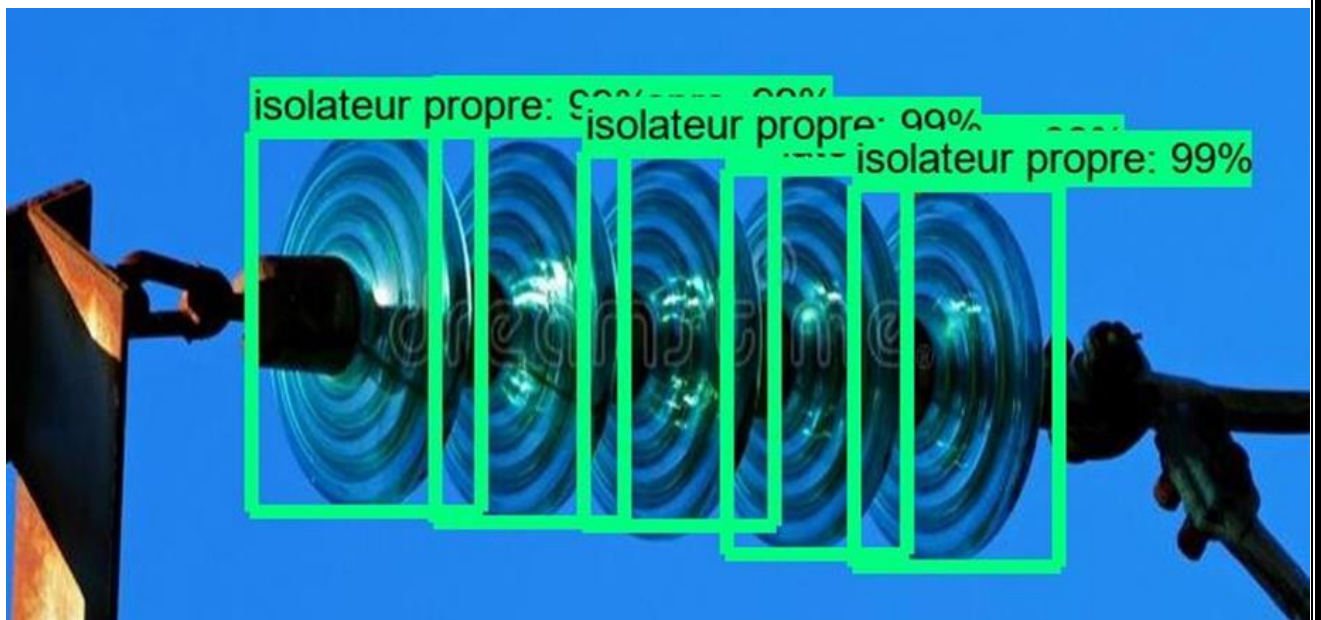


Figure III-22 Chain of Clean Insulators

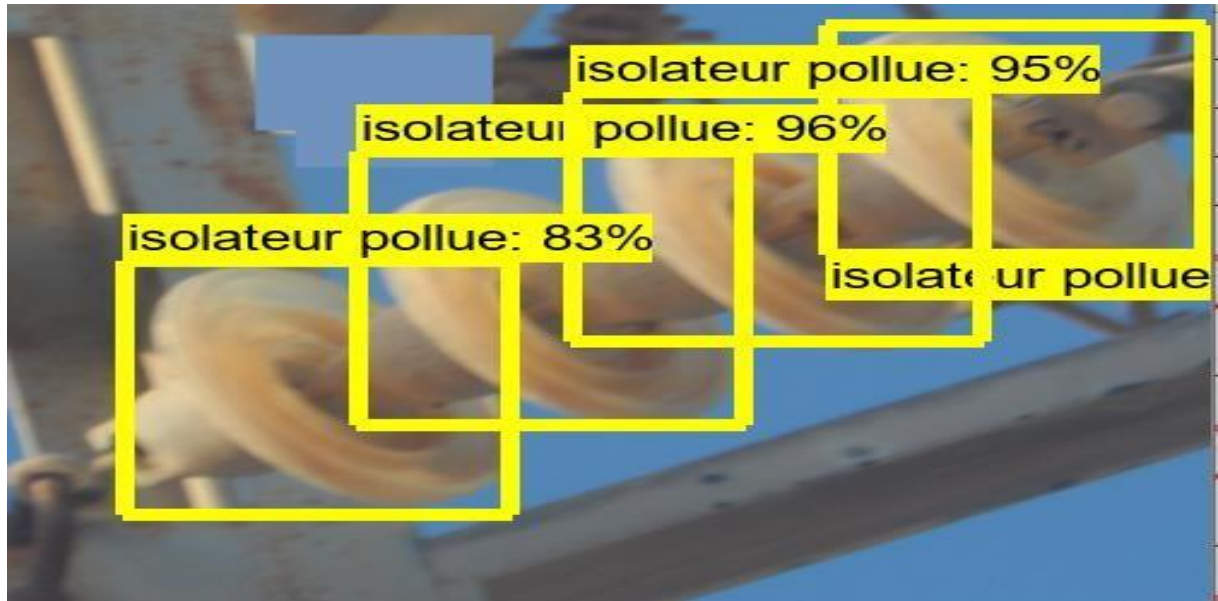


Figure III-23 Chain of Polluted Insulators

III.4 Conclusion

We have successfully developed a model for recognizing insulators using static images, an image captured by a webcam, and finally, a moving image in a video. This model allows for detecting whether the insulator is clean or polluted. Our model was trained using artificial intelligence techniques incorporated in the Tensor Flow library, programmed in Python.

The results obtained demonstrate that our model successfully detects the condition of insulators both in a chain and individually.

General Conclusion

The main objective of this work was to use artificial intelligence techniques to diagnose the surface condition of high-voltage insulators through object detection tools. The TensorFlow library was a crucial element in the realization and development of our project due to its rich variety of functions, particularly in image and video processing.

In this study, we developed a model capable of detecting insulators and determining their condition, whether clean or polluted. Our model was trained using artificial intelligence techniques incorporated in the TensorFlow library, programmed in Python. We compiled numerous images of high-voltage glass insulators in both clean and polluted states.

This method enables computers to diagnose the surface condition of insulators simply through photos, videos, or a camera. To obtain more accurate results, it is necessary to:

- Use a larger number of photos in the database.
- Use high-quality images.
- Use smaller image sizes for faster training.
- Capture all sides of the object to be detected.
- Adopt a maximum number of steps during training.

As a future perspective of our work, we hope that in upcoming final year projects, the detection and monitoring of the surface condition of high-voltage insulators can be expanded to include other types of insulators (such as ceramic insulators). Additionally, we aim to integrate our model into robots and unmanned drones to automatically control and clean the insulators.

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